The Network Effects of Fiscal Adjustments*

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Abstract

This paper investigates the effects of fiscal adjustments plans based on government expenditure (EB) and on taxation (TB) on the US economy throughout the production network. We employ spatial econometric techniques, to capture the distinction between demand shocks that propagate upstream in the network and supply shocks that propagate downstream. The differences in the network propagation of TB and EB plans explain 65% of the difference in their total output effect. This result proposes a new interpretation of the empirical evidence that fiscal adjustments based on government spending cuts are less costly in terms of losses in output growth than those based on tax increases. TB plans show a stronger downstream propagation, while EB plans show a stronger upstream propagation. Manufacturing plays a central role in the propagation of both TB and EB plans.
We also find evidence of delayed network effects within dynamic framework, as timing is relevant in the network propagation of fiscal shocks. The concept of network multipliers in the study of industry-specific shocks is also introduced, as it can be useful in the design of efficient policies.

Keywords: industrial networks, fiscal adjustment plans, output growth.
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1 Introduction

This paper studies the propagation of fiscal adjustment plans through the industrial network. Fiscal adjustments based on changing taxation work mainly as supply-side adjustments, while expenditure-based adjustments are the typical demand-side adjustments. As their propagation is different, the size of their final effect on total output depends on the input-output matrix elements. The empirical analysis of a network-based propagation mechanism can be interesting to explain the asymmetric output effect of tax-based and expenditure-based fiscal adjustments.

This paper also contributes to understand how much each sector is "*vulnerable*" to fiscal adjustments that hit all the sectors at the same time and in the same fashion, as it is the case with tax-based adjustments, or in an industry-specific fashion, as it is the case for an expenditure-based plan.
This second line of investigation leads naturally to a measure of "real systemic risk". Real, because the focus is on the real economy and its industrial sectors; systemic risk, because as done in the financial literature, the effects of an idiosyncratic sectoral shock on the whole economy are considered.
In other words, we pose the following question: how much the contraction generated by a public expenditure cut in a given sector will amplify to the whole economy?

Macroeconomic theory has traditionally attributed the large impact of fiscal adjustments on the real economy to the propagation mechanism that amplifies the initial impulse. Such a propagation mechanism has been firstly identified with the Keynesian Multiplier, which concentrates on the demand-side effects (see Diamond, 1982, and Christiano, Eichenbaum, and Rebelo, 2011). However, propagation to the real economy also depends on changes in the incentives of workers and firms, the supply side of the economy (see for example Christiano, Eichenbaum, and Rebelo, 2011). While the propagation through the Keynesian Multiplier always implies stronger output effects of expenditure-based adjustments than tax-based adjustments, the results can be different in a model that includes supply-side effects. Alesina, Barbiero, et al., 2017 introduce the possibility of persistent adjustment plans in a standard New Keynesian framework to show that when fiscal adjustments are close to permanent, spending cuts are less recessionary than tax hikes.
The empirical literature on the macroeconomic effects of fiscal policies has notoriously found a wide range of estimates and is far from reaching a consensus for fiscal multipliers. A new fact, however, is consistently confirmed by a number of recent papers (e.g. Ramey, 2018, Alesina, Favero, and Giavazzi, 2015, Guajardo, Leigh, and Pescatori, 2014). Fiscal consolidations implemented by raising taxes imply larger output losses compared to consolidations relying on reductions in government spending. In this paper, we explore a new propagation mechanism of fiscal policy with the ultimate goal of shedding light on this new fact in the empirical evidence.

The study of propagation of fiscal adjustment plans through the industrial network is related to the work on the network effects of macroeconomic shocks, see: Gabaix, 2011, Acemoglu, Vasco M Carvalho, et al., 2012, Vasco M Carvalho, 2014, Acemoglu, Akcigit, and Kerr, 2016 and Ozdagli and Weber, 2017, Bouakez, Rachedi, Emiliano, et al., 2018, Auerbach, Gorodnichenko, and Murphy, 2019 and Cox et al., 2020. In particular, in Auerbach, Gorodnichenko, and Murphy, 2019, the authors use micro-level data on local defense spending and find the potential for large fiscal spillovers among entities that are strongly integrated economically. Differently from them, we focus on fiscal consolidations using US data over the period 1978-2014 and a spatial autoregressive panel data model. The adoption of spatial econometric techniques to study the network effect of fiscal policy is not new and can be dated back to Case and Rosen, 1993.

Studying the propagation of fiscal adjustments through input-output linkages produces some interesting theoretical implications. As shown by Acemoglu, Akcigit, and Kerr, 2016, theory predicts that supply-side shocks propagate downstream more powerfully than upstream: customers of directly hit sectors are affected more strongly than their suppliers. The converse is true for demand shocks that propagate more powerfully upstream.

The reason for this asymmetric pattern lies in the fact that supply-side shocks change the prices faced by customer industries, while demand-side shocks have much smaller effects on prices and propagate upstream. In the simplified benchmark model studied in much of the literature (Long Jr and Plosser, 1983 and Acemoglu, Vasco M Carvalho, et al., 2012), both production functions and consumer preferences are Cobb-Douglas (so that income and substitution effects cancel out), and the asymmetry in the propagation of demand and supply shocks becomes extreme as there is no upstream effect from supply-side shocks and no downstream effect from demand-side shocks. However, results are robust to different specifications and more sophisticated settings; for instance, in Bouakez, Rachedi, Emiliano, et al., 2018, the authors study the effects of government spending shocks in the US by allowing different propagation mechanisms, and find that downstream propagation is entirely outweighed by upstream propagation.

Fiscal adjustments based on changing taxation work mainly as supply-side adjustments, while expenditure-based adjustments are one of the typical demand-side adjustments. As their propagation is different, the size of their final effect on total output depends on the input-output matrix elements. The empirical analysis of a network-based propagation mechanism of fiscal adjustment can be interesting to provide an assessment of the theoretical mechanism's relevance and its capability to explain the new fact in the empirical literature.

In this sense, our results provide further evidence that government spending shocks have a stronger upstream propagation and therefore behave more like a pure demand shock. Furthermore, we find that taxes have a stronger downstream propagation, thus behaving more as supply-side shocks.

Overall, we find that the downstream propagation of tax-based (TB) fiscal adjustment plans (our measure of tax shocks) is stronger than the upstream propagation of expenditure-based (EB) fiscal plans (our measure of government spending shocks), to the extent that the difference in the network effect of TB and EB plans is capable of explaining up to 65% of the difference in their total output effect.

The inclusion of a production network also allows the study of heterogeneous effects across industries of fiscal adjustments. The network analysis of the transmission of macroeconomic shocks is based on the intuition that input-output linkages can neutralize the law of large numbers because local shocks that hit sectors central to the network do translate into aggregate fluctuations.

In this sense, our heterogeneity analysis finds that Manufacturing is a central sector in the economy and plays a significant role in the propagation of fiscal policy. In particular, sectors that heavily rely on Manufacturing, Finance, and Professional Services as suppliers are the ones mostly hit by TB fiscal adjustment plans. On the contrary, the Mining sector is the one most severely hit by EB fiscal adjustments, and Retail is the one least affected; a result which is consistent both with the theory of upstream propagation of demand shocks and with the nature of Mining and Retail, respectively located at the top and the bottom of the supply chain (maximum and minimum room for upstream spillovers).

The knowledge of what sectors are more vulnerable to fiscal adjustments and what are more harmful in terms of propagating the shocks is interesting not only because it increases our overall comprehension of the economy, but also, because it allows the design of industry-specific fiscal policies aimed at minimizing the output loss generated by fiscal contractions. This constructive purpose to the network analysis of fiscal policy is also mentioned in Bouakez, Rachedi, Emiliano, et al., 2018 and it can be traced back to Horvath, 2000.

Even if both government and tax shocks have historically been interpreted as aggregate shocks, the study of its finer decomposition is not irrelevant. Concerning government spending shocks, Ramey and Shapiro, 1999 already proposed an industry-specific decomposition of government spending, while Ramey, 2011 showed how exogenous fluctuations in government spending are driven by military build-ups, which can be seen as industry-specific shocks to Manufacturing. Very recently, Cox et al., 2020 have confirmed how government spending is highly concentrated in relatively few firms and sectors, and how idiosyncratic variation dominates the fluctuation of spending. Therefore, asking if a spending cut from sector X is more recessionary than a cut from sector Y, is a relevant question, as changes in government spending are implemented as industry-specific shocks.

There are examples of introductions of industry-specific taxes, such as Windfall Profit Tax of 1980 and in general excise ad valorem, at the moment we do not know what their output effect is. Moreover, new industry-specific taxes could be implemented in the next years, and we need a framework to study their effect. For instance, think of the current debate around a Carbon tax, or the proposed introduction of a Web tax discussed in Europe, or again, the possibility of directly hitting the Finance sector with a Tobin tax. Analogously to the government spending case, wondering whether an industry-specific tax to sector X is more recessionary than one directed to sector Y, is also a relevant question.

Since our analysis is centered on the study of aggregate fiscal adjustments, we will provide only a partial answer to the above questions by developing a methodological framework.

The rest of this paper is organized as follows. We start by illustrating in Section 2 the theoretical mechanism of the network diffusion of a tax shock and a government expenditure shock. Section 3 describes how an empirical specification consistent with the theoretical mechanism can be identified and estimated. Section 4 illustrates the database; Section 5 shows our results; Section 6 provides some robustness checks and eventually, Section 7 concludes.

2 Theoretical Framework

Our empirical strategy is based on the estimation and simulation of both a static and a dynamic spatial autoregressive panel data model (see Elhorst, 2003 for the static specification and Yu, De Jong, and L.-f. Lee, 2008 for the dynamic one). In practice, we adopt an empirical model designed to capture the propagation of fiscal policy in the industrial network. Our specification is consistent with the closed-form solution of a benchmark model designed to analyze the network transmission of demand and supply shocks (Long Jr and Plosser, 1983, Acemoglu, Vasco M Carvalho, et al., 2012 and Acemoglu, Akcigit, and Kerr, 2016). Such a theoretical model serves the purpose of illustrating the economic mechanism which we believe is at the basis of the differences in the output effect of TB versus EB fiscal adjustment plans, discussed in Alesina, Favero, and Giavazzi, 2015, and more in general, at the basis of the larger output effect of tax hikes versus spending cuts.

The model considers a perfectly competitive economy with n sectors, where the market clearing condition for the generic industry i is:

$$y_i = c_i + \sum_{j=1}^{n} x_{ji} + G_i \tag{1}$$

where c_i is household's consumption of good produced by industry i; x_{ij}[1] is the quantity of goods produced in industry j used as inputs by industry i; G_i are government purchases, funded by imposing either a lump sum or a sales-type tax:[2]

$$\sum_{i=1}^{n} p_i G_i = T + \tau \sum_{i=1}^{n} p_i y_i \tag{2}$$

[1] In Equation (1) we actually have x_{ji}, that is, the amount of good i used as input by industry j; we then sum over the j-s to obtain the total demand of good i from all the industries.

[2] For example, an excise is a special type of sales tax, which is sector-specific. Excise tax might be of two types: ad valorem (percentage of values of a good) and specific (tax paid per unit). The excise tax may be paid by the producer, retailer, and consumer. Moreover, it might be taken on federal, state, and local levels.

Each sector solves the following profit maximization problem:

$$\max_{l_i,\{x_{ij}\}_{j=1}^n} (1-\tau)\cdot p_i \cdot y_i - wl_i - \sum_{j=1}^{n} p_j x_{ij}$$

with a production function similar to the one in Acemoglu, Vasco M Carvalho, et al., 2012 and Vasco M Carvalho, 2014:[3]

$$y_i = l_i^{\alpha_i^l} \cdot (\prod_{j=1}^{n} x_{ij}^{\alpha_{ij}})^{\rho}$$

All alpha's are non negative, and we assume constant return to scale: $\alpha_i^l + \rho \cdot \sum_{j=1}^{n} a_{ij} = 1$. Parameter ρ will be crucial in our empirical specification, since it is the coefficient in front of the spatial variables, which capture the network effect (see section 3). Notice here, that thanks to the Cobb-Douglas specification, ρ can be interpreted as the share of intermediates in production.

The economy is populated by a representative agent, who maximizes utility subject to a budget constraint:

$$\max_{l,\{c_i\}_{i=1}^n} (1-l)^{\lambda} \cdot \prod_{i=1}^{n} c_i^{\beta_i}$$
$$\text{s.t.} \sum_{i=1}^{n} p_i c_i \leq wl - T$$

with $\sum_{i=1}^{n} \beta_i = 1$.

Firms and households take all prices as given, and the market-clearing conditions are satisfied in the goods market and the labor market. Government actions are taken as given and the wage is chosen as a numeraire $(w = 1)$. We refer to our Online Appendix for all the details of the model.

Network effect of a tax shock

By log-differentiating the equations which characterize the equilibrium the following closed-form expression of a tax shock effect is obtained:[4]

$$d\log y_i = d\log(1-\tau) + \alpha_i^l \cdot d\log(1-T) + \rho \underbrace{\cdot \sum_{j=1}^{n} a_{ij} \cdot d\log y_j}_{\text{downstream spatial variable}} \tag{3}$$

[3]We omit the productivity component because we are not interested in studying productivity shocks.

[4]Along this section we assume both $G_i = 0$ and $dG = 0$: no change in government spending and taxes are financed with a negative lump sum transfer T which behaves as a tax deduction.

Now, we introduce the input-output matrix A which collects all the coefficients of the Cobb-Douglas production function, in this way we can rewrite equation (3) in matrix form:

$$\underset{n\times 1}{d\log \mathbf{y}} = \mathbf{1}_n \cdot d\log(1-\tau) + \underset{n\times 1}{\boldsymbol{\alpha}^l} \cdot d\log(1-T) + \rho \cdot \underset{n\times n}{A} \cdot \underset{n\times 1}{d\log \mathbf{y}}, \tag{4}$$

where $\mathbf{1}_n$ denotes a column vector of ones of length n.

The above expression can be simplified by collecting the dependent variable $d\log \boldsymbol{y}$ on the left hand side of the expression. By doing this, we obtain the following closed form expression[5]:

$$d\log \boldsymbol{y} = -\underbrace{(I_n - \rho \cdot A)^{-1} \cdot \mathbf{1}_n}_{\text{downstream propagation}} \cdot \frac{\tau}{1-\tau} \cdot d\log\tau - \mathbf{1}_n \frac{T}{1-T} \cdot d\log T \tag{5}$$

The sectoral propagation of a tax adjustment is driven by the elements in the rows of the matrix $H := (I_n - \rho \cdot A)^{-1}$, which represents the Leontief inverse matrix. Notice that $H \cdot \mathbf{1}_n = \mathbf{1}_n + \rho \cdot A \cdot \mathbf{1}_n + \rho^2 \cdot A^2 \cdot \mathbf{1}_n + ...$, therefore, the downstream propagation depends on the rows of A, and describe how much intermediates sector i purchases from all other sectors. We can see this from the FOC of firm i with respect to x_{ij}:

$$a_{ij} \propto \frac{p_j \cdot x_{ij}}{p_i \cdot y_i} \approx \frac{\text{SALES}_{j\to i}}{\text{SALES}_i} \tag{6}$$

Therefore, the network propagation mechanism of a sales-type tax shock propagates downstream: at first each sector is hit by a tax shock; then firms re-optimize and increase their own price; by consequence, customer-industries face higher prices of their inputs and therefore need to also increase their own price, thus triggering a cascade effect which moves downstream from the top of the production network. This mechanism is also illustrated in our theoretical setting by the expression:

$$d\log \boldsymbol{p} = \frac{\tau}{1-\tau} \cdot H \cdot \mathbf{1}_n \cdot d\log\tau, \tag{7}$$

where $d\log \boldsymbol{p}$ represents the vector of price changes. Notice that, prices change only in response to a tax shock. Basically, in our setting, a tax shock is the analogue of a productivity shock in Acemoglu, Akcigit, and Kerr, 2016 and Vasco M Carvalho, 2014: it is a supply side shock which generates spillovers that trickle down to the bottom of the supply chain via production network through the price mechanism.[6]

[5]Thanks to Cobb-Douglas functional form assumption, $(I_n - \rho \cdot A)^{-1} \cdot \boldsymbol{\alpha}^l = \mathbf{1}_n$

[6]We are aware that more sophisticated models and different type of taxes can actually generate upstream propagation, thus behaving more like a demand side shock and therefore confirming the hybrid nature of taxes (both supply and demand side). We will take this into account in Section 6.

Network effect of a spending shock

Now let's move to government spending shocks and assume that both $\tau = 0$ and $d\tau = 0$. Except for the inclusion of parameter ρ and a slightly different notation, the following derivations are one to one found in Acemoglu, Akcigit, and Kerr, 2016; we repeat them for the sake of clarity of the exposition. After log-differentiating the equations that characterize the equilibrium of the model described above, we obtain the following expression:

$$d\log y_i = -\frac{\beta_i}{1+\lambda} \cdot \sum_{j=1}^{n} \cdot \frac{p_j \cdot y_j}{p_i \cdot y_i} \cdot d\tilde{G}_j + \underbrace{\rho \cdot \sum_{j=1}^{n} \hat{a}_{ji} \cdot d\log y_j}_{\text{upstream spatial variable}} + d\tilde{G}_i, \tag{8}$$

where $\tilde{G}_i := \frac{G_i}{y_i}$ and $\hat{a}_{ji} := \frac{x_{ji}}{y_i} = a_{ji}\frac{p_j y_j}{p_i y_i}$.

We can rewrite equation (9) in a compact matrix form:

$$\underset{n\times 1}{d\log \mathbf{y}} = \rho \cdot \underset{n\times n}{\hat{A}^T} \cdot \underset{n\times 1}{d\log \mathbf{y}} + (I_n + \underset{n\times n}{\tilde{\mathbf{\Lambda}}}) \cdot \underset{n\times 1}{d\tilde{\mathbf{G}}}, \tag{9}$$

where:

$$\tilde{\mathbf{\Lambda}} = \begin{bmatrix} -\frac{\beta_1}{1+\lambda} & -\frac{\beta_1}{1+\lambda} \cdot \frac{p_2 \cdot y_2}{p_1 \cdot y_1} & \cdots & -\frac{\beta_1}{1+\lambda} \cdot \frac{p_n \cdot y_n}{p_1 \cdot y_1} \\ -\frac{\beta_2}{1+\lambda} \cdot \frac{p_1 \cdot y_1}{p_2 \cdot y_2} & -\frac{\beta_2}{1+\lambda} & \cdots & -\frac{\beta_2}{1+\lambda} \cdot \frac{p_n \cdot y_n}{p_2 \cdot y_2} \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{\beta_n}{1+\lambda} \cdot \frac{p_1 \cdot y_1}{p_n \cdot y_n} & -\frac{\beta_n}{1+\lambda} \cdot \frac{p_2 \cdot y_2}{p_n \cdot y_n} & \cdots & -\frac{\beta_n}{1+\lambda} \end{bmatrix}$$

and:

$$\hat{A} = \begin{bmatrix} a_{11} & a_{12} \cdot \frac{p_1 \cdot y_1}{p_2 \cdot y_2} & \cdots & a_{1n} \cdot \frac{p_1 \cdot y_1}{p_n \cdot y_n} \\ a_{21} \cdot \frac{p_2 \cdot y_2}{p_1 \cdot y_1} & a_{22} & \cdots & a_{2n} \cdot \frac{p_2 \cdot y_2}{p_n \cdot y_n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} \cdot \frac{p_n \cdot y_n}{p_1 \cdot y_1} & a_{n2} \cdot \frac{p_n \cdot y_n}{p_2 \cdot y_2} & \cdots & a_{nn} \end{bmatrix} = A * \underbrace{\begin{bmatrix} 1 & \frac{p_1 \cdot y_1}{p_2 \cdot y_2} & \cdots & \frac{p_1 \cdot y_1}{p_n \cdot y_n} \\ \frac{p_2 \cdot y_2}{p_1 \cdot y_1} & 1 & \cdots & \frac{p_2 \cdot y_2}{p_n \cdot y_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{p_n \cdot y_n}{p_1 \cdot y_1} & \frac{p_n \cdot y_n}{p_2 \cdot y_2} & \cdots & 1 \end{bmatrix}}_{S} = A * S$$

where the last identity is meant to underscore the connection between $\hat{A}$ and A, the standard input-output matrix, and S represents a scaling matrix.[7]

As done for the case of taxes, we can rewrite equation (9) in its closed form expression:

$$\underset{n\times 1}{d\log \mathbf{y}} = \underbrace{(I_n - \rho\cdot \hat{A}^T)^{-1}}_{\text{upstream propagation}} \cdot (I_n + \tilde{\mathbf{\Lambda}})\cdot \underset{n\times 1}{d\tilde{\mathbf{G}}} \tag{10}$$

where $\tilde{\mathbf{\Lambda}}$ represents second order GE effects which come from the fact that the government budget constraint holds.

Equation (10), tells us that the sectoral propagation of a spending shock is driven by the elements in the columns of $\hat{A}$, which describe a sector's sales to other industries. For instance, when G_i decreases, sector i faces a negative demand shock, and reacts by contracting its output and by purchasing less input: those sectors which are suppliers of input to sector i, are negatively affected and also shrink their output and purchase less input, and so on and so forth. This type of spillovers represents the aforementioned upstream propagation of demand side shocks.

To conclude this section, two qualifying remarks. First, although the Cobb-Douglas specification is crucial to determine the asymmetric propagation of demand and supply shocks, this result is robust to the adoption of alternative specifications; for instance, Vasco M. Carvalho et al., 2016 adopts a CES production function which allows both upstream and downstream propagation.

Second, the theoretical framework has been kept fairly basic to convey the idea of the underlying economic mechanism in action. Bouakez, Rachedi, Emiliano, et al., 2018 study the network propagation of spending shocks by adopting a much more sophisticated DSGE model, which is calibrated to match the moments of the US economy. In our paper, we estimate the effect of fiscal adjustments (our measure of tax and spending shocks) using a spatial autoregressive panel data model, adopting a more empirical approach.

However, regressing an output growth variable $d\log y_i$ over some spatial variables ($\sum_{j=1}^{n} a_{ij}\cdot d\log y_j$ and $\sum_{j=1}^{n} \hat{a}_{ji}\cdot d\log y_j$) and some exogenous shocks ($d\log\tau$ and $d\log\tilde{G}_j$) via spatial autoregression, has also a theoretical underpinning, shown by equations (5) and (10).

3 From Theory to Empirics

This section illustrates the empirical strategy we employ to capture the propagation of TB and EB fiscal adjustment plans throughout the production network. We show how fiscal adjustment plans, exogenous with respect to output growth, are constructed. Then the empirical model is illustrated and estimated to derive a measure of the output effects of fiscal adjustments.

[7] where $*$ denotes the Hadamard product, or element wise product.

3.1 Fiscal Adjustments

First, following the narrative identification strategy (C. D. Romer and D. H. Romer, 2010, Alesina, Favero, and Giavazzi, 2019) fiscal adjustments that are exogenous with respect to output fluctuations are selected by looking at their motivation in official documents. Then, following Alesina, Favero, and Giavazzi, 2019, we acknowledge that fiscal consolidation policy is implemented through multi-year plans that involve an intertemporal and an intratemporal dimension.[8]

The intratemporal dimension depends on the fact that adjustment plans are implemented with a mix of measures on the expenditure side and the revenue side. Governments (US included) tend to implement their fiscal policy adjustments using fiscal plans, which constitute a blend of tax increases and spending cuts to be implemented over the years. Therefore, identifying pure tax hikes and pure spending cuts is impossible since they tend to happen at the same time. On the other hand, fiscal adjustment plans can be identified.

The intertemporal dimension is relevant because plans involve both measures that are implemented upon announcement (the unanticipated component of the plan) and measures that are announced for the future years (the anticipated component of the plan). We identify plans as sequences of fiscal corrections announced at time t to be implemented between time t and time $t + K$, where K is the anticipation horizon. In practice, fiscal adjustments, which we denote by f_t, are made of three components: f_t^u, the unexpected adjustments (announced upon implementation at time t); $f_{t,0}^a$, the past announced adjustments (implemented at time t but announced in the previous years); f_t^f the future announced corrections.
In particular, we have:

1. The *unanticipated fiscal shocks* at time t as the surprise change in the primary surplus at time t:

$$f_t^u = tax_t^u + exp_t^u$$

   where tax_t^u is the surprise increase in taxes announced at time t and implemented in the same year, and exp_t^u is the surprise reduction in government expenditure also announced at time t and implemented in the same year.

2. In order to define the *anticipated fiscal shock*, we need some more notation. First of all, denote as $tax_{t,j}^a$ and $exp_{t,j}^a$ the tax and expenditure changes announced by the fiscal authorities at date t with an anticipation horizon of j years (*i.e.* to be implemented in year $t+j$). Notice that we can define the observed anticipated

[8] For a detailed discussion of our identification strategy see Section 4.2.

shocks in period t as follows:

$$
\begin{aligned}
tax^a_{t,0} = &\quad tax^a_{t-1,1} \\
tax^a_{t,j} = &\quad \underbrace{tax^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(tax^a_{t,j} - tax^a_{t-1,j+1}\right)}_{\textit{New shock}}, \quad \text{with } j \geqslant 1 \\
exp^a_{t,0} = &\quad exp^a_{t-1,1} \\
exp^a_{t,j} = &\quad \underbrace{exp^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(exp^a_{t,j} - exp^a_{t-1,j+1}\right)}_{\textit{New shock}}, \quad \text{with } j \geqslant 1
\end{aligned}
$$

Finally, we obtain the anticipated (and implemented) fiscal shocks:

$$
f^a_{t,0} = \quad tax^a_{t,0} + exp^a_{t,0}
$$

3. The <u>*anticipated future shocks*</u> are made of all these shocks already scheduled by the government which have to be implemented within K years from their announcement:

$$
f^f_t = \sum_{j=1}^{K} tax^a_{t,j} + \sum_{j=1}^{K} exp^a_{t,j}
$$

As anticipated above, fiscal corrections in each year are made of three components:

$$
f_t = f^u_t + f^a_{t,0} + f^f_t
$$

Therefore, fiscal plans are capable of taking into account the correlation between current and future fiscal shocks, as well as the contemporaneous correlation between tax and spending shocks which is recorded in the data (see Table I). The cost of this, is that we lose the concept of pure tax and pure government spending shocks. Nevertheless, we are still able to identify a proxy for both pure tax shocks and pure expenditure shocks: in fact, plans can be classified into two categories. We label as "tax based" (TB) a fiscal plan which is made more of tax increases than spending cuts. Viceversa, if a plan is made of expenditure cuts more than tax increases, then the plan is labelled as "expenditure based" (EB). In formula:

$$
\text{if } \left(tax^u_t + tax^a_{t,0} + \sum_{j=1}^{K} tax^a_{t,j}\right) > \left(exp^u_t + exp^a_{t,0} + \sum_{j=1}^{K} exp^a_{t,j}\right) \tag{11}
$$

$$
\text{then } TB_t = 1 \text{ and } EB_t = 0,
$$

$$
\text{else } TB_t = 0 \text{ and } EB_t = 1, \forall t
$$

where TB_t and EB_t are dummies that takes on value 1 if the plan is labelled TB or EB respectively. By construction TB and EB plans are mutually exclusive and the labelling is almost never marginal,[9] as we will show in Figure 4. However, we record years where $TB_t = EB_t = 0$, since no fiscal adjustment takes place.

At this point, we can define our proxies for tax and spending shocks as "TB fiscal adjustment plans" and "EB fiscal adjustment plans":

$$f_t^{\tau} = f_t \cdot TB_t$$
$$f_t^{\gamma} = f_t \cdot EB_t.$$

Notice an important distinction between TB and EB fiscal adjustment plans: even if both are aggregate shocks coming from the federal government, a TB plan will impact all the industries in the same fashion, but the same is not valid for EB plans since they are made predominantly by spending cuts which affect sectors in different ways.[10] In other words, since the purchases of government goods and services differ across sectors, we assume EB adjustments to impact each industry in an idiosyncratic way. Taking this into consideration, and using the decomposition of fiscal plans, we have that:

$$f_t^{\tau} = f_t \cdot TB_t = (f_t^u + f_{t,0}^a + f_t^f) \cdot TB_t \quad \forall i = 1, ..., n$$
$$f_{i,t}^{\gamma} = \omega_i \cdot f_t \cdot EB_t = \omega_i \cdot (f_t^u + f_{t,0}^a + f_t^f) \cdot EB_t$$

where n is the number of industries we consider, and ω_i is an industry specific weight which transforms an aggregate EB fiscal adjustment into an idiosyncratic one. We construct the government spending weights following Acemoglu, Akcigit, and Kerr, 2016, who weigh the spending adjustments using the input-output matrix, to construct industry-specific spending shocks. In particular, we pre-multiply each spending shock by the the elements of the last row of matrix $\hat{A}$, since the n^{th} row of the transformed input-output matrix corresponds to the government sector in the BEA decomposition. Therefore, the generic element of the weight-vector $\boldsymbol{\omega}$ is estimated in this way:

$$\omega_j = \frac{Sales_{i \to G}}{Sales_i}, \quad i \neq n$$

where "G" is the label of the Government sector.

3.2 Empirical strategy

Our procedure to capture the effect of fiscal adjustment plans on the value added growth of each industry using a spatial lag, explicitly acknowledges that the presence of a network generates spatial correlation among the

[9]There were no marginal cases, when it was not possible to decide whether the plan is tax-based or expenditure-based.
[10]We thank Roberto Perotti for this point.

industries. Therefore, the most natural identification strategy would be regressing industry value added growth on the fiscal adjustments and a spatial lag. The adoption of this framework, is consistent with the model discussed in the previous section that provides a theoretical connection between industry value added growth, fiscal shocks and a spatial lag.[11] Therefore, our empirical strategy is based on the estimation of the following equation:

$$\Delta y_{i,t} = \alpha_i + \tau \cdot f_t^{\tau} + \rho^{down} \cdot \Delta y_{i,t}^{down} + \gamma \cdot f_{i,t}^{\gamma} + \rho^{up} \cdot \Delta y_{i,t}^{up} + \nu_{it} \tag{12}$$

where

$$\Delta y_{i,t}^{down} = \sum_{j \neq i}^{n} a_{ij} \cdot \Delta y_{j,t} \qquad\qquad \Delta y_{i,t}^{up} = \sum_{j \neq i}^{n} \hat{a}_{ji} \cdot \Delta y_{j,t}$$

represent the spatial variables which capture the industrial network as defined in Section 2.[12] Notice that we have omitted the main diagonal in the above definition; this is done to match the conditions which ensure the consistency of the MLE which we will employ in section 5 (for details on consistency see L.-F. Lee, 2004 and in particular Yu, De Jong, and L.-f. Lee, 2008).[13] f_t^{τ} and f_t^{γ} account for the tax and expenditure fiscal adjustments respectively; α_i is an industry specific fixed effect; ν_{it} is a normally distributed error term: $\nu_{it} \sim \mathcal{N}(0, \sigma_i^2)$.

Since unanticipated, anticipated and future components can have different effects on value added growth, we allow for different coefficients; therefore Equation (12) becomes:

$$\Delta y_{i,t} = \alpha_i + \rho^{down} \cdot \Delta y_{i,t}^{down} + \underbrace{\boldsymbol{\tau}^T \cdot \boldsymbol{f}_t \cdot TB_t}_{\text{tax}} + \rho^{up} \cdot \Delta y_{i,t}^{up} + \underbrace{\boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t \cdot \omega_i \cdot EB_t}_{\text{spending}} + \nu_{i,t} \tag{13}$$

where

$$\boldsymbol{\tau}^T \cdot \boldsymbol{f}_t = \begin{bmatrix} \tau^u & \tau^a & \tau^f \end{bmatrix} \cdot \begin{bmatrix} f_t^u \\ f_t^a \\ f_t^f \end{bmatrix} \qquad\qquad \boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t = \begin{bmatrix} \gamma^u & \gamma^a & \gamma^f \end{bmatrix} \cdot \begin{bmatrix} f_t^u \\ f_t^a \\ f_t^f \end{bmatrix}$$

the T superscript denotes the transposition operation.

Before bringing the above model to the data, we need to address one last issue. In equation (13), the spatial variables do not interact with the occurrence of TB and EB shocks. This implies that the direction (either downstream or upstream) of the propagation of fiscal adjustment plans in the network is undetermined. However, we would like to capture the propagation of fiscal adjustments in a specific direction of the network in order to

[11] We do not however perform structural estimation of the model, which is used only as an illustrative framework of the propagation mechanism.

[12] From now on we use τ as the coefficient standing in front of the tax-based fiscal adjustment plan.

[13] The results we obtain are not dependent on this assumption. In the Online Appendix we provide the baseline results of Section 5.1 using network matrices with the main diagonal.

compare different theories. TB adjustments, being mainly made of tax hikes, should behave more as supply-side shocks, and therefore, should propagate downstream: changes in suppliers' output flow down to customer industry i. On the other hand, the EB adjustments, being mainly made of demand shocks (spending cuts), have a network effect that should propagate upstream: variations in customers' output flows up to supplier industry i.

Moreover, from a purely statistical perspective, $\Delta y_{i,t}^{down}$ and $\Delta y_{i,t}^{up}$ exhibit a non-negligible correlation level and therefore, estimating reliably ρ^{up} and ρ^{down} in Equation (13), would be hard because of multicollinearity reasons.

These problems are solved by interacting the specific network with the specific dummy: the downstream spatial variable ($\Delta y_{i,t}^{down}$) is multiplied by TB_t, while the upstream spatial variable ($\Delta y_{i,t}^{up}$) is multiplied by EB_t. In this way, we let TB adjustments to propagate downstream and EB adjustments to propagate upstream, as theory seems to predict. The distinction between demand and supply shocks provides a theoretical justification for the interaction of the shocks with the networks: the downstream channel is activated when a TB fiscal adjustment plan occurs, and the upstream channel is activated when an EB fiscal adjustment plan occurs[14].

Including this network-shocks interactions in the model, allows us to rewrite Equation (13) as:

$$\Delta y_{i,t} = \alpha_i + \left(\rho^{down} \cdot \Delta y_{i,t}^{down} + \boldsymbol{\tau}^T \cdot \boldsymbol{f}_t\right) \cdot TB_t + \left(\rho^{up} \cdot \Delta y_{i,t}^{up} + \boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t \cdot \omega_i\right) \cdot EB_t + \nu_{i,t} \tag{14}$$

the above model is still nested into a static spatial autoregression (SAR) panel data model (see Elhorst, 2003 and Anselin, Le Gallo, and Jayet, 2008). In Section 6.3, we also control for time dependence in value added growth, by including a first order time lag, thus turning the static SAR panel model into a dynamic one (see Yu, De Jong, and L.-f. Lee, 2008).

It could be argued that, instead of using a SAR model, a standard panel data model with several "cross-terms" representing the first-order, second-order, and higher-order degrees of connection should have been preferred, as in Hale, Kapan, and Minoiu, 2019. However, when the network is persistent, and even higher-order propagation effects are relevant, the number of variables to be included would increase accordingly, thus increasing indefinitely the number of coefficients to estimate. Instead, a spatial variable is capable of capturing the entire feedback effect: an infinite number of degrees of connection whose impact decays geometrically.[15]

[14]Since plans are hybrid (both made of tax and expenditure shocks) and the supply side nature of taxes is questionable, we will test different interactions in the robustness section (see section 6.1).

[15]In the Online Appendix, we carry out the decomposition of the effects of fiscal adjustment plans on output by order of connections, and we find that the adoption of a spatial lag is justified, since even higher-order degrees of connection matter in the production network.

3.3 Interpretation of output effects

Using vector notation we rewrite equation (14) as follows:

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha} + \left(\underbrace{\mathbf{1}_n}_{n\times 1} \cdot \underbrace{\boldsymbol{\tau}^T \cdot \boldsymbol{f}_t}_{1\times 1} + \rho^{down} \cdot A_0 \cdot \Delta \boldsymbol{y}_t \right) \cdot TB_t + \\ + \left(\underbrace{\boldsymbol{\omega}}_{n\times 1} \cdot \underbrace{\boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t}_{1\times 1} + \rho^{up} \cdot \hat{A}_0^T \cdot \Delta \mathbf{y}_t \right) \cdot EB_t + \boldsymbol{\nu}_t \tag{15}$$

where A_0 and $\hat{A}_0$ represent the original input-output matrices seen in Section 2, with zero entries in their main diagonals. $\boldsymbol{\omega} = [\omega_1, ..., \omega_n]^T$ is the vector of industry specific weights for the EB plans; $\boldsymbol{\alpha} = [\alpha_1, ..., \alpha_n]^T$ is the vector of fixed effects. Suppose we want to study the marginal effect of a fiscal adjustment of size 1 (that is, 1% of GDP in our dataset). Firstly, we need to determine how the plan is distributed in its three components: unanticipated, anticipated and future respectively. Therefore, we define the following weights:

$$\boldsymbol{s_\tau} = \begin{bmatrix} s_\tau^u & s_\tau^a & s_\tau^f \end{bmatrix} \quad \text{with } \boldsymbol{s_\tau} \cdot \mathbf{1}_3 = 1$$
$$\boldsymbol{s_\gamma} = \begin{bmatrix} s_\gamma^u & s_\gamma^a & s_\gamma^f \end{bmatrix} \quad \text{with } \boldsymbol{s_\gamma} \cdot \mathbf{1}_3 = 1$$

where $\boldsymbol{s_\tau}$ is a 3 by 1 vector of weights of the components of the fiscal plan when the plan is TB; $\boldsymbol{s_\gamma}$ is the the analogue of $\boldsymbol{s_\tau}$ for EB plans. The marginal effect of a fiscal plan, is defined as the weighted average of the marginal effects of the single components. Basically, we multiply the Jacobian of equation (15) by the weights $\boldsymbol{s_\tau}$ ($\boldsymbol{s_\gamma}$ for EB plans) which represent how much each component matters in the composition of a fiscal plan. In matrix notation we have:

$$\left(\frac{\partial \Delta \mathbf{y}}{\partial \boldsymbol{f}_t} \mid TB_t = 1 \right) = \underbrace{(I_n - \rho^{down} \cdot A_0)^{-1}}_{\boldsymbol{H}^{TB}} \cdot \mathbf{1}_n \cdot \boldsymbol{s}'_{\boldsymbol{\tau}} \cdot \boldsymbol{\tau} = \mathbf{H}^{TB} \cdot \mathbf{1}_n \cdot \boldsymbol{s}'_{\boldsymbol{\tau}} \cdot \boldsymbol{\tau}, \tag{16}$$

$$\left(\frac{\partial \Delta \mathbf{y}}{\partial \boldsymbol{f}_t} \mid EB_t = 1 \right) = \underbrace{(I_n - \rho^{up} \cdot \hat{A}_0^T)^{-1}}_{\boldsymbol{H}^{EB}} \cdot \boldsymbol{\omega} \cdot \boldsymbol{s}'_{\boldsymbol{\gamma}} \cdot \boldsymbol{\gamma} = \mathbf{H}^{EB} \cdot \boldsymbol{\omega} \cdot \boldsymbol{s}'_{\boldsymbol{\gamma}} \cdot \boldsymbol{\gamma}. \tag{17}$$

Given estimates for $\rho^{down}, \rho^{up}, \boldsymbol{\tau}, \boldsymbol{\gamma}$ and values for the weights $\boldsymbol{s_\tau}$ and $\boldsymbol{s_\gamma}$, the output effect of fiscal adjustments on each sector's value added growth, becomes observable.

Example: TB plan output effect in a 3 industries economy

To illustrate the procedure, consider a simple example with three industries ($n = 3$) for which the relevant adjustment is exclusively a tax-based one ($TB_t = 1$). To ease notation we denote ρ^{down} simply by ρ. From equation (15) we have:

$$\underbrace{\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \end{bmatrix}}_{\Delta \mathbf{y}} = \underbrace{\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}}_{\boldsymbol{\alpha}_t} + \underbrace{\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}_{\mathbf{1}_3} \cdot \boldsymbol{\tau}^T \cdot \underbrace{\begin{bmatrix} f_t^u \\ f_t^a \\ f_t^f \end{bmatrix}}_{\boldsymbol{f}_t} + \underbrace{\begin{bmatrix} 0 & a_{12} \cdot \rho & a_{13} \cdot \rho \\ a_{21} \cdot \rho & 0 & a_{23} \cdot \rho \\ a_{31} \cdot \rho & a_{32} \cdot \rho & 0 \end{bmatrix}}_{\rho \cdot A_0} \cdot \underbrace{\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \end{bmatrix}}_{\Delta \boldsymbol{y}_t} + \underbrace{\begin{bmatrix} \nu_{1t} \\ \nu_{2t} \\ \nu_{3t} \end{bmatrix}}_{\boldsymbol{\nu}_t}$$

Then, the output effect a TB fiscal plan is:

$$\begin{aligned} \left(\frac{\partial \Delta \mathbf{y}}{\partial \boldsymbol{f}_t} \mid TB_t = 1 \right) &= \underbrace{\begin{bmatrix} \frac{\partial \Delta \mathbf{y}}{\partial f_t^u} & \frac{\partial \Delta \mathbf{y}}{\partial f_t^a} & \frac{\partial \Delta \mathbf{y}}{\partial f_t^f} \end{bmatrix}}_{\text{Jacobian } (n \times 3)} \cdot \begin{bmatrix} s_\tau^u \\ s_\tau^a \\ s_\tau^f \end{bmatrix} \\ &= \begin{bmatrix} 1 & -a_{12} \cdot \rho & -a_{13} \cdot \rho \\ -a_{21} \cdot \rho & 1 & -a_{23} \cdot \rho \\ -a_{31} \cdot \rho & -a_{32} \cdot \rho & 1 \end{bmatrix}^{-1} \cdot \mathbf{1}_3 \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau \\ &= \frac{1}{d} \cdot \begin{bmatrix} 1 - \rho^2 \cdot a_{23} a_{32} & \rho \cdot a_{12} + \rho^2 \cdot a_{32} a_{13} & \rho \cdot a_{13} + \rho^2 \cdot a_{12} a_{23} \\ \rho \cdot a_{21} + \rho^2 \cdot a_{23} a_{31} & 1 - \rho^2 \cdot a_{31} a_{13} & \rho \cdot a_{23} + \rho^2 \cdot a_{21} a_{13} \\ \rho \cdot a_{31} + \rho^2 \cdot a_{21} a_{32} & \rho \cdot a_{32} + \rho^2 \cdot a_{31} a_{12} & 1 - \rho^2 \cdot a_{21} a_{12} \end{bmatrix} \cdot \mathbf{1}_3 \cdot \boldsymbol{\tau}' \cdot \boldsymbol{s}_\tau, \end{aligned}$$

where, d is the determinant of matrix $(I_3 - \rho \cdot A_0)$:

$$d = 1 - \rho^2 \cdot (a_{12} a_{21} + a_{13} a_{31} + a_{32} a_{23}) - \rho^3 \cdot (a_{12} a_{23} a_{31} + a_{21} a_{13} a_{32}) \,.$$

Given the above result, we provide a full analytic breakdown of the effect of a tax shock on sector 1:

- The "*Direct Effect*": gives the response of value added in industry 1 to the TB adjustment if this industry were the only one affected by it; in other words it represents the tax shock direct effect on sector 1. Analytically:

$$\frac{1 - \rho^2 \cdot a_{23} a_{32}}{d} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau = \big(1 + \frac{\rho^2 \cdot (a_{13} a_{31} + a_{12} a_{21}) + \rho^3 \cdot (a_{12} a_{23} a_{31} + a_{21} a_{13} a_{32})}{d} \big) \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau$$

  From the above expression, we can tell apart two components of the direct effect:

  1. The "*Instantaneous Effect*", namely the term $\boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau$, which delivers the instantaneous effect (in the sense of no network feedback) on industry 1.
  2. The "*Network Direct Effect*", that is the network effect triggered by a tax shock which hits only sector 1 itself, called "*feedback loop*" by LeSage and Pace, 2009.

- The "*Indirect Effect*": the effect on industry 1 of a shock that hits all the industries except for industry 1 itself. In this simple case, it can be broken down into two components:

  1. $\frac{\rho \cdot a_{12}+\rho^2 \cdot a_{32}a_{13}}{d} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau$ gives the response of value added in industry 1 to the TB adjustment if industry 2 were the only one affected by it.
  2. $\frac{\rho \cdot a_{13}+\rho^2 \cdot a_{12}a_{23}}{d} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau$ gives the response of value added in industry 1 to the TB adjustment if industry 3 were the only one affected by it.

  The summation of the two components returns the indirect effect.

- The "*Total Effect*": is the summation of the direct and indirect effect.

Since we are interested in the effect generated by the industrial network, we move away from the standard spatial autoregression literature which focuses on the direct and indirect effect.[16] We prefer to focus on a new measure which captures the whole effect of the network instead:

$$\begin{aligned} Total = Direct + Indirect &= \big(\underbrace{Instantaneous + Network\ Direct}_{Direct}\big) + Indirect \\ &= Instantaneous + \big(\underbrace{Network\ Direct + Indirect}_{Network}\big) = Instantaneous + Network. \end{aligned}$$

Analytically, the *Network effect* in our 3 industries economy is:

$$\Big(\underbrace{\frac{\rho^2 \cdot (a_{13}a_{31} + a_{12}a_{21}) + \rho^3 \cdot (a_{12}a_{23}a_{31} + a_{21}a_{13}a_{32})}{d}}_{Network\ Direct} + \underbrace{\frac{\rho \cdot a_{12} + \rho^2 \cdot a_{32}a_{13}}{d} + \frac{\rho \cdot a_{13} + \rho^2 \cdot a_{12}a_{23}}{d}}_{Indirect}\Big) \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_\tau$$

Basically we shift the feedback loop of the Direct effect into the Indirect effect, to obtain a more comprehensive measure of network spillovers. Our results are not driven by this different classification, since the Network Direct effect does not account for more than 3-4% of the Total Effect.

To conclude, when in Section 5 we report our results, we provide an average of the effects across industries; for this reason, we refer to them as Average Total Effect, Average Instantaneous Effect and Average Network Effect.

4 Data

4.1 Industrial Networks

Value Added

In our baseline specification, the dependent variable Δy_{it} is industry value-added. Value-added is the difference between an industry's or an establishment's total output and the cost of its intermediate inputs. It equals

[16] See the break down illustrated in LeSage and Pace, 2009.

gross output (sales or receipts and other operating income, plus inventory change) minus intermediate inputs (consumption of goods and services purchased from other industries or imported). Value-added consists of compensation of employees, taxes on production and imports less subsidies (formerly indirect business taxes and non-tax payments), and gross operating surplus (formerly "other value added").
We employ annual data from the BEA database; in particular, we choose industry value-added at the disaggregation level of 15 sectors.

Input-Output matrices

The Bureau of Economic Analysis (BEA) provides I-O tables that estimate the elements $SALES_{j\to i}/SALES_i$ for each sector.[17] We identify matrix A with the industry-by-industry total requirement table for year 1997, since it is the closest in time to our dataset of fiscal adjustments.[18] The reason why we choose the empirical counterpart of matrix A with these ratios should be clear after recalling the connections between the Cobb-Douglas coefficients of the production function and the FOC with respect to x_{ij}, outlined in expression (6) in the theory section. Notice that this procedure is standard in the production network literature, see for instance, Acemoglu, Akcigit, and Kerr, 2016. Our downstream network is represented as a directed graph in the following figure:

Insert Figure 1

In Figure 1 two facts are salient: first, the central role of Manufacturing and its crucial role as input suppliers to many other sectors; second, it is remarkable to see how both Finance and Professional Services are central in the network, even though their connections are not in absolute terms as relevant as the ones of Manufacturing.

Concerning the upstream propagation channel, the construction of $\hat{A}$ follows the steps outlined in section 2; we calculate the scaling matrix S using industry value-added sales available also on the BEA website and take the Hadamard product with matrix A, namely: $\hat{A} = A * S$. The upstream network is represented in Figure 2:

Insert Figure 2

Figure 2 shows the industrial network stressing the centrality of each sector as a customer to other sectors (weighted in-degree). It is evident that Manufacturing is a crucial customer for many industries, such as Mining, Agriculture, Wholesale, Professional Services, Transportation and Utilities; which are therefore exposed a lot to its demand's fluctuations. The most central sectors (those ones which purchase from many sectors) are Professional Services, Finance and Transportation.

Finally, following the SAR literature we row-normalize both A and $\hat{A}$.[19] Normalization ensures two things: first, numerical stability when estimating the spatial coefficients via MLE; second, interpretation of the spatial

[17] In the Online Appendix of the paper, we dedicate a whole section to explain in depth all the steps required to construct matrix A starting from raw data.

[18] Actually, the choice of which year to take for the table is not very important. In the Online Appendix we show that the tables exhibit only minor differences over the years.

[19] Results with non-row-normalized data are robust and are available in the Online Appendix of the paper.

variables as a weighted average of other industries value-added.

4.2 Database of Exogenous Fiscal Adjustment Plans for US

We identify fiscal adjustments exogenous with respect to output fluctutions by adopting the narrative method (C. D. Romer and D. H. Romer, 2009, C. D. Romer and D. H. Romer, 2010). This method refers to presidential speeches, congressional debates, budget documents, and congressional reports to identify the size, timing, and principal motivation for all major postwar tax policy actions. Legislated changes are then classified into endogenous (those induced by short-run counter-cyclical concerns and those taken because of change in government spending) and exogenous (those that are responses to the state of government debt or concerns about long-run economic growth).

We adopt the annual database on fiscal adjustment plans constructed by Alesina, Favero, and Giavazzi, 2015 and concentrate on US data only. We provide a detailed description of the data in the Online Appendix of the paper.

As anticipated in Section 3, the primary motivation for using fiscal adjustment plans instead of separate shocks is the correlation between them:

Table I: Correlation matrix of Fiscal Adjustments

	tax_t^u	$tax_{t,0}^a$	tax_t^f	exp_t^u	$exp_{t,0}^a$	exp_t^f
tax_t^u	1	0.0413	0.5702	0.5962	-0.1260	0.1047
$tax_{t,0}^a$	0.0413	1	0.0376	0.0981	0.3606	0.3105
tax_t^f	0.5702	0.0376	1	-0.0469	0.0192	0.1805
exp_t^u	0.5962	0.0981	-0.0469	1	-0.0498	0.0140
$exp_{t,0}^a$	-0.1260	0.3606	0.0192	-0.0498	1	0.7816
exp_t^f	0.1047	0.3105	0.1805	0.0140	0.7816	1

Table I: Where tax_t^u is the surprise increase in taxes announced at time t and implemented in the same year, and exp_t^u is the surprise reduction in government expenditure announced at time t and implemented in the same year. Instead $tax_{t,0}^a$ and $exp_{t,0}^a$ are anticipated tax and expenditure changes announced by the fiscal authorities in advance and executed at time t, while tax_t^f and exp_t^f are anticipated tax and expenditure changes announced by the fiscal authorities in advance to be executed in the future.

Table I shows that the correlation between unanticipated tax and unanticipated expenditure adjustments is 0.5962; the correlation between future anticipated tax and unanticipated tax is 0.5702. As both intertemporal and intratemporal dimensions matter, it is worth to consider fiscal adjustment plans.

Concerning the future components of the fiscal adjustment plans, we set the maximum anticipation horizon to three years. We do this since, in our sample, there are only a few occurrences of policy shifts anticipated four and five years ahead. Their number is too small to allow us to include them in our estimation. Notice that by doing this we are also consistent with Pescatori et al., 2011's database, where fiscal plans almost never extend beyond a 3-years horizon.

Concerning expenditure shocks, it is essential to notice that Alesina, Barbiero, et al., 2017 disentangle transfers from taxes and government spending. They show that the difference in output responses is not driven by the inclusion of transfers among other public spending measures.

Figure 3 represents our fiscal shocks database. Following Alesina, Favero, and Giavazzi, 2015, we scale all the measures by GDP on the year before the consolidation occurs in order to avoid potential endogeneity issues. The solid line represents the left-hand side of inequality (11), that is, the total tax adjustment fiscal plans; the dashed line instead, represents the right-hand side of inequality (11), that is, the total expenditure adjustment fiscal plans. The light gray areas represent the years when a TB fiscal plan occurs ($TB_t = 1$); we identify two TB periods: 1978-1981 and 1985-1988. The darker areas account for the years when an EB fiscal plan occurs ($EB_t = 1$); we identify two EB periods: 1990-1998 and 2011-2013.

Insert Figure 3

If we sum the tax and expenditure components of each year (solid and dashed line in Figure 3), we obtain the fiscal adjustment for that year, namely f_t. Figure 4 calculates the share of tax versus expenditure components in each fiscal adjustment plan:

Insert Figure 4

Figure 4 emphasizes the hybrid nature of the plans: EB plans are mainly made of spending cuts rather than tax hikes; on average, only 20% of an EB fiscal adjustment comes from a tax increase. On the other hand, TB plans are all pure tax hikes except for the year 1988, which is the result of a mixed fiscal plan: around 30% of it comes from a spending cut.

5 Empirical Results

Equation (15) is a panel specification that allows for tracking the effect on output growth of EB and TB based fiscal adjustment plans. Total adjustments are separated into their three components, and each component is allowed to have a different impact on output growth by allowing separate coefficients on the unexpected (τ^u and γ^u), announced (τ^a and γ^a) and future (τ^f and γ^f) components of the fiscal adjustments.

We estimate the coefficients of the model via maximum likelihood (see Anselin, Le Gallo, and Jayet, 2008 and LeSage and Pace, 2009). In particular, we develop a Maximum Likelihood Estimator for our panel specification.[20] To take into account the different volatility of the sectors (for instance, mining and agriculture exhibit a much higher volatility relative to all the other sectors), we allow for heteroskedasticity.

[20]In the Online Appendix of the paper, we provide a full analytic derivation of the estimator.

Equation (15) can be rewritten in this way:

$$\underset{n\times 1}{\Delta y_t} = \rho^{down} \cdot \underset{n\times n}{A_0} \cdot \underset{n\times 1}{\Delta y_t} \cdot TB_t + \rho^{up} \cdot \underset{n\times n}{\hat{A_0^T}} \cdot \underset{n\times 1}{\Delta y_t} \cdot EB_t + \underset{n\times(n+6)}{X_t} \cdot \underset{(n+6)\times 1}{\beta} + \nu_t \tag{18}$$

where

$$X_t = \begin{bmatrix} I_n & f_t^u \cdot TB_t \cdot \mathbf{1}_n & f_t^a \cdot TB_t \cdot \mathbf{1}_n & f_t^f \cdot TB_t \cdot \mathbf{1}_n & f_t^u \cdot EB_t \cdot \boldsymbol{\omega} & f_t^a \cdot EB_t \cdot \boldsymbol{\omega} & f_t^f \cdot EB_t \cdot \boldsymbol{\omega} \end{bmatrix}.$$

$$\beta = \begin{bmatrix} \boldsymbol{\alpha}^T & \boldsymbol{\tau}^T & \boldsymbol{\gamma}^T \end{bmatrix}^T$$

$$\nu_t \sim \mathcal{N}(\mathbf{0}_n, \Omega), \quad \Omega = diag(\sigma_1^2, ..., \sigma_n^2), \quad \nu_t \perp \nu_j \ \forall t \neq j.$$

No serial correlation in the error terms is assumed.

The static specification of the model and the other assumptions make the Δy_t observations independent on each other over time, a result which is motivated by the low persistence of industry value-added growth rate when measured yearly. This assumption will be relaxed in section 6.3, when an autoregressive component will be added to the baseline model.

In order to calculate the MLE, the standard approach in spatial econometrics is followed: derive the log-likelihood, and then concentrate it with respect to the spatial coefficients (see Anselin, Le Gallo, and Jayet, 2008 or LeSage and Pace, 2009). In the Online Appendix, we provide a detailed derivation of the log-likelihood and its Fisher Information matrix, which will be employed in the construction of standard errors.

The maximum likelihood estimates are reported in Table II:[21]

Table II: Maximum Likelihood Estimates for the Baseline Model.

	MLE	*Std. Dev.*	*t-stat*	$Pr(x<0)$	*1%*	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*	*99%*
ρ^{down}	0,499	0,075	6,662	0,000	0,324	0,375	0,403	0,425	0,499	0,573	0,595	0,623	0,673
ρ^{up}	0,259	0,083	3,119	0,001	0,066	0,123	0,153	0,177	0,259	0,342	0,366	0,397	0,453
τ_u	-0,246	1,640	-0,150	0,559	-4,061	-2,937	-2,349	-1,879	-0,247	1,388	1,855	2,448	3,563
τ_a	-1,940	1,289	-1,505	0,934	-4,928	-4,060	-3,591	-3,218	-1,943	-0,657	-0,285	0,182	1,076
τ_f	-1,060	0,552	-1,920	0,972	-2,342	-1,968	-1,767	-1,611	-1,063	-0,511	-0,352	-0,147	0,229
γ_u	-1,467	1,905	-0,770	0,779	-5,873	-4,597	-3,913	-3,360	-1,467	0,435	0,983	1,660	2,962
γ_a	0,196	1,052	0,187	0,425	-2,253	-1,535	-1,148	-0,848	0,197	1,242	1,541	1,932	2,647
γ_f	-0,282	0,476	-0,594	0,723	-1,399	-1,063	-0,892	-0,755	-0,283	0,189	0,325	0,498	0,827

Table II: *a) MLE reports the estimates of the paramters; b) Std. Dev. reports the standard deviations of the Monte Carlo simulated distribution (thus taking into account correlation among parameters estimates); c) the t-statistics can be interpreted as an asymptotic t-statistic since the normality of the MLE is an asymptotic result. d) $Pr(x<0)$ represents the fraction of negative values when we simulate the parameters using their marginal asymptotic distribution. e) The last ten columns represent the percentiles of the simulated distributions.*

The asymptotic and small sample properties of the MLE of a dynamic SAR panel data model with fixed effects (which nests our static specification), are provided in Yu, De Jong, and L.-f. Lee, 2008.

[21] The marginal distributions are obtained via Monte Carlo simulation, by exploiting the asymptotic properties of the MLE. In practice, we draw values of the estimated coefficients from the asymptotic distribution $\mathcal{N}(\hat{\theta}, \mathcal{I}^{-1}(\hat{\theta}))$.

5.1 The average effect of TB and EB Fiscal Adjustment Plans

The effect of a fiscal adjustment plan is constructed as illustrated in Section 3.3. In practice, we replace the parameters in Equations (16) and (17) with our maximum likelihood estimates and we choose weights $\boldsymbol{s}_\tau$ and $\boldsymbol{s}_\gamma$ to distribute the 1% of GDP fiscal adjustment plan in its 3 components. By definition of an "unexpected shock", the anticipated component is set to zero. Regarding the unanticipated and future components, we draw them from a uniform distribution centered on the average style of TB and EB plans. This procedure will make our results robust to the way we distribute the shock between its unanticipated and future components.[22] We construct a distribution for the effects of fiscal adjustment plans by following routine: 1) we draw the parameters from the asymptotic distribution as done to construct Table II; 2) we construct the fiscal adjustment plan by randomly distributing the 1% shock among its three components, as outlined above; 3) we calculate the total, instantaneous and network effects of the fiscal adjustments, as described in section 3.3; 4) we average their values across sectors; 5) we repeat this procedure 100,000 times. In this way, we obtain a distribution for each of the average effects.

We report the results of the effect of plans in Table III, which summarizes our main finding:[23]

Table III: The Average Output Effects of Fiscal Adjustment Plans

	Mean	*%*	*Std. Dev.*	$Pr(x<0)$	*1%*	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*	*99%*
Ave. Tax Total	-1,827	1,000	1,185	0,958	-5,117	-3,912	-3,356	-2,950	-1,725	-0,696	-0,419	-0,074	0,550
Ave. Tax Instant.	-0,863	0,473	0,497	0,958	-2,011	-1,676	-1,500	-1,357	-0,865	-0,371	-0,227	-0,041	0,309
Ave. Tax Network.	-0,963	0,527	0,726	0,958	-3,272	-2,302	-1,889	-1,610	-0,841	-0,309	-0,182	-0,032	0,236
Ave. Exp. Total	-0,587	1,000	0,759	0,798	-2,849	-1,866	-1,497	-1,245	-0,541	0,103	0,289	0,536	1,047
Ave. Exp. Instant.	-0,430	0,732	0,548	0,798	-2,018	-1,343	-1,087	-0,916	-0,406	0,077	0,217	0,403	0,779
Ave. Exp. Network.	-0,157	0,268	0,231	0,798	-0,935	-0,564	-0,426	-0,338	-0,120	0,022	0,065	0,130	0,291

Table III: *a) Mean, reports the mean of the average (across sectors) effects, of the Monte Carlo simulated distribution; b) % represents the share of the mean effect coming from the instantaneous and network components of the total effect. c) Std. Dev. reports the standard deviations of the Monte Carlo simulated distribution (thus taking into account correlation among parameters estimates); d) the t-statistics can be interpreted as an asymptotic t-statistic since the normality of the MLE is an asymptotic result. e) $Pr(x<0)$ represents the fraction of negative values when we simulate the parameters using their marginal asymptotic distribution. f) The last ten columns represent the percentiles of the simulated distributions.*

First of all, notice that consistently with the new fact in the literature, we find that tax-based fiscal adjustments imply larger output losses, compared to expenditure-based consolidation: the mean of the Average Total Effect of TB plan amounts to -1.83, while the mean of the Average Total Effect of an EB plan is -0.59.

Furthermore, the Average Network Effect of a TB plan contributes to 52.7% of the total output effect, suggesting the relevance of the industrial network in the propagation of the TB fiscal adjustments.

On the other hand, the effect of the industrial network for the propagation of an EB plan, measured by the proportion of the Average Total Effect coming from the Average Network Effect, is much smaller than the one of a TB plan: it is only 26.8%.

In addition, the differences in the Average Total Effect of an EB and TB plan explained by differences in

[22] See Online Appendix for a more thorough technical explanation of this procedure.

[23] Results for Bayesian MCMC are also available in the Online Appendix of the paper.

the Average Network Effect, can be estimated by adopting the following descriptive statistic:

$$\frac{\left|\overline{Ave.\ \ Tax\ Net.} - \overline{Ave.\ \ Exp.\ \ Net.}\right|}{\left|\overline{Ave.\ \ Tax\ Tot.} - \overline{Ave.\ \ Exp.\ \ Tot.}\right|} = \frac{|-0.963 - (0.157)|}{|-1.827 - (-0.597)|} = 65.53\% \tag{19}$$

Therefore, 65.53% of the differences in the Average Total Effect of TB and EB plans is related to differences in their network effects.

Overall, a smaller Average Total Effect of EB plans on the economy and significantly lesser importance of the network is found. This result suggests that TB plans have a stronger propagation in the network than EB plans. Theoretically speaking, a TB plan is comparable to a supply shock which propagates in the network via the price mechanism illustrated in Section 2, while an EB plan is more similar to a demand shock, which operates upstream through the decreased-demand mechanism, also illustrated in Section 2. This result suggests that the price mechanism is stronger than the decreased-demand one. Therefore, the asymmetric propagation seems to be due to different reactions of economic agents to demand and supply shocks.

Finally, our results suggest that different propagation mechanisms in the production network can explain both theoretically and empirically, a great part of the differences in the output effect of TB and EB plans, and to a certain degree, tax and expenditure shocks.

5.2 Industry level analysis

5.2.1 The industry specific effect of TB and EB Fiscal Adjustment Plans

In this section we break down the average total output effect of fiscal adjustment plans into its sectoral components. Our goal is purely illustrative: we want to show how differently sectors are hit by a 1% fiscal plan in our simulation.

In order to do this, we firstly re-run our analysis of Section 5.1, by employing non-row normalized I-O matrices. This will make us lose the interpretation of the spatial variables as a weighted average of the dependent one (standard assumption in spatial econometrics), but allows us to observe the heterogeneous effects of plans on single industries.[24] In Figure 5 we report a full breakdown of the effects:

Insert Figure 5

The Top-panels of Figure 5 report the industry level distributions of the effects of TB and EB plans. Compared with the averaged ones of section 5.1, industry level's distribution are more centered towards zero, that is, they are less statistically significant. This a consequence of not averaging: in section 5.1 the results are an average across sectors, and therefore the variance is scaled by the cross-section size.[25]

[24]The problem of employing row-normalized matrices is that $(I_n - \rho \cdot A)^{-1} \cdot \mathbf{1}_n = \frac{1}{1-\rho} \cdot \mathbf{1}_n$ as long as $A \cdot \mathbf{1}_n = \mathbf{1}_n$. Our baseline results of Section 5.1, are robust to the adoption of a non-row-normalized matrix and they are available in our Online Appendix.

[25]To better grasp this concept, just think of an i.i.d. sequence X_i; by the Lindberg-Levy CLT we have that $\bar{X} \approx \mathcal{N}(\mu, \frac{\sigma^2}{n})$, while

Since TB plans hit sectors all in the same fashion and share the same fiscal multipliers $\boldsymbol{s}_\tau^T \cdot \boldsymbol{\tau}$, the heterogeneous effect comes from the centrality of each sector in the downstream network defined by matrix A:

$$(\text{Output effect of TB plan})_i = \boldsymbol{e}_i^T \cdot \underbrace{(I_n - \rho^{down} \cdot A)^{-1} \cdot \mathbf{1}_n}_{\text{“Passive Customerness”}} \cdot (\boldsymbol{s}_\tau^T \cdot \boldsymbol{\tau}) \tag{20}$$

where $\boldsymbol{e}_i$ is a vector of zeros except for entry i, which is one.

In expression (20) we denote by "Passive Customerness" the downstream (eigenvector) centrality measure $(I_n - \rho^{down} \cdot A)^{-1} \cdot \mathbf{1}_n$.[26] This measure tells us how much each sector is subject (passive) to fluctuations coming from its suppliers, and therefore how much its status as a customer (customerness) affects its output's fluctuations.

From the left panel of Figure 5, the most severely harmed sectors from the TB plan are Construction, Entertainment, Transportation, Agriculture, and Education/Health Care. Notice that these sectors are the ones most connected by downstream input flows coming from Manufacturing (see the directed graph of Figure 1). It seems, therefore, that Manufacturing is behaving as an explosive fuse in the downstream propagation mechanism. On the contrary, Professional Services and Finance are the least subject to TB fiscal adjustment plans. Similar to Manufacturing, they also play a central role in propagating TB plans downstream; however, unlike Manufacturing, they rely less on other suppliers, thus minimizing their exposure to downstream negative spillovers.

In the case of EB plans, the heterogeneity of the output effect of sectors comes in part from the fact that the Government purchases from them in a different fashion (recall the industry specific weights ω_i), and in part from an eigenvector centrality measure which captures the upstream propagation mechanism:

$$(\text{Output effect of EB plan})_i = \boldsymbol{e}_i^T \cdot \underbrace{(I_n - \rho^{up} \cdot \hat{A}^T)^{-1} \cdot \boldsymbol{\omega}}_{\text{“Passive Supplierness”}} \cdot (\boldsymbol{s}_\gamma^T \cdot \boldsymbol{\gamma}) \tag{21}$$

where the "Passive Supplierness" centrality, summarizes how much each sector is subject (passive) to fluctuations coming from its customers, and therefore by how much the status of supplier (supplierness) affects its output's fluctuations.

Mining is by far the sector mostly hit by an EB plan, with a median contraction of -1.2%; which is exactly the same median contraction registered by the Finance sector during a TB plan, which, conversely, is the least hit sector; this fact underscores again the more recessionary effect of TB plans compared to EB plans. On the other hand, Retail is the least affected sector. These results make a lot of sense: Retail is, by nature, a sector that does not have many B-2-B relationships since its customers are mainly consumers; Retail has very

the variance of X_i is greater and corresponds to σ^2.

[26]The above term is also referred to as a Katz-Bonacich centrality. For further details on centrality measures we remand to Vasco M Carvalho, 2014.

little exposure to other sectors' demand. On the contrary, Mining is a sector which, by nature, only sells to industries, thus heavily exposing it to upstream spillovers coming from reduced demand of other sectors. In particular, recalling Figure 2, we notice that those sectors that sell massively to Manufacturing are those ones that are more damaged by EB plans.

5.2.2 Industrial Systemic Risk and Efficient Policy Making

In the previous section we explored the effect of a fiscal plan on every single sector. We analyzed how much each sector is "*vulnerable*" to an aggregate shock that hit all the sectors at the same time and in the same fashion, in the case of a TB plan, and in an industry-specific fashion, for an EB plan. In this section, we explore the effect of a pure industry-specific shock on the rest of the economy. In this sense, we are exploring a measure of "real systemic risk": real, because we focus on the real economy and its industrial sectors; systemic risk, because as done in the financial literature, we look at the effects of an idiosyncratic sectoral shock on the whole system. In other words, we pose the following question: "how much a sector could be "*harmful*" for the whole system?"

These considerations becomes particularly relevant when a given expenditure cut has to be allocated among different sectors. Which allocations of the cut across sectors minimizes the aggregate output loss associated with the fiscal adjustment? The same arguments applies to tax increases, think, for example, of the introduction of a new industry-specific tax, such as a "Carbon tax"; a "Web tax"; or a "Tobin tax". A Carbon tax would hit mainly the Manufacturing and Agriculture sectors; a Web tax would hit the Information sector, while a Tobin type tax would hit mainly the Finance sector. Which of them would be more likely to generate the greatest output loss? Notice also that industry-specific taxes are not only a potential new fiscal innovation like the ones cited above, but for instance, in our fiscal adjustment plans database, we record the introduction of new excise taxes. In 1980 the government introduced the Windfall Profit Tax, which we can interpret as a Mining sector-specific tax. In 1987 the Omnibus Budget Reconciliation Act introduced manufacturing excise taxes on certain vaccines and on telephone services, which can be related to the Manufacturing and Services sectors, respectively.

The effect of a generic industry-specific fiscal shock would be obtained by summing up the elements in the i^{th}-column of the Leontief Inverse:

$$(\text{Total Output effect}_i) = \underbrace{\mathbf{1}_n^T \cdot (I_n - \rho_{\theta,W} \cdot W)^{-1} \cdot \boldsymbol{e}_i}_{\text{Active Centrality Measure}} \cdot \theta_i \tag{22}$$

where θ_i represents an unknown fiscal multiplier of an industry i specific shock; W represents a network; $\rho_{\theta,W}$ represents the spatial coefficient associated with network W and shock θ. For instance, in our analysis, we have focused on two types of networks (A and $\hat{A}^T$) and two types of shocks (TB and EB fiscal adjustment plans).

Since we do not estimate the effect of industry-specific shocks, we cannot employ our estimates of $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$ for answering the question of how much an industry-specific shock would hit the rest of the economy. However, if we assume that for an industry-specific tax increase, the estimates of the spatial coefficient ρ^{down} would not change that much from the ones obtained in the analysis of a TB plan, then we can reliably employ our estimates of ρ^{down} to calculate the "active centrality measure" of equation (22). Analogously, we can employ our estimates of ρ^{up} to calculate the active centrality measure of an industry-specific spending cut.

Here, the term "active" is in contrast with the previous notation of "passive"; the latter focuses on the rows of the Leontief inverse and captures the effect on a single industry; the former focuses on the columns of the Leontief inverse and captures the effect triggered by an industry. For the downstream propagation of an industry specific tax increase, we therefore calculate:

$$(\text{Active Supplierness})_i := \mathbf{1}_n^T \cdot (I_n - \rho^{down} \cdot A)^{-1} \cdot \boldsymbol{e}_n^i \tag{23}$$

The "active supplierness" represents by how much a supply shock to sector i affects (active) the rest of the economy through its customers, that is, through the downstream propagation channel (price-increase mechanism); in other words it summarizes by how much the status of supplier (supplierness) of industry i affects all its customers. It represents the network multiplier of an industry specific tax increase.

Analogously, we define the counterpart of expression (23) for industry specific spending cuts:

$$(\text{Active Customerness})_i := \mathbf{1}_n^T \cdot (I_n - \rho^{up} \cdot \hat{A}^T)^{-1} \cdot \boldsymbol{e}_n^i \tag{24}$$

The "active customerness" captures how much a spending cut to sector i affects (active) the rest of the economy through its suppliers; in other words it summarizes by how much the status of customer (customerness) of industry i affects its suppliers through the upstream propagation channel (decreased-demand mechanism). It represents the network multiplier of an industry specific spending cut.

In Figure 6 we report on the right side the Active Customerness centrality and on the left side the Active Supplierness:

Insert Figure 6

As anticipated above, since we don't estimate industry specific fiscal coefficients (namely θ_i in equation (24)), we can't calculate the output effect of industry specific shocks. However, ceteris paribus, those output effects will be proportional to the active centrality measures, whose simulated values are shown in Figure 6.

From the left bottom panel, notice that the sectors which have the largest network multipliers are Manufacturing, Service, and Finance. This result is consistent with their central position in the downstream network illustrated by figure 1. On the other hand, the network multiplier associated with Information is smaller. This result suggests that a Carbon tax could have the worst network effects on the economy, compared to a Tobin type tax, and in particular to a Web tax targeting the Information sector. Of course, we are not saying that decisions around what type of tax to introduce should be made only on the network multiplier criterion, but at the same time, we also believe that the policymaking process should take this spillovers effects into account.

Concerning the introduction of an industry-specific spending cut, the network multipliers measured by the Active Customerness centrality, clearly show that Manufacturing behaves as a potential explosive fuse, with a network multiplier of more than twice as much as Education and Health Care. This is consistent with the directed graph of Figure 2: where Manufacturing is the most central node while Education and Health Care is the most remote sector in the upstream network.

As long as the fiscal coefficients θ_i are not estimated, we cannot assess which industry-specific shock will generate the greatest output loss. However, we illustrated how an industry-specific fiscal shock could impact the economy through a combination of a fiscal coefficient θ_i and a network multiplier represented by an active centrality measure. We provided estimates of each sector's network multipliers for both the downstream (tax increase) and upstream (spending cut) propagation channels. Our illustrative exercise illustrates the importance of the analysis of industry-specific fiscal shocks and their network effects for the design of efficient fiscal adjustment policies.

6 Robustness

6.1 Inverted propagation channels

We anticipated in Section 3 that exploring different interactions between the plans and the networks is a worthy experiment that allows to appreciate which economic theory seems to be closer to the real world: are TB (or EB) plans more like supply or a demand-side shock? What type of propagation prevails: downstream or upstream? Do TB plans still have a stronger network effect than EB plans, when the propagation direction is inverted?
In order to answer these questions, we conduct the experiment of "switching the dummies", that is, we now estimate the following "inverted" model:

$$\underset{n\times 1}{\Delta y_t} = \rho^{down} \cdot \underbrace{A_0 \cdot \Delta y_t \cdot EB_t}_{\text{EB downstream}} + \rho^{up} \cdot \underbrace{\hat{A_0^T} \cdot \Delta y_t \cdot TB_t}_{\text{TB upstream}} + X_t \cdot \beta + \boldsymbol{\nu}_t \tag{25}$$

By doing this, we force the TB plans to propagate upstream and, therefore behaving more like a demand shock; conversely, EB plans now are forced to propagate downstream, thus behaving as a supply shock that affects prices.
Treating TB plans as demand-side shocks has a theoretical justification, which we pointed out already in

section 2: TB plans are almost entirely made of tax shocks, and tax shocks can also behave as demand shocks. On the other hand, EB plans are more hybrid and contain a mix of tax and expenditure shocks; therefore, it is reasonable to assume they can also have a downstream propagation, thus behaving as supply shocks. Furthermore, as underscored in Bouakez, Rachedi, Emiliano, et al., 2018, the construction of a quite general model can allow even pure government spending shocks, to affect prices and propagate downstream, as a supply shock does.

We estimate Equation (25) via MLE, as done in the baseline specification. Results are reported in Table IV:[27]

Table IV: Maximum Likelihood Estimates of the "Inverted" Model

	MLE	*Std. Dev.*	*t-stat*	$Pr(x<0)$	*1%*	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*	*99%*
ρ^{down}	0,146	0,082	1,781	0,037	-0,045	0,012	0,041	0,065	0,147	0,228	0,252	0,282	0,338
ρ^{up}	0,499	0,085	5,897	0,000	0,303	0,359	0,390	0,414	0,499	0,583	0,607	0,637	0,695
τ_u	-0,089	1,651	-0,054	0,523	-3,907	-2,798	-2,204	-1,733	-0,095	1,564	2,038	2,642	3,740
τ_a	-1,350	1,310	-1,030	0,849	-4,400	-3,497	-3,033	-2,660	-1,344	-0,048	0,324	0,795	1,691
τ_f	-0,855	0,564	-1,516	0,936	-2,171	-1,781	-1,579	-1,415	-0,853	-0,296	-0,134	0,070	0,463
γ_u	-1,102	1,903	-0,579	0,720	-5,524	-4,236	-3,540	-2,990	-1,096	0,791	1,340	2,020	3,317
γ_a	0,684	1,057	0,647	0,258	-1,774	-1,053	-0,669	-0,369	0,683	1,736	2,041	2,417	3,148
γ_f	-0,297	0,474	-0,626	0,734	-1,402	-1,077	-0,904	-0,768	-0,297	0,176	0,312	0,481	0,806

Table II: *a) MLE reports the estimates of the paramters; b) Std. Dev. reports the standard deviations of the Monte Carlo simulated distribution (thus taking into account correlation among parameters estimates); c) the t-statistics can be interpreted as an asymptotic t-statistic since the normality of the MLE is an asymptotic result. d) $Pr(x<0)$ represents the fraction of negative values when we simulate the parameters using their marginal asymptotic distribution. e) The last ten columns represent the percentiles of the simulated distributions.*

Notice that ρ^{down} is now less significant than ρ^{up}: regardless of the direction of propagation within the network, the spatial correlation among industry value added is stronger during years where a TB plan occurs. This is another indication of the stronger network effect of TB plans.

As done for the baseline analysis of Section 5, we carry out the analogous fiscal shock Monte Carlo simulation. Table V reports the simulated output effects of TB and EB adjustment plans using the "inverted" model:

Table V: The Output Effect of TB and EB plans in the "Inverted" Model

	Mean	*%*	*Std. Dev.*	$Pr(x<0)$	*1%*	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*	*99%*
Tax Total	-1.455	1.000	1.218	0.906	-4.950	-3.615	-3.006	-2.584	-1.340	-0.314	-0.035	0.301	0.936
Tax Instant.	-0.668	0.459	0.507	0.906	-1.840	-1.496	-1.316	-1.170	-0.670	-0.168	-0.019	0.167	0.534
Tax Network	-0.787	0.541	0.750	0.906	-3.257	-2.178	-1.723	-1.424	-0.648	-0.135	-0.015	0.126	0.409
Exp. Total	-0.486	1.000	0.649	0.790	-2.343	-1.557	-1.264	-1.060	-0.457	0.110	0.276	0.498	0.968
Exp. Instant.	-0.397	0.818	0.526	0.790	-1.860	-1.254	-1.029	-0.871	-0.382	0.093	0.231	0.418	0.799
Exp. Network	-0.088	0.182	0.148	0.770	-0.604	-0.355	-0.263	-0.202	-0.056	0.015	0.039	0.081	0.199

Table V: *a) Mean, reports the mean of the average (across sectors) effects, of the Monte Carlo simulated distribution; b) % represents the share of the mean effect coming from the instantaneous and network components of the total effect. c) Std. Dev. reports the standard deviations of the Monte Carlo simulated distribution (thus taking into account correlation among parameters estimates); d) the t-statistics can be interpreted as an asymptotic t-statistic since the normality of the MLE is an asymptotic result. e) $Pr(x<0)$ represents the fraction of negative values when we simulate the parameters using their marginal asymptotic distribution. f) The last ten columns represent the percentiles of the simulated distributions.*

Table V shows that the share of the effect of a TB adjustment attributable to the network does not change

[27]Results for Bayesian MCMC are also available in the Online Appendix of the paper.

(still more than 50%), but the magnitude of the effect is now reduced: from an Average Total Effect of almost -1.83% we move to -1.46%. The statistical significance of the effect is also reduced.
On the government spending side, the share of the Average Network Effect of EB plans, decreases from 27% to 18%; the magnitude of the Average Total Effect passes from -0.6% to -0.5%, and the effect is not statistically significant. Because of the almost total disappearance of the network propagation for the EB plans, the statistic calculated in expression (19) increases up to 72.14%, that is, most of the differences in the output effect of TB and EB plans is attributable to differences in the network propagation.
Furthermore, the almost null downstream propagation of EB plans is consistent with the quantitative results in Bouakez, Rachedi, Emiliano, et al., 2018: their calibrated model allows both downstream and upstream propagation of government spending shocks, however, they find that the upstream propagation outweighs by far the downstream one. Our results validate with a more empirical framework their more theoretical results.

In order to provide a more quantitative assessment of the relative performance of the "baseline" versus the "inverted" models, we carry out a Vuong test (see Vuong, 1989) for non-nested models. We obtain more evidence in favor of the baseline model, with a p-value of 24%; however, it is not enough to reject the null hypothesis of "superiority of the baseline model against the inverted".

The results of this experiment can be summarized in several interesting facts. Firstly, TB plans propagate more strongly in the network than EB plans, regardless of the direction of propagation.
TB plans have stronger and more significant output effect when we let them propagate downstream, thus suggesting two possible explanations: 1) TB plans are more like supply shocks than demand shocks and therefore, they propagate more effectively downstream rather than upstream; 2) TB plans are equally a demand and a supply shock, but the downstream propagation which works through the price mechanism is stronger than the upstream propagation which works through the decreased-demand mechanism. One of the two is true, but it is hard to tell which one holds.
Lastly, EB plans have a much stronger upstream propagation than downstream, consistent with the results in Bouakez, Rachedi, Emiliano, et al., 2018.

6.2 Placebo

Ozdagli and Weber (2017) points out that the estimation of a SAR model might capture a spurious correlation between the spatial variables and the dependent one, rather than a real underlying economic network. In order to rule out this possibility, we apply a slightly modified version of their placebo test. The idea is to: 1) simulate new spatial matrices; 2) carry out the same analysis done in section 5; 3) repeat step one and step two several times; 4) compare the results of the placebo experiments to the original one.
If the initial results are driven by spurious correlation, then the results obtained in the placebo experiments

should not differ, in terms of magnitude and statistical significance, from the one obtained using the original network matrices. On the other hand, if the industrial network really matters, the weights given by the original spatial matrices should be the "real" ones, and therefore should deliver superior results.

In practice, we simulated several new spatial matrices using different methods in order to be robust to different simulation procedures.[28] Overall, we collected 500 placebo experiments, the results of which have been summarized by a pair: the mean of the Average Network Effect (magnitude) and the ratio between the mean of the Average Network Effect and its standard deviation (statistical significance, via asymptotic t-statistic). We compare every placebo experiment with the original result through a scatter plot: the mean lies on the horizontal axis while the asymptotic t-stat lies on the vertical axis. Figure 7 shows the results:

Insert Figure 7

If the original spatial matrix is capturing a structural network, we expect the initial results to have stronger effects, both in absolute terms (strongly negative mean) and statistical terms (strongly negative asymptotic t-statistic). Therefore, we expect the original spatial matrix results to be located in the south-west part of the scatter-plot. Results are reassuring: notice that in Figure 7, the red dot, which represents the baseline results, stands in the bottom-left part of the figures relative to the bulk of the remaining blue dots, which represent a placebo simulation each. Therefore, our results are not driven by a spurious correlation but reflect the existence of a true underlying economic network.

6.3 Dynamics

So far, our baseline model did not include any time lags; we had at least two valid justifications for adopting a fully static specification: 1) our database is observed at yearly frequency; 2) industry value-added growth rates are not very persistent. However, despite the disaggregation and the low frequency, some sectors (in particular 7 out of 15) still show a non-negligible autocorrelation. Therefore, we decided to check whether our results were robust to the inclusion of a lagged variable.

Equation (18), now becomes:

$$\underset{n\times 1}{\Delta y_t} = \underbrace{\underset{n\times n}{\mathbf{\Phi}} \cdot \underset{n\times 1}{\Delta y_{t-1}}}_{\text{Time Linkage}} + + \underbrace{\rho^{down} \cdot \underset{n\times n}{A_0} \cdot \underset{n\times 1}{\Delta y_t} \cdot TB_t + \rho^{up} \cdot \underset{n\times n}{\hat{A}_0'} \cdot \underset{n\times 1}{\Delta y_t} \cdot EB_t +}_{\text{Spatial Linkage}}$$

$$+ \underset{n\times(n+6)}{X_t} \cdot \underset{(n+6)\times 1}{\beta} + \nu_t \tag{26}$$

where $\mathbf{\Phi} = diag(\phi_1, \phi_2, ..., \phi_n)$, represents a diagonal autoregressive matrix. This type of model is mentioned in Anselin, Le Gallo, and Jayet, 2008 and it is referred to as "*time-space simultaneous model*". By leaving anything

[28]See the Online Appendix of the paper, for complete details on the placebo procedure.

else unaffected, we estimate Equation (26) via Conditional Maximum Likelihood; again the small sample and asymptotic properties of its MLE are studied in Yu, De Jong, and L.-f. Lee, 2008. Since our asymptotics entails to leave the number of sectors n constant while letting the number of years T increase, the bias coming from the fixed effects disappears, as in a standard dynamic panel with fixed effects (where the bias is of order $O(T^{-1})$). The results are summarized by cumulative impulse response functions, constructed by simulating a fiscal adjustment plan of 1% of GDP. Unlike the static baseline version of the model, here the fiscal plan is rolled over year by year, that is, the future components of the simulated plan will have an impact as an anticipated component in the following years. For instance, if we simulated the following plan:

Unexpected	*Anticipated*	*1 year ahead*	*2 years ahead*	*3 years ahead*	*Total*
.3	0	.1	.4	.2	1

then, in year 1, the economy would receive a 1% shock distributed in its three components (unexpected, anticipated, and future) according to the scheme outlined in the table above. In year 2, the effect would be transmitted via the autoregressive matrix $\mathbf{\Phi}$; moreover, the economy would receive another anticipated shock of .1 and a future shock of $.6(= .4 + .2)$, which would be rolled over from the previous year future components. In year 3, the economy would receive another anticipated shock of .4 and another future shock of .2 and so on. In this way, the overall shock the economy receives over the entire simulation is greater than 1%, thus complicating the comparison with the static specification of Section 5 (we expect larger output effects). Except for this, the Monte Carlo simulation is analogous to the one carried out in the static framework of Section 5 (and it is therefore robust to the underlying uncertainty around the composition of the fiscal plan).

The median cumulative impulse response functions are plotted in Figure 8 with confidence bands represented by the 5^{th} and 95^{th} percentile of their distributions:

Insert Figure 8

The exact values of the cumulative impulse responses showed in Figure 8 are reported in Table VI:

Table VI: Cumulative Impulse Response Function (12 years horizon)

Horizon	*0 Year*	*1 year*	*2 years*	*3 years*	*4 years*	*5 years*	*6 years*	*7 years*	*8 years*	*9 years*	*10 years*	*11 years*	*12 years*
Ave. Tax Tot.	0.000	-1.063	-2.368	-3.390	-4.112	-4.496	-4.744	-4.909	-5.024	-5.106	-5.168	-5.212	-5.244
Ave. Tax Inst.	0.000	-0.741	-1.651	-2.372	-2.897	-3.189	-3.382	-3.513	-3.605	-3.672	-3.721	-3.757	-3.784
Ave. Tax Network	0.000	-0.316	-0.703	-0.991	-1.184	-1.276	-1.331	-1.367	-1.391	-1.408	-1.420	-1.429	-1.436
Ave. Exp. Tot.	0.000	-0.735	-0.930	-0.906	-0.681	-0.640	-0.620	-0.611	-0.605	-0.601	-0.598	-0.597	-0.596
Ave. Exp. Inst.	0.000	-0.585	-0.734	-0.710	-0.522	-0.490	-0.474	-0.467	-0.463	-0.460	-0.458	-0.457	-0.456
Ave. Exp. Network	0.000	-0.126	-0.168	-0.169	-0.135	-0.127	-0.123	-0.121	-0.120	-0.120	-0.119	-0.119	-0.119

Table VI: *Cumulative Average Effects of fiscal plans on economic growth; the numbers represents the median of their corresponding Monte Carlo simulated distribution. The first year represents the effect of a 1% fiscal plan. The future components of the plan become anticipated components implemented from year two until year four; therefore, the overall shock is larger than 1%.*

Notice that EB adjustment plans have basically no dynamics: the effect after one year is very similar to the long-run effect; furthermore, the results are not far from the ones obtained in the static model (see Table III).

The Average Network Effect accounts for 17% of the Average Total Effect after one year, and 20% at the end of the period. In this sense, for EB plans our baseline results are robust to the inclusion of dynamics.

On the other hand, results for TB fiscal adjustments suggest that the dynamic propagation is not negligible but small. After year 4 (the last year where a future component of the plan is implemented), the median cumulative impulse response function starts flattening, and after four years (year 8 in the graph), there is no more time transmission of the shock.

Interestingly, the inclusion of a time propagation channel reduces the importance of the industrial network and, in particular, of its downstream spatial propagation: the magnitude of ρ^{down} decreases from .49 in the static specification to .30 in the dynamic one. This fact causes a reduction in the importance of the mean Average Network Effect, which now accounts for "only" 30% of the mean Average Total Effect after one year, and 27% of it in the last year.

One possible explanation to this result is the following: suppose that downstream propagation takes time to occur; then, this implies that we are omitting a variable in our dynamic specification $A \cdot \Delta y_{i,t-1}$ (spatial and time lag). In general, this implies that the propagation coming from a *delayed network effect* is actually captured by the time-lagged average instantaneous part, with the consequence that we underestimate the Average Network Effect. The time propagation of sectoral shocks in a network is a field still to be explored.[29] Nevertheless, first clear evidence of a delayed effect of downstream spatial spillovers is provided in Smets, Tielens, and Van Hove, 2019: the authors show that the autocorrelation between inflation in crude oil's price and synthetic rubber's price spikes after three months, then the autocorrelation between inflation in synthetic rubber's price and tires' price also spikes after three months but, the autocorrelation between inflation in tires' price and transport costs, spikes after 16 months. Therefore downstream propagation does seem to have a delayed effect.

Regardless of the reduction in the relevance of the industrial network, our dynamic specification confirms that TB plans are more recessionary than EB plans, uniformly over the years. Moreover, the difference between the output effect of TB plans and EB plans explained by differences in the network effect, now spans from 57.6% after one year (comparable to the results of the static framework and the 1% size of the shock) to the 28% in the long run, whose reduction can be explained by delayed network effects.

Overall, the main empirical results are robust when a dynamic model is adopted. Research on delayed spillovers and timing of network propagation is important to shed further light on the industrial network effects.

7 Conclusions

We have investigated how fiscal plans propagate through the industrial network in the US economy along two different dimensions: 1) the comparison between the average effects of TB and EB plans; 2) the heterogeneity

[29] We thank Johannes Wieland for pointing out the relevance of timing in the propagation.

of the effects across industries.

A stronger contractionary output effect of TB adjustment plans relative to EB adjustment plans is found. In particular, the average total effect of a 1% of GDP tax-based adjustment plan is estimated to an average contraction of 1.83% in GDP while an EB plan is estimated to lead to a much smaller contraction of 0.59% in GDP. These estimates are very close to those found in a multi-country study of OECD economies by Alesina, Favero, and Giavazzi, 2015. The different network transmission mechanism of EB and TB adjustments offers a new interpretation of the estimated heterogeneous effects in the intersectoral panel. Interestingly, the industrial propagation network effect accounts for more than half of the total impact of TB based adjustment on output while in case of EB adjustments, the share of the propagation through the industrial network is of about half of that observed for TB plans.

Our robustness analysis shows that forcing the TB adjustment to flow counterfactually upstream produces a statistically weaker empirical model. The counterfactual evidence is even stronger for the EB adjustment plans. Placebo test demonstrates that our results are not driven by spurious correlation, but indeed industrial network matters for the propagation of the fiscal adjustment plans. The empirical results are robust to the inclusion in the specification of a time lag of the dependent variable, although this generates a slight reduction in network relevance. However, as explained in Section 6.3, we do believe that such a reduction could be explained by network delayed effects, as suggested by the evidence provided by Smets, Tielens, and Van Hove, 2019.

Regarding the second dimension of results, we provide estimates of the output effect of fiscal adjustments for each sector. We found that sectors mainly connected downstream to Manufacturing, such as Construction, Entertainment, Transportation, Agriculture, and Education, are most severely hit by TB plans, while Finance and Services are the ones least harmed by TB plans. When we measure the network multipliers, it turned out that Manufacturing, Services, and Finance seem to be the most harmful sectors in terms of propagating downstream the negative spillovers of a supply shock.
EB plans show a higher heterogeneity since they are mainly made of spending cuts, which is implemented differently sector by sector. The sectors hit most severely by EB plans are Mining, Information, Transportation, and Services. On the other hand, Education/Health Care, and especially Retail, are the ones least affected by them. The sectors which exhibit the highest upstream network multiplier are still Manufacturing, which overall seems to behave as an explosive fuse.

Generally speaking, our research fits into this recent trend, which aims at bridging micro and macro by breaking down an aggregate economy into its sectoral levels, thus increasing our comprehension of how aggregate shocks propagate and affect the economy. Bouakez, Rachedi, Emiliano, et al., 2018 and Cox et al., 2020 follow this line of research. We plan further research on real systemic risks, heterogeneous effects of fiscal policy and their implications for optimal policymaking.

8 Figures

Figure 1: Graph of downstream connection of US 15 industries-level economy

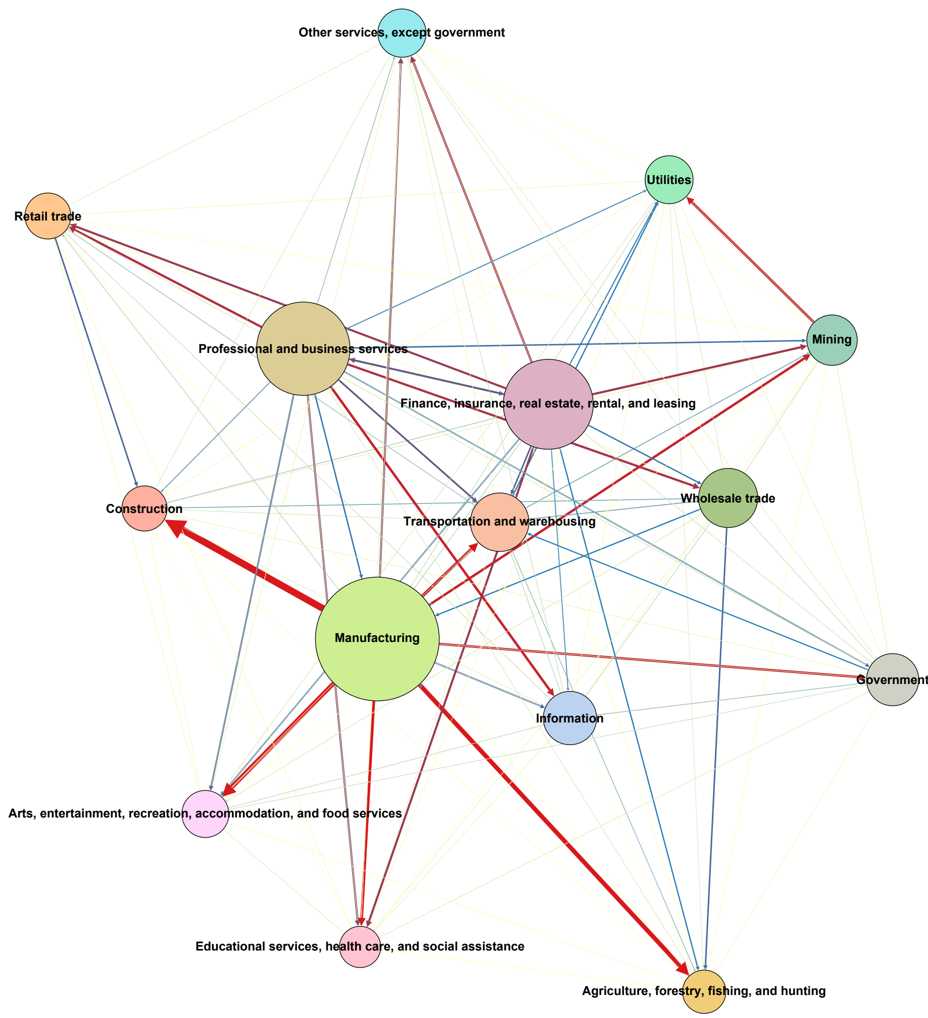

Figure 1: directed graph of the downstream network, constructed from matrix A. Any arrow represents an input flow from one sector to another one; the size of the arrows is proportional to the magnitude of that flow. The size of nodes reflect the weighted outdegree (sum of the columns of matrix A). The graph is made with the open-source software Gephi.

Figure 2: Graph of upstream connection of US 15 industries-level economy

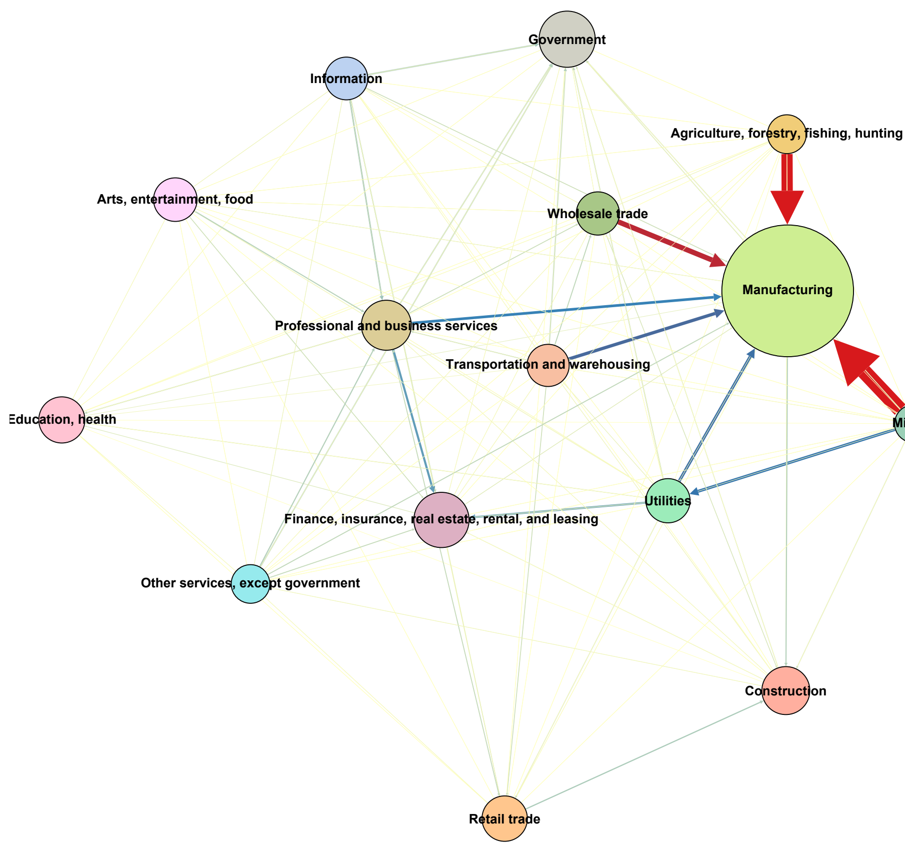

Figure 2: directed graph of the upstream network, constructed from matrix $\hat{A}$. Any arrow represents an input flow from one sector to another one; the size of the arrows is proportional to the magnitude of that flow. The size of nodes and the centrality measure of the graph, reflect the weighted indegree of each sector (sum of the rows of matrix $\hat{A}$). The graph is made with the open-source software Gephi.

Figure 3: Fiscal Adjustments Database

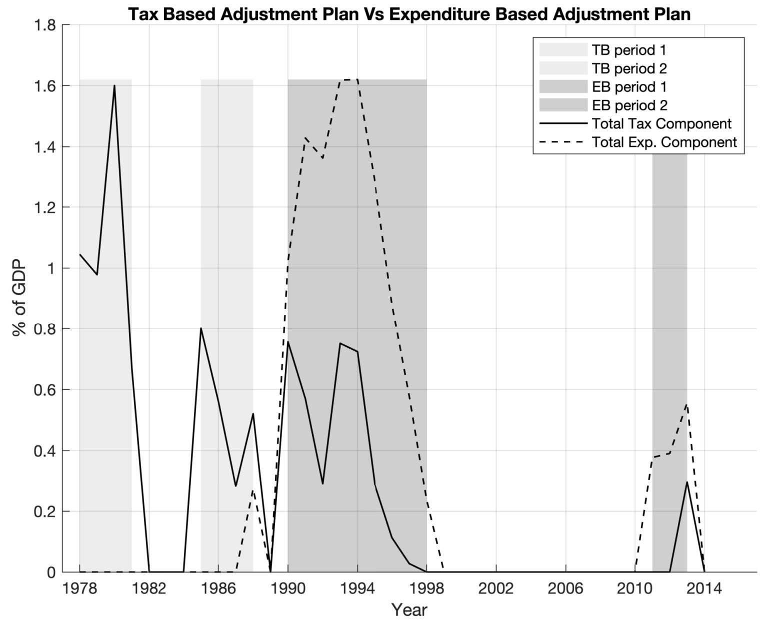

Figure 3: The solid line is the total tax adjustment fiscal plans; the dashed line is the total expenditure adjustment fiscal plans. The light gray areas represent the years when a TB fiscal plan occurs ($TB_t = 1$); the darker areas represent the years when an EB fiscal plan occurs ($EB_t = 1$).

Figure 4: Tax and Expenditure Share

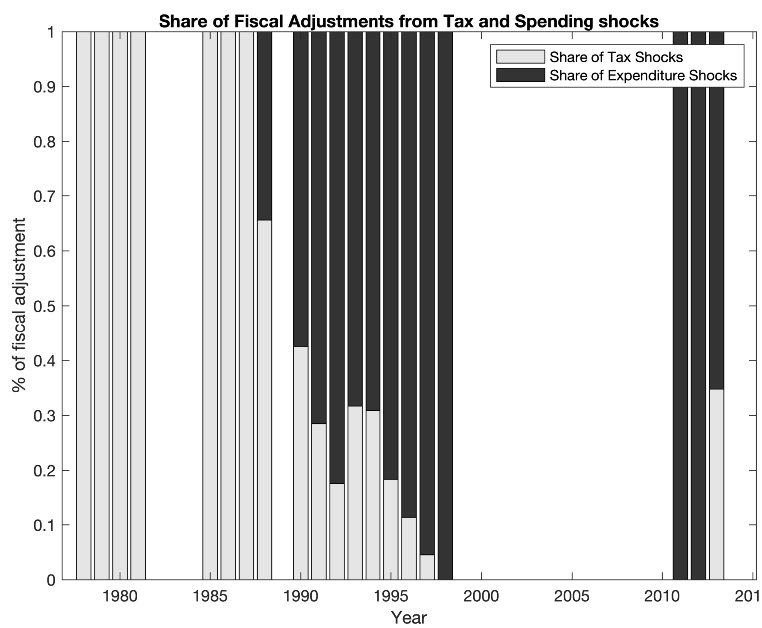

Figure 4: A decomposition of the fiscal adjustments. Share of fiscal adjustments from tax and spending shocks. The light gray areas represent the share of the fiscal adjustment coming from tax shocks; the darker areas represent the share of the fiscal adjustment coming from expenditure shocks.

Figure 5: Heterogenous Effect of (1% of GDP) Fiscal Adjustment Plan

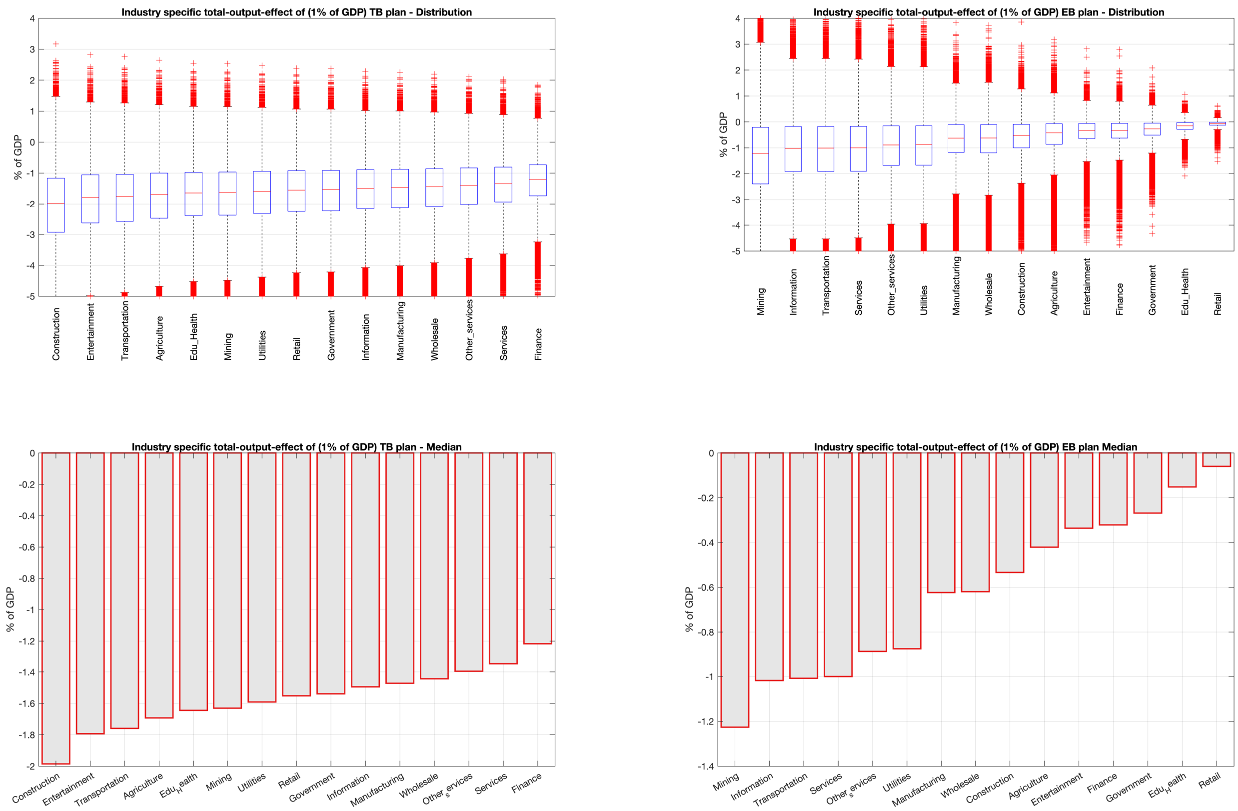

Figure 5: top-left panel: Box-plot of the industry-specific total effect of (1% of GDP) TB plan; top-right panel: Box-plot of the industry-specific total effect of (1% of GDP) EB plan; bottom-left: median of industry-specific total effect of (1% of GDP) TB plan; bottom-right: median of industry-specific total effect of (1% of GDP) BB plan. Industries are shown in descending order relative to their absolute value median effect.

Figure 6: Active Centrality: Industries' "Harmfulness"

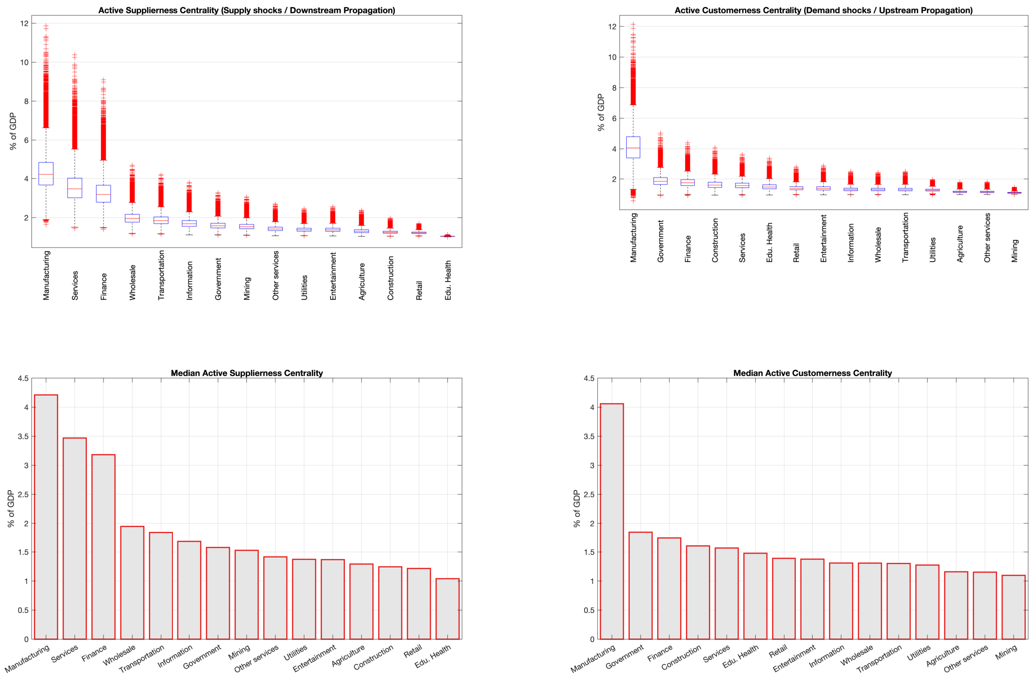

Figure 6: top-left panel: Box-plot of the downstream active centrality measures (Active Supplierness); top-right panel: Box-plot of the upstream active centrality measures (Active Customerness); bottom-left: median level of active supplierness; bottom-right: median level of active customerness. Industries are shown in descending order relative to their absolute value median effect. Randomness is given by the uncertainty around the values of the spatial coefficients ρ^{down} *and* ρ^{up}*; whose value are estimated here via Monte Carlo, as done in Section 5.1.*

Figure 7: Pooled Placebo Test (500 simulations)

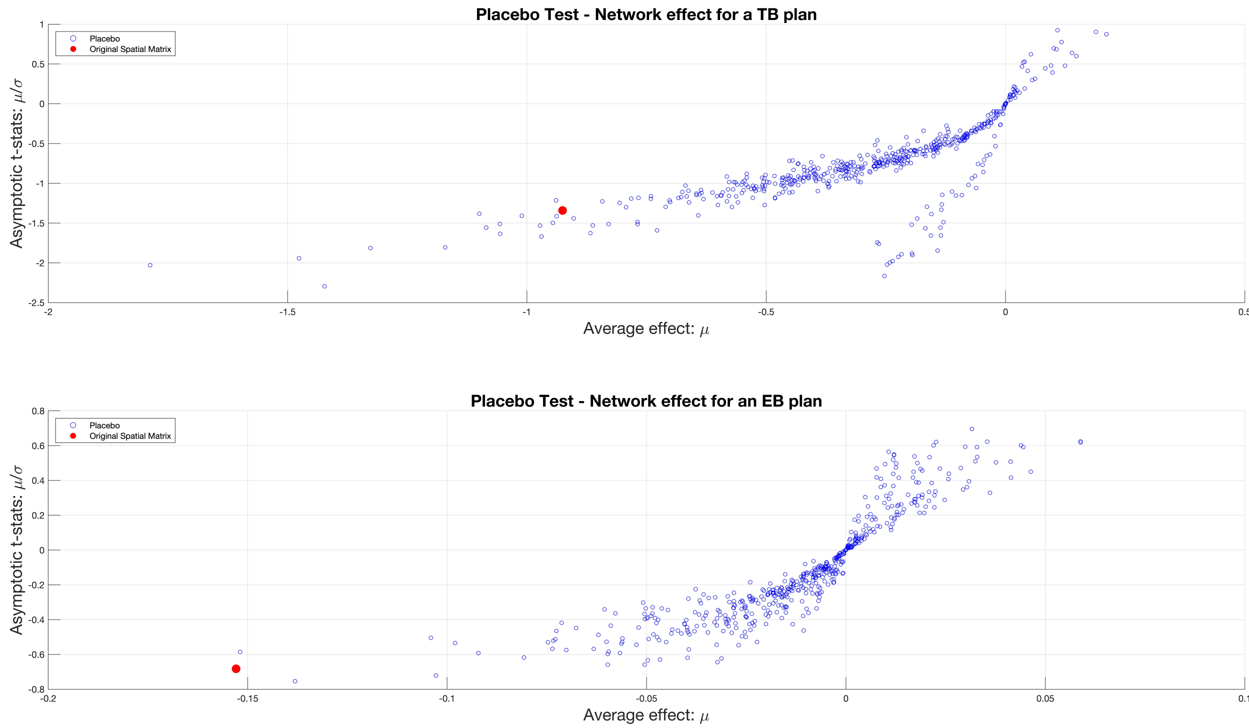

Figure 7: A scatter plot with 500 placebo experiments: the mean and the asymptotic t-statistic of the Average Network Effect of the simulated fiscal plan distributions. The mean lies on the horizontal axis, while the asymptotic t-stat lies on the vertical axis. The red dot accounts for the results obtained by employing the real matrices A and $\hat{A}^T$*. From Table III, we have that the pair that summarizes the TB red dot is* $(-0.963, -0.963/0.726 = -1.326)$ *and the EB red dot is* $(-0.157, -0.157/0.231 = -0.680)$.

Figure 8: Cumulative Impulse Response Functions

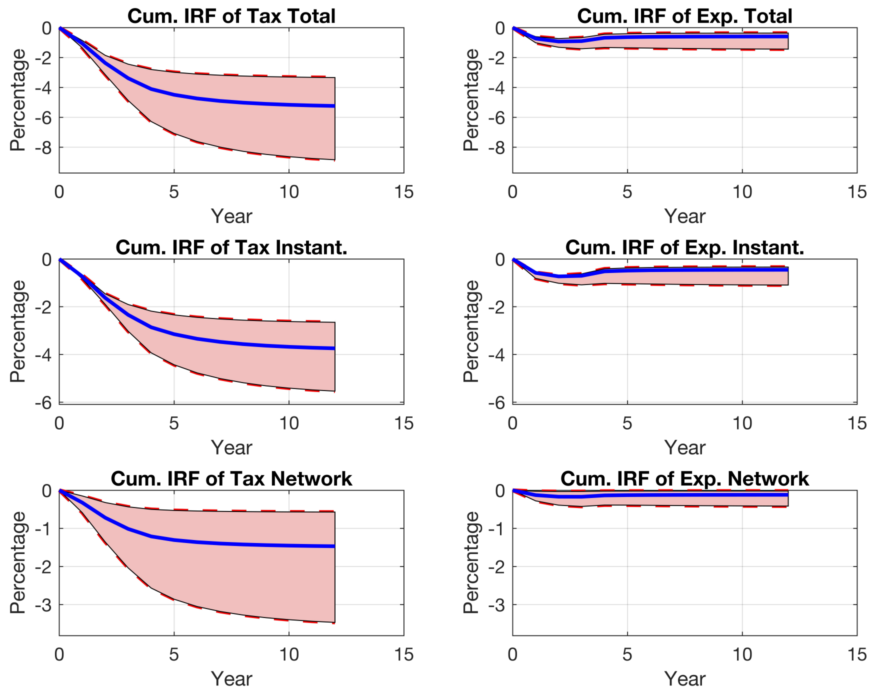

Figure 8: in the left column the median cumulative impulse responses for TB plans, while in the right column are reported results for the EB plans (blue solid lines). The first row represents the average total effect; the second row the average instantaneous effect while the third and last row represents the average network effect. Confidence intervals (red dotted lines) are constructed taking the 5^{th} *and* 95^{th} *percentiles of the Monte-Carlo-simulated distributions.*

References

[1] Daron Acemoglu, Ufuk Akcigit, and William Kerr. "Networks and the macroeconomy: An empirical exploration." In: *NBER Macroeconomics Annual* 30.1 (2016), pp. 273–335. DOI: 10.1086/685961.

[2] Daron Acemoglu, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. "The network origins of aggregate fluctuations." In: *Econometrica* 80.5 (2012), pp. 1977–2016. DOI: 10.3982/ECTA9623.

[3] Alberto Alesina, Omar Barbiero, Carlo Favero, Francesco Giavazzi, and Matteo Paradisi. "The effects of fiscal consolidations: Theory and evidence." In: (2017). DOI: 10.3386/w23385.

[4] Alberto Alesina, Carlo Favero, and Francesco Giavazzi. *Austerity. When it works and when it doesn't.* Princeton University Press, 2019.

[5] Alberto Alesina, Carlo Favero, and Francesco Giavazzi. "The output effect of fiscal consolidation plans." In: *Journal of International Economics* 96 (2015), S19–S42. DOI: 10.1016/j.jinteco.2014.11.003.

[6] Luc Anselin, Julie Le Gallo, and Hubert Jayet. "Spatial panel econometrics." In: *The econometrics of panel data*. Springer, 2008, pp. 625–660.

[7] Alan J Auerbach, Yuriy Gorodnichenko, and Daniel Murphy. *Local Fiscal Multipliers and Fiscal Spillovers in the United States*. Tech. rep. National Bureau of Economic Research, 2019. DOI: 10.3386/w25457.

[8] Hafedh Bouakez, Omar Rachedi, Santoro Emiliano, et al. "Sectoral heterogeneity, production networks, and the effects of government spending." In: *Cahiers de recherche. Centre interuniversitaire de recherche en economie quantitative, CIREQ* (2018).

[9] Vasco M Carvalho. "From micro to macro via production networks." In: *Journal of Economic Perspectives* 28.4 (2014), pp. 23–48. DOI: 10.1257/jep.28.4.23.

[10] Vasco M. Carvalho, Makoto Nirei, Yukiko U. Saito, and Tahbaz-Salehi Alireza. "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake." In: *Cambridge Working Paper Economics: 1670* (2016). DOI: 10.17863/CAM.7827.

[11] Anne C Case and Harvey S Rosen. "Budget spillovers and fiscal policy interdependence." In: *Journal of public economics* 52.3 (1993), pp. 285–307.

[12] Lawrence Christiano, Martin Eichenbaum, and Sergio Rebelo. "When is the government spending multiplier large?" In: *Journal of Political Economy* 119.1 (2011), pp. 78–121. DOI: 10.1086/659312.

[13] Lydia Cox, Gernot Muller, Ernesto Pasten, Raphael Schoenle, and Michael Weber. *Big g*. Tech. rep. National Bureau of Economic Research, 2020.

[14] Peter A Diamond. "Aggregate demand management in search equilibrium." In: *Journal of political Economy* 90.5 (1982), pp. 881–894. DOI: 10.1086/261099.

[15] J Paul Elhorst. "Specification and estimation of spatial panel data models." In: *International regional science review* 26.3 (2003), pp. 244–268.

[16] Xavier Gabaix. "The granular origins of aggregate fluctuations." In: *Econometrica* 79.3 (2011), pp. 733–772. DOI: 10.3982/ECTA8769.

[17] Jaime Guajardo, Daniel Leigh, and Andrea Pescatori. "Expansionary austerity? International evidence." In: *Journal of the European Economic Association* 12.4 (2014), pp. 949–968. DOI: 10.1111/jeea.12083.

[18] Galina Hale, Tumer Kapan, and Camelia Minoiu. "Shock transmission through cross-border bank lending: Credit and real effects." In: (2019). DOI: 10.17016/FEDS.2019.052.

[19] Michael Horvath. "Sectoral shocks and aggregate fluctuations." In: *Journal of Monetary Economics* 45.1 (2000), pp. 69–106. DOI: 10.1016/S0304-3932(99)00044-6.

[20] Lung-Fei Lee. "Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models." In: *Econometrica* 72.6 (2004), pp. 1899–1925.

[21] James LeSage and Robert Kelley Pace. "Introduction to spatial econometrics." In: (2009). DOI: 10.1111/j.1538-4632.2010.00797.x.

[22] John B Long Jr and Charles I Plosser. "Real business cycles." In: *Journal of political Economy* 91.1 (1983), pp. 39–69. DOI: 10.1086/261128.

[23] Ali Ozdagli and Michael Weber. "Monetary policy through production networks: Evidence from the stock market." In: (2017). DOI: 10.3386/w23424.

[24] Andrea Pescatori, Mr Daniel Leigh, Jaime Guajardo, and Mr Pete Devries. "A new action-based dataset of fiscal consolidation." In: 11-128 (2011). DOI: 10.5089/9781462346561.001.A001.

[25] Valerie A Ramey. "Identifying government spending shocks: It's all in the timing." In: *The Quarterly Journal of Economics* 126.1 (2011), pp. 1–50.

[26] Valerie A Ramey. "Ten Years after the Financial Crisis: What Have We Learned from the Renaissance in Fiscal Research?" In: *Journal of Economic Perspectives* (2018).

[27] Valerie A Ramey and Matthew D Shapiro. *Costly capital reallocation and the effects of government spending*. Tech. rep. National Bureau of Economic Research, 1999.

[28] Christina D Romer and David H Romer. "A narrative analysis of postwar tax changes." In: *Unpublished paper, University of California, Berkeley (June)* (2009). DOI: 10.1.1.370.4762.

[29] Christina D Romer and David H Romer. "The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks." In: *American Economic Review* 100.3 (2010), pp. 763–801. DOI: 10.1257/aer.100.3.763.

[30] Frank Smets, Joris Tielens, and Jan Van Hove. "Pipeline pressures and sectoral inflation dynamics." In: (2019). DOI: 10.2139/ssrn.3346371.

[31] Quang H. Vuong. "Likelihood ratio tests for model selection and non-nested hypotheses." In: *Econometrica* (1989). DOI: 10.2307/1912557.

[32] Jihai Yu, Robert De Jong, and Lung-fei Lee. "Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large." In: *Journal of Econometrics* 146.1 (2008), pp. 118–134.