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Global Value Chains and the Business Cycle

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Abstract: In this paper I investigate the role of position in global value chains in the transmission of final demand shocks and the cyclicality and volatility of trade. Relying on a production network model with propagation via procyclical inventory adjustment, I show how shocks can magnify or dissipate upstream. I test the theoretical results empirically using input-output data. I find that industries far from consumers respond to final demand shocks up to twice as much as final goods producers. I also document the critical role of the position in the global value chain for countries' cyclical macroeconomic response: i) controlling for bilateral similarity in global value chain position eliminates the standard correlation between similarity in industrial structure and bilateral output comovement; ii) two indicators, measuring the number of steps of production embedded in the trade balance and the degree of mismatch between exports and imports, explain between 10% and 50% of the volatility and the cyclicality of net exports.

Keywords: global value chains, business cycle, inventory, shock amplification, production networks.

Chaînes de création de valeur mondiales et cycle économique

Abstract : Ce papier analyse le rôle de la position au sein des chaînes de création de valeur dans la transmission de chocs de demande finale et la cyclicalité et volatilité des échanges commerciaux. En me basant sur un modèle de réseau de production avec propagation via un ajustement pro-cyclique des stocks, je montre que les chocs peuvent être amplifiés ou réduits en amont. Je teste empiriquement ces résultats théoriques sur des données entrées-sorties. Je démontre que les industries qui sont éloignées des consommateurs répondent jusqu'à deux fois plus que les producteurs de biens finis aux chocs de demande finale. Je documente également le rôle crucial que joue la position dans la chaîne de valeur en termes de réponse macroéconomique cyclique pour les pays : i) une fois les similarités bilatérales en termes de position dans la chaîne de valeur prises en compte, toute corrélation entre composition industrielle et production disparaît ; ii) deux indicateurs mesurant respectivement le nombre d'étapes de production intégrées dans la balance commerciale et le degré d'inadéquation entre les exportations et les importations expliquent entre 10% et 50% de la volatilité et de la cyclicité des exportations nettes.

Mots-clefs : Chaînes de création de valeur, cycle économique, stocks, amplification des chocs, réseaux de production.

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1 Introduction[1]

In the last decades, global production and trade have shifted towards more integrated production chains. The rising importance of global value chains (GVC) increased the degree of interconnectedness among economies. This shift has changed both production and trade. Production now involves a larger fraction of foreign inputs.[2] As a consequence, trade now features predominantly intermediate goods.[3]

The increased fragmentation of both domestic and cross border production and its implications for the propagation of shocks has been the subject of a large literature stemming from Acemoglu et al. (2012). The structure of the production network and its frictions have been shown to be a determinant of volatility and absorption of shocks (Miranda-Pinto, 2019; Huneeus, 2019). Less is known about whether shocks amplify in sequential production setups.

In light of the observed fragmentation of production, in this paper I study how demand shocks amplify upstream (meaning further away from consumers) in production chains. I analyse how this phenomenon, coupled with countries' industrial composition (distribution of sectoral output shares) can partially explain the heterogeneous behaviour (cyclicality and volatility) of trade along the business cycle.

This paper starts from the empirical observation that different sectors and different countries position themselves at different stages of global production chains. This heterogeneity should imply, in light of the bullwhip effect (upstream amplification of shocks)[4], that countries exhibit heterogeneous responses to demand shocks. If shocks amplify upstream, both sectors and countries further away from consumption should display, for a given shock, a higher output response than their less upstream counterparts.

To study this problem, I build a model of network propagation of exogenous shocks to final demand through procyclical inventory adjustment. The model features a flexible production network structure and exogenous inventory adjustment. The theoretical analysis provides a condition under which final demand shocks amplify or dissipate upstream in a production chain. In the model firms face stochastic final demand and hold a fraction of expected demand in inventories. Both the network structure and the inventory parameter are exogenous. As final demand changes firms adjust production to meet demand. However, whenever final demand shocks are not independent across time a change in demand today

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[2]Between 1994 and 2014 the share of foreign value added of gross exports increase from 17 to 27% (see Andrews et al., 2018).

[3]The share of final manufacturing goods trade over total trade has been steadily declining and is now stable below 30% (OECD, WTO and World Bank, 2014).

[4]Bullwhip effect is how the literature has labeled the phenomenon of upstream amplification of shocks in production chains, for theoretical analyses see Lee et al. (2004), Metters (1997) and Chen et al. (1999).

provides information on the expected demand tomorrow. This implies that firms will also adjust production to change the stock of inventories. Given the assumption on the inventory policy, this adjustment is always procyclical. These changes in production propagate through the network potentially magnifying or dissipating. In particular the pattern of propagation is characterized by the interplay of an inventory (amplification) and a network (amplification/dissipation) effect.

The model shows how the amplification/dissipation patterns depend crucially on two forces: the degree of procyclicality of inventories and the strength of a sector's outward connections. To better exemplify the mechanics, start from a line network. In this setting shocks are passed one to one to input suppliers, hence the network effect is absent. In production networks the inventory channel is the only one active, which implies that shocks exponentially magnify upstream. This intuition carries through in general networks. However when every node is characterized by an arbitrary number of inward and outward links the network effect can fully undo the inventory amplification channel. In particular, networks characterized by weak linkages will be able to dampen final demand shocks as they travel upstream. On the other hand, networks with few very strong links may amplify them if the connections become stronger further away from consumption.

I empirically test this relationship by means of a shift-share instrument design. The instrument is based on estimated destination specific demand shocks and the fraction of industry output that is consumed in that destination. This design allows me to study the causal effect of these sector specific shocks and how they generate differential output response depending on the industry's position in production chains. I show that, for a given final demand shock, more upstream sectors display larger output responses than less upstream producers. In particular, I find that sectors located 4 production steps from consumption respond 50-80% more than final goods producers. Such a shift (from 1 to 4 steps away) corresponds to moving from the 20^{th} to 90^{th} percentile of the distance from consumption distribution. This finding is robust to the inclusion of network importance measures, past output, a rich set of fixed effect and alternative ways of estimating demand shocks. A similar result is obtained when comparing the variances of output growth for a given variance of demand shocks.

Additionally, I document that the higher responsiveness of output of more upstream industries is verified independently of the sign of the shock. However, industries respond more to negative demand shocks than to positive ones.

In light of this amplification result, I study how countries' industry structure and composition can explain some known macroeconomic empirical regularities. The underlying hypothesis is that if distance from consumption generates heterogeneous response at the industry level, then countries with different industry compositions should behave differently over the business cycle. I start by addressing a result of multiple papers in the international economics literature (Clark and van Wincoop, 2001; Imbs, 2004; Ng, 2010) showing that economies with similar production structure have higher output comovement. I build on this result by showing that, controlling for the similarity of GVC positioning, the importance of industrial structure is significantly reduced. The interpretation of this result is that industrial structure (measured as sector shares of output) masks a large heterogeneity in production chains location in a value chain, which is unaccounted for by the previous literature.

Furthermore, I show that the observed cross-sectional heterogeneity in countries' volatility and cyclicality of net exports (see Uribe and Schmitt-Grohé, 2017) can be rationalized by studying the GVC position of their trade flows. In particular, countries that import and export upstream show higher volatility of trade. Furthermore, countries that tend to export upstream and import downstream tend to have a higher procyclicality of the trade balance. These measures of GVC position explain between 10% and 50% of the volatility and cyclicality of net exports.

2 Literature Review

First, this paper is related to the growing body of research on global value chains and their structures. Notably Antràs and Chor (2013), Antràs et al. (2012) and Antràs and Chor (2018) study both theoretically and empirically the recent developments in the structure of global production. They also provide a set of measures to compute the upstreamness of a sector, defined as the expected distance from final consumption. I build on their findings and on Alfaro et al. (2019a) by extending the measure of upstreamness (distance from consumption) to disentangle bilateral differences and composition effects. Such measure can provides information on a sector's upstreamness with respect a specific destination market. This further decomposition is key to compute the upstreamness of countries' trade flows. If one were not to separate the position versus different destinations, it would not be possible to identify the upstreamness of exports from the one of output. This measure also allows the study of how the same industry is positioned differently depending on the trade counterpart.

Secondly, this paper is close to the literature on inventories as an amplification device. This problem has been studied at several levels of aggregation. Altomonte et al. (2012) use firm level transaction data to show that firms producing intermediate goods have a more pronounced response to the crisis than final goods producers. Zavacka (2012) shows that industry trade flows from US trading partners display volatility which is increasing in the industries' distance from final consumers in response to the crisis. Finally, there is a large body of literature discussing the macroeconomic effect of inventories as a trigger of amplification. Alessandria et al. (2010) show that procyclical inventory adjustments significantly contributes to the propagation and amplification of macroeconomic fluctuations. These papers all consider exogenous variation given by the financial crisis to evaluate the responsiveness of different sectors or firms to the shock, depending on whether they produce intermediate or final goods. They do so by assuming that the crisis is a shock of the same magnitude for all sectors and hence any difference in output response is due to the position in the production chain. The methodological approach of this paper allows to dispense of this assumption as the shift-share design constructs sector specific shocks. This implies that one can study the response to shocks of equal magnitude without having to assume the same exposure to a single shock.

The existence and the implication of upstream amplification has been extensively analysed by work in the management and operation research literatures. The underlying mechanism is often thought to be generated by either technology (shipping lags and order batching) or information (compounding forecasting error) frictions. These frictions imply that firms optimally hold stocks of finished or unfinished products.[5] In this paper I borrow the kernel of this literature by modelling the inventory choice in reduced form, assuming that firms want to hold a fixed share of their future expected demand. This assumption implies that final demand shocks may amplify upstream through procyclical inventory adjustment.

Thirdly, this paper relates to the growing literature on shocks in production networks. This line of research, stemming from Carvalho (2010) and Acemoglu et al. (2012) studies the role of network structure in the propagation of idiosyncratic industry level shocks. This paper investigates a similar problem. I study how aggregate final demand shocks travel through the network and whether they amplify or dampen. Acemoglu et al. (2016) show that demand shock propagate through linkages between firms and that the extent of sectoral response depends on the centrality of the network. Carvalho et al. (2016) show that the disruption cause by the 2011 earthquake in Japan travelled both upstream and downstream in the network. Both papers build models in which, provided input substitutability, shocks always diffuse and dampen. This feature comes from the existence of labor as an outside input. This paper builds a similar model, explicitly allowing for forces generating potential amplification in the network.

This paper also relates to the growing literature on firm-level and sectoral volatility in trade. Kramarz et al. (2016) show that firms' sales portfolios feature a skewed distribution of sales shares, implying that firms may be unable to smooth away some sources of variation. At a more macro level, di Giovanni and Levchenko (2009) show that sectors with higher trade openness are more volatile. This finding is consistent with the empirical results of the present paper, as sectors involved in trade tend to have more complex products (hence be more upstream, all else equal) and to have a larger share of inventories. Both these features would produce higher volatility through the lenses of the model presented here. Additionally, di Giovanni and Levchenko (2010) and di Giovanni et al. (2018) show that international trade and vertical linkages are a driver for shocks across borders, thereby increasing business cycle comovement. Relative to this literature, this paper provides an additional channel through which sectoral heterogeneity and trade can be amplification

[5] For some of the theoretical contributions in this area, see Lee et al. (2004), Metters (1997) and Chen et al. (1999).

devices for shocks both domestically and across borders.

Furthermore, the role of production specialization in explaining business cycle behaviour has been studied, among others by Kohn et al. (2017). They show that cross-country differences in sectoral specialization patterns can explain half of the difference in GDP volatility between emerging and developed economies. They also show that this feature is mostly due to heterogeneity in responses to international relative prices. These findings are related to a set of the results I present in this paper, particularly on how the mismatch in the production chain positions of exports and imports can explain part of the observed cyclical behaviour of a country's net exports.

More generally, the cross-country heterogeneity in the volatility and cyclicality behaviour of trade balances has been discussed in the literature. Possible rationales for these differences normally rely on the inability of developing countries to access insurance devices or on the different nature of the shocks they are subject to (see Aguiar and Gopinath, 2007). My analysis shows that the heterogeneity in the position of industries within countries can partially explain the observed differences, providing a complementary rationalization to the existing theories.

The rest of the paper is structured as follows: Section 3 describes a simple model of amplification through inventories along a value chain. Section 4 describes the data used for the empirical analysis. Section 5 provides the methodology. Section 6 presents the main results of the paper, while Section 7 provides a set of robustness checks. Finally, Section 8 discusses future steps and concludes.

3 Model

This section describes a model which builds on the intuition in Zavacka (2012) on how inventories may drive upstream amplification. The simplest version of the model studies how sequential production on line networks can produce amplification. The second part generalizes to any network structure to show that depending on the features of the network itself final demand shocks can be amplified or dissipated upstream

3.1 Production on a Line

The setup consists of a partial equilibrium model with one final good, whose demand is stochastic, and $N-1$ stages that are sequentially used to produce the final good. Throughout I will use industry, sector and firm interchangeably. The structure of this production network is a line, where stage N provides inputs to stage $N-1$ and so on until stage 0 where goods are consumed.

The demand for each stage n in period t is D_t^n with $n \in \{0, N\}$ and stage 0 demand, which is the final stage, is stochastic and follows an AR(1) with persistence $\rho \in (-1, 1)$ and a positive drift $\bar{D}$. The error terms is distributed according to some finite variance distribution F on a bounded support. $\bar{D}$ is assumed to be large enough relative to the variance of the error so that the demand is never negative.[6] Formally, final demand in period t is

$$D_t^0 = (1-\rho)\bar{D} + \rho D_{t-1}^0 + \epsilon_t,\, \epsilon_t \sim F(0,\sigma).$$

The production function is linear so that for any stage n, if production is Y_t^n then this also represents the demand for stage $n+1$, D_t^{n+1}. This implies $Y_t^n = D_t^{n+1}$.

Stage 0 production is the sum of the final good demand and the change in inventories. Inventories at time t for stage n are denoted by I_t^n. Firms hold a share α of expected demand as inventories from the previous period. Firms know the stochastic process and choose production to have α% of expected demand, thereby adjusting inventories accordingly.

$$\begin{aligned} Y_t^0 &= D_t^0 + I_{t+1}^0 - I_t^0 \\ &= D_t^0 + \alpha(E_t D_{t+1}^0 - E_{t-1} D_t^0) \\ &= D_t^0 + \alpha(\rho D_t^0 - \rho D_{t-1}^0). \end{aligned}$$

By linearity of the production function, given the production Y_t^0, firms at stage 0 will demand D_t^1 as inputs

$$D_t^1 = Y_t^0.$$

Using the same procedure as in the equation above

$$\begin{aligned} Y_t^1 &= D_t^1 + \alpha(\rho D_t^1 - \rho D_{t-1}^1) \\ &= (1+\alpha\rho)[D_t^0 + \alpha(\rho D_t^0 - \rho D_{t-1}^0)] - \alpha\rho[D_{t-1}^0 + \alpha(\rho D_{t-1}^0 - \rho D_{t-2}^0)] \\ &= D_t^0(1+\alpha\rho)^2 - 2\alpha\rho(1+\alpha\rho)D_{t-1}^0 + (\alpha\rho)^2 D_{t-2}^0. \end{aligned}$$

Forwarding the relationship to stage n, industry output is

$$Y_t^n = \sum_{s=0}^{n+1} (-1)^s \binom{n+1}{s} (1+\alpha\rho)^{n+1-s} (\alpha\rho)^s D_{t-s}^0.$$

Taking a derivative of the nth stage output with respect to the contemporaneous stochastic component, meaning D_t^0, we have

$$\frac{\partial Y_t^n}{\partial D_t^0} = (1+\alpha\rho)^{n+1}. \tag{1}$$

This expression states that any shock to the final demand traveling upstream gets

[6] The inclusion of the positive drift does not change the inventory problem since for storage the relevant statistic is the first differenced demand.

magnified at rate $(1+\alpha\rho)$ for each stage. The literature labels this result the *bullwhip effect*.

This prediction hinges on two main assumptions: procyclical inventory adjustment and persistence of demand shocks. The former is shown to be data and model consistent by Khan and Thomas (2007). In particular, they show that procyclical adjustment is an optimal choice for firms facing fixed costs of ordering intermediate goods. In the present setup, for simplicity, storage is carried out at the output level.

In Appendix A.1, I extend the model to account for heterogeneous storability of goods. The main result on upstream amplification remains even when some industries' output is not storable.

Appendix A.2 relaxes the assumption of linear inventory policy, i.e. α being a constant. Using a general formulation of the inventory function, I derive a condition for amplification in the line network. Amplification occurs whenever the generic function $\alpha(\cdot)$ is "not too elastic", in a sense specified in the Appendix.

Section 2 in the Online Appendix uses data from the NBER CES Manufacturing Industry database to assess the likelihood of these assumption. The data show that empirically the α function is decreasing and slightly convex, thereby falling in the set that would generate amplification in this model.

Finally, note that in this setting, due to production taking place on a line with only one endpoint, the structure of the network does not play a role in determining the degree of amplification.

In the next section, I extend the model with a more realistic production structure, such that the network itself shapes the degree of propagation of demand shocks.

3.2 Network Structure and Amplification

In this section I extend the model to study how the structure of the production network interplays with the inventory amplification mechanism.

In this model the network is characterized by an input requirements matrix A, in which there are possible cycles and self-loops.[7] The network has a terminal node given by final consumption

Assume consumers demand a stochastic number of consumption baskets D_t. This follows the stochastic process[8]

$$D_t = (1-\rho)\bar{D} + \rho D_{t-1} + \epsilon_t,\ \epsilon_t \sim F(0,\sigma).$$

The composition of the consumption basket is generated through a Leontief aggregator

[7]An example of a cycle is if tires are used to produce trucks and trucks are used to produce tires. An example of a self loop is if trucks are used in the production of trucks, technically this is the case if some diagonal elements of the input requirement matrix are positive, i.e. $\exists r : [A]_{rr} > 0$.

[8]This is equivalent to having a stochastic income process and linear preferences over the consumption basket.

over varieties

$$D_t = \min_{s \in S} \left\{ \frac{D_{s,t}}{\beta_s} \right\},$$

where S is a finite number of available products and β_s the consumption weight of good s. This formulation implies that $D_{s,t} = \beta_s D_t$ for s solving the minimization problem.

Firms produce using recipes with fixed input requirements. This is generated through Leontief production functions

$$Y_{s,t} = \min_{l_{s,t}, M_{s,t}} \left\{ \frac{l_{s,t}}{1-\gamma_s}, \frac{M_{s,t}}{\gamma_s} \right\},$$

where l_s is the labour used by industry s, M_s is the input bundle and γ_s is the input share for sector s. The input bundle is aggregated as

$$M_{s,t} = \min_{r \in R} \left\{ \frac{Y_{rs,t}}{a^{rs}} \right\},$$

where Y_s is the value of output of sector s, Y_{rs} is the value of output of industry r used in sector s production and a^{rs} is an input requirement, namely, the value of Y_{rs} needed for every unit of Y_s in value terms. R is the set of industries directly supplying inputs to sector s.

I maintain throughout that firms want to hold an α fraction of expected demand as beginning of period inventory. This implies that output of final goods producers, denoted by the superscript 0, is

$$Y_{s,t}^0 = \beta_s [D_t + \alpha\rho(D_t - D_{t-1})].$$

This also represents the input demand of sector s to its suppliers, once it is rescaled by the input requirement. Hence output of producers 1 step of production removed from consumption is

$$\begin{aligned} Y_{r,t}^1 = {} & \sum_s \gamma_s a^{rs} \beta_s [D_t + \alpha\rho(D_t - D_{t-1})] + \\ & \alpha\rho \left[\sum_s \gamma_s a^{rs} \beta_s [D_t + \alpha\rho(D_t - D_{t-1})] - \sum_s \gamma_s a^{rs} \beta_s [D_{t-1} + \alpha\rho(D_{t-1} - D_{t-2})] \right]. \end{aligned}$$

Where $\sum_v \tilde{a}^{kv}$ is the outdegree on a node k, namely the sum of the shares of output of all industries v coming from input k. Iterating forward to generic stage n, and then defining the following object

$$\chi_k^n \equiv \underbrace{\sum_v \gamma_v a^{kv} \sum_q \gamma_q a^{vq} ... \sum_r \gamma_r a^{or} \sum_s \gamma_s a^{rs} \beta_s}_{n \text{ sums}},$$

then output at stage n is given by

$$Y_{k,t}^n = \chi_k^n \sum_{i=0}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i}. \tag{2}$$

In equation 2 the structure of the network is summarized by χ_k^n, while the rest of the equation represents the inventory effect.

In this setup, the effect of a change in contemporaneous demand on output is

$$\frac{\partial Y_{k,t}^n}{\partial D_t} = \chi_k^n (1+\alpha\rho)^{n+1}. \tag{3}$$

Where the first term summarizes the network effect and the second term represents the inventory amplification. Equations 3 is a generalization of equation 1, which accounts for the network structure.

Finally, assume that firms produce at multiple stages of production, such that

$$Y_{k,t} = \sum_{n=0}^{\infty} Y_{k,t}^n.$$

To formalize the definition of output as a function of the features of the network I need to make a technical assumption. This assumption will be discussed further later in the section. An alternative set of assumptions that yield the same results are shown in Appendix A.4.

Assumption 1 (Existence of Non-Negative Leontief Inverse)
The economy is characterized by an allocation matrix $\tilde{P}$ whose elements $\tilde{p}^{vq} \equiv (1+\alpha\rho)\frac{\gamma_q M_{vq}}{Y_v}$ are such that $\sum_q \tilde{p}^{vq} \leq 1$, $\forall v$ and $\exists k : \sum_q \tilde{p}_{kq} < 1$.

This assumption ensures that the Leontief Inverse $[I - \tilde{A}]^{-1}$ exists and is non-negative. Where $\tilde{A} \equiv A\hat{\Gamma}$ and $\hat{\Gamma} = \text{diag}\{\gamma_1, ..., \gamma_R\}$.

The result is a straightforward application of the result in Dietzenbacher (2005). The proof is restated in Appendix A.3 and then adapted to the present case. This condition is equivalent to requiring that industries sell a large enough fraction of their output to final consumers . [9]

[9] To see this equivalence in the baseline case without inventories and labour input, note that $Y_v = \sum_u M_{vu} + \beta_u D$, dividing by Y_v, $1 = \sum_u p^{vu} + \frac{\beta_u D}{Y_v}$, hence if there is one industry k such that $\beta_k > 0$, then $\sum_u p_{ku} < 1$.

Under this assumption it is possible to derive the following Lemma:

Lemma 1 (Sectoral Output)
The sectoral output of a generic industry k is given by

$$Y_{k,t} = \sum_{n=0}^{\infty} \chi_k^n \sum_{i=0}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i}. \tag{4}$$

Furthermore, the fraction of output that is determined only by contemporaneous demand, denoted $\tilde{Y}_{kt}$, can be written as

$$\tilde{Y}_{k,t} = (1+\alpha\rho)\tilde{L}_k B D_t, \tag{5}$$

where B is the $S \times 1$ vector of demand shares and $\tilde{L}_k$ is the k^{th} row of the inventory augmented Leontief inverse, defined as

$$\tilde{L} = [I + (1+\alpha\rho)\tilde{A} + (1+\alpha\rho)^2 \tilde{A}^2 + ...] = [I - (1+\alpha\rho)\tilde{A}]^{-1}.$$

Where $\tilde{A} \equiv A\hat{\Gamma}$ and $\hat{\Gamma} = \mathrm{diag}\{\gamma_1, ..., \gamma_R\}$.

Proof. See Appendix A.3. ∎

The statement in Lemma 1 shows that this model collapses to the standard characterization of output in production networks when there is no inventory adjustment ($\alpha = 0$ or $\rho = 0$). The second part of the statement also shows that contemporaneous output is analogous to the standard definition, provided that the Leontief inverse is augmented with the inventory term.

From Lemma 1 it is possible to characterize the following comparative statics on the output responsiveness to final demand shocks.

Proposition 1 (Comparative Statics)
This proposition formalises the comparative statics on the responsiveness of output to final demand shocks

a) *The effect of change in contemporaneous aggregate demand on sectoral output is given by*

$$\frac{\partial Y_{k,t}}{\partial D_t} = (1+\alpha\rho)\tilde{L}_k B]. \tag{6}$$

b) *Furthermore a change in the composition of demand, defined as a marginal increase in the s^{th} element of the vector B (β_s), paired with a marginal decrease of the r^{th} element (β_r), changes the output response to aggregate demand as follows:*

$$\Delta_\beta \frac{\partial Y_{k,t}}{\partial D_t} \equiv \frac{\partial}{\partial \beta_s}\frac{\partial Y_{k,t}}{\partial D_t} - \frac{\partial}{\partial \beta_r}\frac{\partial Y_{k,t}}{\partial D_t} = (1+\alpha\rho)[\tilde{\ell}_{ks} - \tilde{\ell}_{kr}]. \tag{7}$$

where $\tilde{\ell}_{ks}, \tilde{\ell}_{kr}$ are elements of $\tilde{L}$.

c) *Lastly, a comparative static that changes the structure of the network path from industry k to final consumption leads to a change in the responsiveness of output given by*

$$\Delta_{\tilde{L}} \frac{\partial Y_{k,t}}{\partial D_t} = (1+\alpha\rho)\Delta \tilde{L}_k B, \tag{8}$$

where the change in the network is summarized by $\Delta \tilde{L}_k$.

The first result in Proposition 1 states that the change in output response to shifts in aggregate demand, following a variation of the demand composition, depends on the relative magnitude of the appropriate elements of the augmented Leontief matrix. Effectively a change in demand composition implies a change in the position of the firm in the network. This, in turn, affects output responsiveness to changes in demand.

The second part of the Proposition characterizes the change in output response following a change in the network. This comparative static is a direct change of the firm's position in the network, hence the change in output response.

These results are best understood via two examples, one changing demand composition in a specific fashion and another changing technology.

Before discussing these examples it is worth pointing out that in this setting, average distance from consumption, which the literature labels upstreamness (see Antràs et al. (2012)), is defined as

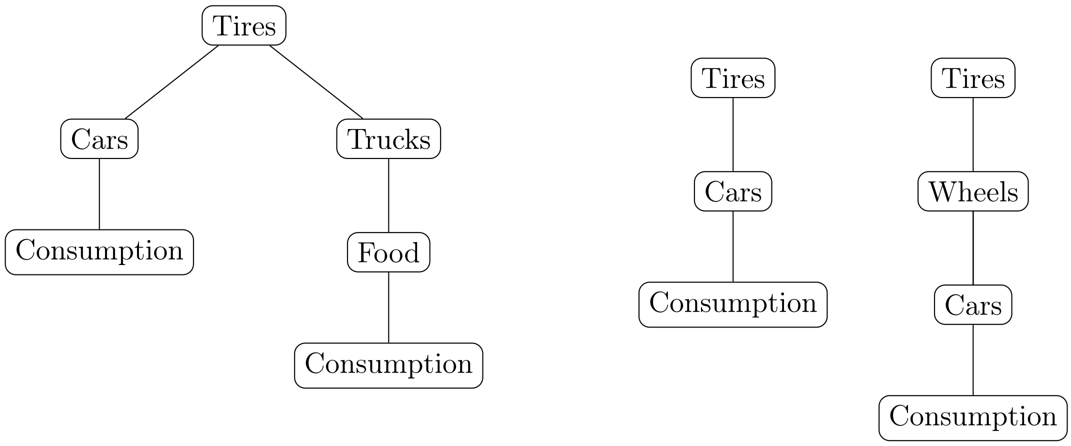
$$U_k = \sum_{n=0}^{\infty} (n+1) \frac{Y_k^n}{Y_k}. \tag{9}$$

This definition is useful to think about how output response changes as one varies the position of a given industry in the production chain.

Example 1 (Change in Demand Composition)**.** Slightly abusing notation, denote β_{ks}^n the weight of a final good s that is n stages removed from sector k. To exemplify this, think of a tires producer. The output is used to produce cars and trucks, cars are consumed while trucks are used as input by the food industry, and food is a final good. In this example tires are at both distance 2 and 3 from consumers. This case is illustrated in Figure 1a.

To study how distance from consumption changes the responsiveness of output to final demand shocks, consider an infinitesimal increase in β_{ks}^n (food in the example) coupled with an equally sized decrease in β_{kr}^{n-1} (cars). Note that this comparative static implies a marginal increase in the industry upstreamness. To see this note that more of the sector's output is now used for a longer chain than before. Denoting the elements of $\tilde{A}$ as $\tilde{a}^{rs}$ for

Figure 1: Comparative Statics



(a) Change in Demand Composition: for given total consumption, food consumption increases and car consumption decreases

(b) Technology Shift: an extra step of production is added to the existing chain

generic sectors r, s, the change in demand implies

$$\begin{aligned}
\Delta_\beta \left(\frac{\partial Y_{k,t}}{\partial D_t} \right) &= \chi_k^n (1+\alpha\rho)^{n+1} - \chi_k^{n-1}(1+\alpha\rho)^n \\
&= (1+\alpha\rho)^n \left[(1+\alpha\rho) \underbrace{\sum_v \tilde{a}^{kv} \sum_q \tilde{a}^{vq} \sum_p \tilde{a}^{qp} ... \sum_r \tilde{a}^{mr} \tilde{a}^{rs}}_{\text{n sums}} - \underbrace{\sum_q \tilde{a}^{kq} \sum_p \tilde{a}^{qp} ... \sum_r \tilde{a}^{mr} \tilde{a}^{rs}}_{\text{n-1 sums}} \right] \\
&= (1+\alpha\rho)^n \underbrace{\sum_p \tilde{a}^{qp} ... \sum_r \tilde{a}^{mr} \tilde{a}^{rs}}_{\text{n-2 sums}} \left[(1+\alpha\rho) \sum_v \tilde{a}^{kv} \sum_{q \in Q} \tilde{a}^{vq} - \sum_{q \in Q'} \tilde{a}^{kq} \right]. \quad (10)
\end{aligned}$$

Equation (10) shows the effect of marginally moving more upstream on the responsiveness of output to demand shocks. In particular, note that the sign of the change is determined by the sign of the square bracket. The first term in the bracket states that moving more upstream implies exposure to one more step of amplification due to inventory adjustment but also to one more layer of production, denoted by the product of the two outdegrees. This quantity needs to be compared with the outdegree at stage $n-1$, being the last term in the bracket.

Assuming that the outdegrees are invariant to the stage of production, meaning that

$\sum_{q\in Q}\tilde{a}^{vq} = \sum_{q\in Q'}\tilde{a}^{kq}$ in equation (10), then the responsiveness of output will increase if

$$\underbrace{(1+\alpha\rho)}_{\text{inventory effect}} \underbrace{\sum_v \tilde{a}^{kv}}_{\text{network effect}} -1 > 0.$$

This result states that if the inventory amplification effect dominates the network dissipation effect, then shocks will be magnified upstream. Note that the outdegree $\sum_v \tilde{a}^{kv}$ can be larger than 1, meaning that amplification could occur even in the absence of inventories.

This result is equivalent to the statement in Proposition 1. This can be seen by noting that the two quantities compared are two neighbouring elements, particularly the n^{th} and $n-1^{th}$ of the geometric series of inventory augmented input requirement matrices. Namely

$$\begin{aligned}(1+\alpha\rho)[\tilde{\ell}_{ks}-\tilde{\ell}_{kr}] =& \\ &= (1+\alpha\rho)[I+(1+\alpha\rho)\tilde{A}+...+(1+\alpha\rho)^{n-1}\tilde{A}^{n-1}+(1+\alpha\rho)^n\tilde{A}^n]_k- \\ &-(1+\alpha\rho)[I+(1+\alpha\rho)\tilde{A}+...+(1+\alpha\rho)^{n-1}\tilde{A}^{n-1}]_k \\ &= (1+\alpha\rho)^n\tilde{A}^{n-1}[(1+\alpha\rho)\tilde{A}-1]_k.\end{aligned}$$

Which is equivalent to the statement in this example.

The previous example shows that a change in the demand composition affecting the industry position can lead to more or less responsiveness to aggregate demand shifts. Similarly, an increase in the industry upstreamness generated by the introduction of an additional step in the production chain implies a change in responsiveness of output. This comparative static can be thought of as a new necessary step in the production of some final good. The next example formalises the result.

Example 2 (Technology Shift)**.** The second comparative statics example is the addition of a new step of production. In the case of the tires producer this would be equivalent to moving from a tires-cars-consumption chain to a tires-wheels-cars-consumption one. This is illustrated in Figure 1b.

An increase in an industry's upstreamness generated by one additional production step in an existing chain, implies an increase in the responsiveness of output to final demand shocks if

$$\underbrace{(1+\alpha\rho)}_{\text{inventory effect}} \underbrace{\sum_v \tilde{a}^{kv}}_{\text{network effect}} -1 > 0.$$

The result in Example 2 shows that the same result on amplification or dissipation of demand shocks can be generated by a change in the demand composition or by a change in the supply chain structure, provided that they alter the firm's position in the same way. Finally, note that the assumption that the outdegree is independent of firm's position is not required for Example 2 since the comparative static is adding a production step to an existing chain.

This result can be seen as a special case of the second comparative static in Proposition 1. In particular, adding a production step to an existing chain implies premultiplying by $(1+\alpha\rho)A$. In this case, the change in output is given by

$$\Delta_{\tilde{L}} \frac{\partial Y_{k,t}}{\partial D_t} = (1+\alpha\rho)\Delta\tilde{L}_k B.$$

From this one can obtain the main statement of this example. This can be seen as

$$\begin{aligned}(1+\alpha\rho)\Delta\tilde{L}_k B &= (1+\alpha\rho)\tilde{L}_k B[\Delta\tilde{L}_k B - 1]\\ &= (1+\alpha\rho)\tilde{L}_k B[(1+\alpha\rho)\tilde{A}_v - 1]\\ &= (1+\alpha\rho)\tilde{L}_k B[(1+\alpha\rho)\sum_v \tilde{a}^{kv} - 1].\end{aligned}$$

Which yields the desired equivalence.

It is worth discussing how these two examples relate to one another and why they yield equivalent results. The two comparative statics differ in the origin of the variation: in example 1 there is a change in composition of demand that alters the position of the industry in the production chain; in example 2 the change is on the technology, or the network. The key assumption such that the two results coincide is the one laid out in example 1, namely that the outdegree is independent of the stage of production. Without this assumption the two results differ since moving from the shorter path from industry k to consumption to the longer one implies comparing two different sets of outdegrees, as can be seen in equation 10. The assumption effectively implies looking at identical paths that only differ in one step of production, which is observationally equivalent to the comparative static in example 2.

3.3 Discussion

The results in examples 1 and 2 state that increasing an industry's distance from consumption could generate amplification or dissipation depending on whether the inventory or the network effect prevails. The latter is ambiguous since the outdegree is potentially larger than 1, which would produce amplification even if firms do not hold inventories (i.e. α=0).

The object $\sum_v \tilde{a}^{kv}$ in the model can be observed in the data. As shown in Figure 1 in the Online Appendix, in the World Input Output Database (WIOD) for the year 2000, the outdegree distribution ranges between 0 and 9.3, with 87% of the sample displaying an outdegree lower than 1.

This implies that most of the industries in the sample lie in the empirically interesting case in which the network can dissipate demand shocks as the distance from consumption increases.

Furthermore, in the WIOD data the correlation between industry upstreamness and outdegree is .3 (see Figure 2 in the Online Appendix), suggesting that the further from consumption the higher the number of industries served by a given sector. This correlation should suggest that the higher the upstreamness, the more likely it is that the condition in examples 1 and 2 is satisfied.

It is also worth noting that the inventory effect could change the sign if α was negative. This would be evidence of the stock of inventory being used as a precautionary device by firms. Looking at the sample in the NBER CES dataset industries, the inventory-to-future-sales ratio is on average .15, ranging from .02 to .48. This can be thought of as a proxy for α if agents correctly forecast demand.[10] Further details on inventories in the NBER CES dataset are provided in Section 2 in the Online Appendix.

The key assumption of the model is stated in Assumption 1. This requires that industries sell a large enough fraction of output to final consumers. As shown in Dietzenbacher (2005) there are two independent sufficient conditions that ensure existence and non-negativity of the Leontief inverse. The first one, which is the most used in the literature, relies on the column-sums of the input matrix A to be bounded above by 1. This assumption is problematic in the context of this model because such an assumption would need to be imposed on $(1 + \alpha\rho)\tilde{A}$ and the presence of inventories could make it easily violated. Furthermore, such an assumption would mechanically impose that the network can never amplify final demand shocks. The second sufficient condition in Dietzenbacher (2005) is the one used in this paper. In the textbook case (see Miller and Blair, 2009, ,p 62) the assumption requires that at least one sector serve final consumers. In this model, due to the presence of inventories, the requirement is stronger, namely that the fraction of output not sold to consumers is weakly smaller than $(1 + \alpha\rho)^{-1}$ (in the standard model it needs to be weakly smaller than 1).

One additional source of heterogeneity that is not modeled in this setup is possible heterogeneity in inventory shares (see Appendix A for a discussion of this case). Zavacka (2012) reports that, for the sample of manufacturing industries in the NBER CES dataset, the correlation between inventory share and upstreamness is -0.127, implying that industries further away from consumption hold a lower fraction of output in inventories. Such a correlation suggests that the inventory force may fade as one increases upstreamness, thereby making the condition in examples 1 and 2 less likely to be verified.

The result in the examples imply that it is empirically unclear whether one should observe output responses that increase or decrease with the distance from consumers.
The remainder of this paper uses the World Input-Output Database to empirically assess the effect of industries' distance from consumption on the responsiveness of output to final demand shocks.

[10] The sample only includes manufacturing industries, which implies that the estimates for the average α is presumably an upper bound for the WIOD sample, which contains service industries.

4 Data

The main source of data in this paper is the World Input Output Database (2016 release, see Timmer et al., 2015). This contains the Input-Output structure of sector to sector flows for 44 countries from 2000 to 2014 at the yearly level. The data is available at the 2-digit ISIC revision 4 level. The total number of sectors in WIOD is 56. This amounts to 6,071,296 industry to industry flows and 108,416 industry to country flows for every year in the sample. The full coverage of the data in terms of countries and industries is shown in Table 6 and 7 in the Appendix. Additional data on macroeconomic aggregates of countries is taken from the Penn World Table 9 (see Feenstra et al., 2015).

The structure of the WIOD data is represented in Figure 2

Figure 2: World Input Output Table

			Input use & value added							**Final use**			**Total use**
			Country 1			$\cdots$	Country J			Country 1	$\cdots$	Country J	
			Industry 1	$\cdots$	Industry S	$\cdots$	Industry 1	$\cdots$	Industry S				
Intermediate	Country 1	Industry 1	Z_{11}^{11}	$\cdots$	Z_{11}^{1S}	$\cdots$	Z_{1J}^{11}	$\cdots$	Z_{1J}^{1S}	F_{11}^{1}	$\cdots$	F_{1J}^{1}	Y_1^1
		$\cdots$	$\cdots$	Z_{11}^{rs}	$\cdots$	$\cdots$	$\cdots$	Z_{1J}^{rs}	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
		Industry S	Z_{11}^{S1}	$\cdots$	Z_{11}^{SS}	$\cdots$	Z_{1J}^{S1}	$\cdots$	Z_{1J}^{SS}	F_{11}^{S}	$\cdots$	F_{1J}^{S}	Y_1^S
inputs	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	Z_{ij}^{rs}	$\cdots$	$\cdots$	$\cdots$	$\cdots$	F_{ij}^{r}	$\cdots$	Y_i^r
	Country J	Industry 1	Z_{J1}^{11}	$\cdots$	Z_{J1}^{1S}	$\cdots$	Z_{JJ}^{11}	$\cdots$	Z_{JJ}^{1S}	F_{J1}^{1}	$\cdots$	F_{JJ}^{1}	Y_J^1
supplied		$\cdots$	$\cdots$	Z_{J1}^{rs}	$\cdots$	$\cdots$	$\cdots$	Z_{JJ}^{rs}	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
		Industry S	Z_{J1}^{S1}	$\cdots$	Z_{J1}^{SS}	$\cdots$	Z_{JJ}^{S1}	$\cdots$	Z_{JJ}^{SS}	F_{J1}^{S}	$\cdots$	F_{JJ}^{S}	Y_J^S
Value added			VA_1^1	$\cdots$	VA_1^S	VA_j^s	VA_J^1	$\cdots$	VA_J^S				
Gross output			Y_1^1	$\cdots$	Y_1^S	Y_j^s	Y_J^1	$\cdots$	Y_J^S	$\cdots$			

The World Input-Output Table represents a world economy with J countries and S industries per country. The $(S \times J)$ by $(S \times J)$ matrix whose entries are denoted by Z represents flows of output used by other industries as intermediate inputs. Specifically Z_{ij}^{rs} denotes the output of industry r in country i used as intermediate input by industry s in country j. In addition to the square matrix of input use the table provides the flows of output used for final consumption. These are denoted by F_{ij}^r, representing output of industry r in country i consumed by households, government and non-profit organizations in country j. Following the literature I denote $F_i^r = \sum_j F_{ij}^r$, namely output of sector r in country i consumed in any country in the world. By the definition of output, all rows sum to the total production of an industry. Finally the Table provides a row vector of value added for every industry, this implies that columns too sum to sectoral output.

Output can be defined in two alternative ways which are represented in the last column and last row, respectively. First output is given by the sum of production used as input and used for final consumption

$$Y_i^r = \sum_j \sum_s Z_{ij}^{rs} + \sum_j F_{ij}^r.$$

Alternatively it can be defined as the sum of inputs and value added

$$Y_j^s = \sum_r \sum_i Z_{ij}^{rs} + VA_j^s.$$

The next Section describes how this data can be used to construct measures of distance from final consumers both globally and to specific partner countries.

5 Methodology

This section describes the methodology used in this paper. It starts by reviewing the existing measure of upstreamness as distance from final consumption proposed by Antràs et al. (2012) and then extends it to disentangle the distance from final consumption of a specific partner country. Next it shows how to compute the sales share in the industry portfolio accounting for indirect linkages. This allows to evaluate the exposure of industry output to specific partner country demands fluctuations even when goods reach their final destination by passing through third countries. Finally, it discusses the fixed effect model and the shift share design used to extract and aggregate country and time specific demand shocks from the final consumption data.

5.1 Upstreamness

The measure of upstreamness of each sector counts how many stages of production there are between the industry output and final consumers proposed by Antràs et al. (2012). The index can be thought of as a duration, counting on average the number of intermediate steps between production and consumption. The measure is bounded below by 1, when the entirety of sectoral output is used directly for final consumption.

Antràs et al. (2012) provide a characterization of Upstreamness based on counting the steps between production and consumption. In particular the index is constructed by assigning value 1 to the share of output directly sold to final consumers, value 2 to the share sold to consumers after it was used as intermediate by another industry and so on.[11] Formally:

[11] This measure is shown to be equivalent to an alternative formulation proposed by Fally (2012). This characterization is based on a recursion such that upstreamness of sector r is computed as 1 plus the weighted upstreamness of industries that use the output of sector r as intermediate input. Formally, the upstreamness for sector r in country i is computed as

$$U_i^r = 1 + \sum_{s=1}^{S} \sum_{j=1}^{J} b_{ij}^{rs} U_j^s,$$

where b_{ij}^{rs} is defined as Z_{ij}^{rs}/Y_i^r. This denotes the dollar amount of sector r output from country i used by industry s output in country j.

$$U_i^r = 1 \times \frac{F_i^r}{Y_i^r} + 2 \times \frac{\sum_{s=1}^S \sum_{j=1}^J a_{ij}^{rs} F_j^s}{Y_i^r} + 3 \times \frac{\sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \sum_{k=1}^K a_{ij}^{rs} a_{jk}^{st} F_k^t}{Y_i^r} + ... \quad (11)$$

where F_i^r is output of sector r in country i consumed anywhere in the world and Y_i^r is the total output of sector r in country i. a_{ij}^{rs} is dollar amount of output of sector r from country i needed to produce one unit of output of sector s in country j, defined analytically as $a_{ij}^{rs} = Z_{ij}^{rs}/Y_j^s$. This formulation of the measure is effectively a weighted average of output, where the weights are the number of steps of production between the specific share of output and final consumption.

This measure can be computed by rewriting it in matrix form:

$$U = \hat{Y}^{-1}[I - A]^{-2}F, \quad (12)$$

where U is a $(J \times S)$ by 1 vector whose entries are the upstreamness measures of every industry in every country. $\hat{Y}^{-1}$ denotes the $(J \times S)$ by $(J \times S)$ diagonal matrix whose diagonal entries are the output values of all industries. The term $[I - A]^{-2}$ is the power of the Leontief inverse, in which A is the $(J \times S)$ by $(J \times S)$ matrix whose entries are all a_{ij}^{rs} and finally the vector F is an $(J \times S)$ by 1 whose entries are the values of the part of industry output that is directly consumed.
The matrix formulation in equation 12 holds as long as $\sum_i \sum_r a_{ij}^{rs} < 1$, which is a natural assumption given the definition of a_{ij}^{rs} as input requirement.[12] Under this condition the matrix formulation of equation 11 is

$$\begin{aligned} U &= \hat{Y}^{-1}[F + 2AF + 3A^2F + 4A^3F + ...] = \hat{Y}^{-1}[I + 2A + 3A^2 + 4A^3 + ...]F = \\ &= \hat{Y}^{-1}[I - A]^{-2}F \end{aligned}$$

The condition on the sum of input requirements ensures that the infinite series of weighted A matrices converges to $[I - A]^{-2}$.

As equation 11 shows, the value of upstreamness of a specific industry r in country i can only be 1 if all its output is sold to final consumers directly, formally this requires that $Z_{ij}^{rs} = 0, \forall s, j$, which immediately implies that $a_{ij}^{rs} = 0, \forall s, j$.

When I compute the measure of upstreamness I apply the inventory correction suggested by Antràs et al. (2012), the discussion of the method is left to the Appendix.

Table 8 provides the list of the most and least upstream industries in the WIOD sample. Predictably services are very close to consumption while raw materials tend to be very upstream.

The Online Appendix provides additional summary statistics and stylized facts on

[12] For this not to be true one would need that some industry has negative value added since $\sum_i \sum_r a_{ij}^{rs} > 1 \Leftrightarrow \sum_i \sum_r Z_{ij}^{rs}/Y_j^s > 1$, meaning that the sum of all inputs used by industry s in country j is larger than the value of its total output.

sectors' and countries' positions in GVCs.

5.2 Bilateral Upstreamness

The measure outlined above describes the position of each industry in each country with respect to all countries' final consumers.
In this section I discuss how to construct a similar measure for bilateral flows.
To inspect how upstream a country's export flow is, one could simply weight the industry level upstreamness with the industry share of export flows. On a bilateral level, denoting export of industry r from country i to j as X_{ij}^r, this would imply computing

$$U_{ij} = \frac{\sum_{r=1}^{S} X_{ij}^r U_i^r}{\sum_{r=1}^{S} X_{ij}^r}.$$

This measure however does not exactly capture the distance of the export of country i from consumers of country j. The index above reweighs the distance from all consumers in the world by export industry shares towards a specific partner. This is not equivalent to measuring the distance from the consumers of a specific partner country. To do so one needs to build a different measure in which only country j final consumption is accounted for. However it is important to maintain that the intermediate steps can go through any country in the world. This measure is then, for each industry r in country i to a specific destination country j

$$U_{ij}^r = \frac{1 \times F_{ij}^r + 2 \times \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + 3 \times \sum_s \sum_k \sum_t \sum_m a_{ik}^{rs} a_{km}^{st} F_{mj}^t + ...}{F_{ij}^r + \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + \sum_s \sum_k \sum_t \sum_m a_{ik}^{rs} a_{km}^{st} F_{mj}^t + ...} \quad . \tag{13}$$

This definition is the bilateral counterpart of equation 11. There are two key differences between the two: firstly, F is replaced by F_j, meaning that instead of accounting for global final consumption only chains whose final node is country j consumption are included; secondly, the denominator is not the total output of industry i in country r, this is replaced by the part of sectoral output that will eventually be consumed in country j. As before it is intuitive to think about this measure as a weighted average where the weights are the steps of production.

Similarly to the global upstreamness, this measure can be computed through its matrix form, for all industries in all countries towards j. First note that the numerator of equation 13 can be written in matrix form as

$$F_j + 2AF_j + 3A^2F_j + ... = [I + 2A + 3A^2 + 4A^3 + ...]F_j = [I - A]^{-2}F_j.$$

Where the last equality assumes again that $\sum_i \sum_r a_{ij}^{rs} < 1$. The denominator can be written as

$$F_j + AF_j + A^2F_j + A^3F_j + ... = [I + A + A^2 + A^3 + ...]F_j = [I - A]^{-1}F_j.$$

Denote by the subscript $\cdot j$ the upstreamness of the flows from all industries with destination j. The resulting matrix form definition is

$$U_{\cdot j} = C_{\cdot j}^{-1}[I - A]^{-2}F_j. \tag{14}$$

Where F_j is the vector of final consumption of country j and $C_{\cdot j}$ is a diagonal square matrix whose diagonal elements are the elements of the vector $[I - A]^{-1}F_j$.

The whole set of $U^r_{i,j}$ can be used to map out a full network of bilateral relations of trade where the $U^r_{i,j}$ represent the distance from the different terminal nodes.

It is important to note that the upstreamness measure, both at the industry and at the bilateral level, suffers from one limitation due to data aggregation. The I-O tables do not report flows within industry-country cells, meaning that the measure will record an extra production step only if goods flow either across industry, across countries or both. If some industry-country cell systematically trades within itself more than other industry-country cells, the upstreamness of the former will be downward biased due to all the missing within cell flows.

5.3 Sales Portfolio Composition

As shown in the model in Section 3 there is a key role of the network path from industries' output to final consumption. In the model there is only one source of final demand, however, in the data, different countries may have different demand processes. This implies that to evaluate the sectoral exposure to demand one needs to study the direct and indirect sales portfolio composition.

The standard measure of sales portfolio composition studies the relative shares in a firm's sales represented by different partner countries, see Kramarz et al. (2016). Such a measure however may overlook indirect dependencies through third countries. To exemplify such a problem, take the manufacturing of wood in Canada, the output of this industry can be used both by final consumers and by firms as intermediate input. Assume that half of its production is sold directly to Canadian consumers and the other half to the furniture manufacturing industry in the US. The standard portfolio measure would state that the sales composition of the industry is split halfway between Canada and the US. This, however, is not necessarily true since the US industry may sell its output back to Canadian consumers. Take the extreme example of the whole US furniture industry output being exported back to Canada, then the only relevant demand for the Canadian wood manufacturing industry is the one from Canadian consumers.

This example illustrates that, particularly for countries that are very interconnected through trade, measuring portfolio composition only via direct flows may ignore a relevant share of final demand exposure.

Using the Input-Output structure of the data it is possible to account for these indirect links when analysing sales portfolio composition.

Define the share of output of industry r in country i that is eventually consumed by country j as

$$\xi_{ij}^{r} = \frac{F_{ij}^{r} + \sum_s \sum_k a_{ik}^{rs} F_{kj}^{s} + \sum_s \sum_k \sum_t \sum_m a_{ik}^{rs} a_{km}^{st} F_{mj}^{t} + ...}{Y_i^r}. \tag{15}$$

The first term in the numerator represents output from sector r in country i directly consumed by j, the second term accounts for the fraction of output of sector r in i sold to any producer in the world which is then sold to country j for consumption. The same logic applies to higher order terms. By the definition of industry output

$$\sum_j \xi_{ij}^{r} = 1.$$

One can then use these shares to aggregate destination specific demand shocks η_j, at the industry level,

$$\eta_i^r = \sum_j \xi_{ij}^{r} \eta_j.$$

This aggregation weighs each country specific demand shock η_j by the exposure of industry r in country i to the final demand of country j, represented by the sales portfolio share ξ_{ij}^{r}.

As a final remark the next proposition formalises the link between the standard upstreamness measure and the bilateral version, through the sales portfolio shares.

Proposition 2 (Bilateral Upstreamness)
The upstreamness measure proposed by Antràs et al. (2012) can be obtained as a weighted average of bilateral upstreamness using as weights the bilateral sales portfolio shares.

$$U_i^r = \sum_j \xi_{ij}^{r} U_{ij}^{r}. \tag{16}$$

Hence one could interpret the present discussion as a further decomposition of the standard upstreamness measure based on the portfolio composition and bilateral positioning.

Proof. See Appendix A.3. ■

5.4 Aggregation of Upstreamness Measures

From the industry level bilateral upstreamness it is possible to aggregate it into the following measures

$$\begin{aligned}
\text{Output} \qquad U_i^Y &= \frac{\sum_{r=1}^S y_i^r \sum_{j=1}^J \xi_{ij}^r U_{ij}^r}{\sum_{r=1}^S y_i^r \sum_{j=1}^J \xi_{ij}^r}, \\
\text{Bilateral Exports} \qquad U_{ij}^X &= \frac{\sum_{r=1}^S \xi_{ij}^r y_i^r U_{ij}^r}{\sum_{r=1}^S \xi_{ij}^r y_i^r}, \\
\text{Total Exports} \qquad U_i^X &= \frac{\sum_{r=1}^S y_i^r \sum_{j\neq i}^J \xi_{ij}^r U_{ij}^r}{\sum_{r=1}^S y_i^r \sum_{j\neq i}^J \xi_{ij}^r}, \\
\text{Bilateral Imports} \qquad U_{ij}^M &= \frac{\sum_{r=1}^S \xi_{ji}^r y_j^r U_{ji}^r}{\sum_{r=1}^S \xi_{ji}^r y_j^r}, \\
\text{Total Imports} \qquad U_i^M &= \frac{\sum_{j\neq i}^J \sum_{r=1}^S \xi_{ji}^r y_j^r U_{ji}^r}{\sum_{j\neq i}^J \sum_{r=1}^S \xi_{ji}^r y_j^r}.
\end{aligned}$$

Where superscripts Y, X and M denote total output, exports and imports. All these measures are computed at yearly level.

The upstreamness of output is computed by aggregating industry level upstreamness through sectoral output shares. The measures for the flows aggregate the industry upstreamness via the combination of industry output shares and sales portfolio shares. This allows to exclude the part of output that is consumed domestically. The distinction between total and bilateral upstreamness is key for the correct calculation of the trade flows measures.

Given the set of bilateral upstreamness measures it is possible to build two novel indicators for the total steps embedded in a trade balance and the degree of mismatch between what a country exports and what it imports.
The rationale for these two measures are that, given the heterogeneous amplification of shocks along production chains, the distance from consumption of trade flows has implications on the cyclical movement and the volatility of a country's trade balance.
First, I define total upstreamness, unweighted and weighted by trade flows, as

$$\begin{aligned}
U_{i,j}^{TOT} &= U_{i,j}^X + U_{i,j}^M, \\
{U_{i,j}^{TOT}}_w &= \frac{X_{i,j} U_{i,j}^X + M_{i,j} U_{i,j}^M}{X_{i,j} + M_{i,j}}.
\end{aligned}$$

This measure contains information about how upstream both flows are.

Second, by taking the difference one can build a measure of mismatch of the upstreamness of exports and imports for any given partner country.

$$U_{i,j}^{NX} = U_{i,j}^{X} - U_{i,j}^{M},$$
$$U_{i,j}^{NX}{}_{w} = \frac{X_{i,j}U_{i,j}^{X} - M_{i,j}U_{i,j}^{M}}{X_{i,j} + M_{i,j}}.$$

I will relate these two indicators to volatility and cyclicality of net exports.

5.5 Estimating Demand Shocks

To evaluate what is the total demand innovation that affects a specific industry one needs to estimate country specific demand shocks.
I do so by means of a fixed effect model applied to the change in final consumption.[13]
Define the output of industry r in country i that is consumed by country j at time t as F_{ijt}^{r} and denote f_{ijt}^{r} its natural logarithm. Then the fixed effects model used to estimate demand innovations takes the following form

$$\Delta f_{ijt}^{r} = \eta_{jt} + \nu_{ijt}^{r}. \tag{17}$$

Where ν_{ijt}^{r} is a normal distributed error term. The country and time specific demand innovations would then be the series of $\hat{\eta}_{jt}$.[14] This set of fixed effects extracts the change in consumption of destination market j at time t that is common to all sellers.
Recall that the goal is to generate shocks for a specific industry r in country i. Using 17 it could be that industry r chooses how much to sell to j and it is a sizeable fraction of j's consumption. This will bias η_{jt}. Thus, one cannot claim exogeneity of η_{jt} to industry r in country i. To further insure exogeneity, I estimate a different model for every producing country i, specifically

$$\Delta f_{kjt}^{r} = \eta_{jt}(i) + \nu_{kjt}^{r} \quad k \neq i \tag{18}$$

For each industry r of country i, we need a shock that removes the possible choice mentioned above. Therefore, I estimate country's j fixed effect using all industries of all countries except those of country i.

These can be aggregated as described above into producing industry r effective demand shocks

$$\hat{\eta}_{it}^{r} = \sum_{j} \xi_{ijt-1}^{r} \hat{\eta}_{jt}(i). \tag{19}$$

Where the portfolio shares are lagged to eliminate the dependence of portfolio shares themselves on simultaneous demand innovations. This procedure implies that sales from i

[13] A similar approach is used by Kramarz et al. (2016) and Alfaro et al. (2019b).
[14] Different fixed effects model to estimate demand innovations are used as robustness checks.

do not affect $\hat{\eta}_{jt}(i)$ and, therefore, $\hat{\eta}_{it}^{r}$.

The identification of demand shocks relies on the rationale that the fixed effect model in equation 17 captures the variation that is common to all industries when selling to a specific partner country in a given year. The estimation makes the demand shocks exogenous to the producing industry, thereby providing the grounds for causal identification of their effects on output growth.

This approach to instrumenting industry specific shocks is labelled in the literature as shift-share instrument approach. The methodology is discussed in Adão et al. (2019). The identifying assumption for this model is that shocks are exogenous to industries, conditional on the shares. Formally

$$(Y(0), B) \perp\!\!\!\perp H | \Xi \tag{20}$$

Where H is the vector of shocks and Ξ is the vector of shares, $Y(0)$ is the potential outcome and B is the vector of coefficients. This assumption cannot be tested directly, however if H and Ξ are orthogonal, meaning that current shares are uncorrelated with future demand shocks, the concerns on the validity of the instrument are partially mitigated. I provide this test in Appendix D.

The identifying assumption is effectively that shocks are as good as randomly assigned conditional on the shares. As shown in Adão et al. (forthcoming) a further assumption is needed for inference, namely that shocks are independent across sectors.

In this setting the large number of industries ensures plausible random assignment of the shifters as they are estimated as common component across all sectors in the sample.

6 Results

This section provides the results from the empirical analysis. These consist of a first set of findings regarding how demands shocks amplify along the value chain to industry output. Secondly, I provide evidence for the similarity in GVC positioning of countries' output being the key driver of bilateral output comovement. Lastly, I show that countries differ in their trade balance cyclical behaviour depending on the position of their production and consumption in GVCs.

6.1 Demand Shock Amplification and GVC Positioning

The model described in Section 3 provides a relationship between demand shocks by final consumers and changes in output at different stages of the supply chain. The model suggests that, in absence of network effects, amplification is exponential in distance from consumption (as in the line network). In more complex networks the responsiveness to final demand shocks might dissipate along the production chain if the network dampening effect is strong enough.

To empirically test which effect prevails I use the demand shocks extracted by the fixed effects model in equation 18. The estimated outcome is a vector of innovations for every destination country in every period. To aggregate these shocks at the producing industry I use the portfolio shares described above. Using equation 19 one has a vector of "relevant" demand shocks at the producing industry time level.

In all the analysis in the remainder of this section I drop values of industry output growth rates larger than 100%. The 98^{th} percentile of the industry growth distribution is 69%. The results are consistent with different cuts of the data and without dropping any entry.

These shocks are positively correlated with the industry output growth rates and explain 23% of their variance, as shown in Table 1.

Table 1: Industry Output Growth and Demand Shocks

	(1) $\Delta \ln Y_{it}^r$
$\hat{\eta}_{it}^r$	0.641^{***}
	(0.00650)
Constant	0.0700^{***}
	(0.000940)
N	31921
R^2	0.234

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the table shows the regression of the growth rate of industry output on the weighted demand shocks that the industry receives.

Quantitatively, the estimation suggests that a 1 percentage point increase in the growth rate of final demand produces a .64 increase in the growth rate of industry output.

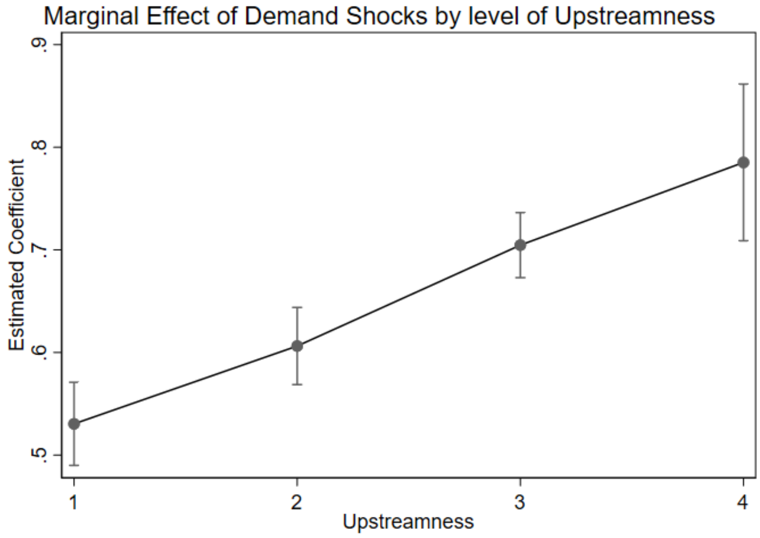
The exogeneity of the estimated demand shocks allows for a causal identification of their effect on output growth. In particular, to test the model prediction I run an econometric model in which the exogenous demand shock can be considered a treatment and the upstreamness level is a moderator of the treatment effect.

I split the upstreamness distribution into dummies taking values equal 1 if $U_i^r \in [1, 2]$ and $[2, 3]$ and so on. Formally, I estimate

$$\Delta \ln(Y_{it}^r) = \sum_j \beta_j \mathbb{1}\{U_{it}^r \in [j, j+1]\}\hat{\eta}_{it}^r + \nu_{it}^r, \qquad j = \{1, 2, 3, 4\}. \tag{21}$$

Since only 2% of the observations are above 5, I include them in the last indicator function, $\mathbb{1}\{U_{it}^r \in [4, \infty)\}$. The resulting coefficients are plotted in Figure 3 while the regression output is displayed in Table 10 in the Appendix.

Figure 3: Effect of Demand Shocks on Output Growth Standard Deviation by Upstreamness Level



Note: the figure shows the marginal effect of demand shocks on industry output changes by industry upstreamness level. The vertical bands show the 95% confidence intervals around the estimates. Note that due to relatively few observations above 5, all values above have been included in the $U \in [4, 5]$ category.

The results suggest that the same randomly assigned demand growth rate shock produces largely heterogeneous responses in the growth rate of industry output. Particularly industries located between one and two steps from consumers respond approximately 40% less than industries located 4 or more steps away. This results, which is robust across different fixed effects specifications, highlights how amplification along the production chain can generate sizable heterogeneity in output responses.

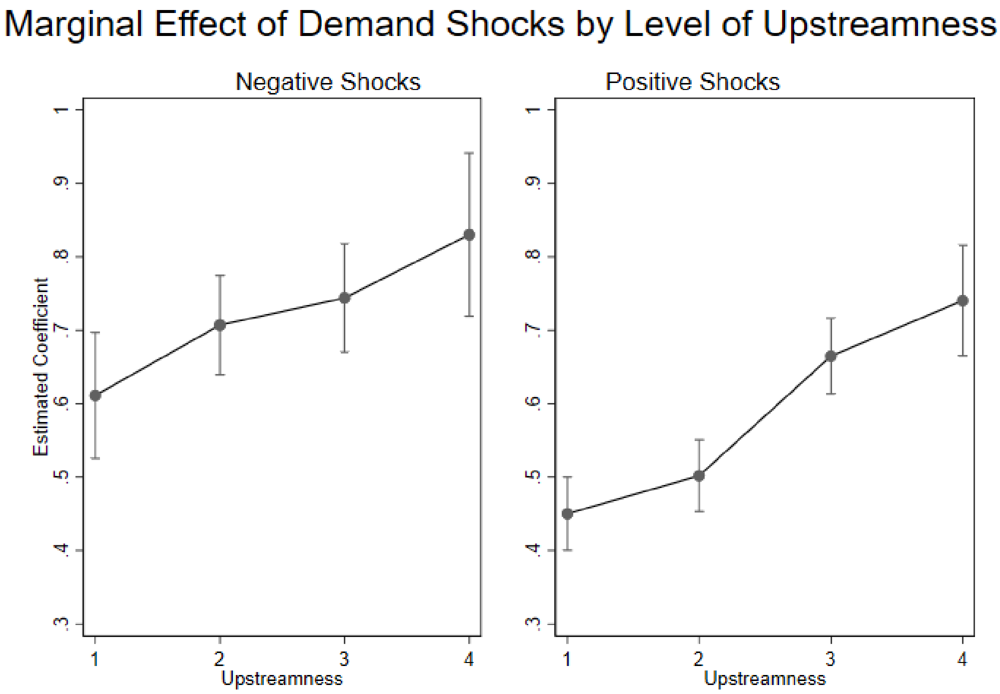
This estimation also suggests that every additional unit of distance from consumption increases the responsiveness of industry output to demand shocks by approximately .09, which represents 14% of the average response.

I further decompose this effect depending on the sign of the demand shock. This analysis aims at studying whether the amplification described above is independent of whether firms receive a positive or negative demand innovation.

Specifically I re-estimate the model by interacting the upstreamness dummies with an indicator for the sign of the shock. The result in Figure 4 suggests that amplification takes place in both instances. However sectoral output responds between 10 and 20% more to negative demand shocks for all levels of upstreamness, suggesting an asymmetric effect.

This asymmetry is possibly due to a differential response in terms of network formation and disruption or to heterogeneous constraints in shock absorption capacity. An example of the latter could be firms choosing capacity utilization. In the presence of negative shocks firms can reduce plants utilization, thereby amplifying shocks upstream. When faced with positive shocks firms are bounded above by the existing plants and may be unwilling to pay the fixed cost to permanently increase capacity. Such an asymmetry could produce the observed empirical result.

Figure 4: Effect of Demand Shocks on Output Growth Standard Deviation by Upstreamness Level



Note: the figure shows the marginal effect of demand shocks on industry output changes by industry upstreamness level, divided by the sign of the demand shock. The vertical bands show the 95% confidence intervals around the estimates. Note that due to relatively few observations above 5, all values above have been included in the $U \in [4, 5]$ category.

6.2 Network Importance

The theoretical model suggests that the degree of amplification or dissipation depends on a combination of industry position and importance in the network. The former, in the model, carries an effect due to inventory amplification. The available data does not allow me to directly test this mechanism. However it is possible to measure the theoretical objects defining the network in the model. In particular it is possible to compute, for every industry, the outdegree and the Leontief inverse coefficient. Defined as

$$outdegree_i^r = \sum_j \sum_s \tilde{a}_{ij}^{rs},$$
$$leontief_i^r = \sum_j \sum_s \tilde{\ell}_{ij}^{rs},$$

where $\tilde{a}_{ij}^{rs}$ is an element of $\tilde{A}$ and $\tilde{\ell}_{ij}^{rs}$ is an element of $\tilde{L}$. These can be added to the previous regressions as controls.

The results of the estimation including these network measures is displayed in Table 11 in the Appendix. All the conclusions for the baseline estimation are confirmed both qualitatively and quantitatively.

As a second robustness check for the network role, I also estimate the following regression

$$\Delta \ln Y_{it}^r = \beta_1 \hat{\eta}_{it}^r + \beta_2 U_{it}^r \times \hat{\eta}_{it}^r + \beta_3 outdegree_{it}^r \times \hat{\eta}_{it}^r + \beta_4 leontief_{it}^r \times \hat{\eta}_{it}^r + \epsilon_{it}^r.$$

The coefficients of interest are β_2, β_3 and β_4 which show how a sector's position, outdegree and leontief coefficient change the effect of demand shocks on output growth. The results of this estimation are reported in Table 2. The results show that the marginal effect of a 1 percentage point change in final demand on the growth rate of output increases by approximately 8 percentage points for every additional upstreamness level. Hence an industry at distance 1 will respond $.40 + .08$ while an industry at distance 2 will respond $.40 + 2 \times .08$. This result is robust to the inclusion of the measures of network importance.

Table 2: Marginal Effect of Demand Shocks on Output Growth by Upstreamness Level

	(1) $\Delta \ln Y_{it}^r$	(2) $\Delta \ln Y_{it}^r$	(3) $\Delta \ln Y_{it}^r$	(4) $\Delta \ln Y_{it}^r$
$\hat{\eta}_{i,t}^r$	0.404***	0.404***	0.398***	0.383***
	(0.0324)	(0.0325)	(0.0329)	(0.0332)
$U \times \hat{\eta}_{i,t}^r$	0.0842***	0.0838***	0.0796***	0.0832***
	(0.0114)	(0.0113)	(0.0115)	(0.0115)
$outdegree \times \hat{\eta}_{i,t}^r$		0.00218		-0.0997**
		(0.0163)		(0.0376)
$leontief \times \hat{\eta}_{i,t}^r$			0.00884*	0.0342***
			(0.00467)	(0.0118)
Constant	0.0705***	0.0705***	0.0706***	0.0707***
	(0.00209)	(0.00209)	(0.00210)	(0.00210)
N	31921	31921	31921	31921
R^2	0.239	0.239	0.239	0.239

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of log industry output on demand shocks both in isolation and interacted with the measure of upstreamness of the industry. Columns 2-4 include the interactions of demand shocks with network importance measures as the sectoral outdegree and the sector's cumulative Leontief inverse coefficient. Standard errors are clustered at the producing industry level.

6.3 Business Cycle and Global Value Chains

In light of the evidence regarding how shocks propagate and amplify in production chains I move to the analysis of how industrial structure and sector position in GVCs can affect countries' business cycle behaviour.

A common finding in cross country studies of bilateral output comovement is that the similarity of industrial structure is a key predictor of bilateral comovement (see Clark and van Wincoop, 2001; Imbs, 2004; Ng, 2010).

The standard measure of of similarity in sectoral composition is defined as

$$IS_{ij} = 1 - \sum_r |s_i^r - s_j^r|.$$

Where s_i^r is the industry output share of sector r in country i. This measure evaluates the difference in the sectoral shares of countries' output, however it does not account for within sector heterogeneity and differences in sector positions in production chains (see Figure 5 in the Appendix). I build a similar measure for the similarity in GVC positioning by computing

$$US_{ij} = 1 - \frac{1}{S}\sum_r^S \frac{|U_i^r - U_j^r|}{(U_i^r + U_j^r)/2}.$$

The difference is rescaled by the pairwise mean so that $US_{ij} \in (-1, 1]$ and high values correspond to similar positioning of sectors.

I then estimate the importance of the two measures of similarity in predicting the degree comovement in the cyclical components of output by running

$$\rho_{ij} = \beta_1 IS_{ij} + \beta_2 TI_{ij} + \beta_3 US_{ij} + \gamma_i + \gamma_j + \epsilon_{ij}.$$

Where ρ_{ij} is the correlation between the cyclical component of output of country i and country j and $TI_{ij} = \frac{X_{ij}+M_{ij}}{Y_i+Y_j}$ is a commonly used measure of bilateral trade intensity.
The results, shown in Table 3, suggest that the predictive power of the measure of industrial structure similarity vanishes when the regression is augmented with the index of upstreamness similarity. This evidence highlights how the position of countries' industries in production chains is a more relevant indicator of bilateral comovement. In Columns (5) and (6) I add the interaction term between the two measures of similarities. Such inclusion shows that, in the specification without country fixed effects, the industry composition metric turns negative, highlighting that the positive effect of similarity and comovement mostly runs through its joint effect with the measure of positioning. The result in Column (6) suggests that the industry similarity measure now captures possible substitutability between the two countries' output, whereas the complementarity, that drives the positive comovement, is absorbed by the interaction. Lastly, when one includes country fixed effects

Table 3: Comovement and Industry Structure

	(1)	(2)	(3)	(4)	(5)	(6)
	$\rho_{i,j}$	$\rho_{i,j}$	$\rho_{i,j}$	$\rho_{i,j}$	$\rho_{i,j}$	$\rho_{i,j}$
$IS_{i,j}$	0.171***	-0.0234	0.313***	0.0514	-1.621***	-0.172
	(0.0403)	(0.0401)	(0.0735)	(0.0735)	(0.306)	(0.266)
$TI_{i,j}$	15.27***	12.45***	10.96***	8.602***	10.36***	8.361***
	(2.347)	(2.174)	(2.055)	(1.947)	(2.181)	(1.967)
$US_{i,j}$		1.068***		1.554***	0.357**	1.458***
		(0.0823)		(0.147)	(0.158)	(0.184)
$US_{i,j} \cdot IS_{i,j}$					2.137***	0.297
					(0.406)	(0.340)
Constant	0.586***	-0.139**			0.380***	
	(0.0159)	(0.0578)			(0.114)	
Country FE	No	No	Yes	Yes	No	Yes
N	946	946	944	944	946	944
R^2	0.0796	0.219	0.587	0.634	0.241	0.635

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of the bilateral comovement of the cyclical component of output over measures of industry composition and upstreamness similarity between countries. Columns 3 and 4 include 2 sets of country fixed effects.

both the IS measure and its interaction with US are not statistically significant.

6.4 Global Value Chains and Trade along the Business Cycle

Building on these results I study how industry composition and GVC position can shed some light on the observed cross-country heterogeneity in trade balances behaviour over the business cycle.

Given the previous discussion on the amplification of shocks upstream in a value chain, two main facts should be found in the data:

1. Countries with higher total upstreamness should display higher volatility. Fixing the covariance between export and import, for a given demand shock, higher upstreamness implies higher response.

2. Countries with higher net upstreamness should display more procyclical trade balances. For a given global demand shock the response of the more upstream flow should be larger than the less upstream flow one. This implies that with positive net upstreamness, exports should respond more than imports, generating a more procyclical trade balance.

In this analysis I use the country aggregated indicators described in the Methodology section:

$$\begin{aligned}
U_{i,t}^{TOT} &= U_{i,t}^{X} + U_{i,t}^{M}, \\
U_{i,j}^{TOT}{}_{w} &= \frac{X_{i,j}U_{i,j}^{X} + M_{i,j}U_{i,j}^{M}}{X_{i,j} + M_{i,j}}, \\
U_{i,t}^{NX} &= U_{i,t}^{X} - U_{i,t}^{M}, \\
U_{i,j}^{NX}{}_{w} &= \frac{X_{i,j}U_{i,j}^{X} - M_{i,j}U_{i,j}^{M}}{X_{i,j} + M_{i,j}}.
\end{aligned}$$

I average them across years to study their relation with volatility and cyclicality measures.

To evaluate the first potential relationship I regress the log of the standard deviation of a country's trade balance on the log of its trade balance total upstreamness, specifically

$$\ln \sigma_i^{NX} = \beta_0 + \beta_1 \ln U_i^{TOT} + \epsilon_i. \tag{22}$$

The result of this estimation is displayed in Table 4 and in Figure 6 in the Appendix. The regression shows a positive correlation, with an estimated effect of 7% increased volatility for a 1% increase in the total upstreamness of the trade balance. To check that this correlation is not entirely driven by a country's development level, I add log per capita GDP and the result remains consistent. The upstreamness measure explains 25% of the observed cross-sectional variability in net exports volatility.

Table 4: Volatility and Total Upstreamness

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln \sigma_{nx}$	$\ln \sigma_{nx}$	$\ln \sigma_{nx}$	$\ln \sigma_{nx}$	$\ln \sigma_{nx}$	$\ln \sigma_{nx}$
$\ln U^{TOT}$	7.661***	8.227***	7.626***			
	(2.199)	(2.604)	(2.323)			
log per capita income		0.200			0.186	
		(0.376)			(0.385)	
U^{NX}			0.0544			
			(0.624)			
$\ln U_w^{TOT}$				7.620***	8.133***	7.048***
				(2.224)	(2.539)	(2.229)
U_w^{NX}						0.575
						(0.453)
Constant	-6.733	-9.856	-6.659	-1.376	-3.898	-0.634
	(4.251)	(7.489)	(4.495)	(2.770)	(5.953)	(2.766)
N	44	44	44	44	44	44
R^2	0.244	0.251	0.244	0.243	0.249	0.273

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of the log of the standard deviation of a country's detrended trade balance on the log of total upstreamness. Column (2) adds log per capita income as a control, while Column (3) includes the net upstreamness measure. Columns 4-6 replicate the analysis with the weighted upstreamness measures.

The results hold when using total upstreamness weighted by trade flows. It is also worth mentioning that the inclusion of the index of net upstreamness does not change the results, highlighting how it is really the total steps embedded in the trade balance that correlates with its volatility.

A similar approach is taken for the second relation, regressing the country specific correlation between net exports and output, both detrended, over the measure of trade balance net upstreamness.

$$\rho_i(NX, Y) = \beta_0 + \beta_1 U_i^{NX} + \epsilon_i. \tag{23}$$

The results are displayed in Table 5 and in Figure 7 in the Appendix. The correlation between the two measures is positive, suggesting that indeed a higher positive mismatch between the position of exported and imported good can affect the degree of procyclicality of the trade balance. In particular the regression shows that a 1 point increase in net upstreamness of trade may increase the cyclicality of net exports between .47 and .58. These results imply that a one standard deviation increase in net upstreamness implies a 1/3 standard deviation increase in the degree of procyclicality of the trade balance. The net upstreamness measure is able to explain 10% of the variance of the trade balance and output correlations. The relation is again robust to controlling for the degree of development of the country. In this case using the weighted version of the net upstramness measure changes the results quantitatively. In particular with this index the effect of a 1 point increase generates approximately a 1 point increase in the cyclicality. This can be read as a 1 standard deviation increase in the weighted net upstreamness implies a 3/4 of a standard deviation increase in procylicality. The explanatory power of this measure also increases significantly to approximately 50% of the observed cross country variation.

Finally it is worth mentioning that these results are robust to the inclusion of total upstreamness, suggesting that the mismatch dimension is the one explaining the variation in the data.

7 Robustness Checks

In this section I provide a set of robustness tests for the analysis of upstream amplification of shocks.

7.1 Ordinal Effects of Upstreamness

First I estimate a similar model to the main specification in the results section but I use ordinal measures from the upstreamness distribution. Namely I interact the industry level shocks with dummies taking value 1 if an industry belongs to an upstreamness decile.

Table 5: Cyclicality and Net Upstreamness

	(1)	(2)	(3)	(4)	(5)	(6)
	$\rho_{nx,y}$	$\rho_{nx,y}$	$\rho_{nx,y}$	$\rho_{nx,y}$	$\rho_{nx,y}$	$\rho_{nx,y}$
U^{NX}	0.561***	0.469**	0.580***			
	(0.195)	(0.235)	(0.218)			
log per capita income		0.159			0.0293	
		(0.158)			(0.0956)	
U^{TOT}			-0.0547			
			(0.145)			
U_w^{NX}				0.955***	0.941***	1.002***
				(0.139)	(0.144)	(0.131)
U_w^{TOT}						-0.291
						(0.206)
Constant	0.00327	-1.619	0.388	-0.0254	-0.322	0.996
	(0.0902)	(1.612)	(1.036)	(0.0645)	(0.967)	(0.736)
N	44	44	44	44	44	44
R^2	0.0987	0.127	0.102	0.505	0.506	0.530

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of the correlation between a country's detrended trade balance and its detrended output on the measure of net upstreamness. Column (2) adds log per capita income as a control, while Column (3) includes the total upstreamness measure. Columns 4-6 replicate the analysis with the weighted upstreamness measures.

Formally the estimated model is

$$\Delta \ln(Y_{it}^r) = \sum_j \beta_j \mathbb{1}\{U_{it}^r \in D_j\}\hat{\eta}_{it}^r + \nu_{it}^r \qquad , j = \{1...10\}. \tag{24}$$

Where D_j denotes the mass between $j-1^{th}$ and the j^{th} deciles of the upstreamness distribution. The results are shown in Figure 8 (and in regression form in Column 1 of Table 12) in the Appendix. The estimation suggests that moving upward in production chains increases the responsiveness of output to final demand shocks. The effect almost doubles when moving from the first to the last decile. This corresponds to moving from 1.17 to 4.37 production stages away from final demand.

As in the main specification, the results suggest that the output response to demand shocks increase with distance from consumption. Ordinally the estimation states that moving from the first to the last decile of the distribution implies an increase in the output response from .49 to .76 percentage points. Note that all the results in this section are robust to the inclusion of industry, country and upstreamness decile fixed effects.

Secondly, I run a model in which instead of using industry output growth rates I use their standard deviation over time, regressed on the standard deviation of the relevant final demand shocks. Formally

$$\sigma_{\Delta \ln(Y_{it}^r)} = \sum_j \beta_j \mathbb{1}\{U_{it}^r \in D_j\}\sigma_{\hat{\eta}_{it}^r} + \nu_i^r \qquad , j = \{1...10\}. \tag{25}$$

The results, plotted in Figure 9 suggest that relationship still holds for the standard deviations. In particular, moving from the first to the last decile of the upstreamness distribution entails a change in the effect of one point of the standard deviation of shocks on the standard deviation of output growth from .71 to 1.22. The results of the estimation are displayed in Column 2 of Table 12 in the Appendix.

Quantitatively, the estimation suggests that the standard deviation of growth increases of 0.04 for every decile of upstreamness. The average standard deviation of output growth in the sample is .16, which implies that moving upward between any upstreamness decile produces a 25% increase in output standard deviation. This is also equivalent to half a standard deviation of the outcome.

7.2 Alternative Fixed Effects Models

In the previous section, I used the fixed effect model used to gauge the idiosyncratic demand shocks. Such model may be confounding other sources of variation. To inspect this possibility I use two alternative econometric models to extract the demand shocks.

In the first one I follow more closely Kramarz et al. (2016) and include producer fixed effects, γ_{it}^r is the fixed effect for the producing industry r in country i at time t, namely

$$\Delta f_{ijt}^r = \gamma_{it}^r + \eta_{jt} + \delta_t + \nu_{ijt}^r. \tag{26}$$

The third alternative, that is closer to the specification used in the main results, uses only partner country year fixed effect but excludes domestic industries, formally

$$\Delta f_{ijt}^r = \eta_{jt} + \delta_t + \nu_{ijt}^r, \quad \forall i \neq j. \tag{27}$$

The condition that $i \neq j$ ensures that domestically produced goods used for final consumption are not included in the estimation. The underlying rationale is that these industries would be the ones whose non demand related variation (think of supply shocks) may be highly correlated with demand shocks themselves.

The results of these two procedures for the cardinal effect of upstreamness (equation 21) are presented in Table 13 and the binscatters are presented in the Appendix in Figures 10 and 11.

The results remain consistent with the previous findings. When the producing industry variation is absorbed upon computing the demand shocks the relationship between the effect of the shocks and upstreamness flattens out at high distance from consumption. This can be seen by the relatively small difference between the effect of shocks at upstreamness between 3 and 4 and above 4. The opposite result is observed when excluding domestic industries in computing demand shocks. The relationship becomes steeper.

As a further robustness check I include a different set of fixed effects in the estimation. Namely I include year, producing country, producing industry and upstreamness level fixed effects. The results are displayed in Table 14 in the Appendix.

The inclusion of these additional sets of fixed effects changes the magnitude of the results, reducing the effect of a 1pp demand shock from .47pp to .25pp for the industries with upstreamness between 1 and 2 and similarly for all other levels. The qualitative result however remains robust in that industries' responsiveness to demand shocks remains ranked according to distance from consumption. All the specifications suggest that for the same shock industries very far from consumption respond between 1.5 and 2 times as much as industries close to final consumers.

I propose two additional robustness checks that use shocks estimated with different specifications. The first analysis employs shocks to log final consumption, rather than to the growth rate of final consumption and estimates the elasticity of different industries to demand shocks. Formally I estimate

$$f_{ijt}^r = \gamma_{it}^r + \eta_{jt} + \delta_t + \nu_{ijt}^r,$$

where f_{ijt}^r is the log of final consumption in destination country j of output from industry r in country i. This specification implies that the estimated destination-time specific innovations are in terms of log consumption. I then aggregate these innovations at the industry level and use them to estimate

$$\ln(Y_{it}^r) = \sum_j \beta_j \mathbb{1}\{U_{it}^r \in [j, j+1]\}\hat{\eta}_{it}^r + \nu_{it}^r, \qquad j = \{1, 2, 3, 4\}.$$

In this context the estimated β_j represent the different elasticities of output to demand changes.

The last method I use to test the robustness of the results consists of using the methodology employed in the main result to estimate demand shocks (estimated on growth rates) and then using the base year of final consumption to determine the level of the shock. In other words I construct, for every destination country $\hat{F}_{jt} = F_{jt-1}\hat{\eta}_{jt}$, where $\hat{\eta}_{jt}$ is the exogenous component of the growth rate and F_{jt-1} is the level in the first year of the sample. One can then have level innovations of demand for every industry, once appropriately aggregated through portfolio weights. I then run the same log-log specification to estimate the elasticity of industries at different levels of production to demand shocks.

The results of these two robustness checks are displayed in Tables 15 and 16 in the Appendix, respectively. Qualitatively they confirm the increasing elasticity of output to demand shocks once one moves further away from consumers. These results are robust to the inclusion of several sets of fixed effects, thereby assessing only within variation.

Lastly, as discussed in previous work studying the effect of demand shocks and their propagation in the network (see Acemoglu et al., 2016) I include lags of the output growth rate. The results of the estimation are shown in Table 17 and Figure 12 in the Appendix. This robustness check confirms the results of the main estimation both qualitatively and quantitatively.

8 Conclusions

This paper starts from the premise that firms and sectors position themselves at different stages of production chains. I model this aspect, together with a flexible production network structure and procyclical inventory adjustment, to show that demand shocks can amplify or dissipate in the network. Two potentially counteracting effects are at play in this model. First, procyclical inventory adjustment can produce amplification of demand shocks along the production chain. Secondly, the structure of the network can either dissipate or amplify shocks.

In particular, if the network features small outdegrees (smaller than 1), it may be able to dissipate demand shocks travelling upstream, provided that the inventory amplification channel is relatively small. On the other hand, networks featuring nodes with high outward connections (high outdegree) may strengthen the amplification generated through inventories.

Then, I empirically test the demand shock propagation using data from the World

Input-Output Database. I apply a shift-share instrumental design, using as exogenous demand shocks the destination country-time specific variation across all selling industries and aggregate them using industries' sales portfolio shares.

Regressing sectoral output growth on these industry specific shocks, I find that moving from upstreamness between 1 and 2 to upstreamness above 4, implies an output response to a 1 percentage point demand change from .53 to .78 percentage points.

Furthermore splitting the sample in upstreamness deciles and using as outcome the standard deviation of output growth, I find that moving from the first to the last decile of the distribution implies a 71% increase in the volatility of output growth.

These results provide evidence for amplification of demand shocks travelling upstream in production chains. Through the lenses of the model, this can be interpreted as either the network effect amplifying shocks or the inventory channel overturning the network dissipation effect.

These results remain unchanged when controlling for measures of network importance. Hence one can conclude that the observed heterogeneity in the elasticity of output to demand shocks is driven solely by the position in the production chain.

Given these findings, I study how countries' industrial structure composition and positioning affects their business cycle behaviour.

Firstly, I show that controlling for an index of bilateral similarity in countries' GVC position eliminates the correlation between bilateral comovement in cyclical output and measures of sectoral composition similarity.

The last result of this paper relates two novel indicators of a country's trade balance with its cyclicality and volatility. In particular, using a measure of how many steps of production are embedded in a country's net exports, I show that a 1% increase in this index correlates with 8% higher trade balance volatility. This measure explains approximately 25% of the trade balance volatility. Secondly, using a measure of the mismatch between the upstreamness of exports and the one of imports, I show that a 1 standard deviation increase in such measure correlates with an increase in trade balance cyclicality between 1/3 and 3/4 of a standard deviation, explaining between 10% and 50% of its variation alone. This result is stemming from the intuition that, since export and imports enter the trade balance with opposite signs, and, since higher upstreamness implies higher responsiveness to shocks, a country with high net upstreamness is expected to have a more procyclical trade balance, ceteris paribus.

This paper represents a first attempt at studying how global value chains and industrial structure affect sectors and countries business cycle behaviour in trade. There is no existing theory embodying the elements described in this paper, namely upstream amplification in the network and heterogeneous sectoral composition of countries. The theoretical analysis of these features and their ability to explain the observed cross-country heterogeneity in trade in business cycle is a promising avenue for future research.

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Appendix

A Model Extensions and Proofs

A.1 Heterogeneous Storability

Assume that different sectors have different storage ability (think of some service industry being part of the production chain). Rewriting the model just described with stage specific storage, indexed by α_n implies the following amplification structure

$$Y_t^0 = D_t^0 + \alpha_0(\rho D_t^0 - \rho D_{t-1}^0).$$

From this, output at stage 1 is

$$\begin{aligned} Y_t^1 = & D_t^0 + \alpha_0\rho D_t^0 - \alpha_0\rho D_{t-1}^0 + \\ & + \alpha_1\rho D_t^0 + \alpha_1\alpha_0\rho^2 D_t^0 - \alpha_1\alpha_0\rho^2 D_{t-1}^0 - \\ & - \alpha_1\rho D_{t-1}^0 - \alpha_1\alpha_0\rho^2 D_{t-1}^0 + \alpha_1\alpha_0\rho^2 D_{t-2}^0, \end{aligned}$$

and at stage 2

$$\begin{aligned} Y_t^2 = & \left[(1+\alpha_0\rho+\alpha_1\rho+\alpha_1\alpha_0\rho^2)D_t^0 - (\alpha_0\rho + 2\alpha_1\alpha_0\rho^2 + \alpha_1\rho)D_{t-1}^0 + \alpha_1\alpha_0\rho^2 D_{t-2}^0\right](1+\alpha_2\rho) - \\ & - \alpha_2\rho\left[(1+\alpha_0\rho+\alpha_1\rho+\alpha_1\alpha_0\rho^2)D_{t-1}^0 - (\alpha_0\rho + 2\alpha_1\alpha_0\rho^2 + \alpha_1\rho)D_{t-2}^0 + \alpha_1\alpha_0\rho^2 D_{t-3}^0\right]. \end{aligned}$$

This implies that contemporary amplification at this stage is

$$\begin{aligned} \frac{\partial Y_t^2}{\partial D_t^0} &= (1+\alpha_0\rho+\alpha_1\rho+\alpha_1\alpha_0\rho^2)(1+\alpha_2\rho) \\ &= (1+\alpha_0\rho)(1+\alpha_1\rho)(1+\alpha_2\rho). \end{aligned}$$

Assume that stage 1 producers are in an industry whose product is not storable ($\alpha_1 = 0$), then amplification becomes

$$\frac{\partial Y_t^2}{\partial D_t^0} = (1+\alpha_0\rho)(1+\alpha_2\rho).$$

At a generic stage n, this relationship becomes

$$\frac{\partial Y_t^n}{\partial D_t^0} = \prod_{i=0}^{n}(1+\alpha_i\rho).$$

This states that sectors whose goods are not storable do not contribute to upstream amplification but they do not erase the amplification coming from other sectors in the economy. They simply pass whatever shock the receive from customers to suppliers one-to-one.

A.2 Non-linear Inventory Functions

The key assumption of the model presented in Section 3.1 is that the inventory policy is a constant fraction of expected demand. In this section I extend the setup to a generic inventory function and characterize the necessary condition to observe upstream amplification.

Define the fraction of expected future demand held as inventories by firms as

$$\alpha_t^n(\mathbb{E}_t D_{t+1}^n) \equiv \frac{I_t^n(\mathbb{E}_t D_{t+1}^n)}{\mathbb{E}_t D_{t+1}^n}$$

Note that the model in the main body is nested as the special case $\alpha_t^n = \alpha$, $\forall n, t$.

At the generic stage n,

$$Y_t^n = D_t^n + I_t^n(\mathbb{E}_t D_{t+1}^n) - I_{t-1}^n(\mathbb{E}_{t-1} D_t^n) = D_t^n + \alpha_t^n \mathbb{E}_t D_{t+1}^n - \alpha_{t-1}^n \mathbb{E}_{t-1} D_t^n$$

Hence

$$\begin{aligned}
\frac{\partial Y_t^n}{\partial D_t^0} &= \frac{\partial D_t^n}{\partial D_t^0} + \frac{\partial \alpha_t^n(\mathbb{E}_t D_{t+1}^n)}{\partial D_t^0} \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \frac{\partial \mathbb{E}_t D_{t+1}^n}{\partial D_t^0} \\
&= \frac{\partial D_t^n}{\partial D_t^0} + \frac{\partial \alpha_t^n(\mathbb{E}_t D_{t+1}^n)}{\partial \mathbb{E}_t D_{t+1}^n} \frac{\partial \mathbb{E}_t D_{t+1}^n}{\partial D_t^0} \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \frac{\partial \mathbb{E}_t D_{t+1}^n}{\partial D_t^n} \frac{\partial D_t^n}{\partial D_t^0} \\
&= \frac{\partial D_t^n}{\partial D_t^0} + \alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \frac{\partial \mathbb{E}_t D_{t+1}^n}{\partial D_t^n} \frac{\partial D_t^n}{\partial D_t^0} \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \rho \frac{\partial D_t^n}{\partial D_t^0} \\
&= \frac{\partial D_t^n}{\partial D_t^0} + \alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \rho \frac{\partial D_t^n}{\partial D_t^0} \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \rho \frac{\partial D_t^n}{\partial D_t^0} \\
&= \frac{\partial D_t^n}{\partial D_t^0} \left[1 + \alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \rho \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \rho\right]
\end{aligned}$$

note that with linear inventories the last equation simplifies to $\frac{\partial D_t^n}{\partial D_t^0}(1 + \alpha\rho)$.

As $D_t^n = Y_t^{n-1}$

$$\frac{\partial Y_t^n}{\partial D_t^0} = \frac{\partial Y_t^{n-1}}{\partial D_t^0} \left[1 + \alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \rho \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \rho\right]$$

Amplification occurs iff

$$\frac{\partial Y_t^n}{\partial D_t^0} > \frac{\partial Y_t^{n-1}}{\partial D_t^0}$$

Hence the condition for amplification is

$$\begin{aligned}
&1 + \alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \rho \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) \rho > 1 \Leftrightarrow \\
&\alpha_t^{n\prime}(\mathbb{E}_t D_{t+1}^n) \mathbb{E}_t D_{t+1}^n + \alpha_t^n(\mathbb{E}_t D_{t+1}^n) > 0
\end{aligned}$$

Since $\mathbb{E}_t D_{t+1}^n > 0$, such condition, for functions of the type $\alpha(\cdot) > 0$, is immediately satisfied by any non-decreasing function. For decreasing functions, this boils down to

$$\frac{a'(x)x}{a(x)} > -1$$

This defines a class of functions in terms of their elasticity. This is verified for all decreasing strictly concave functions and for all less than isoelastic decreasing strictly convex functions (e.g. $a(x) = x^\beta$, $-1 < \beta < 0$).

As shown in Section 2 of the Online Appendix, the estimated α function satisfies this property as $\hat{\beta} = -.012$.

A.3 Proofs

Proposition 3 (Dietzenbacher, 2005)
For $p^{vu} \equiv \frac{M_{vu}}{Y_v}$, where p^{vu} are elements of the allocation matrix P. The condition $\sum_u p^{vu} \leq 1$, $\forall v$ and $\exists k : \sum_u p_{ku} < 1$ is sufficient for the Leontief inverse $[I-A]^{-1}$ to exist non-negative

Proof. The accounting equation of this economy is $Y = M\underline{1} + F$, where Y is output, M is the input-output matrix in terms of values, $\underline{1}$ is a vector of ones and F is the final consumption vector.
The condition above ensures that all elements of the right hand side are non-negative (from the condition on the p^{vu} it immediately follows that at least one element of F is positive).
The condition above implies that the matrix P satisfies the Brauer-Solow condition, which ensures that $[I - P]^{-1}$ exists non-negative.
From the accounting equation $M = A\hat{Y} = \hat{Y}P$, where $\hat{Y} = \text{diag}\{Y_1, ..., Y_R\}$. Hence $A = \hat{Y}P\hat{Y}^{-1}$. From this $[I-A]^{-1} = [I-\hat{Y}P\hat{Y}^{-1}]^{-1} = [\hat{Y}\hat{Y}^{-1}-\hat{Y}P\hat{Y}^{-1}]^{-1} = \hat{Y}[I-P]^{-1}\hat{Y}^{-1}$.
Hence $[I - A]^{-1}$ exists positive since $[I - P]^{-1}$ and $\hat{Y}$ are positive. ■

In my economy the matrix that needs to be invertible and non-negative is

$$(1 + \alpha\rho)\tilde{A} = (1 + \alpha\rho)M\hat{Y}^{-1}\hat{\Gamma}.$$

Define then a matrix $\tilde{P}$ satisfying the following property: $\hat{A} = \hat{Y}\tilde{P}\hat{Y}^{-1}$. Then, following the same steps of the previous proof, I look for a sufficient condition on $\tilde{P}$ such that $(1 + \alpha\rho)\tilde{A} \geq 0$.

A sufficient condition for $[I - \tilde{P}]^{-1} \geq 0$ (which implies $(1 + \alpha\rho)\tilde{A} \geq 0$ from the proof above) is that the row-sums of of $\tilde{P}$ are all weakly below 1 and at least one is strictly. The matrix is populated by elements of the form

$$\tilde{p}^{vq} = (1 + \alpha\rho)\frac{\gamma_q M_{vq}}{Y_v}.$$

Hence the sufficient condition is $(1+\alpha\rho)\sum_q \frac{\gamma_q M_{vq}}{Y_v} \leq 1$, $\forall v$ and $\exists k : (1+\alpha\rho)\sum_q \frac{\gamma_q M_{kq}}{Y_k} < 1$, as stated in Assumption 1.

This is equivalent to requiring that industries sell a large enough fraction of output to final consumers. To see this, note that, if output is defined as $Y = M\underline{1} + F$, then the sufficient condition is equivalent to

$$(1+\alpha\rho)\left(1-\frac{F_v}{Y_v}\right) \leq 1, \forall v \wedge \exists k : (1+\alpha\rho)\left(1-\frac{F_k}{Y_k}\right) < 1.$$

Proof of Lemma 1. The first part of the Lemma follows immediately from the definition of output at a specific stage n and total sectoral output being the sum over stage specific production.

The proof of the second part requires the following steps: first rewrite total output as

$$\begin{aligned}
Y_{k,t} &= \sum_{n=0}^{\infty} \chi_k^n \sum_{i=0}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i} = \\
&= \sum_{n=0}^{\infty} \chi_k^n (1+\alpha\rho)^{n+1} D_t + \sum_{n=0}^{\infty} \chi_k^n \sum_{i=1}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i} = \\
&= \tilde{Y}_{k,t} + \sum_{n=0}^{\infty} \chi_k^n \sum_{i=1}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i}.
\end{aligned}$$

Define $\tilde{a}_{rs}$ the elements of the matrix $\tilde{A}$, namely the input requirement rescaled by the input share of the using industry. Focusing only on the first term, $\tilde{Y}_{kt}$ can be rewritten, using the definition of χ_k^n, as

$$\begin{aligned}
\tilde{Y}_{k,,t} &= (1+\alpha\rho)\beta_k D_t + (1+\alpha\rho)^2 \sum_s \tilde{a}^{ks} \beta_s D_t + (1+\alpha\rho)^3 \sum_r \tilde{a}^{kr} \sum_q \tilde{a}^{rq} \beta_q D_t + ... \\
&= (1+\alpha\rho)[I + (1+\alpha\rho)\tilde{A} + (1+\alpha\rho)^2 \tilde{A}^2 + ...]_k B D_t \\
&= (1+\alpha\rho)[I - (1+\alpha\rho)\tilde{A}]_k^{-1} B D_t \\
&= (1+\alpha\rho)\tilde{L}_k B D_t.
\end{aligned}$$

Where the equality between the first two rows is given by rewriting it $\tilde{Y}_{kt}$ as the k^{th} element of the stacked column vector of output across sectors, which allows to rewrite the right hand side as a series of input requirement matrices (A and its powers). The equality between the second and the third row follows from the convergence of a geometric series of matrices. . Finally, the last step follows from the definition of the inventory augmented Leontief inverse and concludes the proof. ■

Proof of Example 1. Using Equation (10), together with the assumption $\sum_{q\in Q} \tilde{a}^{vq} = \sum_{q\in Q'} \tilde{a}^{kq}$ allows to rewrite the effect of the marginal change in positioning on the responsiveness of output as

$$\Delta_{\beta}\left(\frac{\partial Y_{k,t}}{\partial D_t}\right) = (1+\alpha\rho)^n \sum_q \tilde{a}^{vq} \sum_p \tilde{a}^{qp} ... \sum_r \tilde{a}^{mr}\tilde{a}^{rs}\left[(1+\alpha\rho)\sum_v \tilde{a}^{kv} - 1\right].$$

The sign of this change is determined by the sign of the bracket for $\rho > 0$. Since, with positively autocorrelated shocks ($\rho > 0$), the first term in the bracket is always weakly larger than one, this equation is negative, implying increasing dissipation along the network, only if $\sum_v \tilde{a}^{kv} < 1$. The change is positive, implying amplification (or increasing dissipation), if the outdegree of the node is larger than 1 or if the inventory effect is strong enough to overcome the network dissipation effect. ■

Proof of Example 2. Using Equation (10), implies

$$\Delta_{\tilde{L}}\left(\frac{\partial Y_{k,t}}{\partial D_t}\right) = (1+\alpha\rho)^n \chi_k^{n-1}\left[(1+\alpha\rho)\sum_v \tilde{a}^{kv} - 1\right].$$

Which is positive if $(1+\alpha\rho)\sum_v \tilde{a}^{kv} - 1 > 0$.

■

Proof of Proposition 2. Denote $\tilde{U}_i^r$ the weighted average for a specific industry r in country i:

$$\begin{aligned}
\tilde{U}_i^r &= \sum_j \xi_{ij}^r U_{ij}^r = \\
&= \sum_j \frac{F_{ij}^r + \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + ...}{Y_i^r} \frac{1 \times F_{ij}^r + 2 \times \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + ...}{F_{ij}^r + \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + ...} \\
&= \sum_j \frac{1 \times F_{ij}^r + 2 \times \sum_s \sum_k a_{ik}^{rs} F_{kj}^s + ...}{Y_i^r} \\
&= \frac{1 \times \sum_j F_{ij}^r + 2 \times \sum_s \sum_k a_{ik}^{rs} \sum_j F_{kj}^s + ...}{Y_i^r} \\
&= \frac{1 \times F_i^r + 2 \times \sum_s \sum_k a_{ik}^{rs} F_k^s + ...}{Y_i^r} = U_i^r,
\end{aligned}$$

where the equality between the fourth and the fifth line follows from $F_i^r = \sum_j F_{ij}^r$. ■

A.4 Alternative Condition for Existence

This section lays out an alternative path to grant existence of a non-negative Leontief Inverse.

The following Lemma formalizes the same concepts of Lemma 1 relying on the following assumption: $(1+\alpha\rho)\sum_r \tilde{a}^{rs} < 1, \forall s$. This condition replaces Assumption 1. The meaning of this condition is discussed later in the section.

Lemma 2 (Sectoral Output)
The sectoral output of a generic industry k is given by

$$Y_{k,t} = \sum_{n=0}^{\infty} \chi_k^n \sum_{i=0}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i}. \tag{28}$$

Furthermore, if $(1+\alpha\rho)\sum_r \tilde{a}^{rs} < 1, \forall s$, the fraction of output that is determined only by contemporaneous demand, denoted $\tilde{Y}_{kt}$, can be written as

$$\tilde{Y}_{k,t} = (1+\alpha\rho)\tilde{L}_k B D_t, \tag{29}$$

where B is the $S \times 1$ vector of demand shares and $\tilde{L}_k$ is the k^{th} row of the inventory augmented Leontief inverse, defined as

$$\tilde{L} = [I + (1+\alpha\rho)\tilde{A} + (1+\alpha\rho)^2\tilde{A}^2 + ...] = [I - (1+\alpha\rho)\tilde{A}]^{-1}.$$

Where $\tilde{A} \equiv A\hat{\Gamma}$ and $\hat{\Gamma} = \mathrm{diag}\{\gamma_1, ..., \gamma_R\}$.

Proof. The first part of the Lemma follows immediately from the definition of output at a specific stage n and total sectoral output being the sum over stage specific production.

The proof of the second part requires the following steps: first rewrite total output as

$$\begin{aligned}
Y_{k,t} &= \sum_{n=0}^{\infty} \chi_k^n \sum_{i=0}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i} = \\
&= \sum_{n=0}^{\infty} \chi_k^n (1+\alpha\rho)^{n+1} D_t + \sum_{n=0}^{\infty} \chi_k^n \sum_{i=1}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i} = \\
&= \tilde{Y}_{k,t} + \sum_{n=0}^{\infty} \chi_k^n \sum_{i=1}^{n+1} (-1)^i \binom{n+1}{i} (1+\alpha\rho)^{n+1-i} (\alpha\rho)^i D_{t-i}
\end{aligned}$$

Secondly, focusing only on the first term, $\tilde{Y}_{kt}$ can be rewritten, using the definition of χ_k^n, as

$$\begin{aligned}
\tilde{Y}_{k,,t} &= (1+\alpha\rho)\beta_k D_t + (1+\alpha\rho)^2 \sum_s \tilde{a}^{ks}\beta_s D_t + (1+\alpha\rho)^3 \sum_r \tilde{a}^{kr} \sum_u \tilde{a}^{ru}\beta_u D_t + ... \\
&= (1+\alpha\rho)[I + (1+\alpha\rho)\tilde{A} + (1+\alpha\rho)^2\tilde{A}^2 + ...]_k B D_t \\
&= (1+\alpha\rho)[I - (1+\alpha\rho)\tilde{A}]_k^{-1} B D_t \\
&= (1+\alpha\rho)\tilde{L}_k B D_t
\end{aligned}$$

Where the equality between the first two rows is given by rewriting it $\tilde{Y}_{kt}$ as the k^{th} element of the stacked column vector of output across sectors, which allows to rewrite the right hand side as a series of input requirement matrices ($\tilde{A}$ and its powers). The equality between the second and the third row follows from the convergence of a geometric series of matrices with column sums in the unit circle. This step requires the following assumption: $(1+\alpha\rho)\sum_r \tilde{a}^{rs} < 1, \forall s$. Finally, the last step follows from the definition of the inventory augmented Leontief inverse and concludes the proof. ■

Without relying on Assumption 1, the augmented Leontief inverse exists non-negative if the column sum of the matrix of input requirements, scaled by $(1+\alpha\rho)$, lies in the unit circle. This assumption implies that the input requirement matrix, rescaled by the inventory term, satisfies the Brauer-Solow condition. This ensures directly the non-negativity of $[I - \tilde{A}]^{-1}$.

Given the estimates for α and assuming the highest possible value of ρ, meaning close to 1, the rescaling factor lies between 1 and 1.5. This would imply that, at most, the column sum of the input requirement matrix cannot exceed .67. The column sum of the input requirement matrix is the indegree of the using industry. As shown in the Online Appendix, the distribution of indegree in the WIOD data ranges from 0 to .99. The average indegree is .48 and approximately 80% of the sample has an indegree lower than .67. If, instead of using the most conservative assumption, namely that all industries have the highest possible inventory-to-future-sales ratio, I use the average (15%), then this would require an indegree that is at most .87, which is the case for 99% of the WIOD sample.

Besides the plausibility of this assumption, it is worth pointing out that this condition carries important implications for amplification and dissipation dynamics. In this economy it is never true that the output response to shocks can increase if one lengthens a chain by one node and not altering the rest of the network. To see this imagine a simple chain that connects sector 1 to sector 2, where the latter is a final good producer. Imagine that $(1+\alpha\rho)\tilde{a}^{12} = .9$. Adding a sector between the two, say sector 3 with $(1+\alpha\rho)\tilde{a}^{13} = .5$ and $(1+\alpha\rho)\tilde{a}^{32} = .9$. The new chain now implies a response of sector 1 to changes in D of $.9 \cdot .5 = .45$. All cases in which the fraction of input used by sector 2 generated by this chain remains constant cannot generate amplification. In this example this restriction is that $(1+\alpha\rho)\tilde{a}^{12} = (1+\alpha\rho)\tilde{a}^{32} = .9$

This implies that the last part of example 2 cannot be true in this economy.

The next subsection derives a further restriction on the set of networks that characterize the economy such that all of the arguments in example 2 still go through.

A.4.1 Directed Acyclic Graphs Economies

The model derived in the last section applies to economies with general networks defined by the input requirement matrix A, a vector of input shares Γ and a vector of demand weights B. I now restrict the set of possible networks to Directed Acyclic Graphs (DAGs) by making specific assumptions on A and Γ. This subset of networks feature no cycle between nodes. For example the networks in Figure 1 are both DAGs. This particular set of graphs have specific necessary but not sufficient conditions:

1. no self-loops: $a_{rr} = 0, \forall r$

2. at least one source node: $\exists s : \gamma_s = 0$

3. at least one sink node: $\exists u : \sum_p a^{up} = 0$

These conditions can be read as: i) no industry uses itself as input; ii) there is at least one industry that does not use other sectors' output as input; iii) there is at least one industry that is not used by any other sector as input. Only if these three conditions are satisfied the network can be acyclic.[15]

Definition 1 (Directed Acyclic Graph)
A Directed Acyclic Graph is a directed graph in which all paths of the form $\tilde{a}^{rs}...\tilde{a}^{ur}$ are equal to zero. Such paths are cycles since the have the same start and end point.

The next proposition provides a bound for the maximal length of a path in such a graph.

Proposition 4 (Longest Path in Directed Acyclic Graph)
In an economy with a finite number of sectors R, whose production network is a Directed Acyclic Graph, there exists an $N \leq R$ such that $(1+\alpha\rho)^n \tilde{A}^n = [0]_{R\times R}$, $\forall n \geq N \wedge (1+\alpha\rho)^n \tilde{A}^n \neq [0]_{R\times R}$, $\forall n < N$. Such N is the longest path in the network and is finite.

Proof. A path in a graph is a product of the form $(1+\alpha\rho)\tilde{a}^{rs}...(1+\alpha\rho)\tilde{a}^{uv} > 0$. A cycle in such graph is a path of the form $(1+\alpha\rho)\tilde{a}^{rs}...(1+\alpha\rho)\tilde{a}^{ur}$ (starts and ends in r). The assumption that there are no cycles in this graph implies that all sequences of the form $(1+\alpha\rho)\tilde{a}^{rs}...(1+\alpha\rho)\tilde{a}^{ur} = 0$ for any length of such sequence. Suppose that there is a finite number of industries R such that the matrix A is $R \times R$. Take a path of length $R+1$ of the form $(1+\alpha\rho)\tilde{a}^{rs}...(1+\alpha\rho)\tilde{a}^{uv} > 0$, it must be that there exists a subpath taking the form $(1+\alpha\rho)\tilde{a}^{rs}...(1+\alpha\rho)\tilde{a}^{ur}$, which contradicts the assumption of no cycles. Hence the longest path in such graph can be at most be of length R.
The elements of the matrix $\tilde{A}^n$ take the form $\sum_u \tilde{a}^{vu}...\sum_s \tilde{a}^{ps}$, where the sequence has length n. The elements of all matrices $\tilde{A}^n$ with $n > R$ have all zero elements as they sum paths equal to zero. ■

In this economy the condition for existence of the non-negative Leontief Inverse is much milder as shown in the next proposition.

Proposition 5 (Existence of Non-Negative Leontief Inverse)
An economy with a finite number of sectors R, whose production network is a Directed Acyclic Graph has a non-negative Leontief Inverse if $(1+\alpha\rho)^{-1}$ is not an eigenvalue of $\tilde{A}$.

Proof. From Proposition 4 the economy has finite length paths. This implies that one can write the bounded Neumann series of matrices as

[15] Note that these are not sufficient because one could have $\tilde{a}^{rs} > 0 \wedge \tilde{a}^{sr} > 0$, which would imply a loop between r and s.

$$
\begin{aligned}
\tilde{P} =& I + (1+\alpha\rho)\tilde{A} + ... + (1+\alpha\rho)^{N-1}\tilde{A}^{N-1} + (1+\alpha\rho)^{N}\tilde{A}^{N} = \\
=& (I - (1+\alpha\rho)\tilde{A})^{-1}[I - (1+\alpha\rho)^{N+1}\tilde{A}^{N+1}].
\end{aligned}
$$

The technical condition for this statement to be true is that the inverse of $I - (1+\alpha\rho)\tilde{A}$ exists. This is true provided that 1 is not an eigenvalue of $(1+\alpha\rho)\tilde{A}$. This is guaranteed by $(1+\alpha\rho)^{-1}$ not being an eigenvalue of $\tilde{A}$.[16] It is also worth pointing that the conditions defining a DAG imply that zero is one of the eigenvalues of $(1+\alpha\rho)\tilde{A}$. ■

In this specific setting the condition for existence of the matrix $\tilde{P}$ is much less stringent than the one for $\tilde{L}$ in the previous section. In particular the existence of these matrices imply that output is bounded, in a DAG however, since the longest path is finite, there can be amplification anywhere.

An economy featuring such a network can have $(1+\alpha\rho)\sum_r \gamma_s a^{rs} > 1, \forall s$, implying that the conditions to have amplification (or decreasing dissipation) moving upstream in the network are more likely to be satisfied.

As a last remark it is worth pointing out that the assumption that network is a Directed Acyclic Graph is stronger than needed to ensure finiteness of output with amplification. The less restrictive case would be an economy that can feature cycles but such cycles always have indegree lower than 1. This condition implies that shocks can magnify outside cycles but not inside.

[16]If that was the case then the eigenvalues of $I - (1+\alpha\rho)\tilde{A}$ would be zero.

B WIOD Coverage

Table 6: Countries

country	
Australia	Ireland
Austria	Italy
Belgium	Japan
Bulgaria	Republic of Korea
Brazil	Lithuania
Canada	Luxembourg
Switzerland	Latvia
China	Mexico
Cyprus	Malta
Czech Republic	Netherlands
Germany	Norway
Denmark	Poland
Spain	Portugal
Estonia	Romania
Finland	Russian Federation
France	Slovakia
United Kingdom	Slovenia
Greece	Sweden
Croatia	Turkey
Hungary	Taiwan
Indonesia	United States
India	Rest of the World

Table 7: Industries

Industry	Industry
Crop and animal production	Wholesale trade
Forestry and logging	Retail trade
Fishing and aquaculture	Land transport and transport via pipelines
Mining and quarrying	Water transport
Manufacture of food products	Air transport
Manufacture of textiles	Warehousing and support activities for transportation
Manufacture of wood and of products of wood and cork	Postal and courier activities
Manufacture of paper and paper products	Accommodation and food service activities
Printing and reproduction of recorded media	Publishing activities
Manufacture of coke and refined petroleum products	Motion picture
Manufacture of chemicals and chemical products	Telecommunications
Manufacture of basic pharmaceutical products and pharmaceutical preparations	Computer programming
Manufacture of rubber and plastic products	Financial service activities
Manufacture of other non-metallic mineral products	Insurance
Manufacture of basic metals	Activities auxiliary to financial services and insurance activities
Manufacture of fabricated metal products	Real estate activities
Manufacture of computer	Legal and accounting activities
Manufacture of electrical equipment	Architectural and engineering activities
Manufacture of machinery and equipment n.e.c.	Scientific research and development
Manufacture of motor vehicles	Advertising and market research
Manufacture of other transport equipment	Other professiona activitiesl
Manufacture of furniture	Administrative and support service activities
Repair and installation of machinery and equipment	Public administration and defence
Electricity	Education
Water collection	Human health and social work activities
Sewerage	Other service activities
Construction	Activities of households as employers
Wholesale and retail trade and repair of motor vehicles and motorcycles	Activities of extraterritorial organizations and bodies

Table 8: Highest and Lowest Upstreamness Industries

Industry	Upstreamness
Activities of extraterritorial organizations and bodies	1
Human health and social work activities	1.14
Activities of households as employers	1.16
Education	1.22
Public administration and defence	1.22
Accommodation and food service activities	1.66
$\vdots$	$\vdots$
Construction	3.96
Manufacture of wood and of products of wood and cork, except furniture	4.22
Manufacture of fabricated metal products, except machinery and equipment	4.27
Manufacture of machinery and equipment n.e.c.	4.28
Manufacture of other non-metallic mineral products	4.39
Mining and quarrying	4.52
Manufacture of basic metals	5.13

C Inventory Adjustment

Antràs et al. (2012) define the measure of upstreamness based on the Input-Output tables. This measure implicitly assumes the contemporaneity between production and use of output. This is often not the case in empirical applications since firms may buy inputs and store them to use them in subsequent periods. This implies that before computing the upstreamness measure one has to correct for this possible time mismatch.

The WIOD data provides two categories of use for these instances: net changes in capital and net changes in inventories. These categories are treated like final consumption, meaning that the data reports which country but not which industry within that country absorbs this share of output.

The WIOD data reports as Z_{ijt}^{rs} the set of inputs used in t by sector s in country j from sector r in country i, independently of whether they were bought at t or in previous periods.
Furthermore output in the WIOD data includes the part that is stored, namely

$$Y_{it}^{r} = \sum_{s}\sum_{j} Z_{ijt}^{rs} + \sum_{j} F_{ijt}^{r} + \sum_{j} \Delta N_{ijt}^{r}. \tag{30}$$

As discussed above the variables reporting net changes in inventories and capital are not broken down by using industry, i.e. the data contains ΔN_{ijt}^{r}, not ΔN_{ijt}^{rs}.

This feature of the data poses a set of problems, particularly when computing bilateral upstreamness. First and foremost including net changes in inventories into the the final consumption variables may result in negative final consumption whenever the net change is negative and large. This cannot happen since it would imply that there are negative elements of the F vector when computing

$$U = \hat{Y}^{-1}[I - A]^{-2}F.$$

However, simply removing the net changes from the F vector implies that the tables are not balanced anymore. This is also problematic since then, by the definition of output in equation 30 it may be the case that the sum of inputs is larger than output. When this is the case $\sum_i \sum_r a_{ij}^{rs} > 1$, which is a necessary condition for the convergence result, as discussed in the Methodology section.

To solve this set of problems I apply the the inventory adjustment suggested by Antràs et al. (2012). This boils down to reducing output by the change of inventories. This procedure however requires an assumption of inventory usage. In particular, as stated above, the data reports ΔN_{ijt}^{r} but not ΔN_{ijt}^{rs}. For this reason, the latter is imputed via a proportionality assumption. Namely is sector s in country j uses half of the output that industry r in country i sells to country j for input usages, then half of the net changes in inventories will be assumed to be used by industry s. Formally:

$$\Delta N_{ijt}^{rs} = \frac{Z_{ijt}^{rs}}{\sum_s Z_{ijt}^{rs}} \Delta N_{ijt}^{r}.$$

Given the inputed vector of ΔN_{ijt}^{rs}, output of industries is corrected as

$$\tilde{Y}_{ijt}^{rs} = Y_{ijt}^{rs} - \Delta N_{ijt}^{rs}.$$

Finally, whenever necessary, Value Added is also adjusted so that the the columns of the I-O tables still sum to the corrected gross output.

This corrections insure that the necessary conditions for the matrix convergence are always satisfied.

D Test of Exogeneity of Instruments

As discussed in the main text the indentifying assumption for the validity of the shift share design is conditional independence of shocks and potential outcomes. Since this assumption is untestable a provide some evidence that the shares and the shocks are uncorrelated to reduce endogeneity concerns.

I test the conditional correlation by regressing the shares on future shocks and industry fixed effect. Formally

$$\xi_{ijt}^{r} = \beta \hat{\eta}_{jt+1}(i) + \gamma_{it}^{r} + \epsilon_{ijt}^{r}. \tag{31}$$

This estimation yields the following result

Table 9: Test of Exogeneity of Instruments

	ξ_{ijt}^{r}
$\hat{\eta}_{jt+1}(i)$	-0.0121
	(0.00762)
N	1517824
R^2	0.00284

Clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The test shows that the two are uncorrelated, suggesting that the shift share instrument is valid.

E Results

Table 10: Effect of Demand Shocks on Output Growth by Upstreamness Level

	(1) $\Delta \ln Y_{it}^{r}$
Uptreamness in [1,2]	0.530***
	(0.0202)
Uptreamness in [2,3]	0.606***
	(0.0188)
Uptreamness in [3,4]	0.705***
	(0.0158)
Uptreamness in [4, ∞)	0.785***
	(0.0381)
Constant	0.0705***
	(0.00208)
N	31921
R^2	0.238

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of industry output growth rates on demand shocks interacted with dummies taking value 1 if the Upstreamness level of the industry is in a given interval, e.g. [1,2].

Table 11: Effect of Demand Shocks on Output Growth by Upstreamness Level

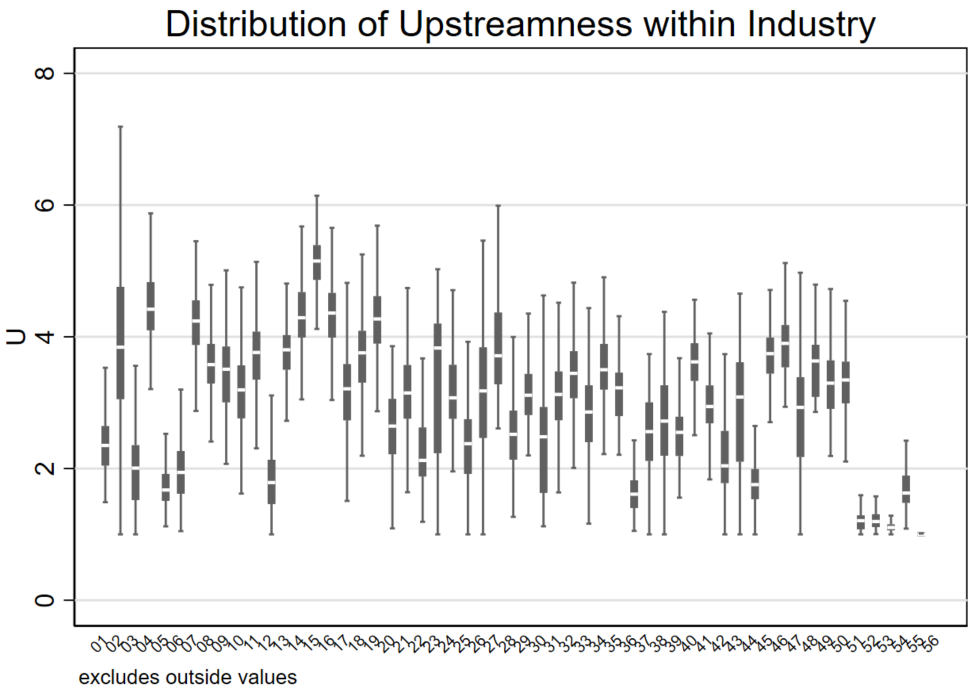
	(1)	(2)	(3)	(4)
	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$
Uptreamness in [1,2]	0.530***	0.530***	0.531***	0.530***
	(0.0202)	(0.0201)	(0.0202)	(0.0200)
Uptreamness in [2,3]	0.606***	0.606***	0.607***	0.605***
	(0.0188)	(0.0188)	(0.0188)	(0.0189)
Uptreamness in [3,4]	0.705***	0.706***	0.705***	0.705***
	(0.0158)	(0.0157)	(0.0158)	(0.0157)
Uptreamness in [4, ∞)	0.785***	0.788***	0.787***	0.785***
	(0.0381)	(0.0383)	(0.0386)	(0.0386)
Sector Outdegree		0.0110***		0.0323***
		(0.00258)		(0.00952)
Sector Leontief Coefficient			0.00129	-0.00648*
			(0.00101)	(0.00339)
Constant	0.0705***	0.0646***	0.0675***	0.0680***
	(0.00208)	(0.00259)	(0.00342)	(0.00408)
N	31921	31921	31921	31921
R^2	0.238	0.240	0.239	0.241

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

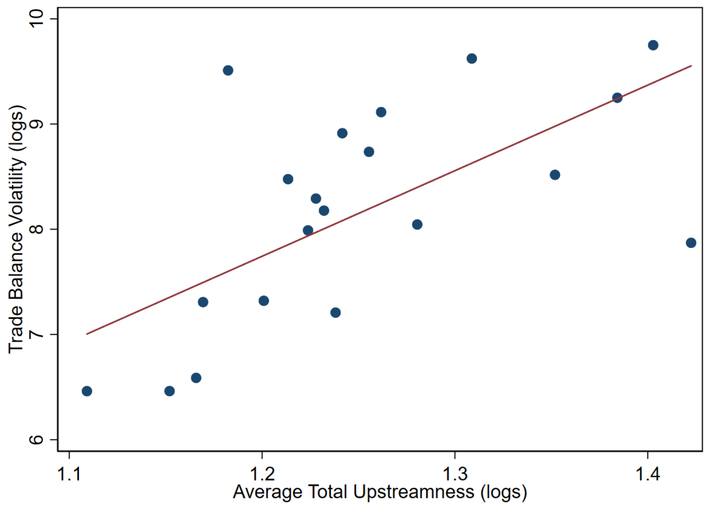
Note: this table displays the results of the regression of growth rate of industry output on demand shocks interacted with dummies taking value 1 if the Upstreamness level of the industry is in a given interval, e.g. [1,2]. Columns 2-4 include measures of network importance at the industry level. In particular the sector's outdegree and the cumulative Leontief inverse coefficient. Standard errors are clustered at the producing industry level.

Figure 5: Within Sector Upstreamness Distribution



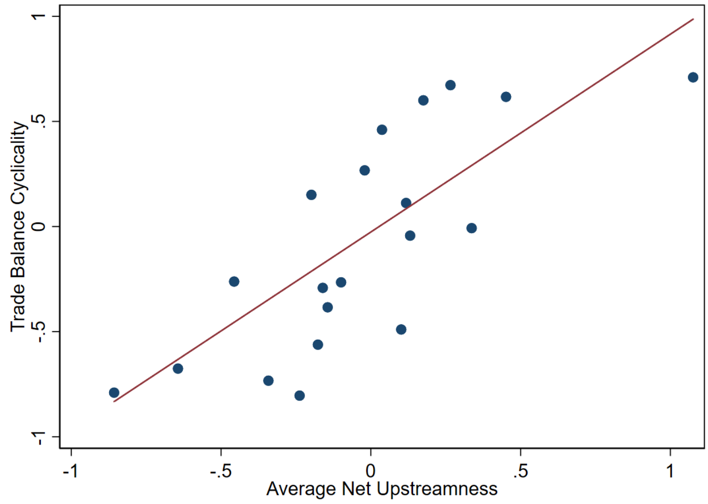
Note: the graph plots the within sector box plot of upstreamness across all countries and years.

Figure 6: Volatility and Total Upstreamness



Note: the graph displays the binscatter of the relationship between the log of the standard deviation of a country's trade balance and the log of the average embedded content (U^{TOT}). The graph is produced after controlling for log per capita GDP of the country.

Figure 7: Cyclicality and Net Upstreamness



Note: the graph displays the binscatter of the relationship between the cyclicality of the trade balance, measured as the correlation between the trade balance and output, and the measure of mismatch in the trade balance (U^{NX}). The graph is produced after controlling for log per capita GDP of the country.

F Robustness Checks

Table 12: Effect of Demand Shocks on Output Growth by Upstreamness Decile

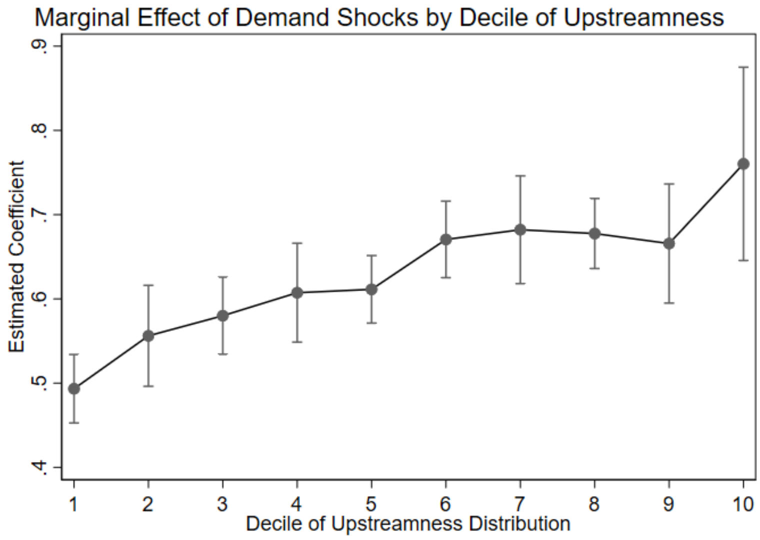
	(1)	(2)
	$\Delta \ln Y_{it}^r$	$\sigma_{\Delta \ln Y_{it}^r}$
decile 1	0.493***	0.864***
	(0.0203)	(0.0561)
decile 2	0.556***	0.927***
	(0.0299)	(0.0679)
decile 3	0.580***	1.047***
	(0.0228)	(0.0583)
decile 4	0.607***	1.067***
	(0.0293)	(0.0582)
decile 5	0.611***	1.049***
	(0.0200)	(0.0531)
decile 6	0.671***	1.085***
	(0.0227)	(0.0488)
decile 7	0.682***	1.174***
	(0.0319)	(0.0470)
decile 8	0.678***	1.108***
	(0.0208)	(0.0371)
decile 9	0.666***	1.231***
	(0.0353)	(0.0425)
decile 10	0.760***	1.323***
	(0.0573)	(0.0981)
N	31921	2327
R^2	0.197	0.708

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

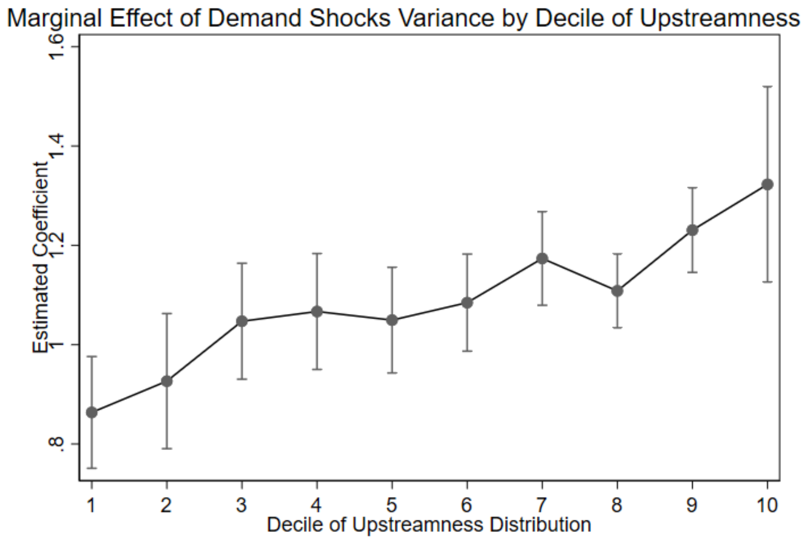
Note: this table displays the results of the regression of industry output growth rates on demand shocks interacted with dummies taking value 1 if the upstreamness level of the industry belongs to a specific decile of the upstreamness distribution. Column (1) displays the regression of output growth rate on demand shocks, while Column (2) shows the regression of the industry specific variance of output growth rates on the variance of the demand shocks said industry faces.

Figure 8: Effect of Demand Shocks on Output Growth by Upstreamness Decile



Note: the figure shows the marginal effect of demand shocks on industry output changes by industry upstreamness decile. The vertical bands show the 95% confidence intervals around the estimates.

Figure 9: Effect of Demand Shocks on Output Growth Standard Deviation by Upstreamness Decile



Note: the figure shows the marginal effect of the variance of demand shocks on the variance of industry output changes by industry upstreamness decile. The vertical bands show the 95% confidence intervals around the estimates.

Table 13: Effect of Demand shocks by level of Upstreamness

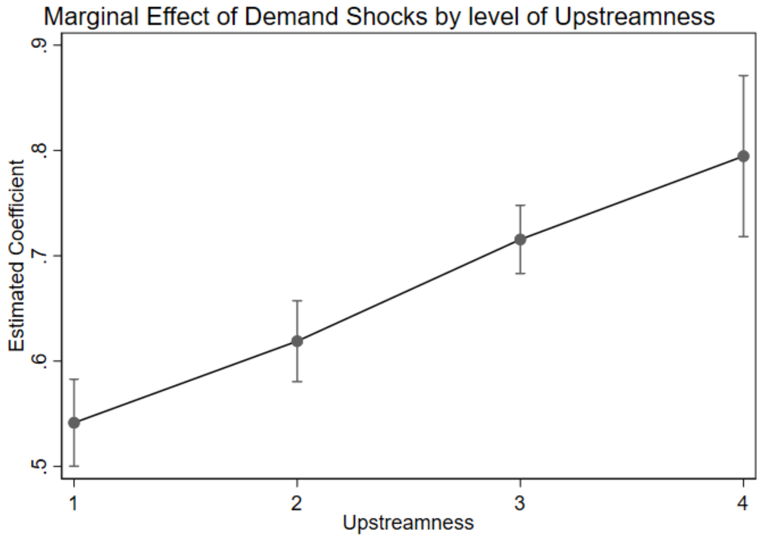
	(1) Supply Shocks Included $\Delta \ln Y_{it}^{r}$	(2) Domestic Industries Included $\Delta \ln Y_{it}^{r}$
Uptreamness in [1,2]	0.541***	0.358***
	(0.0206)	(0.0114)
Uptreamness in [2,3]	0.619***	0.493***
	(0.0192)	(0.0165)
Uptreamness in [3,4]	0.715***	0.579***
	(0.0162)	(0.0183)
Uptreamness in [4,∞)	0.795***	0.675***
	(0.0382)	(0.0436)
Constant	0.0712***	0.0662***
	(0.00209)	(0.00211)
N	31921	31921
R^2	0.239	0.164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

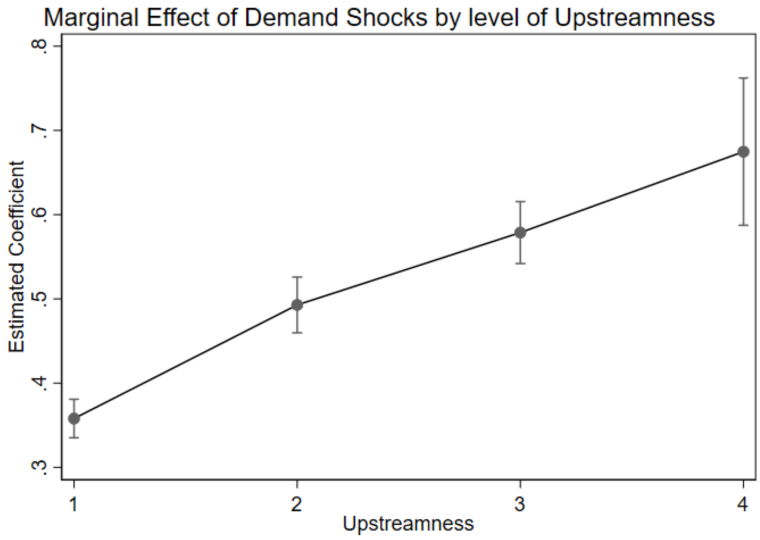
Note: this table displays the results of the regression of industry output growth rates on demand shocks interacted with dummies taking value 1 if the upstreamness level of the industry is in a given interval, e.g. [1,2]. Column (1) runs the model on the demand shocks estimated absorbing producing industry-year variation. Column (2) uses the demand shocks calculated by excluding domestic industries final goods consumption.

Figure 10: Effect of Demand Shocks on Output Growth by Upstreamness Level - Supply Shocks Included



Note: the figure shows the marginal effect of the variance of demand shocks on the variance of industry output changes by industry upstreamness level. The vertical bands show the 95% confidence intervals around the estimates. Note that due to relatively few observations above 4, all values above have been included in the U=4 category.

Figure 11: Effect of Demand Shocks on Output Growth by Upstreamness Level - Domestic Industries Excluded



Note: the figure shows the marginal effect of the variance of demand shocks on the variance of industry output changes by industry upstreamness level. The vertical bands show the 95% confidence intervals around the estimates. Note that due to relatively few observations above 4, all values above have been included in the U=4 category.

Table 14: Effect of Demand shocks by level of Upstreamness

	(1) $\Delta \ln Y_{it}^r$	(2) $\Delta \ln Y_{it}^r$	(3) $\Delta \ln Y_{it}^r$	(4) $\Delta \ln Y_{it}^r$	(5) $\Delta \ln Y_{it}^r$
Uptreamness in [1,2]	0.530***	0.360***	0.359***	0.225***	0.222***
	(0.0202)	(0.0750)	(0.0788)	(0.0718)	(0.0721)
Uptreamness in [2,3]	0.606***	0.415***	0.414***	0.280***	0.276***
	(0.0188)	(0.0574)	(0.0593)	(0.0714)	(0.0709)
Uptreamness in [3,4]	0.705***	0.481***	0.484***	0.338***	0.333***
	(0.0158)	(0.0777)	(0.0751)	(0.0884)	(0.0884)
Uptreamness in [4, ∞)	0.785***	0.529***	0.544***	0.385***	0.381***
	(0.0381)	(0.0761)	(0.0762)	(0.0985)	(0.0985)
Constant	0.0705***	0.0688***	0.0689***	0.0678***	0.0678***
	(0.00208)	(0.00821)	(0.00809)	(0.000222)	(0.000192)
Time FE	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes
Level FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes
N	31921	31921	31921	31921	31921
R^2	0.238	0.277	0.280	0.403	0.409

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of industry output growth rates on demand shocks interacted with dummies taking value 1 if the upstreamness level of the industry is in a given interval, e.g. [1,2]. Column (1) displays the result of the simple OLS without any fixed effect. Column (2) adds year fixed effects. Column (3) includes both year and upstreamness level fixed effects. Column (4) adds producing country fixed effects and column (5) includes also producing industry fixed effects.

Table 15: Effect of Demand Shocks on Output by Upstreamness Level

	(1)	(2)
	$\ln Y_{it}^r$	$\ln Y_{it}^r$
Uptreamness in [1,2]	1.750***	0.140**
	(0.172)	(0.0646)
Uptreamness in [2,3]	2.992***	0.183**
	(0.160)	(0.0723)
Uptreamness in [3,4]	3.930***	0.256***
	(0.140)	(0.0570)
Uptreamness in $[4,\infty)$	4.438***	0.399***
	(0.0988)	(0.0648)
Time FE	No	Yes
Country FE	No	Yes
Industry FE	No	Yes
N	32588	32588
R^2	0.421	0.648

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of log industry output on demand shocks interacted with dummies taking value 1 if the Upstreamness level of the industry is in a given interval, e.g. [1,2]. Standard errors are clustered at the producing industry level in column 1 and at the producing industry, country and year level in column 2.

Table 16: Effect of Demand Shocks on Output by Upstreamness Level

	(1)	(2)
	$\ln Y^r_{it}$	$\ln Y^r_{it}$
Uptreamness in [1,2]	1.035***	0.578***
	(0.00407)	(0.0393)
Uptreamness in [2,3]	1.105***	0.598***
	(0.00548)	(0.0408)
Uptreamness in [3,4]	1.191***	0.635***
	(0.0155)	(0.0411)
Uptreamness in [4,∞)	1.253***	0.681***
	(0.0330)	(0.0412)
Time FE	No	Yes
Country FE	No	Yes
Industry FE	No	Yes
N	31634	31634
R^2	0.987	0.952

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of log industry output on demand shocks interacted with dummies taking value 1 if the Upstreamness level of the industry is in a given interval, e.g. [1,2]. Standard errors are clustered at the producing industry level in column 1 and at the producing industry, country and year level in column 2.

Table 17: Effect of Demand Shocks on Output Growth by Upstreamness Level

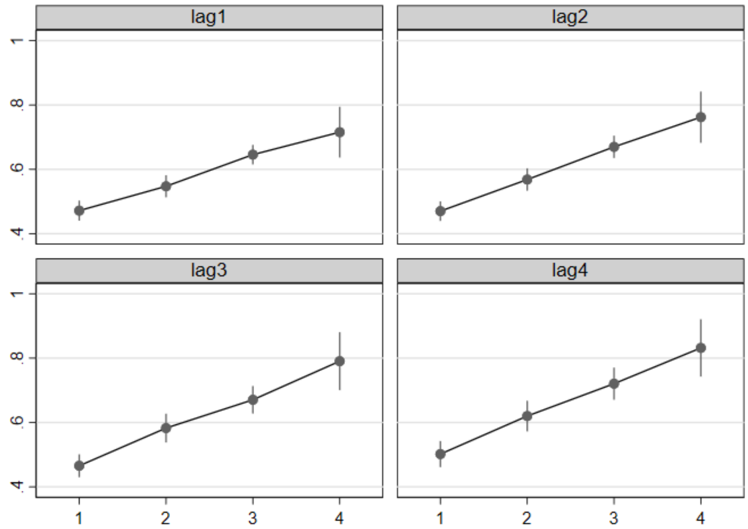
	(1)	(2)	(3)	(4)	(5)
	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$	$\Delta \ln Y_{it}^r$
Uptreamness in [1,2]	0.530***	0.472***	0.470***	0.465***	0.502***
	(0.0202)	(0.0156)	(0.0152)	(0.0178)	(0.0202)
Uptreamness in [2,3]	0.606***	0.547***	0.568***	0.583***	0.620***
	(0.0188)	(0.0172)	(0.0174)	(0.0224)	(0.0238)
Uptreamness in [3,4]	0.705***	0.646***	0.670***	0.670***	0.721***
	(0.0158)	(0.0151)	(0.0172)	(0.0213)	(0.0249)
Uptreamness in [4, ∞)	0.785***	0.716***	0.762***	0.790***	0.832***
	(0.0381)	(0.0393)	(0.0397)	(0.0450)	(0.0444)
L. $\Delta \ln Y_{it}^r$		0.0864***	0.0339***	0.0404***	0.0347**
		(0.0107)	(0.0115)	(0.0130)	(0.0171)
L2. $\Delta \ln Y_{it}^r$			0.0899***	0.0155	0.0214**
			(0.0122)	(0.0103)	(0.0104)
L3. $\Delta \ln Y_{it}^r$				0.0828***	0.0699***
				(0.00856)	(0.00899)
L4. $\Delta \ln Y_{it}^r$					0.0303***
					(0.00928)
Constant	0.0705***	0.0739***	0.0752***	0.0758***	0.0773***
	(0.00208)	(0.00218)	(0.00290)	(0.00334)	(0.00383)
N	31921	29077	26392	23887	21509
R^2	0.238	0.287	0.322	0.359	0.357

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table displays the results of the regression of industry output growth rates on demand shocks interacted with dummies taking value 1 if the Upstreamness level of the industry is in a given interval, e.g. [1,2]. The first column of the table includes the first lag of the dependent variable, the other columns progressively add lags up $t-4$.

Figure 12: Effect of Demand Shocks on Output Growth by Upstreamness Level - Output Growth Lags



Note: the figure shows the marginal effect of the variance of demand shocks on the variance of industry output changes by industry upstreamness level. The vertical bands show the 95% confidence intervals around the estimates. Note that due to relatively few observations above 4, all values above have been included in the U=4 category. The first panel of the figure includes the first lag of the dependent variable, the other panels progressively add lags up $t-4$.

Online Appendix

Not for Publication

1 Descriptive Statistics

This section provides additional descriptive statistics on the World Input-Output Database (WIOD) data.

1.1 Degree Distributions

After calculating the input requirement matrix A, whose elements are $a_{ij}^{rs} = Z_{ij}^{rs}/Y_j^s$. One can compute the industry level in and outdegree

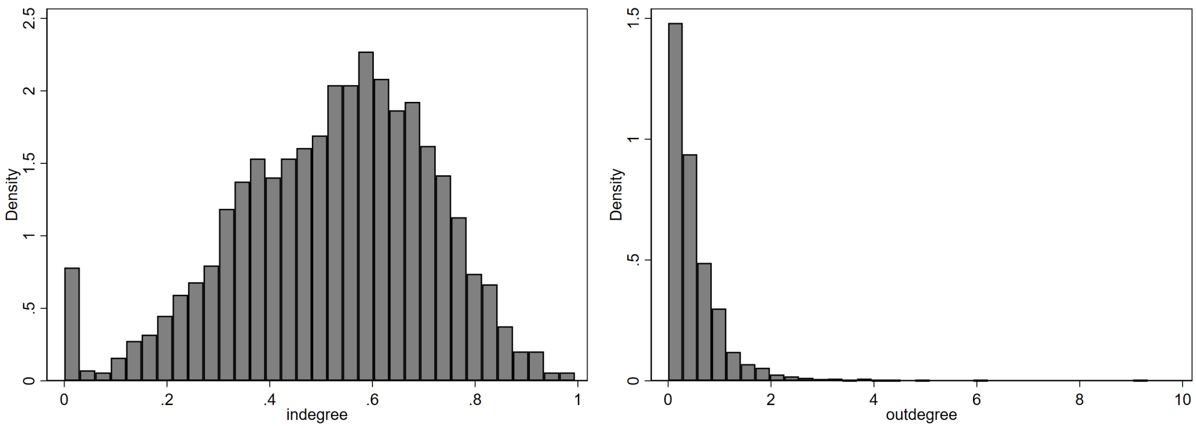
$$indegree_i^r = \sum_i \sum_r a_{ij}^{rs}, \tag{32}$$

$$outdegree_i^r = \sum_j \sum_s a_{ij}^{rs}. \tag{33}$$

The indegree measures the fraction of gross output that is attributed to inputs (note that $indegree_i^r = 1 - va_i^r$ where va_i^r is the value added share).

The weighted outdegree is defined as the sum over all using industries of the fraction of gross output of industry r in country i customers that can be attributed to industry r in country i. This measure ranges between 0, if the sector does not supply any inputs to other industries, and $S * J$, being the total number of industries in the economy, if industry r in country i is the sole supplier of all industries. In the data the average weighted outdegree is .52.

The distributions of these two measures are in Figure 1.

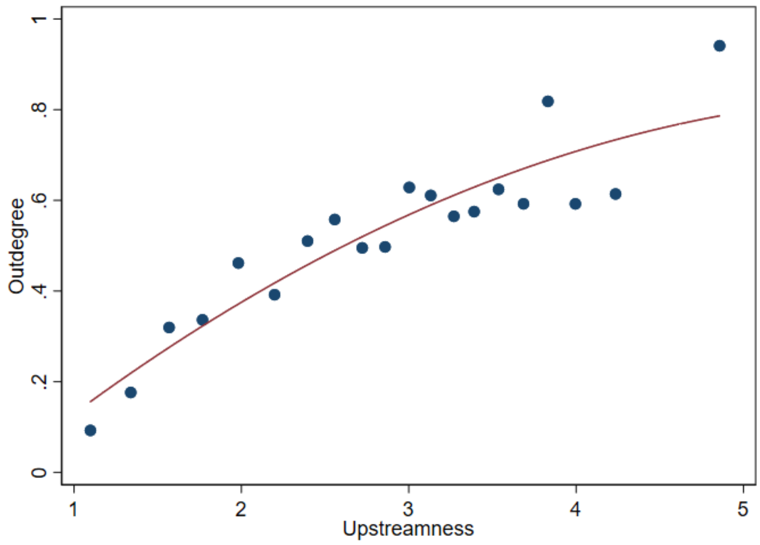


(a) Indegree (b) Outdegree

Figure 1: Degree Distributions

In the WIOD sample industries' outdegree positively correlate with upstreamness, which suggests that industries higher in production chains serve a larger number (or a higher fraction) of downstream sectors. This relationship is shown in Figure 2.

Figure 2: Outdegree and Upstreamness



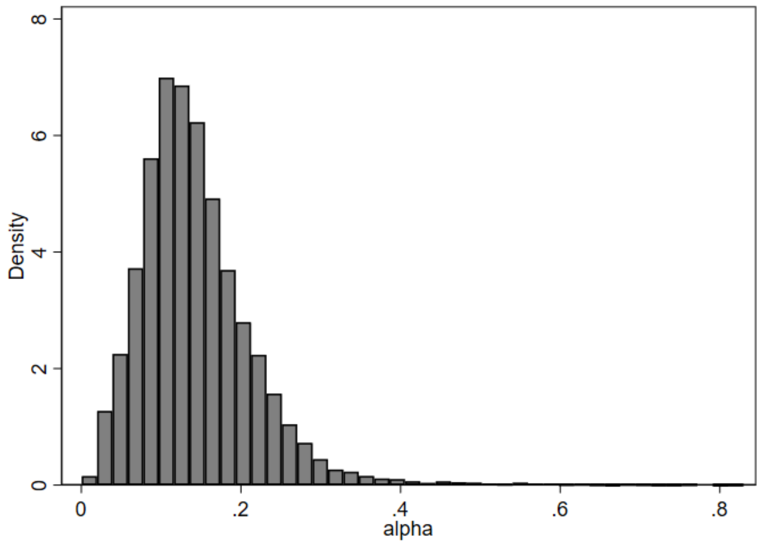
Note: the figure plots the binscatter of industries' outdegree and upstreamness.

2 Inventories

In the model presented in this paper part of the amplification is driven by procylical inventory adjustment. The WIOD data does not provide industry specific inventory stock or change, eliminating the possibility of a direct test of the mechanism.

To provide partial evidence of the behaviour of inventories I use the NBER CES Manufacturing Industry data. This publicly available dataset covers 473 US manufacturing industries at the 6-digit NAICS from 1958 to 2011. The data contains industry specific information about sales and end of the period inventories. As mentioned in the main body of the paper, computing the parameter $\alpha \equiv I_t/\mathbb{E}_t D_{t+1}$ as $\alpha_t = I_t/D_{t+1}$ provides a set of numbers between 0 and 1, with an average of approximately 15%. Figure 3 shows the distribution of α across all industries and years.

Figure 3: Distribution of α



In the model the key assumption is that α is a constant across industries and time. This would imply that inventories are a linear function of sales. Figure 4 shows the scatter plot of the end of the period stock of inventories as a function of current sales (the same picture arises for next period sales). The data is first demeaned at the sectoral level to partial out industry specific differences and only exploit within sector variation. The graph includes a quadratic fit.

Figure 4: Inventories and Sales

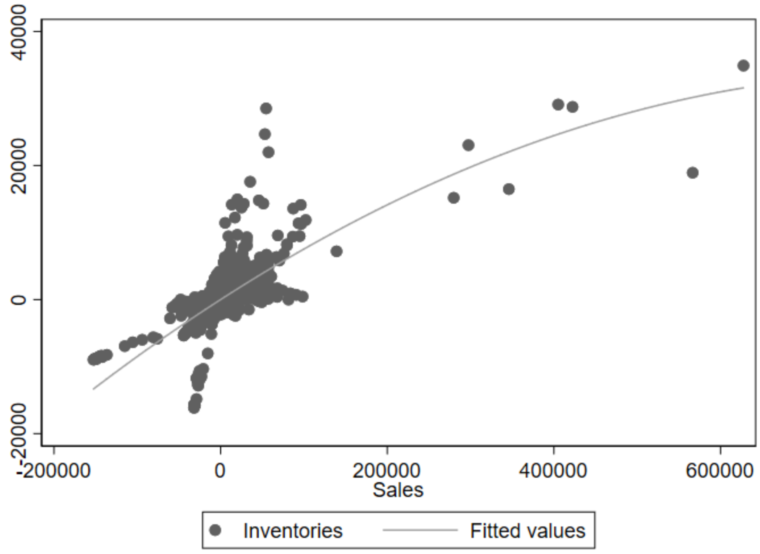
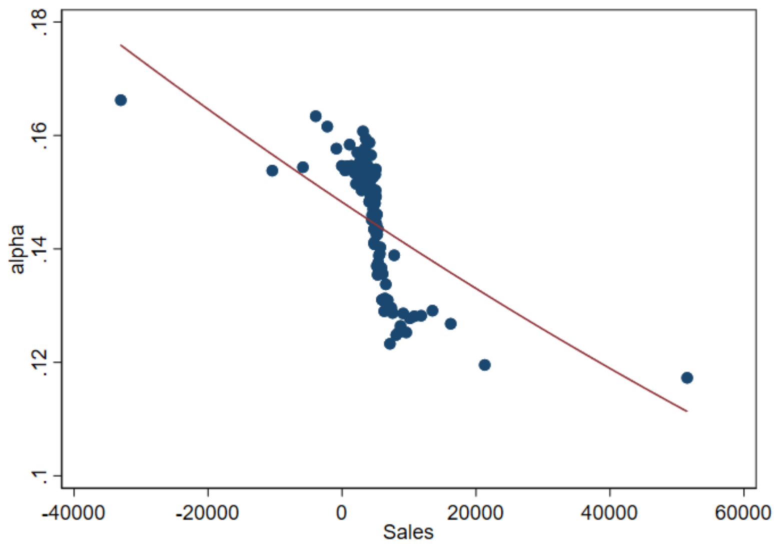


Figure 4 suggests that linearity assumption is relatively close to the data when sales are below the 90th percentile of their distribution. At very high sales level the function significantly deviates from linearity. As discussed in section A.2 all the results go through, provided that the function is not "too concave", in a sense specified there. The necessary condition is expressed in terms of the semi-elasticity of α. The assumptions made there are that α is positive and a decreasing function of demand. Furthermore, to observe amplification, one needs the function to be either strictly concave or "not too convex". Figure 5 shows the binscatter for the relationship between α and sales, after controlling for sector and year fixed effects. The plot includes a quadratic fit.

Figure 5: α and Sales



The graph shows that α is indeed decreasing, positive and slightly convex. Table 1 provides the results for the fixed effects regression of inventories and α over sales in columns 1 and 2. Column 3 provides the estimates of the change in inventories over the change in sales, to test procyclical adjustments.

Table 1: Inventories and Sales

	(1)	(2)	(3)	(4)
	I_t	α_t	α_t	ΔI_t
S_t	0.0669***	-0.000000177***		
	(0.000439)	(2.79e-08)		
$ln(S_t)$			-0.0128***	
			(0.000608)	
ΔS_t				0.0119***
				(0.000546)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	24912	24912	24912	24439
R^2	0.821	0.713	0.717	0.0886

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table shows the results of the estimation of inventories response to sales. Column (1) shows the regression of end of the period inventories on current sales. Column (2) shows the regression of α on contemporaneous sales, while Column (3) uses the log of sales. Column (4) displays the results for the changed in inventories regressed on the change in sales.

As shown in Column 4 a positive change in sales correlates with a positive change in inventories, suggesting that the latter are procyclically adjusted. Furthermore, as shown in Column 3, for the class of functions $\alpha(x) = x^{\beta}$, the estimated functions satisfies the condition for amplification laid out in Section A.2 of the Appendix.

3 Stylized Facts

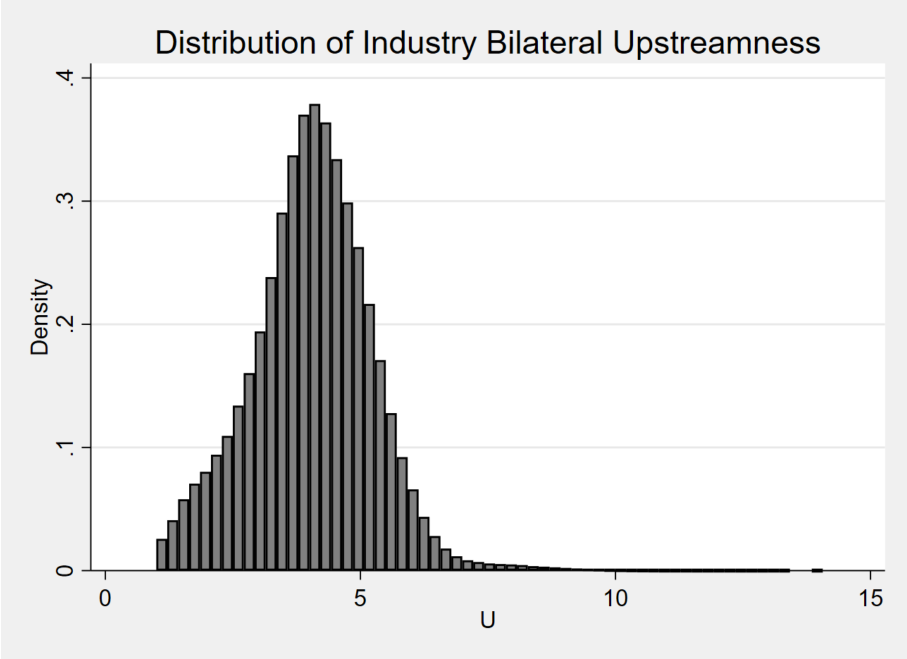
This sections provides a set of novel stylized facts regarding how countries place themselves in global value chains depending on their degree of development, the salient features of industry sales portfolios and some well known features of trade over the business cycle. These empirical regularities extend the facts discussed by Antràs and Chor (2018) and Miller and Temurshoev (2017).

3.1 GVC Positioning and Development

Industries place themselves at different stages of production chains depending on their country of origin and the specific partner country they are trading with. This section provides a set of descriptive statistics about the measure and GVC positioning.

First I plot the distribution of bilateral upstreamness for all industry-partner country-year combinations. This amounts to 1,626,240 different points for U^r_{ijt}.

Figure 6: Distribution of Industry Bilateral Upstreamness

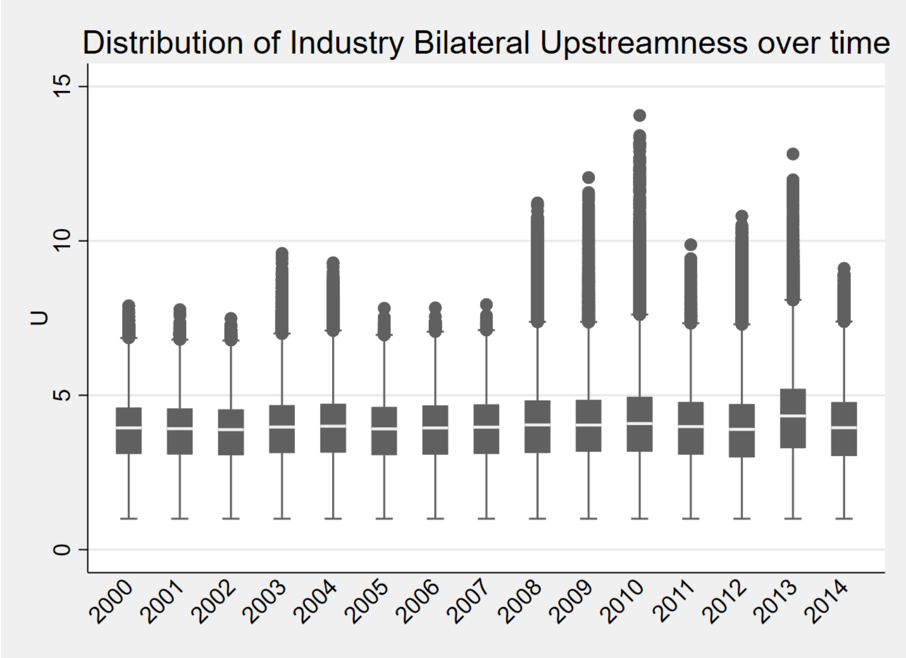


Note: the figure plots the distribution of industry specific bilateral upstreamness pooling all industries, partner countries and years.

The distribution is right skewed, with the average upstreamness being approximately 4 and a long right tail with values up to 14. The central 80% of the distribution lies between 2.5 and 5.5 production stages away from final consumption.

The evidence suggests that over the sample period (2000-2014) the bulk of the distribution did not move, as evidenced by Figure 7 which provides the time specific box plot of the industry bilateral upstreamness measure.

Figure 7: Distribution of Industry Bilateral Upstreamness over time



Note: the figure shows the box plots of the year specific distribution of bilateral industry upstreamness

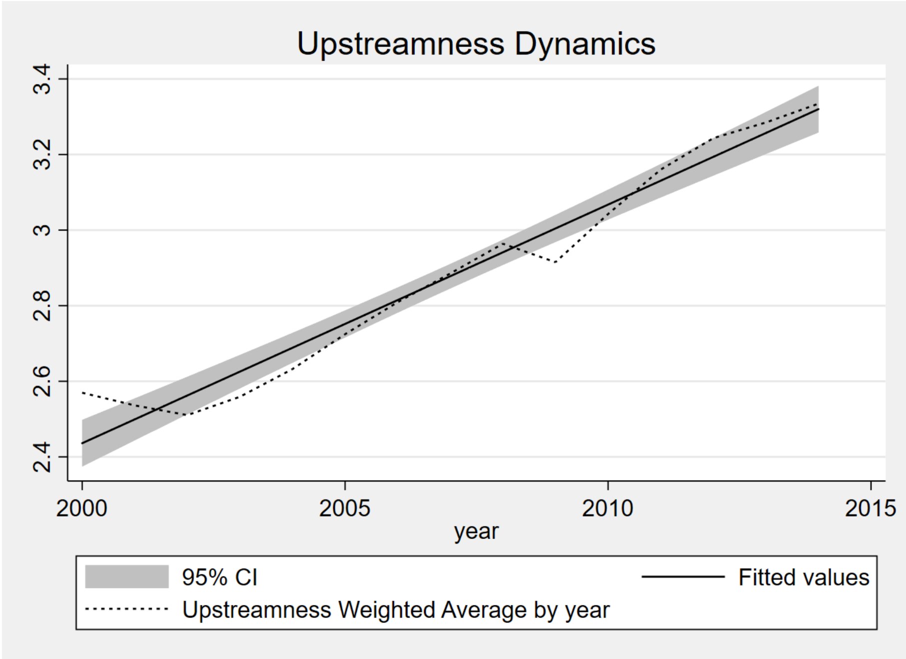
The graph also suggests that over time the right tail of the distribution shifted further to the right. This may be evidence of increasing length of production processes for those products that were already complex in nature.

To study more in detail the dynamic behaviour I plot the weighted average of the upstreamness measure, using as weights the size of the industry-country shares.

$$U_t = \frac{\sum_i \sum_r y_{it}^r U_{it}^r}{\sum_i \sum_r y_{it}^r}. \tag{34}$$

Figure 8 suggests that even if the distribution has not shifted significantly, the complexity of production processes did increase over time.

Figure 8: Upstreamness Dynamics



Note: the figure shows the dynamics of the weighted upstreamness measure computed as described in equation 34. It includes the estimated linear trend and the 95% confidence interval around the estimate.

To assess which channel explains the observed increase in upstreamness I apply the decomposition proposed by Foster et al. (2001) to the weighted upstreamness changes , namely

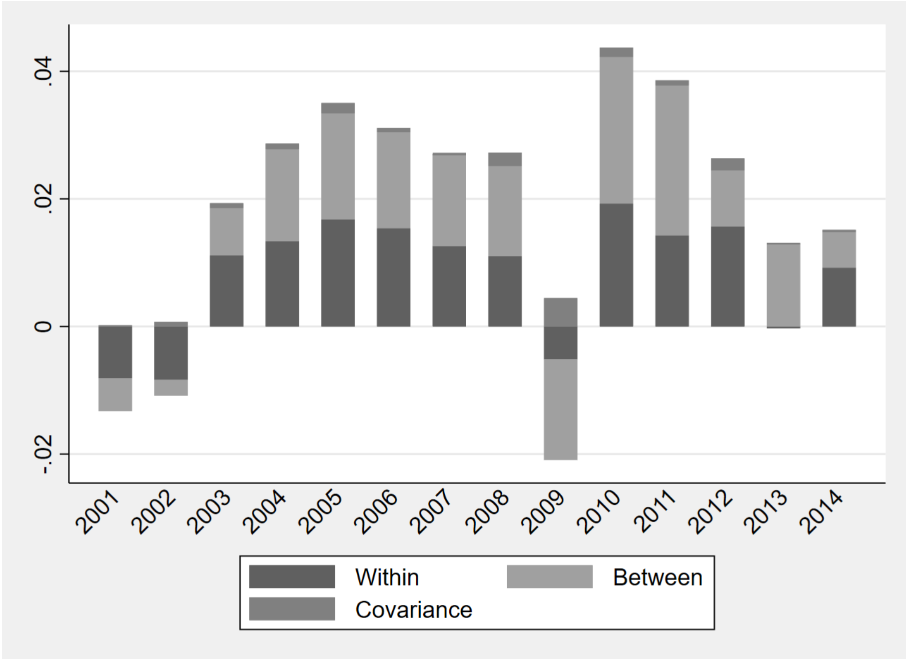
$$\Delta U_t = \sum_i \sum_r \underbrace{\Delta U_{it}^r w_{it-1}^r}_{Within} + \underbrace{U_{it-1}^r \Delta w_{it}^r}_{Between} + \underbrace{\Delta U_{it}^r \Delta w_{it}^r}_{Covariance}. \tag{35}$$

Where $w_{it}^r = \frac{y_{it}^r}{\sum_r y_{it}^r}$ is the industry r output weight within country i. This decomposition separates the contribution to the outcome changes in changes within, namely, given the weights, changes in the level of upstreamness; between, given the level of upstreamness, changes in industry weights and the covariance term.[17]

The results of the decomposition are plotted in Figure 9. The analysis suggests that the observed changes in average upstreamness over time are due to the Within and Between components in equal shares, implying that most of the growth is stemming from large flows increasing the length of the production process and flows of complex goods becoming larger over time. One last interesting stylized fact stemming from the decomposition is that the covariance terms is always positive, independently of whether the average upstreamness is increasing or decreasing in a given year. This suggests that the reallocation is such that flows of products becoming more complex (or further away from consumption) are increasing in relative size or flows becoming less complex are decreasing in their relative importance. This is true even in 2009 during what the literature has labeled the *Great Trade Collapse*, see Baldwin (2011), suggesting that the effect of the crisis was heterogeneous on flows with different degrees of complexity. The specific contributions are displayed in Table 2.

[17] I dispense of the two terms for the contribution of entrants and exiters since given the aggregate nature of the data virtually no flow is zero.

Figure 9: Upstreamness Dynamics Decomposition



Note: the figure shows the stacked contributions (in levels) of the different components of the changes in the weighted upstreamness measure calculated as shown in equation 35.

Table 2: Upstreamness Dynamics Decomposition Contributions

	mean	sd	min	max
within	.4744478	.1917807	-.0215916	.8264168
between	.5242279	.2169459	.2443104	1.010596
cov	.0013245	.0862674	-.270217	.0776356

Note: this tables shows the results from the decomposition of the changes of the weighted upstreamness measure. The table displays the contribution of the different components, namely the *within*, representing changes of the upstreamness level given the weights, *between*, representing changes in the weights given the level of upstreamness, and the *covariance* term, being the simultaneous changes in the level of upstreamness and the weights.

In order to further inspect possible determinants of industry positioning I turn to the analysis of the correlations between the measure and economic development, proxied by GDP per capita. To evaluate this I construct the weighted upstreamness by origination country, using as weights industry output shares

$$U_{it} = \frac{\sum_r y_{it}^r U_{it}^r}{\sum_r y_{it}^r}, \tag{36}$$

and run the following model

$$\ln U_{it} = \beta \ln y_{it} + \delta_t + \epsilon_{it}. \tag{37}$$

The results of this estimation are provided in Table 3 (and plotted in Figure 10). The model shows that there is a positive correlation between a country's economic development and how upstream its industries tend to be. Note that the relationship seems to be consistent only within country, meaning that the initial levels of upstreamness and development are uncorrelated, but that, given a country's baseline, the correlation turns positive and significant. Specifically, a 1% increase in per capita GDP results in a .2% increase in the measure of industry upstreamness. The relationship remains consistent when controlling for the country size, proxied by log GDP, which negatively correlates with the degree of upstreamness, suggesting that larger countries' industries tend to be closer to final consumption.

Table 3: Weighted Upstreamness and Economic Development

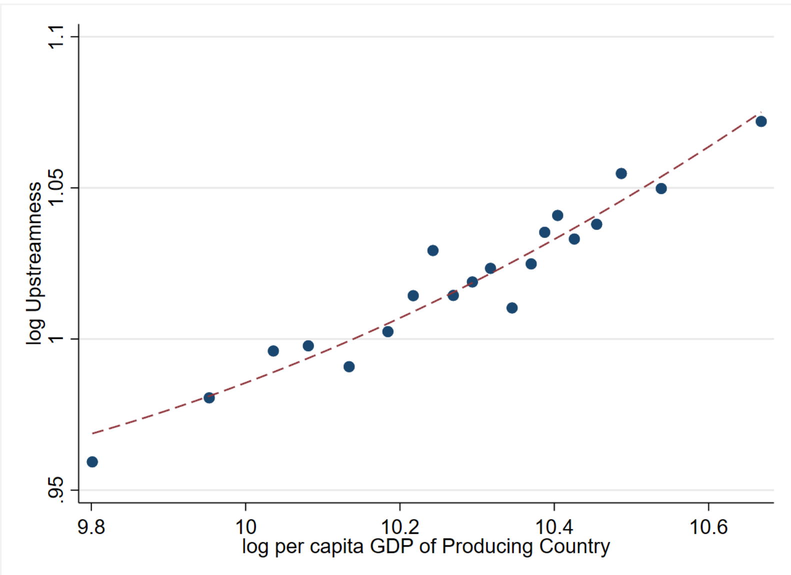
	(1) log Upstreamness	(2) log Upstreamness	(3) log Upstreamness	(4) log Upstreamness
log per capita GDP of Producing Country	-0.00591	-0.00639	0.114***	0.201***
	(-1.11)	(-1.21)	(12.02)	(4.32)
log GDP of Producing Country		0.00937***		-0.0917*
		(2.96)		(-1.90)
Time FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
N	660	660	660	660
R^2	0.0840	0.0963	0.929	0.929

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table presents the results of the regression of the log of upstreamness on the producing country per capita GDP. Weighted upstreamness is computed as described in equation 36. Column (1) shows the results of the model including only time fixed effects. Column (2) adds the log of GDP of the producing country as a control. Finally Columns (3) and (4) replicate the models in (1) and (2) but include country fixed effects.

Figure 10: Industry Bilateral Upstreamness and Economic Development



Note: the figure shows the binscatter of the regression of log upstreamness on log per capita GDP of the producing country. The red dotted line shows the quadratic fit line.

Next I turn to how industries position themselves depending on the partner country's degree of economic development. First I construct the weighted upstreamness by partner country as

$$U_{\cdot jt} = \frac{\sum_i \sum_r y_{it}^r U_{ijt}^r}{\sum_i \sum_r y_{it}^r},$$

and estimate the following econometric model

$$\ln U_{\cdot jt} = \beta \ln y_{jt} + \delta_t + \epsilon_{jt}. \tag{38}$$

The results in Table 4 (and plotted in Figure 11) suggest that the correlation between industry bilateral upstreamness and partner country development is negative, with a 1% increase in the purchasing country per capita GDP implying a .5% drop in the industry bilateral upstreamness measure. The relationship turn insignificant when controlling for partner country size, suggesting that the larger the partner country the closer to consumption industries are when trading with it.

Table 4: Bilateral Industry Upstreamness and Partner Country Economic Development

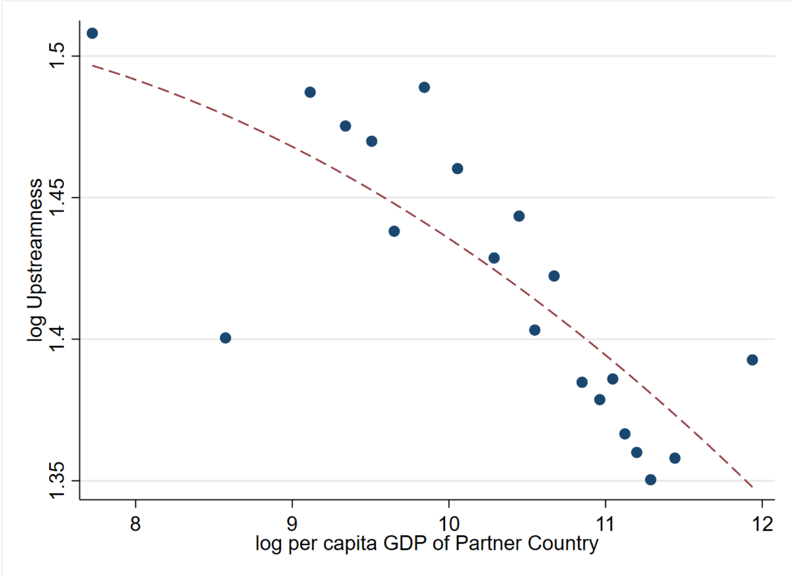
	(1) log Upstreamness	(2) log Upstreamness	(3) log Upstreamness	(4) log Upstreamness
log per capita GDP of Partner Country	-0.0363***	-0.0357***	-0.0563***	0.0813
	(-11.10)	(-11.27)	(-4.00)	(1.18)
log GDP of Partner Country		-0.0129***		-0.146**
		(-6.82)		(-2.04)
Time FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
N	660	660	660	660
R^2	0.306	0.352	0.690	0.692

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table presents the results of the regression of the log of upstreamness on the partner country per capita GDP. Weighted upstreamness is computed as described in equation 38. Column (1) shows the results of the model including only time fixed effects. Column (2) adds the log of GDP of the partner country as a control. Finally Columns (3) and (4) replicate the models in (1) and (2) but include country fixed effects.

Figure 11: Industry Bilateral Upstreamness and and Partner Country Economic Development



Note: the figure shows the binscatter of the regression of log upstreamness on log per capita GDP of the partner country. The red dotted line shows the quadratic fit line.

A further interesting empirical regularity is that countries tend to trade among each other following a specific pattern of specialization in bilateral flows. Figure 12 displays the pattern of bilateral net upstreamness over the difference in log per capita income between the two countries. What emerges is a strong positive correlation. This suggests that when developed economies trade with emerging economies they sell upstream goods and buy downstream ones. Similarly when countries with comparable levels of development trade their net upstreamness is relatively more concentrated around zero, suggesting that they trade in similarly upstream or complex goods. To estimate this relationship I run the following model

$$U_{ijt}^{NX} = \beta \Delta \ln y_{ijt} + \nu_{ijt}. \tag{39}$$

Where $U_{ijt}^{NX} = U_{ijt}^{X} - U_{ijt}^{M}$, $\Delta \ln y_{ijt} = \ln y_{it} - \ln y_{jt}$ with $\ln y_{it}$ denoting log per capita income of country i at time t.

The estimates of this relationship are displayed in Table 5. Note that the regression does not include within country flows (bet upstreamness and income differences are zero by definition) and since both the measures are symmetric ($U_{ijt}^{NX} = -U_{jit}^{NX}$) it only includes pairs once, independently of the direction of the flows, i.e. it drops flows from j to i whenever flows from i to j are in the data, hence the sample size is $J \times (J-1)/2 \times T$, where J is the number of countries.

The estimation suggests that the higher the difference in per capita GDP the higher the difference in net upstreamness. In particular when developed countries trade to developing ones they export more upstream than they import and viceversa. Quantitatively the results state that increasing the difference in log per capita GDP by one point produces a .19 increase in the bilateral net upstreamness.

Table 5: Net Bilateral Upstreamness and per capita GDP difference

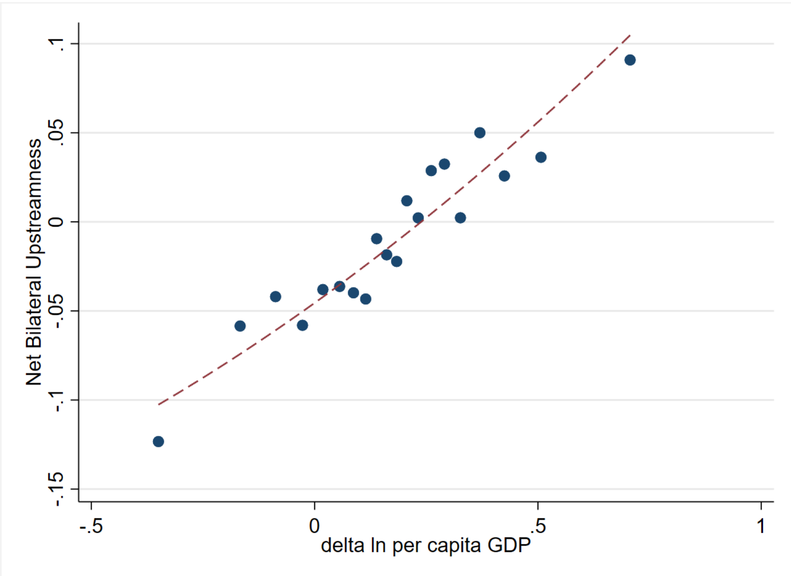
	(1)	(2)
	U_{ijt}^{NX}	U_{ijt}^{NX}
Log per capita Income Difference	0.196***	0.196***
	(11.78)	(16.91)
Time FE	Yes	Yes
Country FE	Yes	No
Partner Country FE	Yes	No
Pair FE	No	Yes
N	14190	14190
R^2	0.529	0.785

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: this table presents the results of the regression of Net Bilateral upstreamness on the difference in log per capita GDP of the producing and partner country. Column (1) includes time and country fixed effects, while columns (2) replaces the countries fixed effects with country pair fixed effects. Standard errors are clustered accordingly.

Figure 12: Net Bilateral Upstreamness and per capita GDP difference



Note: the figure shows the binscatter of the regression of Net Bilateral upstreamness on the difference in log per capita GDP of the producing and the partner country. The red dotted line shows the quadratic fit line.

3.2 Sales Portfolio Composition

The distribution of sales portfolio shares is computed as described in the methodology. The goal of this section is to study whether there composition of sales portfolios would allow for demand shocks diversification. Table 6 reports the summary statistics of the portfolio shares for all industries and all periods.

Table 6: Portfolio Shares Summary Statistics

	count	mean	sd	min	max	p25	p50	p90	p95	p99
portfolio share	1522475	.0227	.1029	3.33e-13	.9999	.0004	.0017	.026	.0659	.7143
domestic portfolio share	34632	.6146	.2744	.0001	.9999	.4176	.6674	.9442	.9793	.9974
export portfolio share	1487843	.0089	.0273	3.33e-13	.962	.0003	.0016	.0199	.0418	.1224

Note: the table displays the summary statistics of the sales portfolio shares. Shares equal to 0 and 1 have been excluded. The latter have been excluded because they arise whenever an industry has 0 output. No industry has an actual share of 1.

The first noticeable feature of the data is that the distribution is very skewed, with the median share being equal to .01%. The skewness is largely driven by domestic sales, which mostly lie in the very right tail of the [0,1] interval. The median of domestic sales is 67%. This also points to relatively low share of trade, even when accounting for third countries linkages. The predominant relevant demand for industry is still the domestic one. The bin scatters of the two distributions are shown in Figure 13.

The distribution of all portfolio shares is skewed. To test the skewness of the distribution, I replicated the methods by di Giovanni et al. (2011) and Axtell (2001). These methods are used to estimate the coefficient of the power law according to which the data is thought to be distributed. Note that portfolio shares cannot be really distributed as a power law due to the inherent bounded support. This procedure is effectively just a way to assess how skewed their distribution is.
The procedure to estimate the coefficient of the power law relies on the definition of the distribution

$$P(S > s) = Cs^{-\zeta},$$

which can be estimated in log log as

$$\ln(P(S > s)) = \ln(C) - \zeta \ln(s).$$

Alternatively it can be studied by regressing the log of the (rank-0.5) on the log of the shares themselves as suggested by Gabaix and Ibragimov (2011). The estimation is

$$\ln(Rank_i - 0.5) = \beta_0 + \zeta \ln(s_i) + \epsilon_i.$$

These two procedures yield very similar results, reported in Table 7. The estimated power law coefficient being approximately .38, suggests that the distribution has a very fat tail. For this reason the scope for diversification is limited, particularly regarding domestic shocks.

Table 7: Portfolio Shares Regressions

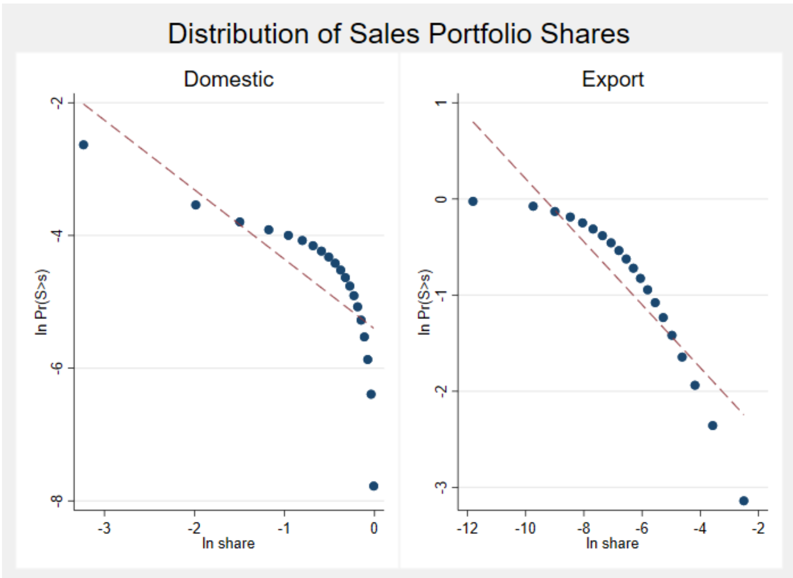
	(1) ln(Pr(S>s))	(2) ln Rank
ln s	-0.373***	0.394***
	(-45.46)	(106.69)
Constant	-3.401***	15.77***
	(-70.08)	(761.84)
N	1522474	1522475
R^2	0.770	0.857

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: shares equal to 0 and 1 have been excluded. The latter have been excluded because they arise whenever an industry has 0 output. No industry has an actual share of 1.

Figure 13: Portfolio Shares Distributions



Note: the figure shows the binscatter of the regressions of the log of the countercumulative frequency sales portfolio shares on the log of the of the portfolio shares. The left panel displays the relationship for domestic sales and right panel for export sales. The red dotted line represent the estimated fit of the regression.

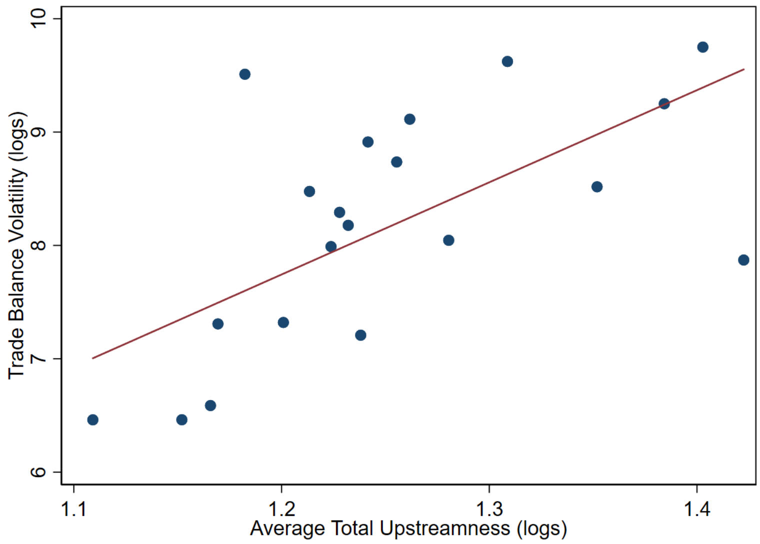
The main takeaway from this analysis is that trade is still relatively limited in the industry sales portfolio and given the high heterogeneity in the portfolios themselves demand shocks may not be diversified away.

3.3 Business Cycle Facts

Net Export Volatility

The first empirical regularity in international macroeconomics is that emerging economies display a larger volatility of net exports than developed countries. This fact is evident from Figure 14. The figure displays the log of the standard deviation of the trade balance against the log of per capita income. In order to detrend the trade balance I follow Uribe and Schmitt-Grohé (2017) and rescale the trade balance by the trend component of output before taking the quadratic trend.

Figure 14: Volatility and Development



The graph displays a negative correlation between the volatility of the trade balance and the degree of development of the country, measured by per capita GDP.

Net Export Cyclicality

The second business cycle fact is that emerging economies display more countercyclical trade balances than developed countries. In Figure 15 I plot the correlation of the detrended trade balance (as described above) with log quadratically detrended output[18] from the World Bank data. The correlation with log per capita income is significantly positive.

[18]Unless otherwise specified detrending is performed by HP filtering the series. The results presented are robust to alternative methods like log quadratic detrending.

Figure 15: Cyclicality and Development