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The Private Income Tax Shock Premium

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Abstract

This paper investigates the asset pricing implications of tax policy changes. News about tax cuts decreases future tax revenues and increases future consumer demand and output. Using cross-sectional variation in industry exposure to structurally identified tax news, I develop a factor mimicking private income tax shocks. I construct an investment strategy, which generates annualized risk-adjusted returns of 5.16 % over the Fama-French 3-factor model. I rationalize the finding by arguing that firms with more elastic demands bear higher consumption risk, which works through a wealth effect.

Keywords: **tax shocks, asset prices, risk premia**

JEL Codes: G10, G12, E62

1 Introduction

The rapid increase in public debt following fiscal stabilization measures in response to the recent financial crisis has raised questions about future tax policy and its impact on the economy. Previous fiscal policy research finds that tax cuts have little to no effects (Hausman and Poterba (1987); Blanchard and Perotti (2002); Romer and Romer (2010)) or only expansionary effects in the short run (Kneller et al.1999); Mountford and Uhlig (2009); Mertens and Ravn (2012)). Given the diversity of tax policy instruments and their different transmission mechanisms, it is imperative to distinguish between taxes levied on corporate profits and those levied on personal income. Mertens and Ravn (2013) can differentiate between personal and corporate income shocks and show that personal income tax cuts increase aggregate GDP and employment and stimulate private consumption. Using industry-level sales data recent work by Todorova and Turgut (2018) shows that exogenous private income shocks have a direct effect on consumer demand and an indirect higher-order demand effect due to input adjustments transmitted through the production network. However, there is a paucity of research that studies the impact of private income tax shocks on financial asset prices. I aim to fill this gap in the literature.

Changes in consumer demand resulting from tax policy changes affect firm cash flows and investment decisions, which in their turn should be reflected in asset prices. Studying this effect is a challenging endeavor, first, because tax policy is endogenous and, second, because there are few observations available for a robust empirical analysis. I follow the approach by Mertens and Ravn (2013), who propose to use the informational content of narrative measures in exogenous tax shifts in a structural vector autoregressive (SVAR) framework. The main idea is to impose that narrative measures of tax shocks are correlated with the latent tax shock but are orthogonal to other structural shocks. This is an attractive estimation strategy because it combines the features of SVARs and narrative methods, but at the same time addresses key criticisms against them. It does not require making strong assumptions regarding the structural parameters and produces a long time-series of shocks.

This paper aims to investigate how exogenous changes in the private income tax code affect asset prices on the financial market. To this end, I exploit variation in the exposures of industry returns to structurally identified private income shocks to construct an asset pricing factor, which mimics tax shock risk (PMP). I test whether the PMP factor is priced in the cross-section of returns and whether it carries a risk premium.

The main hypothesis of the paper is that the PMP asset pricing factor carries a positive risk premium. The hypothesis is motivated by the following economic mechanism. Following a tax increase, consumers experience

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high consumption states. High tax exposure firms earn higher returns when consumption is high and low returns when consumption is low. In equilibrium, their revenues of high tax exposure industries co-move more with marginal utility than low tax exposure industries, which yields higher expected returns.

2 Data and Methodology

2.1 Data

Stock return data for companies listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ is obtained from CRSP. Following the asset pricing literature, I exclude firms in the heavily regulated utilities and financial sectors[2].

Accounting data is from the Compustat database. I follow the standard finance literature to calculate fundamental ratios (Fama and French (1993)). The market value of equity (ME) is stock price times the number of shares outstanding computed each year at the end of June. Book value of equity (BE) is calculated as the book value of stockholders' equity given in Compustat plus deferred taxes and investment tax credits minus the book value of the preferred stock. The book value of the preferred stock is calculated using redemption, liquidation or par value, depending on the availability of data. All variables are winsorized at the 99 % level.

2.2 Identification

The main challenge in estimating the impact of fiscal policy on asset prices is identification. Tax policy poses a particular difficulty first because tax changes are likely to be endogenous, and second because policy instruments are highly diverse. To overcome these issues, I follow recent advances in the fiscal policy literature and obtain a time-series of private income tax shocks, which are: (1) exogenous, (2) unanticipated by market participants and (3) orthogonal to other tax policy instruments.

One strand of the fiscal policy research relies on information contained in government documents, presidential speeches and Congressional documents to narratively identify tax changes. Romer and Romer (2010) identify 51 significant legislated federal tax acts during the period 1947-2006 and a total of 110 separate changes in tax liabilities. I only focus on those tax liability changes, which the authors classify as exogenous: "the changes were not motivated by current or projected economic conditions". This includes tax changes that were either introduced without any reference to the current state of the economy or were motivated by budget deficits.

Next, I differentiate between anticipated and unanticipated tax shocks by using a timing convention. This is an important distinction because unanticipated tax changes affect asset prices after they have been implemented, whereas anticipated changes may have an impact way ahead of their introduction. I only focus on tax acts, where the difference between the announcement date and the implementation date is less than 90 days. Finally, I retain only changes related to private income tax.

Despite addressing endogeneity concerns and anticipatory effects, using the narrative approach to study the impact of tax changes on asset prices is still problematic for a couple of reasons. First, it assumes that there is a one-to-one mapping between narrative shocks and structural shocks. Second, it is prone to measurement error due to personal bias and judgment. Third, it produces with very few non-zero observations (12 in our case). Moreover, conditional of a tax change occurring in our sample the correlation between narrative private income and corporate income changes is 0.42. Although tax changes are not countercyclical, they are still introduced with the objective to improve economic growth. So when both tax rates are adjusted simultaneously, it is not surprising that this happens in the same direction. Another reason could be related to fixed costs of the passing of legislative actions. Insofar as this positive correlation is not random, it is inappropriate to treat private income tax changes as unrelated to exogenous changes in corporate income liabilities. Moreover, the effect of these policies on asset prices is likely to be very different. Research by Croce et al. (2012) shows that corporate taxes affect asset prices through three main channels: (1) distorting profits and investment; (2) reducing the cost of debt through a tax shield; and (3) depressing

[2] These are firms with SIC codes between 4900-4949 and 6000-6999.

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productivity growth. Private income tax shocks, on the other hand, affect household income are more likely to have an impact on asset prices through a demand channel.

To overcome these concerns, I follow Mertens and Ravn (2013) use the information contained in the narrative accounts to identify shocks in a structural vector-autoregressive framework (SVAR). I assume that the narrative measures correlate with the latent tax shocks, but are uncorrelated with other structural shocks. This approach produces a long time-series of private income tax shocks, which is robust to measurement error. Appendix 6 contains details about the estimation procedure.

3 Empirical Results

3.1 Macroeconomic Dynamics

I start the analysis by investigating the time-series relationship between aggregate stock market returns and personal income tax rates. My main hypothesis is that personal income tax increases should predict a drop in earnings and, hence a decrease in returns on the stock market. To test this, I estimate the impulse responses using a simple vector auto regression (VAR). Specifically, we estimate the following specification:

$$Y_t = A(L)Y_{t-1} + \epsilon_t \qquad (1)$$

where $Y_t = [APITR_t, Ret_t, RGDP_t, Debt_t]$, $A(L)$ is a polynomial lag operator and ϵ_t is a vector of white-noise disturbances. All variables have been seasonally-adjusted. I include up to four lags of each variable. Figure 1 presents the orthogonalized impulse response function (IRF), where the response variable is aggregate stock market returns (Ret_t) and the impulse variable is the average personal income tax rate (APITR). The shaded areas are the 95-% confidence intervals. A one standard deviation increase in APITR leads to a drop in stock returns of about 1 % in the following two to four quarters.

These results indicate that the relationship between stock returns and tax rates is significant and economically meaningful in the aggregate. In the next session, I proceed by providing cross-sectional evidence on the relationship between stock returns and tax policy and investigate the asset pricing implications.

3.2 Single-sorts

To estimate the impact of private income tax shocks on asset prices, I run the following cross-sectional regression using 3-digit SIC industry returns:

$$r_{i,t+1} - r_{f,t+1} = \alpha_{i,t+1} + \beta_{i,t}^{PI} Tax_t^{PI} + \epsilon_{i,t+1} \qquad (2)$$

where i stands for the 3-digit SIC industry, $r_{i,t+1} - r_{f,t+1}$ is excess expected return and Tax_t^{PI} is a structural private income tax shock. I use a 5-year (20 observations) rolling window with quarterly data to estimate conditional betas ($\beta_{i,t}^{PI}$). I form industry-level portfolios in order to reduce stock level idiosyncratic noise. However, all results hold on the firm-level as well. I report summary statistics of industry betas in Table 1. The average beta is 0.16 with a standard deviation of 2.06 and a positive skewness of 2.40. I document substantial heterogeneity in industry sensitivity to private income shocks with betas roughly distributed in the interval between -4.76 and 5.83. Industries with large and negative exposure are high tax exposure industries: an increase in the tax rate decreases their earnings and leads to a drop in their stock prices. Industries with a positive (and possibly large) beta are low tax exposure industries. Table 2 lists the most and the least sensitive industries. Industries such as "New and Used Cars", "Metal Cans and Shipping Containers", "Wood Buildings and Mobile Homes" are the most exposed to changes in the private income tax code, whereas industries such as "Broadwoven Fabric Mills, Cotton", "Computer and Data Processing Services", "Metal Mining Services" and "Drugs" are the least exposed.

At each point in time I sort industries into 5 quintiles based on their sensitivity to tax policy news. Industries in the first quintile are high tax exposure industries ($\beta_{i,t}^{PI} < 0$). Industries in the fifth quantile are characterized as low tax exposure industries ($\beta_{i,t}^{PI} > 0$).

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Next, I investigate the risk-adjusted expected excess returns by tax exposure quantile with respect to the CAPM and Fama-French 3-Factor model. I run the following time-series regressions:

$$r_{p,t+1} - r_{f,t+1} = \alpha_p + \beta_{p,CAPM} CAPM_t + \epsilon_{p,t} \quad (3)$$

and

$$r_{p,t+1} - r_{f,t+1} = \alpha_p + \beta_{p,CAPM} CAPM_t + \beta_{p,SMB} SMB_t + \beta_{p,HML} HML_t + \epsilon_{p,t} \quad (4)$$

and report the estimated α_p's in Table 3. I find that expected risk-adjusted returns monotonically decrease with increasing exposure to private income tax shocks. The difference in returns between industries in the highest quintile and the lowest quintile is 0.64 % and 0.49 % with respect to the CAPM and Fama-French 3-Factor models. The result is highly statistically significant and economically meaningful: the return spread amounts to 2.56 % and 1.96 % annually.

3.3 The Role of Demand Elasticity

The question that naturally arises is what drives the large return spread between high (H) and low (L) private income tax exposure industries. To compare the two portfolios Table 4 presents the loadings on the market ($Mktrf$), size (SMB) and value size (HML) factors and to aggregate consumption in durable goods ($Cons.Durables$). Statistically, there is no difference between the market factor betas for the H and L portfolios. This result indicates that the higher risk premium that the H portfolio commands with respect to the L portfolio is not driven by differences in market risk. The H portfolio is slightly tilted towards small-cap firms ($\beta^H_{SMB} < 0$) and to growth firms ($\beta^H_{HML} < 0$). However, the differences are economically very small.

Interestingly though, the returns of the H portfolio co-move positively with aggregate consumption in durable goods, whereas the returns of the L portfolio co-move negatively. The spread $\beta_{H,cons.durables} - \beta_{L,cons.durables} = 0.68$ and is highly statistically significant. This evidence indicates that industries, which are highly exposed to the changes in the private income tax rate, are industries which, on average, produce durable goods, whereas industries with low private income tax sensitivity produce non-durable goods. Durable goods include e.g. residential homes, cars, home appliances, sports equipment etc. Non-durable goods can be roughly classified as consumables such as food and beverages, clothing, utilities etc. A major difference between durables and non-durables is the responsiveness of demand to changes in income i.e. the income elasticity of demand. For example, demand for durable goods such as cars is elastic, whereas demand for necessities, such as food, is relatively inelastic[3].

These results suggest that the main difference between the H and L portfolio is the exposure to wealth effect from unanticipated tax news. I use this information to construct a factor mimicking personal income tax shocks.

3.4 Tax-mimicking Portfolio

Instead of using macroeconomic factor themselves, asset pricing studies often replace them with their mimicking portfolios. The theoretical argument for such a practice in asset pricing tests is provided in early studies by Breeden (1979) and Huberman et al. (1987). In our case, the average tax policy beta is relatively low ($\beta^{PI} = 0.16$). Using mimicking portfolios instead of macroeconomic factors bypasses the problem of weak statistical correlation studied in Kleinbergen (2009). By projecting the tax shock factor on base assets (i.e. portfolios), naturally the resulting portfolio has higher correlation with asset returns, so that their betas are higher. Constructing mimicking portfolios is commonly interpreted as a method to remove the noise contained in macroeconomic factors, while keeping only the information, which is relevant for asset pricing. This way, inference on risk premia using mimicking portfolios is considered to be more informative compared to that using the original macroeconomic variables (Vassolou (2009); Adrian et al. (2014); Kleibergen and Zhan (2014)).

[3] A long-standing literature in industrial organization has documented both theoretically and empirically substantial industry heterogeneity in demand elasticity. Refer to early work by Pigou (1910); Deaton (1986); Pagoulatos and Sorensen (1986).

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Following the conventional asset pricing literature, at each point in time I form a mimicking portfolio of private income tax risk, which is long in high-tax exposure industries and short in low-tax exposure industries ($H - L$). I call this portfolio PMP for ease of notation. Since PMP is constructed using information up to time t and we look at the impact on expected returns i.e. at time $t + 1$, the portfolio does not suffer from look-ahead bias.

3.5 Cross-sectional Regression

To test whether the newly constructed PMP factor is priced in the cross-section of returns, I follow the two-step procedure proposed by Fama and Macbeth (1973). In the first step, I estimate factor betas in a time series regression:

$$r_{p,t+1} - r_{f,t+1} = \alpha_p + \beta_{p,PMP} PMP_t + \epsilon_{p,t} \quad (5)$$

I use 3-digit SIC code idustry portfolios on a quarterly frequency. In the second step, I use β_{PMP} as right-handside variables to estimate the factor premium λ_{PMP}:

$$r_p - r_f = \lambda_0 + \lambda_{PMP} \beta_{p,PMP} + \psi_p \quad (6)$$

Table 5 shows that the PMP factor has a positive price of risk and earns a quarterly risk-premium of 1.45 % or 5.8 % annually. Augmenting the model to include the market factor (column (2)) or the three Fama-French factors ($Mktrf$, SMB and HML in column (3)) does not affect the statistical significance of the estimates and reduces only slightly the risk premium. For example, the PMP factor earns an annual risk-premium of 5.16 % over the Fama-French 3 Factor model (1993).

The economic intuition behind this result is the following. Consumption is high for high-tax exposure industries during low-tax states (i.e. good, high-wealth states for households) and conversely, consumption is low when the private income tax rate increases (i.e. bad low-wealth states for households). This introduces a positive co-movement between the earnings of high-tax exposure industries and the tax rate. Therefore, an investor requires a premium to hold high tax exposure firms due to consumption risk.

4 Discussion

4.1 Risk-free rate and Reverse Causality

One concern in the analysis could be that risk-premia are affected by changes in the risk-free rate. For example, if the government uses tax revenues to pay back government debt, the risk-free rate could increase. The contemporaneous correlation between the risk-free rate and PI Shocks is 0.129 and 0.098 within 1-period lag. In Table 6 I address the issue of reverse causality. The results indicate that private income tax shocks respond much more powerfully to changes in the risk-free rate rather than the reverse. For example, a 1 % increase in R_f increases next-period private income tax shock rate by 13.71 %. On the other hand, a 1 % increase in the PI shock increases the next-period R_f by 0.003 %. These findings indicate that changes in the private income tax rate have a minor impact on the risk-free rate and are unlikely to affect risk-premia in the market.

4.2 Relationship to Other Macroeconomic Shocks

Another concern could be that the PI shocks I construct are related to other non-tax structural shocks. To ensure that this is not the case I regress PI on a range of macroeconomic shock variables previously discussed 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 (2018)), economic uncertainty (Geopolitical Risk Index[4] and Economic Policy Uncertainty Index[5]) and news (Barsky and Sims (2011), Beaudry and Portier (2014)). The evidence in Table 7 is reassuring because it shows that PI shocks are orthogonal to most of the macroeconomic shocks commonly used in the literature, except for some monetary policy shock measures. However, in those cases, the magnitude of the relationship is economically

4 https://www.policyuncertainty.com/gpr.html
5 https://www.policyuncertainty.com/

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very low. For example, a 1 % surprise increase in the monetary policy rate in a given quarter is associated with a 0.04 % increase in the private income tax rate. The reason why correlations with structural macroeconomic variables are so low is that I retain only exogenous, unanticipated tax shocks, which were not motivated by counter-cyclical policy considerations. The evidence in Table 7 supports my premise that private income tax shocks are correctly and precisely identified. This is an important result, which allows me to make causal statements about the impact of private income tax shocks on asset prices and risk premia.

5 Conclusion

This paper studies the asset pricing implications of tax policy changes. I find that unanticipated tax cuts decrease future tax revenues and increase future consumer demand and output. Using structurally identified tax news, I develop an asset pricing factor mimicking private income tax shocks. The investment strategy long in high-tax exposure industries and short in low-tax exposure industries generates annualized risk-adjusted returns of 5.80 %. Both the time-series and cross-sectional tests show that the private income tax shocks risk premium survives the CAPM and the Fama-French 3-factor model.

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Figure 1: Impulse Response Function

The figure shows the response of excess industry returns to a 1 standard deviation increase in the average personal income tax rate (APITR).The Impulse-Response Function (IRF) is based on a VAR with 4 variables: industry excess returns, average personal income tax rate (APITR), real GDP (RGDP) and government debt (DEBT) and a lag lenth of 4.

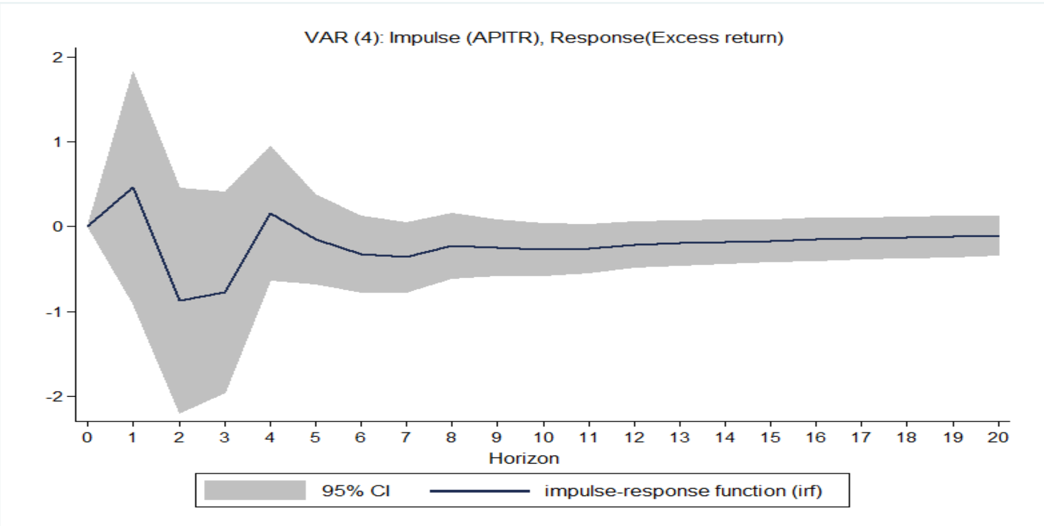

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Table 1: Summary Statistics of Private Income Tax Shock Betas

This table reports summary statistics of betas estimated from time-series regressions of excess industry returns on private income tax shocks.

Panel A: Moments of the Distribution	
Mean	0.16
St.Dev	2.06
Skewness	2.40
Panel B: Percentiles	
1 %	-4.75
5 %	-2.18
50 %	0.14
95 %	2.66
99 %	5.83

Table 2: Top and Bottom Industries by the sensitivity to structural PI Shocks

The table reports the average 3-digit SIC industry beta to structural private income tax shocks.

SIC	Industry	β
551	New and Used Car Dealers	-12.7
341	Metal Cans and Shipping Containers	-8.90
245	Wood Buildings and Mobile Homes	-7.26
415	School Buses	-5.64
124	Coal Mining Services	-4.46
⋮	⋮	⋮
221	Broad woven Fabric Mills, Cotton	3.18
737	Computer and Data Processing Services	2.91
108	Metal Mining Services	2.73
283	Drugs	2.05
738	Misc. Business Services	1.67

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Table 3: Single-sorts

This table reports risk-adjusted excess returns from factor model regressions. T-stats are shown in parentheses using Newey-West standard errors with 2 lags. Significance at the 10 %, 5% and 1% level is given by *, ** and *** respectively.

	(H)	(2)	(3)	(4)	(L)	(H-L)
α^{CAPM}	0.47*	-0.08	-0.25***	-0.25***	-0.27***	0.64**
	(1.67)	(-1.46)	(-4.79)	(-4.49)	(-3.53)	(2.20)
α^{3FF}	0.19**	-0.03	-0.20***	-0.24***	-0.30***	0.49***
	(1.99)	(-0.48)	(-3.60)	(-4.18)	(-3.79)	(3.94)

Table 4: Demand Sensitivity

This table reports industry sensitivities to aggregate consumption in durable goods. T-stats are shown in parentheses using Newey-West standard errors with 2 lags. Significance at the 10 %, 5% and 1% level is given by *, ** and *** respectively.

	(H)	(L)	(H-L)
$Cons.Durables$	0.42***	-0.26*	0.68***
	(2.51)	(-1.90)	(3.50)
$Mktrf$	0.06***	0.08***	-0.02
	(4.06)	(7.43)	(-1.09)
SMB	-0.17***	-0.09***	-0.08***
	(-9.20)	(-5.49)	(-3.24)
HML	-0.06***	0.04***	-0.10***
	(-3.41)	(2.88)	(-4.48)
$Constant$	6.78***	-4.46**	11.24***
	(2.54)	(2.03)	(3.24)

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Table 5: Cross-sectional Regressions

This table reports quarterly percentage premia calculated using Fama-Macbeth two-pass procedure. T-stats are shown in parentheses using Newey-West standard errors with 2 lags. Significance at the 10 %, 5% and 1% level is given by *, ** and *** respectively.

	(1) PMP	(2) CAPM	(3)FF 3 Factor
PMP	1.45***	1.32***	1.29***
	(3.20)	(4.00)	(5.47)
$Mktrf$		1.20	1.08
		(0.15)	(0.09)
SMB			-0.25***
			(-7.36)
HML			8.30
			(1.47)
$Constant$	0.13	-0.01	-0.03
	(0.67)	(-0.25)	(-0.23)

Table 6: Robustness: Risk-Free Rate

This table reports the relationship between the risk-free rate and private income tax shocks. T-stats are shown in parentheses using Newey-West standard errors with 2 lags. Significance at the 10 %, 5% and 1% level is given by *, ** and *** respectively.

	(1) PI Shock	(2) R_f
$R_{f,t}$	-9.15***	.
	(-25.83)	
$R_{f,t-1}$	13.71***	.
	(42.09)	
PI_t	.	0.004***
		(33.15)
PI_{t-1}	.	0.003***
		(25.56)

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R^2, %	3.30	1.37

Table 7: Macroeconomic Shock Variables

The table reports the results of regressing PIshocks on a range of macroeconomic shock variables. T-stats are reported in parentheses. Significance at the 1%, 5% and 10% is given by ***, ** and * respectively.

Shock	Source	PI Tax Shock
Federal Spending	Ramey and Zubairy (2018)	0.027
		(1.35)
Federal Spending (Unanticipated)	Caggiano et al. (2015)	-0.028
		(0.034)
Federal Spending (Anticipated)	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 (2018)	0.022
		(0.36)
Monetary Shock (Unanticipated)	Nakamura and Steinsson (2018)	0.049*
		(1.63)
Uncertainty	GPR Index	0.01
		(1.00)
Uncertainty	EPU Index	0.042
		(1.40)
News	Barsky and Sims (2011)	0.017*
		(1.70)
News	Beaudry and Portier (2014)	0.03
		(0.30)

Appendix: Recovering the True Structural Shocks

This section outlines how true structural shocks are recovered in proxy SVAR framework of Mertens and Ravn (2013). The model is given by

$$Y_t = \delta(L)Y_{t-1} + u_t \quad (1)$$

$$u_t = B\varepsilon_t \quad (2)$$

$$\varepsilon_t = Au_t \quad (3)$$

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where Y_t is $k \times 1$ vector of endogenous variables and $\delta(L)$ is a lag matrix polynomial for the autoregressive form of the model. u_t is a $k \times 1$ vector of reduced form shocks with covariance matrix Σ and ε_t is a $k \times 1$ vector of serially uncorrelated, normally distributed structural shocks with identity covariance matrix. The equations 1.2 and 1.3 determines the relationship between reduced form and structural shocks. The B is a $k \times k$ matrix and can be represented as following

$$\underset{k\times k}{B} = \begin{pmatrix} \underset{q\times q}{B_{11}} & \underset{q\times(k-q)}{B_{12}} \\ \underset{(k-q)\times q}{B_{21}} & \underset{(k-q)\times(k-q)}{B_{22}} \end{pmatrix}$$

where q is the number of instruments available. In Mertens and Ravn (2013), $k = 7$ and $q = 2$ and APITR (ACITR) is ordered first (second) or second (first) and the authors show that it is possible to identify matrices B_{11} and $B_{21}$when the instruments satisfy the relevance and exogeneity conditions. Hence, using B_{11} and B_{12}, it is possible to estimate the responses of the variables to the personal income or corporate tax shocks without recovering the true structural shocks. However, our interest is to recover the structural shocks to the personal income and corporate taxes and to do so, we need to identify the first two rows the A matrix. Assume that the first two rows of the vector Y_t include APITR and ACITR; hence, the first two rows of u_t are the reduced form shocks of APITR and ACITR. Denote these first two rows of u_t as u_t^S and the rest as $u_t^*$and apply the same for the vector ε_t. Then we can represent equation 1.3 as following

$$\begin{pmatrix} \underset{2\times1}{\varepsilon_t^S} \\ \underset{5\times1}{\varepsilon_t^*} \end{pmatrix} = \begin{pmatrix} \underset{2\times2}{A_{11}} & \underset{2\times5}{A_{12}} \\ \underset{5\times2}{A_{21}} & \underset{5\times5}{A_{22}} \end{pmatrix} \begin{pmatrix} \underset{2\times1}{u_t^S} \\ \underset{5\times1}{u_t^*} \end{pmatrix}$$

where ε_t^S is the structural shock vector that we aim to recover. If we are able to identify matrices A_{11} and A_{12}, we can recover the structural shock vector ε_t^S since we already estimated the reduced form shocks $u_t = ((u_t^S)', (u_t^*)')'$. To identify A_{11} and A_{12}, we will use the results of the inverse of the partitioned matrices. The inverse of partitioned matrices of the B matrix is given by (hat denotes the identified matrices)

$$B^{-1} = \begin{pmatrix} \left(\hat{B}_{11} - B_{12}B_{22}^{-1}\hat{B}_{21}\right)^{-1} & -\left(\hat{B}_{11} - B_{12}B_{22}^{-1}\hat{B}_{21}\right)^{-1}B_{12}B_{22}^{-1} \\ -\left(B_{22} - \hat{B}_{21}\hat{B}_{11}^{-1}B_{12}\right)^{-1}\hat{B}_{21}\hat{B}_{11}^{-1} & \left(B_{22} - \hat{B}_{21}\hat{B}_{11}^{-1}B_{12}\right)^{-1} \end{pmatrix}$$

Since $A = B^{-1}$, the first two rows the matrix A, $A_1 = [A_{11} \quad A_{12}]$, is equal to

$$A_1 = \left(\hat{B}_{11} - B_{12}B_{22}^{-1}\hat{B}_{21}\right)^{-1} \begin{pmatrix} 1 \\ -B_{22}'^{-1}B_{12}' \end{pmatrix} \tag{4}$$

and the unknown in the equation 1.4 is $B_{12}B_{22}^{-1}$. To obtain an expression for this term, first, we can rewrite the relationship between the matrix B and estimated covariance matrix $\hat{\Sigma}$ as following (remember that $BB' = \Sigma$)

$$B_{12}B_{12}' = \hat{\Sigma}_{11} - \hat{B}_{11}\hat{B}_{11}' \tag{5}$$

$$B_{22}B_{12}' = \hat{\Sigma}_{21} - \hat{B}_{21}\hat{B}_{11}' \tag{6}$$

$$B_{22}B_{22}' = \hat{\Sigma}_{22} - \hat{B}_{21}\hat{B}_{21}' \tag{7}$$

and second, we can rearrange the equation 1.6 into

$$B_{22}'^{-1}B_{12}' = B_{22}'^{-1}B_{22}^{-1}\left(\hat{\Sigma}_{21} - \hat{B}_{21}\hat{B}_{11}'\right) \tag{8}$$

and third, the term $B_{22}'^{-1}B_{22}^{-1}$ is given by the inverse of equation 1.7. Combining these, equation 1.8 becomes

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$$\widehat{B_{22}'^{-1}B_{12}'} = \left(\hat{\Sigma}_{22} - \hat{B}_{21}\hat{B}_{21}'\right)^{-1}\left(\hat{\Sigma}_{21} - \hat{B}_{21}\hat{B}_{11}'\right) \tag{9}$$

and the first two rows of matrix A is given by

$$\hat{A}_1 = \left(\hat{B}_{11} - \left(\widehat{B_{22}'^{-1}B_{12}'}\right)'\right)^{-1}\begin{pmatrix}1 \\ -\widehat{B_{22}'^{-1}B_{12}'}\end{pmatrix} \tag{10}$$

Finally, the structural shocks of interest are equal to

$$\varepsilon_t^S = \hat{A}_{11}u_t^S + \hat{A}_{12}u_t^* \tag{11}$$