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Essays in Fiscal Policy

PhD in	Economics and Finance
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Abstract

This thesis comprises three essays that analyze how fiscal policy affects the macroeconomy. Each essay investigates a particular feature of fiscal policy propagation. The first essay, using a vector autoregression method in the empirical part and an imperfect information DSGE model in the theoretical part, shows that consumer confidence, output, and consumption increase in response to fiscal news shocks, shocks to anticipated future government spending. Further analysis provides evidence that consumer confidence is an important component in the transmission of fiscal news shocks on the real economy, particularly on the consumption. The second essay uses a Local Projection Method in the empirical part and a New-Keynesian DSGE model in the theoretical part. It illustrates that public investment shocks increase economic activity in the short-run through its spending feature and in the long-run through its productivity feature. Both empirical and theoretical results indicate that public investment is an important fiscal policy tool to stimulate the economy in the near-term and to improve the fundamentals in the long-term. The third essay, prepared with Zornitsa Todorova, provides evidence that production networks are an important mechanism in the transmission of the tax shocks to the real economy. The spatial autoregression (SAR) estimation shows that private income tax shocks travel upstream, from customers to suppliers, and more than half of the total effect of the tax shocks on revenues is due to higher-order demand effects as a result of network linkages.

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Finally, I express my deepest gratitude and love and dedicate this thesis to my closest family: to Agnieszka, and my mother, father, sister, brother, nephew, and niece. Their unconditional support and patience have provided me with an unlimited source of motivation and energy for finalizing this scholarly endeavor.

For my family,
and
for Agnieszka.

Contents

Preface

In this thesis, I study the propagation of fiscal policy shocks throughout the macroeconomy from various perspectives.

In Chapter 1, I identify the impact of fiscal spending policy on consumer confidence and offer an alternative explanation for the crowding-in effect of government spending on consumption found in data. I construct a fiscal news variable using the Survey of Professional Forecasters (SPF) to control for the anticipated component of future government spending. I find evidence on the presence of imperfect information in SPF forecasts. I show how to account for imperfect information in a VAR setting to identify fiscal news shocks. The VAR estimates an increase in consumer confidence, output, and consumption in response to a fiscal news shock. To explain the empirical evidence, I develop a DSGE model with imperfect information à la Lorenzoni (2009). In the model, fiscal news shock moves up confidence if the shock induces consumers to estimate higher government demand relative to the taxes. The estimation of the model shows that the upswing in confidence is able to explain the increase in consumption observed in data.

In Chapter 2, I study the dynamic impacts of public investment shocks by addressing fiscal foresight using novel data. The yearly public investment announcements provided by Turkish data are used to construct narrative news series and to identify the shocks. I show that the news series carry relevant information and have significant predictive power over the public investment outlays. The estimation using the local projection method shows that the impulse responses of the output and the other macroeconomic variables are positive and significant in the first couple of years, and there is a larger second-round effect after seven to nine years. The largest impact occurs in the transportation and health sectors. A New Keynesian DSGE model with rule-of-thumb consumers and productive public sector can account for the empirical findings. The indirect inference estimation points to the short-run effect of spending and the long-run effect of productivity after positive shock in public investment. Both empirical and theoretical results indicate that public investment is an important fiscal policy tool to stimulate the economy in the near-term and to improve the fundamentals in the long-term.

In Chapter 3, Zornitsa Todorova and I investigate whether exogenous tax shocks propagate through production networks. A static model with intermediate inputs predicts that the reaction of industries to tax shocks follows a spatial autoregression (SAR) and that the effect propagates upstream (from customers to suppliers). To test this empirically, we use quarterly sales data for US industries for the period 1972- 2003. We show that private income tax shocks travel upstream, and provide evidence that between 55 to 70 percent of the total effect on sales is due to higher-order demand effects. Our results suggest that production networks are an important mechanism through which tax shocks transmit to the real economy.

Chapter 1

Fiscal News, Imperfect Information and Confidence

1.1 Introduction

The protracted low economic activity during the Great Recession is often attributed to the collapse in consumer confidence.[1] Several economists and policy-makers have proposed the use of fiscal policy to restore confidence in the economy and to recover from the recession.[2] In the beginning, the "confidence channel" of fiscal policy, defined as the impact of fiscal policy on the economy through its effect on consumer confidence, was met with hesitation due to the lack of empirical and theoretical backing.[3] Nevertheless, some studies provide evidence in support of the "confidence channel". On the empirical side, Bachmann and Sims (2012) show that in US data, confidence is critical in the transmission of government spending shocks during slack times. On the theoretical side, Guimaraes et al. (2016) develop a static model with imperfect information where government spending can affect agents' beliefs about other agents' investment and production decisions.

However, a significant part of government spending is anticipated, a phenomenon

[1]For example, Russell Roberts stated on Forbes.com on January 23, 2009, "But the economy is not stagnant because of a lack of spending. The economy is stagnant because of a lack of confidence in the future. Government spending on bridges, roads and new schools will stimulate the construction industry. But without confidence, the benefits will not spread to the rest of the economy."

[2]Robert Shiller remarked on The Wall Street Journal on January 27, 2009, "We must be certain that programs to solve the current financial and economic crisis are large enough, and targeted broadly enough, to impact public confidence."

[3]N. Gregory Mankiw quoted on his blog on January 27, 2009, "Yale's Bob Shiller argues that confidence is the key to getting the economy back on track. I think a lot of economists would agree with that . . . The sad truth is that we economists don't know very much about what drives the animal spirits of economic participants. Until we figure it out, it is best to be suspicious of any policy whose benefits are supposed to work through the amorphous channel of confidence."

called fiscal foresight. Fiscal foresight implies that the agents may receive news about future fiscal policy in advance and update their expectations before the actual policy is implemented. Hence, fiscal news about future government spending could be more influential in shaping the confidence rather than the actual spending itself.[4]

This paper provides evidence on the "confidence channel" of fiscal policy by measuring the impact of fiscal news on consumer confidence, and by determining the transmission of fiscal policy on the real economy through its effect on confidence, particularly on consumption.[5] I construct the evidence in two steps. First, through the identification of shocks to the fiscal news in a structural vector autoregression (SVAR), and second through the lenses of a structural dynamic stochastic general equilibrium model (DSGE) with households' heterogeneity, imperfect information, and fiscal news. In the SVAR, fiscal news is proxied by the revisions to government spending forecasts from the Survey of Professional Forecasters, SPF hereon, and confidence is proxied by the University of Michigan Consumer Sentiment Expectations Index. In the DSGE, movements in consumer confidence are modeled as shifts in the expectations of the agents about future disposable income and aggregate output due to the innovations in fiscal news.

The empirical evidence consists of two steps. In the first step, I construct a fiscal news variable by using ex-ante revisions of government spending forecasts from the Survey of Professional Forecasters.[6] The SPF forecasts exhibit two important features; first, they carry out relevant information about future government spending, and second, average ex-ante forecast revisions predict average ex-post forecast errors.[7] The second feature is a new empirical fact suggesting that SPF data might be generated by a model of imperfect information rational expectations since this group of models can account for predictable forecast errors, as shown by Coibion and Gorodnichenko (2015).

In the second step, I run a medium-sized VAR to measure the response of confidence and real variables to a fiscal news shock.[8] The estimation delivers positive

[4]Fiscal news can be defined as the information at time t that induces agents to revise their expectations about government spending at time $t+h$, h periods ahead. However, this information can be composed of two components: an unpredictable component due to the new information arriving at time t and a predictable component due to the slow adjustment of information from previous periods and systematic response to business cycle fluctuations. I am interested in identifying the unpredictable component, defined as fiscal news shock, and measure its impact.

[5]Consumer confidence is defined as the expectations of agents about the individual and aggregate state in the near future. I discuss how consumer confidence is measured in the next section.

[6]The detailed information about SPF forecasts is provided in the next section. The ex-ante revision means the difference between the forecast of government spending, made at time t, for the next quarters, and the forecast, for the same quarters, made at time $t-1$.

[7]The ex-post forecast errors are simply the difference between the realized government spending at time $t+h$ and its forecast made at time t.

[8]The fiscal news shock is an exogenous change in the fiscal news variable that predicts future

and significant response of confidence, output, and consumption to a shock. To determine the role of confidence, I compute the responses of consumption and output to the fiscal news shock by shutting off the response of confidence to the same shock. The responses of consumption and output are smaller in magnitude in the first few quarters, and the difference is statistically significant for the first two quarters when the response of confidence is held constant. My empirical findings suggest that confidence is a critical component in the transmission of fiscal policy on the real economy, particularly in the short-run.

To understand the mechanism embedded in fiscal policy that fosters the confidence of the agents, I construct an island model with imperfect communication à la Lorenzoni (2009), where I add a government sector. The imperfect information present in SPF forecasts motivates the model with dispersed information.[9] The representative agent in each island receives noisy signals about government spending and lump-sum tax directed to them. Hence, the agents do not observe the true value of the aggregate states; instead, they use the signals to infer the values of them.[10]

The variance structure of these two signals is the critical feature enabling the model to generate waves of optimism and to have an increase in private consumption in response to a fiscal news shock.[11] If the variance of the idiosyncratic noise in the government spending signal is sufficiently small relative to the variance of the noise in the tax signal, the agent expects island-specific government spending to be higher relative to the island-specific lump-sum tax. This increases expectations of permanent income, which in turn causes an increase in expected consumption. The current consumption increases as well since it depends positively on expected consumption through the Euler equation. The mechanism works the same on each island, and each agent increases current consumption in response to the fiscal news shock as a result of an optimistic future income. The island-level optimism translates into aggregate optimism that is the theoretical counterpart of the surge in confidence found in the empirical section.

I confront the model with data by estimating the key parameters by minimizing the distance between the model's impulse responses and those estimated by the SVAR. The estimation supports the main feature of the model; large variance of the

government spending.

[9]In addition to the evidence provided in the empirical section consistent with the presence of imperfect information structure of government spending forecasts, Coibion and Gorodnichenko (2015) provide evidence in favor of imperfect information structure of macro variables such as inflation, output, industrial production, and unemployment using SPF forecasts.

[10]The agents also receive signals of the local productivity, price index and private demand, and aggregate inflation and productivity, so they do not observe any aggregate state perfectly.

[11]The word "optimism" is used to define higher expected permanent income relative to the full information rational expectations benchmark.

idiosyncratic noise in the tax signal and small variance of the idiosyncratic noise in the government demand signals. However, the estimation brings out two additional features that are necessary to have an observed increase in aggregate consumption: sticky prices and large mark-ups. The sticky prices prevent a price spike that would otherwise decrease quantities consumed and inform agents about aggregates. The large mark-ups bring a higher increase in profits and income for a given increase in government demand that increase the amounts consumed.

To test the main feature of the model, I run a counterfactual by fixing the variance of the idiosyncratic noises in the tax and government demand signals to the same number. I keep the remaining parameters at their estimated values. The counterfactual estimation generates a decrease in consumption in response to a fiscal news shock. The reason is that the government demand and tax signals share a similar variance structure, and agents do not expect higher government demand relative to the tax directed to their island. The agents expect lower future disposable income that drives the confidence downwards; as a result, government spending crowds-out private consumption as in standard RBC models.

The paper contributes to the literature in three distinct ways. First, this is the first dynamic model that allows fiscal policy to generate waves of optimism through its effect on the perceived future income of the agents. Second, the paper introduces the impact of fiscal policy on consumer confidence as a critical mechanism generating the crowding-in effect of government spending on consumption. Third, the model shows how a policy variable can create movements in confidence. The literature presents the changes in confidence as a function of animal spirits, noise shocks orthogonal to the fundamentals, or news about future productivity, as in Barsky and Sims (2012). In this paper, the fiscal news shock produces temporary movements in confidence.

The remainder of this introduction is the literature review. The next section describes fiscal news and the identification of fiscal news shock under imperfect information. Section 1.3 presents the empirical results. Section 1.4 describes the DSGE model, and Section 1.5 estimates it. Section 1.6 concludes.

1.1.1 Related Literature

Empirical Fiscal Policy

The closest papers to mine from an empirical point of view are Ramey (2011), Auerbach and Gorodnichenko (2012a), Bachmann and Sims (2012), Forni and Gambetti (2016), and Alesina et al. (2015). Ramey (2011) creates a military news series about future military spending due to foreign political events and embeds this news into VAR. She finds that, in response to a military news shock, GDP increases, but consumption of non-durables plus services decreases. Auerbach and Gorodnichenko (2012a) control for the fiscal foresight by splicing Greenbook and SPF government spending forecasts of the next quarter and find larger fiscal multipliers during recessions. Bachmann and Sims (2012) is the first work that explores the role of confidence in the transmission of fiscal policy. The authors find that surprise shocks in government spending increase confidence only during slack times. Forni and Gambetti (2016) construct a fiscal news series using the sum of SPF government spending forecast revisions. They find an increase in output and consumption in response to a fiscal news shock. I extend their work by incorporating confidence and show that the response of confidence is critical for the increase in consumption in response to a shock. Finally, Alesina et al. (2015) explore the confidence and fiscal policy channel using exogenous fiscal adjustment plans of OECD countries. The authors find that spending-based fiscal adjustment fuels business confidence. On the contrary, this paper finds an increase in confidence in the US data in response to the higher expected future government spending. Besides, the paper provides a framework to identify fiscal news shocks under imperfect information environment.

Government Spending and Private Consumption

This paper is also a part of a vast literature trying to rationalize the crowding-in effect of government spending on consumption. Ravn et al. (2006) develop a model with deep habit formation and countercyclical mark-ups that produces positive responses of consumption and wages to government spending shocks. Galí et al. (2007) propose a Neo-Keynesian DSGE model with liquidity-constrained consumers. In their model, the wages increase in response to a government spending shock if mark-ups are countercyclical. The aggregate consumption increases if the share of liquidity-constrained consumers is non-negligible since those consumers increase their consumption as a result of higher wages. Christiano et al. (2011) show that when the zero lower bound on the nominal interest rate binds, the real interest rate falls in response to a government spending shock. This drives up private spending. In their model, the government spending multiplier is larger than one. The closest to my paper in this strand is Murphy (2015). The author extends Lorenzoni (2009)'s imperfect information island model with island-level government demand and tax signals, where only the former has a persistent component. This structure of the signals creates a mechanical upward shift in the expected future income of the agents that explains the increase in aggregate consumption in response to a government spending shock. The key difference between his model and my model is that I introduce a persistent component in island-level tax signals in addition to the government demand signals. This augmented signal structure prevents the mechanical upward shifts in expected future income; instead, the informational content of the signals becomes the key factor that shifts the expected future income of the agents upwards or downwards. Furthermore, I introduce fiscal news and confront the model with data.[12]

Imperfect Information and Expectations

There have been many papers that have stressed the importance of imperfect information such as Woodford (2001), Mankiw and Reis (2002), and Mackowiak and Wiederholt (2009). A specific strand in this literature introduces imperfect information on technology and stresses beliefs of future productivity and output. The prominent works in this strand of the literature are Beaudry and Portier (2006), Lorenzoni (2009), and Barsky and Sims (2012). In this type of models, agents do not observe the productivity; rather, they receive signals about productivity that are composed of a technology shock, fundamental shock that shifts the productivity, and a noise shock, misperception shock that does not shift productivity. However, agents cannot determine whether the signal is due to technology or noise shock. Hence, they misperceive part of the noise shock as a technology shock. As a result, both types of shocks initially increase the realized output and the expected future output and productivity due to higher perceived productivity. However, agents gradually learn the true nature of the signal they observe. If the signal is due to noise shock, the realized and expected output revert to the initial level. If the signal is due to technology shock, the realized and expected output moves to a new long-run level. Hence, only the noise, shock orthogonal to the fundamentals, induces a transient shift in the expectations of the agents. This paper introduces a fiscal spending policy to generate temporary movements in the expectations. The shifts in the expectations are not orthogonal to the model's variables; fiscal news shock shifts them. However, these shifts are temporary; the realized and expected output reverts to the initial level. Hence, the innovations in expectations are the result of a policy shock, and they return to initial levels after several periods.

[12] Croce et al. (2012) develop a representative agent model with stochastic endogenous growth and long-run model uncertainty and show that government spending shock decreases future consumption. This is because, with model uncertainty, the agent overestimates the expected value of future taxes that lowers the expected disposable income. In this paper, government spending increases expected disposable income because agents underestimate the expected value of taxes to be imposed on their island. A survey about future tax expectations would shed light on which mechanism is present in data.

1.2 Fiscal News and Imperfect Information

This section discusses the properties of the SPF government spending forecasts, derives an empirical specification to test the presence of imperfect information in the SPF forecasts, and finally, defines the fiscal news variable and discuss the implications of imperfect information in the identification of fiscal news shock.

1.2.1 The SPF Government Spending Forecasts

Government spending is anticipated to some degree since the changes in fiscal policy are usually implemented with a lag, a phenomenon called fiscal foresight.[13] This phenomenon poses two difficulties in the estimation of a VAR that does not control for fiscal foresight. First, the government spending shocks recovered through VAR residuals are predictable, as shown by Ramey (2011) and Leeper et al. (2013). This feature is called the non-fundamentalness of VAR.[14] Second, the agents may react to the anticipated changes in fiscal policy even before the implementation takes place. Consider the American Recovery and Reinvestment Act of 2009 (ARRA). It is a fiscal stimulus package enacted in February 2009 with an estimated spending of around $550 billion. This spending did not occur immediately; instead, it was dispersed over the years. However, the agents received news about future fiscal spending when ARRA was enacted and could update their expectations with this news since it was already in their information set. Hence, the fiscal news about future government spending might be more influential in shaping the response of the economy through the change in expectations rather than the actual spending itself. In such a case, a VAR without these "news" cannot capture the impact of the shocks on the anticipated future government spending.

To tackle these two difficulties, I endow VAR with a fiscal news variable, a proxy for anticipated future government spending, following the approach developed by Forni and Gambetti (2016).[15] I use the SPF federal government spending growth forecasts to construct fiscal news. It is useful to discuss the properties of SPF forecasts before going into the construction of fiscal news and the estimation of VAR. In the US SPF, professional forecasters are asked to provide forecasts of macroeconomic variables for both the present quarter and up to four quarters ahead. SPF

[13] Leeper et al. (2012) calibrate the forecast range of government spending three to four quarters. Mertens and Ravn (2011) estimate that tax policy changes are subject to a six-quarter median implementation lag.

[14] The non-fundamentalness arises because the information set of the VAR econometrician is narrower than the agents, and structural shocks cannot be recovered through VAR residuals.

[15] The other approaches proposed in the literature to address fiscal foresight are narrative military news by Ramey (2011), and excess returns to defense contractors by Fisher and Peters (2010).

forecasters do not know the current value of these macroeconomic variables, which are only released with a lag. The information set of survey respondents includes the BEA's advance report data, which contains the first estimate of GDP (and its components) for the previous quarter. The deadline for responses is the second to third week of the middle month of each quarter.

The variable of interest is the SPF forecasts on 'real federal government consumption expenditures and gross investment growth' series. The mean of the single period forecast is the following

$$F_t(h) = E_t g_{t+h} = \frac{1}{N}\sum_{i=1}^{N}\left[E_{i,t}g_{t+h}\right],\ for\ h = 1, 2, 3, 4, \tag{1.1}$$

where $E_{i,t}$ denotes the expectations of an individual respondent, N is total number of respondents in the survey and g_{t+h} is the government spending growth in period h that is $g_{t+h} = \frac{G_{t+h}-G_{t+h-1}}{G_{t+h-1}}$, where G is the real government spending.. The mean of the cumulative forecast is following

$$F_t(1, H) = \sum_{h=1}^{H}\left[E_t g_{t+h}\right] = \sum_{h=1}^{H}\left[\frac{1}{N}\sum_{i=1}^{N}\left[E_{i,t}g_{t+h}\right]\right],\ for\ H = 2, 3, 4. \tag{1.2}$$

Figure 1.1 shows the evolution of single period (Eq 1.1) and cumulative (Eq 1.2) mean forecast series for the two and four quarters ahead and the historically realized growth rates.

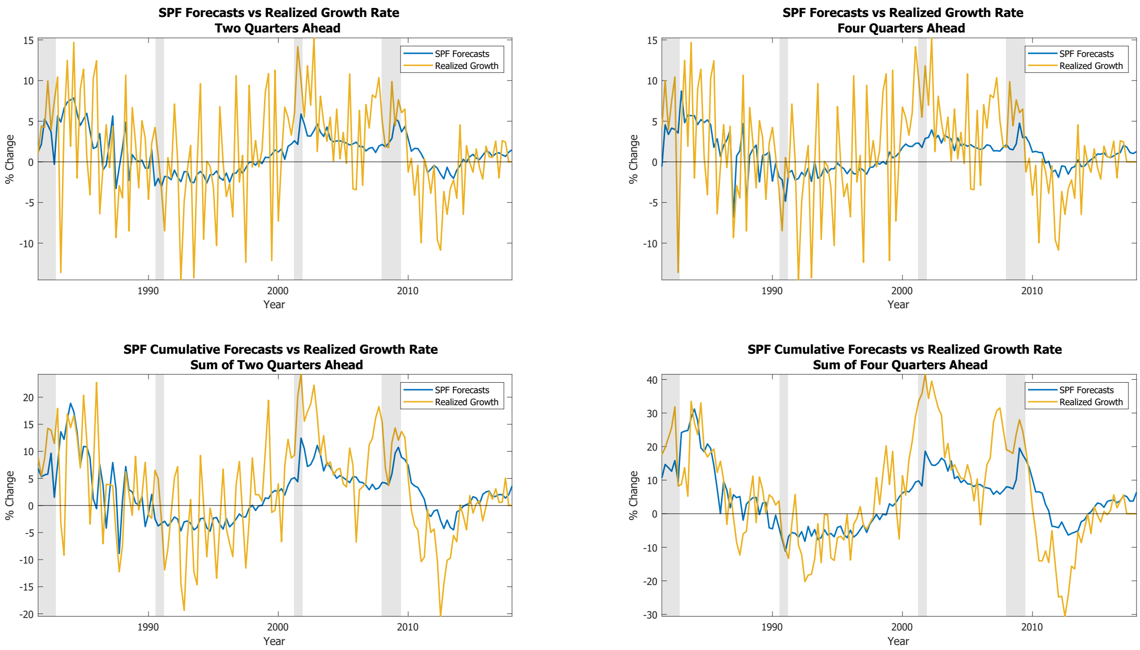

Figure 1.1: SPF Government Spending Forecasts and Historically Realized Growth Rates

Notes: The figure plots the SPF mean expected growth rate for the second and fourth future quarters in top and their cumulative in bottom, (blue) and the realized growth rates (yellow). Grey shaded areas indicate the NBER business cycle contraction dates.

For example, the blue line in the top-left panel of Figure 1.1 displays the two quarters ahead mean SPF government spending growth forecast that is $F_t(2) = E_t g_{t+2}$, and yellow line captures the two quarters ahead realized government spending growth that is $g_{t+2} = \frac{G_{t+2}-G_{t+1}}{G_{t+1}}$.

As is evident in Figure 1.1, the correlation with realized growth rates is higher for the cumulative forecasts relative to the single period forecasts. This may point that single period forecasts are subject to mistiming of news because of the legislative and implementation delays in government spending. I run a simple test by regressing realized government spending growth rates on the forecasts of the same horizon to gauge the informational content of each forecast series from Equations 1.1 and 1.2 by using the following equations

$$g_{t+h} = c + \beta F_t(h) + error_t;\ for\, h = 1,2,3,4 \tag{1.3}$$

$$\sum_{h=1}^{H} g_{t+h} = c + \beta F_t(1,H) + error_t;\ for\, H = 2,3,4. \tag{1.4}$$

Table 1.1 displays the adjusted R^2 and the F-Statistic from these regressions. The cumulative forecasts have higher R^2, and explain a large variation of the future government spending relative to the single period forecasts. The results suggest that cumulative forecasts carry more information about future fiscal spending.

Table 1.1: Informational Content of SPF Forecasts

	$F_t(1)$		$F_t(2)$		$F_t(3)$		$F_t(4)$		$F_t(1,2)$		$F_t(1,3)$		$F_t(1,4)$	
Dependent Variable	R^2	F-Stat	R^2	F-Stat	R^2	F-Stat	R^2	F-Stat	R^2	F-Stat	R^2	F-Stat	R^2	F-Stat
g_{t+1}	0.29	30.0												
g_{t+2}			0.26	42.9										
g_{t+3}					0.25	28.0								
g_{t+4}							0.24	36.6						
$\sum_{h=1}^{2} g_{t+h}$									0.43	25.1				
$\sum_{h=1}^{3} g_{t+h}$											0.54	29.3		
$\sum_{h=1}^{4} g_{t+h}$													0.59	34.2

Notes: OLS estimates of the projection of growth in government spending, g_{t+j} on the forecast $F_t(h)$ defined in equation 1.1 for each $h = \{1,2,3,4\}$ and cumulative government spending growth $\sum_{h=1}^{H} g_{t+h}$ on the cumulative forecast $F_t(1,H)$ defined in equation 1.12 for each $H = \{2,3,4\}$. g_{t+h} is the log change of government spending between period $t+h$ and $t+h-1$ and $\sum_{h=1}^{H} g_{t+h}$ is the cumulative log change of government spending between period $t+H$ and t. R^2 and F-Stat correspond to the adjusted R-squared and the value of F-statistics for each equation, respectively.

Another feature evident in Figure 1.1 is that forecasts about government spending are more stable than the original series, and they generally underestimate the movements of the actual spending. In other words, expectations adjust sluggishly to the new information. This feature seems to support the hypothesis that SPF government spending forecast data is generated in a model of imperfect information rational expectations. I provide the intuition and the formal test of this hypothesis in the next subsection following the work of Coibion and Gorodnichenko (2015).

1.2.2 The Nature of the SPF Forecasts

In this subsection, I augment the methodology developed in Coibion and Gorodnichenko (2015) with a news shock to define the concepts used and to clarify the assumptions of the identification approach. Assume that government spending follows an AR(1) process

$$g_t = \rho g_{t-1} + \varepsilon_{t-1}, \tag{1.5}$$

where ε_{t-1} is fiscal news shock. Agents cannot directly observe g_t and ε_t but instead receive signals $s^1_{i,t}$ and $s^2_{i,t}$ such that

$$s^1_{i,t} = g_t + \eta_{i,t}, \quad \eta_{i,t} \sim N(0, \sigma^2_\eta) \tag{1.6}$$

$$s^2_{i,t} = \varepsilon_t + \omega_{i,t}, \quad \omega_{i,t} \sim N(0, \sigma^2_\omega). \tag{1.7}$$

The first signal reveals information about current fiscal spending, and the second signal reveals information about current fiscal news shock. Each agent i then generates forecast of government spending given their information sets via Kalman filter

$$E_{i,t} g_t = K s^1_{i,t} + (1 - K)\, E_{i,t-1} g_t, \tag{1.8}$$

where K is the Kalman gain which represents the relative weight given to new information relative to previous forecasts. After averaging Equation 1.8 across agents and rearranging, the following relationship between ex post mean forecast errors and ex ante mean forecast revisions holds

$$g_{t+h} - E_t g_{t+h} = \frac{1-K}{K} \left(E_t g_{t+h} - E_{t-1} g_{t+h}\right) + \varepsilon_{t+h-1,t}, \tag{1.9}$$

where $\varepsilon_{t+h-1,t}$ is the forecast error.[16] Equation 1.9 says that the ex post mean forecast error across individuals is predictable using ex ante mean forecast revisions if $K \neq 0$. I test the implications of equation 1.9 by running the following regression

$$g_{t+3} - E_t g_{t+3} = c + \beta \left(E_t g_{t+3} - E_{t-1} g_{t+3}\right) + \delta z_t + error_t, \tag{1.10}$$

where $g_{t+3} - E_t g_{t+3}$ is the average year-ahead government spending forecast errors

[16] The derivation of the equations 1.8 and 1.9 are given in Appendix A.1.

across agents, and z_t is the additional control.

Table 1.2: Tests of Government Spending Expectations Process

	Additional control: z_t				
Forecast Error	None	Government Spending Growth	Average Federal Tax Rate	Debt-to-GDP Ratio	Average Unemployment Rate
c	0.587	0.579	-3.429^{**}	3.488	4.284^{**}
	(0.56)	(0.62)	(1.38)	(2.63)	(1.75)
$E_t g_{t+3} - E_{t-1} g_{t+3}$	0.968^{*}	0.967^{*}	0.933^{*}	0.887	1.012^{*}
	(0.52)	(0.51)	(0.55)	(0.71)	(0.58)
Additional control: z_t		0.001	0.439^{***}	-0.044	-0.591^{*}
		(0.12)	(0.16)	(0.03)	(0.30)
Observations	146	146	146	146	146
R^2	0.02	0.02	0.03	0.03	0.03

Notes: The table reports coefficient estimates for Equation 1.10. The additional controls are current quarter values except government spending growth that is lagged by one quarter. Newey-West standard errors are in parentheses

In Equation 1.10, the coefficient β should be equal to zero if forecasts are made by the rational agents with full information and should be larger than zero if forecasts are made by the rational agents subject to information rigidities. I construct forecast errors by subtracting mean of SPF forecasts made at time t from real-time data available h quarter after the period of forecasts made.[17]

The estimate of the regression from Equation 1.10 gives $\hat{\beta} = 0.968$ (s.e. $= 0.52$) as displayed in Table 2. As a result, the null of full information rational expectations at the 10 percent level of statistical significance is rejected. The estimates imply that information frictions are economically and statistically significant. What is the implication of the information frictions for an econometrician using aggregate data? Is it possible to identify fiscal news shocks under informational frictions using SVAR? The next subsection provides answers to these questions.

1.2.3 Fiscal News

The fiscal news variable is defined as the difference between the time t forecast of time $t+h$ government spending and the time $t-1$ forecast of time $t+h$ government spending (see Ricco (2015), and Forni and Gambetti (2016)). In other words, fiscal news is the government spending forecast revisions between time t and time $t-1$.

[17] I use the first vintages of real-time data set for macroeconomists from the SPF website.

It aims at capturing the information arriving at time t about future government spending.

Using the system of equations 1.5,1.6 and 1.9, one can obtain the following relationship between the fiscal news and forecast revisions

$$\underbrace{E_t g_{t+h} - E_{t-1} g_{t+h}}_{news_t^h} = \frac{1-K}{K} \left(\underbrace{E_{t-1} g_{t+h} - E_{t-2} g_{t+h}}_{news_{t-1}^h} \right) + \psi \varepsilon_t, \qquad (1.11)$$

where $E_t g_{t+h}$ is the time t average forecast of government spending growth for time $t+h$, and ψ is the coefficient of the time t fiscal news shock.[18] The fiscal news at time t consists of two terms; the gradual adjustment of the information at time $t-1$ and the partial incorporation of fiscal news shock occurred at time t. Under the perfect information environment, the first term would disappear, and the coefficient ψ would be equal to one. However, due to imperfect information, the agents do not perfectly observe the fiscal news shock and $\psi = \rho^{h-1} M < 1$, where M is the ratio of the fiscal news shock variance to the fiscal news signal variance given in Equation 1.7.[19] Besides, the agents slowly incorporate the information from previous period captured by the term $\frac{1-K}{K}$. Hence, to correctly identify the fiscal news shocks, one should also control for fiscal news from the previous period.

How to construct the fiscal news variable for the empirical estimation? Using the SPF forecast revisions, one can construct three single periods, one, two, and three quarters ahead, and two cumulative, the sum of first two and first three quarters ahead, news variables. Table 1.1 shows cumulative forecasts have larger explanatory power with an increasing horizon; hence, I construct the fiscal news variable as a sum of forecast revisions over the next three quarters, that is

$$news_t^{1,3} = \sum_{h=1}^{3} \left[E_t g_{t+h} - E_{t-1} g_{t+h} \right]. \qquad (1.12)$$

The variable $news_t^{1,3}$, the sum of the forecast revisions of the next three quarters, aims at capturing the fiscal spending news arriving at time t. However, as shown in Equation 1.11, part of this variable is a function of $news_{t-1}^{1,3}$, its lagged value, due to the slow adjustment of information from time $t-1$. Hence, one should control for this lagged component to isolate the true fiscal news shock at time t, that is ε_t. On the other hand, government spending may respond to the business cycle fluctuations that is not taken into account in Equation 1.13 for simplicity, and one should also control for these fluctuations as well to remove the predictable component in $news_t^{1,3}$.

[18] The derivation of Equation 1.11 is provided in Appendix A.1.

[19] By projecting news shock to the signal in Equation 1.7, the expected value of fiscal news shock is equal to $E_{i,t}\varepsilon_t = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\omega^2} s_{i,t}^2$. This gives $M = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\omega^2}$.

I introduce SVAR in the next section to isolate the news shock component of fiscal news variable by controlling its endogenous response to the macroeconomic variables plus its adjustment to past expectations revisions.

1.3 Empirical Framework and Results

The empirical model is the following VAR system

$$X_t = M + B(L)X_{t-1} + u_t, \tag{1.13}$$

where X_t is a vector of endogenous variables, M is constant, $B(L)$ denote P-order lag polynomials, and u_t is the vector of reduced-form residuals having zero-mean. The baseline analysis refer to the vector X_t in the following order; $X_t = (conf_t, g_t, t_t, c_t, y_t, i_t, news_t^{1,3})'$, where $conf_t$ is the expected consumer sentiment index from survey of consumers published by University of Michigan, g_t is the log of federal government consumption and investment expenditures, t_t is the average federal tax receipt divided by GDP, c_t is the log of real private consumption (sum of durables,non-durables and services), y_t is the log of real GDP, i_t is the effective federal funds rate, and $news_t^{1,3}$ is the fiscal news variable from Equation 1.12.[20] The nominal variables are converted to real values by dividing the implicit GDP deflator provided by the Federal Reserve Bank of St. Louis. The period is $1981Q4 - 2018Q1$.

The expected consumer sentiment index (ICE = Index of Consumer Expectations) is calculated as follows; each month survey asks the following questions to the households:

X1 = "*Now looking ahead--do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?*"

X2 = "*Now turning to business conditions in the country as a whole--do you think that during the next twelve months we'll have good times financially, or bad times, or what?*"

X3 = "*Looking ahead, which would you say is more likely--that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?*",

[20] The fiscal variables are constructed using the Bureau of Economic Analysis' NIPA table 3.2

and then computes the relative scores (the percent giving favorable replies minus the percent giving unfavorable replies, plus 100) for each of the three index questions. Then, ICE is calculated as follows

$$ICE = \frac{X_1 + X_2 + X_3}{4.1134} + 2.0,$$

where 4.1134 is 1966 base period total, and 2.0 is a constant to correct for sample design changes from the 1950s. [21]

I estimate the model in Equation 1.13 with a lag-length of four based on Akaike information criterion. Identification is obtained by imposing a Cholesky scheme with the order of the variables as in vector X_t. In this approach, the fiscal news shock is identified as the last Cholesky shock in the above VAR system. The identification scheme with fiscal news variable ordered last allows the current period real variables to have an impact on the expectations of the future government spending. I analyze the implications of this ordering versus alternative strategies in the robustness section.

It is worth to stress that this identification scheme is consistent with the structure of fiscal news delivered by models of imperfect information, such as in Equation 1.11. By controlling for past fiscal news (forecast revisions), the VAR structure isolates the contemporaneous structural shocks from components due to the gradual adjustment of information.

1.3.1 Fiscal News Shocks

Figure 1.2 shows the identified fiscal news shocks and the Ramey Military News series. Both series display comovement during important events; however, fiscal news shock also captures the changes in fiscal spending besides military events such as Tax Reform Act of 1986. Moreover, in some cases like Gulf War or 9/11, fiscal news shocks anticipate Ramey Military News.[22]

The aim of incorporating fiscal news is to resolve the issue of non-fundamentalness. To verify that the shocks do not contain any predictable component, I perform the non-fundamentalness test proposed by Forni and Gambetti (2014b).[23]

[21] The design of the survey will guide the construction of the confidence index using the model variables in Section 1.4.

[22] Caggiano et al. (2015) show that SPF government spending forecast revisions Granger causes Ramey Military News.

[23] The logic of the test is that if a set of variables are informationally sufficient, no other variable or set of variables can Granger cause it. The procedure of the test is to extract principal components from a large data-set and to test whether principal components Granger cause identified shocks. The assumption here is that factors estimated by the principal components are informationally sufficient; hence, they are not predictable.

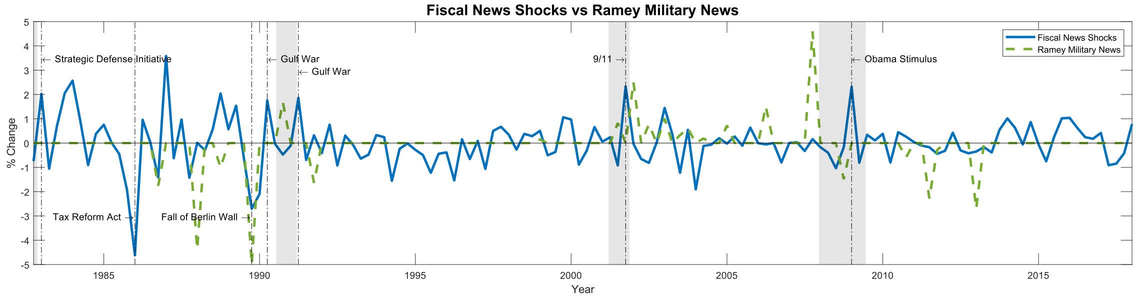

Figure 1.2: Fiscal News Shocks vs Ramey Military News

Notes: The figure shows the identified fiscal news shock (blue) after estimation of equation 1.13 and Ramey News variable (green). Grey shaded areas indicate the NBER business cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events.

I regress the fiscal news shocks on the lagged values of principal components extracted from a large set of macroeconomic variables. Table 1.3 presents the results, and the identified fiscal news shocks pass the orthogonality test.

Table 1.3: Fundamentalness Test

No. of principal components	1	2	3	4	5	6
1 lag	0.90	0.92	0.98	1.00	0.33	0.45
2 lag	0.92	0.99	0.99	1.00	0.52	0.65
3 lag	0.56	0.76	0.81	0.92	0.33	0.38
4 lag	0.71	0.89	0.84	0.94	0.50	0.46

Notes: Each entry of the table reports the p-value of the F-test in a regression of the news shock on $1, 2, 3, 4$ *lags of the the first* j *principal components,* $j = 1, ..., 6$

Another desired feature of the identified shock is that it is not correlated with other shocks. To check whether this is the case, I document the relationship between fiscal news shocks and several measures of structural shocks and variables available from the existing literature. I estimate the models

$$\hat{\varepsilon}_t = \gamma + \beta_i z_{it} + u_{jt}, \tag{1.14}$$

where $\hat{\varepsilon}_t$ is the identified fiscal news shock and z_{it} indicates the structural shock (variable) i at time t. Rejecting the null hypothesis of no correlation ($\beta_i^j = 0$) suggests that the identified fiscal news shock correlates with the structural shock (variable) i. I collect the estimated shocks (variables) from the literature, and the sources are given in Table 1.4.

The results reported in Table 1.4 indicate that the fiscal news shocks do not pick up tax, confidence, monetary, and economic news shocks. Moreover, they are uncorrelated with the uncertainty index and utilization-adjusted TFP series. The last point is crucial because fiscal multipliers would be overestimated if fiscal news shocks occur when the state of the economy starts improving. However, low and insignificant correlation with TFP series suggests this is not the case. The positive and significant correlation of fiscal news shocks with Military News of Ramey and Zubairy (2018) is not surprising since both series aims to identify the shocks related to future government spending.

Table 1.4: Correlation Test

Shock	Source	Anticipated Shock		Obs
		β^a	SE	
Military News	Ramey and Zubairy (2018)	14.58***	5.47	1982Q4-2015Q4
Tax	Romer and Romer (2010)	−0.15	0.45	1982Q4-2006Q4
Surprise Tax	Mertens and Ravn (2012)	0.12	0.28	1982Q4-2006Q4
Anticipated Tax	Mertens and Ravn (2012)	−0.28	0.28	1982Q4-2006Q4
Consumer Sentiment	Forni et al. (2017)	0.03	0.08	1982Q4-2011Q1
Anticipated Monetary	Nakamura and Steinsson (2018a)	−0.96	0.95	1995Q1-2014Q1
Surprise Monetary	Nakamura and Steinsson (2018a)	−0.90	0.56	1995Q1-2014Q1
Uncertainty	Baker et al. (2016)	0.01	0.1	1982Q4-2018Q1
TFP	Fernald (2014)	−0.01	0.03	1982Q4-2018Q1
News	Barsky and Sims (2012)	0.07	0.14	1982Q4-2007Q3
News	Beaudry and Portier (2014)	0.13	0.09	1982Q4-2012Q3

Notes: The tests are run by regressing $\hat{\varepsilon}_t$ on z_{it} (see equation 1.14), where $\hat{\varepsilon}_t$ is the identified fiscal news shock and z_{it} is indicated in the rows of the table. White heteroscedasticity-consistent standard errors are reported.

The results from the Tables 1.3 and 1.4 provide strong evidence that the identified fiscal news shocks are unpredictable and represent exogenous events orthogonal to the information set of the agents.

1.3.2 Impulse Responses

Figure 1.3 displays the impulse response functions to a fiscal news shock. The responses are normalized to have the maximum response of government spending equal to one.

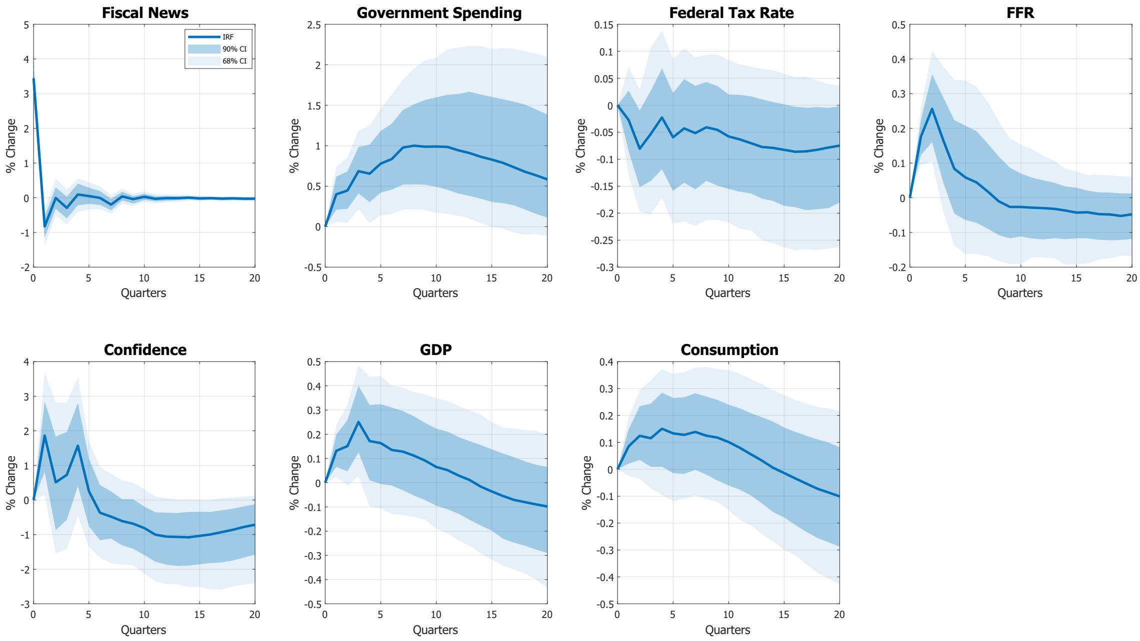

Figure 1.3: Impulse Responses to a Fiscal News Shock

Notes: Solid blue lines show the point estimates of impulse responses to fiscal news (anticipated government spending) shock from the VAR system in equation 1.13. The dark-blue area is 68% confidence region, and the light-blue area is 90% confidence region.

The government expenditures do not change on impact but increase sharply in the next four periods. The fiscal news is expected to capture the movements in future government spending; hence, the estimation is consistent with the informational content of the fiscal news variable. GDP increases slightly after the initial period and remains positive for around three years. An interesting result appears in the average federal tax rate; the response is negative and does not revert to the initial point. The average federal tax rate is federal tax receipts over GDP, and observing the increase in GDP federal tax receipts decumulate and move to a lower level, at least for the first three years. Considering the spike of debt in the sample of the estimation, the response of the average federal tax rate ratio is consistent with data. The estimation also suggests that higher government spending expenditures are funded by higher debt.

The responses of consumer confidence and consumption are the focal point of the paper. The consumer confidence does not change on impact but spikes in the next period. The positive response continues around two years and turns to negative afterward. The response of the consumption is similar to the response of confidence. It does not move on impact but shifts upwards in the next period. It reverts to the initial point after the third year and eventually goes to negative. This positive response of consumption to the higher expected future government spending reinforces the results from the previous literature using SPF forecasts and is in contrast with the neoclassical predictions.

The responses displayed in Figures 1.3 show that government spending announcements could be used to foster the expectations of the consumers even before the actual implementation of the fiscal policy.

1.3.3 Robustness Checks

The results from the previous section indicate the relevance of fiscal news shock on confidence and consumption. In this part, I conduct several robustness checks to ensure that the results remain robust under alternative specifications. In particular, I consider following checks;[24]

Alternative Orderings of the Variables

In the baseline estimation, I order fiscal news variable last and consumer confidence first, assuming that fiscal news does not have a contemporaneous impact on other variables in the system. I relax this assumption and order fiscal news first to have a contemporaneous impact on all variables in the system, including confidence. Second, I order the confidence indicator third to remove any contemporaneous impact of the non-fiscal variables in the system on fiscal variables. Figure 1.4 exhibits the impulse responses under these two alternative orderings. The responses of confidence, output, and consumption are very similar to the baseline estimation; however, the magnitudes of GDP and consumption responses are larger under both specifications.

Controlling for Expectations

The agents and forecasters may not only observe news related to government spending but also related to the other variables such as GDP, technology, unemployment, and inflation, and the current fundamentals of the economy may be affected due to this news, as well. I address this issue in two different ways. First, I include SPF GDP growth forecasts into the system, GDP News, and order them first. In doing so, I enlarge the information set of the agents. Second, I regress fiscal news onto the

[24]For sake of brevity, I plot all the impulse responses under these checks in Figure 1.4

forecasts of GDP, unemployment, and inflation to clear the impact of other news on fiscal news. I use the residual of this regression as a new fiscal news variable, which I call purged-news, and reestimate equation 1.13. The shape of the responses is very similar to the baseline case, as shown in Figure 1.4 and the magnitudes of the estimated responses are slightly larger for GDP and consumption. The findings confirm baseline results and suggest that fiscal news captures the expectations related to fiscal events.

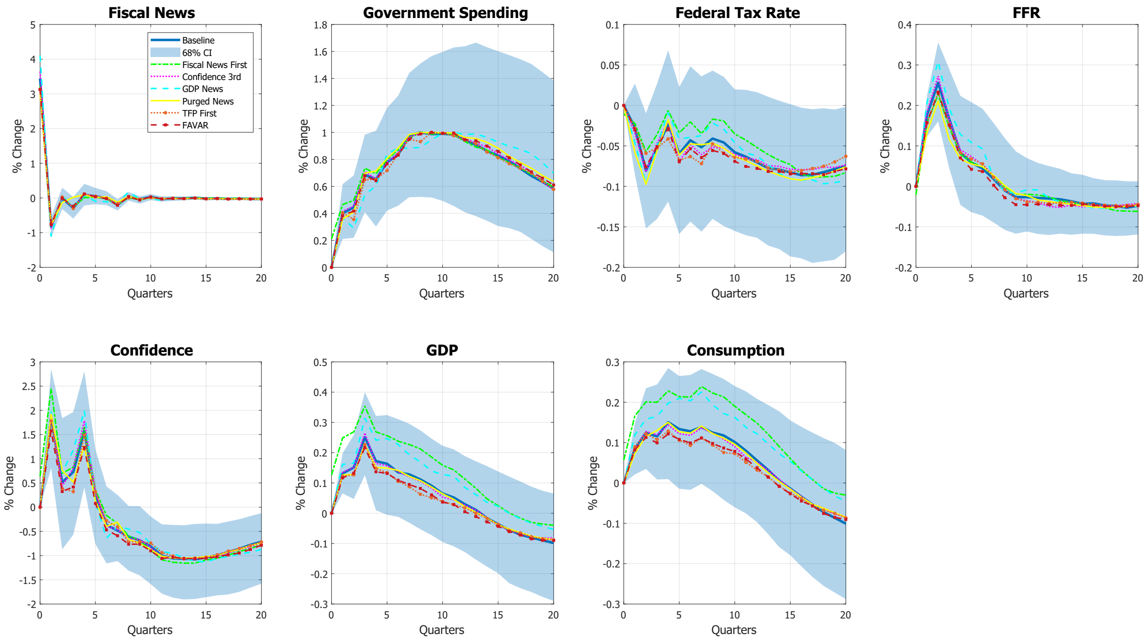

Figure 1.4: Impulse Responses to an Anticipated Government Spending Shock under different specifications

Notes: Solid blue lines are baseline, dash-dot green lines are proxy for future government spending ordered last, point magenta lines are confidence ordered fourth, dashed cyan lines are GDP news ordered first, solid yellow lines are purged fiscal news shock, solid grey lines with asteriks are small VAR, solid orange lines with circles are FAVAR and solid red lines with squares current consumer sentiment index estimates of impulse responses to a fiscal news (anticipated government spending) shock from Bayesian VAR. The shaded area is 68% confidence interval of baseline estimation.

Alternative VAR specifications

The baseline VAR is a medium-size model with a set of key macroeconomic variables to capture all possible dynamic relationships crucial to isolate the impact of current and expected government spending. However, even though the baseline model supplies rich specification and passes the non-fundamentalness test, still it might suffer from an omitted-variable problem, which may bias the results of the baseline scenario. To address this possible issue, I consider two different VAR models. First, I estimate factor-augmented VAR (FAVAR) by extracting factors from a large data set and adding these factors into my VAR. In particular, I consider a data set composed of 109 time-series and extract common factors applying principal component method. Following Bernanke et al. (2005), I extract two common factors that explain the largest share of variance of the series in the large data set and enlarge my data vector with these factors. Second, I include a measure of total factor productivity (TFP) into the baseline specification and order first to ensure that the identified fiscal news shocks are not related to the movements in TFP. I use the real-time, quarterly series on TFP for the U.S. business sector, adjusted for variations in factor utilization (labor effort and capital's workweek), constructed by Fernald (2014).[25] The estimated responses under both specifications are very similar to the baseline responses as shown in Figure 1.4.

Further Robustness Checks

The results are robust to a variety of further checks of the baseline model, which include:

(i) the estimation of small VAR to check whether the estimated baseline model suffers from over-parameterization (whether the estimated model includes more variables than the true data generating process);

(ii) the estimation of VAR with debt variable to check whether omitting a debt feedback can result in incorrect estimates;

(iii) inserting Ramey military news into the baseline VAR to control for the predictability of fiscal news shocks;

(iv) the estimation of VAR using pre-crisis sample (1981Q4:2007Q4) to check whether the results are driven by zero lower bound episode;

(v) the estimation of VAR using per capita real variables to control for the effect of the population in the estimation, if any.

These additional robustness checks confirm the solidity of the baseline results that are available in Appendix A.2.

1.3.4 The Role of Confidence

Consumer confidence and consumption react positively and significantly to the fiscal news shock, especially in the short-run, under various specifications. The path of the responses of both variables is quite similar, suggesting a positive link between

[25]The TFP series are available from Fernald's website: http://www.johnfernald.net/TFP

confidence and consumption. Following Bachmann and Sims (2012), I study the role of confidence in determining the real effects of a fiscal news shock by performing a counterfactual exercise and estimating the impulse responses conditional to a fixed level of confidence. I implement the approach adopted by Sims and Zha (2006) and generate a hypothetical sequence of confidence shocks to keep the response of confidence fixed to zero at each horizon. In this way, the responses of output and consumption reflect the effect of a fiscal news shock in a hypothetical situation where confidence is held constant.[26]

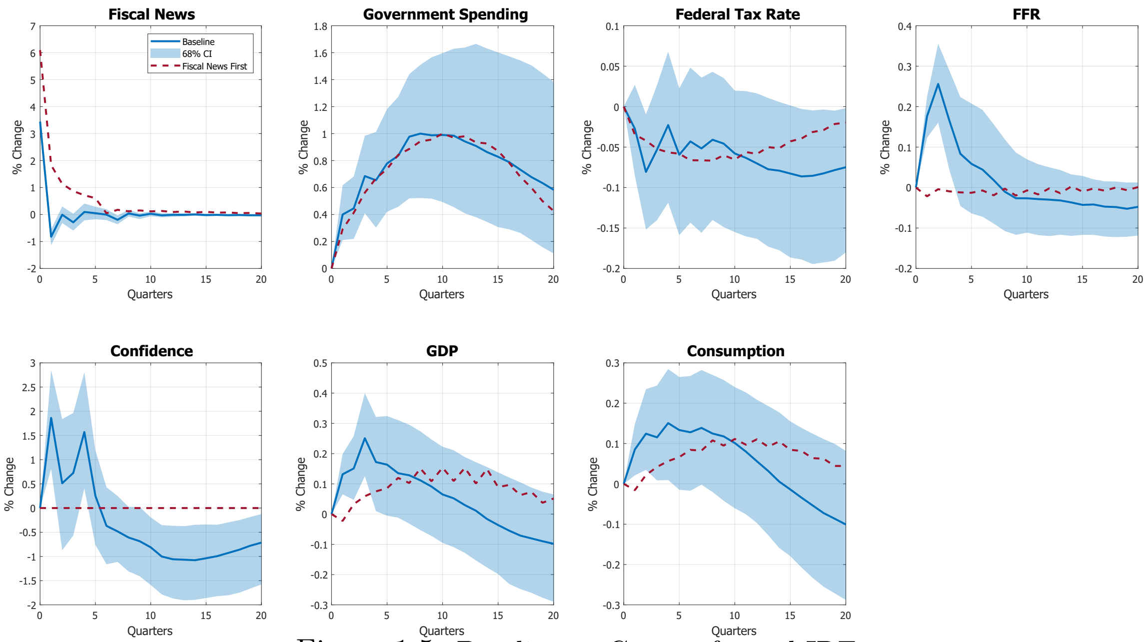

Figure 1.5: Baseline vs Counterfactual IRFs

Notes: Solid blue lines are impulse responses to fiscal news shock estimated from VAR specified in equation 1.13 and the dark-blue area is 68% confidence interval. The dashed red lines are the hypothetical impulse responses when confidence is not allowed to respond to the fiscal news shock.

Figure 1.5 plots the estimated counterfactual impulse responses when confidence is held fix along with the baseline responses. The counterfactual responses of the output and consumption are much smaller for the first ten to eleven periods relative

[26] Sims and Zha (2006) study the role of the systematic component of monetary policy in the transmission of other shocks. Their approach is to combine a hypothetical sequence of policy innovations with an initial shock to offset the systematic response of policy at each horizon. The main disadvantage of this approach is that it ignores the Lucas critique by assuming that the agents are surprised by the hypothetical policy shocks at each horizon without adapting their expectations to the new policy. However, as Sims and Zha point out, this assumption is acceptable to some extent because it would take some time for agents to learn that policy will not respond. It is not trivial to assume that agents will immediately understand the policy changes and take them as permanent. This approach is more suitable for my short-run counterfactual analysis, and it is reasonable to assume that agents will be surprised by confidence shocks for the next 5 quarters. Bachmann and Sims (2012) give a more detailed explanation about how to compute the hypothetical shocks.

to the baseline responses. In fact, the response of consumption is negative in the first period under the counterfactual scenario.

I construct a test based on the difference between the responses estimated under baseline and counterfactual.[27] Figure 1.7 plots the difference of the responses for the first four quarters along with 68% confidence bands. In the first two quarters, although marginally, the difference turns out to be significant. These results highlight the importance of confidence in the transmission of fiscal policy shock in the short-run since the response of confidence is key in explaining the positive responses of output and consumption in response to a fiscal news shock for the first two quarters.

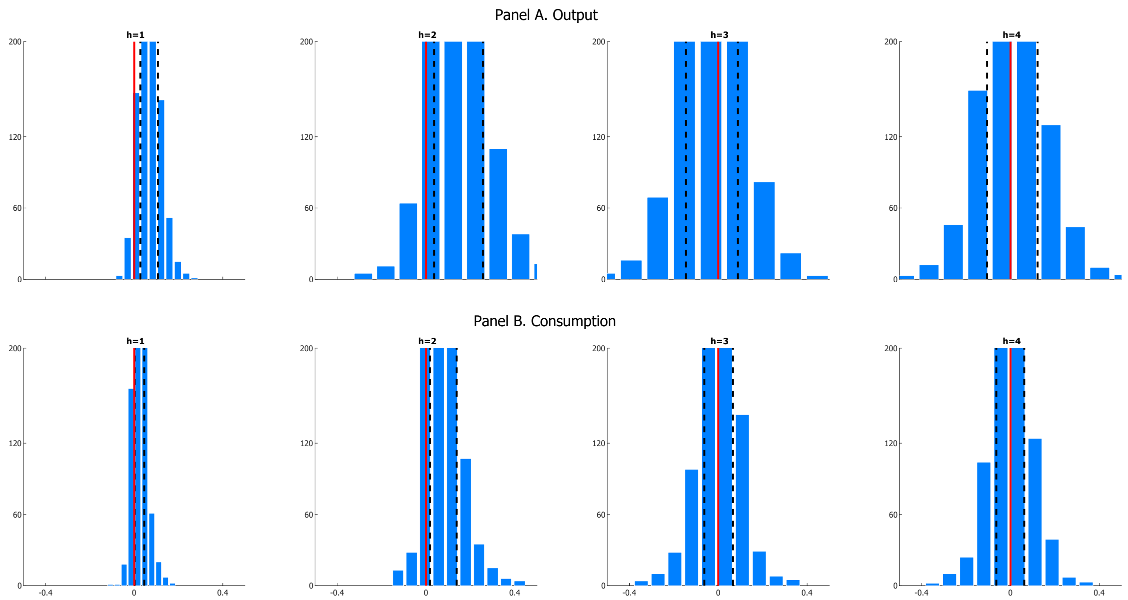

Figure 1.6: Difference in Responses between Baseline and Counterfactual

Notes: The top and bottom panel plot the empirical densities of differences computed as responses in baseline minus responses in counterfactual for GDP and consumption, respectively.

Table 1.5 presents the fiscal multipliers under baseline and counterfactual scenarios. I calculate the multiplier as following

$$mult_H = \frac{\sum_{h=1}^{H} y_h}{\sum_{h=1}^{H} g_h} \times \frac{\bar{Y}}{\bar{G}}, for\ H = \{4, 8, 12, 16\} \tag{1.15}$$

that is the ratio of cumulative response of output to the cumulative response of government spending multiplied by the average output-to-government spending ratio.[28]

[27] I compute differences of output and consumption responses between baseline and counterfactual conditional on the same set of draws of the stochastic elements of the VAR model.

[28] Ramey and Zubairy (2018) warn against this practice by noticing that, in a large US data sample spanning the 1889–2011 period, the output-over-public spending ratio varies from 2 to 24 with a mean of 8. Hence, the choice of a constant value for such ratio may importantly bias the estimation of the multipliers. In my sample, the mean value of such a ratio is 5.15, and it varies

The baseline one-year and two-year multipliers are 1.80 and 1.21, respectively, and they are both statistically significant. The counterfactual multipliers are much lower when confidence channel is shut down, 0.82, and 0.78 for one and two-year multipliers, respectively. The large difference between baseline and counterfactual multipliers for one-year and two-year horizons reinforces the results from Figure 1.5 and points to the importance of confidence in the real effects of fiscal news shocks.

Table 1.5: Fiscal Multipliers

Horizon	1-year	2-year	3-year	4-year
Baseline	1.80 $[0.86, 3.14]$	1.21 $[0.29, 2.64]$	0.80 $[0.03, 2.04]$	0.58 $[-0.22, 1.71]$
Counterfactual (w/o confidence)	0.82 $[0.22, 1.68]$	0.78 $[0.39, 1.36]$	0.78 $[0.40, 1.45]$	0.80 $[0.38, 1.65]$

Notes: Estimated fiscal multipliers for an anticipated (news) government spending shock. The first row presents the multipliers from baseline estimation and the second row from counterfactual estimation in which confidence is not allowed to respond to the fiscal news shock. The numbers in brackets indicate the 68% confidence intervals from the distribution of multipliers.

In summary, this subsection documents the crucial role of the confidence in the crowd-in effect of government spending on consumption, and empirical findings reveal the confidence as an important transmission channel of fiscal policy. However, one question still remains open: Why consumer confidence increases with higher expected government spending? To answer this question, I construct an informational friction model with a government that is the subject of the next section.

1.4 Model

1.4.1 Setup

This section describes the economy with informational frictions that extends the work of Lorenzoni (2009) by introducing government sector. There is a continuum of islands indexed by $l \in [0,1]$ and each island l is inhabited by a representative consumer that owns a continuum of price-setting firms producing differentiated goods indexed by $m \in [0,1]$. The consumer from island l loves a variety of goods and consumes the goods produced in a subset of other islands. This subset is denoted by $\mathcal{B}_{l,t} \subset [0,1]$ that is randomly selected by nature each period. Symmetrically, the

from 4.61 to 5.81. Hence, the commonly adopted ex post-conversion from the estimated elasticities to dollar values does not appear to be a concern for this exercise.

firms in island l are visited by a subset $\mathcal{F}_{l,t} \subset [0,1]$ of consumers coming from other islands. The random assignment is such that the mass of goods in $\mathcal{B}_{l,t}$, and mass of consumers in $\mathcal{F}_{l,t}$ are constant. There is perfect labor immobility across islands, so the consumer located in island l provides labor only for the firms in island l.

The firms set the nominal price of their output in each period, and they fully satisfy all demand at that price. Information is common to a consumer and firm within an island but not shared across islands. The agent in island l observes only local productivity, private and public demand for final good and taxes, the prices of the goods in his consumption basket, and a common noisy signal of aggregate fiscal news shock, technology and inflation. The agent uses this information to predict the values of the aggregates in the economy. The bond market is the only centralized market. The consumers can trade nominal one-period bonds but cannot fully insure against idiosyncratic shocks.

Consumers

The consumer in island l maximizes

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_{l,t}, N_{l,t}) \tag{1.16}$$

with

$$U(C_{l,t}, N_{l,t}) = \log C_{l,t} - \frac{N_{l,t}^{1+\chi}}{1+\chi} \tag{1.17}$$

and

$$C_{l,t} = \left(\int_{\mathcal{B}_{l,t}} \int_0^1 C_{m,j,l,t}^{(\gamma-1)/\gamma} dm dj \right)^{\gamma/(\gamma-1)}, \tag{1.18}$$

where $C_{m,j,l,t}$ is the consumption of the variety m produced in island j by the consumer in island l at time t, χ is the inverse Frisch elasticity of labor supply, and γ captures the elasticity of substitution among differentiated goods. The budget constraint of the consumer in island l is given by

$$Q_t B_{l,t+1} + \int_{\mathcal{B}_{l,t}} \int_0^1 P_{m,j,t} C_{m,j,l,t}^{(\gamma-1)/\gamma} dm dj = B_{l,t} + W_{l,t} N_{l,t} + \int_0^1 \Pi_{m,l,t} dm + T_{l,t}. \tag{1.19}$$

In the above equation, $B_{l,t+1}$ is holdings of nominal bonds that trade at price Q_t, $W_{l,t}$ is the nominal local wage, $\Pi_{m,l,t}$ is the profits of firm m, and $T_{l,t}$ is the island-specific lump-sum tax discussed in detail later. For each island, there are now two relevant price indices. The first is the local producer price index that includes the prices of all the varieties produced in island l

$$P_{l,t}=\left(\int_0^1 P_{m,l,t}^{1-\gamma}dm\right)^{1/(1-\gamma)}, \tag{1.20}$$

and the second is the consumer price index that includes all the varieties consumed in island l

$$\overline{P}_{l,t}=\left(\int_{\mathcal{B}_{l,t}} P_{j,t}^{1-\gamma}dj\right)^{1/(1-\gamma)}. \tag{1.21}$$

The maximization of 1.16 subject to 1.19 and a no-Ponzi-game condition gives the following optimality conditions

$$C_{m,j,l,t}=\left(\frac{P_{m,j,t}}{\overline{P}_{l,t}}\right)^{-\gamma}C_{l,t} \tag{1.22}$$

$$N_{l,t}^{\chi}=\frac{W_{l,t}}{\overline{P}_{l,t}C_{l,t}} \tag{1.23}$$

$$Q_t=\beta\mathbb{E}_{l,t}\left[\frac{C_{l,t}}{C_{l,t+1}}\frac{\overline{P}_{l,t}}{\overline{P}_{l,t+1}}\right]. \tag{1.24}$$

The equation 1.22 gives the demand for good m produced in island $j\in\mathcal{B}_{l,t}$ by the consumer in island l. The equations 1.23 and 1.24 state the optimal labor supply and no-arbitrage conditions, respectively and $\mathbb{E}_{l,t}$ denotes the expectation of the agents located in island l. Aggregating the demand of all consumers in $\mathcal{F}_{l,t}$ gives the total private demand for the good produced by firm m in island l that is equal to

$$Y_{m,l,t}^{P}=\int_{\mathcal{F}_{l,t}}\left(\frac{P_{m,l,t}}{\overline{P}_{j,t}}\right)^{-\gamma}C_{j,t}dj. \tag{1.25}$$

The total demand for good m produced in island l, $Y_{m,l,t}^{D}$, consists of demand from the private sector, $Y_{m,l,t}^{P}$, and demand from the public sector, $Y_{m,l,t}^{G}$, the nature of which is discussed below. The economy-wide price index is defined as

$$P_t=\left(\int_0^1 P_{l,t}^{1-\gamma}dl\right)^{1/(1-\gamma)}. \tag{1.26}$$

Government

The government purchases goods from each island at the local price and impose lump-sum taxes on each island and maintains a balanced budget. Her budget constraint is

$$\int_0^1 P_{m,l,t} Y^G_{m,l,t} dmdl = \int_0^1 T_{l,t} dl \tag{1.27}$$

with $Y^G_{m,l,t}$ stands for the government's demand for good m produced in island l. I assume that government demand for the output good of firm m in island l is a function of the good's price and the aggregate price level such that

$$Y^G_{m,l,t} = \left(\frac{P_{m,l,t}}{P_t}\right)^{-\gamma} G_t, \tag{1.28}$$

where G_t is the real aggregate government expenditure. Plugging 1.28 into 1.27 and aggregating across firms and islands gives

$$P_t G_t = T_t, \tag{1.29}$$

where T_t is the total tax receipts of the government in this economy.

Firms and Technology

Firms are price-setters à la Calvo (1983), and in each period, on each island, a fraction $1 - \theta$ of firms are allowed to reset their price. Let $P^*_{l,t}$ denotes the optimal price for a firm who can adjust its price in island l at time t. The total demand for the firm m in island l is given by

$$Y_{m,l,t} = P^{-\gamma}_{m,l,t} \left[\int_{\mathcal{F}_{l,t}} \overline{P}^{\gamma}_{j,t} C_{j,t} dj + P_t G_t \right] \tag{1.30}$$

that is the sum of demand from the private sector and government. The production function is

$$Y_{m,l,t} = A_{l,t} N_{m,l,t}, \tag{1.31}$$

where $N_{m,l,t}$ is labor input and $A_{l,t}$ is the island-specific productivity. The log of island specific-productivity, that is $\log A_{l,t} = a_{l,t}$ is given by

$$\log A_{l,t} = x_t + \eta^a_{l,t}, \tag{1.32}$$

where x_t is aggregate permanent component of technology and $\eta^a_{l,t}$ is island-specific temporary component of technology with distribution $N(0, \sigma^2_{\eta^a})$ and satisfies $\int_0^1 \eta^a_{l,t} dl = 0$.[29] The x_t is a random walk process given by

$$x_t = x_{t-1} + \nu_t, \tag{1.33}$$

[29] In the equations that follow, lower-case variables represent the log deviations of the corresponding upper-case variable from their steady-state values unless otherwise specified.

where ν_t is i.i.d aggregate technology shock with distribution $N(0, \sigma_\nu^2)$. The problem of this firm is to maximize

$$\mathbb{E}_{l,t} \sum_{s=t}^{\infty} \theta^t Q_{l,t+s} \left(P_{m,l,t+s} Y_{m,l,t+s} - W_{l,t+s} N_{m,l,t+s} \right) \tag{1.34}$$

subject to demand relation given in 1.30, the technological constraint given in 1.31 and $P_{m,l,t+s} = P_{l,t}^*$. The solution to the firm's problem is given by

$$P_{l,t}^* = \frac{\gamma}{\gamma - 1} \frac{\mathbb{E}_{l,t} \sum_{s=t}^{\infty} (\beta\theta)^t U_{c,t+s} W_{l,t+s} P_{t+s}^{\gamma} Y_{t+s}}{\mathbb{E}_{l,t} \sum_{s=t}^{\infty} (\beta\theta)^t U_{c,t+s} P_{t+s}^{\gamma} Y_{t+s}}. \tag{1.35}$$

1.4.2 Log-Linearized Model

Government

I assume that the log-linear government spending obeys the following AR(1) process

$$g_t = \rho_g g_{t-1} + \phi_e e_t, \tag{1.36}$$

where e_t is the fiscal news process at time t and ϕ_e is the coefficient of fiscal news on actual government spending. The fiscal news also follows the AR(1) process such that

$$e_t = \rho_\varepsilon e_{t-1} + \varepsilon_{t-1}, \tag{1.37}$$

where ε_{t-1} is the fiscal news shock that is i.i.d over time with distribution $N(0, \sigma_\varepsilon^2)$. The log-linear approximation of the government budget constraint given in 1.29 is

$$\tau_t = \theta_G (p_t + g_t) \tag{1.38}$$

where $\tau_t = \int_0^1 \tau_{l,t} dl$ and θ_G is the steady-state government spending-to-GDP ratio in the above equation.

Signals

Each agent observes signals of aggregate states (technology and inflation) and signals of local states (island-specific productivity, consumer prices, private and government demand, and tax). Agents form expectations of aggregate and local states using these signals. First, I discuss the island-specific signals. The agents observe the local productivity with the signal given in Equation 1.32

$$a_{l,t} = x_t + \eta_{l,t}^a. \tag{1.39}$$

I assume that the random selection of islands in $\mathcal{B}_{l,t}$ is such that the consumer price index for island l in log-linear deviations from steady-state is

$$\overline{p}_{l,t} = p_t + \eta_{l,t}^{CPI}, \tag{1.40}$$

where $\eta_{l,t}^{CPI}$ has distribution $N(0, \sigma^2_{\eta^{CPI}})$ and satisfies $\int_0^1 \eta_{l,t}^{CPI} dl = 0$.This assumption prevents the agents to infer the aggregate shocks from their observation of the local consumer price index. The log-linearized version of private demand faced by firm m in island l in equation 1.25 is given by

$$y^P_{m,l,t} = \int\limits_{\mathcal{F}_{l,t}} \left(\gamma \overline{p}_{j,t} + c_{j,t}\right) dj - \gamma p_{m,l,t}. \tag{1.41}$$

I assume that the random selection of islands in $\mathcal{F}_{l,t}$ is such that the equation 1.41 takes the form

$$y^P_{m,l,t} = c_t - \gamma \left(p_{m,l,t} - p_t\right) + \eta^P_{l,t}, \tag{1.42}$$

where c_t, p_t and $p_{m,l,t}$ are log-linear deviations of aggregate consumption, price and local price of good m from steady-state and $\eta^P_{l,t}$ has distribution $N(0, \sigma^2_{\eta^P})$ and satisfies $\int_0^1 \eta^P_{l,t} dl = 0$. Again, this assumption prevents the agents from inferring the aggregate shocks from their observation of the local production. I define the private demand signal the agent in island l receives as following

$$d^P_{l,t} = c_t + \gamma p_t + \eta^P_{l,t}. \tag{1.43}$$

The signal $d^P_{l,t}$ corresponds to the intercept of the private demand function for producers in island l at time t. It expresses the local private demand as a function of aggregates that will allow me to write the system in the state-space form later. I assume that the government spending in equation 1.28 takes the form

$$y^G_{m,l,t} = g_t - \gamma \left(p_{m,l,t} - p_t\right) + \xi^G_{l,t} + \eta^G_{l,t}, \tag{1.44}$$

where g_t is is log-linear deviation of aggregate government spending, $\eta^G_{l,t}$ has distribution $N(0, \sigma^2_{\eta^G})$ and satisfies $\int_0^1 \eta^G_{l,t} dl = 0$. The term $\xi^G_{l,t}$ denotes the persistent component of government demand such that

$$\xi^G_{l,t} = \rho_\xi \xi^G_{l,t-1} + \mu^1_{l,t}, \tag{1.45}$$

where $\mu^1_{l,t}$ has distribution $N(0, \sigma^2_{\mu^1})$ and satisfies $\int_0^1 \mu^1_{l,t} dl = 0$. The assumption in Equation 1.44 plays a similar role of Equation 1.42 and prevents the agents from inferring the aggregate shocks from their observation of the local government demand. The idiosyncratic but persistent component of government demand in Equation 1.45 is necessary for the fiscal policy to alter the expectations of the forward-looking agents.I define the government demand signal the agent in island l

receives as

$$d^G_{l,t} = \varepsilon_t + \gamma p_t + \xi^G_{l,t} + \eta^G_{l,t}. \tag{1.46}$$

The signal $d^G_{l,t}$ serves the same purpose of the signal in equation 1.43 and allows me to express the local government demand as a function of aggregates. [30]The tax process in each island l is given by

$$\tau_{l,t} = \tau_t + \xi^\tau_{l,t} + \eta^\tau_{l,t}, \tag{1.47}$$

where $\tau_{l,t} = \frac{T_{l,t}-T_l}{Y}$and $\tau_t = \theta_G\,(p_t + g_t)$. Moreover, $\eta^\tau_{l,t}$ has distribution $N(0, \sigma^2_{\eta^\tau})$ and satisfies $\int_0^1 \eta^\tau_{l,t} dl = 0$. The term $\xi^\tau_{l,t}$ captures the persistent component of lump-sum tax such that

$$\xi^\tau_{l,t} = \rho_\xi \xi^\tau_{l,t-1} + \mu^2_{l,t}, \tag{1.48}$$

where $\mu^2_{l,t}$ has distribution $N(0, \sigma^2_{\mu 2})$ and satisfies $\int_0^1 \mu^2_{l,t} dl = 0$. The assumption in Equation 1.47 prevents the agents from inferring the aggregate shocks from their observation of the local taxes. I define the government demand signal the agent in island l receives as

$$d^\tau_{l,t} = \tau^e_t + \xi^\tau_{l,t} + \eta^\tau_{l,t}, \tag{1.49}$$

where $\tau^e_t = \theta_G\,(p_t + \varepsilon_t)$.[31] Hence, the agents expect taxes to move with the fiscal news rather than the actual government spending.

Now I discuss the aggregate signals; all agents in the economy observe signal s^x_t regarding the permanent component of the productivity process

$$s^x_t = x_t + \vartheta_t, \tag{1.50}$$

where ϑ_t is the i.i.d. noise shock with distribution $N(0, \sigma^2_\vartheta)$. Hence by observing this signal, the agents will erroneously expect higher productivity in the economy following noise shock since technology shock ν_t is i.i.d. (see Equation 1.33). Finally, following Lorenzoni (2009), the nominal interest rate is given by

$$i_t = (1-\rho_i) i^* + \rho_i i_{t-1} + \varphi \tilde{\pi}_t, \tag{1.51}$$

where ρ_i and φ are known by all agents and $\tilde{\pi}_t$ is a signal of realized aggregate

[30]The government demand signal given in equation 1.46 is different than the government spending equation in 1.44. The intuition behind this formulation of the government demand signal is that the agents expect fiscal news to become actual spending in the next period.

[31]The aggregate tax term, τ^e_t, in Equation 1.49 is different than the true tax process τ_t. I use this modified term for the tax signal to be consistent with the government demand signal given in Equation 1.46.

inflation

$$\tilde{\pi}_t = \pi_t + \omega_t, \tag{1.52}$$

where ω_t is an i.i.d. normal shock, with zero mean and variance σ^2_{ω} . The noisy signal of inflation prevents agents from perfectly inferring aggregate prices from the interest rate. In summary there are total of seven signals; two of them are aggregate signals, all agents observe same two signals, and five of them are island-specific, only the agent in the island that receives signals observes those.

Confidence

The Index of Consumer Expectations used in empirical analysis is calculated as an average of three forward-looking questions; expectations about personal income and aggregate business conditions in the next 12 months and about economic conditions in the next five years. I construct model confidence index based on the first two questions as follows

$$conf_t = \frac{\sum_{h=1}^{4} \int \mathbb{E}_{l,t}\left[y^d_{l,t+h}\right] + \sum_{h=1}^{4} \int \mathbb{E}_{l,t}\left[y_{t+h}\right]}{2}, \tag{1.53}$$

where $y^d_{l,t+h}$ is the disposable income of the agent in island l and y_{t+h} is the aggregate output h period ahead. The first term in Equation 1.53 aims to capture the expectations of personal income and second term aims to capture the expectations of aggregate business conditions in the next four quarters (12 months). It is possible to show that the average expectations of individual disposable income can be written as follows

$$\int \mathbb{E}_{l,t}\left[y^d_{l,t+h}\right] = \theta_C \mathbb{E}_{l,t}\left[c_{t+h}\right] - \theta_G \mathbb{E}_{l,t}\left[p_{t+h}\right], \tag{1.54}$$

where c_{t+h} and p_{t+h} are aggregate consumption and price h period ahead and θ_C and θ_G are steady-state consumption and government spending over GDP , respectively. The average expected individual disposable income is function of aggregate variables and it is possible to calculate its value using the law of motion for states given in Equation 1.63.

1.4.3 Equilibrium

Individual Optimality Conditions

Using the optimality equation given in 1.24, the Euler equation of the consumer in island l is

$$c_{l,t} = \mathbb{E}_{l,t}\left[c_{l,t+1}\right] - i_t + \mathbb{E}_{l,t}\left[\overline{p}_{l,t+1}\right] - \overline{p}_{l,t} \tag{1.55}$$

and the budget constraint in 1.19 takes the form

$$\beta b_{l,t+1} = b_{l,t} + p_{l,t} + y_{l,t} - \theta_C \overline{p}_{l,t} - \theta_C c_{l,t} - \tau_{l,t}, \tag{1.56}$$

where $b_{l,t} = \frac{B_{l,t}-B_l}{Y}$, $y_{l,t}$ is the total demand, details given in below, and θ_C is steady-state consumption-to-GDP ratio. The log-linear approximation of the price optimality condition in 1.35 is equal to

$$p^*_{l,t} = (1-\beta\theta)\left(w_{l,t} - a_{l,t}\right) + \beta\theta\mathbb{E}_{l,t}\left[p^*_{l,t+1}\right] \tag{1.57}$$

and the law of motion for local producer price index is

$$p_{l,t} = \theta p_{l,t-1} + (1-\theta)p^*_{l,t}. \tag{1.58}$$

Using demand signals in 1.43 and 1.46 and tax signal in 1.47, I can rewrite the equations 1.41 and 1.42 as a function of observables, the local price firms choose and the demand and tax signals. The total demand for the goods produced in island l is the sum of private and public demand

$$y_{l,t} = \theta_C y^P_{l,t} + \theta_C y^G_{l,t}. \tag{1.59}$$

Defining total demand signal as

$$d_{l,t} = \theta_C d^P_{l,t} + \theta_C d^G_{l,t} \tag{1.60}$$

allows to express the final demand as a function of local price and tax in addition to the total demand and tax signals

$$y_{l,t} = d_{l,t} - d^\tau_{l,t} + \tau_{l,t} + \gamma p_{l,t}. \tag{1.61}$$

Proof: See Appendix A.5.

Using Equations 1.23,1.31,1.58, and 1.61, one can rewrite the equation 1.57 as following

$$p_{l,t} - p_{l,t-1} = \lambda\left(\overline{p}_{l,t} + c_{l,t} - p_{l,t} - a_{l,t}\right) + \lambda\chi\left(d_{l,t} - d^\tau_{l,t} + \tau_{l,t} - \gamma p_{l,t} - a_{l,t}\right) + \beta\mathbb{E}_{l,t}\left[p_{l,t+1} - p_{l,t}\right]. \tag{1.62}$$

The expectation term on the very right hand side of the equation 1.62 is island-specific and each island has different information set. Hence, one cannot simply iterate the expectations and aggregate them across islands.

Learning and Aggregation

The economy's aggregate dynamics can be described using notation similar to that in Lorenzoni (2009). The variables $z_{l,t} = \left(x_t, g_t, e_t, c_t, p_t, i_t, \xi^G_{l,t}, \xi^\tau_{l,t}\right)'$ describe the dynamics of aggregate macro variables. The state of the economy is captured by the infinite dimensional vector $\mathrm{Z}_{l,t} = (z_{l,t}, z_{l,t-1}, ...)$. I am looking for a linear equilibrium where the law of motion for

$$\mathrm{Z}_{l,t} = \mathrm{A}\mathrm{Z}_{l,t-1} + \mathrm{B}\mathrm{u}^1_{\mathrm{l,t}} \tag{1.63}$$

with $u^1_t = \left(\nu_t, \varepsilon_t, \omega_t, \mu^1_{l,t}, \mu^2_{l,t}\right)'$ and the rows of A and B conform to the laws of motion for $z_{l,t}$. To solve for a rational expectations equilibrium, I conjecture that $p_{l,t}$ and $c_{l,t}$ follow the rules

$$p_{l,t} = q_b b_{l,t} + q_p p_{l,t-1} + q_a a_{l,t} + q_\tau \tau_{l,t} + q_d d_{l,t} - q_s d^\tau_{l,t} + q_z \mathbb{E}_{l,t}\left[\mathrm{Z}_{l,t}\right] \tag{1.64}$$

$$c_{l,t} = -\overline{p}_{l,t} + m_b b_{l,t} + m_p p_{l,t-1} + m_a a_{l,t} + m_\tau \tau_{l,t} + m_d d_{l,t} - m_s d^\tau_{l,t} + m_z \mathbb{E}_{l,t}\left[\mathrm{Z}_{l,t}\right]. \tag{1.65}$$

The equation 1.64 represents the optimal pricing policy of the firms in island l (aggregated across firms) and the equation 1.65 represents the optimal consumption policy of the representative consumer in island l. The agents use the Kalman filter to form expectations about the state variables

$$\mathbb{E}_{l,t}\left[\mathrm{Z}_{l,t}\right] = \mathbb{E}_{l,t-1}\left[\mathrm{Z}_{l,t}\right] + \mathrm{C}\left(s_{l,t} - \mathbb{E}_{l,t-1}\left[\mathrm{s}_{l,t}\right]\right), \tag{1.66}$$

where $\mathrm{s}_{l,t}$ is the vector of signals observed by the agents in island l

$$\mathrm{s}_{l,t} = \left(s^x_t, a_{l,t}, \overline{p}_{l,t}, d^P_{l,t}, d^G_{l,t}, \tau_{l,t}, i_t\right)', \tag{1.67}$$

and C is the matrix of Kalman gains. There exists a matrix Ξ such that average expectations of the aggregate state variables are a linear function of the states themselves:

$$\Xi \mathrm{Z}_t = \int_0^1 \mathbb{E}_{l,t}\left[\mathrm{Z}_t\right] dl. \tag{1.68}$$

A rational expectations equilibrium consists of matrices $\mathrm{A}, \mathrm{B}, \mathrm{C}, \Xi$ and vectors $q_b, q_p, q_a, q_\tau, q_d, q_s, q_z$ and $m_b, m_p, m_a, m_\tau, m_d, m_s, m_z$ that are consistent with agents' optimization, Bayesian updating, and with market clearing in the goods, labor, and private bonds markets. The computation method used to solve for the equilibrium is an adaptation of Lorenzoni (2009) and the details are in Appendix A.4.

1.5 Model Estimation

I now discuss the methodology for evaluating the model in the light of the empirical findings. I divide the parameter space into two sets; calibrated and estimated.

1.5.1 Calibrated Parameters

The first set includes calibrated parameters based on the data and other studies. I choose the standard values of 0.99 for discount factor, β, and1 for inverse Frisch elasticity, χ. The average government spending to GDP ratio is equal to 0.19 for the sample period. I adopt the values from Lorenzoni (2009) for standard deviations of aggregate technology shock, $\sigma_v = 0.0077$, and noise in inflation, $\sigma_\omega = 0.0015$ and standard deviations of noises in local productivity signal, $\sigma_{\eta^A} = 0.15$, CPI signal, $\sigma_{\eta^{CPI}} = 0.02$, and private demand signal, $\sigma_{\eta^P} = 0.11$, since these parameters have same interpretation both in Lorenzoni (2009)'s model and my model. I set the standard deviation of fiscal news shock from the empirical section that gives $\sigma_\varepsilon = 0.0201$. I select Taylor rule coefficients from Christiano et al. (2005), $\rho_i = 0.8$ and $\phi = 1.5$. Table 5 summarizes the calibrated parameters.

Table 1.6: Calibrated Parameters

	Parameter	Value	Source
β	Discount factor	0.99	Standard value
χ	Inverse Frisch elasticity	1.0	Standard value
θ_G	Steady-state government spending/output ratio	0.19	Sample mean
ρ_i	Persistency of monetary policy rule	0.8	Christiano et al. (2005)
ϕ	Response of monetary policy rule to inflation	1.5	Christiano et al. (2005)
σ_ν	Std. dev. of technology shock	0.0077	Lorenzoni (2009)
σ_ω	Std. dev. of noise in inflation	0.0015	Lorenzoni (2009)
σ_{η^A}	Std. dev. of noise in productivity signal	0.15	Lorenzoni (2009)
$\sigma_{\eta^{CPI}}$	Std. dev. of noise in CPI signal	0.02	Lorenzoni (2009)
σ_{η^P}	Std. dev. of noise in private demand signal	0.11	Lorenzoni (2009)
σ_ε	Std. dev. of fiscal news shock	0.0201	SVAR

Table 1.7 displays the estimates of the parameters in Θ. The results strongly support less noisy government demand signal relative to the tax signal; the standard error of the idiosyncratic noise in the public demand signal is $\sigma_{\eta^G} = 0.01$ whereas the standard error of the idiosyncratic noise in the tax signal is $\sigma_{\eta^\tau} = 1.99$.[32] I impose symmetry in the estimation of the standard error of the noises in the persistent component of government demand and tax signals, and I obtain $\sigma_{\mu^1} = \sigma_{\mu^2} = 0.1026$. I obtain very persistent AR parameter in island-level government demand and tax that is $\rho_\xi = 0.99$.

[32]These values are the lower bound for σ_{η^G} and higher bound for σ_{η^τ}

The government spending is more persistent than the fiscal news, $\rho_g = 0.9793$ and $\rho_\varepsilon = 0.7158$, respectively, and the fiscal news becomes actual government spending slowly over time since $\phi_\varepsilon = 0.0865$. The probability of fixed price is very high relative to the literature, $\theta = 0.99$, and the opposite is true for the elasticity of substitution among goods, $\gamma = 1.5$. This suggests that government demand shocks may not be inflationary as other demand shocks and may not cause frequent changes in prices. The literature on the various impact of different demand shocks on prices is limited and can be an interesting avenue for further research.

Unfortunately, the key parameters, $\sigma_{\eta^G}, \sigma_{\eta^\tau}, \sigma_{\mu^1}$ and σ_{μ^2}, are not statistically significant. The estimates are robust to the specification of Φ; however, the standard errors are generally large for these parameters.

1.5.2 Estimated Parameters

The second set includes the parameters that I estimate by minimizing a measure of the distance between empirical impulse responses and the model responses. The parameters to be estimated are related to the fiscal side of the model.

I select $(g_t, conf_t, c_t, y_t)$ as variables of interest because these variables are both present in the model and empirical VAR. Denote the estimated parameter vector with Θ and the model responses to the fiscal news shock with $\Psi(\Theta)$. Let $\hat{\Psi}$ be the $n \times 1$ vector of empirical estimates of the VAR impulse responses to the fiscal news shock.[33] The estimate of Θ, vector of parameters, solves

$$\min_{\Theta} \left(\Psi(\Theta) - \hat{\Psi}\right)' \Omega \left(\Psi(\Theta) - \hat{\Psi}\right) \tag{1.69}$$

where Ω is a $n \times n$ weighting matrix. The null hypothesis states that VAR model is true and the model fits the data; then the optimal weighting matrix would be equal to $\Omega = \Lambda^{-1}$, the diagonal matrix with the inverse of the sample variances of VAR impulse responses. Given that the aim of the model is to document the impact of fiscal news shock on consumption and output, I specify $\Omega = \Upsilon \Lambda^{-1}$, where$\Upsilon$ is an $n \times n$ matrix that puts smaller weights to the responses over time. This way, I fit the model to the moments of high interest, and at the same time, I get consistent yet inefficient estimates.

Table 1.7 displays the estimates of the parameters in Θ. The results strongly support less noisy government demand signal relative to the tax signal; the standard error of the idiosyncratic noise in the public demand signal is $\sigma_{\eta^G} = 0.01$ whereas the standard error of the idiosyncratic noise in the tax signal is $\sigma_{\eta^\tau} = 1.99$.[34] I impose

[33] I choose first eleven periods of the responses to match; hence, $n = 11$.
[34] These values are the lower bound for σ_{η^G} and higher bound for σ_{η^τ}

symmetry in the estimation of the standard error of the noises in the persistent component of government demand and tax signals, and I obtain $\sigma_{\mu^1} = \sigma_{\mu^2} = 0.1026$. I obtain very persistent AR parameter in island-level government demand and tax that is $\rho_\xi = 0.99$.

Table 1.7: Estimated Parameters

	Parameter	Value	Std. Err.
θ	Probability of fixed price	0.99	0.89
γ	Elasticity of substitution	1.5	0.98
ρ	Persistency of government spending	0.98	0.24
ρ_ε	Persistency of fiscal news	0.72	0.47
ϕ_ε	Elasticity of gov. spending to fiscal news	0.09	0.02
ρ_ξ	AR parameter in persistent gov. demand and tax	0.99	0.19
$\sigma_{\mu^{1,2}}$	Std. dev. of persistent gov. demand and tax	0.10	10.33
σ_{η^G}	Std. dev. of noise in gov. demand signal	0.01	1.49
σ_{η^τ}	Std. dev. of noise in tax signal	1.99	218.33

The government spending is more persistent than the fiscal news, $\rho_g = 0.9793$ and $\rho_\varepsilon = 0.7158$, respectively, and the fiscal news becomes actual government spending slowly over time since $\phi_\varepsilon = 0.0865$. The probability of fixed price is very high relative to the literature, $\theta = 0.99$, and the opposite is true for the elasticity of substitution among goods, $\gamma = 1.5$. This suggests that government demand shocks may not be inflationary as other demand shocks and may not cause frequent changes in prices. The literature on the various impact of different demand shocks on prices is limited and can be an interesting avenue for further research.

Unfortunately, the key parameters, $\sigma_{\eta^G}, \sigma_{\eta^\tau}, \sigma_{\mu^1}$ and σ_{μ^2}, are not statistically significant. The estimates are robust to the specification of Φ; however, the standard errors are generally large for these parameters.

1.5.3 The Model IRFs and the Role of Confidence

The impulse response functions of the estimated model and VAR to a unit fiscal news shock are represented by the solid red and blue lines in Figure 1.7, respectively. Several results deserve close attention. First, the model does well at accounting for the dynamic response of the U.S. economy to a fiscal news shock in the short-run. The model responses lie within the one-standard-deviation confidence interval computed from the VAR estimates. The model responses of consumption and confidence are similar to the empirical ones, especially in the first several quarters.[35] Second, the model does well in accounting for the crowding-in effect of government spending on private consumption.

In the model, one period after the fiscal news shock hits the economy, the confidence spikes as in data. Why? The confidence index is a positive function of expected consumption and a negative function of expected prices. The expected consumption of each agent is higher following fiscal news shock due to higher disposable income as a result of higher expected government demand relative to the taxes at island-level. The expected prices do not change significantly because of highly rigid prices. As a result of higher expected consumption and almost constant expected prices, confidence index shifts upwards. The Euler equation in 1.55 implies that current consumption moves one-to-one with expected future consumption. Hence, with higher expected future consumption, current consumption increases as well.

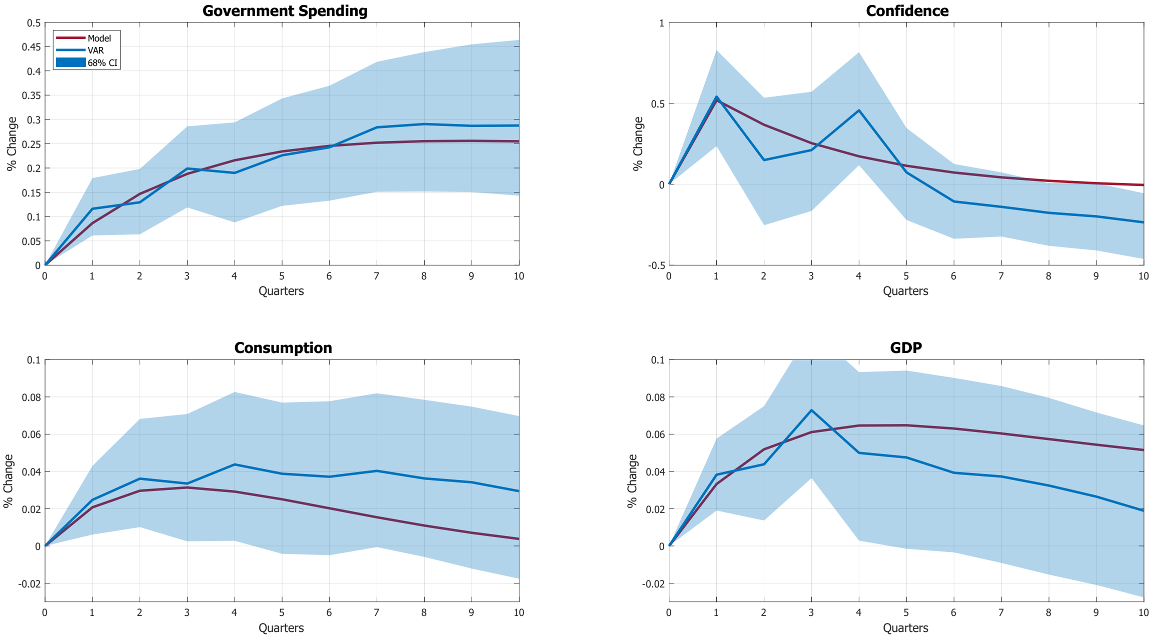

Figure 1.7: The Responses to Fiscal News Shock, Model versus VAR

Notes: Red solid lines represent the estimated model and blue solid line represents VAR estimates with 68% confidence intervals.

I conduct a counterfactual experiment to test the main mechanism of the model that generates upswings in confidence. I fix the standard deviations of idiosyncratic noises in government spending and tax signals to a small number such that $\sigma_{\eta^G} = \sigma_{\eta^\tau} = 0.001$. In this way, both signals have the similar information content. I keep

[35] I rescale the model's confidence index by multiplying by two.

all the remaining parameters at their estimated values.

Figure 1.8 presents the responses of the variables of interest under VAR, baseline estimation, and counterfactual scenario. The difference in the response of consumption to the fiscal news shock under baseline and counterfactual is remarkable. Under the counterfactual, the responses of confidence and consumption to the fiscal new shock are negative. The confidence given in Equation 1.53 moves down due to the decrease in the expected future disposable income and moves up due to the increase in average expected output. In the counterfactual, the agents expect lower future disposable income because they expect government spending and taxes directed to their island to be the same. This generates a negative wealth effect. On the other hand, as a result of higher future government spending, they expect aggregate output to increase. Overall, the former outweighs the latter, and confidence moves down. The decrease in confidence produces a decrease in current consumption, as well. The exercise shows the role of confidence in larger fiscal multipliers; when confidence does not move up in response to a fiscal news shock, the response of consumption turns to negative, and the response of GDP shrinks.

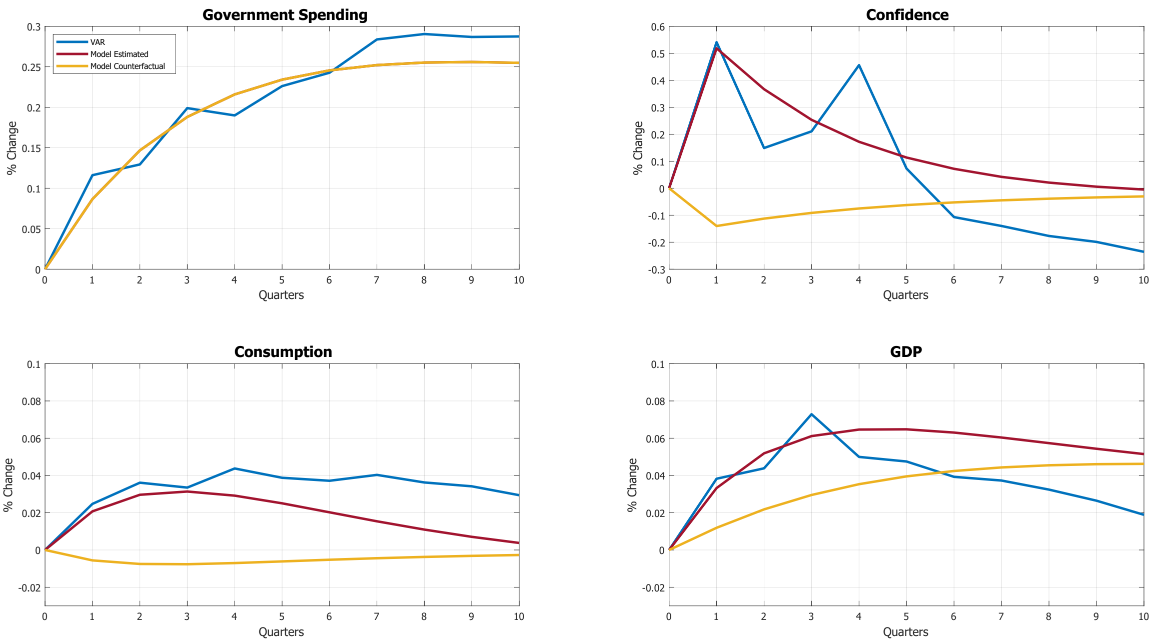

Figure 1.8: The Responses to Fiscal News Shock, Imperfect Information Model versus Perfect Information Model

Notes: Red line represents imperfect information model, blue line represents empirical VAR, green line represents perfect information model and yellow line represents fixed idiosyncratic noise model.

The counterfactual exercise confirms that the small noise in the government demand but the large noise in the tax signal is the primary mechanism of the model that generates an increase in consumption in response to a fiscal news shock. The estimation shows that this mechanism is present in the data. This is the novel result the paper brings into the fiscal policy literature; the confidence rise as a key transmission channel of the fiscal policy. The fiscal news shock improves the expectations of the agents about their future income due to the higher perceived demand relative to the perceived tax obligations as a consequence of the imperfect information.

1.6 Conclusion

The last decade witnessed the surge of interest to understand the impact of consumer confidence on real variables. In the meantime, confidence is proposed as an important transmission mechanism of fiscal policy. This paper is both an empirical and theoretical attempt to explore the confidence channel of discretionary fiscal measures on the economy, particularly on consumption. I exploit proxy for fiscal news using SPF government spending forecasts in a medium-size SVAR model to identify the fiscal news shocks in an empirical setting. I develop an island model with information frictions and government to understand the mechanism embedded in fiscal policy that could shift the expectations of the agents about the state of the economy.

First, I document that SPF government spending forecasts are subject to informational frictions. Second, I show how to account for these frictions to identify the true fiscal news shocks in an SVAR setting. The empirical results suggest that confidence, consumption, and output react positively to fiscal news shocks, especially in the short-run. The counterfactual analysis shows that the responses of consumption and GDP to fiscal news shock is much smaller when the response of confidence is fixed to the same shock. The analysis reveals the key role played by the confidence in the transmission of fiscal news shocks on the real variables.

The island model with imperfect communication a la Lorenzoni (2009) incorporated with the government sector is the first step in documenting the confidence channel of government spending in the business cycles literature. The frictions in communication prevent agents from reaching the same expectations about economic activity, and the agents use noisy signals to infer the government demand and taxes directed to their island. The noisy fiscal news leads to higher expected disposable income at the individual level if an agent expect government to purchase goods more from his island but levy taxes more on other islands. This mechanism creates optimistic expectations (higher expected income and consumption relative to the full information benchmark) about local and aggregate economic activity driven by the fiscal news shocks.

In particular, the upward shift in the expectations of future economic activity that occurs simultaneously among the agents in the model is the theoretical counterpart of the observed increase in consumer confidence. The higher expected disposable income after fiscal news shock fuels the confidence in the economy and increases the output and private consumption. From a policy perspective, empirical and theoretical findings suggest that fiscal spending can enhance the effect of the policies through its impact on confidence.

A promising avenue for future research could be to determine the situations when the fiscal policy announcements send clear signals about demand-side. This might be the case in recession or high economic uncertainty times or when the fiscal policy is well-designed so it can convince the agents about it is impact on the demand-side. Another exciting extension could be to introduce habit formation and see whether highly rigid prices are still necessary to have observed responses of consumption in data.

Chapter 2

Identifying Public Investment Shocks: Evidence From Turkey

2.1 Introduction

Public investment supports the delivery of key public services through the provision of social and economic infrastructure. The accumulation of public capital by means of these provisions can contribute to the economy-wide productivity and output growth, and these relationships are well-documented in theoretical literature (see Romp and De Haan (2007) and Bom and Ligthart (2014) for an extensive survey). In addition, public investment can be used as a major tool in countercyclical fiscal policy. In the Great Recession, many developed and emerging countries declared fiscal stimulus packages with a significant share of infrastructure investments such as the American Recovery and Reinvestment Act in the United States and European Economic Recovery Plan in the European Union. The short-run stabilization and long-run growth effects provide the rationale to stimulate the weak demand in advanced economies through increasing public investment (see, for example, European Commission 2014).

Even though the theoretical literature is well-founded, the empirical research on the dynamic impacts of public investment is sparse. The reason of this paucity stems from the unique nature of the public investments that makes difficult to identify the shocks. The public investments are multi-year investments, and they are subject to implementation lags. Hence when the investments are announced and authorized, the agents anticipate the outlays several periods in advance. Since only the outlays appear in public investment data, the fiscal foresight of the agents is highly likely to cause biased estimates of the public investment multipliers when solely the outlays are used in the estimation (see Leeper et al. 2013). In addition, the estimation of yearly data poses an endogeneity problem since it is unrealistic to assume that current investment decisions are orthogonal to current economic conditions.

To identify the shocks correctly and to address the above challenges, one would seek to use the news or announcements related to the public investments. However, such time-series data is not available for most of the public investments, and one would need to create his or her own series. This is challenging because the public investments are not one time investments and subject to amendments; therefore, the news series require updates.

The main motivation of this paper is to identify the public investment shocks by constructing a narrative news series for public investments by using novel Turkish data, called the Public Investment Programme. The Public Investment Programme published every year by the Turkish Ministry of Development captures the information related to the future public investments and addresses the above challenges in identifying public investment shocks.[1] The content of the program includes the remaining value of the investment projects that are already started but not completed and the new projects that are going to be undertaken. Hence, there is a strong reason to believe that agents can anticipate future public investment outlays in advance by using the information provided in the program. The program is announced in the first or the second week of each year before spending and output start flowing. Therefore, the timing of the program provides a rationale that announcements are exogenous to the current economic conditions.

I will use these two features of the program to identify the shocks in public investments. First, I construct a news series by calculating the expected present discounted value of future public investments. Second, I identify the news shocks by regressing news series onto the lagged real and policy variables plus expectations of future economic conditions. The shocks will reflect the change in the expectations of the agents driven by the announcements of the future public investments exogenous to the current economic conditions.

I study the effects of public investment shocks using Jordà (2005)'s local projection method. The output and consumption increase in response to a public investment shock, whereas the response of private investment is similar but not significant. There is a positive and significant contemporaneous impact on output, consumption, and unemployment, and the impact disappears after the third or fourth year. There is a second-round positive effect on these variables starting after year six, a possible long-run effect of the public investment. The news shock increases the

[1] The State Planning Organization of Turkey publishes the Public Investment Programme until 2011.

public investment outlays over the next four to five years, and the largest impact comes in the first year. The response of the private investment is not significant in all years, suggesting that public investment is neither complementary nor substitute for the private investment.

The detailed structure of the public investment program allows to identify the shocks in different types of the public investment. This is the secondary motivation of this paper since, at least to my knowledge, this will be the first paper that explores the heterogeneous impact, if any, of different types of the public investments by addressing exogeneity and foresight.[2] Moreover, over the last decade, there is an ongoing debate in Turkey such that some believed that one of the main factors behind the uninterrupted government of the ruling party since the year of 2003 is the large public investments in health and transportation sectors.[3] I aim to contribute to this debate by measuring the impact of the several types of public investments and determining whether health and transportation investments have a larger impact relative to the other types of investments.

The findings indicate that the largest impact on output comes from health, transportation, and education investments. The responses are positive and significant for the first two to three years. Interestingly, the energy investments do not have any effect on the output on impact, and the sign of the impact becomes negative after the third year until the fifth year. The relative weight of the sectors in the output and the intensity of the public capital used by the sectors in the production are the key drivers of the heterogeneous impact of public investments.

I conduct several robustness checks to ensure the validity of the results. In the first check, I estimate a VAR, and the results do not change significantly in the short-run but mitigated in the long-run. In additional checks, I add, (i) dummy for the years of recession, (ii) additional lags of the control variables, and (iii) lagged shock, and the results do not change significantly. In the second check, I define an alternative news variable to assess the plausibility of the results and find smaller responses in all variables.

The paper is organized as follows. The remainder of this section provides the literature review. In Section 2.2, I describe the Public Investment Programme in detail and discuss how I identify and construct the measure of the shock. Section 2.3 presents empirical estimation, results, and robustness checks. In section 2.4,

[2]Perreira (2001) identify different types of public investment and find the largest impact after core infrastructure investments. However, his analysis do not address endogeneity and anticipation issues.

[3]The government investments in health and transportation sectors are doubled between the years 2014 and 2002 in real terms. (Source: Author's own calculations)

I introduce an alternative definition of news variable and perform its estimation. Section 2.5 presents the theoretical model, and Section 2.6 estimates it. The last section concludes with policy recommendations and directions for further studies.

2.1.1 Literature Review

The first empirical study measuring the effect of public infrastructure on private output is the seminal work of Aschauer (1989) and has received great attention in the literature. His findings provide large private output elasticity of core infrastructure, around 0.24. However, the results obtained using the production approach has been criticized on the econometric grounds. The variables in the estimation of the univariate production function are non-stationary and the OLS estimates are spurious. In addition, the conclusions about causality are uncertain because of the possible reverse causality, and the estimation lacks feedback among the variables.

The early studies allowing the dynamic feedback among the variables are conducted by Pereira (2000) and Pereira (2001) using a vector autoregression (VAR). He finds, using yearly US data, the elasticity of private output to aggregate public investment around 0.04 and multiplier of 4.5. However, his approach requires a questionable assumption that current public investment decisions are exogenous to the current economic conditions. Moreover, he does not account for anticipation effects likely to occur in infrastructure investments.

The seminal work of Blanchard and Perotti (2002) uses quarterly data to ensure government spending is orthogonal to the current economic conditions. They assume that spending decisions are predetermined and order first in Cholesky decomposition to identify the shocks. They find that government spending shocks increase GDP, consumption, hours, and wages. The subsequent studies, such as Fatás and Mihov (2001), Galí et al. (2007), and Pappa (2009), using the same approach, find similar results. These studies look at the effect of non-defense cumulative government spending; however, without considering fiscal foresight in their estimations and without separating the government consumption and investment.

Ramey and Shapiro (1998) is the first study taking into account the anticipation effects using the narrative technique to create a dummy variable for major military buildups. They isolate the political events exogenous to the current state of the economy to ensure causality. The follow-up works of Edelberg et al. (1999) and Burnside et al. (2004) incorporate the war dates in VAR and order first in Cholesky decomposition to create expectational VARs, a term first used by Perotti (2011). Mostly, they find that spending shock increases GDP while it lowers consumption and investment. Even though they account for anticipation, these studies focus solely on the effects of military spending.

The importance of anticipation effects is well-documented by Leeper et al. (2013) in their theoretical framework. They show that econometric analysis fail to model foresight obtains biased estimates of output multipliers. The implementation lags in the fiscal policy decision expose the government spending to be anticipated by the agents. Hence, not only the military spending but also other types of government spending are subject to fiscal foresight.

Auerbach and Gorodnichenko (2012a) use OECD government spending forecasts to take into account anticipation effects and identify exogenous shocks for panel of OECD countries. They employ local projection method and they distinguish the effects in recessions and expansions. In another paper, Auerbach and Gorodnichenko (2012b) use next period government spending forecasts of Survey of Professional Forecasters (SPF) to identify government spending shocks. In both studies, they find higher spending multiplier in recessions than in expansions. In addition, they breakdown the spending component and find higher multiplier in favor of public investment.

In a similar spirit, Forni and Gambetti (2014a) construct news variable using SPF data, in an open economy setting, by summing up the forecast revisions of the government spending growth over the next three quarters to identify the news shocks. They find a larger impact of news shock on GDP and more persistent government spending after the news shocks leading to higher interest rate and appreciation of the US dollar. Caggiano et al. (2015) extend the identification of Forni and Gambetti (2014a) to a non-linear context using the Smooth Transition VAR approach and find a large, positive, and significant impact of news shock in deep recessions. In another important paper that takes into account fiscal foresight, Alesina et al. (2015) conclude that spending cuts are less costly than tax adjustments in terms of output losses after using multi-year fiscal adjustment plans of 16 OECD countries.

In all the mentioned works above except Pereira (2000), Pereira (2001) and Auerbach and Gorodnichenko (2012b), government spending is considered as a sum of government consumption and investment purchases. The first research only focusing on the impact of infrastructure investments and paying attention to the long-term anticipation effects, more than one-year, is carried out by Leduc and Wilson (2013). They forecast highway grants to the states by using institutional formulas made of state-specific factors exogenous to the state's current economic conditions. They find a positive contemporaneous impact of highway spending shock on output, which disappears after the second year and another significant effect from sixth to eighth years. However, their results cannot be converted to aggregate multipliers because state fixed effects net out any wealth effects. They rely on a theoretical model to calculate aggregate multiplier, and they find the lower bound of peak multiplier around 3.

Another paper measuring the effect of public investment is by Abiad et al. (2015). They use OECD public investment forecasts for a panel of OECD countries, and employ the local projection method in the spirit of Auerbach and Gorodnichenko (2012a). They find a short-term multiplier of 0.4 and a medium-term multiplier of 1.5. The question of whether OECD forecasts capture whole anticipation effects remains an open issue since the horizon of OECD forecasts is one year.

The relations between public investment, private investment and output also have received attention for Turkey. Ismihan et al. (2005), using the vector error correction mechanism, finds that macroeconomic instability in Turkey shatters the complementarity between public and private investment in the long-run. Altay and Altin (2008) estimate a two-sector production function approach and conclude that public investments have a positive impact on output even though the effect of total government spending is negative. Şen and Kaya (2015) find the positive Keynesian impact of government spending in the short-term, which disappears in the long-run for Turkey. The recent paper by Çebi (2016) finds peak government spending multiplier of 1.5 with a larger impact of government investment relative to government consumption on output. Çebi and Ozdemir (2016), using quarterly Turkish data from 1990 to 2015, estimate the peak public investment and government consumption multipliers 2.32 and 2.06, respectively. They show that multipliers are higher in recessionary episodes relative to expansionary ones.

2.2 News and Identification

2.2.1 Public Investment Programme

The first Public Investment Programme, PIP hereon, was issued in the year 1963. Since then, it has been published every year, mostly in the first month of the year.[4] The preparation of PIP starts with a guide published in the Official Gazzette in the second half of the preceding year, mostly between August and October. The guide states goals and scope, the sectoral and regional priorities of the public investments, and the general principals and procedures to comply with for the preparation of PIP. The common goals and the priorities of the guides since 1983 are set to achieve long-

[4]The dates of the publications are provided in the Appendix B.1.

term growth, to stimulate private investments, and to decrease regional disparities.[5] Moreover, the appropriation funds for each ministry, and institutions are stated in the PIP guide and the next year's expected public investment spending should not exceed these funds.

The ministries and other public institutions prepare their investment projects based on the goals, priorities, and procedures stated in the PIP guide and submit these projects to the Ministry of Development.[6] The submitted projects can be new projects as well as on-going ones, and the details of each project, such as value, cumulative spending, completion rate, and the social and economic benefits, should be specified. The Ministry of Development collects all the investment projects and prepare PIP. However, to be published, the amount of next year's expected spendings must be stated in the next year's government budget and approved in the parliament.[7] These spendings are the appropriated funds expected to become outlays in the next year.[8]

It is important to remember that most of these projects are ready investments; hence, they are already gone through the planning and approval processes by the ministries and the institutions. Normally, the approval of the projects is subject to legal and governmental regulations, and these may cause lags and uncertainty for the projects to be implemented.[9] Thereof, using the information in PIP mitigates these problems; however, the projects announced in PIP becomes public investment spending over the years, and the implementation lags between announcement and outlays mentioned in Leeper et al. (2010) exist.[10][11] In addition, there is strong reason to believe that these investment projects are orthogonal to the current economic conditions since the planning and approval of the projects require some time

[5] The other goals and priorities can be different depending on the year; for example, in the guide of 1997, it is stated that the projects should comply with the policies aiming at decreasing the budget deficits and inflation rate, and such statement does not exist in the guide of the year 2016.

[6] Until 2011, the projects were submitted to the State Planning Organization (SPO); however, SPO is incorporated into the newly established Ministry of Development in year 2011.

[7] In Turkey, the government budget is approved in December and goes into effect from the 1st of January, beginning of the fiscal year.

[8] I use outlay, spending, and expenditure interchangeably.

[9] To be confirmed, projects must be approved by different institutions and local authorities. Therefore, there is an implementation lag when the projects are first planned, and public investments are initiated. It is difficult to measure this lag because different projects are subject to different legal procedures.

[10] Since the projects are already approved, agents might receive signals of the project during the planning or approval processes. Hence, the anticipation in PIP could be predicted. However, even the agents receive signals, a project that is not listed in PIP is not going to be undertaken in that year.

[11] In Leeper et al. (2010), the part of the authorized spending becomes government investment every year and the implementation lags between announcements and outlays can distort the inferences about the impact of government spending.

to be completed suggesting that public investment projects are unlikely to react to business cycles, but investment spendings might react to the current economic conditions since they are yearly decided.

The program lists all the public investment projects that are already started yet not completed and new projects that are going to be undertaken. However, it does not list the projects that are fully completed and uncompleted but became unfeasible for further spending. In other words, PIP only contains the projects that are expected to build public capital in the future. The information given for each project in PIP consists of the value or total cost of the project, the expected cumulative spending up to the current year after the beginning of the investment, and the announcement year's expected spending.[12] The PIP does not give information about the expected spendings per year over the next years nor the spendings of completed projects.

In order to give a better idea of how the public investment projects listed in PIP look like, Table 2.1 lists a sample of the public investment projects in the transportation sector taken from 2015 PIP, published on 14th of January 2015. In the first row, the total value of the project covers the amount of investment to be spent on the projects from the beginning until the completion. The expected cumulative spending is the amount that has spent so far on the project from the beginning year of the project until the year when PIP is published. The expected spending is the authorized funds to spend on the projects in the announcement year. The second row stands for the total transportation investment projects; third row stands for the total railway investment projects and fourth row for the fast railway project between Istanbul and Ankara. The same information is given for all projects for the ten different sectors in the PIP.

The information given in PIP is useful to anticipate future public investments. Considering Table 2.1, the difference between the total value and the expected cumulative spending gives the expected future value of the transportation investments as of the year 2015. Since these values are in already 2015 prices, the difference gives the present value of the future public investments in transportation. The duration to complete the projects can be found simply by dividing the present value to the expected spending in 2015.[13] The same information is given for all types of public investments, and the present value of future public investments can be calculated

[12]The cumulative spending is in expected terms because of the timing since the projects are submitted before the end of the year when the total spending for the last year is not known completely.

[13]The same method is used by the public officials in determining the duration of the projects to be completed.

in a similar fashion. This structure of PIP provides strong evidence that outlays are known to the agents in advance, meaning that agents can anticipate the future public investment outlays before it actually incurs. Thus, considering the biases fiscal foresight pose, one would not want to use outlays in estimating the impact of public investments, and this motivates exploitation of the information given in the Public Investment Programme for the analysis.

Table 2.1: The sample public investment projects in the transportation sector in 2015 Public Investment Programme

Project Name	Total Value of Project	Total Expected Cumulative Spending in 2014	Total Expected Spending in 2015
Total Transportation	217.361.443 TL	103.316.410 TL	14.500.534 TL
Total Railway	69.953.000 TL	23.328.541 TL	6.960.000 TL
Ankara-Istanbul Fast Railway	9.912.917 TL	7.336.682 TL	651.617 TL

There are a couple of issues to consider regarding the design and content of PIP. Even though the projects are planned before the announcement year implying that they are orthogonal to current economic conditions, the government can use PIP by including or removing the projects in response to a slowdown in economic activity or news about future output. Therefore, to fully isolate the contemporaneous impact of economic conditions on PIP, one should control for the information set of the agents that also captures the expectations of the future state of the economy as of the time when the announcements made.

The other issue is related to the credibility of the announcements made in PIP. The government that announces many projects or projects with large amounts increases the total value of the projects in PIP may not accomplish the goals and finish all the projects because of the budget constraints. In that case, funds can be allocated to certain projects, and the remaining projects without receiving any funds become unfeasible to invest. This is what happened during the second half of the 90s in Turkey. The net present value of the projects sharply increased; however, the funds remained roughly similar to the previous years, and the duration of the projects became longer. The funds went to the projects that are important politically or economically, and the other projects did not receive funds and became unfeasible over the years. The unfeasible projects removed from PIPs gradually starting with the second half of the 2000s.[14] The Figure 2.1 shows the present value, number, and duration of projects in PIP per year for the years between 1983 and 2016. As evident in Figure 2.1, the duration plays an important role, and the longer the duration of the projects, the more likely the projects become unfeasible. The significant changes in the duration of the projects will constitute a basis in assessing the credibility of PIPs in the analysis, discussed in detail in the next section.

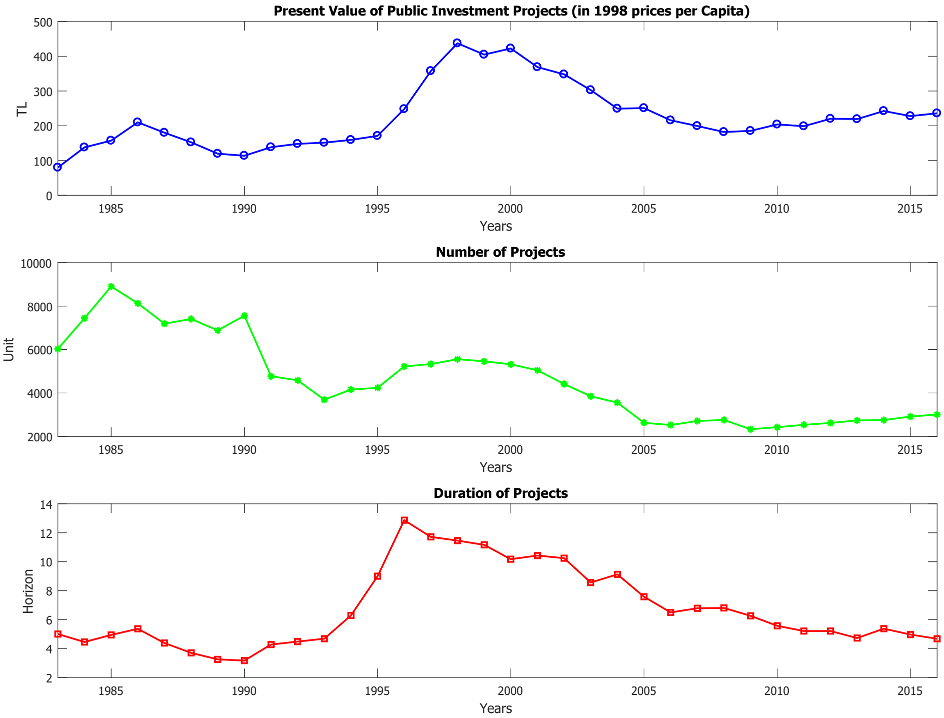

Figure 2.1: The net present value and duration of the public investment projects between 1983-2016

To summarize, the forecastability of the public investment outlays and the timing convention of the announcements will be used in the empirical strategy for two purposes. First, to address the issues of fiscal foresight and second, to remove the endogenous component of the public investment spending in response to current economic conditions. Moreover, the credibility issue in the PIP is addressed by using the duration of the projects given in PIP.

[14]Unfortunately, the Public Investment Programme or any other source does not provide information about the number of projects which become unfeasible and discarded. Therefore, I limit myself to the few information given in the newspapers concerning the number of projects and feasibility to draw a general conclusion.

2.2.2 Identification

The identification of the public investment shocks is done in few steps that rest on the information and timing of the projects given in PIPs. In the first step, the present value of the future public investments is calculated. Let k and H to be the beginning and the ending periods of the project, respectively, and t as the announcement year. The announcements are made at the beginning of the year t, and denote the expectations of the agents formed at the time of the announcements as E_t^P. The nowcast and actual values of the output and the public investment are different since expectations are formed at the beginning of the year and actual values are gathered at the end of the year, i.e. $E_t^P(Y_t) \neq Y_t$ and $E_t^P(G_t) \neq G_t$ where Y_t and G_t stand for yearly per capita output and public investment, respectively.

By using the notations above, the total value of the projects per capita in PIP is equal to:

$$TV_t = \sum_{h=-k}^{-2} G_{t+h} + E_t^P G_{t-1} + \sum_{h=0}^{H_t} E_t^P G_{t+h} \tag{2.1}$$

The expectation operator at time t for government investment at $t-1$ might seem awkward; however, remember that the information related to the projects is submitted before the end of year $t-1$, and the institutions submit expected spending for year $t-1$ rather than the actual spending. This is the reason that $E_t^P G_{t-1} \neq G_{t-1}$ and the information is in expected terms. The expected cumulative spending of the projects, the outlays incurred from the beginning of the project until year $t-1$ is equal to:

$$CS_t = \sum_{h=-k}^{-2} G_{t+h} + E_t^P G_{t-1} \tag{2.2}$$

The difference between the total value and cumulative spending is equal to the present value of the future public investments per capita at time t:

$$TV_t - CS_t = E_t^P[PV_t] = \sum_{h=0}^{H_t} E_t^P G_{t+h} \tag{2.3}$$

This present value is in year t prices, and by using the official deflator published with the PIP guide, the present value can be converted to year $t-1$ prices by dividing to the deflator. Then, multiplying this by the GDP deflator gives the value at constant prices.

The unknown in the present value formula of equation 2.3 is the horizon H_t and it can be calculated by dividing present value to the next year's expected spending: $H_t = E_t^P[PV_t]/E_t^P G_t$. Using this formula reveals that duration H_t is not constant across the years and it ranges from three to twelve years from 1983 to 2016, as already shown in Figure 2.1. To be comparable across different periods, the horizon of future public investments should be the same. One possibility is to construct a formula in the spirit of Leduc and Wilson (2013) by extending the horizon of anticipation to infinity. Another possibility is to keep H_t constant across periods, and this method also points to the credibility issue discussed in the previous section.

In the baseline estimation, I choose to keep H_t constant, and in the extension presented in Appendix B.2 I use H_t derived from PIP and extend the horizon to infinity. The reason to keep H_t constant in the baseline version is that Turkish data suggest that the longer duration increases the probability of the projects to become unfeasible and decreases the credibility of PIPs. The data also suggest that the average duration to complete the projects is around six years for two different samples; 1963-1982 and 1983-2016. I maintain simplifying assumption of credibility by using this average duration of six years in a way such that the agents give zero probability to the projects with duration longer than six years and one to the projects with duration less or equal to six years. In other words, if the duration is twelve years, the agents believe only 50% of the projects are credible, and if the duration is three years, agents believe the projects are 100% credible and will double in six years. Of course, it may take more than six years to complete some investments, or some investments completed in three years may not be rebuilt again in the next three years. However, the average duration gives good proxy with respect to the credibility of PIPs considering the facts mentioned early.

I define the expected present value of the public investments over the next six years and define them as narrative news series in the spirit of Ramey (2011). I construct news series for each year from 1983 to 2016 and news received at year t is equal to:

$$\tilde{e}_t(0,5) = \sum_{h=0}^{5} E_t^P(\tilde{G}_{t+h}) \tag{2.4}$$

where $\tilde{G}_t$ is the real per capita public investment spending, and the news variable $\tilde{e}_t(0,5)$ stands for the sum of expected real per capita public investments from t to $t+5$ at the beginning of year t.

Table 2.2 shows the relevance of the news variable on the cumulative government investments for different horizons. To derive the statistics, I regress log of cumulative real per capita public investment spending on the log of the news variable $\tilde{e}_t(0,5)$. The news variable has high R^2 for the years from 0 to 3 and significant F-statistic for the same years. However, the explanatory power loses strength starting from year 4.[15] These findings are in line with the structure of PIP. The increase in the

[15]The results do not change if the horizon is extended to nine years, and both R-squared and

value of the projects stimulates public investment spending in the first few years; however, the inclusion of new projects over time reduces the explanatory power of PIP after several years.

Table 2.2: The Explanatory Power of News Series

Horizon (Cumulative Public Investment)	(1) R-squared	(2) F-statistic
0	0.685	67.289 (0.0002)
1	0.516	31.921 (0.0003)
2	0.347	15.435 (0.004)
3	0.195	6.789 (0.0146)
4	0.068	1.956 (0.1733)
5	0.009	0.229 (0.6362)
6	0.003	0.065 (0.8016)

Note: The columns (1) and (2) show statistics from a regression of log cumulative real per capita public investment spending on log of current news variable, $\tilde{e}_t(0,5)$*. The parentheses denote p-values. The sample covers years from 1984 to 2016.*

To identify the shock, I cannot take for granted that the news variables are exogenous to current economic conditions, as opposed to Ramey (2011). In a similar way of Forni and Gambetti (2014a), I propose the following strategy to identify the public investment news shocks. The time t news variable is regressed on time $t-1$ information set of agents, and the residual is the identified news shock.[16] Assume information set at $t-1$ consists of news, output, government investment spending, government consumption expenditure, debt-to-GDP ratio, and tax rate all in per capita real terms and regress time t news variable as follows:

$$e_t(0,5) = \alpha + \psi_e e_{t-1}(0,5) + \psi_y y_{t-1} + \psi_{gi} g^I_{t-1} + \psi_{gc} g^C_{t-1} + \psi_d debt_{t-1} + \psi_t tax_{t-1} + \psi_f FR_t + \varepsilon_{1,t} \tag{2.5}$$

where the news variable is in logs, denoted as $e_t(0,5)$, as well as all the other variables, except *debt* and *tax*, already in percentage terms, and the very last regressor FR_t also in percentage terms. The term FR_t is the OECD forecast revisions for GDP growth in Turkey in year t, the difference of the growth forecasts made in the second half and first half of the year $t-1$. It is included to capture the response of the government to news about the future growth of the economy through public

F-statistic remain very low for the following years.

[16] Here, I use AIC and BIC to determine the length of the lag in the regression, and both criteria suggest lag equal to one.

investments.[17] This term is included in the regression to control for forward-looking nature of the policy and ensure the exogeneity of the shock. If the government responds to surprises in the growth forecasts, the residual in the equation 2.5 would be confounded. The residual $\varepsilon_{1,t}$ in the equation 2.5 is the identified public investment shock, henceforth $shock_t$. It contains information about future public investments that are unexpected by the agents before the announcements made at year t.

The first assumption says that the agents may receive signals about the future public investments before PIP is published, but they do not react to these signals before the announcements are made. In other words, the first assumption pronounces that PIP is the only relevant variable for the agents to form expectations about future government investment spending. The second assumption ensures the exogeneity of the identified shock. The third assumption implies that Equation 2.5 captures the expectation formation of the agents to the announcements.

The public investment shock, with the specified assumptions, is exogenous because the announcements are made at the beginning of the year before actual investment spending and output starts flowing. Hence, the news shock takes into account anticipation effects and is exogenous to the current economic conditions and addresses the problems posed by fiscal foresight and endogeneity of the yearly public investment spending to the current economic conditions.

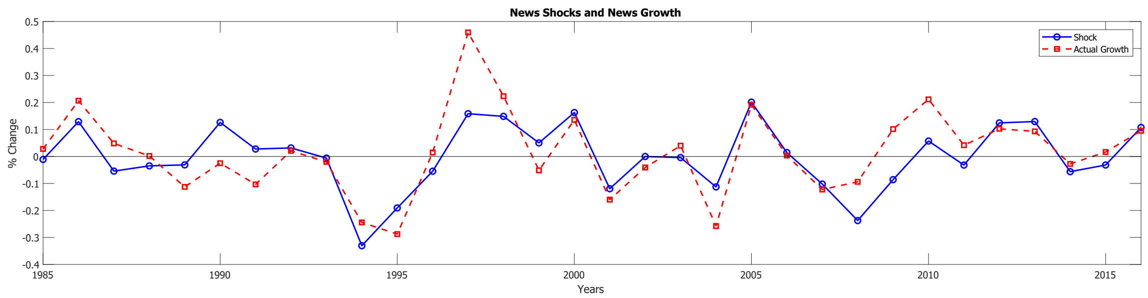

Figure 2.2: The growth of the news variable and the news shock over time

Notes: The figure shows the identified public investment news shock (blue) after estimation of equation 2.5 and growth of news series (dashed red).

Figure 2.2 shows how the growth in the news variable and news shocks behave between the years 1985 to 2016 after the identification using Equation 2.5, and they mostly overlap except for a few years. There was an economic crisis in Turkey in the year of 1994, and one of the precautions taken by the government is to cut the budget deficit in Turkey by decreasing government spending. The impact of the

[17] I have to assume that output forecasts of the government and OECD are the same to account for growth surprises in the data. In addition, OECD forecasts should not contain systemic forecast errors so that changes in the growth expectations are due to fundamental variables.

crisis and following government policy is the lower public investment announcements in the program of the year 1995. The years 1997 and 2005 witnessed a significant increase in public investment projects in transportation and health.

2.3 Empirical Framework and Results

2.3.1 Econometric Model and Data

The objective of this section is to use the news shock identified in the previous section to measure the impact of public investment on GDP and other variables. To do so, I employ Jordà (2005) local projection method to estimate impulse response functions. The baseline specification is:

$$y_{t+h} = \alpha_h + \delta^h \hat{shock}_t + \phi_h(L)X_t + u_{y,t+h} \tag{2.6}$$

for $h = 0, 1, ..., 9$ where y_t is the logarithm of real GDP per capita, $\hat{shock}_t$ is the identified public investment shock (the residual of the equation 2.5 termed by $\varepsilon_{1,t}$) in the previous section and X_t are the control variables that are real GDP per capita, government consumption per capita, real public investment spending per capita, all in logs and debt-to-GDP ratio and tax revenue-to-GDP ratio. $\phi_h(L)$ is a polynomial in the lag operator. The coefficient δ^h identifies the impulse response function of real GDP at time $t+h$ to the shock at time t. Each equation is estimated separately for each horizon h, and lags of the variables are included to control for any anticipation effects that can be missed by the shock. I use AIC and BIC information criteria to determine the length of the lags, and both tests gives lag length equal to one; hence, equation 2.6 is regressed on shock and one period lagged values of the control variables. In the robustness checks, alternative lag lengths are considered, and the results turn out to be similar to the baseline estimation. I use heteroscedasticity and autocorrelation consistent covariance estimators to take into account the serial correlation in the error term inherent in these types of specifications.

I estimate equation 2.6 using Turkish data from 1982 to 2016. Since I use the lags of the variables in the data set, the shock variable is available for the years 1984-2016. Even though the PIP and macro data of Turkey go back to 1963, Turkey became an open economy after 1980. To avoid the strong impact of government on the economy prior to 1980 and to allow for the economy to adjust from the closed economy to an open market economy, the data starting from the year 1982 is used. Before turning into other macroeconomic variables, I start by looking at the effect of the shock on GDP.

Before going into results, it is worthwhile to discuss why I opt for the Local

Projection Method (LPM, hereon). The LPM offers a number of advantages for obtaining impulse responses compared to an estimated VAR (see Jordà (2005) for discussion). First, direct projections are more robust to misspecification with too few lags in the model. The impulse response from a VAR is obtained by recursively iterating on the estimated one-period ahead forecasting model. Thus, this impulse response "is a function of forecasts at increasingly distant horizons, and therefore misspecification errors are compounded with the forecast horizon." as stated by Jordà (2005). This is a particular concern in the current context given that public investment spending, may have real effects many years later. By estimating the impulse response at each forecast horizon separately, the direct projections method avoids this compounding problem. Second, the confidence intervals for IRFs from the direct projections can account for clustering, heteroskedasticity, and serial correlation, whereas bootstrapping is the main tool to compute standard errors for VAR-based IRFs, which can be problematic in small samples.

2.3.2 Results

Panel A of Figure 2.3 shows the impulse response of GDP to the identified public investment shock - that is, the estimates of δ^h- for horizons $h = 0$ to 9 years. The dark shaded band gives the 68% confidence interval and the light shaded area gives the 90% confidence interval. There is a positive and statistically significant increase in output at impact and one-year after in response to the public investment shock. The effect on output becomes negative from years 3 to 5 but then increases again and reaches its peak in year seven and finally fades back to zero in the last year.

Panel B of Figure 2.3 exhibits the estimated response of GDP based on the measure of shock variable using next year's expected public investment spending rather than the total present value. This shock variable can be seen as analogous to Auerbach and Gorodnichenko (2012b) since it only uses a one-year forecast horizon. This measure of shock captures the part of the information given in PIP, next year's expected spending rather than taking into account the full information revealed in PIP. The response in Panel B exhibits similar behavior; however, the magnitude of the response is much less pronounced in all years relative to the response in Panel A.

The responses in Figure 2.3 points to the importance of the anticipation horizon of the agents. If the shock misses the forecast revision of spending for the second year and onward and only uses next year's expected spending, the useful information is discarded, and the responses become smaller relative to the baseline.

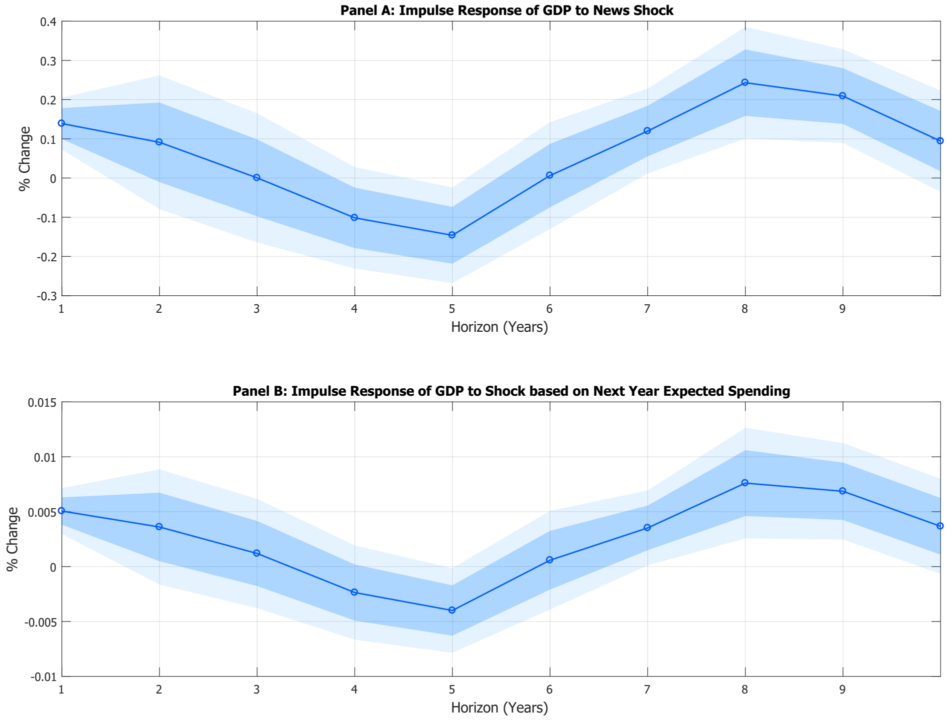

Figure 2.3: IRFs of GDP to Public Investment Shocks

Notes: Panel A displays response of GDP to the shock identified in section 4. Panel B displays response of GDP to the shock using forecast error. Solid lines are point estimates, dark shaded area is 68% CI and light shaded area is 90% CI.

The estimate of the impulse responses of the macroeconomic variables to the public investment news shock is shown in Figure 2.4. I measure the responses for consumption, investment, and unemployment rate by estimating equation 2.6 for each of the variables after enlarging the control variables by including the lagged value of the variable to be estimated. The impulse response of the consumption has a similar shape like GDP; however, the effect is larger on impact. The response of the private investment is similar to the response of GDP to some extent; increases on impact, decreases after two years and again increases for the years 5-8, and finally, the effect disappears. However, the size of the effect is larger relative to GDP but not significant. The impulse response of unemployment has a reverse shape of the IRFs of the previous three variables, and consistent with the results so far, unemployment is low when consumption and investment are high, and it is high when consumption and investment are low.

The IRFs of macroeconomic variables in Figure 2.4 suggest that public investment has a positive and significant effect on the economy in the short-run and long-run. One possible explanation for these findings is that the short-run effect is due to the increased spendings, and the long-run effect is the result of increased productivity.

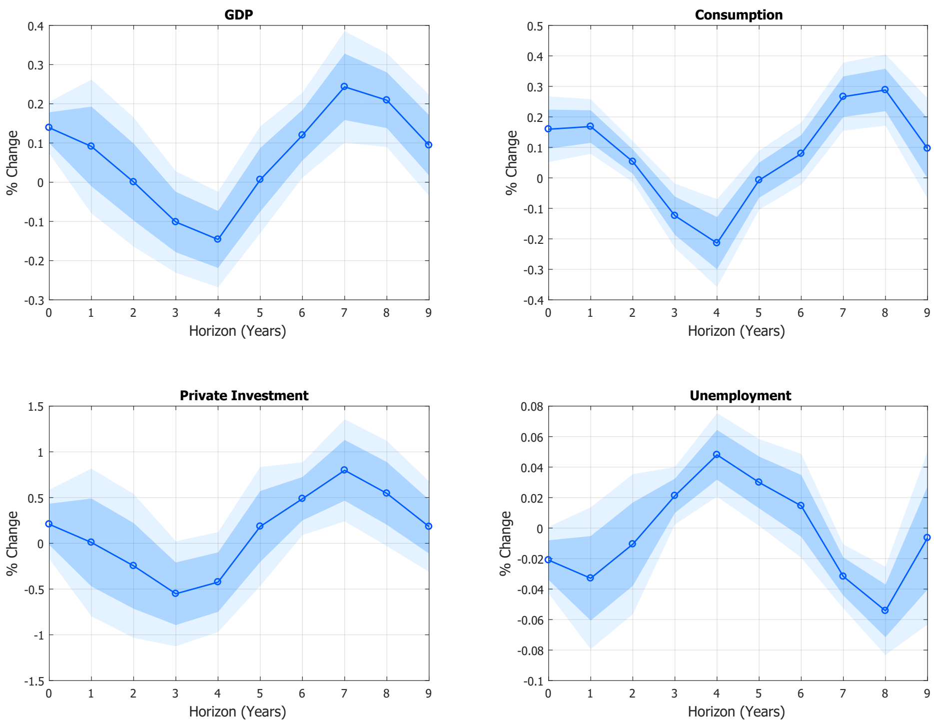

Figure 2.4: IRFs of Macro Variables to Public Investment News Shock

Solid lines are point estimates of shock using equation 2.6. In all figures, dark shaded area is 68% CI and light shaded area is 90% CI.

To assess these findings more precisely, I look at the responses of the variables that could be directly affected by the public investment shocks rather than through general equilibrium channels. The first row of the Figure 2.5 shows the responses of announcements (news) and public investment outlays. As one would expect, the announcements increase on impact and up to four years before starting to decrease, and the effect dies out after the sixth year. The outlays also follow a similar pattern, increase sharply on impact, and positive response holds until the fourth year. Then, the response turns to negative up to the sixth year, and eventually, the response vanishes. One might be surprised by the initial impact of news shock on actual public investment outlays. This is purely due to the timing convention; the news shock is identified at the beginning of the year, whereas the public investment outlay is year-end variable. Hence, there is a one-year difference between the time of the shock and the impact on actual outlay.

The results in Figure 2.5 are consistent with previous findings. The increase in the announcements leads to higher actual spending on public investments in the short-run that increases the consumption, investment, and output through demand effect. In the long-run, starting from year six, the response of outlays is almost zero, meaning that government spending is very close to zero in GDP identity. However, the responses of consumption, investment, and output are positive. This is a piece of convincing evidence for the productivity effect of public investments. This evidence also explains the main reason behind the increase in investment, consumption, and output in the long-term. The second row of Figure 2.5 displays the responses of debt-to-GDP ratio and tax rates. Public debt does not increase on impact and only increases in the years 3-5 and tax rates increase on impact and up to four years to generate the revenue necessary to fuel the spendings on investment and start to fade out after the fifth year.

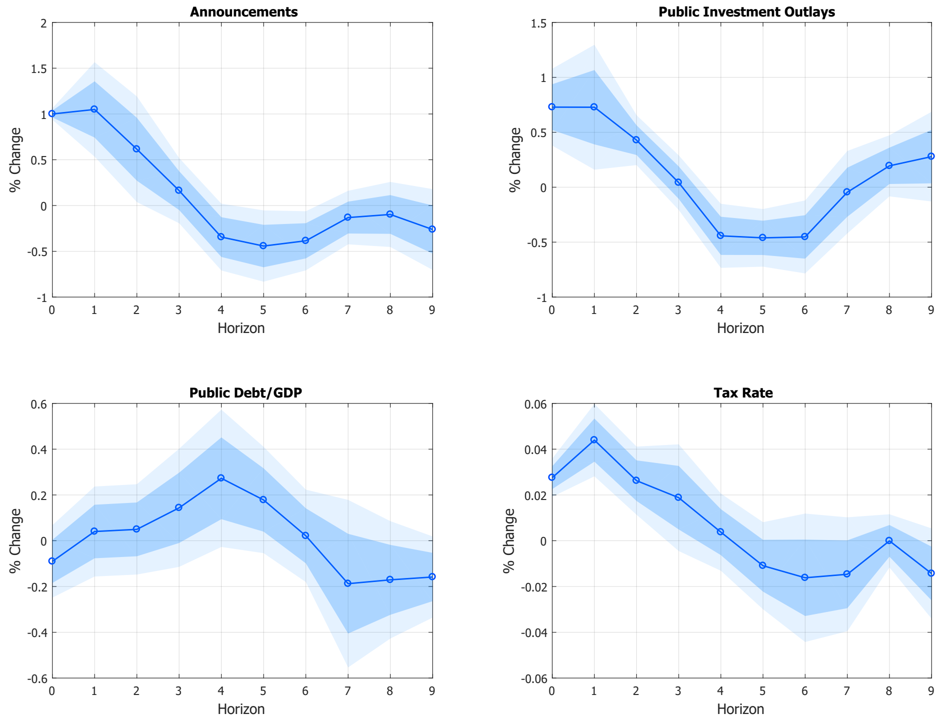

Figure 2.5: IRFs of Policy Variables to Public Investment News Shock

Solid lines are point estimates of shock using equation 2.6. In all figures, dark shaded area is 68% CI and light shaded area is 90% CI.

The results indicate that public debt grows at the same speed as GDP in the initial years, and the government raises taxes to compensate for the increased spendings. Comparing the responses of tax rates and consumption depicts an unobserved effect that offsets the negative wealth effect of the higher tax rates. One of the immediate explanations could be higher wages after positive shock, but, unfortunately, wage data for Turkey does not go back after 1999 that makes the estimation not possible. Another explanation could be a positive wealth effect due to higher real estate prices after public investments. This channel is never studied in the literature and could be a promising avenue for further research.

2.3.3 GDP Multipliers

The coefficient estimated in the previous subsection, δ^h, represents the percentage change in GDP in response to a one-unit change in $shock_t$. The common practice in the literature is to convert the percentage terms into the multipliers by comparing the peak output response to the initial government spending impact effect. However, as argued by Mountford and Uhlig (2009) and Uhlig (2010), the multipliers should be calculated as the integral of the output response divided by the integral of the government spending. I follow this method in calculating the public investment multiplier of Turkey. First, I calculate the cumulative multiplier by taking the ratio of cumulative output response over cumulative public investment response, and I convert these multipliers to Turkish Lira multipliers by multiplying them with the average output-to-public investment spending ratio. Table 2.3 shows both the ratio of the estimated coefficients and TL multipliers.[18]

Table 2.3: The Public Investment Multipliers

Horizon	Ratio of the Estimated Coefficients	TL Multiplier
0	0.1907 $[0.01, 0.38]$	4.0666 $[0.04, 8.09]$
2	0.1223 $[-0.23, 0.47]$	2.6089 $[-4.86, 10.08]$
4	-0.0114 $[-0.40, 0.38]$	-0.2439 $[-8.50, 8.01]$
6	0.1910 $[-0.21, 0.58]$	4.0751 $[-4.32, 12.47]$
8	0.7791 $[0.39, 1.18]$	16.6177 $[8.19, 25.04]$

Note: The ratio of estimated coefficients are $\frac{\sum_0^h \delta_y^h}{\sum_0^h \delta_g^h}$ *and TL multipliers are* $\frac{\sum_0^h \delta_y^h}{\sum_0^h \delta_g^h} * \frac{Y}{G}(mean)$. *The numbers in the brackets are* 68% *confidence intervals.*

The impact and one-year multipliers are 4.066 TL and 3.3695 TL for Turkey, respectively. The recent paper by Çebi and Ozdemir (2016) using Turkish quarterly data from years 1990 to 2015 and employing recursive identification found impact multiplier of 1.42 TL and a one-year multiplier of 2.26 TL for Turkey. These multipliers are smaller than the ones measured in this paper, possibly due to the fiscal foresight in public investments.. Consistent with IRFs in panel A and panel B of Figure 2.3, part of the public investment spending is anticipated and agents reacted

[18] Ramey (2016a) offers an alternative way to estimate the multipliers using an IV approach. I performed the same exercise and found similar results, as shown in Appendix B.3.

to the news before the public investment outlays occur. This is the reason why the multipliers measured after recursive identification using actual outlays are smaller than the multipliers measured using the public investment announcements. The measured TL multiplier on impact is similar to the previous estimate of the public infrastructure multipliers, as in Leduc and Wilson (2013), in which the authors estimate impact multiplier of 2.7. TL multipliers are positive in the first four years with a decreasing trend, turns to negative in years 5 to 6, then turns to a positive value in year 7, similar to the first two years. However, the last three years exhibit very high multipliers relative to literature. The two possible explanations for this phenomenon could be; one, firms in Turkey heavily use public infrastructure and larger public capital accumulated after the completion of the projects leads to a significant increase in output, and second, the long-run responses of the macroeconomic variables are not reliable possibly due to estimation errors.

An interesting feature of public investment spending that is not discussed extensively in the literature is that public investment works are mostly carried out through private contractors. The corresponding public authority writes a contract with the contractors when the project is decided to be undertaken. The contractors proceed with work and submit their bill to the government when the project is completed, partially or completely depending on contract terms. The government then transfers the funds to the contractors, and these funds show up as public investment spending in GDP. However, the contractors already purchased the goods and paid the wages to labor to finish the work and the flow of money goes into economy before public investment expenditures show up in GDP. Hence, the economic activity increases due to public investment work, but this work may or may not appear in GDP depending on the length of the work. Then, one can think output increases in the economy, but he will not attribute this increase to public investment if the payment to the contractor is not transferred in the same quarter or year. This feature of public investment could be another reason for high multipliers since, rather than only using outlay data, I use announcements data. The effects of public investments on GDP can be proxied by these announcements, even outlays do not occur and not appear in GDP data, if the project is already under construction. Hence, announcements control for the time mismatch between actual spendings and their impact on GDP, and multipliers can be large because announcements take into account this unseen effect.

2.3.4 Types of Public Investments

In this part of the paper, I present the effect of different types of public investments on GDP. Public Investment Programme disaggregates the public investment projects into ten different sectors that are agriculture, transportation, health, energy, education, housing, manufacturing, mining, tourism, and other sectors. I utilize this information to construct the news variable for each sector in the program using equation 2.4] but replacing the aggregate news variable with a sectoral news variable, and I identify the news shocks for each type of public investment.I estimate impulse response of GDP to each shock using equation 2.6, and Figure 2.6 shows the results.

The highest initial impact comes from the shocks in the agriculture, transportation, health, and education sectors. The short-run impact of energy and manufacturing investments are nearly zero. As in the case of aggregate shock, the medium-term impact of all shocks in Figure 2.6 is mostly negative, except agriculture that is positive but not significant. The long-run responses are larger in transportation, health, and education. The estimates are positive and significant after year 6 or 7. The energy sector also has a positive long-run effect but zero short-run effect.

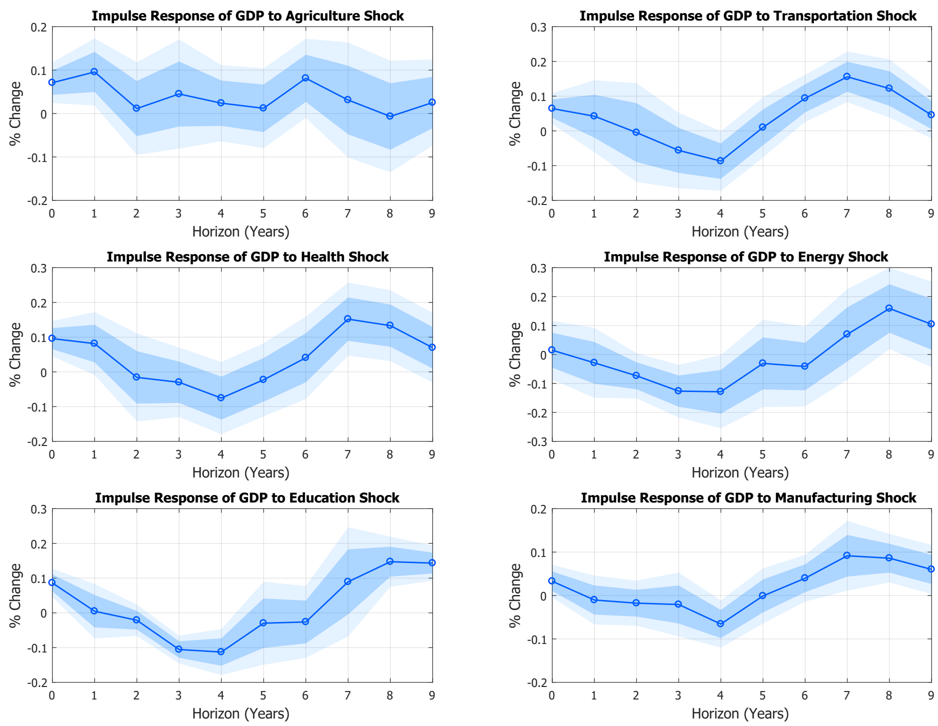

Figure 2.6: The Impulse Response of GDP to Different Public Investment Shocks

Solid lines are point estimates of shock using equation 2.6. In all figures, dark shaded area is 68% CI and light shaded area is 90% CI.

The results are in line with previous works. For example, Easterly and Rebelo (1993) find a high coefficient, from 0.59 to 0.66, of transportation investments on growth using pooled regressions and Pereira and Roca-Sagales (2001) find long-term elasticity of output with respect to transportation investments in Spain for the period 1970-1993 is 0.52. Recent work by Eruygur et al. (2012) done for Turkish data using the VECM approach also confirms the results of the previous works, and the authors conclude that a 10% increase in expenditure in transportation increases output by 3%.

The response of output to energy investments in Turkey also deserves closer attention. To produce energy, Turkey mostly imports raw materials such as natural gas and oil abroad. Hence, energy investments create domestic consumption of energy. However, this consumption goes abroad to import raw materials of energy, and this is why output in the short-run does not produce any positive response. Nonetheless, these investments possibly crowd-in private investments and enhance productivity that produces pronounced long-run effects.

The responses in Figure 2.6 suggest that public investments in transportation, health, and education sectors may be a powerful tool for policy-makers to achieve both short-term and long-term output per capita growth in Turkey.

2.3.5 Alternative Estimation and Robustness Checks

VAR Estimation

In this subsection, I estimate a VAR to measure the impact of the news shock on the macro variables. The baseline specification is a 5-variable VAR; news variable as in equation 2.4, public investment outlays, output, debt-to-GDP ratio, and tax revenue-to-GDP ratio. I maintain the assumption that the news variable is not affected contemporaneously by the other macro variables, and I apply Cholesky decomposition to the variance-covariance matrix of the residuals for the identification. I use AIC and BIC criteria to determine the optimal lag length, again one under both criteria. I extend the baseline VAR specification to measure the response of consumption, private investment, and unemployment by incorporating each variable to the baseline VAR separately and place them after output. I estimate VAR in log-levels, and all variables are in per capita terms except the ratio variables. I use bootstrap to construct confidence intervals. [19]

Figure 2.7 shows the VAR estimated impulse responses of the macro variables to a unit shock in the news variable. Similar to Jorda method output, consumption

[19] I use VAR-Toolbox for the estimation and confidence intervals. The code can be found in the following website: https://sites.google.com/site/ambropo/MatlabCodes

and investment respond positively to the shock on impact, whereas unemployment decreases following the shock. The shape of the point estimates after VAR is similar to the Jorda method as well; however, the point estimates under VAR and Local Projection are not the same. The VAR has a different number of variables relative to Local Projection, and the identified shocks are different. For example, GDP and consumption decrease in the VAR, but they do not go below zero, and their increase in the long-run is not as much pronounced as in Figure 2.4.

In addition, the confidence intervals in VAR are wider, and except for the first two horizons, the point estimates are not statistically significant for all variables. The confidence intervals from direct projection accommodate heteroskedasticity and autocorrelations. The standard errors for VAR are obtained after bootstrapping that can be problematic in small samples. This is one of the reasons that direct projection is preferred as the main estimation method for IRF estimations.

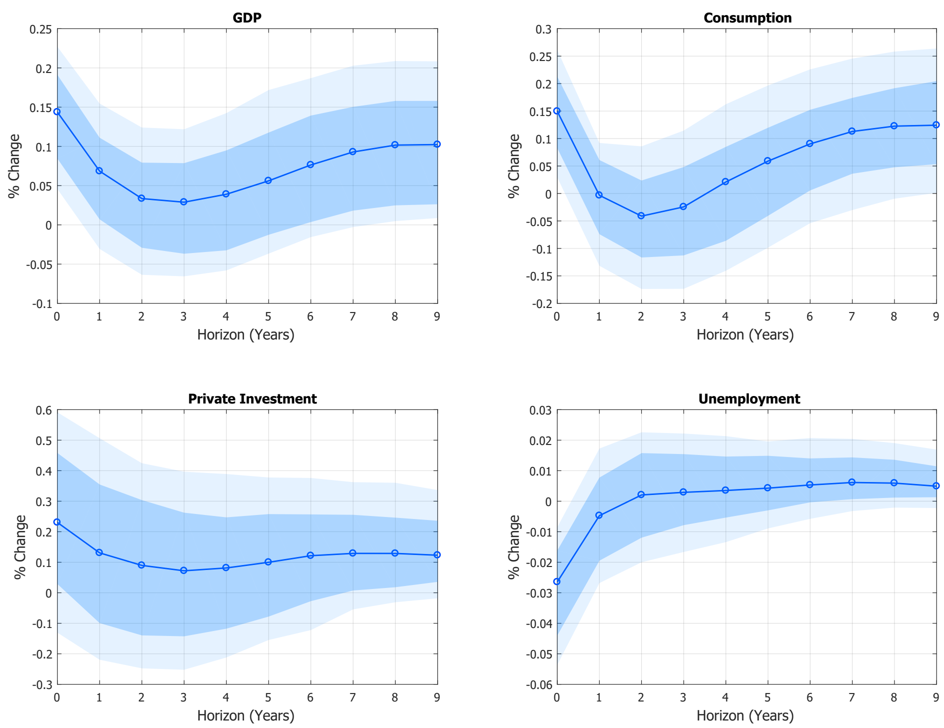

Figure 2.7: VAR estimated impulse responses of macroeconomic variables

Solid lines are point estimates of Cholesky identified VAR shock, dark shaded area is 68% CI and light shaded area is 90% CI.

Figure 2.8 displays the responses of the policy variables to a unit shock in the news variable. The VAR estimated impulse responses are very similar to the responses estimated after using the LPM method as displayed in Figure 2.5. The VAR estimated responses are smoother, and confidence intervals are larger relative to the baseline responses.

In summary, VAR estimation confirms the positive short-run and long-run and almost zero medium-run impact of the public investment spendings on the macroeconomic variables as in line with the results obtained after the LPM estimation. The magnitude of the impact in the short-run is almost the same under both estimation; however, VAR estimation propounds smaller long-run effect and less precision of the point estimates.

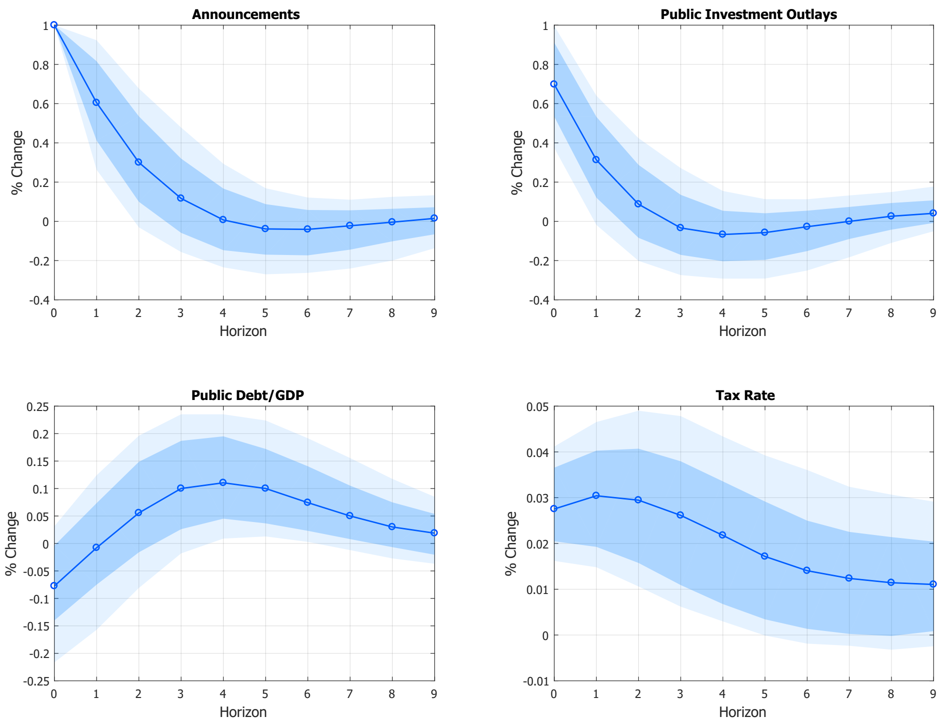

Figure 2.8: VAR estimated impulse responses of policy variables

Solid lines are point estimates of Cholesky identified VAR shock, dark shaded area is 68% CI and light shaded area is 90% CI.

Robustness Checks

I conduct several additional robustness checks to ensure the validity of the baseline estimations. I estimate equation 2.6 under various specifications; (i) including two lags of the control variables, (ii) including cubic trend into the regression for possible low frequency correlation in baseline impulse responses, (iii) including lagged value of identified shock in addition to the controls, (iv) removing OECD growth forecast revisions (no leading indicators), (v) including dummy for year 2001, the year having the largest drop in output across the sample, (vi) including dummies for the recession years that are 1994, 1997, 2001 and 2009.

Figure 2.9 presents the results of the robustness checks. The findings of the main estimation are in line with the specifications above; there is a positive impact in the short-run that turns to negative in the medium-term and returns to positive in the long-run. The responses with four dummies for the crisis years slightly wipes off the short-run effect yet the long-run effect presents. This points to nonlinear effects of public investment shock on the output, as previously shown by Auerbach and Gorodnichenko (2012a) and Caggiano et al. (2015).

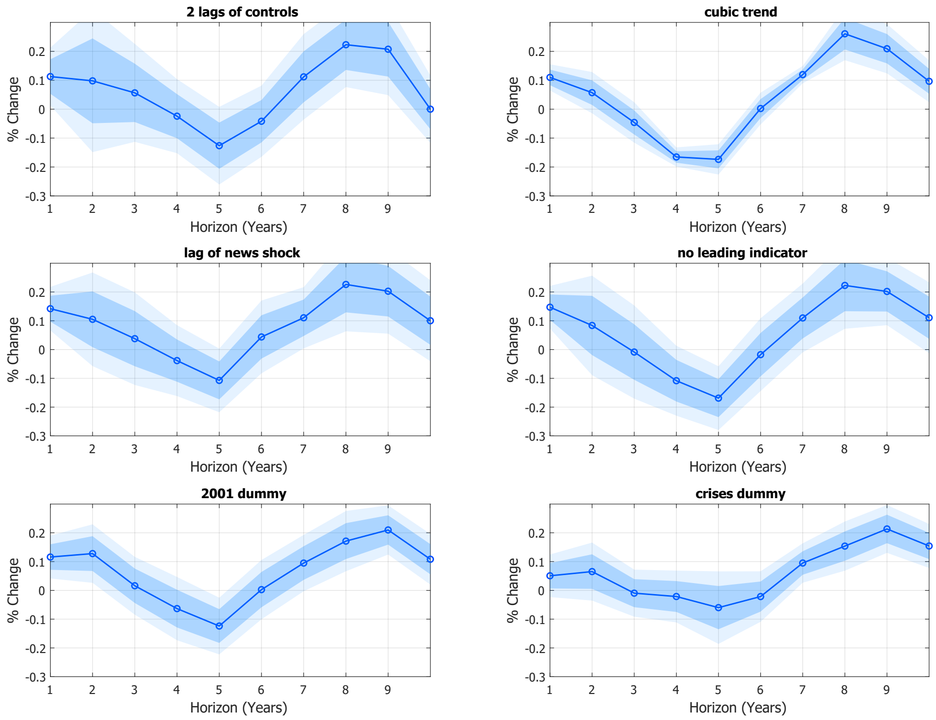

Figure 2.9: Robustness Checks

Solid lines are GDP responses to a public news shock under alternative specifications, and dark shaded area is 68% CI and light shaded area is 90% CI.

The current news variable discards the information after sixth year. I define an alternative news variable to include the information given after sixth year as well and redo all the empirical analysis using this alternative news variable. I label this alternative as full credibility case and present in Appendix B.2.

2.4 Model

This section presents a closed economy model with public capital to provide a theoretical basis for the empirical findings in the previous section. To account for the positive response of the consumption and implementation delays in the public capital expenditures, I augment the standard New Keynesian model with liquidity constrained households and the time-to-build process in public investment.

The main assumptions of the model can be summarized as follows. First, there are two types of households, Ricardian (intertemporal optimizers) and non-Ricardian (rule-of-thumb) households. The rule-of-thumbs households are introduced to have an increase in the consumption after fiscal shock following Galí et al. (2007). The households supply labor and capital to the continuum of intermediate goods firms and the households are the ultimate owners of the capital. The intermediate goods sector is characterized by monopolistic competition and staggered price setting in the style of Calvo (1983). The final goods sector, on the contrary, is characterized by perfect competition and flexible prices with one representative firm. The output of the final good firm is equal to the gross domestic product that is the sum of consumption, private investment, and government consumption and investment. The government consumption is determined stochastically and investment expenses occur through time as a share of the announced value, also a stochastic process, following Leeper et al. (2010) and the revenues are raised through lump-sum taxes imposed on the households. Finally, the central bank sets the interest rate to achieve price stability.

2.4.1 Households

The economy is inhabited by a continuum of infinitely lived households, indexed by $i \in [0, 1]$. The first type of households, called Ricardian or optimizing, have access to capital markets where they can trade a full set of state-contingent securities, and they can buy and sell physical capital without any constraints. The second type of household, called non-Ricardian or rule-of-thumb, does not have access to capital markets, and they only consume their current labor income. It is assumed that a fraction $1 - \lambda$ of the households are Ricardian type and fraction of λ are non-Ricardian type.

Ricardian Households

A typical Ricardian household maximizes its lifetime utility subject to an intertemporal budget constraint. This constraint states that the household's expense, the sum of consumption, investment, and purchase of government bonds cannot exceed income, the sum of wage, capital income, the face value of bonds, dividends, and net governmental transfers. Next, the capital held by the households depreciates at a constant rate, and investments are subject to adjustment costs.

Let C_t^o and N_t^o denote the consumption and labor supply of Ricardian household at time t. The preferences of the household are specified by the discount factor

$\beta \in (0,1)$ and the period utility function $U(C_t^o, N_t^o)$. A typical optimizing household seeks to maximize:

$$\max_{\{C_t^o, N_t^o\}_{t=0}^{\infty}} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t^o, N_t^o), \tag{2.7}$$

subject to the sequence of budget constraints

$$P_t(C_t^o + I_t^o) + \frac{B_{t+1}^o}{R_t} = W_t P_t N_t^o + R_t^K P_t K_t^o + B_t^o + D_t^o - P_t T_t^o, \tag{2.8}$$

and the capital accumulation equation:

$$K_{t+1}^o = (1-\delta_K)K_t^o + \phi(\frac{I_t^o}{K_t^o})K_t^o. \tag{2.9}$$

The first two terms on the right-hand side of the household's budget constraint are labor income $W_t P_t N_t^o$, where W_t is the real wage, P_t is the price level, and N_t^o denotes hours of work and income from renting his capital holdings K_t^o to firms at the (real) rental cost R_t^K. B_t^o is the number of bonds with a face value equal to one unit of a consumption good in period t, which were purchased by the household in period $t-1$. R_t denotes the gross nominal return on bonds purchased in period t. D_t^o denotes dividends from ownership of firms, T_t^o denotes lump-sum taxes (or transfers, if negative) paid by optimizing consumers. C_t^o and I_t^o denote, respectively, consumption and investment expenditures, in real terms and P_t is the price of the final good.

The adjustment of capital level requires adjustment costs and introduced through the term $\phi(\frac{I_t^o}{K_t^o})K_t^o$ that determines the change in the capital stock through investment spending I_t^o. The function $\phi(.)$ is assumed to be increasing, concave and it is further assumed that $\phi'(\delta) = 1$ and $\phi(\delta) = \delta$.

In the rest of the model, I follow Galí et al. (2007) and use the following instantaneous utility function of the form

$$U(C_t^o, N_t^o) = \log C_t^o - \frac{(N_t^o)^{1+\varphi}}{1+\varphi}, \varphi \geq 0, \tag{2.10}$$

where φ is the inverse of Frisch-elasticity of labor supply with respect to wages.

After rearranging, the first-order conditions for the Ricardian household's optimization problem can be written as

$$1 = R_t E_t \left\{\Lambda_{t,t+1}\right\}, \tag{2.11}$$

$$P_t Q_t = E_t \left\{ \Lambda_{t,t+1} \left[R_{t+1}^K + P_{t+1} Q_{t+1} \left((1-\delta) + \phi_{t+1} - \left(\frac{I_t^o}{K_t^o} \right) \phi_{t+1}^{'} \right) \right] \right\}, \tag{2.12}$$

$$Q_t = \frac{1}{\phi'\left(\frac{I_t^o}{K_t^o}\right)}, \tag{2.13}$$

$$W_t = C_t^o (N_t^o)^{\varphi}, \tag{2.14}$$

where Q_t is the real shadow value of capital in place, i.e., Tobin's Q and $\Lambda_{t,t+1}$ is a one-period ahead stochastic discount factor with the following general form

$$\Lambda_{t,t+k} = \beta^k \frac{C_t^o}{C_{t+k}^o} \frac{P_t}{P_{t+k}}. \tag{2.15}$$

Equation 2.11 is the no-arbitrage condition, equation 2.12 is the investment optimality condition and equation 2.13 is the expression for q_t. Equation 2.14 states the optimal labor supply condition. In this model, I assume perfectly competitive labor markets, and each household chooses the optimal amount of labor supply given the market wage.

Rule-of-Thumb Households

The second type of household, non-Ricardian or rule-of-thumb households, do not take part in capital market activities. Therefore, they neither own any capital nor save or borrow funds. Several reasons for their inactivity in the financial markets exist - the households might have no access to the market, their budget constraints are binding (or might be binding in the future), or they are myopic.

They derive utility from the utility function $U(C_t^r, N_t^r)$ subject to the following budget constraint

$$P_t C_t^r = W_t P_t N_t^r - P_t T_t^r. \tag{2.16}$$

As the households do not optimize intertemporally, they consume their whole income:

$$C_t^r = W_t N_t^r - T_t^r. \tag{2.17}$$

It is important to note that the taxes paid by the rule-of-thumb households, T_t^r, can be different from the taxes paid by the Ricardian households, T_t^o. The competitive labor market assumption implies that the following labor supply condition for non-Ricardian households should hold:

$$W_t = C_t^r (N_t^r)^{\varphi} \tag{2.18}$$

2.4.2 Firms

Final Goods Firms

Consumption goods are produced in the final-goods sector, characterized by perfect competition and constant returns to scale. Due to these characteristics, we can assume that there is one single representative firm selling its output at a price equal to the marginal cost. The firm produces the consumption goods using intermediate goods (a continuum of measure of one) by CES technology, and its profit maximization problem can be stated in the following way

$$\max_{X_t(j)} P_t \left(\int_0^1 X_t(j)^{\frac{\epsilon_p - 1}{\epsilon_p}} dj \right)^{\frac{\epsilon_p}{\epsilon_p - 1}} - \int_0^1 P_t(j) X_t(j) dj, \tag{2.19}$$

where $X_t(j)$ is the quantity and $P_t(j)$ is the price of the intermediate good j used in the production. P_t is the final goods price taken as given and $\epsilon_p > 1$ is the elasticity of substitution parameter among the intermediate goods.

The demand schedules follow from the first order conditions of the maximization problem is given by

$$X_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\varepsilon_p} Y_t. \tag{2.20}$$

By plugging equation 2.20 into the profit function of the final goods producer and using the zero profit condition, an expression of the final goods price in terms of the prices of the intermediate goods emerges as following

$$P_t = \left(\int_0^1 P_t(j)^{1-\epsilon_p} dj \right)^{\frac{1}{1-\epsilon_p}}. \tag{2.21}$$

Intermediate Goods Firm

A typical intermediate-goods firm j minimizes its real costs of producing the quantity $Y_t(j)$ demanded by final good sector. The firms use a Cobb-Douglass production technology:

$$Y_t(j) = K_t(j)^{\alpha} L_t(j)^{1-\alpha} (K_{t-1}^G)^{\alpha_G}, \tag{2.22}$$

where $K_t(j)$ and $N_t(j)$ represent the capital and labor services hired by the firm, K_t^G is the aggregate public capital used by the firm j in its production function, and α_G is the elasticity of output with respect to the public capital indicating the productiveness of the public capital. This production function assumes constant returns to scale in private inputs but increasing returns to scale with respect to public capital. The first-order conditions to the solution for cost minimization problem of the firm j, taking rental rate, wages, and public capital as given, imply the following optimal capital/labor ratio

$$\frac{K_t(j)}{N_t(j)} = \left(\frac{\alpha}{1-\alpha}\right)\left(\frac{W_t}{R_t^K}\right), \tag{2.23}$$

and the real marginal cost, common to all firms, is given by

$$MC_t = (\alpha)^{-\alpha}(1-\alpha)^{-(1-\alpha)}\frac{\left(R_t^K\right)^{\alpha}(W_t)^{1-\alpha}}{(K_{t-1}^G)^{\alpha_G}}. \tag{2.24}$$

Price setting by intermediate firms is done in a staggered way; that is, firms cannot change their prices optimally in every period. Instead, it is assumed that only a fraction of the firms reset their prices every period. This proportion is set stochastically in a way proposed by Calvo (1983). Each firm resets its price with probability $1-\theta$ each period, independently of the time elapsed since the last adjustment. Thus, each period a measure $1-\theta$ of producers reset their prices, while a fraction θ keep their prices unchanged.

In what follows, I will show how intermediate-goods firms set their prices optimally (because the firms are symmetric, I omit the subscript at the optimal price term). First, assume that the firms which change their prices set the optimal prices at the level of P_t^*. Then the price level in period t is:

$$P_t = \left[\theta P_{t-1}^{1-\epsilon_p} + (1-\theta)\left(P_t^*\right)^{1-\epsilon_p}\right]^{\frac{1}{1-\epsilon_p}} \tag{2.25}$$

which follows from equation 2.21.

A firm resetting its price in period t will seek to maximize

$$\max_{P_t^*}\sum_{k=0}^{\infty}\theta^k E_t\left\{\Lambda_{t,t+k}Y_{t+k}(j)\left(\frac{P_t^*}{P_{t+k}} - MC_{t+k}\right)\right\} \tag{2.26}$$

subject to $Y_{t+k}(j) = X_{t+k}(j) = \left(\frac{P_t^*}{P_{t+k}}\right)^{-\varepsilon_p} Y_{t+k}$. The first order condition associated with Equation 2.26 is:

$$\sum_{k=0}^{\infty}\theta^k E_t\left\{\Lambda_{t,t+k}Y_{t+k}(j)\left(\frac{P_t^*}{P_{t+k}} - \mu^p MC_{t+k}\right)\right\} = 0 \tag{2.27}$$

where $\mu^p = \dfrac{\epsilon_p}{\epsilon_p - 1}$ is the gross price mark-up holds in a zero inflation steady state.

2.4.3 Monetary Policy

The central bank in this model determines the nominal interest rate by following a simple version of the Taylor rule (Taylor (1993)):

$$r_t = r + \phi_\pi \pi_t, \tag{2.28}$$

where $r_t = R_t - 1$ is the nominal interest rate, r is the steady state interest rate ($r = \beta^{-1} - 1$) and the parameter$\phi_\pi \geq 0$ captures the response of interest rate to the inflation. This Taylor rule is a simplified version of the general rule, and the monetary policy seeks to stabilize the price level only, disregarding the level of the output gap.

2.4.4 Government

The government's expenditures consist of three parts - the first is the repayment of one-year bonds, the second is government consumption, and the third is public investment expenditures or outlays. The government raises revenue through lump-sum taxes imposed on the households and the face value of bonds, which mature in the next period. At every period t, the government uses revenues to repay bonds issued in the previous period and to finance the government consumption and investment expenditures in this period. The government budget constraint can be written as

$$\frac{B_{t+1}}{R_t} + P_t T_t = B_t + P_t G_t^C + P_t G_t^I, \tag{2.29}$$

where $T_t = \lambda T_t^r + (1-\lambda) T_t^o$. A fiscal policy rule is determined in a way to prevent explosive deviations of government debt and government expenditures from the steady-state values normalized by the steady-state income. The fiscal policy rule has the following form

$$t_t = \phi_b b_t + \phi_{gc} g_t^c + \phi_{gi} g_t^i, \tag{2.30}$$

where $g_t^c = \dfrac{G_t^C - G^C}{Y}, g_t^i = \dfrac{G_t^I - G^I}{Y}, t_t = \dfrac{T_t - T}{Y}$ and $b_t = \dfrac{(B_t/P_{t-1}) - (B/P)}{Y}$ that are deviations of government consumption and investment expenditures, taxes and real bond holdings from their steady-state values normalized by steady -ate output. In the steady-state, we assume a balanced budget ($T = G$) and zero debt level ($B = 0$). Apparently, the policy parameters ϕ_b, ϕ_{gc} and ϕ_{gi} are positive constants. A fiscal policy rule in the form of equation 2.30 assumes fiscal adjustments occur immediately.

The government consumption (in terms of its deviations from the steady-state normalized by the steady-state of output) follows an AR(1) process

$$g_t^c = \rho_g g_{t-1}^c + \epsilon_{gc,t}, \tag{2.31}$$

where $0 < \rho_g < 1$ and $\epsilon_{g,t}$ is a white noise process with constant variance σ_g^2 that represents a shock to the government consumption.

The government investment spending process affects the dynamics of fiscal policy in significant ways. In this model, public capital is accumulated through government investment subject to a time-to-build process, reflecting the lags between project announcement and completion as observed in reality. The time-to-build process separates the "stock" of public investment from the "flow" of public investment. The announcements delivered by the government and approved in the parliament, called appropriation, provide the present value of the public investment projects and can be viewed as expected stock of public investment. The flow of public investment, however, depends on the rate at which actual spending occurs. It is generally the case for public spending projects that the proportion of investment that occurs each period is a fraction of the authorized appropriation. This modeling approach is similar to the one developed by Leeper et al. (2010), and it distinguishes the accumulation of public capital stock from others in the literature, which typically assumes that authorized spending is immediately implemented (i.e., stock equals flow) and is immediately productive.

Specifically, let N be the number of years between approved announcements and completing a project. Following the functional form adopted in Leeper et al. (2010), the law of motion for public capital is given by

$$K_t^G = (1 - \delta_G) K_{t-1}^G + A_{t-N}, \tag{2.32}$$

where A denotes the net present value of the announced public investments. Equation 2.32 captures the time-to-build assumption. As an example, suppose that the government announces at time $t - 4$ for a railway project that takes four years to build ($N = 4$). Then the railway cannot be used in production until time t.

Investment outlays to complete the announced projects typically occur over time. To capture this, let the sequence $(\omega_0, \omega_1, ..., \omega_N)$ denote the spending rates from the date the announcement is made (0) to the period before project completion ($N - 1$). The completed portion of public investment at time t is then given by:

$$G_t^I = \sum_{n=0}^{N-1} \omega_n A_{t-n}, \tag{2.33}$$

where $\sum_{n=0}^{N-1} \omega_n = 1$. Continuing with the railway example, the railway may not be usable for four years but government investment expenditure increases during this time as the construction of the railway takes place. The rate at which the construction takes place is parameterized by the ωs. Authorizations of government investment are assumed to follow the process

$$\log A_t = \rho_A \log A_{t-1} + \varepsilon_{A,t}, \tag{2.34}$$

where $\epsilon_{A,t}$ is a white noise process with constant variance σ_A^2 and represents the shocks to the announcements.[20] Specification 2.33 for government investment is motivated by the observation that the amount of government investment announced often deviates substantially from contemporaneous outlays, as discussed in the previous section and shown in Table 1.4. I choose $N = 6$ in the model to be consistent with the empirical estimation performed in the previous section.

2.4.5 Equilibrium Conditions

The equilibrium of the economy described by this model is characterized by the following conditions:

- Households, intermediate and final-goods firms maximize their optimization problems in each time period t.
- The government and monetary authority follows the specified rules.
- Aggregation conditions are given by a weighted average of the corresponding variables for each consumer type
  - Consumption: $C_t = \lambda C_t^r + (1-\lambda)C_t^o$.
  - Labor supply: $N_t = \lambda N_t^r + (1-\lambda)N_t^o$.
  - Capital: $K_t = (1-\lambda)K_t^o$.
  - Investment: $I_t = (1-\lambda)I_t^o$.
- Market clearing requires that the following conditions are satisfied for all t
  - Labor market: $N_t = \int_0^1 N_t(j)dj$.
  - Capital: $K_t = \int_0^1 K_t(j)dj$.
  - Intermediate Inputs: $Y_t(j) = X_t(j)\ for\ \vee j$.
  - Final Goods: $Y_t = C_t + I_t + G_t^C + G_t^I$.

2.4.6 Log-linearized equilibrium conditions

In this section, I will present the log-linear approximation of equilibrium conditions around their steady-state values. From now on, the lower-case letters will denote the natural logarithm of a variable or a log-deviation of a variable from its steady-state value.

[20] It is the theoretical counterpart of the news shock identified in the previous section

Households

The log-linear equations describing the dynamics of Tobin's Q and its relationship with investment are given respectively by

$$q_t = \beta \mathrm{E}_t \left\{q_{t+1}\right\} + \left[1 - \beta\left(1-\delta\right)\right] \mathrm{E}_t \left\{r^k_{t+1} - p_{t+1}\right\} - \left(r_t - \mathrm{E}_t\left\{\pi_{t+1}\right\}\right), \tag{2.35}$$

$$i_t - k_t = \eta q_t. \tag{2.36}$$

Capital accumulation equation is approximated by the following equation

$$k_{t+1} = (1-\delta)k_t + \delta i_t. \tag{2.37}$$

The log-linearized Euler equation for optimizing households is given by

$$c^o_t = \mathrm{E}_t\left\{c^o_{t+1}\right\} - \left(r_t - \mathrm{E}_t\left\{\pi_{t+1}\right\}\right), \tag{2.38}$$

where $c^o_t = \dfrac{C^o_t - C^o}{C}$. Under perfectly competitive markets, wage-schedule consistent with balanced growth is approximated by

$$w_t = c_t + \varphi n_t. \tag{2.39}$$

Consumption for rule-of-thumb households is given, letting $c^r_t = \dfrac{C^r_t - C^r}{C}$, to a first order approximation by

$$c^r_t = \left(\frac{WN^r}{C^r}\right)(w_t + n_t) - \left(\frac{Y}{C^r}\right) t^r_t, \tag{2.40}$$

where $t^r_t = \dfrac{T^r_t - T^r}{Y}$. Following Galí et al. (2007), the steady-state consumption among different types of households is assumed to be equal, i.e., $C^o = C^r = C$. This outcome can always be guaranteed by the appropriate choice of transfers between the households. In particular, under the above assumption, the log-linearized expressions for aggregate consumption and hours take the following simple form

$$c_t = \lambda c^r_t + (1-\lambda)c^o_t, \tag{2.41}$$

$$n_t = \lambda n^r_t + (1-\lambda)n^o_t. \tag{2.42}$$

When the decisions of both types of households are plugged into the equation, we obtain an aggregate equilibrium condition for consumption

$$c_t = E_t\left\{c_{t+1}\right\} - \sigma\left(r_t - E_t\left\{\pi_{t+1}\right\}\right) - \Theta_n E_t\left\{\Delta n_{t+1}\right\} + \Theta_t E_t\left\{\Delta t^r_{t+1}\right\}, \tag{2.43}$$

where

$$\sigma = \frac{(1-\lambda)\left[\mu^p \varphi \gamma_c + (1-\alpha)\right]}{\mu^p \varphi \gamma_c + (1-\alpha)(1-\lambda(1+\varphi))},$$

$$\Theta_n = \frac{\lambda(1-\alpha)(1+\varphi)\varphi}{\mu^p\varphi\gamma_c + (1-\alpha)(1-\lambda(1+\varphi))},$$

$$\Theta_t = \frac{\lambda\mu^p\varphi}{\mu^p\varphi\gamma_c + (1-\alpha)(1-\lambda(1+\varphi))},$$

and $\gamma_c = \frac{C}{Y}$ is the steady state share of consumption on output. The log-linear relationship in equation 2.43 is the only one dependent on the share of rule-of-thumb households λ. Also notice that as this share approaches zero, we obtain an analogue of the standard dynamic IS curve

$$c_t = \mathrm{E}_t\left\{c_{t+1}\right\} - \left(r_t - \mathrm{E}_t\left\{\pi_{t+1}\right\} - \rho\right).$$

From the previous equations, one can observe that the presence of rule-of-thumb households makes the growth of aggregate consumption directly dependent on the growth of employment and also on the growth of taxes, even when they are not distortionary.

Firms

The dynamics of inflation as a function of the deviations of the average logarithm of markup from its steady state can be obtained from Equation 2.25 and Equation 2.27

$$\pi_t = \beta E_t\left\{\pi_{t+1}\right\} - \lambda_p\mu_t^p, \tag{2.44}$$

where $\lambda_p = \frac{(1-\beta\theta)(1-\theta)}{\theta}$, and

$$\mu_t^p = (y_t - n_t) - w_t, \tag{2.45}$$

when we ignore constant terms. The latter equation is equivalent to

$$\mu_t^p = (y_t - k_t) - r_t^k. \tag{2.46}$$

A first order approximation of the aggregate production yields

$$y_t = \alpha k_t + (1-\alpha)n_t + \alpha_G k_{t-1}^G \tag{2.47}$$

Government

Let denote the steady state interest rate as $\rho = \beta^{-1} - 1$. By log-linearization of government budget constraint (Equation 2.29), one obtains

$$b_{t+1} = (1+\rho)(b_t + g_t^C + g_t^I - t_t). \tag{2.48}$$

Plugging in the fiscal policy rule (Equation 2.30) yields

$$b_{t+1} = (1+\rho)(1-\phi_b)b_t + (1+\rho)(1-\phi_{gc})g_t^C + (1+\rho)(1-\phi_{gi})g_t^I. \tag{2.49}$$

In order to obtain stationary process of the level of debt, I need to impose a condition that is $(1+\rho)(1-\phi_b) < 1$, or equivalently $\phi_b > \dfrac{\rho}{1+\rho}$. The log-linearization of public investment authorization equation is given by

$$a_t = \rho_A a_{t-1} + \epsilon_{A,t}. \tag{2.50}$$

Defining $\hat{a}_t = \dfrac{A_t - A}{Y}$ as the deviation of public investment authorizations from the steady-state normalized by the steady-state of output, the first order approximation for public capital accumulation can be written as

$$k_t^G = (1-\delta_G)k_{t-1}^G + \hat{a}_{t-5}\frac{Y}{A}, \tag{2.51}$$

where $\dfrac{Y}{A}$ is the steady state output to public investment expenditure ratio. The log-linearized approximation of public investment expenditure (outlay) in equation 2.33 becomes

$$g_t^i = \sum_{n=0}^{N-1} \omega_n \hat{a}_t, \tag{2.52}$$

where $g_t^i = \dfrac{G_t^I - G^I}{Y}$.

Monetary authority

The policy function of the central bank is already in the log-linear form so there is no need to transform it further.

Market clearing

By a simple log-linearization, one obtains:

$$y_t = \gamma_c c_t + \gamma_i i_t + g_t^C + g_t^I, \tag{2.53}$$

where $\gamma_i = \dfrac{I}{Y}$ denotes the steady state share of investments on total output.

2.5 Model Estimation

2.5.1 Calibrated Parameters

I calibrate the model by matching some empirical moments of Turkish data and following the standard values in the literature. Table 2.4 displays the value for the each parameter to be calibrated. I set yearly steady state gross real rate ρ equal to 1.0526. This is the sample mean calculated using the Fisher equation. This value gives yearly discount factor β as 0.95, which implies a quarterly discount factor of 0.9873, and it is consistent with the literature. The elasticity of labor supply is taken to be 2, implying $\varphi = 0.5$, according to Natalucci et al. (2002). Parameter α from the Cobb-Douglas production function of the final goods sector represents the elasticity of output with respect to capital. Also, it represents the share of capital income when markets are competitive, and factors of production are paid their marginal products. Similarly, parameter $1 - \alpha$ represents the share of output that is paid to labor. I set α equal to 0.4 following the recent work of Yuksel (2013).

Table 2.4: Calibrated Parameters

	Parameter	Value	Source
ρ	Steady-state gross real rate	1.0526	Sample mean
β	Discount factor	0.95	$\beta = 1/(1+\rho)$
φ	Inverse Frisch elasticity	0.5	Natalucci et al. (2002)
α	Share of private capital in production	0.4	Yuksel (2013)
α_G	Share of public capital in production	0.1	Leeper et al. (2010)
δ_K	Depreciation of private capital	0.1	Standard value
δ_G	Depreciation of public capital	0.1	Own calculation
K^G/Y	Steady-state public capital/output ratio	0.5	To derive δ_G
G^I/Y	Steady-state public investment/output ratio	0.05	Sample mean
G^C/Y	Steady-state government consumption/output ratio	0.15	Sample mean
μ^p	Steady-state Mark-up	1.1	Standard value
θ	Share of firms not adjust prices	0.75	Galí et al. (2007)
η	Elasticity of investment/capital ratio to q	1	Galí et al. (2007)

The productivity of public capital, α_G, is critical to determine the effects of government investment. Unfortunately, aggregate data to estimate this parameter is not available. I follow Leeper et al. (2010) and set α_G equal to 0.1. I use the standard value of a depreciation rate in the literature and set δ equal to 0.1. The depreciation rate of public capital is not measurable directly from data, and I use standard value of 0.1 for δ_G. This value also implies steady-state public capital to output ratio equal to 0.5. I set steady state government consumption to output ratio $\gamma_{gc} = \dfrac{G^C}{Y}$ equal to 0.15 and steady-state public investment expenditure to output $\gamma_{gi} = \dfrac{G^I}{Y}$ equal to 0.05 using the sample means of these ratios. I set steady-state mark up μ^p equal to 1.1 which gives $\epsilon^p = 11$ that is the elasticity of substitution among intermediate goods.

The literature does not provide a consensus on the estimate of parameter θ, which is the probability that a firm will not adjust its price during the next period. That is, this parameter represents the inflexibility of prices in the intermediate goods sector. Following Galí et al. (2007), I set θ equal to 0.75, which corresponds to an average price duration of one year. I set η (elasticity of investment with respect to q) equal to 1, again following Galí et al. (2007).

2.5.2 Estimated Parameters

I estimate the remaining parameters by minimizing a measure of distance between the empirical responses (Section 4.2) and theoretical model responses. To obtain theoretical model responses, I employ simulated method moments. In particular, I feed the calibrated parameters into the model and define set with upper and lower bound for the parameters to be estimated. Denote Θ as the vector of parameters to be estimated and Ω as the parameter feasibility set. I simulate 500 data points using the model after generating random shock $\epsilon_{A,t}$ in the announcements A_t and use this artificial data set to estimate the LPM described in section 4.1. I take the mean responses of the estimation that are a function of Θ.

Let $\hat{\Psi}$ be the $n \times 1$ vector of empirical estimates from the LPM and $\Psi(\Theta)$ be a vector collecting the mean estimates of the LPM using simulated data generated from the model.[21] The estimate of Θ, a vector of parameters, is the solution to the following minimization problem:

$$\hat{\Theta} = arg \min_{\Theta \in \mathit{\Omega}} \left(\Psi(\Theta) - \hat{\Psi} \right)' \Phi \left(\Psi(\Theta) - \hat{\Psi} \right), \tag{2.54}$$

where $\mathit{\Omega}$ is the set of admissible values for the parameters Θ and Φ is a $n \times n$ weighting matrix. For practical purposes, I use the inverse of the matrix with the sample variances of Jorda impulse responses on the main diagonal. Table 2.5 summarizes the estimates of the parameters. The estimates show a small response of tax to changes in government consumption and investment expenditures but a large response to an increase in public debt. The share of the rule-of-thumb

[21] Assume that the number of variables is four and the horizon is ten. Then $n = 40$.

consumers among the households turns out to be 0.47 that is estimated first time in the literature for Turkish data. The estimation suggests that nearly half of the households are liquidity constrained in Turkey and do not have access to capital markets.

Table 2.5: Estimated Parameters

	Parameter	Value
ρ_A	Persistence of news shock	0.6574
ω_0	Share of announcements becomes public investment outlay in first year	0.6329
ω_1	Share of announcements becomes public investment outlay in second year	0.1095
ω_2	Share of announcements becomes public investment outlay in third year	0.1095
ω_3	Share of announcements becomes public investment outlay in fourth year	0.0452
ω_4	Share of announcements becomes public investment outlay in fifth year	0.0452
ϕ_{gi}	Response of tax to public investment spending	0.0271
ϕ_b	Response of tax to debt	0.5478
ϕ_{gc}	Response of tax to government consumption	0.1097
ϕ_π	Taylor-rule coefficient on inflation	1.3696
λ	Share of rule-of-thumb consumers	0.47

2.5.3 Impulse Responses

Figure 2.10 shows the impulse responses estimated using local projection method on model-simulated data and compares them with empirical counterparts. Before going into such comparison, it is important to note that the presence of liquidity constrained consumers in the model generates a different response of consumption to a public investment news shock relative to a model with only Ricardian consumers. A similar government spending process was used by Leeper et al. (2010), where the authors develop model only with optimizing agents, and they show that consumption decreases in the short-run after the shock even though output increases.

Figure 2.10 shows the IRFs for macroeconomic variables. The solid blue line presents the empirical IRFs, and the dashed red lines present the IRFs estimated from model-simulated data. The initial and short-run responses of output and consumption are similarly estimated under real and model-simulated data. Both variables increase on impact and decay over the next three to four years and hit the zero line. In this sense, the existence of liquidity constrained consumers in the model is consistent with the empirical findings. However, the model is not capable of capturing the positive long-run impact of public investments on output and consumption since the IRFs are almost zero. To check whether this is because of the calibrated productivity of public capital parameter α_G, which is set to 0.1, I run the simulation with α_G equal to 0.3, holding all else being constant. [22]

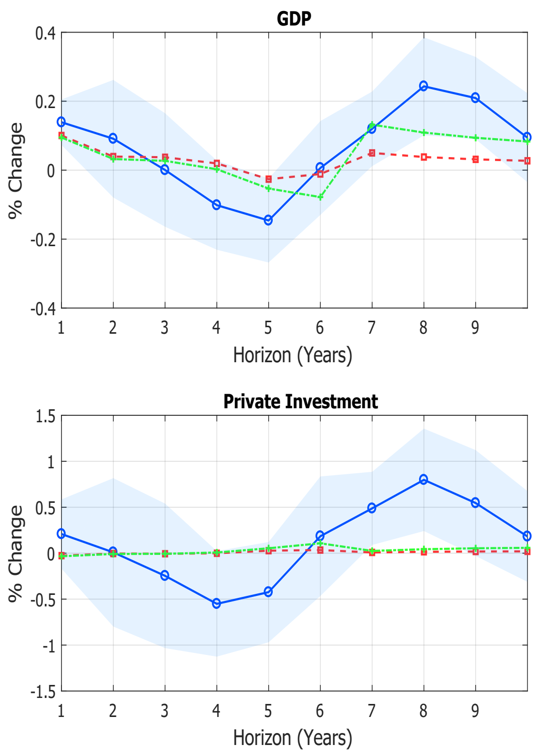

Figure 2.10: IRFs of macroeconomic variables to a public investment news shock - Model vs. Empirical

In figures, solid blue line presents IRFs from Local Projection Method, dashed red line and green line exhibit IRFs from DSGE estimation with $\alpha_G = 0.1$ and $\alpha_G = 0.3$, respectively.

The IRFs from the simulated model with new value of α_G are shown in green dashed point lines. The large responses of output and consumption starting from period 7 are consistent with public capital accumulation equation 2.51. It takes five years for the announcements to become public capital, and one year lagged value of public capital is used in the production function. The model's response with higher value of α_G is capable of generating the large long-run positive responses of output and consumption, especially for the latter one. The results imply that the elasticity of output to public capital is significantly larger in Turkey relative to the US and other developed countries. Turkey is an emerging economy, and public capital stock was much less relative to the advanced economies, especially in the beginning of the 80s. Agénor and Neanidis (2015) show the importance of the direct and indirect effects of public capital on output through spending, innovation, human capital, and transportation costs for growth. The results suggest that similar arguments could

[22]This value is consistent with the recent findings of Serdaroğlu (2016).

be valid for Turkey, and public investments have a major impact on output.

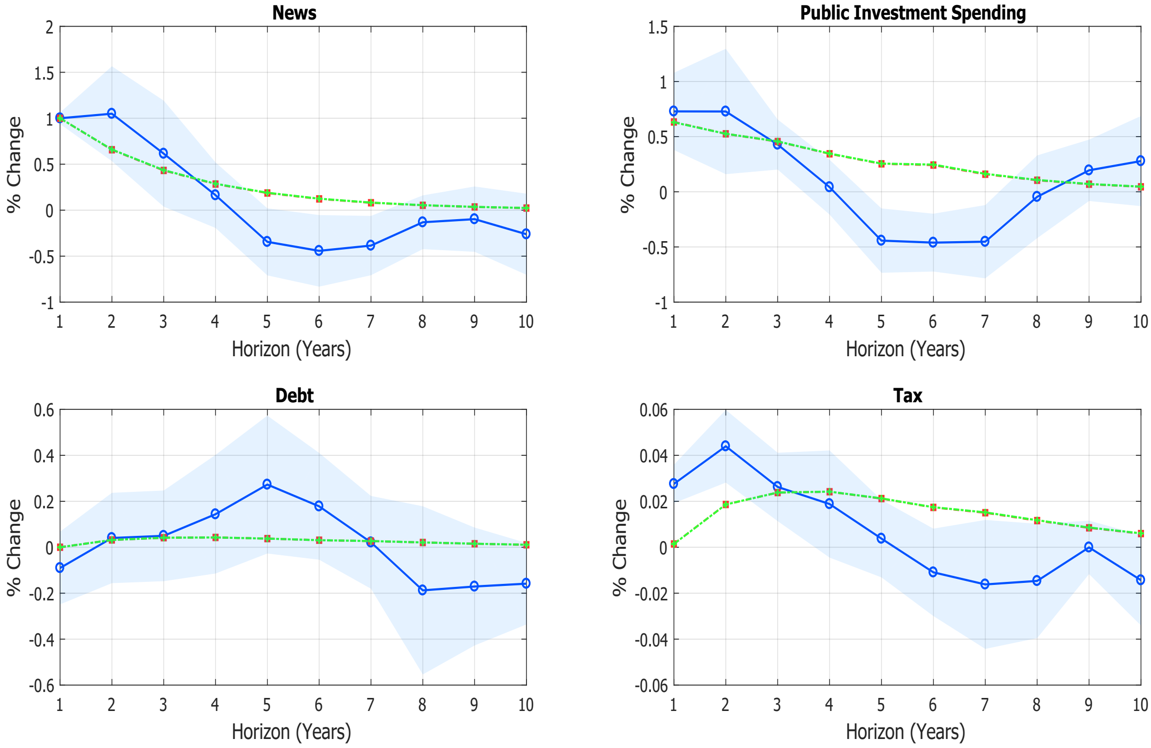

Figure 2.11: IRFs of policy variables to a public investment news shock - Model vs. Empirical

In figures, solid blue line presents IRFs from Local Projection Method, dashed red line and green line exhibit IRFs from DSGE estimation with $\alpha_G = 0.1$ *and* $\alpha_G = 0.3$*, respectively.*

Turning to the policy variables, the model produces responses that are similar to the empirical ones. Figure 2.11 shows the IRFs for news, public investment outlay, debt-to-GDP and tax revenues over GDP. The news and spendings spike on impact and decay over time. The same also holds for tax rate. The model response of debt is smaller relative to the empirical one. The model with distortionary taxes may capture the movements in debt better.

2.6 Conclusion

This paper analyzes the dynamic effects of public investment on the economy. The prior literature on the dynamic fiscal multipliers mostly refrains from studying this type of government spending because of several unique and challenging features inherent in the public investment. First, the public investments are multi-year projects, and the investment typically involves long implementation lags between when projects are announced and when actual government outlays show up. This feature makes the standard measure of government spending unsuited for the purpose of identifying shocks, particularly to government infrastructure investment since agents may react to the information of forthcoming spending through announcements before actual spending.

Second, public investments are mostly built up through private contractors. The contractors send their bills once they complete, partially or fully depending on the contract, the public investment projects, and the government pays the bill, and actual outlays show up in data. However, contractors hire workers and pay suppliers before receiving government funds. Therefore, the money goes into the economy through contractors before government outlays appear in data. To account for the flow of funds to the economy, using the expected value of the investment rather than the outlays is more appropriate.

Finally, a defining characteristic of government infrastructure investment is that it is at least intended to increase the economic efficiency or productivity of the private sector. Productivity-enhancing government spending should have different macroeconomic effects than other types of government spending. For instance, the standard neoclassical negative wealth effect of increased government spending is potentially offset if agents recognize the positive wealth effect generated by the higher future productivity.

Given these unique features, this paper utilized the Public Investment Programme announced in Turkey at the beginning of every year since 1963. The Public Investment Programme contains information about the present value of the public investment projects to be completed that allows capturing the knowledge of forthcoming spending. The timing of announcements, beginning of every year, enables orthogonality between the future spending decisions and current economic conditions. In addition, in most of the years, the program is prepared to promote long-term growth, to alleviate the regional disparities and to crowd-in private investment. These features indicate that rather than the short-term goals, the long-term goals constitute the main objectives of the program.

I utilize the information from the program to construct a news variable and identify the shock as today's anticipated future spendings in the public investment projects orthogonal to current economic conditions. I estimate the Jorda local projection method to measure the impact of shocks and find that public investment shocks positively affect GDP over two specific horizons. There is a significant impact in the first couple of years and then a larger second-round effect after six to eight years. There is a large permanent effect, as GDP does not go back to pre-shock levels after ten years. The multipliers that I calculate from these IRFs are large, roughly four on impact and significantly larger eight to ten years. These values are mostly above the fiscal multipliers in the literature and point to the large effect of public investment on the economy. The alternative robustness checks mostly confirm the initial estimates and findings.

The useful feature of Turkish data is that the program disaggregates the public investment projects into different sectors. I use the same identification method for different public investments and find the larger impact of transportation, health, and education investments on the output. The results suggest that the investments in those sectors may be a powerful tool for policy-makers to achieve both short-term and long-term output per capita growth in Turkey.

In the final part of the paper, I estimate a closed economy DSGE model to interpret the empirical findings. I apply the local projection method to the simulated data and find the similar short-run impact of public investment shock on aggregate output and consumption, both in sign and magnitude. However, the responses after year five are less pronounced in the model relative to real data suggesting the possible indirect effects of public investment on the economy in the long-run.

One of the possible extensions of the paper is to introduce a noise component in the news variable since the projects in the Public Investment Programme are subject to changes over time. This implies that part of the announcements does not become actual public investment spending. That would enable us to identify the impact of noisy announcements on the economy in the short-run and long-run.

Another extension could be to explore the state-dependent impact of public investment shocks. The identification of non-linear effects is important, especially for policy decisions. If the effects are larger in recessions as the recent literature suggests, then during the crisis period, it is advisable to increase public investment spendings to stimulate the economy rather than to cut the expenditures because of the budget deficit or other stabilization concerns.

Chapter 3

Tax Shocks Through Production Networks

3.1 Introduction

Following the global financial crisis and recession, government deficits and debt have risen around the world. This will eventually require fiscal consolidation, which has recently brought tax policy as one relevant fiscal policy instrument to the forefront of debates in academia, institutions and the media. Given their distortionary nature, understanding how tax shocks transmit to the real economy becomes a fundamental question. However, much of the existing research on fiscal policy focuses on the effect of tax changes on aggregate GDP, consumption and investment.[1] There is a paucity of literature that studies the transmission mechanism on a more micro level. This paper contributes to the debate by proposing a new transmission mechanism of private income tax policy, which works through the sectoral input-output production network.

Recent work shows that the input-output structure of the economy is an important channel through which idiosyncratic shocks transmit and translate into aggregate fluctuations (see Gabaix (2011), Acemoglu et al. (2012), Acemoglu et al. (2016)). Building on this literature, this paper investigates whether the same type of mechanism is active and quantitatively important for the transmission of private income tax shocks. Suppose that the private income (PI) tax rate decreases. A tax cut may directly increase the demand for computers. Computer manufacturers may then increase their demand for keyboards, which on its turn increases the demand

[1] Previous fiscal policy research finds that tax cuts have little to no effects Hausman and Poterba (1987), Blanchard and Perotti (2002), and Romer and Romer (2010) or expansionary effects in the short run Kneller et al. (1999), Mountford and Uhlig (2009), and Mertens and Ravn (2012).

for plastic granulates and ultimately crude oil, generating higher-order demand effects. Moreover, due to the non-linearity of production networks, the effect may feed back to computer producers, because manufacturers of keyboards, plastics and crude oil demand more computers. The main result of this paper is that between 60 and 70% of the overall effect of private income tax shocks is due to higher-order network effects.

Quantifying the magnitude of network effects following a tax shock is a challenging task because it requires the correct identification of PI shocks and the identification of network effects. To address the former, we follow Mertens and Ravn (2013) and use a narrative measure of exogenous unanticipated tax shocks. The identified tax shocks are then used in a spatial autoregressive model (SAR), which allows us to decompose the total effect of the tax policy shocks into a direct effect and a network effect.

Spatial econometrics typically identifies spillovers across units or “neighbors”, connected to each other through geographic proximity, family and friendship linkages, infrastructure etc. The existence, direction and magnitude of the effect is governed by the spatial weight matrix. In this paper, the spatial weight matrix identifies production linkages between 61 industries in the US. Data is organized as input-output (IO) tables and collected from the Bureau of Economic Analysis (BEA). Finally, quarterly sales data for individual firms from CRSP/Compustat is merged with industry-level IO tables.

Despite its intuitive appeal, one major criticism against the SAR model is the ad hoc choice of the spatial weights matrix, which poses difficulties in the structural interpretation of the spillover effects. To corroborate our empirical strategy we develop a simple model with intermediate inputs in the spirit of Acemoglu et al. (2016) and Ozdagli and Weber (2017). We show that the theoretical model empirically translates to a SAR model and arrives at the BEA IO tables as the appropriate weighting matrix. Therefore, the contribution of the paper is to provide a clear structural interpretation of the transmission mechanism on the one hand, and on the other, to use novel tools from spatial econometrics to quantify the importance of network effects.

The main result of the paper is that network effects account for between 60% to 70% of the total industry reaction following a PI tax shock. In terms of economic magnitudes, a 1 percentage point increase in the PI tax rate reduces industry sales by 0.65% during the four quarters following the occurrence of the shock. The result is robust to the inclusion of quarter, industry and quarter-industry fixed effects and controlling for government spending, debt, inflation, short-term interest rates and unemployment. The result demonstrates that exposure to the production network is an important factor driving industrial production, which is distinct from industry co-movement and other factors, previously studied in the macroeconomic literature.

Our model predicts that demand-side shocks, such as private income tax shocks, transmit only upstream in production networks through adjustments in input quantities. However, this theoretical result is a direct consequence of Cobb-Douglas production preferences and technology. In reality, there could also be a downstream effect, which is activated through changes in prices. We address this debate in the empirical literature by showing although both effects are present in the data, the upstream transmission of PI shocks is much stronger that the downstream one.

A major doubt regarding our empirical strategy is that we mechanically find large network effects, because we regress industry sales on a weighted average of industry sales. If this were indeed true, any random network would produce large network effects. We construct a random input-output matrix, which matches the main features of the observed input-output matrix: (1) it is sparse, and (2) only very few sectors are important customers to the rest of the economy (Herskovic (2018)). Using such a simulated matrix, we attribute only 20% of the overall effect to network spillovers, compared to 60% in the baseline estimation. Although not random, the magnitude of the result is still larger than what sparsity alone would predict. The reason why the SAR model attributes a larger proportion of network effects is that it simultaneously accounts for spillovers along the entire production chain: i.e. spillovers from customers, from customers of the customers and so on. Sparsity only considers direct linkages between a customer and a supplier industry (1^{st}-order connections). For comparison, the magnitude of network effects predicted by sparsity alone is 60% lower than the effect predicted by the SAR model. These results emphasize the importance of higher-order network effects, which are driven by the particular structure of the economy.

In our model we impose constant sensitivity of industries to private income tax shocks, conditional only on the position of an industry in the IO network, captured by the Leontief inverse. There is reason to believe that industries have heterogeneous exposures, which on its turn could bias the estimation of network effects. Reassuringly, allowing for heterogeneous betas cannot explain the large network effect we document.

To conclude, we demonstrate that our empirical findings are consistent with a dynamic model with nominal frictions in the form of sticky wages. We simulate the model under different assumptions of the utility function and fiscal policy rules and run our spatial regressions on simulated data taking the input-output matrix as given. We find that the predictions of the dynamic model match very well our empirical results. Across different specifications of the model, we obtain network effects account for approximately 60% of the overall effect of PI shocks on industry sales.

3.1.1 Related Literature

This paper contributes mainly to three strands of the literature. First, it relates to the literature, which studies how microeconomic (idiosyncratic) shocks transmit through the production network and contribute to aggregate volatility. Traditionally, the idea that idiosyncratic shocks could contribute to aggregate fluctuations was discarded due to the diversification argument, raised by Lucas (1977): at sufficiently disaggregated levels of the economy, shocks to individual sectors cancel out and have no impact on the aggregate economy. However, seminal papers by Carvalho (2008) and Acemoglu et al. (2012) show that the network structure could be an important channel for the transmission of shocks. The main argument put forth in these papers relies on the fat-tailedness of the network links distribution. If there are general purpose sectors, i.e. sectors that play disproportionately important role as input suppliers to other sectors, then these sectors act as hubs and propagate the sector-specific shocks to the rest of economy and generate aggregate fluctuations. Building on inter-sectoral linkages, Boehm et al. (2015) and Carvalho et al. (2016) study the firm-level impact of supply-chain disruptions after the occurrence of the Tohoku earthquake in Japan in 2011. The former paper finds evidence for cross-country spillovers of the supply shock and the latter shows that input-output linkages can account for 1.2% decrease in GDP of Japan in the year following the earthquake. Acemoglu et al. (2016) document downstream propagation of sector-specific supply shocks, total factor productivity or number of patents, and sector-specific upstream propagation of demand shocks, Chinese import competition and industry-level government spending. Auerbach et al. (2019) find both positive effects of Department of Defense (DoD) spending on local industries that supply intermediate inputs and positive spillover effects on industries that are not directly linked to the recipient industry.

We contribute to the literature by providing cross-sectional evidence on the role of production networks for the transmission of macroeconomic shocks. An important contribution in this area is the work by Ozdagli and Weber (2017), who show that a significant portion of the response of the stock market to monetary policy announcements is due to network linkages. Our paper is closest to Briganti et al. (2018), who study how fiscal adjustments propagate through industrial networks. They find that tax-based adjustments propagate downstream, whereas expenditure-based adjustments propagate downstream. Our findings are complementary to theirs, because we focus on a specific tax-based instrument, namely private income shocks. To the best of our knowledge, this is the first paper to provide both theoretical and empirical evidence for their transmission through production networks. Our results stress the importance of higher-order demand effects and can be used to inform policy.

Second, this paper relates to the literature that studies the impact of fiscal policy on the real economy. Most of prior work has focused on the aggregate effect of fiscal policy on GDP, consumption and investment.[2] Perotti et al. (2007) identify industry-level government spending shocks around two major military build-ups and find positive effects on real wages.More recently, Nekarda and Ramey (2011) provide industry evidence on the effect of government spending on output, real wages and productivity, whereas Nakamura and Steinsson (2014) and Giavazzi and McMahon (2012) investigate the effect on a regional and household levels respectively. We complement the fiscal policy literature by studying instead the impact of tax policy on the sectoral level. We propose a new mechanism for the transmission of tax shocks to the real economy. The main intuition from our paper is that the economy's production network provides a microfoundation for the transmission of tax shocks.

Third, the paper relates to a nascent literature on spatial econometrics in economics. Traditionally, spatial autoregressive models been extensively applied to research questions in regional science, economic geography and international trade.[3] Empirically, SAR models have been applied to study regional unemployment differentials (Elhorst (2003)), property tax rates (Allers and Elhorst (2005), Bordignon et al. (2003)), inflation (Elhorst et al. (2017)), air quality (Kim et al. (2003)), European regional per capita GDP (Le Gallo and Ertur (2003)). SAR models in economics have began to gather momentum in the recent years. Fernandez (2006) derives a spatial version of the capital asset pricing model (CAPM) and uses the results to perform value-at-risk simulations. Blasques et al. (2016) and Eder and Keiler (2015) study systemic risk and spillovers in the CDS market. We contribute to the field by applying the methods of spatial econometrics to a new question in economics: transmission of tax shocks through production networks.

[2]See Blanchard and Perotti (2002), Romer and Romer (2010), Barro and Redlick (2011), Perotti (2012), Auerbach and Gorodnichenko (2012a), and Mertens and Ravn (2013) among others. For a recent review on macroeconomic shocks that drive economic fluctuations see Ramey (2016b).

[3]For early studies review the work of Cliff et al. (1981), Upton et al. (1985). More recent contributions to the theory and estimation of SAR models include, but are not limited to, Anselin and Bera (1998), Anselin et al. (1996), Kelejian and Prucha (1998), LeSage and Pace (2009), Arbia (2006), Lee (2004), and Bivand et al. (2008).

3.2 Benchmark Model

Consider a static economy where production takes place at n distinct nodes, each specializing in a different good. These goods serve a dual role in the economy: on the one hand, each good is potentially valued by households and government as final consumption; on the other hand, the same good can be used as an intermediate input to be deployed in the production of other goods. Households provide labor services elastically to the goods' producers in the economy in exchange of wage, pay lump-sum taxes to the government and spend all the resulting disposable income in the consumption of the n goods. The government maintains a balanced budget; finance the purchases of n final goods with income and lump-sum taxes imposed on the households and issues/repays debt.

3.2.1 Firms

There are n different industries in perfectly competitive environment with the following Cobb-Douglas production function

$$y_i = e^{z_i} l_i^{\alpha_i} \left[\prod_{j=1}^{n} x_{ij}^{a_{ij}} \right]^{\rho_i}, \tag{3.1}$$

where l_i is the labor hired by sector i, α_i is the share of labor, ρ_i is the share of total intermediate input used in the production, x_{ij} is the amount of intermediate good used by industry i that is supplied by industry j, a_{ij} is the share of the intermediate good such that $\sum_{j=1}^{n} a_{ij} = 1$, and z_i is Hicks-neutral industry-specific productivity shock that captures the change in technology and other unobservable factors affecting productivity. The production function is assumed to exhibit constant returns to scale and the labor and total intermediate input share sum to unity

$$\alpha_i + \rho_i \sum_{j=1}^{n} a_{ij} = 1. \tag{3.2}$$

The goods are used as an intermediate input by other sectors or as final consumption by households and government. The market clearing condition for sector i can be written as:

$$y_i = c_i + \sum_{j=1}^{n} x_{ji} + G_i, \tag{3.3}$$

where c_i is the demand by households, x_{ji} is the intermediate input supplied by sector i, and G_i is the government demand in sector i that household do not value.

The first-order conditions for the firm's profit maximization problem are

$$\alpha_i^l = \frac{wl_i}{p_i y_i}, \tag{3.4}$$

$$a_{ij} = \frac{p_j x_{ij}}{\rho_i p_i y_i}. \tag{3.5}$$

The first condition imposes the optimal amount of labor share, and second condition imposes the optimal share of good j in the production of good i and defined as the nominal amount of sector i's purchase from sector j divided by the normalized nominal output of sector i by factor share ρ_i.

3.2.2 Households

There is a representative household in the economy with the following Cobb-Douglas preferences

$$u(\mathbf{c}, l) = (1-l)^{\lambda} \prod_{i=1}^{j} c_i^{\beta_i}, \tag{3.6}$$

where c_i is the consumption of good i, β_i is the share of good i in household's consumption basket with values between 0 and 1, and λ is inverse Frisch-elasticity that governs the disutility of labor. The budget of the household reads as following

$$\sum_{i=1}^{n} p_i c_i = (1-\tau)wl - T, \tag{3.7}$$

where p_i is the price of good i. The households receive wage, w, in exchange of labor and pay τ percentage of wage as a personal income tax to the government plus lump-sum tax T and they use all the disposable income for the consumption of n goods. Since this is a static economy, there is no saving in the household's side. The first order conditions for the household's utility maximization problem is

$$\frac{p_i c_i}{\beta_i} = \frac{p_j c_j}{\beta_j}, \tag{3.8}$$

$$\frac{\lambda}{1-l} = \beta_i \frac{(1-\tau)w}{p_i c_i}. \tag{3.9}$$

3.2.3 Government

The government imposes income and lump-sum tax on the households, issues/repays debt B and purchases goods from industries with these funds. We assume that there always exists an outside party, who is willing to buy and sell government debt (e.g. a foreign government). For simplicity, we don't explicitly include this party in the model. In every period, we assume that the government maintains balanced budget and the following equation holds

$$\sum_{i=1}^{n} p_i G_i = \tau wl + T + B. \tag{3.10}$$

3.2.4 Equilibrium

The first part of equilibrium uses budget constraint and FOCs from household's problem. Plugging equation 3.8 into household's budget constraint in equation 3.7 gives:

$$p_i c_i = \beta_i \left[(1-\tau) wl - T \right]. \tag{3.11}$$

Inserting the above expression into the equation 3.9 and taking wage as numeraire derives labor supply as function of taxes

$$l = \frac{(1-\tau) + \lambda T}{(1-\tau)(1+\lambda)}. \tag{3.12}$$

Using the labor supply given above in equation 3.11 gives

$$p_i c_i = \frac{\beta_i}{1+\lambda} (1 - \tau - T). \tag{3.13}$$

Now assume that government increases personal income tax τ, but do not change lump-sum tax and government purchases, both $dT = dG = 0$. Hence, increase in tax revenues are used to pay the government debt, $d\tau = dB$. Now, differentiate the equation 3.13

$$d(p_i c_i) = -\frac{\beta_i}{1+\lambda} d\tau. \tag{3.14}$$

Equation 3.14 shows that increase in personal income tax results in decrease in nominal consumption, depending on the share of the good in the consumption basket. This is the end of the first part of the equilibrium.

The second part of equilibrium uses production function, market clearing and FOCs from firm's problem. Differentiating equation 3.5 and rearranging gives:

$$d(p_i x_{ji}) = d(p_j y_j) \rho_j a_{ji}, \tag{3.15}$$

and using market clearing condition from equation 3.3 and assuming $dG_i = 0$ gives the following

$$d(p_i y_i) = d(p_i c_i) + \sum_{j=1}^{n} d(p_i x_{ji}). \tag{3.16}$$

Now use equation 3.14 for the first term and 3.15 for the second term on the right hand-side of the equation 3.16 and rearrange to get

$$d\ln y_i = \sum_{j=1}^{n} \rho_j \hat{a}_{ji} d\ln y_j - \frac{1}{p_i y_i}\frac{\beta_i}{1+\lambda} d\tau, \tag{3.17}$$

where $\hat{a}_{ji} = \frac{p_i x_{ji}}{\rho_j p_i y_i}$, that is, the share of good i used by sector j normalized by the nominal output of sector i. Define matrix $\hat{\mathbf{A}}$ as following

$$\hat{\mathbf{A}} = \begin{bmatrix} \hat{a}_{11} & \hat{a}_{12} & \cdots & \hat{a}_{1n} \\ \hat{a}_{21} & \hat{a}_{22} & \cdots & \hat{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{a}_{n1} & \hat{a}_{n2} & \cdots & \hat{a}_{nn} \end{bmatrix}, \tag{3.18}$$

and matrix $\boldsymbol{\Lambda}$ as following

$$\boldsymbol{\Lambda} = \begin{pmatrix} -\frac{1}{p_1 y_1}\frac{\beta_1}{1+\lambda} \\ -\frac{1}{p_2 y_2}\frac{\beta_2}{1+\lambda} \\ \vdots \\ -\frac{1}{p_n y_n}\frac{\beta_n}{1+\lambda} \end{pmatrix}. \tag{3.19}$$

Using the matrices from equations 3.18 and 3.19, we can rewrite equation 3.17 in following compact form

$$d\ln \mathbf{y} = \boldsymbol{\Lambda} d\tau + \boldsymbol{\rho}\hat{\mathbf{A}}^{\mathbf{T}} d\ln \mathbf{y}. \tag{3.20}$$

Equation 3.20 has the form of the autospatial regression. Rearranging one more time:

$$d\ln \mathbf{y} = \left(\mathbf{I} - \boldsymbol{\rho}\hat{\mathbf{A}}^{\mathbf{T}}\right) \boldsymbol{\Lambda} d\tau, \tag{3.21}$$

and equation 3.21 tells us that personal income tax shocks propagates upstream (from customers to the suppliers).

3.3 Empirical Framework

3.3.1 The Spatial Autoregressive Model

The spatial autoregressive model (SAR) is given by the following empirical specification

$$\Delta sales_{iq} = \beta_0 + \rho W_{ij} \Delta sales_{iq} + \beta_1 TaxShock_q + \varepsilon_{iq} \tag{3.22}$$

where $\Delta sales_{iq}$ measures the change in an industry's sales between the previous four quarters and the quarters $q+h$ to $q+3+h$ after the policy change, β_0 is an intercept term and $TaxShock_q$ is an exogenous tax shock. More precisely, the dependent variable is calculated as follows

$$\Delta sales_{iq} = \frac{\frac{1}{4}\sum_{s=q+h}^{q+h+3} sales_{is} - \sum_{s=q-4}^{q-1} sales_{is}}{TA_{iq-1}} \times 100 \tag{3.23}$$

$sales_{iq}$ is net sales in a given qarter q and TA_{iq} is total assets. We use four quarters before and after the policy change to address the issue of seasonality and we scale by total assets to normalize the change. We consider the case of $h = 0$ as our baseline specification.

The spatial autoregressive parameter ρ is the main object of interest in this model. It indicates the importance of network connections for the propagation of tax shocks and is interpreted as a measure for network spillover effects. Testing for the presence of spillovers is tantamount to the following hypothesis:

$$H_0 : \rho = 0$$

$$H_1 : \rho \neq 0$$

If the null hypothesis is rejected, values of $\rho > 0$ indicate that the shocks are propagated through the network; if $\rho < 0$ the shock is absorbed by the system[4]. W [5] is a row-normalized spatial weights matrix, whose entries give production linkages between industries[6]. The model assumes that W is exogenously given and stable over time. Rows correspond to customer-industries and columns correspond to supplier industries. Then, the i^{th} -column of W gives the fraction of output of industry i used in the production of all industries j. Entries on the main diagonal of W give sales to own industry (e.g. tire producers selling to car manufacturers). For example, if entry $w_{21} > 0$, this means that industry 1 is a supplier to industry 2. In the spatial econometrics jargon, the two industries are said to be neighbors. Note that W gives downstream propagation (from suppliers to customers), whereas its transpose W^T gives upstream effects (from customers to suppliers). The empirical counterpart of W is the BEA Input-Output matrix, which is described in Section

[4]If the spatial parameter is statistically indistinguishable from zero, then the SAR model collapses to the standard Ordinary Least Squares (OLS) model.

[5]W is the empirical counterpart of the $\hat{A}$ matrix in the theoretical model. To make the distinction explicit between the empirical and theoretical weighting matrix, a different notation is used

[6]In the traditional application of SAR models, the "spatial" structure refers to geographic distance. This paper uses economic distance instead.

4.5.

The term $W_{ij}\Delta sales_{iq}$ is constructed as a linear combination of neighboring values to each observation. It is important to note that these entries are industry-specific and capture the heterogeneity of production linkages. In contrast, the shock variable $TaxShock_q$ is a global variables, whose entries are common to all industries in the market.

Stacking in vector form and solving for $\Delta sales_{iq}$, the result is a reduced-form equation:

$$\Delta sales_q = (I_N - \rho W)^{-1} (\beta_0 \iota + \beta_1 TaxShock_q + \varepsilon_q) \tag{3.24}$$

The term $(I_N - \rho W)^{-1}$ is called a spatial multiplier. The model bears a close resemblance to the time-series literature,in the sense that $W$is the spatial analog of the lag operator L. Whereas $L.\Delta sales$ measures the potential spillover from time time t to $t-1$, $W\Delta sales$ specifies spillovers from one industry to another.

3.3.2 Direct and Indirect Network Connections

For a row-normalized matrix $W$and for values $|\rho| < 1$, the spatial multiplier exists, the model is uniquely specified[7] and the infinite series converges:

$$V(W) = (I_N - \rho W)^{-1} = \sum_{q=0}^{\infty} \rho^q W^q = I_N + \rho W + \rho^2 W^2 + \dots \tag{3.25}$$

The q^{th} power of the matrix W collects the total number of links both direct and indirect in the entire network originating from node i and ending in node j. These powers correspond to observations themselves (zero-order), immediate neighbors (first-order), neighbors of neighbors (second-order) etc. The greatest challenge in understanding the mechanism of propagation is to capture the importance of indirect links.

Example 1 Consider the following simplified example with 3 industries. Connections are captured in the matrix A:

$$A = \begin{pmatrix} 0 & 5 & 0 \\ 0 & 1 & 4 \\ 0 & 0 & 0 \end{pmatrix}$$

The matrix reads like this: industry 1 buys 5 units of output from industry 2;

[7]Generally, it is possible to show that the matrix $(I_N - \rho W)$ is nonsingular for all values of the parameter in the space$(-\frac{1}{\lambda}, \frac{1}{\lambda})$, where λ is the largest eigenvalue of the matrix (see Kelejian and Prucha (1998), (1999)). For a row-normalized matrix the condition is trivially satisfied since and so, for values the model is well-defined.

industry 2 buys 1 unit from itself and 4 units from industry 3; industry 3 does not sell to other industries. The row-normalized counterpart of the matrix A is W:

$$W^1 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0.20 & 0.80 \\ 0 & 0 & 1 \end{pmatrix}$$

First-order neighbors are: $1 \to 2$; $2 \to 2$ and 3. The *second-order* neighbors are neighbors to the *first-order* neighbors i.e. W^2:

$$W^2 = \begin{pmatrix} 0 & 0.20 & 0.80 \\ 0 & 0.04 & 0.16 \\ 0 & 0 & 0 \end{pmatrix}$$

Hence, the *second-order* neighbors to industry 1 are industries 2 and 3: : $1 \to 2 \to$ 2 and 3. Similarly, more distant connections are given by higher powers of W.

Intuitively, the condition $|\rho| < 1$ captures the idea that distant connections are less important than direct connections. In this sense the spatial parameter serves as a discount factor, which assigns decreasing influence to higher-order neighbors, where the decay declines geometrically as the order increases. If $\rho = 0.5$, then $\rho^2 = 0.25, \rho^3 = 0.125$ etc. In the context of a production network, the magnitude of ρ reflects the degree to which shocks are transmitted locally or to the entire network. Small values for ρ weight the local structure more, while large values take into consideration the position of an industry in the production network as a whole.

3.3.3 Parameters Interpretation

Conditional on orthogonality of regressors, parameter estimates in a linear regression have straightforward interpretation as partial derivatives of the dependent variable with respect to the independent variables. This arises because of assumed linearity and independence of the observations in the model. When the model contains spatial lags of the dependent variable, interpretation of the parameters becomes more complicated, because the model incorporates a richer information set. In a spatial context, a change in any given explanatory variable will have an impact on an industry's sales (direct effect) and potentially an impact on the sales of other related industries (indirect effect). For this reason, spatial autoregressive models require special attention to the interpretation of the parameters (LeSage and Pace (2009)).

To see more clearly the complication of parameter interpretation, define

$$S(W) = \left((I_N - \rho W)^{-1} - I_N\right) I_N \beta \tag{3.26}$$

Collect covariates in X and estimates in β and rewrite the model as:

$$\Delta sales_q = \beta X_q + S\left(W\right) X_q + V\left(W\right) \varepsilon_q \tag{3.27}$$

Consider again the previous example with three industries at a particular point in time q. The data-generating process can be expanded to the following:

$$\begin{pmatrix} \Delta sales_{1q} \\ \Delta sales_{2q} \\ \Delta sales_{3q} \end{pmatrix} = I_N \beta \times \begin{pmatrix} X_q \\ X_q \\ X_q \end{pmatrix} + \begin{pmatrix} S\left(W\right)_{11} & S\left(W\right)_{12} & S\left(W\right)_{13} \\ S\left(W\right)_{21} & S\left(W\right)_{22} & S\left(W\right)_{23} \\ S\left(W\right)_{31} & S\left(W\right)_{32} & S\left(W\right)_{33} \end{pmatrix} \times \begin{pmatrix} X_q \\ X_q \\ X_q \end{pmatrix} + V\left(W\right) \varepsilon_q$$

with $S\left(W\right)_i$ indicates the i^{th} element of the matrix $S\left(W\right)$. Focusing on industry 1, the following obtains:

$$\Delta sales_{1q} = \underbrace{\beta X_q}_{\text{Direct Effect}} + \underbrace{S\left(W\right)_{11} X_q}_{\text{Feedback Effect}} + \underbrace{S\left(W\right)_{12} X_q + S\left(W\right)_{13} X_q}_{\text{Indirect Effect}} + V\left(W\right)_1 \varepsilon_q$$

with $V\left(W\right)_1$ referring to the first row of the matrix $V\left(W\right)$. The sales of industry 1 depends the *direct effect* of the shock as if network connections were severed (β) and two network effects: a *feedback effect*[8] due to the shock hitting industry 1 and coming back to it through the network $S\left(W\right)_{11}$) and an *indirect effect* ($S\left(W\right)_{12} + S\left(W\right)_{13}$) due to spillovers from intermediates production. For example, $S\left(W\right)_{12}$ denotes the response of industry 1's sales to the change in the sales of industry 2 due to the tax policy shock.

Following LeSage and Pace (2009), it is possible to define four scalars, which summarize the *total, direct, feedback* and *indirect* effects:

1. *Average Direct Impact*: β . This is the effect as if all network connections were shut down.

2. *Average Indirect Effect*: $\frac{1}{N}\iota_N' \left[S\left(W\right) - tr\left(S\left(W\right)\right)\right]$. The sum across the i^{th} row of $S\left(W\right)$ minus the i^{th} entry on the diagonal gives the impact on an individual industry resulting from changing the tax policy shock by the same amount across all N industries.

3. *Average Feedback Effect*: $\frac{1}{N}\iota_N' tr\left(S\left(W\right)\right)$. The average of the diagonal elements of $S\left(W\right)$ gives the effect of an industry's response travelling back to itself through the network.

4. *Average Total Effect*: the sum of average direct, feedback and indirect effects.

[8]It has to be noted that first-order feedback effects arise because industries sell/buy output to themselves (e.g. 1→ 1); higher-order feedback effects arise because of impacts passing through "neighboring" industries and coming back to the industry itself: e.g. 1→ 2→ 1 (second-order) and 1→ 2→ 3→ 1 (third-order).

Therefore, the response of an industry's sales to the tax policy shock is determined by the input-output matrix W, the spatial autoregressive parameter ρ , which denotes the strength of the network spillover effects, and the parameter β .

3.3.4 Tax Shocks

The key challenge when estimating the effect of tax policy changes is identification. This is particularly challenging because of endogeneity and because of diversity of the policy instruments. To address endogeneity, we use a narrative approach due to Romer and Romer (2010) to identify exogenous tax changes for a quarterly sample over 1950:Q1-2006Q3. Romer and Romer (2010) describe almost 50 legislative changes, providing information about the magnitude, timing and motivation of the policy. An attractive feature of this approach is that it summarizes relevant characteristics from a very large information set. The implicit assumptions are that (1) the narratively identified tax shocks map one-to-one with the true structural shocks and that (2) they are orthogonal to all non-tax structural shocks. Due to the construction method, we acknowledge that the tax shocks are identified up to some personal bias and measurement error.

The construction of our tax shock variables follows closely Mertens and Ravn (2012). The authors decompose total tax liability changes into: corporate income tax liabilities (CI), individual income tax liabilities (II), employment taxes (EM) and a residual category of other revenue changing tax measures (OT). The OT group is discarded in the analysis, because it is very heterogeneous and II taxes and EM taxes are combined into private income (PI) tax category due to the limited number of observations. To comply with assumption (2), we retain only those shocks that are unrelated to the current state of the economy. Mertens and Ravn (2012) distinguish between anticipated and unanticipated changes based on the implementation lag. They retain only those policy changes where the difference between the date on which the tax change becomes law and the date on which it is implemented is less than one quarter. To comply with data availability issues for 3-digit industry output levels, we limit the sample to 1972Q1-2006Q3. We focus on private income tax, which leaves us with 11 tax shock observations. To convert tax liability changes into the corresponding average tax policy changes, we compute the following:

$$\Delta T_q^{PI} = \frac{\left(II\ tax\ liability\ change_q + EM\ tax\ liability\ change_q\right)}{Personal\ taxable\ income_{q-1}} \tag{3.28}$$

$$\Delta T_q^{CI} = \frac{CI\ tax\ liability\ change_q}{Corporate\ profits_{q-1}} \tag{3.29}$$

Finally, given a tax change, the correlation between PI and CI shocks in our sample is 0.36. Therefore, it is inappropriate to treat the PI tax shocks as being uncorrelated with the exogenous corporate tax rate. There are a number of explanations for this positive correlation. Although narrative records contain only changes that were not explicitly motivated by countercyclical considerations, it is plausible to assume that they were implemented in view of long-term goals for economic growth. Therefore, it is not surprising that both private income and corporate income tax shocks are adjusted in the same direction.

In order to isolate the impact of only one of the tax rates, it is imperative that we control for changes in the other. We do so by regressing demeaned private income tax shocks on corporate income tax shocks and using the residuals:

$$\Delta T_q^{PI} = \beta_0 + \beta_1 \Delta T_q^{CI} + \epsilon_q^{PI} \tag{3.30}$$

Let $\Delta T_q^{PI*} = \epsilon_q^{PI}$ be the tax shock variable used in the subsequent analysis.

To demonstrate that the tax shocks we construct are empirically unrelated to other non-tax structural shocks, we regress T_q^{PI*} on a variety of macroeconomic shock variables previously identified in the literature such as: federal spending (Ramey and Zubairy (2018), Caggiano et al. (2015)), consumer sentiment and business confidence (Forni et al. (2017)), monetary policy shocks (Tenreyro and Thwaites (2016), Nakamura and Steinsson (2018a)), economic uncertainty (Geopolitical Risk Index[9] and Economic Policy Uncertainty Index[10]) and news (Barsky and Sims (2011), Beaudry and Portier (2014)). The evidence in Table 3.1 suggests that our measure of tax shocks is orthogonal to most of the macroeconomic shocks commonly used in the literature with the exception of some monetary policy shock measures. Although statistically significant, the economic magnitude of the relationship is very low. For example, a 1 % surprise increase in the Federal Reserve target policy rate in a given quarter is associated with a 0.04 % increase in the private income tax rate. Intuitively, correlations with structural macroeconomic variables are low because we retain only exogenous, unanticipated tax shocks, which were not motivated by counter-cyclical policy considerations. These results indicate that private income tax shocks are correctly and precisely specified, which allows us to make causal statements about the transmission of tax policy through the production network.

Finally, we test the following empirical specifications for private income shocks.

$$\Delta sales_{iq} = \beta_0 + \rho W_{ij}^{Upstream} \Delta sales_{iq} + \beta_1 \Delta T_q^{PI*} + \varepsilon_{iq} \tag{3.31}$$

in the interval $[q-4, q+4]$ where q denotes the quarter in which a policy change

[9] https://www.policyuncertainty.com/gpr.html

[10] https://www.policyuncertainty.com/

is implemented. The model is estimated as a pooled cross-section without explicitly taking into consideration the time dimension of the data. The presence of $\rho W_{ij}^{Upstream} \Delta sales_{iq}$ introduces cross-sectional correlation in the error-terms and renders the OLS estimates inconsistent. Hence, the model is estimated using maximum likelihood (ML). Standard errors are calculated using 1000 simulated parameter values.

Table 3.1: Exogeneity Test

Shock	Source	Personal Income Tax Shock
Federal Spending	Ramey and Zubairy (2018)	0.027 (1.35)
Surprise Spending	Caggiano et al. (2015)	−0.028 (0.034)
Anticipated Spending	Caggiano et al. (2015)	−0.285 (1.14)
Consumer Sentiment	Forni et al. (2017)	0.002 (0.20)
Business Sentiment	Forni et al. (2017)	−0.015 (1.50)
Monetary Shock-Linear	Tenreyro and Thwaites (2016)	0.009*** (3.00)
Monetary Shock-Nonlinear	Tenreyro and Thwaites (2016)	0.001 (0.16)
Monetary Shock-Anticipated	Nakamura and Steinsson (2018b)	0.022 (0.36)
Monetary Shock-Surprise	Nakamura and Steinsson (2018b)	0.049* (1.63)
Uncertainty - GPR Index	Caldara and Iacoviello (2018)	0.01 (1.00)
Uncertainty - EPU Index	Baker et al. (2016)	0.042 (1.40)
News	Barsky and Sims (2011)	0.017* (1.70)
News	Beaudry and Portier (2014)	0.03 (0.30)

Notes: The table reports the estimates of regressing private income tax shocks on a series of macroeconomic shock variables. T-stats are reported in parentheses. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.

3.3.5 Input-Output Matrix *W*

We combine the USE and MAKE tables at three-digit level published by Bureau of Economic Analysis (BEA) to construct industry-by-industry matrix to identify the upstream and downstream linkages in the economy. Define the following square matrix with the total amount output of each industry placed on the main diagonal and zeros elsewhere

$$g = \begin{pmatrix} Y_1 & 0 & \dots & 0 \\ 0 & Y_2 & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & Y_n \end{pmatrix}$$

where Y_1 is the output of the industry that corresponds to the first column industry of USE table, Y_2 second column and so on. We use above g matrix and USE table to determine the amount of a commodity used by an industry per dollar of output of that industry. We call this matrix INPUT, which is a commodity-by-industry matrix and given by

$$INPUT = USE \times g^{-1}$$

Now define a square matrix with the total amount of each commodity's output listed on the main diagonal and zeros elsewhere

$$q = \begin{pmatrix} C_1 & 0 & \dots & 0 \\ 0 & C_2 & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & C_n \end{pmatrix}$$

where C_1 is the output of the commodity that corresponds to the first column industry of MAKE table, C_2 second column and so on. We use above q matrix and MAKE table to determine the the proportion of the total output of that commodity produced in each industry. We call this matrix SHARE, which is an industry-by-commodity matrix and given by

$$SHARE = MAKE \times q^{-1}$$

We use INPUT and SHARE matrices to calculate the percentage of industry i's inputs purchased from industry j and label the resulting matrix DOWNSTREAM

$$DOWNSTREAM = (SHARE \times INPUT)'$$

Notice that we transpose the matrice multiplication in the parenthesis in the above equation to have buyer industry in the rows and sellers in the columns. To derive upstream linkages, we do the following multiplication

$$UPSTREAM = \left(DOWNSTREAM \times \frac{Output_i}{Output_j} \right)'$$

where $Output_i$ is the output of ith row industry (buyer) and $Output_j$ is the output of jth column industry (seller) of UPSTREAM matrix and multiplication in the parenthesis is transposed to have seller industry in the rows and buyer in the columns. Finally, we normalize the UPSTREAM matrix so that the intermediate input shares sum to one for each seller industry and this corresponds to the transpose of our theoretical $\hat{A}$ matrix given in equation 1.18 and also to the W matrix in our empirical specification.

3.4 Empirical Results

3.4.1 Summary Statistics and Network Dependence

A useful visual tool for exploratory spatial analysis is the Moran Scatter Plot(Figure 3.1). It allows to assess similarities between neighboring observations. The horizontal axis gives the values of industry output ($\Delta sales$) and is called the response axis. The vertical axis gives the weighted average of the corresponding observations on the response axis ($W\Delta sales$)[11]. If the I/O weights matrix W did not contain any relevant information, observations would be randomly scattered in the plot. This is not the case and data points are located about a line. In fact, for roughly 90 % of the industries higher output of the customers correlates with higher output of their suppliers. Thus, the Moran Scatter Plot offers preliminary evidence for the relevance of the production network structure for the transmission of tax shocks. Table 3.2 discusses in detail the number and strength of network connections, excluding own-industry links. The average supplier in the sample is connected to 60 customers, which means that there are no isolated industries in the sample. The number of linkages to very small customers (less than 1 % of sales) accounts for 42.50 out the total number of non-zero links. The number of links to small customers (1-5 % of sales) is 14.23, to medium-sized ones (5-20 % of sales) is 2.62 and to large customers ($>$ 20 % of sales) is 0.64 respectively. The summary statistics indicate that the production network is relatively sparse i.e. industries have many connections with very small weights. All industries are connected to their own industry. Furthermore, within-industry sales account for 13 % of total sales, which stresses the importance to differentiate between network effects originating from within and across industry connections.

[11]The graph considers only upstream links i.e. customer-supplier links, but the conclusions also hold for downstream (supplier-customer) relationships.

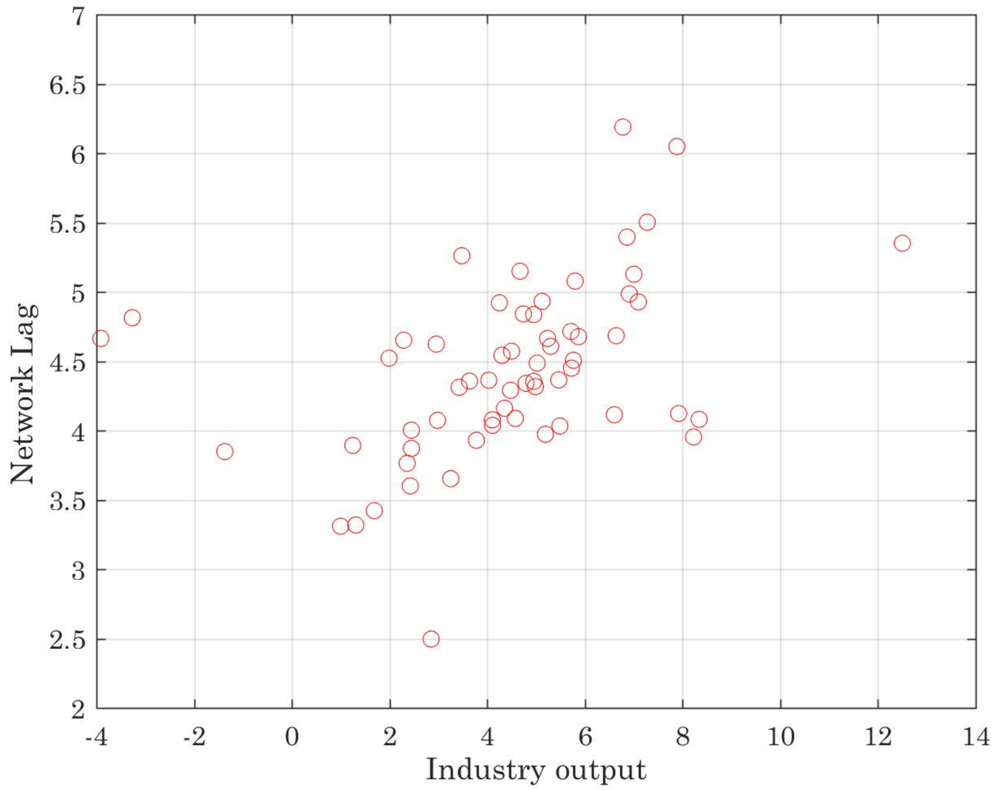

Figure 3.1: Network Dependence

Notes: The figure plots Moran's Scatterplot. Industry output is averaged over the sample period and $W^{Average}$ is used to compute the upstream (i.e. customer-supplier links) network lag.

Table 3.2: Summary Statistics of Production Linkages

	mean	standard deviation	min	max
number of non-zero links	60	0	60	60
number of links to very small customers	42.50	7.32	28	56
number of links to small customers	14.23	7.02	2	30
number of links to medium customers	2.62	1.79	0	6
number of links to large customers	0.64	0.97	4	4

Notes: The table gives summary statistics for an average supplier industry. Very small customers are those that buy less than 1% of total supplier sales; small customers between $1-5\%$; medium customers between $5-20$ and large customers $\geq 20\%$. Own industry connections are not counted.

3.4.2 Baseline Results

Panel A of Table 3.3 presents the results for equation 3.31, our baseline model, in which we regress industry sales on tax shocks (column (1)) and a weighted average of industry sales (column (2)-column(5)). A private income tax rate, which is 1 percentage point higher than expected, reduces industry sales by 1.41 %. Column (2) shows that the ML estimate for β and ρ is highly statistically significant. To comply with the theoretical model, which requires constant intermediate input shares, the model uses an average weighting matrix W^{AVG}, which is computed by averaging over the IO tables for the reference period 1973-2003. The dependent variable in all baseline results is $\Delta sales_{iqh}$ with $h = 0$. The positive estimate for ρ means that the effect of the shock is transmitted through the network. Economically, the negative estimate of β suggests that higher than expected tax rate reduces industry sales, which is consistent with the findings of previous studies.

Table 3.3: Baseline results

	(1) OLS	(2) SAR: W^{AVG}	(3) SAR: W_t	(4) SAR: W_{t-1}	(5) SAR: W_{t-1}
		Panel A. Point Estimates			
ρ		0.57^{***}	0.66^{***}	0.66^{***}	0.56^{***}
		(10.38)	(14.67)	(14.30)	(11.13)
β_1	-1.41^{***}	-0.60^{**}	-0.41^{**}	-0.40^{**}	-0.85^{**}
	(-4.98)	(-2.07)	(-2.21)	(-2.15)	(-2.23)
quarter FE	NO	NO	NO	NO	YES
ind. FE	NO	NO	NO	NO	YES
Ind-Quarter FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	NO	YES
Adj. R^2, %	1.94	35.20	36.00	35.95	66.73
N	61	61	61	61	61
T	12	12	12	12	12
Observations	732	732	732	732	732
		Panel B. Decompositions			
Direct Effect	NA	-0.60^{**}	-0.41^{**}	-0.40^{**}	-0.85^{**}
		(-2.09)	(-2.17)	(-2.15)	(-2.16)
Indirect Effect	NA	-0.73^{**}	-0.76^{**}	-0.71^{**}	-1.02^{**}
		(-1.98)	(-2.14)	(-2.11)	(-2.09)
Feedback Effect	NA	-0.07^{**}	-0.06^{**}	-0.05^{**}	-0.09^{**}
		(-2.10)	(-2.22)	(-2.30)	(-2.18)
Total Effect	-1.07^{***}	-1.40^{**}	-1.23^{**}	-1.16^{**}	-1.96^{**}
	(-4.98)	(-2.11)	(-2.21)	(-2.18)	(-2.19)
Network/Total	NA	56.90%	66.66%	65.51%	56.8%

*Notes: The table reports the results of regressing industry-level output on tax shocks and a spatial lag. Column (1) gives the OLS estimates of the standard model; columns (2)-(5) report maximum likelihood estimates for the spatial autoregressive model (SAR). Controls: average personal and corporate income tax rate, government spending, government debt, inflation, short-term interest rate, unemployment. Panel A reports point-estimates of the results; Panel B reports decomposition of the total reaction into direct and network effects. T-stats are reported in parentheses. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.*

Panel B of Table 3.3 gives the decomposition of the total effect into a direct, indirect and feedback effect. Network effects (indirect and feedback) constitute 57 % of the total effect. Notably, feedback effects account for roughly 7 %, which is reassuring evidence showing that the large network effects we document are not driven by own-industry production linkages. Interestingly, recall that within-industry sales account for 13 % of sales. This re-emphasizes the non-linear nature of networks, where spillovers are driven not only by the strength, but also by the direction of the link.

In Table 3.4 we document the effect of the shock over a longer horizon. We observe a hump-shaped pattern: the response of industries intensifies over $h = 1$ to $h = 3$ and then it slowly decreases after $h = 4$. The effect is virtually 0 after horizon length longer than 10 i.e roughly a year after the shock. Moreover, the relative impact of the network decreases over time. For comparison, for $h = 0$ network effects constitute 57 % of the total effect,whereas for $h = 10$ the network effect amounts to 47 %. Importantly, after $h = 3$ network effects are statistically indistinguishable from zero, which provides additional evidence that the result is not merely a statistical artefact. Although the production network is physically always present, the transmission through it is only activated conditional on a tax shock hitting the economy.

Table 3.4: The Effect of PI Shocks on Industrial Output Over Time

	horizon							
	0	1	2	3	4	6	8	10
Direct Effect	-0.60^{**}	-0.79	-0.77^{**}	-0.77^{*}	-0.80	-0.69	-0.19	-0.34
	(-2.09)	(-2.03)	(-2.00)	(-1.83)	(-1.44)	(-0.95)	(-0.63)	(0.04)
Indirect Effect	-0.73^{**}	-0.99^{**}	-1.04^{**}	-1.00	-0.84	-0.87	-0.18	0.29
	(-1.98)	(-2.00)	(-2.01)	(-1.48)	(-1.43)	(-0.94)	(-0.61)	(0.04)
Feedback Effect	-0.07^{**}	-0.09^{**}	-0.09^{*}	-0.08	-0.08	-0.07	-0.02	0.02
	(-2.10)	(-2.09)	(-1.88)	(-1.49)	(-1.29)	(-1.07)	(-0.23)	(0.29)
Total Effect	-1.40^{**}	$-1.82**$	-1.99^{*}	-1.85	-1.72	-1.63	-0.39	0.65
	(-2.11)	(-2.02)	(-1.78)	(-1.55)	(-1.44)	(-1.33)	(-0.63)	(0.05)
Network	56.90%	59.34%	56.78%	58.37%	53.48%	57.66%	51.28%	47.69%

*Notes: The table reports the results of regressing industry-level output on a spatial lag and private income tax shocks. See text for more details on the construction of the dependent variable. The model uses an average weighting matrix W over the period 1972-2003. T-stats are reported in parentheses. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.*

Our results are in closely in line with Mertens and Ravn (2013), who find that 1 percentage point increase in the tax rate reduces real GDP per capita by 1.4

% on impact and by up to 1.8 % after three quarters. We extend their work by proposing a new transmission channel, which operates through production linkages in the economy.

3.4.3 Time Varying W

Our choice of a constant weighting matrix is motivated by two aspects. First, our theoretical model with Cobb-Douglas production specifies a constant share of intermediate inputs. Second, the SAR model assumes that the W matrix is stable over time and that links are endogenously determined by technology. However, our time frame (1972-2006) is marked by important technological breakthroughs such as the invention of the silicon chip and its mass production in the 1960s, computerization in the 1990s and the Internet revolution in the 2000s. These events could disrupt the production process by creating new links between industries or increasing/decreasing the intensity of the connections. To reflect potential changes in the production structure of the economy over time, in columns (3) and (4) of Table 3.3 the model introduces a time-varying and lagged time-varying weighting matrix. Results indicate that imposing a constant W does not overstate the magnitude of the network effect.

3.4.4 Network Effect vs. Co-movement

Industry sales are likely to co-move even in the absence of a production network, because they are exposed to common factors, reflecting the state of the economy. Since failing to account for such factors could overstate the magnitude of the network effect, in column (5) of Table 3.3 we control for government spending, debt, inflation, short-term interest rates and unemployment. Furthermore, we include quarter, industry and quarter-industry fixed effects to account for unobservable industry-specific or time period characteristics. We find that the magnitude of the network effect is reduced by approximately 15 %, but it remains strongly statistically significant. Although we acknowledge that some of the effect we find is driven by exposure of industries to common factors, the majority of the spillovers we document are driven by the production structure of the economy.

3.4.5 Upstream vs. Downstream Propagation

Our theoretical model predicts that private income tax shocks travel *only* upstream: from customers to their suppliers. This pattern emerges from the fact that demand-side shocks cause affected industries to adjust their production levels, and hence, their input demands. However, the result follows from the assumption of Cobb-Douglas production technology and consumer preferences, so that income and substitution effects cancel out. Empirically, it is also possible that the downstream channel is active, in which case private income tax shocks change the prices faced by customer industries and trigger downstream propagation. To assess which of the two channels is more powerful, we run the following specification[12]:

$$\Delta sales_{iq} = \beta_0 + \rho W_{ij}^{Upstream} \Delta sales_{iq} + \theta W_{ij}^{Downstream} \Delta sales_{iq} + \beta_1 \Delta T_q^{PI*} + \varepsilon_{iq} \quad (3.32)$$

where $W_{ij}^{Upstream} \Delta sales_{iq}$ is weighted by customer sales and $W_{ij}^{Downstream} \Delta sales_{iq}$ is weighted by supplier sales. The estimate of θ is very close to zero and statistically insignificant, whereas the estimate for ρ is virtually unchanged compared to the baseline specification (Table 3.5).

Table 3.5: Upstream vs. Downstream Transmission

	(1) ΔT_q^{PI*}	(2) ΔT_q^{PI}
ρ	0.62***	0.53***
	(6.85)	(4.50)
θ	−0.008	0.21*
	(−0.07)	(1.90)
β_1	−0.37*	−0.25*
	(−1.90)	(−1.89)
Adj R^2, %	35.3	32.14
N	61	61
T	12	12
Observations	732	732

*Notes: The table reports the results of regressing industry-level sales on an upstream and downstream spatial lags and private income tax shocks. T-stats are reported in parentheses. ΔT_q^{PI*} refers to private income tax shocks orthogonal to corporate income tax shocks, ΔT_q^{PI} are raw, unadjusted tax shocks. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.*

In column (2) instead, we use raw private income shocks (i.e. unadjusted for the impact of corporate income taxes). Two points are worth mentioning here. First, we find that downstream effects are active ($\theta = 0.21$) and that the magnitude of upstream effects is slightly reduced ($\rho = 0.53$). Second, the reason why we find downstream effects is because in this specification our measure of private income tax shocks is correlated with corporate income tax shocks, which are supply-side shocks and transmit from suppliers to customers. This empirical result is important because it confirms the theoretical prediction that private income shocks propagate *upstream* through production networks and demonstrates that our measure of private

[12] The model is well-defined for $|\rho + \theta| < 1$

income shocks is not confounded by other fiscal policy adjustments.

3.4.6 Higher Order Demand Effects

The results in the previous sections reveal that the magnitude of spillover effects is considerably higher than what would be predicted by just looking at the number and strength of direct connections between industries i.e. by sparsity. To gain further insights into the propagation of the tax shocks, it is interesting to partition the network effect by order of the neighbors. Recall that according to the infinite series decomposition in Section 3.3.2, network orders are given by the powers of W: observations themselves (0-order), immediate neighbors (1^{st}-order), neighbors of immediate neighbors (2^{nd}-order) and so on. Table 3.6 shows spatially-partitioned network effects associated with orders 1 to 5[13].

Table 3.6: Higher-order Demand Effects

W-order	Total	Direct	Indirect	Feedback
W^0	-0.60	-0.60	0.00	0.00
W^1	-0.34	0.00	-0.28	-0.05
W^2	-0.19	0.00	-0.18	-0.01
W^3	-0.11	0.00	-0.11	-0.00
W^4	-0.06	0.00	-0.06	-0.00
W^5	-0.04	0.00	-0.04	-0.00
$\sum_{q=0}^{5} \rho^q W^q$	1.34	0.60	-0.67	-0.06

Notes: The table reports higher-order demand effects associated with powers of W. Regressions refer to model (2) in Table 3.3.

Feedback effects die out very quickly and after the second order are essentially zero. Indirect network effects, on the other hand, exhibit notably slower decay. Importantly, effects falling on orders greater than one are economically large. These findings indicate the sparsity of the W matrix alone cannot explain the results, because it disregards the crucial role that higher-order demand play in the transmission process. For comparison, considering only first-order connections (i.e. W^1 would understate the magnitude of network effects by approximately 53%. The key features of the SAR model, which make it adept to study network effects of tax policy, are its ability to capture simultaneously higher-order linkages and to account for non-linearities in the network structure.

[13]The first 5 network orders account for 98.6 % of overall network effect. Note that if the spatially partitioned effects are cumulated over all powers of W until empirical convergence of the infinite series, these would exactly equal the magnitudes reported in the last row of Table 3.3.

3.5 Robustness and Discussion

3.5.1 Heterogeneity

One concern in the analysis could be that imposing a constant beta across industries biases our estimate of ρ upwards. Estimating a large number of parameters is typically problematic in a full information ML framework. Fortunately, it is possible to estimate the model with heterogeneous betas using the log-likelihood concentrated with respect to β and σ, the noise variance parameter associated with ϵ as in LeSage and Pace (2009). Essentially, ρ is estimated by maximizing the likelihood obtained by replacing all other parameters with their least squares estimates[14]. We assume that industries have heterogeneous sensitivity to private income tax shocks, which is constant over time:

$$\Delta sales_{iq} = \beta_{0i} + \rho W_{ij}^{Upstream} \Delta sales_{iq} + \beta_{1i} \Delta T_q^{PI*} + \varepsilon_{iq} \tag{3.33}$$

Column (1) of Table 3.7 shows that imposing constant beta across industries seems to bias the estimated exposure (β_1) upwards, but it has no impact on the estimate of ρ. The results of this section suggest that imposing a constant sensitivity across industries cannot explain the large network effect of private income tax shocks on industry sales.

Table 3.7: Robustness

	(1) Heterogenous Effects	(2) Simulated W	(3) Permute columns	(4) Permute rows
ρ	0.66^{***}	0.20^{***}	0.31^{***}	0.29^{***}
	(30.17)	(2.97)	(4.03)	(3.81)
β_1	-0.48^{***}	-1.11^{***}	-0.96^{***}	-0.97^{***}
	(-1.95)	(-3.71)	(-2.73)	(-2.23)
Adj R^2, %	67.71	4.18	17.31	15.04
N	61	61	61	61
T	12	12	12	12
Observations	732	732	732	732

*Notes: The table reports the results of regressing industry-level sales on a spatial lag and private income tax shocks. T-stats are reported in parentheses. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.*

[14] Standard errors can be recovered from the full-model maximum likelihood by numerically evaluating the Hessian. The reader is referred to LeSage and Pace (2009) *Chapter 3:Maximum Likelihood Estimation* for more details about the estimation procedure.

3.5.2 Random I/O Matrices

Another concern is that we mechanically find large network effects, because we regress industry sales on a weighted average of industry sales. To address this, a simulated input-output matrix is used as an input to the SAR model. The histogram of industry linkages shows that the empirical input-output matrix is sparse and its distribution is heavily right-skewed (Figure 3.2). This means that a small number of sectors are important suppliers to the rest of the economy. We simulate an input-output matrix, which inherits those two features of the data. We draw random numbers from a Generalized Pareto distribution with shape parameter $k = 1.0347$, scale parameter $sigma = 0.0040$ and location parameter $l = 0.0001$. To derive these parameters, we minimize the squared distance between the empirical distribution function and the estimated distribution. Column (2) of Table 3.7 shows that the bias in estimating the spatial parameter ρ is likely to be very small. The model obtains a $\rho = 0.20$, which is nearly three times smaller than the baseline estimate of 0.44.

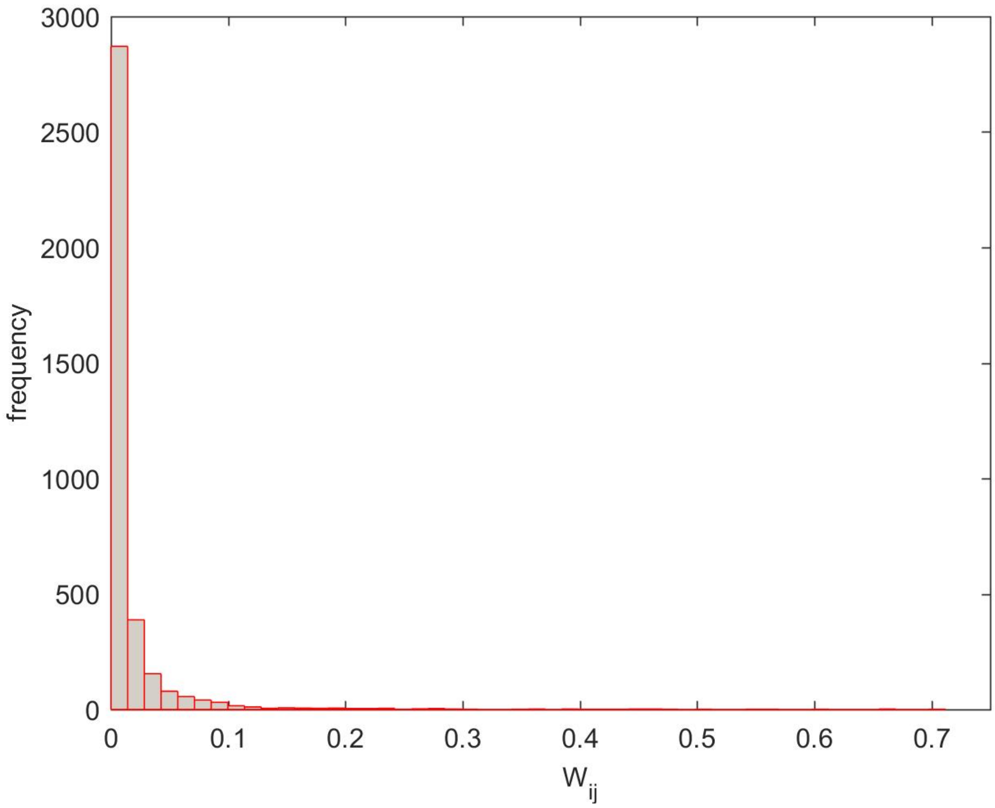

Figure 3.2: Histogram of Network Linkages

Drawing random numbers from a fitted distribution might alter the distribution of links. Therefore, in columns (3) and (4) of Table 3.7, we take the actual input-output matrix as given and only permute the rows and columns, simulating the model 1000 times. We find that the mean point estimate of ρ that are 46 % lower than our baseline specification. Furthermore, in all 1000 simulations the estimated value of ρ is lower than the baseline estimate. Hence, we conclude that the particular structure of the network is driving factor of the transmission of private income shocks.

3.6 Dynamic Model

Our empirical results lend support to the prediction of the static network model, which shows that personal income tax shocks propagate upstream (from customers to their suppliers). However, in a static model it is not possible to account for dynamic fiscal adjustments. This could be a problem for the estimation if the response of government spending to the changes in tax revenue has a sizable effect on the propagation of the tax shock through network linkages. Another concern could be that there is a confounding factor driving the results, which despite our extensive robustness checks, we were not able to detect. In this section, we build and calibrate a dynamic model to address these concerns and to rationalize the size of the network effects we find empirically.

3.6.1 Model Environment

We keep the notation similar to the static model as much as possible. The firm side of the model remains essentially the same. The preferences of the households are given by

$$U(\mathbf{C}, L) = log\mathbf{C_t} - \xi \frac{L_t^{1+\chi}}{1+\chi}, \tag{3.34}$$

where $\mathbf{C}$ is the consumption basket of the household, L is labor supply, χ is inverse Frisch elasticity and ξ is a scalar. The consumption basket of the household is given by

$$\mathbf{C_t} = \prod_{i=1}^{n} \omega_{ci}^{-\omega_{ci}} C_{it}^{\omega_{ci}}, \tag{3.35}$$

where ω_{ci} is the share of good i in total consumption. The budget constraint of the household reads

$$P_t C_t = (1-\tau_t) W_t L_t + \sum_{i=1}^{n} \pi_{it} - T_t, \tag{3.36}$$

where τ_t is the personal income tax rate, π_{it} are the profits transferred to the household from industry i and T_t are the lump-sum taxes (or transfers if negative). The optimality conditions of the household problem are given by

$$\xi L_t^{\chi} = (1-\tau_t)\frac{W_t}{P_t C_t}, \tag{3.37}$$

$$P_{it}C_{it} = \omega_{ci}P_t C_t, \tag{3.38}$$

where the first and last equations express the labor-leisure choice and consumption choice of industry i good, respectively. The government maintains balanced budget

$$\tau_t W_t L_t + T_t = P_t G_t, \tag{3.39}$$

and total tax revenues are equal to the total spending. The tax rates are dynamic in the model and follows the following exogenous process

$$\tau_t = (1-\rho_\tau)\bar{\tau} + \rho_\tau \tau_{t-1} + \varepsilon_t^\tau, \tag{3.40}$$

where $\bar{\tau}$ is the steady-state personal income tax rate, ρ_τ is the persistency parameter and ε_t^τ is iid normal such that: $\varepsilon_t^\tau \sim \mathcal{N}(0, \sigma^2_{\varepsilon^\tau})$. The government spending is constant share of tax revenues

$$G_t = (\tau_t W_t L_t)^{\psi_g}, \tag{3.41}$$

where ψ_g determines the response of government spending to the tax revenue streams. We model the government spending process as a function of tax shocks to remove the discretionary fiscal spending component and focus on the impact of the cyclical government spending on the transmission of the personal income tax policy. Finally, the market clearing conditions are given by

$$Y_{it} = C_{it} + \sum_{j=1}^{n} X_{ji,t} + G_{it}, \tag{3.42}$$

$$P_t G_t = \sum_{i=1}^{n} P_{it} G_{it}, \tag{3.43}$$

$$L_t = \sum_{i=1}^{n} L_{it}, \tag{3.44}$$

$$W_t = \sum_{i=1}^{n} w_i W_{it}. \tag{3.45}$$

The equation 3.42 is the market clearing condition for industry i and equation 3.43 is market clearing for government spending. The equations 3.44and 3.45 give aggregate labor, linearly sum of hours worked in all industries, and aggregate wage, weighted average of sectoral wages.

We solve the model by log-linearizing the equations around deterministic steady-state. The steady-state solution and log-linearized equations are given in Appendix. As a final note, we assume wages are perfectly rigid at each period t.

3.6.2 Calibration

We calibrate the model to match key moments in data and consider alternative scenarios for robustness checks. We set steady-state government spending-to-gdp ratio and personal income tax rate 0.09 and 0.22 and the persistency of tax rate to $\rho_\tau = 0.97$ following Leeper et al. (2010). We set the standard deviation of the personal income tax shock $\sigma_{\varepsilon^\tau} = 0.12$, the value we obtained from the demeaned narrative tax series of Mertens and Ravn (2013).

We calibrate η_i to match our model implied industry-specific steady-state labor share to the average total value added over output of each industry from USE tables at 3 digit NAICS level since our model does not contain capital. We set ω_{ci}, the share of industry i in the total consumption, by measuring the average ratio of final consumption in each industry over sum of total consumption. We sum intermediate input plus final demand from federal and state&local government at each industry level and divide these values over total sum to derive the industry-specific government shares. We set $\chi = 2$ and calibrate ξ to have steady-state labor supply equal to $1/3$.

We also consider two different values for the parameter ψ_g, in the first case we set $\psi_g = 0$ so the government spending does not react to the changes in tax rates and in the second case we set $\psi_g = 0.5$ giving us 0.5% change in the government spending after 1% change in the tax revenue. We set these values to understand the how the fiscal adjustments affect the propagation of the tax shocks over the industry linkages. Moreover in the first case we set $\bar{g} = 0$, so we completely eliminate the government side in the model.

We perturbate the values of χ, ρ_τ and $\sigma_{\varepsilon^\tau}$, one in each time, as an additional check.

3.6.3 Simulation Results

We simulate the model over 228 periods and discard the first and last 50 observations to end up with 128 data points to match with our empirical sample. We run the simulations over 100 times. We add normally distributed iid noise to the data generating process in each simulation. We present results in Table 3.8

Table 3.8: Simulation

Benchmark	Variation	$\psi_g = 0$		$\psi_g = 0.5$	
		ρ	β	ρ	β
		0.56	-0.02	0.63	-0.01
		(34.19)	(-15.60)	(42.53)	(-9.26)
$\chi_g = 2$	$\chi_g = 4$	0.47	-0.016	0.59	-0.01
		(25.13)	(-19.56)	(37.36)	(-13.13)
$\rho_\tau = 0.97$	$\rho_\tau = 0.90$	0.28	-0.05	0.58	-0.007
		(12.44)	(-25.45)	(35.50)	(-16.47)
$\sigma_{\varepsilon^\tau} = 0.12$	$\sigma_{\varepsilon^\tau} = 1$	0.60	-0.07	0.49	-0.015
		(2.38)	(-19.42)	(26.71)	(-18.64)

Notes: The table reports results from estimating our baseline specification on simulated data from the dynamic model of Section 7. We simulate each model calibration 50 times for 128 quarters and report the mean estimates and mean t-stats.

In our benchmark calibration an increase in the PI tax rate results in a drop of sales ($\beta_1 < 0$) and the result is transmitted through the production network ($\rho > 0$). Interestingly, we are able to match very closely the fractions of network effects across specifications to our empirical estimates.

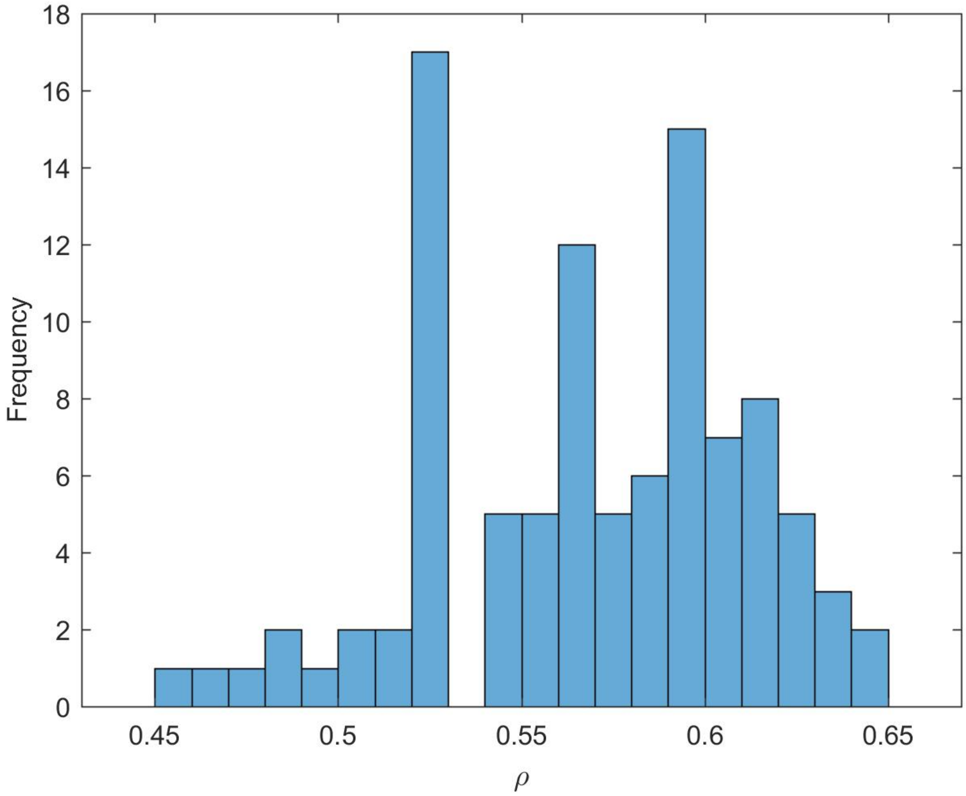

Figure 3.3: Histogram of Network Linkages

Notes: The figure plots a histogram of the spatial autoregressive parameter ρ estimated from simulations of the dynamic model.

Figure 3.3 shows the histogram of ρ across simulation rounds. The parameter is very precisely estimated and its distributions is approximately normal. Moreover, neither introducing government spending, nor changing the fundamental parameters of the model has a large impact on the estimates of ρ.

Finally, in Table 3.9 we estimate the model on simulated data imposing that shocks propagate downstream. In all cases we find that the upstream effect is significantly larger than the downstream effect.

These results indicate that our SAR framework is robust to relaxing some of the assumptions of the static theoretical model and that upstream production linkages are an important determinant of the exposure of industry sales to private income tax shocks.

Table 3.9: Simulation: Downstream Propagation

Benchmark	Variation	$\psi_g = 0$		$\psi_g = 0.5$	
		ρ	β	ρ	β
		0.37	-0.05	0.51	-0.04
		(16.24)	(-24.67)	(26.57)	(-22.07)
$\chi_g = 2$	$\chi_g = 4$	0.27	-0.03	0.53	-0.02
		(10.97)	(-25.83)	(27.48)	(-21.62)
$\rho_\tau = 0.97$	$\rho_\tau = 0.90$	0.13	-0.07	0.51	-0.02
		(4.88)	(-27.73)	(26.74)	(-22.66)
$\sigma_{\varepsilon^\tau} = 0.12$	$\sigma_{\varepsilon^\tau} = 1$	0.22	-0.08	0.39	-0.03
		(0.75)	(-19.80)	(17.55)	(-23.63)

Notes: The table reports results from estimating our baseline specification on simulated data imposing that the effect is transmitted downstream. We simulate each model calibration 50 times for 128 quarters and report the mean estimates and mean t-stats.

3.7 Conclusion

This paper investigates whether exogenous tax shocks propagate through production networks. We develop a static model with intermediate inputs, which predicts that the reaction of industries to tax shocks follows a spatial autoregression (SAR) and that the effect propagates upstream (from customers to suppliers). To test this empirically, we use quarterly sales data for US industries for the period 1972-2003. We confirm that private income tax shocks travel upstream and we show that between 55 to 70 percent of the total effect on sales is due to higher-order network effects. The importance of production networks for the transmission of tax shocks suggests that macroeconomic models should take into account linkages between industries when setting and evaluating policy decisions.

Our results open new avenues of research, such as the importance of different sectors for the transmission of shocks and optimal tax policy when the economy is characterized by a network. We intend to address these questions in our future work.

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Appendix A

Appendix to Chapter 1

A.1 Simple Imperfect Information Model

Assume the following AR(1) government spending process

$$g_t = \rho g_{t-1} + \varepsilon_{t-1}, \tag{A.1}$$

where ε_{t-1} is the fiscal news shock. Assuming information rigidities, agents cannot directly observe g_t and ε_t but instead receive signals $s^1_{i,t}$ and $s^2_{i,t}$ such that

$$s^1_{i,t} = g^d_t + \eta_{i,t}, \quad \eta_{i,t} \sim N(0, \sigma^2_\eta) \tag{A.2}$$

$$s^2_{i,t} = \varepsilon_t + \omega_{i,t}, \quad \omega_{i,t} \sim N(0, \sigma^2_\omega). \tag{A.3}$$

The first signal reveals information about current fiscal spending and second signal reveals information about fiscal news shock. Each agent i then generates forecasts (conditional expectations) given their information sets via the Kalman filter

$$E^i_t \begin{pmatrix} g_t \\ \varepsilon_t \end{pmatrix} = E^i_t \begin{pmatrix} g_{t-1} \\ \varepsilon_{t-1} \end{pmatrix} + \begin{pmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{pmatrix} \left(\begin{matrix} s^1_{i,t} \\ s^2_{i,t} \end{matrix} - E^i_{t-1} \begin{pmatrix} s^1_{i,t} \\ s^2_{i,t} \end{pmatrix} \right), \tag{A.4}$$

where K_{11}, K_{12}, K_{13} and K_{14} are the entries of Kalman gain matrix.[1] Denote $K = K_{11}$ and $M = K_{22}$. By using the fact that $E^i_{t-1} s^2_{i,t} = E^i_{t-1} \varepsilon_t = 0$, the forecast of government spending at individual level is equal to

$$E^i_t g_t = (1 - K)\, E^i_{t-1} g_t + K s^1_{i,t} + K_{12} s^2_{i,t}, \tag{A.5}$$

and the forecast of fiscal news shock at individual level is equal to

$$E^i_t \varepsilon_t = K_{21} \left(s^1_{i,t} - E^i_{t-1} s^1_{i,t} \right) + M s^2_{i,t}. \tag{A.6}$$

[1] One can show that $K_{12} = K_{21} = 0$ since the two signals are orthogonal to each other.

By averaging the equations A.5 and A.6 across agents and using the fact that $K_{12} = K_{21} = 0$, the aggregate forecasts are given by

$$E_t g_t = (1-K)\, E_{t-1} g_t + K g_t, \tag{A.7}$$

$$E_t \varepsilon_t = M \varepsilon_t. \tag{A.8}$$

Rearranging Equation A.7 gives

$$g_t - E_t g_t = \frac{1-K}{K} \left[E_t g_t - E_{t-1} g_t \right]. \tag{A.9}$$

Now iterate Equation A.1 one period ahead and subtract the time t expectations

$$g_{t+1} - E_t g_{t+1} = \rho g_t + \varepsilon_t - \rho E_t g_t - E_t \varepsilon_t. \tag{A.10}$$

Now use Equations A.8 and A.9 in Equation A.10 to get

$$g_{t+1} - E_t g_{t+1} = \rho \frac{1-K}{K} \left[E_t g_t - E_{t-1} g_t \right] + (1-M)\, \varepsilon_t. \tag{A.11}$$

Finally, using the fact that$E_t g_{t+1} = \rho E_t g_t + E_t \varepsilon_t$ in Equation A.11 gives

$$g_{t+1} - E_t g_{t+1} = \frac{1-K}{K} \left[E_t g_{t+1} - E_{t-1} g_{t+1} \right] + \left(1 - \frac{M}{K} \right) \varepsilon_t. \tag{A.12}$$

Iterating Equation A.12 h period ahead gives

$$g_{t+h} - E_t g_{t+h} = \frac{1-K}{K} \left[E_t g_{t+h} - E_{t-1} g_{t+h} \right] + \sum_{j=2}^{h} \rho^{h-j} \varepsilon_{t+j-1} + \rho^{h-1} \left(1 - \frac{M}{K} \right) \varepsilon_t, \tag{A.13}$$

that is Equation 1.9 in the main text. Rearranging Equation A.13 gives

$$E_t g_{t+h} - E_{t-1} g_{t+h} = (1-K) \left[E_{t-1} g_{t+h} - E_{t-2} g_{t+h} \right] + \rho^{h+1} (K-M)\, \varepsilon_{t-1} + \rho^{h-1} M \varepsilon_t. \tag{A.14}$$

If $K \approx M$, the term $\rho^{h+1}(K-M)$ approaches to zero and the error term gives the current period fiscal news shock that is $\rho^{h-1} M \varepsilon_t$.

A.2 Further Robustness Checks

Small VAR

I construct small VAR to check whether the estimated baseline model suffers from over-parameterization (whether the estimated model includes more variables than the true data generating process). Small VAR includes variables in the following order: consumer confidence, government spending, output, consumption, ad fiscal news variables. The impulse responses from small VAR are presented in Figure

A.1 and the shape of the responses are very similar to the baseline estimation even though the magnitudes are larger.

Ramey News Variable

Even though the fiscal news shocks pass the exogeneity test, the identified shocks were found to be correlated with Ramey Military News variable. To check whether the results in baseline case are driven by the unique informational content of my proxy of future government spending and not driven by it's correlation with another fiscal news variable, I add Ramey news variable into my baseline vector and order it first. I exhibit the results in Figure A.1 with Ramey News ordered first and the estimation produces almost identical responses relative to the baseline case. These findings offer additional evidence that the proxy contains unique information related to the future government spending and this unique content drives the baseline results.

Subsample

The effective federal funds rates were almost zero after the midst of Great Recession until mid of 2015, a period called zero lower bound, and this zero lower bound period might have large impact on the results. To check whether this is the case, I reestimate my baseline VAR using sample from 1981$Q3$ to 2017$Q4$. The results are in Figure A.1 under title Pre-Crisis and the responses are similar to the baseline estimates even though the first several quarters produce smaller effects.

Per Capita Real Variables

The baseline estimation uses aggregate real variables in VAR since the aim is to measure the aggregate responses. However, population increased more than 50% in the US in the last 50 years and to control for any impact of larger population in the sample period, per capita real variables are used in this robustness check. The real GDP, consumption and federal government spending are divided into U.S. civilian noninstitutional population series of FRED to obtain per capita real variables. The results are almost same as in baseline estimation.

Debt

Favero and Giavazzi (2007) show that the level of the debt-to-GDP ratio is an important factor in determining the effects of fiscal policy. This is because a feedback from the level of debt-to-GDP ratio to government spending and taxes is necessary for stability of the debt that is present in data. To test whether omitting debt in VAR results in biased estimates, I include debt into VAR and order it fourth after taxes. The responses are very similar to the baseline estimates with slightly larger response of GDP and consumption. This robustness check shows that baseline VAR without debt does not suffer from omitted variable bias.

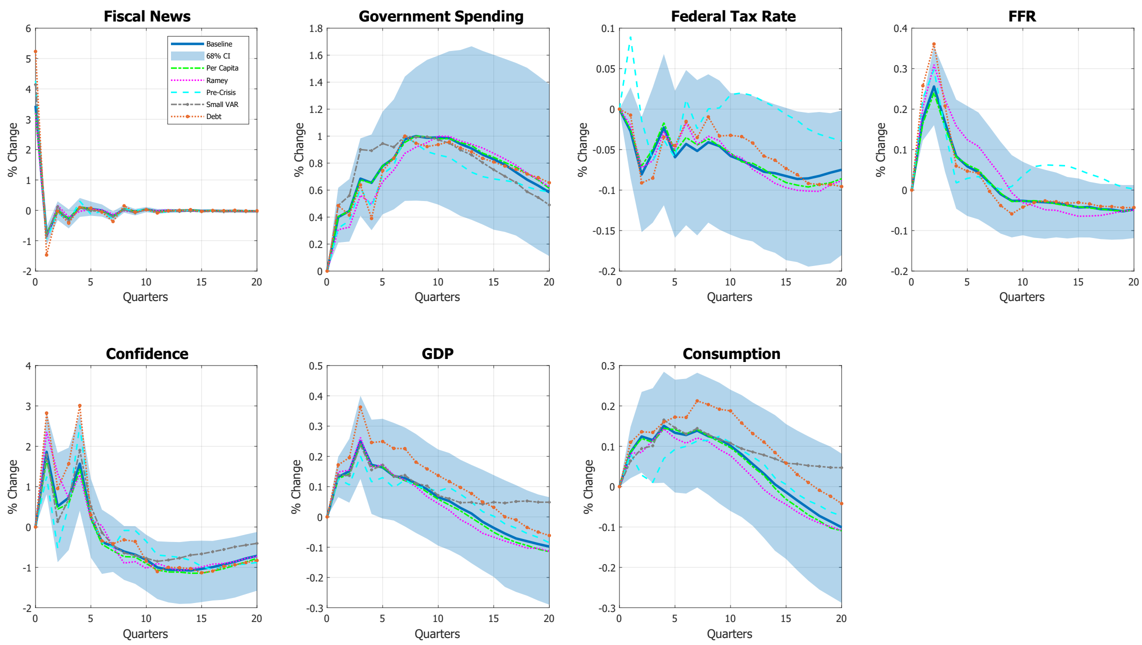

Figure A.1: Impulse Responses to a Fiscal News Shock under Further Robustness Checks

Notes: Solid blue lines are baseline, point orange lines with circles are FAVAR, dash-dot green lines are forecasts of tax revenue-to-GDP ratio included and ordered fourth,, point magenta lines are confidence ordered fourth, dashed cyan lines are subsample from 1981Q3 to 2007Q4, and dash-dot gray lines are Ramey news variable ordered first estimates of impulse responses to a fiscal news (anticipated government spending) shock from Bayesian VAR. The shaded area is 68% confidence interval of baseline estimation.

A.3 Fiscal Multipliers

Table A.1: Fiscal Multipliers

Horizon	1-year	2-year	3-year	4-year
	1.80	1.21	0.80	0.58
Baseline	$[0.86, 3.14]$	$[0.29, 2.64]$	$[0.03, 2.04]$	$[-0.22, 1.71]$
	2.63	1.91	1.51	1.16
Fiscal News first	$[1.28, 5.31]$	$[0.63, 3.03]$	$[0.32, 2.14]$	$[0.08, 1.70]$
	1.72	1.13	0.76	0.54
Confidence 3rd	$[0.83, 2.62]$	$[0.17, 1.87]$	$[-0.05, 1.39]$	$[-0.26, 1.16]$
	2.50	1.71	1.25	0.94
GDP News	$[1.11, 4.07]$	$[0.42, 2.32]$	$[0.08, 1.65]$	$[-0.15, 1.32]$
	1.63	1.12	0.78	0.54
Purged News	$[1.07, 2.62]$	$[0.64, 2.21]$	$[0.51, 2.03]$	$[0.30, 1.76]$
	1.34	0.98	0.76	0.62
Small VAR	$[0.68, 2.44]$	$[0.36, 2.39]$	$[0.18, 2.23]$	$[0.06, 2.22]$
	1.77	1.19	0.79	0.50
Per Capita	$[0.84, 3.02]$	$[0.34, 2.47]$	$[0.05, 1.88]$	$[-0.19, 1.46]$
	1.70	1.05	0.67	0.48
TFP First	$[0.88, 2.77]$	$[0.24, 1.78]$	$[-0.01, 1.29]$	$[-0.20, 0.98]$
	2.35	1.38	0.82	0.50
Ramey News	$[1.04, 3.65]$	$[0.25, 2.13]$	$[-0.06, 1.45]$	$[-0.32, 1.02]$
	1.39	0.92	0.79	0.59
Pre-crisis	$[0.20, 2.53]$	$[-0.50, 1.25]$	$[-0.57, 1.02]$	$[-0.72, 0.88]$
	2.23	1.72	1.33	1.00
Debt	$[0.71, 4.76]$	$[0.15, 4.25]$	$[0.11, 3.07]$	$[-0.06, 2.57]$
	1.80	1.21	0.80	0.58
FAVAR	$[0.86, 3.14]$	$[0.29, 2.64]$	$[0.03, 2.04]$	$[-0.22, 1.71]$

Notes: Estimated fiscal multipliers for fiscal news shock. The first row presents the multipliers from baseline estimation and from second row to the last row represent the multipliers estimated with specifications in the following order; fiscal news ordered first, confidence ordered third, revisions of gdp growth forecasts ordered first, purged news replaced with baseline news, small VAR where tax and federal funds rate are dropped, per capita real variables, utilization-adjusted TFP series are orederd first, Ramey News variable ordered first, sample from 1981Q4 to 2007Q4, debt-to-GDP ratio ordered fourth and Factor-augmented VAR with two factors. The numbers in brackets indicate the 68% confidence intervals from the distribution of multipliers.

A.4 The Solution Method

The transition equation in 1.63 can be represented as following:

$$\mathrm{Z}_t = \underbrace{\begin{pmatrix} 1 \quad \mathbf{0} \\ 0 \quad \rho_g \quad \phi_e \quad \mathbf{0} \\ 0 \quad \rho_e \quad \mathbf{0} \\ \mathbf{0} \\ \mathrm{A_c} \\ \mathrm{A_p} \\ \left[\begin{array}{cccc} 0_{1x5} & -\phi_i & \rho_i & \mathbf{0} \end{array}\right] + \phi_i \mathrm{A_p} \\ 0_{1\times 7} \quad \rho_\xi \quad \mathbf{0} \\ 0_{1\times 8} \quad \rho_\xi \quad \mathbf{0} \end{pmatrix}}_{\mathrm{A}} \mathrm{Z}_{t-1} + \underbrace{\begin{pmatrix} 1 \quad \mathbf{0} \\ \mathbf{0} \\ 0 \quad 1 \quad \mathbf{0} \\ 0_{1\times 2} \quad 1 \quad \mathbf{0} \\ \mathrm{B_c} \\ \mathrm{B_p} \\ \left[\begin{array}{ccc} 0_{1\times 3} & \phi_i & \mathbf{0} \end{array}\right] + \phi_i \mathrm{B_p} \\ 0_{1\times 4} \quad 1 \quad \mathbf{0} \\ 0_{1\times 5} \quad 1 \quad \mathbf{0} \end{pmatrix}}_{\mathrm{B}} u_t^1, \tag{A.15}$$

where $\mathrm{A_c}, \mathrm{A_p}, \mathrm{B_c}$ and $\mathrm{B_p}$ will be determined in equilibrium.

A.4.1 Optimal Decision Rules

Iterating equation 1.65 one period ahead and plugging into the Euler equation gives

$$c_t = \mathbb{E}_{l,t} \begin{bmatrix} m_b b_{l,t+1} + m_p p_{l,t} + m_a a_{l,t+1} + m_\tau \tau_{l,t+1} + \\ m_d d_{l,t+1} - m_s \tau^s_{l,t+1} + m_z \mathbb{E}_{l,t}\left[\mathrm{Z}_{t+1}\right] \end{bmatrix} - i_t - \overline{p}_{l,t}.$$

Using individual budget constraint in 1.56 and one period ahead total demand and tax signal in 1.60, one can rewrite the above equation as following

$$c_t = \mathbb{E}_{l,t} \begin{bmatrix} \frac{m_b}{\beta}\left(b_{l,t} + (1-\gamma) p_{l,t} + d_{l,t} - \tau^s_{l,t} + \theta_C \overline{p}_{l,t} - \theta_C c_{l,t} - \tau_{l,t}\right) + \\ m_p p_{l,t} + m_a x_{t+1} - m_\tau\left(\theta_G\left(g_{t+1} + p_{t+1}\right) + \xi^\tau_{l,t+1} + \eta^\tau_{l,t+1}\right) + \\ m_d\left(\theta_C c_{t+1} + \gamma p_{t+1} + \theta_G\left(\varepsilon_t + \xi^G_{l,t+1} + \eta^G_{l,t+1}\right)\right) \\ -m_s\left(\theta_G\left(g_{t+1} + \varepsilon_t + \xi^\tau_{l,t+1} + \eta^\tau_{l,t+1}\right)\right) + m_z \mathbb{E}_{l,t}\left[\mathrm{Z}_{t+1}\right] \end{bmatrix} - i_t - \overline{p}_{l,t}.$$

The $t+1$ variables in the above equation can be expressed as functin of $\mathrm{Z}_{\mathrm{l},t}$ and

$\mathbb{E}_{l,t}\eta^{G}_{l,t+1} = \mathbb{E}_{l,t}\eta^{\tau}_{l,t+1} = 0$. After rearranging, the above equation takes the form

$$c_{l,t} = \begin{array}{c} -\overline{p}_{l,t} + \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_b\right) b_{l,t} + \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_d\right) d_{l,t} - \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_s\right) \tau^{s}_{l,t} + \\ \frac{\Phi}{\Psi} q_p p_{l,t-1} + \frac{\Phi}{\Psi} q_a a_{l,t} + \frac{\Phi}{\Psi} q_\tau \tau_{l,t} + \\ + \frac{1}{\Psi}\left(-e_i + \Phi q_z + \begin{bmatrix} (m_d - m_s)\,\theta_G e_\varepsilon + ((m_\tau - m_s)\,\theta_G + m_d\gamma)\, e_p + \\ m_\tau \theta_G e_g + m_a e_x + m_d \theta_C e_c + m_d \theta_G e_{\xi^G} + \\ (m_\tau - m_s)\,\theta_G e_{\xi^\tau} + b_z \end{bmatrix} \mathrm{A}\right) \mathbb{E}_{l,t}\mathrm{Z}_{l,t}, \end{array} \tag{A.16}$$

where $\Psi = \dfrac{\beta + m_b\theta_C}{\beta}$, $\Phi = \dfrac{m_b}{\beta}(1-\gamma) + b_p$ and e is unitary vector that selects corresponding variable from $\mathrm{Z}_{\mathrm{l,t}}$. Matching equations 1.65 and A.16 gives

$$m_p = \frac{1}{\Psi}\Phi q_p,$$

$$m_b = \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_b\right),$$

$$m_\tau = \frac{1}{\Psi}\Phi q_\tau,$$

$$m_d = \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_d\right),$$

$$m_s = \frac{1}{\Psi}\left(\frac{m_b}{\beta} + \Phi q_s\right),$$

$$m_a = \frac{1}{\Psi}\Phi q_a,$$

$$m_z = \frac{1}{\Psi}\left(-e_i + \Phi q_z + \begin{bmatrix} (m_d - m_s)\,\theta_G e_\varepsilon + ((m_\tau - m_s)\,\theta_G + m_d\gamma)\, e_p + m_\tau\theta_G e_g + \\ m_a e_x + m_d\theta_C e_c + m_d\theta_G e_{\xi^G} + (m_\tau - m_s)\,\theta_G e_{\xi^\tau} + b_z \end{bmatrix} \mathrm{A}\right).$$

Plugging equation 1.62 into the equation 1.64 and rearranging gives

$$\Lambda p_{l,t} = \begin{array}{c} p_{l,t-1} - \lambda(1+\chi)\, a_{l,t} + \lambda\left(\overline{p}_{l,t} + c_{l,t}\right) + \lambda\chi\left(d_{l,t} - \tau^{s}_{l,t} + \tau_{l,t}\right) + \\ \beta\mathbb{E}_{l,t}\left[q_b b_{l,t+1} + q_p p_{l,t} + q_a a_{l,t+1} + q_\tau \tau_{l,t+1} + q_d d_{l,t+1} - q_s \tau^{s}_{l,t+1} + q_z \mathbb{E}_{l,t}\left[\mathrm{Z}_{l,t+1}\right]\right]. \end{array}$$

Following the same steps taken for consumption, one can rewrite the above equation as following

$$\Upsilon p_t = \begin{array}{r} p_{l,t-1} + q_b b_{l,t} - \lambda\left(1+\chi\right) a_{l,t} + \lambda\chi\tau_{l,t} + \left(\lambda\chi + q_b\right) d_{l,t} - \left(\lambda\chi + q_s\right)\tau^s_{l,t} + \\ \Omega\left(m_b b_{l,t} + m_p p_{l,t-1} + b_a a_{l,t} + m_\tau \tau_{l,t} + m_d d_{l,t} - m_s \tau^s_{l,t} + m_z \mathbb{E}_{l,t}\left[\mathrm{Z}_t\right]\right) + \\ \beta\begin{bmatrix} \left(q_d - q_s\right)\theta_G e_e + \left(\left(q_\tau - q_s\right)\theta_G + q_d\gamma\right) e_p + q_\tau\theta_G e_g + q_d\theta_C e_c \\ q_a e_x + + \left(q_\tau - q_s\right)\theta_G e_{\xi^\tau} + q_d\theta_G e_{\xi^G} + q_z \end{bmatrix} \mathrm{A}\mathbb{E}_{l,t}\mathrm{Z}_{\mathrm{l,t}}, \end{array} \tag{A.17}$$

where $\Upsilon = \Lambda - \left(1-\gamma\right) q_b - \beta q_b$ and $\Omega = \lambda - \theta_C q_b$ with e is unitary vector that selects corresponding variable from $\mathrm{Z}_{\mathrm{l,t}}$. Matching equations 1.64 and A.17 gives

$$q_p = \frac{1+\Omega b_p}{\Upsilon},$$

$$q_b = \frac{q_p}{1+\Omega b_p}\left(q_b + \Omega b_b\right),$$

$$q_\tau = \frac{q_p}{1+\Omega b_p}\left(\lambda\chi + q_b + \Omega b_\tau\right),$$

$$q_d = \frac{q_p}{1+\Omega b_p}\left(\lambda\chi + q_b + \Omega b_d\right),$$

$$q_s = \frac{q_p}{1+\Omega b_p}\left(\lambda\chi + q_b + \Omega b_s\right),$$

$$q_a = \frac{q_p}{1+\Omega b_p}\left(-\lambda\left(1+\chi\right) + \Omega b_a\right),$$

$$q_z = \frac{q_p}{1+\Omega b_p}\left[\Omega b_z + \beta\begin{bmatrix} \left(q_d - q_s\right)\theta_G e_e + \left(\left(q_\tau - q_s\right)\theta_G + q_d\gamma\right) e_p + q_\tau\theta_G e_g + q_d\theta_C e_c \\ q_a e_x + + \left(q_\tau - q_s\right)\theta_G e_{\xi^\tau} + q_d\theta_G e_{\xi^G} + q_z \end{bmatrix} A\right].$$

A.4.2 Individual Inference

The vector of signals $\mathrm{s}_{\mathrm{l,t}}$ (observation equation) for island l can be written as function of states and idiosyncratic noises

$$\underbrace{\begin{pmatrix} s^x_t \\ a_{l,t} \\ \overline{p}_{l,t} \\ d^P_{l,t} \\ d^G_{l,t} \\ \tau^s_{l,t} \\ i_t \end{pmatrix}}_{\mathrm{s}_{\mathrm{l,t}}} = \underbrace{\begin{pmatrix} e_x + e_\vartheta \\ e_x \\ e_p \\ e_c + \gamma e_p \\ e_e + \gamma e_p + e_{\xi^G} \\ \theta_G\left(e_e + e_p\right) + e_{\xi^\tau} \\ e_i \end{pmatrix}}_{\mathrm{F}} \mathrm{Z}_t + \underbrace{\begin{pmatrix} & \mathbf{0} & \\ & 1 & \mathbf{0} \\ 0_{1\times2} & 1 & \mathbf{0} \\ 0_{1\times3} & 1 & \mathbf{0} \\ 0_{1\times4} & 1 & \mathbf{0} \\ 0_{1\times5} & 1 & \mathbf{0} \\ & \mathbf{0} & \end{pmatrix}}_{\mathrm{G}} \underbrace{\begin{pmatrix} \eta^a_{l,t} \\ \eta^{CPI}_{l,t} \\ \eta^P_{l,t} \\ \eta^G_{l,t} \\ \eta^\tau_{l,t} \end{pmatrix}}_{\mathrm{u}^2_{\mathrm{l,t}}}, \tag{A.18}$$

where e is unitary vector that selects corresponding variable from $\mathrm{Z_{l,t}}$. The prediction rule for the agent in island l using Bayesian updating is equal to

$$\mathbb{E}_{l,t}\mathrm{Z_t} = \mathbb{E}_{l,t-1}\mathrm{Z_{t-1}} + \mathrm{C}\left(\mathrm{s_{l,t}} - \mathbb{E}_{l,t-1}\mathrm{s_{l,t-1}}\right)$$

and C is the Kalman gain matrix. Denote $\sum$ and V to define the variance-covariance matrix for the residuals in Equations A.15 and A.18, respectively. Then Kalman gain matrix is given by

$$\mathrm{C} = \mathrm{PF}'\left(\mathrm{FPF}' + \mathrm{GVG}'\right)^{-1}, \tag{A.19}$$

where $\mathrm{P} = \mathbb{E}_{l,t-1}\left[\mathrm{Z_t Z_t'}\right]$ and must satisfy

$$\mathrm{P} = \mathrm{A}\left(\mathrm{P} - \mathrm{CFP}\right)\mathrm{A}' + \mathrm{B\Sigma B}'. \tag{A.20}$$

A.4.3 Fixed Point

The average first-order expectations regarding the state $\mathrm{Z_{l,t}}$ can be expressed as a function of $\mathrm{Z_{l,t}}$ itself as

$$\int \mathbb{E}_{l,t}\left[\mathrm{Z_t}\right] = \Xi \mathrm{Z_t}.$$

Using the Bayesian updating rule and aggregating across islands gives

$$\int \mathbb{E}_{l,t}\left[\mathrm{Z_t}\right] = \left(\mathrm{I} - \mathrm{CF}\right)\mathrm{A}\mathbb{E}_{l,t-1}\mathrm{Z_{t-1}} + \mathrm{CFZ_t},$$

for all $Z_{l,t}$. Aggregating the individual decision rules in 1.64 and 1.65 gives

$$p_t = q_p p_{t-1} + q_a x_t + q_\tau \theta_G (p_t + g_t) + q_d\left(\theta_C c_t + \theta_G \varepsilon_t + \gamma p_t\right) - q_s \theta_G (p_t + \varepsilon_t) + q_z \Xi \mathrm{Z_{l,t}} \tag{A.21}$$

$$c_t = -\overline{p}_t + m_p p_{t-1} + m_a x_t + m_\tau \theta_G (p_t + g_t) + m_d\left(\theta_C c_t + \theta_G \varepsilon_t + \gamma p_t\right) - m_s \theta_G (p_t + \varepsilon_t) + m_z \Xi \mathrm{Z_{l,t}}. \tag{A.22}$$

Expressing everything in terms of the state $\mathrm{Z_{l,t}}$, the equilibrium coefficients must satisfy

$$\begin{bmatrix} -\left(1 + (m_s - m_\tau)\theta_G - m_d\gamma\right)e_p + m_p e_{p-1} + m_a e_x \\ +m_\tau \theta_G e_g + (m_d - m_s)\theta_G e_\varepsilon + m_d \theta_C e_c + m_z \Xi \end{bmatrix} \mathrm{Z_{l,t}} = 0, \tag{A.23}$$

$$\begin{bmatrix} \left((q_s - q_\tau)\theta_G - q_d\gamma\right)e_p + q_p e_{p-1} + q_a e_x \\ +q_\tau \theta_G e_g + (q_d - q_s)\theta_G e_\varepsilon + q_d \theta_C e_c + q_z \Xi \end{bmatrix} \mathrm{Z_{l,t}} = 0, \tag{A.24}$$

for all $Z_{l,t}$. The equations A.23 and A.24 are used to update the evolution of the state variables until the impulse responses of c_t and p_t to the aggregate shocks converge under the old and updated values of A and B. In the numerical computation, I restrict the values of A_c, A_p, B_c and $B_p$so that they do not respond to the local state variables $\xi^G_{l,t}$ and $\xi^\tau_{l,t}$.

A.5 Proofs

Proof of Equation 1.61

I can rewrite equation 1.30 as

$$Y_{l,t} = \left(\frac{P_{l,t}}{P_t}\right)^{-\gamma} Y_t. \tag{A.25}$$

The log-linearization of Equation A.25 is equal to

$$y_{l,t} = -\gamma(p_{l,t} + p_t) + \theta_C c_t + \theta_G g_t, \tag{A.26}$$

in which I use the fact that $Y_t = C_t + G_t$. The above equation can be rewritten using the equations 1.41 and 1.42 as following

$$y_{l,t} = \theta_C y^P_{l,t} + \theta_G y^G_{l,t}. \tag{A.27}$$

Now, subtract Equation 1.32 from Equation A.27 to get

$$y_{l,t} - \tau_{l,t} = -\gamma(p_{l,t} + p_t) - \theta_G p_t + \theta_C c_t + \theta_C \eta^P_{l,t} + \theta_G \left(\xi^G_{l,t} + \eta^G_{l,t}\right) - \left(\xi^\tau_{l,t} + \eta^\tau_{l,t}\right). \tag{A.28}$$

Now, do the same for the Equations 1.32 and 1.60 to have

$$d_{l,t} - \tau^s_{l,t} = -\gamma(p_{l,t} + p_t) - \theta_G p_t + \theta_C c_t + \theta_C \eta^P_{l,t} + \theta_G \left(\xi^G_{l,t} + \eta^G_{l,t}\right) - \left(\xi^\tau_{l,t} + \eta^\tau_{l,t}\right). \tag{A.29}$$

Since the above two equations are same, it is true that

$$y_{l,t} = d_{l,t} - d^\tau_{l,t} + \tau_{l,t}. \tag{A.30}$$

Appendix B

Appendix to Chapter 2

B.1 The publication dates of the Public Investment Programme

The following table shows the publication dates of the Public Investment Programme from 1983 to 2017.

The year of the program	Publication date	The year of the program	Publication date
1983		2001	5th of January, 2001
1984		2002	10th of January, 2002
1985	7th of January, 1985	2003	10th of April, 2003
1986	29th of April, 1985	2004	11st of January, 2004
1987		2005	9th of January, 2005
1988	26th of April, 1988	2006	7th of January, 2006
1989	21st of December, 1988	2007	13rd of January, 2007
1990	24th of December, 1989	2008	15th of January, 2008
1991	23rd of December, 1990	2009	15th of January, 2009
1992	7th of April, 1992	2010	14th of January, 2010
1993	29th of January, 1993	2011	13rd of January, 2011
1994	13rd of January, 1994	2012	14th of January, 2012
1995	2nd of January, 1995	2013	12nd of January, 2013
1996	17th of May, 1996	2014	14th of January, 2014
1997	24th of January, 1997	2015	14th of January, 2015
1998	22nd of January, 1998	2016	31st of March, 2016
1999	10th of July, 1999	2017	17th of January, 2017
2000	14th of January, 2000		

B.2 Extension (Full Credibility)

In this extension, I renounce the assumption of partial credibility and I introduce full credibility. In other words, agents believe that all the projects announced in PIP are feasible and will be completed on time. Hence, the expectations of the agents with respect to the future public investments are different relative to the partial credibility case. They calculate the discounted present value of the public investments as a sum of two process. First, they use the figures published in PIP so that they obtain the present value of the investments over the next H_t years and second, they discount the yearly expected spending starting from year $H_t + 1$ to infinity. This specification leads to the following discounted present value equation for per capita public investments:

$$\tilde{\eta}_t = \sum_{h=0}^{H_t} E_t^P(G_{t+h}) + \sum_{k=H_t+1}^{\infty} \beta^k E_t^P(G_t) \tag{B.1}$$

where $\tilde{\eta}_t$ stands for the news series under full credibility.

Here, I define the news as the discounted present value of expected future public investment. In equation B.1 first term is the net present value delivered in the public investment program given by equation 2.3. The second term captures the agents expectations for public investment spending after year H_t; the agents believe that yearly public investments will grow at the rate of the average past inflation and they discount this grow with the average nominal rate. Thereof, the discount factor β^k in the second term of equation B.1 is equal to $\beta^k = (1+\pi_t)/(1+i_t)$ where π_t is the inflation rate and i_t is the nominal interest rate. I use 5-year trailing average of the inflation and nominal rates to calculate the discount factor.[1] In this setup, agents consider that announcements are fully credible because all the information in PIP is used.

Table B.1 displays the statistics of regressing log of cumulative public investment spendings on the news variable $\tilde{\eta}_t$ defined in equation B.1, as analogous to table 1.3. An interesting result emerges from table B.1. The explanatory power of the news series is very low in the first four years; however, it increases and becomes significant starting with year 5. [2]

[1]Unfortunately, the data of market expectation for long-term inflation and nominal rates are not available throughout the all sample and I am limited to use past averages as a predictor of future rates.

[2]Both R-squared and F-statistic remain significant when the horizon is extended to nine years.

Table B.1: The Explanatory Power of News Series under Full Credibility

Horizon (Cumulative Public Investment)	(1) R-squared	(2) F-statistic
0	0.222	8.844 (0.0057)
1	0.115	3.891 (0.0578)
2	0.036	1.066 (0.3103)
3	0.001	0.032 (0.8598)
4	0.111	3.372 (0.0773)
5	0.377	15.728 (0.0005)
6	0.535	28.700 (0.0002)

Note: The columns (1) and (2) show statistics from a regression of log cumulative real per capita public investment spending on log of current news variable, $\tilde{\eta}_t$. The parentheses denote p-values. The sample covers years from 1984 to 2016.

The rest of the identification follows section 4.1 and the news variable is regressed onto the lagged values of news and other macro variables to isolate the exogenous anticipated news shock for the public investment. Hence, in the first step η_t, the log of the variable $\tilde{n}_t$, is regressed on explanatory variables using the following equation:

$$\eta_t = \alpha + \psi_e \eta_{t-1} + \psi_y y_{t-1} + \psi_{gi} g^I_{t-1} + \psi_{gc} g^C_{t-1} + \psi_d debt_{t-1} + \psi_t tax_{t-1} + \psi_f FR_t + \varepsilon^F_{1,t} \quad \text{(B.2)}$$

where $\varepsilon^F_{1,t}$ is the identified public investment shock under full credibility. The assumptions mentioned in the previous section for the validity of the estimations are maintained for this section as well. The behaviors of the news shock identified through equation B.2 and the growth of the news variable η_t are shown in the figure B.1. As in the case of partial credibility there is significant decrease in the year 1995 and spike in year 1997; however there is persistent growth in the news starting after year 2010 under full credibility. Moreover, the magnitude of the shocks are generally larger. The figure B.1 shows the importance of the agents' expectation formation process in determining the present value of the future public investments. The process can dramatically alter the timing and magnitude of the shocks.

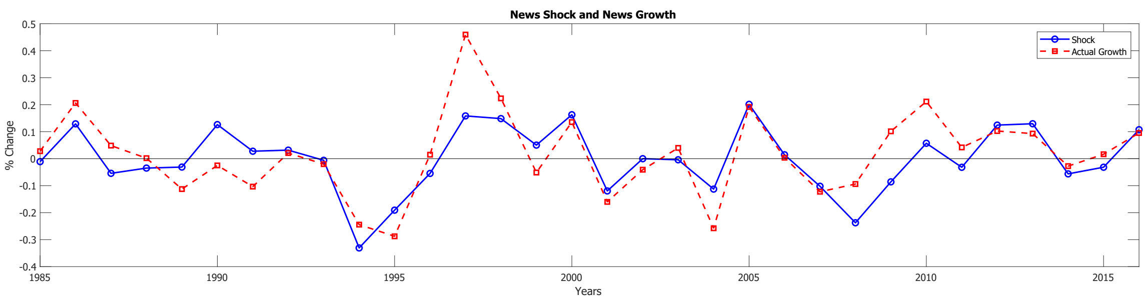

Figure B.1: The news growth and news shock over time - Full Credibility

To document how news shock affect output and other variables under full credibility and to remain comparable and consistent relative to the previous case, in the second step I estimate the Jorda local projection method as following:

$$y_{t+h} = \alpha_h + \delta^h \hat{shock}_t^F + \phi_h(L)X_t + u_{y,t+h} \tag{B.3}$$

for $h = 0, 1, ..., 9$ where y_t is the logarithm of GDP per capita, $\hat{shock}_t^F$ is the identified public investment shock from equation B.2 and X_t are the control variables that are real GDP per capita, government consumption per capita, real public investment spending per capita, all in logs and debt-to-GDP ratio and tax revenue-to-GDP ratio. I use heteroscedasticity and autocorrelation consistent covariance estimators.

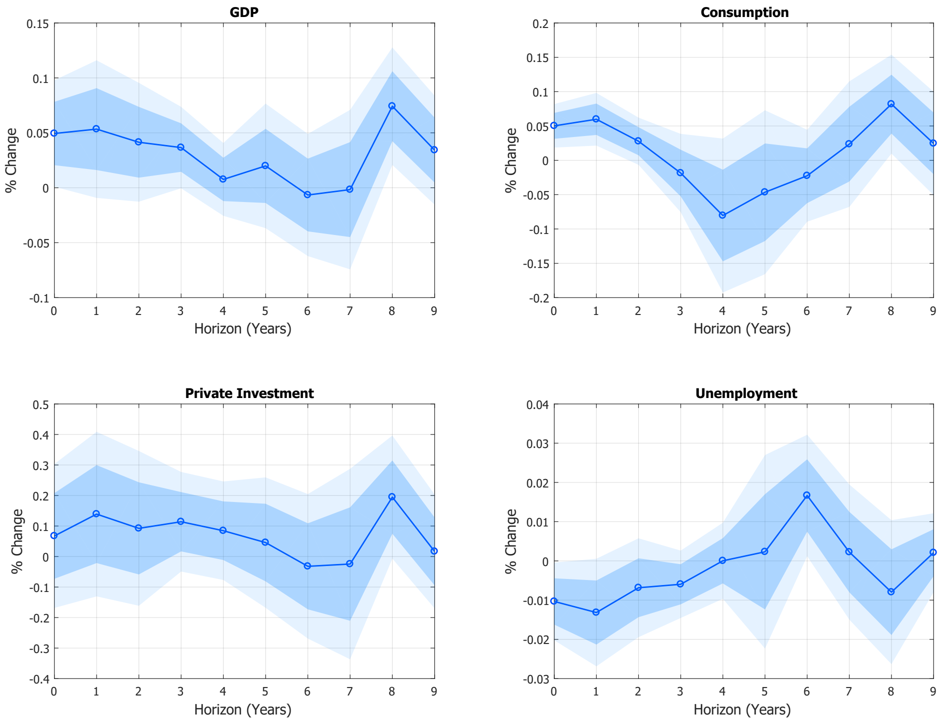

Figure B.2: The Impulse Responses of Macroeconomic Variables under Full Credibility

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

Figure B.2 shows impulse responses of the macro variables to a unit news shock identified under full credibility scenario.The response of output and consumption are both positive and statistically significant on impact and up to three year. The effect is nearly zero for output and slightly negative for consumption afterwards until seventh year. There is temporary spike in eight year which fades out in the last year. The responses of output and consumption are similar to the responses in the previous section; however, the size of the responses are much less pronounced.

The response of unemployment also behaves in a similar fashion but the response of private investment is distinctly different under full credibility case. It positively increases on impact and stays positive up to fifth year, then effect disappears except for the eight year.

The figure B.3 displays the responses of the policy variables to a unit shock. The announcements increase on impact and remains positive up to sixth year and the response of the outlays are similar also. The main difference of the two responses under full credibility case is that they are more persistent and hit zero line couple of years later. In addition, the size of the impact on outlay is much smaller relative to the previous case. The responses of tax is inline with the results such that there is increase after first year to fund the spendings and fade out over time. However, public debt shows slightly different response; a decrease in the first few years and increase afterwards.

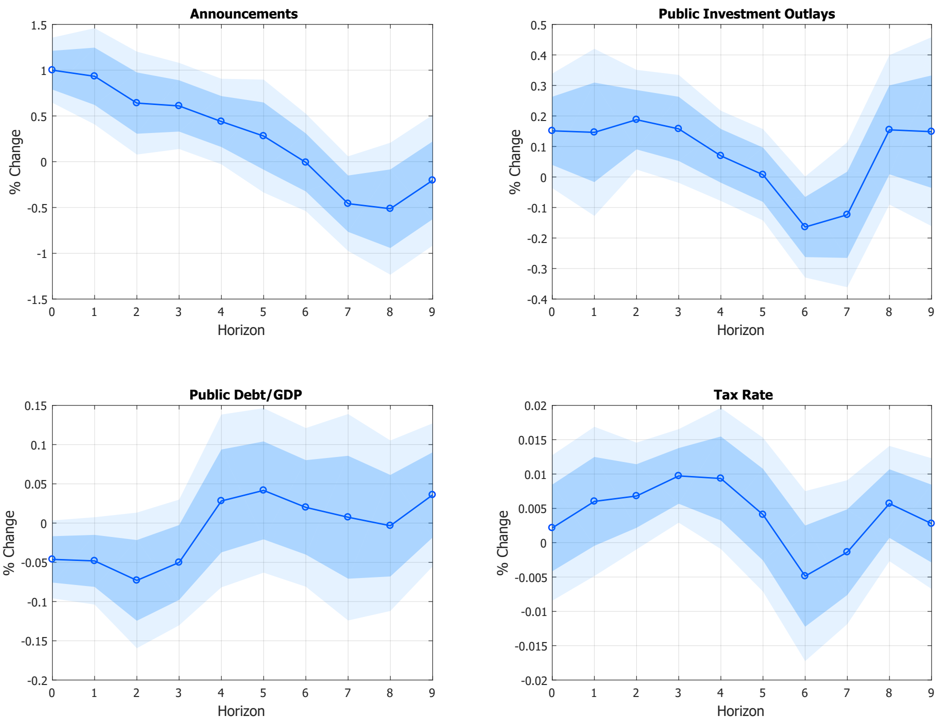

Figure B.3: The Impulse Responses of Policy Variables under Full Credibility

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

What drives the smaller but persistent responses? The explanation lies behind the definition of the news variables in equations 2.4 and B.2. In the latter one, the agents have infinite anticipation period and the value of the news variable is higher relative to the former one. In this case, the size of the shock is greater but the public investment outlays do not change; hence, some of the shock does not become public investment and the response of the outlay is less pronounced. This feature also accommodates the credibility issue, agents believe that all the announcements will be implemented; however, only some of them becomes public investment and as a result, the impact of shock is smaller. On the other hand, announcements do not fade away quickly which helps more persistent public investment outlay which can be attributed to the longer horizon of the agents in equation B.1.[3]

Table B.2 shows the public investment multipliers under full credibility case. Even though the responses are less pronounced, the multipliers are larger relative to the partial credibility case in every year from initial year to sixth year. One of the reason of higher multipliers could be that in the previous case only average duration of the investments are considered and some of useful information to predict the public investment outlays might be discarded which may result in smaller multipliers.

Table B.2: The Public Investment Multipliers under Full Credibility

Horizon	Ratio of the Estimated Coefficients	TL Multiplier
0	0.3266	6.9662
2	0.2972	6.3396
4	0.2645	5.6427
6	0.3632	7.7465
8	0.4680	9.9822

Note: The ratio of estimated coefficients are $\frac{\sum_0^h \delta_y^h}{\sum_0^h \delta_g^h}$ *and TL multipliers are* $\frac{\sum_0^h \delta_y^h}{\sum_0^h \delta_g^h} * \frac{Y}{G}(mean)$

Another reason could be that extending anticipation horizon to infinity through past inflation and nominal rates, the shocks may capture the behavior of the variables not only due to public investment spending but also due to some other factors. In that case, the shocks are confounded and the responses are overestimated. However, in both case the public investment multipliers are largely positive assuring the significant impact of public investment on the output.

In summary, this section manifests the importance of narrative series in identifying the impact of the news shock on the economy. The different methods applied in the construction of the series may result in different outcomes. The explanatory power of news series in predicting the behavior of the variable (public investment outlays, in our case) is the key factor in soundness of the narrative series. Comparison of table 1.3 and table B.1 suggests that news series constructed in subsection 2.2.2

[3] This can also be seen in Figure B.8.

is more reliable than the series constructed in this section since more explanatory power on the future public investment spendings in the short-run is more relevant because it is unlikely that today's investment plan will become actual investment after several years.

B.2.1 Alternative Estimation and Robustness Checks

This subsection estimates VAR and conduct robustness checks using the news variable constructed under full credibility case given in Equation B.1. For sake of brevity, I only present the IRFs in the next three figures. The first two figures are VAR estimates and the third figure is the response of GPD under robustness checks.

VAR Estimation

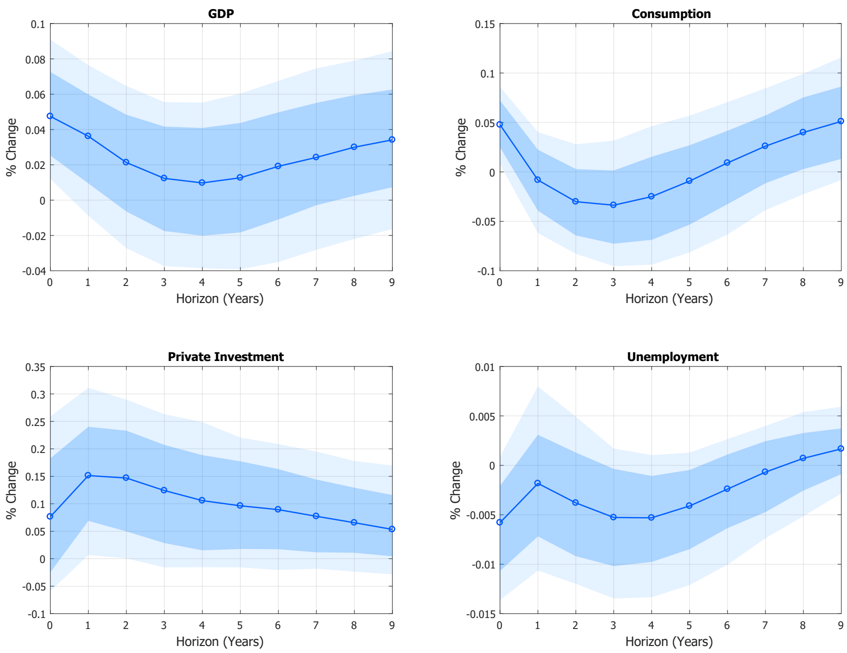

Figure B.4: VAR estimated Impulse Responses of Macroeconomic Variables - Full Credibility

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

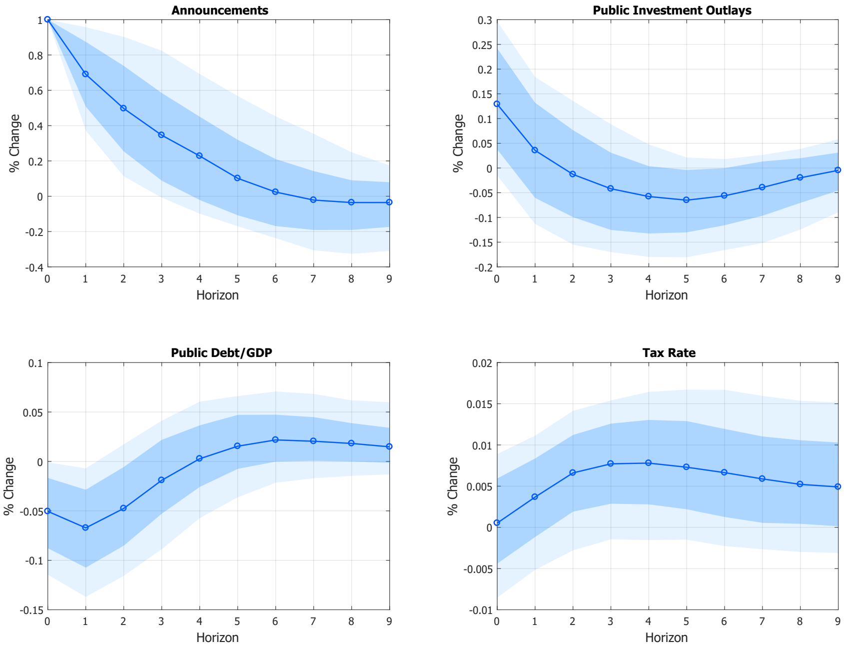

Figure B.5: VAR estimated Impulse Responses of Policy Variables - Full Credibility

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

Robustness Checks

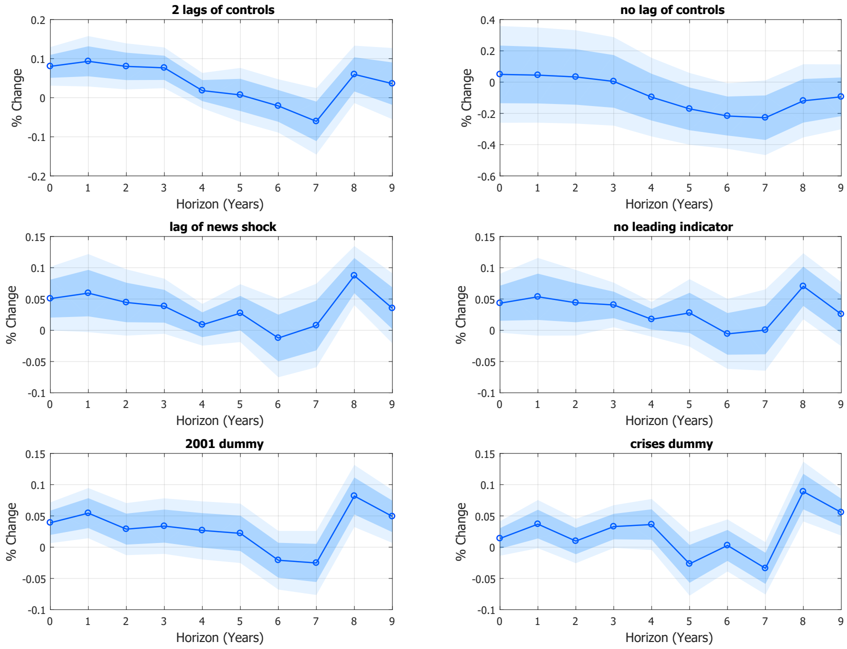

Figure B.6: Robustness Checks - Full Credibility

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

B.2.2 Alternative Identification

The alternative identification uses the news variable from Equation B.1 and applies following formula to obtain the shock

$$shock_t = \frac{\tilde{\eta}_t(0,5) - \tilde{\eta}_{t-1}(0,5)}{0.5 \times \tilde{\eta}_t(0,5) + 0.5 \times \tilde{\eta}_{t-1}(0,5)}. \tag{B.4}$$

The impulses responses obtained from the Local Projection method in response to a shock given in Equation B.4 are shown in the following figures. In general, the magnitude of the responses is smaller relative to the responses estimated using Equation B.3 under full credibility case.

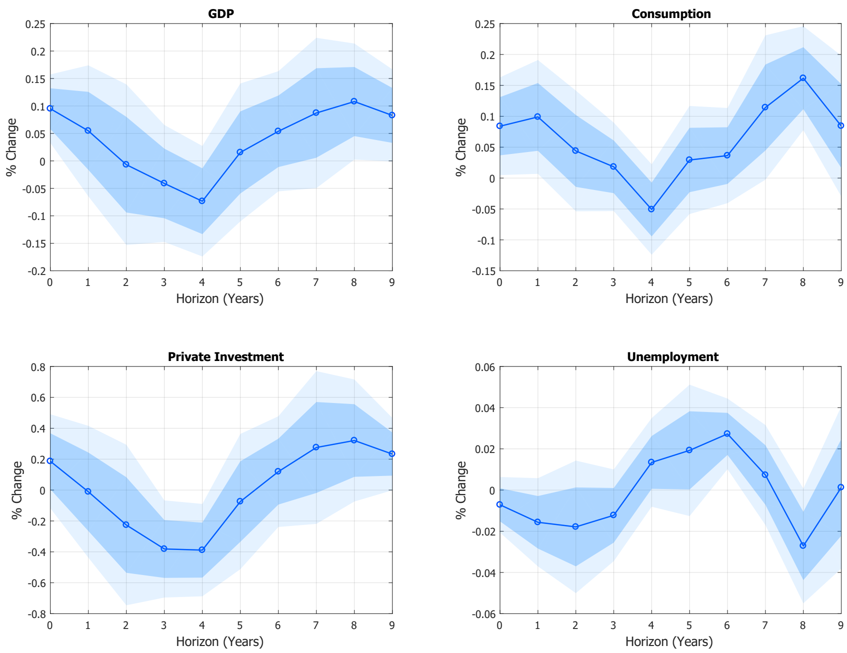

Figure B.7: The Impulse Responses of Macroeconomic Variables - Alternative Identification

Solid lines are point estimates of shock using equation B.3, dark shaded area is 68% CI and light shaded area is 90% CI.

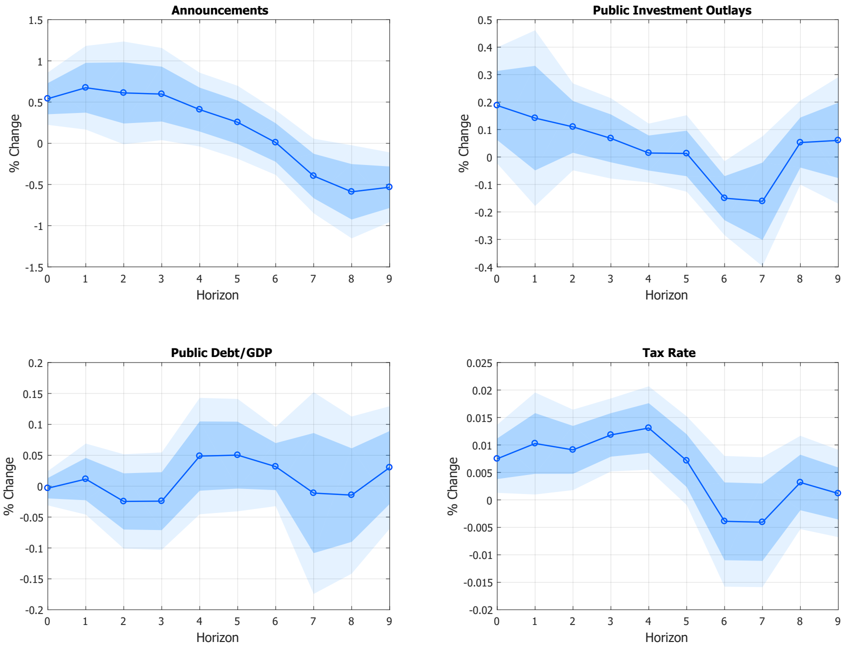

Figure B.8: The Impulse Responses of Policy Variables - Alternative Identification

Solid lines are point estimates of shock using equation B.3. In figures, dark shaded area is 68% CI and light shaded area is 90% CI.

B.3 Instrumental Variable Approach

I use Mountford and Uhlig (2009) approach to calculate the public investment multiplier; multiplying cumulative ratio of estimated output coefficient to public investment coefficient by average real output to public investment ratio. Owyang et al. (2013) found this practice tends to bias multipliers and making them seem much higher during recessions if there is significant variation in real output to government spending ratio in the sample. To address this potential bias, Ramey (2016a) suggests to use Barro and Redlick (2011) transformation to construct variables, $(X_{t+h} - X_{t-1})/Y_{t-1}$ where X is the variable of interest and Y is the output, and then cumulate the transformed variables and reformulate the estimation problem as an instrumental variable estimation.[4] I follow Ramey (2016a)'s approach to check whether the estimated multipliers in Table 1.4 are subject to this bias. I construct new set of variables using Barro and Redlick (2011) transformation and estimate

[4]Ramey (2016a) applied Gordon and Krenn (2010) transformation to construct variables, by dividing variables to the potential output; however, she claimed both transformation method gives similar results. I followed Barro and Redlick (2011) method since there is no reliable source for potential output in Turkey during my sample period.

the following equation

$$\sum_{h=0}^{H} y_{t+h} = \delta_h + m_h \sum_{h=0}^{H} g_{t+h} + \alpha_h x_{t-1} + u_{t+h}, \tag{B.5}$$

where y_t and g_t are the transformed real per capita and public investment and x_{t-1} is the vector of transformed control variables. I use the identified shock in Equation 2.5 as an instrument for the sum of public investment outlays. In this framework the estimated coefficient, m_h, is the TL multiplier for horizon h. I estimate equation B.5 using Newey and West (1986) estimator for possible autocorrelation and heteroskedasticity and the estimated multipliers are shown in B.3. This alternative methodology produces TL multipliers that are very similar to the baseline multipliers in Table 1.4 and confirms that baseline results are not inflated due to the variation in the output to public investment ratio in the sample.

Table B.3: The Public Investment Multipliers

Horizon	TL Multiplier
0	4.3067 $[4.08, 6.54]$
2	2.7964 $[-0.42, 6.02]$
4	-0.1437 $[-5.62, 5.34]$
6	3.0914 $[-8.64, 14.82]$
8	14.5792 $[10.47, 18.69]$

Note: TL multipliers are the estimated coefficient m_h in equation B.5. The numbers in the brackets are 68% confidence intervals.

Appendix C

Appendix to Chapter 3

In this section of appendix we show the steady-state and log-linearized equations for the dynamic model we introduced in section 3.6.

C.1 Dynamic Model

C.1.1 Steady-State

We consider steady-state where all prices are symmetric and normalized to one such that $P = P_i = P_j = 1$.

The labor supply at steady-state is given by the combination of the household budget constraint and equation 3.37:

$$L = \left[\frac{1 - \bar{\tau}}{\xi(1 - \bar{g})} \right]^{\frac{1}{1+\chi}} \tag{C.1}$$

and we set $\xi = 21.06$ to have $L = 1/3$, the standard value in RBC literature. The steady-state values of labor and intermediate input demand at industry level are given by:

$$L_i = \alpha_i \frac{Y_i}{W_i} \tag{C.2}$$

$$X_{ij} = a_{ij} \rho_i Y_i \tag{C.3}$$

and plugging equations C.2 and C.3 into the production gives:

$$Y_i = \left[\alpha_i \frac{Y_i}{W_i} \right]^{\alpha_i} \left[\prod_{j=1}^{n} a_{ij}^{-a_{ij}} \left(a_{ij} \rho_i Y_i \right)^{a_{ij}} \right]^{\rho_i} \tag{C.4}$$

and the simple algebra gives steady-state wage in industry i as following:

$$W_i = \alpha_i \left(\rho_i \right)^{\frac{\alpha_i}{\rho_i}} . \tag{C.5}$$

The market clearing condition for industry i is given by:

$$Y_i = C_i + G_i + \sum_{j=1}^{n} X_{ji} \tag{C.6}$$

where $X_{ji} = a_{ji}\rho_j Y_j$. Define $\hat{a}_{ji} = \dfrac{X_{ji}}{\rho_j Y_i}$ and we can rewrite the equation C.6 as following:

$$Y_i = C_i + G_i + Y_i \sum_{j=1}^{n} \rho_j \hat{a}_{ji} \tag{C.7}$$

or in compact form:

$$Y_i = \left(I - \sum_{j=1}^{n} \rho_j \hat{a}_{ji} \right)^{-1} (C_i + G_i) = H_i \left(C_i + G_i\right) \tag{C.8}$$

The labor supply market clearing condition gives that $L = \sum_{i=1}^{n} L_i$ and using equation C.2, it can be expressed as:

$$L = \sum_{i=1}^{n} \alpha_i \frac{Y_i}{W_i} \tag{C.9}$$

and plugging equation C.8 into the equation C.9 and using the fact that $L = \dfrac{C}{(1-\bar{g})W}$ gives the following:

$$\sum_{i=1}^{n} \alpha_i \frac{H_i \left(C_i + G_i\right)}{W_i} = \frac{C}{(1-\bar{g})W}. \tag{C.10}$$

Now using $C_i = \omega_{ci} C$ and $G_i = \omega_{gi} G$ in addition to $G = \dfrac{\bar{g}}{1-\bar{g}} C$ in equation C.10 gives steady-state aggregate wage as a function of the model's parameters:

$$\sum_{i=1}^{n} \alpha_i \left(\omega_{ci} + \frac{\bar{g}}{1-\bar{g}} \omega_{ci} \right) \frac{H_i}{W_i} = \frac{1}{(1-\bar{g})W} \tag{C.11}$$

Since we have aggregate wage and labor supply, we can derive aggregate consumption and government spending and using the share parameters we can derive industry level consumption and government spending. Plugging the latter values into the equation C.8 gives the steady-state indsutry-level sales. We can derive the intermediate input demand supply using the FOCs and this gives the all steady-state values for the case 2.

If we set $\bar{g} = 0$, we eliminate the government expenditure in the model that gives the steady-state values for case 1 in the dynamic model section.

C.1.2 Log-Linearized Equilibrium

Log-linearizing the equilibrium conditions around the symmetric price steady state, we obtain the following system in terms of nominal variables of interest (lower case letters with tilde denote log-deviations from the steady state):

$$\chi \tilde{l}_t = \tilde{w}_t - \tilde{c}_t - \frac{\tilde{\tau}_t}{(1-\bar{\tau})} \tag{C.12}$$

$$\tilde{c}_t = \frac{1}{1-\bar{g}}\left(\tilde{w}_t + \tilde{l}_t\right) - \frac{\bar{g}}{1-\bar{g}}\tilde{g}_t \tag{C.13}$$

$$\tilde{c}_{it} = \tilde{c}_t, \qquad i = 1, ..., n \tag{C.14}$$

$$\tilde{g}_{it} = \tilde{g}_t, \qquad i = 1, ..., n \tag{C.15}$$

$$\tilde{y}_{it} = \tilde{z}_{ij,t}, \qquad i, j = 1, ..., n \tag{C.16}$$

$$\tilde{y}_{it} = \frac{C_i}{Y_i}\tilde{c}_{it} + \frac{G_i}{Y_i}\tilde{g}_{it} + \sum_{j=1}^{n} \rho_j \hat{a}_{ji} \tilde{z}_{ji,t}, \qquad i = 1, ..., n \tag{C.17}$$

$$\tilde{z}_t = \sum_{i=1}^{n} \frac{Z_i}{Z}\tilde{z}_{it} \tag{C.18}$$

$$\tilde{y}_t = \sum_{i=1}^{n} \frac{Y_i}{Y}\tilde{y}_{it} \tag{C.19}$$

$$\tilde{\tau}_t = \rho_\tau \tilde{\tau}_{t-1} + \varepsilon_t^\tau \tag{C.20}$$

$$\tilde{g}_t = \psi_g(\tilde{\tau}_t + \tilde{w}_t + \tilde{l}_t) \tag{C.21}$$

$$\tilde{w}_t = 0. \tag{C.22}$$

There are total of $N^2 + 3N + 7$ equations that solves for the all variables in the model. The direct effect of the personal tax shocks are similar to the standard RBC model in which first it distorts the labor supply and then aggregate consumption, considering the perfect wage rigidity. Since the households consumes constant fraction of industry-specific good, the variation in the consumption of the good of industry i is equal to the variation in the aggregate consumption.

By plugging equation C.16 into the equation C.17 gives the following expression in matrix form

$$\tilde{\mathrm{Y}} = \rho \hat{W}^T \tilde{\mathrm{Y}} + \frac{C}{Y}\tilde{\mathrm{C}} + \frac{G}{Y}\tilde{\mathrm{G}}, \tag{C.23}$$

where the capital letters with tilde are the vector of industry-level deviations from steady state, ρ is vector of intermediate input share and $\hat{W}^T$ is the network matrix that we employed in our empirical analysis. The equation C.23 has SAR structure and the propagation of the shocks through industry linkages are given by the first term on the right-hand side of the equation C.23. We solve the model using the above set of linearized equations and simulate it through randomly drawn tax shocks. We add normally distributed iid noise with standard deviation of 0.1 to the output of each industry during simulations and run SAR regressions on simulated data.