Inflation and Output Dynamics: Assessing the Strength of Network Effects

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October 29, 2020

PRELIMINARY AND INCOMPLETE

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Abstract

US industries are highly intertwined through complex demand and supply chains. We use a spatial dynamic factor model to assess the strength of network effects in each industry's response to demand shocks. Our analysis relies on a rich panel data set for output, prices, wages and employment at a narrowly defined industry level. We integrate it with BEA input-output tables, trade shares, financial spreads and commodity indices to quantify and analyze the nature of industries and their concomitant strength of network spillovers.

Our empirical methodology allows us to decompose industry level responses into a direct effect and those resulting from network spillovers. Our results indicate that the US Production Sector exhibit strong network spillovers in response to a demand shock. This is particularly true for output, prices and wages where spillovers account for between 50-80% of the average industry response. In contrast, our estimates imply that the response of industry level employment is primarily due to the direct effects of aggregate fluctuations on industry activity. We also document that network spillovers are strongest in tradeable goods industries that are much farther down in the supply chain. As a result of these strong spillovers, the inflation response of tradeable goods industries to demand shocks is weaker compared to the more upstream non-tradeable industries. Effectively, tradeable goods industries exhibit greater price rigidity. Consistent with this finding, tradeable goods industries also exhibit larger fluctuations in output in response to aggregate demand shocks.

1 Introduction

In this paper, we assess the strength of network effects in explaining both industry level and aggregate fluctuations in response to aggregate demand shocks. We use a rich panel data of narrowly defined industries at NAICS 6 digit classification, to estimate a significant network propagation component in the overall contraction of the US real economy, in response to an adverse shock. We characterize the response of industrial activity, measured using employment, output, prices and wages to aggregate demand fluctuations and provide a decomposition of these responses into a *direct effect* and *effects that propagate through the production network*.

As is standard in this literature, the production network is defined through the demand and supply chains embodied in the BEA[1] input-output tables. This network structure implies a specific form of spatial correlation across industries. Our estimation methods focus on identifying the strength of this spatial correlation in propagating shocks through the network. Given the high dimensionality of this narrowly defined industry level data, a natural approach here is to apply FAVAR methods to the simultaneous equation structure implied by the network ([Gilchrist and Zakrajsek, 2019]). Such methods allow one to provide a decomposition of reduced form responses into their associated direct and network effects. To allow for the possibility that the strength of these network spillovers varies with both the time horizon and the variable of interest, we adapt these methods to a local projection setting. The use of local projections in combination with the factor structure allows us to provide both the reduced form response of industry activity, as well as a structural decomposition of this response into direct effects and network effects at any given horizon.

To identify fluctuations in aggregate demand, we consider shocks emanating from the financial sector. Specifically, we identify fluctuations in credit spreads and other financial indicators that are orthogonal to contemporaneous and lagged movements in the macro factors that best characterize fluctuations in industry activity through their factor loadings. As we demonstrate in the paper, shocks to credit conditions imply contractions in growth of aggregate output, aggregate employment, prices and wages. These are best characterized as reflective of adverse aggregate demand conditions.

A tightening of credit conditions leads to an immediate drop in aggregate output and a delayed response of inflation. This pattern is broadly true across industries. However, our reduced form estimates also imply considerable heterogeneity in industry level responses. As we document in the paper, a significant fraction of this heterogeneous response can be traced back to the strength of spillovers implied by the network structure. These network spillovers are strongest for output and wages, and weakest for employment. Inflation exhibits moderate sensitivity to the network channel. Although responses of these variables differ according to the time horizon, the share of the network component is relatively constant over time.

Our estimation results also imply greater contractions in output but more muted response of inflation for the downstream industries to the shocks. This finding follows directly from the network structure of the model. Earlier research by [Gilchrist and Zakrajsek, 2019] documents a similar pattern of response in industries with a high tradeable good share relative to industries with a low tradeable good share. In this paper, we show that this stronger response of output and the weaker response of inflation in high tradeable goods industries can be explained by their position in the production network. In particular, goods with a high tradeable share are predominantly downstream industries. These findings have implications for the degree to which monetary non-neutralities influence aggregate fluctuations depending on the predominance of downstream industries in

[1] Bureau of Economic Analysis

the production activities.

Our baseline estimates restrict network effects to propagate within but not across variables. This is done for the sake of parsimony. We consider two relaxations of this assumption. We first confine our attention to a simplified environment that focuses only on inflation-output dynamics. We then extend our econometric framework to allow for two-way feedback between output growth and inflation through the network. These estimate no network spillovers from inflation to output, but do identify an attenuation in inflation dynamics through the cross effects of fluctuation in output through the network. Nonetheless, these cross effects leave our broad conclusions regarding the strength of network effects unchanged. In the second exercise, we again consider an econometric model with all four variables, but confine cross-variable network spillovers to work through fluctuations in industry level marginal costs. Such cross-variable spillovers are estimated to be insignificant and therefore again do not alter our broad conclusions.

To complete our analysis of assessing the strength of network effects, we propose a New Keynesian Phillips Curve Model, with a continuum of industries and interaction among them through intermediate input use. We analyze our empirical estimation through the lens of this model to isolate the importance of each of the key parameters for the observed network propagation effects. Our empirical investigation provides a natural basis to calibrate the parameters for such network effects model proposed in the recent literature by a number of papers ([Pasten et al., 2017], [Rubbo, 2020]).

2 Empirical Estimation of Network Effects

We start by proposing a simple factor augment spatial simultaneous panel data model to estimate the reduced form impulse responses for each of our industry variables to financial and cost shocks. Then, we modify the model to also estimate the strength of network effects among industries through the input-output inter-linkages. The two baseline models are summarized in the following sections 2.1 and 2.2.

2.1 Demand Shock - Reduced Form Model

In this section, we formulate a reduced form panel data model, to estimate the idiosyncratic impulse responses of price and wage inflation and growth of output and employment for each of the 124 (NAICS 6) industries in our sample from 1992:Q1 - 2018:Q1, in response to financial shocks. We start with a Jorda style specification of our model to trace out the effect of a financial shock measured using shocks to the *excess bond premium* (EBP) à la [Gilchrist et al., 2016] over 12 quarters (3 years). Given the high dimensionality of our industry level data, we use factor analysis to identify aggregate shocks and then estimate their idiosyncratic effect on each of the variables at the industry level. Since a shock to EBP at time t can also have implications on the subsequent path of EBP, we also incorporate the h quarter changes in EBP as observed factor in our regressions orthogonalized to each of the unobserved factors. The main reduced form panel regression model can be summarized in two steps. First, we consider the reduced form responses for each of the industry-variable pair i at a horizon h, in response to the observed ($E^{(h)}$) and unobserved ($F^{(h)}$) time series factors for that horizon.

$$\text{Let,} \quad \Delta_h Y_{i,t} \equiv Y_{i,t+h} - Y_{i,t-1}, \forall h = 0, 1, ..., 11 \quad \text{then,}$$

$$\Delta_h Y_{i,t} = \alpha_0 + \sum_{l=1}^{l=4} \alpha_l \Delta_0 Y_{i,t-l} + \sum_{r=1}^{R} \lambda_{i,r} F_{r,t}^{(h)} + \gamma_i E_t^{(h)} + \epsilon_{it} \ , \tag{1}$$

$$\text{where} \quad E_t^{(h)} := \quad \Delta_h EBP_t = a_0 + \sum_{r=1}^{R} \theta_r F_{r,t}^{(h)} + E_t^{(h)} \tag{2}$$

is the orthogonalized observed factor estimated as residuals from the regression (2) of h horizon change in EBP on the R unobserved factors which were estimated using principal component analysis. In order to consider growth rates, $Y_{i,t}$ denotes the stacked log values of our 4 variables: industrial production index, producer price index, wages and employment respectively. Consequently, R common unobserved factors denote common aggregate shocks across all the variables of interest even though the factor loading are different[2]. In order to get clarity, think of the i dimension being $N * V$, where N is the number of industries (124 in our case) and V is the number of variables (4 in our case).

Second, we estimate the impulse response of each of these factors (both observed and unobserved) for a shock to EBP at time t. This is summarized as follows,

$$\begin{bmatrix} F_{1,t}^{(h)} & ... & F_{R,t}^{(h)} & E_t^{(h)} \end{bmatrix} = \begin{bmatrix} \beta_1 & ... & \beta_R & \beta_{R+1} \end{bmatrix} \times \nu_t + e_t \quad \text{where} \tag{3}$$

$$\nu_t := \quad EBP_t = \hat{a}_0 + \sum_{l=1}^{4} \psi_l EBP_{t-l} + \sum_{l=1}^{4} \xi_{l,r} F_{t-l}^{(0)} + \nu_t \tag{4}$$

is the shock to EBP after removing 4 lagged values of EBP and purging off any effect due to aggregate shocks in the previous 4 quarters summarized by the lagged values of $F^{(0)}$. The reduced form estimate for the response of each industry-variable to a financial shock can then be calculated as follows

$$IRF_i^{(h)} = \begin{bmatrix} \lambda_{i,1} & ... & \lambda_{i,R} & \gamma_i \end{bmatrix}_{NV*(R+1)} * \begin{bmatrix} \beta_1 \\ ... \\ \beta_R \\ \beta_{R+1} \end{bmatrix}_{(R+1)*1} \tag{5}$$

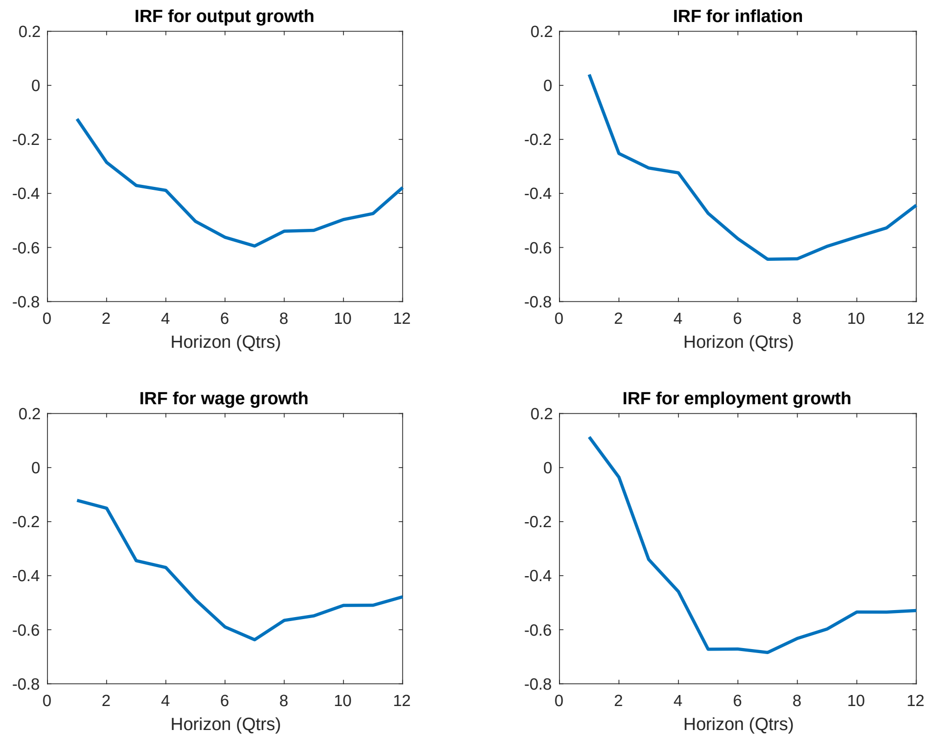
The corresponding impulse responses are then aggregated using employment share weighted sums across each industry and for each variable (v) to quantify the average aggregate effect of financial shocks on each of the variables over 12 quarters. The following figure summarizes the weighted mean impulse responses for the reduced form model where

$$IRF_v^{(h)} = \sum_{j=1}^{N} IRF_i^{(h)}|_v * \frac{Emp_j}{\sum_{n=1}^{N} Emp_n} \tag{6}$$

The horizon is on the x-axis, and each of the variables (output growth, inflation. wage growth and employment growth) is the respective subplot. The y-axis is the corresponding $IRF_v^(h)$ value as described above. An increase in EBP represents a broad-based tightening of financial conditions and it is clearly contractionary. The industry employment share weighted mean impulse responses for output growth and employment growth show a substantial decline. For one standard deviation shock to EBP ($\approx$ 30 bps), annualized growth

[2] To maintain consistency, each of the variables are demeaned (to avoid accounting for constants in the regressions every time) and standardized by their aggregate variable specific median standard deviation value to ensure comparability across variables

Figure 1: Reduced form impulse responses to a financial shock



in output declines by 1.2 pp while employment growth declines by 0.8 pp. At the same time wage growth and inflation are dampened by 0.4 pp and 1 pp respectively[3]. The effects peak at roughly 6-8 quarters, and inflation decline with a lag. The combination of decline in all the 4 variables implies that the deterioration in broad domestic financial conditions delivers a response that is consistent with a reduction in aggregate demand within a New Keynesian Framework.

2.2 Demand Shock - Network Effects Model

Now that we have analyzed the reduced form model in the previous section, we next consider the importance of network effects across industries for different horizons. In particular, we decompose the *direct effect* of the financial shock versus it's *network propagation effect* due to inter-twining of the industries via demand and supply chains.

Weighting Matrix of Industry Inter-Linkages

The primary measure for inter-linkages among industries comes from the BEA Input-Output tables. We follow [Ozdagli and Weber, 2020] in estimating the network structure of dollar trade flows between all the industries in our sample. The BEA input-output tables consist of 2 basic national accounting tables collected using Census Data every 5 years. (1) The 'Make' (M) table shows the production of commodities by industries and (2) The 'Use' (U) table documents the uses of commodities by intermediate and final users. We use the average value of the tables from 2007 and 2012, most closely aligned with our time series duration. We follow the following steps in estimating a row-normalized weighting matrix W.

[3]This accounts for the standardization of each of the variables by appropriately re scaling the regression coefficients

1. We estimate the share of industry i in production of commodity j,

$$S_{ij} = \frac{M_{ij}}{\sum_i M_{ij}} = \frac{\text{Value of i's production of j}}{\text{Total production of j}}$$

2. Then we find the total dollar amount industry i sells to industry j,

$$R_{ij} = \sum_c S_{ic} * U_{c,j} = S_i * U_j$$

3. Next, we find the fraction of industry j's output that is purchased from industry i ,

$$SupShr_{ij} = \frac{R_{ij}}{\sum_i R_{ij}} = \frac{\text{Total dollar amount } i \text{ sells to } j}{\text{Total dollar amount purchased by } j}$$

4. Finally the weighting matrix is the transpose of supply share matrix,

$$W = SupShr'$$

   with rows summing to one. It has an output-input structure, meaning that the values of the weighting matrix W_{ij} gives the amount of demand industry i gets from industry j. Thus each industry j is the downstream firm for industry i when analyzing financial shocks. When the economy faces a broad based contractionary financial shock, it affects the final consumers of industry i directly, but also affects the final consumers in other industries (j) which spills over as industry j changes it's demand for intermediate inputs from industry i.

Simultaneous Spatial Factor Augmented Panel Data Model

We allow for the network structure of dollar trade flows between all industries in our panel data model using simultaneous spatial feedback among industries through the weighting matrix structure outlined above. This network model algorithm is closely related to the one proposed by [Lu, 2017]. Again, due to the high dimensionality of the data, we augment the model with factor analysis to identify aggregate shocks and then estimate the idiosyncratic factor loadings of each industry on the estimated factors. The network structure panel model can also be summarized using two steps, albeit with the addition of quasi-likelihood maximization to estimate the strength of network spillovers. In step one, we estimate three things: (a) the unobserved factors, $F^{(h)}$, and the orthogonalized observed factor, $E^{(h)}$, as before, (b) the factor loadings or response of each industry-variable pair i at horizon h to the factors, and (c) the network effects for each variable $\rho_v^{(h)}$, over different horizons.

$$\text{Let,} \quad \Delta_h Y_{i,t} \equiv Y_{i,t+h} - Y_{i,t-1}, \forall h = 0, .., 11, \quad \rho = [\rho_1, \rho_2, \rho_3, \rho_4]' \otimes \mathbf{1}_{N\times 1} \quad \text{then,}$$

$$\Delta_h Y_{i,t} = \alpha_0 + \rho \sum_{j=1}^{N} W_{ij} \Delta_h Y_{j,t} + \sum_{l=1}^{l=4} \alpha_l \Delta_0 Y_{i,t-l} + \sum_{r=1}^{R} \lambda_{i,r} F_{r,t}^{(h)} + \gamma_i E_t^{(h)} + \epsilon_{it} \ , \tag{7}$$

$$\text{where} \quad E_t^{(h)} := \quad \Delta_h EBP_t = a_0 + \sum_{r=1}^{R} \theta_r F_{r,t}^{(h)} + E_t^{(h)} \tag{8}$$

We estimate 6 unobserved factors, using singular value decomposition, and the observed factor captures the h horizon changes in the EBP orthogonalized to each of the unobserved factors. While all the factor loadings are estimated using factor loadings in a principal component analysis; the estimation of ρ is based on quasi-likelihood maximization using a grid search from 0 to 1, and iterating until convergence. Since the optimization problem is concave in each of the ρ_v variables, we converge on each of the four ρ values one by one, while fixing the others at some initialization value. The quasi-likelihood objective function $L^{(h)}$, for optimizing over network effects for each variable $\rho_v^{(h)}$ is summarized below. Let k denote the iteration step, then we use the results from kth iteration to update for the $k+1$'th terms with ρ updated using grid search maximization in each iteration. The algorithm converges in ρ values as factors and other regression coefficients get appropriately updated.

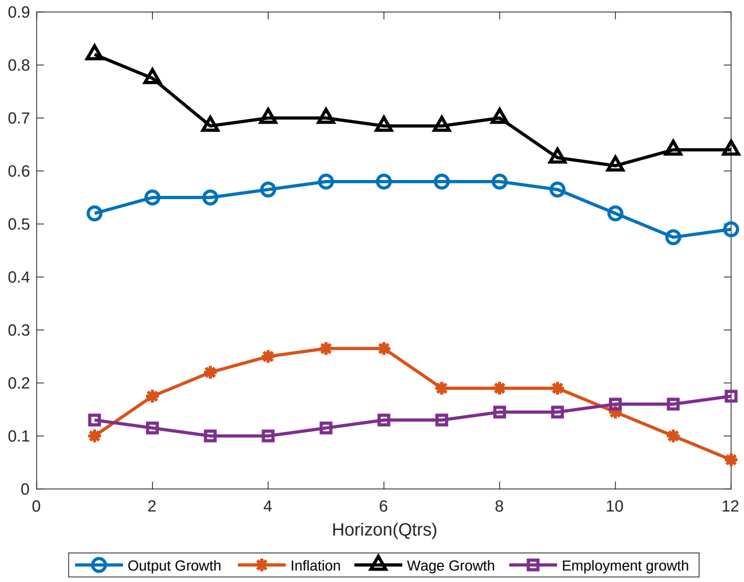
$$\text{Let,}\quad \underbrace{B_t^{(h)}}_{(k+1)} \equiv \left(\Delta_h Y_{i,t} - \underbrace{\rho}_{k+1} \sum_{j=1}^{N} W_{ij} \Delta_h Y_{j,t} - \sum_{l=1}^{l=4} \alpha_l \Delta_0 Y_{i,t-l} - \sum_{r=1}^{R} \lambda_{i,r} F_{r,t}^{(h)} - \gamma_i E_t^{(h)} \right)$$

$$\text{and,}\quad \underbrace{\Sigma_\epsilon}_{(k)} = \underbrace{B_t^{(h)\prime}}_{(k)} \underbrace{B_t^{(h)}}_{(k)}, \quad \text{then,}$$

$$L^h = \max_{\rho} \; \frac{-1}{2NT} \sum_{t=1}^{T} \underbrace{B_t^{(h)\prime}(\rho)}_{(k+1)} \underbrace{\Sigma_\epsilon^{-1}}_{(k)} \underbrace{B_t^{(h)\prime}(\rho)}_{(k+1)} - \frac{1}{2N} \log(|\underbrace{\Sigma_\epsilon(\rho)}_{(k+1)}|) + \frac{1}{N} \log(\mathbf{I} - \rho \otimes W) \tag{9}$$

The estimated network effects coefficient ρ for each variable across different horizons, is summarized in figure 2. Output and wage growth have very strong network spillovers

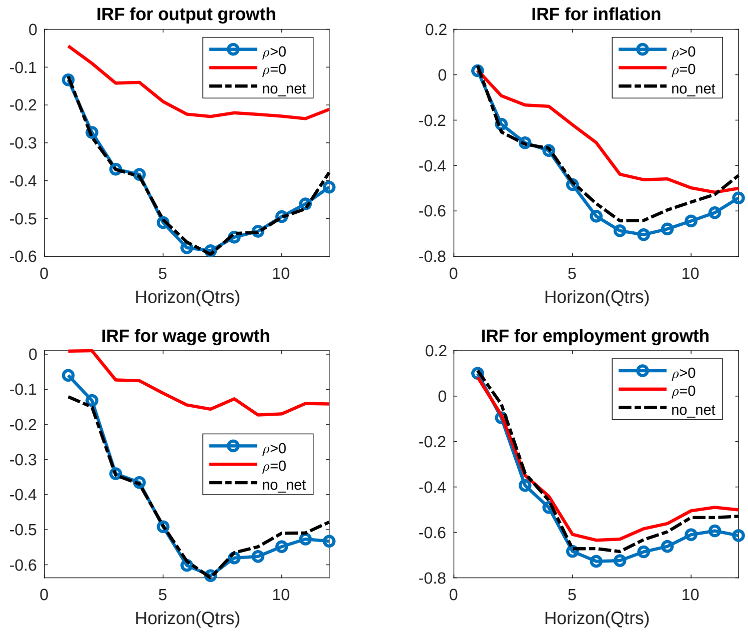
Figure 2: Network Effects Coefficient $\rho_v^{(h)}$



coefficient of 0.5 and 0.75 respectively, and the network effects are persistently strong over three years. Inflation has very small value of ρ in the first quarter at 0.1, but the network effects get stronger to 0.3 over six quarters after which they are dampened and almost negligible by the end of three years. Employment growth has persistently weak network effects in the range of 0.1-0.2 suggesting less inter-twining of labor changes across industries in response to any financial shock.

The structure of the financial shock is the same as that for the reduced form, where we consider shocks to EBP at time t, after controlling for the effects from contemporaneous unobserved factors and 4 quarter lags of EBP. We use the steps from equations 3 to 6 as before for the second part of the networks model estimation; except now the factor structure and regression estimation from the first step also allows for simultaneous spatial feedback between industries via the ρ parameter. The estimated impulse responses are summarized in the following figure 3.

Figure 3: Network Effects impulse responses to a financial shock



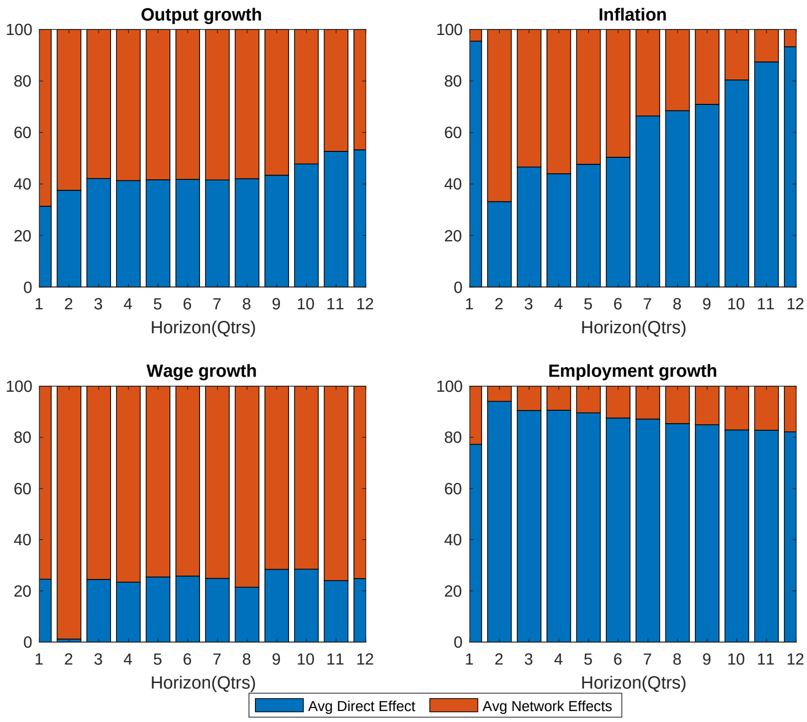
There are two main conclusions that can be drawn from figure 3. First, shutting down the simultaneous spacial feedback in the model with factor structure based on networks attenuates the response of all the variables to a broad-based financial shock. The solid blue lines (with o markers) in the figure show the IRF for positive values of ρ (as estimated in figure 2), that is allowing for feedback among industries through their trade flows. In the same model, if we impose that $\rho = 0$, the propagation factor $= (\mathbf{I} - \rho \otimes W)^{-1})$ denoted by the appropriate Leontief matrix using I-O tables is muted and only the *direct effect* remains as shown by the red solid lines. Just like the conclusion from figure 2, note that employment growth has least network spillover effects, while output growth and wage growth show the highest simultaneous spatial feedback among industries in response to an EBP shock.

Second, we find that the reduced form and the networks model have the same impulse response (blue solid line with o markers versus black dashed lines from figure 1). This is rightly so, because the networks model simply works like a rotations of the four growth variables. If we consider the networks model step one regression equation 7, and re-write it in long form collecting all the $\Delta_h Y$ terms on the left hand side, it becomes equivalent to the reduced form equation with all the coefficients appropriately rescaled by the Leontief inverse matrix, $(\mathbf{I} - \rho \otimes W)^{-1})$. Thus, the overall quantitative values of employment weighted impulse responses for each of the variables are same as that of the reduced form. This networks model provides a succinct decomposition for the significant role played by the inter-twining among industries versus the direct impact of the financial shock to an industry from its' final consumers as shown in figure 3.

Decomposition of Direct Versus Network Effects

The overall Network Model impulse response can be decomposed into *direct effect* defined as response of industries on impact, and the *network effect* defined as all the higher order terms in the simultaneous feedback mechanism. For our networks model, we get an $IRF_i^{(h)}$ defined in equation 5, for each of our industry-variable pair i in response to a financial shock at each horizon h. In the model with networks, this captures only the direct effect of the financial shock on impact (i.e. the red lines in figure 3). However this initial shock from the final consumers affects industry i which in turn affects industry j, and feeds

Figure 4: Acemoglu (2016) decomposition of Network versus Direct Effects



back into i through the supply chain interactions. Thus, the complete effect of the financial shock is measured as $(\mathbf{I} - \rho \otimes W)^{-1}) \times IRF_i^{(h)}$. In this section, we follow [Acemoglu et al., 2016] to define the *average direct effect* as average value of the instantaneous coefficient $IRF_i^{(h)}$ across all industries and variables; and we define the *average total effect* as the average value of the sum of both instantaneous effect and all the higher order terms across industries, $(\mathbf{I} - \rho \otimes W)^{-1}) \times IRF_i^{(h)}$. *Average network effect* is then the difference between average total effect and the average direct effect, i.e. it is only the higher order terms in the spatial feedback. The corresponding values are summarized in figure 4. We find 3 main insights from this decomposition (a) Except prices, network effects are stable across different horizons for output, wages and employment; (b) The heterogeneity in response for output and wages is primarily due to networks not so much due to prices and employment; (c) For inflation, network effects attenuate over time with better price discovery in response to a financial shock.

Thus we propose a simple dynamic simultaneous spacial factor augment panel data model to understand the dynamic responses of output growth, inflation, wage growth and employment growth in response to a broad-based financial shock. We disentangle the role of networks in propagation of responses from various industries, and we find that in general 50-60% of the effects in output and wage growth are accounted for by network effects. Inflation responses are also amplified by networks for the first 2-6 quarters after which they are driven more by direct effects and employment growth responses are primarily due to instantaneous direct response of industries during a financial demand side shock. In order to further investigate the nature of industries which drive the amplification of responses to financial shocks, and how different industries optimize in such times; we exploit the heterogeneity in industry trade shares.

3 Trade Shares and Network Effects

In this section, we classify the industries into two categories of trade exposure - high and low, based on their imports, exports and value added. This data is at a coarser level of NAICS 4-digit classification. We then, examine the the extent to which responses of inflation, output growth, wage growth and employment growth to financial shocks differ (in terms of their reduced form effects and network decomposition) across industries based on their trade exposure.

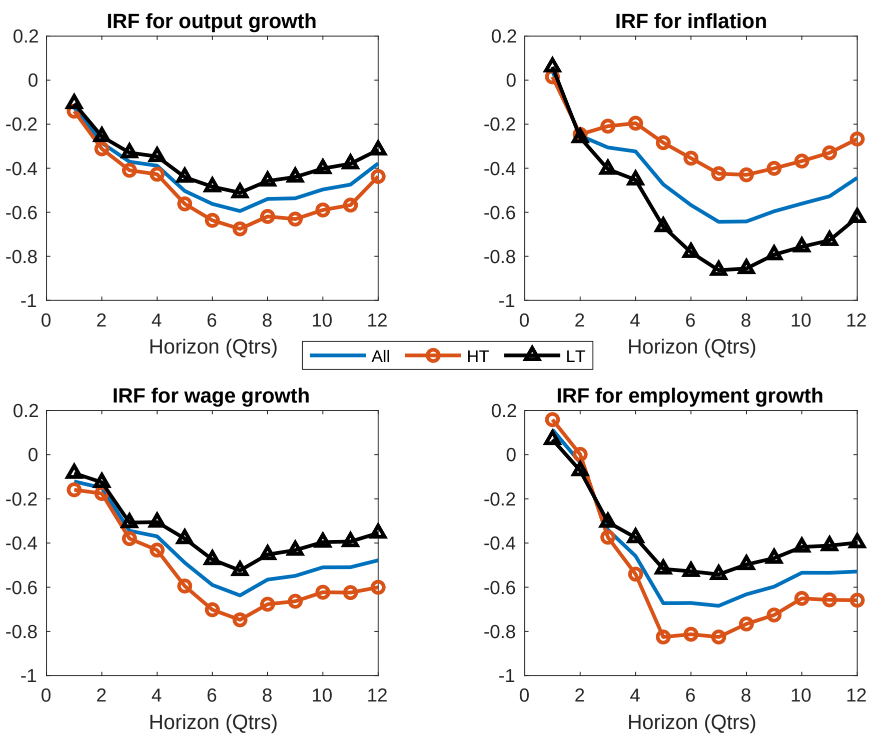
3.1 Reduced Form IRF by trade shares

In figure 5, we consider the impulse responses for high trade (HT) versus low trade (LT) industries summarized using red (with o markers) versus black lines (with Δ markers) respectively. 45% of the industries are categorized as high trade while 55% of the industries are in low trade group. The split is made to ensure approximately 50% share of overall employment in each group, which gives us the cutoff trade share at 5 percent. The corresponding employment weighted average impulse response for each of the groups is estimated as before, albeit for the respective group of industries (all, high trade, and low trade) as follows,

$$IRF_v^{(h,X)} = \sum_{j \in X} IRF_i^{(h)}|_v * \frac{Emp_j}{\sum_{n \in X} Emp_n}, \qquad X \in \{\text{All Industries, HT, LT}\}, \tag{10}$$

where $IRF_v^{(h)}$ is the employment share weighted average impulse response across industries in category X for variable v pair at horizon h to a financial shock to EBP.

Figure 5: Reduced Form impulse responses to a financial shock by trade shares



Our results indicate that industries with high trade exposure exhibit a substantially smaller response (nearly half) of inflation to movements in output induced by the unanticipated changes in the financial conditions, relative to industries with low trade exposure. These differential dynamics occur despite the fact that the effect of such shocks on economic activity is virtually identical across these two industrial groupings. Note that output, wages and employment growth contraction are much worse for the high trade industries, and yet their inflation response is much lower than those for low trade industries. Further, heterogeneity in the responses for inflation are greater than those for the other three variables by trade exposure. The effects also diverge more at after one year of the financial shock. This is aligned with the results proposed in [Gilchrist and Zakrajsek, 2019]. They examine the globalization hypothesis suggesting that, the attenuation of Phillip's Curve over time has been due to increasing share of high trade industries in the US real sector. This paper further supports their results using a different estimation technique and with the addition of network decomposition effects.

The literature has considered heterogeneity based on network centrality, upstream versus downstream nature of the firms and out-degree measures in input-output tables to study the divergent responses of industries to financial shocks over time based on such criteria. In this paper, we use trade shares as that gives us a rather clean segregation of the industries in their behavior, and also contributes to our understanding of the globalization hypothesis. This goes with the caveat though, that trade exposures are highly correlated with the measures of closeness to final consumers and the amount of stickiness industries face due to global versus local nature of their demand. In the next section, we analyze the nature of network effects in driving these reduced form results of figure 5.

3.2 Network effects for impulse responses by trade shares

In this section, we consider the networks model instead of the reduced form model for deriving the factor structure and the concomitant impulse responses. Accordingly, we investigate the interaction between trade exposure and network effects, summarized in figure 6.

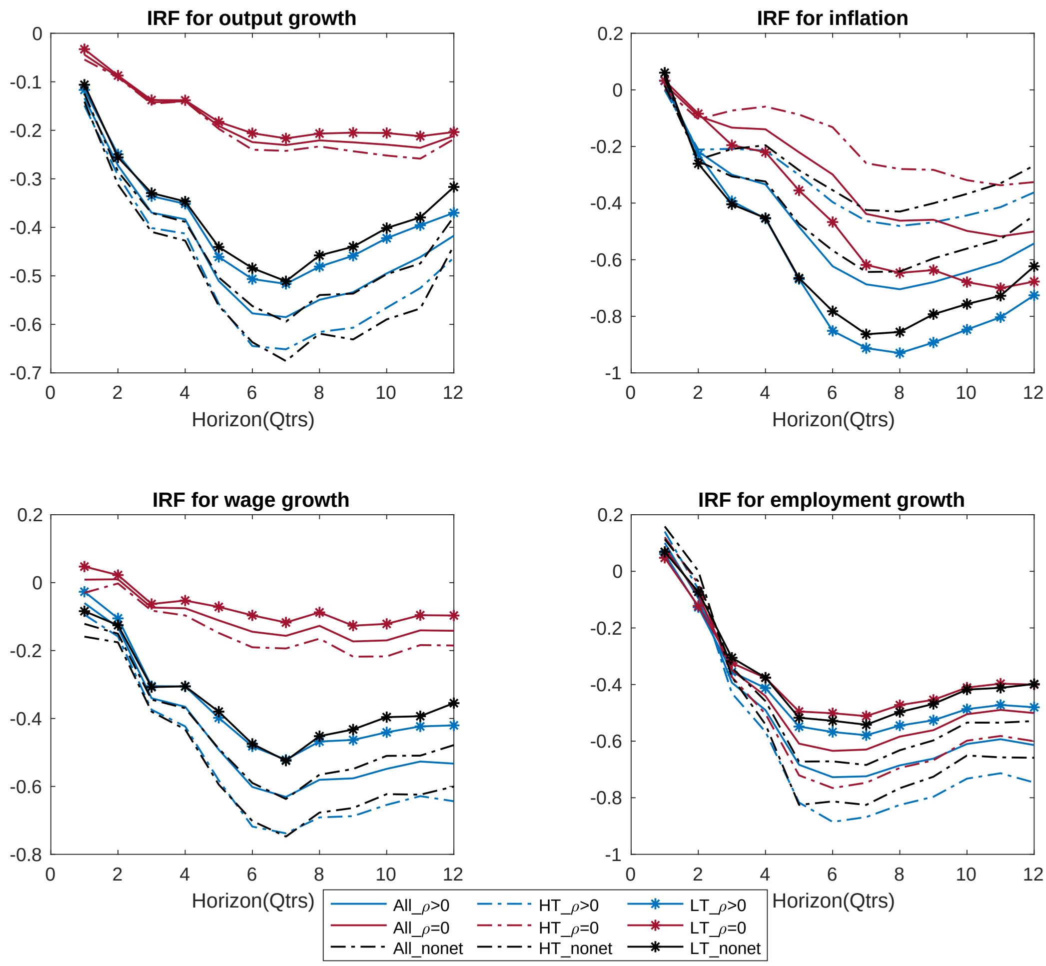
As before, the reduced form model and the network impulse responses (blue and black lines) coincide suggesting that the networks model is merely a rotated form of the reduced form simple model. Second, the network effects significantly amplify the decline in output and wage growth for all categories of industries (all, HT, LT) while the response for employment growth is similar with and without networks. For inflation, the network propagation peaks at 6-8 quarters and then attenuates by the end of three years. Third, the network effects for inflation in response to a financial shock are relatively greater for low trade local demand industries; than for high trade exposure globalized industries. For all the other variables beside inflation, it is instead the high trade industries which have relatively higher network amplification than the low trade industries.

4 Effect of Feedback Across Variables

4.1 Robustness to Inflation and Output Growth Feedback

So far, we have considered variable specific spillovers across industries, but we have not allowed for spillover effects of output growth on inflation and vice versa from one industry to another. In this section, we modify our first stage regression to allow for such feedback. Let IP_i denote log of industrial production index, and PPI_i denote log of producer price index for each industry i, then the model with only feedback between output growth and inflation can be summarized as follows,

Figure 6: Network Model impulse responses to a financial shock by trade shares



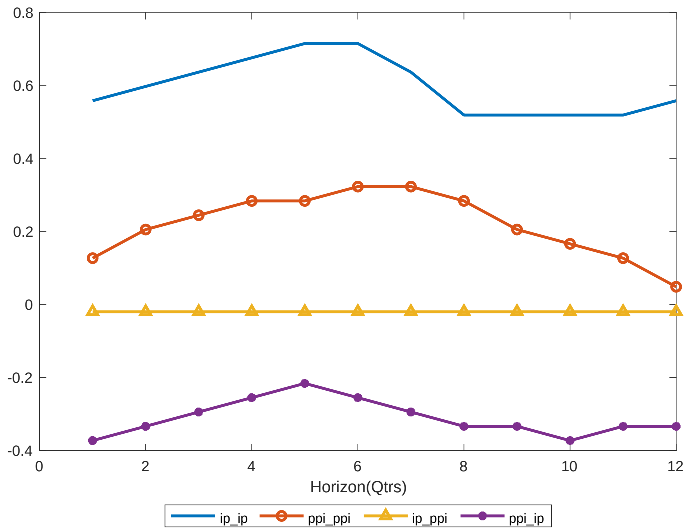
$$\begin{bmatrix} \Delta_h IP_{i,t} \\ \Delta_h PPI_{i,t} \end{bmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix} \otimes W \begin{bmatrix} \Delta_h IP_{j,t} \\ \Delta_h PPI_{j,t} \end{bmatrix} + \sum_{l=1}^{l=4} \alpha_l \begin{bmatrix} \Delta_0 IP_{i,t-l} \\ \Delta_h PPI_{i,t-l} \end{bmatrix} + \tag{11}$$

$$+ \sum_{r=1}^{R} \begin{bmatrix} \lambda_{1,r} \\ \lambda_{2,r} \end{bmatrix}' F_{r,t}^{(h)} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix}' E_t^{(h)} + \begin{bmatrix} \epsilon_{it}^1 \\ \epsilon_{it}^2 \end{bmatrix} , \tag{12}$$

$$\text{where} \quad E_t^{(h)} := \quad \Delta_h EBP_t = a_0 + \sum_{r=1}^{R} \theta_r F_{r,t}^{(h)} + E_t^{(h)} \tag{13}$$

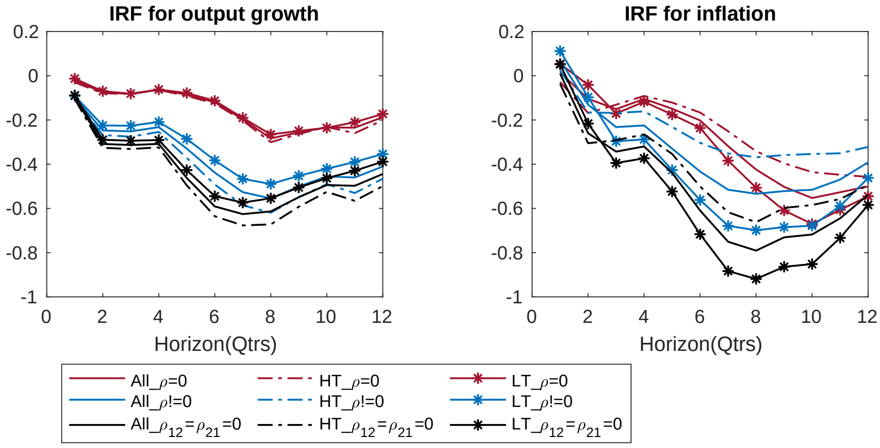
This allows us to measure the impact of spacial simultaneous feedback between industries and across output growth and inflation. Note that the case with $\rho_{12} = \rho 21 = 0$ is the networks model (reduced form total effect) from before, and the case with all $\rho_{ij} = 0$ shows only the direct instantaneous component of the networks model. The case with all $\rho ! = 0$ adds the inter-variables feedback and allows for output responses of industries to also feed into price decisions of other industries. Thus, the financial shock propagates from the response of prices in upstream industries to output decision of the downstream firms, but not vice versa. The network feedback strength of each of the components is summarized in the following figure 7.

Figure 7: Network feedback between output growth and inflation



The within-variable network effects are quite similar as before, how ever the addition of inter-variable feedback now also leads to -0.4 coefficient for output growth in inflation dynamics. On the other had, inflation does not significantly affect the output growth dynamics. The best way to understand the meaning of these values, is to consider the effect of each of the ρ network effects on the impulse response by considering the following three cases: (a) When complete network feed back is allowed that is the Leontief inverse matrix for imputing the IRF is $(I - \rho \otimes W)^{-1}$, (b) when we only consider the within variable feedback but shut down inter-variable interaction, i.e. impose $\rho_{12} = \rho_{21} = 0$, (c) when we only measure the direct instantaneous component of the impulse response without multiplying with the Leontief matrix. Each of these three cases are shown in figure 8. Since, we narrowed down to only output growth and inflation, we only consider 4 unobserved factors for this case. Note that the reduced form estimates (also, the full network effects estimates) are similar as before in black lines. The direct spontaneous effects for all categories of industries, is also shown in red line, similar to what we had in section 2.2.

Figure 8: Effect of feedback between output growth and inflation for IRF



The new addition are the blue lines, which show the attenuation in response of output growth and inflation when we allow for inter-variable feedback between them. In particular, if inflation and output growth can respond to each other across supply chain connections, faster and more flexible adjustments in response to the financial shock could attenuate the extent of the contractionary effect coming from the shock. The mechanism works through the $\rho_{21} = -0.4$ update in the regression framework. Because of that, a one unit shock to EBP dampens the prices by 40%, as price response gets attenuated in response to the output contraction. If we only allowed for price response to price in industries, then it is akin to assuming an inelastic supply in which case a contractionary demand shock leads to the worst possible price decline. However, allowing for inflation-output growth feedback grants some elasticity to industry supply decisions and consequently dampens the price response to a contractionary demand side shock as industries adjust a bit of both price and output. This also explains the dampening of the output response, even through the output dampening is negligible. Finally, in the case of inter-variable feedback (red versus blue lines in figure 8), it is further fortified that low trade industries have stronger network feedback for inflation than high trade industries.

4.2 Robustness to Marginal Cost Feedback

In this section, we allow for feedback among each of the four variables of study, albeit in a special way. We modify the baseline networks model to allow each of our four industry variables - output growth, inflation, wage growth and employment growth to respond to the marginal cost of all the industries through the network structure imposed by the weighting matrix. First, marginal cost (MC) is defined using labor expenditure as a ratio to sales as follows,

$$MC_{i,t} = \log W_{it} + \log EMP_{it} - \log PPI_it - \log IP_{it},$$

where W and EMP are wages and employment respectively. Second, we modify the regression framework in the first step of networks model as follows,

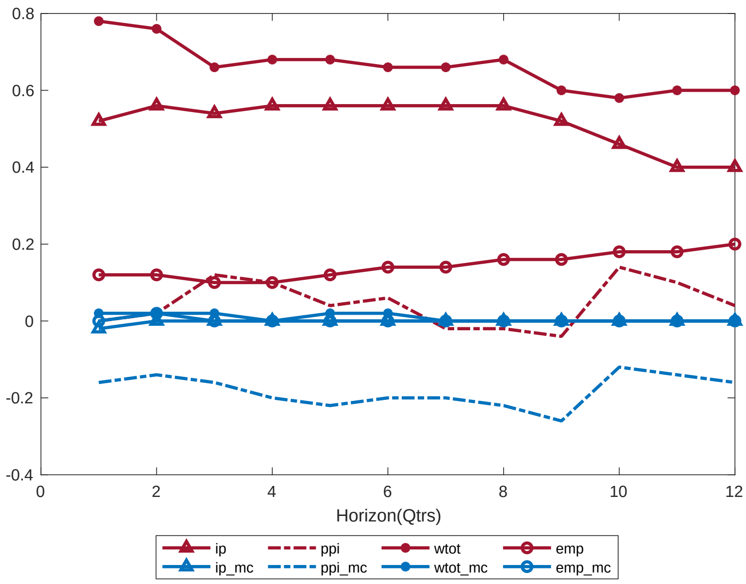
$$\text{Let, } \rho = [\rho_1, \rho_2, \rho_3, \rho_4]' \otimes \mathbf{1}_{N\times 1} \text{ and } \rho_{mc} = [\rho_1^{mc}, \rho_2^{mc}, \rho_3^{mc}, \rho_4^{mc}]' \otimes \mathbf{1}_{N\times 1} \text{ then,}$$

$$\Delta_h Y_{i,t} = \alpha_0 + \rho \sum_{j=1}^{N} W_{ij} \Delta_h Y_{j,t} + \rho_{mc} \sum_{j=1}^{N} W_{ij} \Delta_h MC_{j,t} + \sum_{l=1}^{l=4} \alpha_l \Delta_0 Y_{i,t-l} + \sum_{r=1}^{R} \lambda_{i,r} F_{r,t}^{(h)} + \gamma_i E_t^{(h)} + \epsilon_{it} \,, \tag{14}$$

$$\text{where } E_t^{(h)} := \quad \Delta_h EBP_t = a_0 + \sum_{r=1}^{R} \theta_r F_{r,t}^{(h)} + E_t^{(h)} \tag{15}$$

It is the same regression model as before (having 6 unobserved factors), with the addition of feedback from marginal cost across industries added on the right hand side. The corresponding estimated values of ρ and ρ_{mc} for each of the four variables at 1-12 quarter horizon are summarized in the following figure 9. Note that this specification is

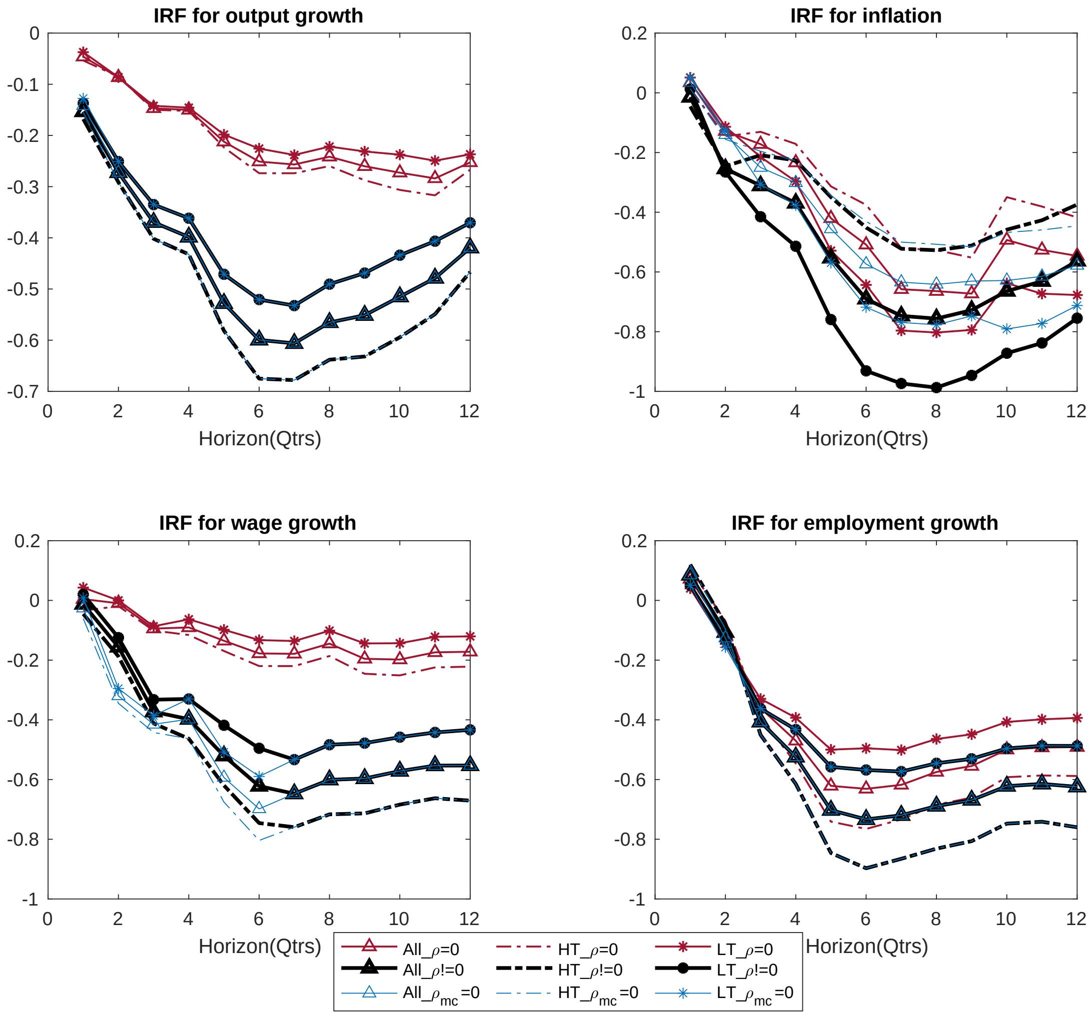
Figure 9: Network feedback from marginal cost



another imperfect rotation of the reduced form model. Thus, output growth, wage growth and employment growth do not change much as their ρ_{mc} coefficients are non-significant for all horizons. For inflation there is a 20% attenuation in responses once inflation is allowed to respond to marginal cost dynamics of downstream industries. The associated impulse response functions are summarized in figure 10.

As suggested by the conclusion we drew above from the estimated ρ_{mc} values, the network model impulse responses are same as section 2.2 for output, employment and wage growth variables. Inflation on the other hand resembles more closely the instantaneous impact (blue versus red lines) than the full propagation from Leontief inverse matrix (in black). This exercise suggests that our proposed networks model is quite robust in its' specification and addition of marginal cost feedback or integrating the feedbacks for inflation and output growth (like in the previous section), does not distort our inference significantly.

Figure 10: Effect of feedback from marginal cost on IRF



5 Implications from a network model

To be added.

6 Conclusion

In this paper, we have estimated that the strength of network effects is significant for industrial output growth, wages and inflation in response to financial and cost shocks. The network effects are stable and persistent over three years from the time of the shock. The inflation-output tradeoff is higher for low trade industries than high trade industries. The network effects are also significantly more for the low trade industries. There is no difference in our reduce form estimates of the impulse responses once we allow for inter-variable feedback across industries. So far, this paper is preliminary and incomplete as we still need to provide the summary of our estimation results for commodity price shocks and the model to calibrate this. Thus, it is a work in progress.

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