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# SHORT-TERM TAX CUTS, LONG-TERM STIMULUS

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**ABSTRACT**

We study the macroeconomic effects of corporate income taxes on innovation and productivity in the United States. Using narrative-identified tax changes from 1950 to 2019, we find that temporary cuts in corporate tax rates lead to persistent increases in R&D, patenting, productivity, output, and broader measures of intangible investment. We interpret these findings with an estimated semi-endogenous growth model, whose implied sufficient statistics for innovation policy, elasticities of patenting with respect to taxes and social returns to R&D are consistent with the existing literature. The model highlights the tax amortization of intangible asset purchases as a key channel through which corporate taxes distort innovation. We provide direct evidence for the model mechanism using firm-level data: a cut in corporate taxes leads to a relative jump in the stock market valuation of the most intangible-intensive companies, followed by a sustained increase in R&D, intangible investment, and patenting, among these firms. Our results suggest that corporate income taxes create a first-order distortion to innovation and that the tax treatment of intangible assets is central to understanding the effects of corporate taxation.

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# 1 Introduction

Productivity growth in advanced economies has slowed markedly over the past two decades. This slowdown has renewed longstanding debates about which policies can possibly raise productivity and output. While there is now extensive empirical evidence on the short-run effects of fiscal policy, there is far less evidence on whether tax policy can sustainably drive aggregate productivity. Does cutting corporate income taxes stimulate innovation and productivity? This paper provides new evidence that it does.

Our first contribution is empirical. Building on the influential narrative identification strategy of Romer and Romer (2010), Ramey (2011), and Mertens and Ravn (2013), we extend the analysis of postwar U.S. tax shocks beyond the short-term horizons that dominate existing studies. Looking at a full decade after the shock proves key. We find that temporary corporate tax cuts lead to a sustained increase in innovation activity, in terms of expenditure —both R&D and broader measures of intangible investment not captured in national accounts— as well as outcomes, measured by patents and trademarks. These responses, in turn, translate into persistent gains in total factor productivity and GDP.

Our second contribution is theoretical. We develop and estimate a semi-endogenous growth model that highlights a previously overlooked mechanism through which corporate income taxes discourages innovation investment. When innovating, firms create intangible assets that reflect the ownership of new ideas. Under U.S. tax law, which allows purchased intangible assets to be amortized over fifteen years rather than fully expensed, corporate taxes lower the market value of ideas by reducing the after-tax profits that they generate without providing offsetting tax relief. A cut in the corporate tax rate reduces this distortion by increasing profits by more than it reduces the value of amortization deductions, making intangible assets more valuable and thereby encouraging innovation. Using model-based counterfactual simulations that vary the tax amortization period, we show that this mechanism can account for the persistent effects of corporate tax cuts on innovation. Importantly, the distortion persists even in the presence of other provisions of U.S. tax law that favor innovation, such as R&D tax credits and full expensing of R&D expenditures, which are both featured in our model.

Quantitatively, the model yields implications that align with notable benchmarks in the literature. The knowledge spillovers and the elasticity of aggregate productivity to innovation intensity implied by our estimates are consistent with the statistics computed by Atkeson and Burstein (2019). The model-implied social returns to R&D are close to those in Bloom et al. (2013), and the long-run elasticity of innovation with respect to corporate taxation is within the range reported by

Akcigit et al. (2021) across U.S. states. Taken together, these results suggest that our model yields plausible estimates of the response of aggregate productivity to innovative investment, with the large effects of corporate tax changes reflecting the significant distortions that this taxation creates for innovation incentives.

We provide firm-level evidence that is consistent with the model's mechanism. Following a corporate tax cut, firms with a high share of intangible asset value —measured by the book value of patents and other intangibles relative to market capitalization— experience a significantly larger increase in stock market valuation relative to companies with low intangible intensity. This immediate price response reflects the asset-pricing channel: tax cuts raise the market value of intellectual property, thereby strengthening incentives to innovate. To examine this link more directly, we analyze the responses of various innovation expenditure measures. As emphasized by Corrado et al. (2009) and Atkeson (2020), national accounts likely understate the scale of intangible investment. We therefore study not only R&D spending, but also broader measures of intangible investment outside the national accounts, as well as patent filings. In line with our theory, all three measures rise gradually and persistently following a tax cut. In contrast, tangible investment and sales respond immediately. These firm-level dynamics mirror the aggregate evidence and underscore the central role of intangible asset valuation in transmitting corporate tax policy to long-run innovation and productivity growth.

Our estimated effects are economically significant. A temporary 1% reduction in the corporate tax rate lasting four years raises total factor productivity by 0.5% after eight years. Using Compustat data, we calculate that in 2023 physical capital expenditures and depreciation accounted for 6.4% and 4.4% of GDP, while intangible expenditures and amortization accounted for 5.5% and 1.3%, respectively. The incidence of intangible investment and its tax amortization on corporate balance sheets is therefore comparable to that of physical capital and its tax depreciation. Yet, while accelerated depreciation and full expensing of capital investment have become standard instruments of corporate tax policy, accelerated amortization of intangibles remains largely overlooked. Moreover, the tax treatment of intangibles is not unique to the United States. Amortization of intellectual property products is a feature of corporate tax systems across both advanced and emerging economies (Appendix A). Amortization periods for purchased patents typically range from 10 to 25 years (compared with 15 years in the United States), suggesting that the mechanism identified in this paper is likely to operate internationally, with effects of corporate tax changes on innovation and productivity that may be even larger than those we estimate for the United States.

**Related literature.** Our analysis is related to several strands of work. An influential empirical literature pioneered by Romer and Romer (2010), Barro and Redlick (2011), Mertens and Ravn (2013), Cloyne (2013), Caldara and Kamps (2012), among many more studies in macroeconomics (e.g. Ramey, 2016) and accounting (e.g. Shevlin et al., 2019), estimate the short-term response of GDP to tax shocks. However, these contributions do not examine productivity and R&D expenditure, nor the responses of macro variables at medium-term horizons, both of which are a main focus of our analysis.

A long-standing tradition in macroeconomics, dating back to Samuelson (1964), Hall and Jorgenson (1967), Auerbach (1983, 2006), and Abel (2007), emphasizes that a system that taxes capital income without providing for immediate expensing of capital purchases distorts investment decisions. With these studies, we share the insight that incomplete expensing makes investment sensitive to tax rate changes. A key distinction, however, is that the capital expenditure analyzed in these earlier works is characterized by diminishing marginal returns, whereas the purchase of intangible assets that we focus on here is most likely associated with increasing aggregate returns due to the non-rival nature of ideas.

Several studies focus on the link between tax changes and innovation. Jaimovich and Rebelo (2017) study an endogenous growth model with non-linear tax effects on growth. Jones (2022) studies optimal taxation for top earners in a model where innovation cannot be perfectly targeted by subsidies. Akcigit et al. (2021) estimate that permanent tax cuts have a sizable impact on patenting across U.S. states and inventors. Ferraro et al. (2023) report significant effects of personal income tax changes on productivity, looking at horizons up to four years. Dechezleprêtre et al. (2023) and Bloom et al. (2013) document large responses of R&D and patenting to changes in R&D tax incentives. Auerbach (2018), Sedlacek and Sterk (2019) study the macroeconomic effects of reforms introduced in TCJA 2017, including the expensing of capital investment. We complement these studies by (i) documenting the persistent economy-wide effects of corporate tax cuts on innovation and productivity, and (ii) focusing on the role of intangible asset amortization in the transmission of corporate taxes.

Growing research efforts, surveyed by Cerra et al. (2022) and including Comin and Gertler (2006), Benigno and Fornaro (2018), Anzoategui et al. (2019), de Ridder (2019), Beaudry et al. (2020), Jordà et al. (2020), Queraltó (2022), Furlanetto et al. (2021), Antolin-Diaz and Surico (2025), Fieldhouse and Mertens (2023), and Fornaro and Wolf (2025), among many others, examine the long-term effects of non-technology shocks. A distinctive feature of our empirical and theoretical analyses is the focus on the medium-term effects of corporate income tax changes.

**Structure of the paper.** In Section 2, we present the narrative identification strategy and the empirical framework. Section 3 summarizes the main findings and reports extensive sensitivity analyses in which we vary the sample, estimation method, specification, and controls. In Section 4, we lay out a semi-endogenous productivity model with tax depreciation on physical capital, tax amortization on intellectual property and distortionary taxes on corporate and personal income. In Section 5, we estimate the structural model, while in Section 6, we provide firm-level evidence on the novel mechanism highlighted by our analysis. Section 7 presents a discussion of our findings, aiming to clarify the most salient economic, accounting, and legislative features of our mechanism. Conclusions are drawn in Section 8. The Appendix contains further results and robustness analyses.

## 2 Empirical Framework

In this section, we describe the narrative approach to identify exogenous variation in income taxes. We then present the empirical models to estimate their dynamic effects and provide details of the estimation procedure. Finally, we present the data that we use in the empirical analysis.

### 2.1 Identification

Our goal is to examine the effects of different tax policy reforms on productivity and innovation. We face at least three empirical challenges. First, we need information on when and how different types of taxes were changed. Second, tax policy is often endogenous because policy levers tend to be adjusted in response to changes in current or prospective economic conditions. Third, given the focus on productivity and innovation, we need econometric methods that are well-suited to elicit any medium-term effect.

We address the first two challenges using the identified corporate and personal income tax changes from Mertens and Ravn (2013). These data are based on the original data set of Romer and Romer (2010), which identified tax changes for the United States from 1950 to 2006. To isolate changes in tax policy that are plausibly "exogenous", Romer and Romer (2010) examine the motivations given by policymakers for all major pieces of Federal tax legislation over this period. Tax changes that were not implemented for reasons related to changes in current or prospective future economic conditions are considered "exogenous". We extend the original sample of Romer and Romer (2010) to 2019, using the distinction between corporate and personal income taxes proposed by Mertens and Ravn (2013). In Appendix B, we provide details of the new bills that we have included and a discussion of the policy makers' motivations that we regard as "exogenous", following the classification pioneered by Romer and Romer (2010).

A quantitative measure of each exogenous reform is constructed using historical revenue projections for the impact of the policy change, as announced at the time of the intervention. These are scaled by nominal GDP, and thus approximate changes in the average tax rate (all else equal). Mertens and Ravn (2013) refine this series by excluding potentially anticipated reforms, defined as tax changes implemented more than 90 days after the announcement. Key for our purpose, Mertens and Ravn (2013) subdivide the Romer and Romer (2010) shocks into corporate and personal tax reforms. This so-called "narrative" approach of looking for quasi-natural experiments from historical episodes has a long tradition in macroeconomic research, as exemplified by Ramey and Shapiro (1998), Ramey (2011), Barro and Redlick (2011), Cloyne (2013), Mertens and Ravn (2012, 2014), Guajardo et al. (2014), and Cloyne et al. (2023), among many others.[1]

## 2.2 Econometric method

As for the econometric method, we need an approach that allows us to draw inference about medium-term effects. Recent studies, including Jordà et al. (2020) and Li et al. (2021), show that this can be achieved by estimation of impulse response functions using local projections (LPs), following Jordà (2005). This is a direct estimate of the impulse response function and does not use coefficient estimates on all the lagged controls to construct the IRF. As a result, this approach is less sensitive to the choice of lag structure and to lag truncation issues that plague VAR methods in finite samples. Moreover, Montiel-Olea et al. (2025) argue that LPs provide a more robust assessment of estimation uncertainty than VARs.[2]

As a starting point, we consider a simple LP where the outcome variables $Z_i$ are regressed directly on the narrative tax measures and controls. In our setting, such a LP can be written as:

$$Z_{i,t+h} = c^{(h)} + \beta_{ct}^{(h)} \epsilon_{ct,t} + \beta_{pt}^{(h)} \epsilon_{pt,t} + b^{(h)} X_{t-1} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{1}$$

where $\epsilon_{ct,t}$ ($\epsilon_{pt,t}$) denotes the narrative measure of exogenous corporate (personal) tax change of Mertens and Ravn (2013) and $X_t$ denotes the control variables.[3] We refer to Equation (1) as the 'Direct' LP model because it treats the narrative measures as the structural shocks and, thus, the

[1] The narrative approach arguably dates back to, at least, Friedman and Schwartz (1963) who examine episodes of unusual monetary policy in the United States. In a modern setting, the approach has been popularized by Romer and Romer (1989) and Romer and Romer (2004). On the government spending side, a number of papers have employed a narrative approach to examine the impact of defence (Ramey and Shapiro, 1998, Ramey, 2011, Crafts and Mills, 2013, Ramey and Zubairy, 2018, Barro and Redlick, 2011) and nondefence spending (Fieldhouse and Mertens, 2023).

[2] As shown by Antolin-Diaz and Surico (2025), Montiel-Olea et al. (2025), Baumeister (2025), the performance of VARs improves once sufficiently long lags are included in the model. In Appendix K.5, we consider a long-lagged VAR with Bayesian shrinkage (Antolin-Diaz and Surico, 2025) as a robustness check. Results are very similar.

[3] For the controls we use lags of the narrative tax measures and lags of the baseline variables in Mertens and Ravn (2013): the personal and corporate tax rates and their tax bases, GDP, government spending, and federal debt.

estimates of $\beta_{ct}^{(h)}$ ($\beta_{pt}^{(h)}$) provide the response to the exogenous corporate (personal) tax change under the assumption that the contemporaneous impact on the personal (corporate) tax shock is zero. The parameters of the direct LP can be estimated by OLS, with heteroscedasticity-robust standard errors as in Montiel-Olea et al. (2025). To keep this preliminary evidence as transparent as possible, we consider a specification with only one lag in the main text and report the estimates using more lags in Appendix Figure K.4.

A concern with this 'Direct' model, however, is that it does not take into account the possibility of measurement error in the narrative tax proxies. This can be dealt with by using the narrative measures as instruments for the latent tax shocks. However, as discussed in Mertens and Ravn (2013), the two tax instruments are contemporaneously correlated (as corporate income taxes and personal income taxes are sometimes changed together in the same piece of legislation). This implies that the information from the instruments is only sufficient to identify a convolution of the latent tax shocks and further restrictions are required to disentangle their effects. We use the methods and specifications described in Mertens and Ravn (2013) to calculate the contemporaneous impulse response matrix $A_0$. We use a Cholesky factorization of the covariance matrix of the identified structural shocks and order last the tax rate that is perturbed in this decomposition. This restricts the direct contemporaneous effect of this shock on the remaining tax rate to be zero while still allowing for indirect effects. In the robustness section, we show that our results are not sensitive to the ordering assumptions.

To construct impulse responses for subsequent horizons, we depart from the VAR framework of Mertens and Ravn (2013). Instead, we estimate a sequence of local projections jointly for the vector of outcome variables $Z_t$ in the Mertens and Ravn (2013) VAR.[4]

$$Z_{t+h} = c^{(h)} + B_1^{(h)} Z_{t-1} + \sum_{j=2}^{P} b_j^{(h)} Z_{t-j} + d^{(h)} x_{t-1} + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{2}$$

where $h$ is the impulse response horizon. At horizon 0, the residuals $u_t$ are related to the structural shocks $\epsilon_t$ via $u_t = A_0 \epsilon_t$. Given the knowledge of the relevant elements of $A_0$, Jordà (2005) shows that the impulse response at horizon $h$ can be calculated as $B_1^{(h-1)} A_0$.[5] We estimate Equation (2) with Bayesian methods and four lags of the controls (Ferreira et al., 2025).[6] This offers three

[4]Mertens and Ravn (2013)'s VAR includes: the two tax rates and tax bases, GDP, government spending and federal debt. We add additional variables of interest to this specification one by one. The control variables $x_t$ account for the Great Financial Crisis and ensure information sufficiency. See Section 2.3 and Appendix D for details.

[5]This formulation of the LP in Jordà (2005) allows us to remain as close as possible to the setup in Mertens and Ravn (2013) while still conducting estimation via local projections. Indeed, the shorter-term effects we estimate below are very close to the short-run IRFs estimated by Mertens and Ravn (2013), which provides a useful benchmark.

[6]Unlike Ferreira et al. (2025), we use agnostic priors. Furthermore, we follow the recommendations by Montiel Olea and Plagborg-Møller (2021) and rely on lag augmentation to correct for serial correlation and draw robust inference

main advantages in our setting. First, the error bands incorporate uncertainty regarding the $A_0$ matrix. Second, the Markov chain Monte-Carlo approach allows us to easily compute joint posterior distributions that can be used to assess statistical differences across shocks and horizons. Third, in Section 5, we use the IRFs produced by model (2) to estimate the structural parameters of an endogenous growth model through IRF matching, for which Bayesian methods are routinely used.

### 2.3 Data

The data set covers the sample 1950Q1-2019Q4, and in its baseline form consists of seven variables as in Mertens and Ravn (2013). The average personal and corporate tax rates are denoted by $APITR_t$ and $ACITR_t$, respectively, while $\ln\left(B_t^{PI}\right)$ and $\ln\left(B_t^{CI}\right)$ are the corresponding tax bases. Government spending is $\ln(G_t)$, while $\ln(DEBT_t)$ stands for federal debt and GDP is represented by $\ln(GDP_t)$. Given our focus on the medium term, we expand this dataset with utilization-adjusted Total Factor Productivity (TFP), hours worked, Research and Development (R&D) expenditure, non-residential investment, personal consumption expenditures, and real wages. All variables, except $APITR_t$ and $ACITR_t$, are expressed in real per capita terms. In Appendix C, we provide a detailed description of all variables and data sources.

## 3 Empirical results

The empirical literature on the macroeconomic effects of tax changes using narrative methods finds large effects on GDP, but only focused on the shorter-term effects over 2 to 5 years without considering at all the responses of productivity and innovation, neither at short nor long horizons. A sizable part of the policy debate, however, is centered around the potential longer-term effects of corporate tax reforms. Despite this, there is little direct evidence on whether tax cuts can boost productivity over the medium-term. In this section, we estimate the dynamic effects of a corporate income tax cut on innovation, productivity, and GDP over a forecast horizon of up to 10 years.

### 3.1 Main findings

Using the models of Section 2, we present the estimated dynamic effects of corporate tax changes on TFP, R&D expenditure and GDP, respectively, as rows of Figure 1. The left column refers to the simple frequentist direct method of Equation (1) while the right column stands for the more sophisticated Bayesian LP specification of Equation (2). Red shaded areas represent confidence sets around the point estimates, which are displayed as solid red lines.

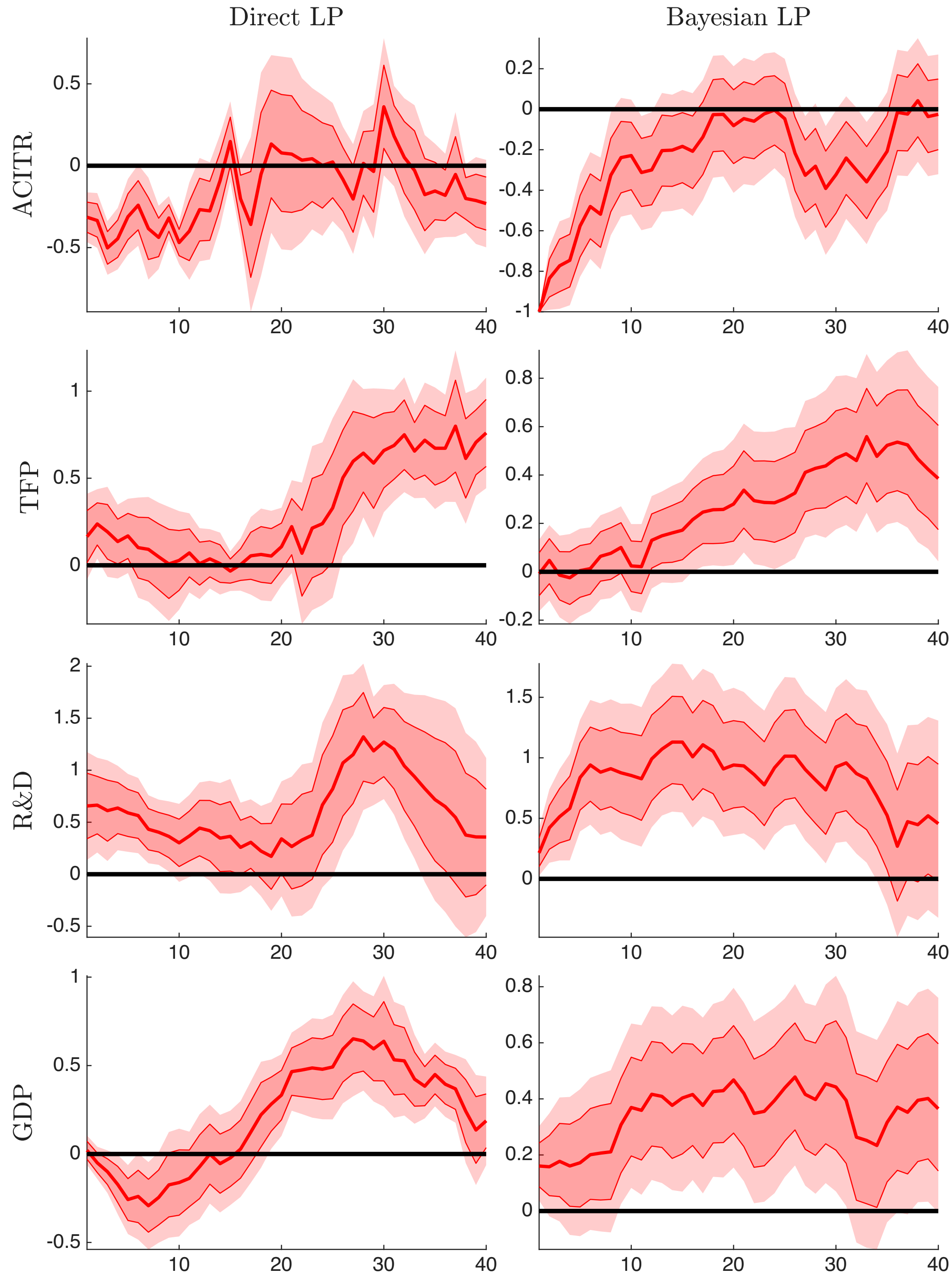
on IRFs at longer horizons. A detailed description of the estimation method is provided in Appendix G.

Despite the very significant differences between the estimation approaches, a consistent picture emerges from Figure 1. First, the corporate tax shock is temporary, reverting to zero after a few years. Second, in sharp contrast, the responses of TFP and GDP are delayed: they increase after three to four years and remain significant until at least year 8, extending well beyond the duration of the tax change itself. Third, the effects on R&D are frontloaded: they rise on impact, persist until year 8, and eventually lose statistical significance. In Appendix H, we further show that corporate tax changes explain up to 25% of medium-term variation in productivity, 20% for GDP, and 15% for R&D expenditure.

We extend the analysis in Figure 1 based on variables in the national accounts to additional measures of intangible investment and innovation. These enter the benchmark vector $Z$ one at a time to limit the number of estimated parameters. The top panel of Figure 2 shows the response of the intangible investment measure by Ewens et al. (2023), which infers firm-level intangible investment at yearly frequency from 'Selling, General, and Administrative' expenses in Compustat. The second and third rows display the responses of the two stocks of firm-owned intangible assets—patents and trademarks. Aggregate real stocks are constructed by aggregating patent and trademark values from Kogan et al. (2017) and Desai et al. (2025) respectively at quarterly frequency, and applying the perpetual inventory method. Patents, as shown by Kogan et al. (2017), capture technological progress and productivity-enhancing innovation; trademarks, according to Desai et al. (2025), capture product innovation, differentiation, and market expansion. Across the three measures and the two estimation methods of Figure 2, corporate tax cuts generate a delayed response, which peaks significantly at the medium-run horizons of 5 to 8 years, consistent with the findings in Figure 1 using national accounts.

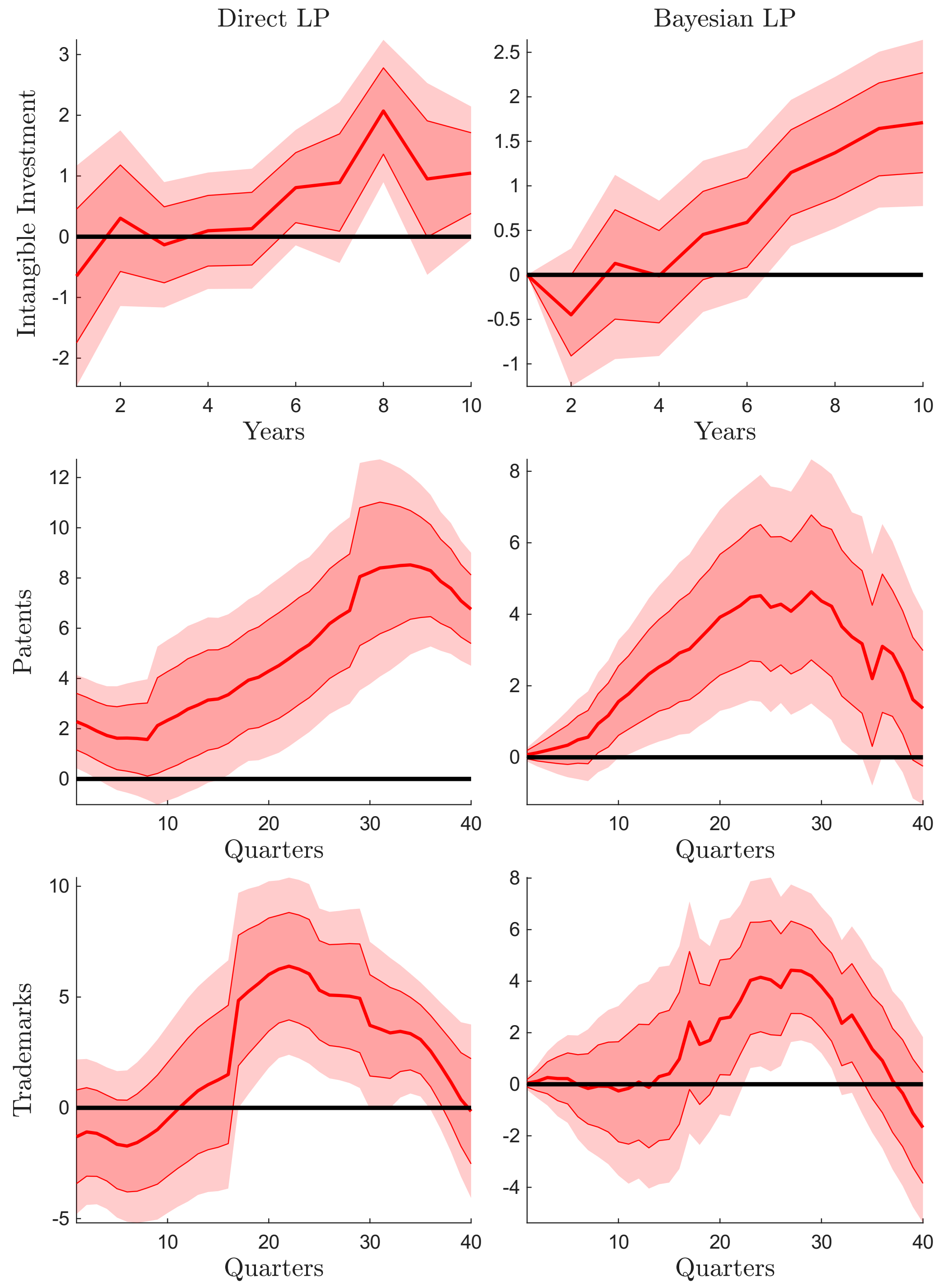
In Appendix Figure I.1, we look at investment, consumption, and wages. This extends both the sample, from 2006 to 2019, and the forecast horizon, from 5 to 10 years, in Mertens and Ravn (2013). The response of investment resembles that of R&D in Figure 1: it is hump-shaped, peaks after four years, and reverts to zero by the end of the horizon. The effects on consumption, real wages and labour productivity are also persistent, and similar to GDP and TFP. In Appendix Figure J.1, we show that, in sharp contrast, the responses of TFP, R&D expenditure and GDP to a personal income tax cut are short-lived, and insignificant at horizons beyond three years. In summary, this section establishes that personal tax changes have short-lived effects while corporate tax changes exert their maximum impact over the medium term. The former finding is consistent with the evidence from earlier studies, while the latter result is, to the best of our knowledge, new.

Figure 1: Response of Tax Rate, TFP, R&D spending and GDP to a Corporate Income Tax Cut




Notes: responses of the average corporate income tax rates (ACITR), TFP, R&D expenditure, and GDP to a corporate income tax rate cut. The left (right) column plots responses estimated via direct (Bayesian) local projections; see Section 2.2 for details on methodology and Appendix C for data description. Shadow areas show the 68% and 90% confidence intervals/central $68^{th}$ and $90^{th}$ credible sets.

Figure 2: Response of Innovation Measures to a Corporate Income Tax Cut




Notes: responses of intangible investment, patent stock, and trademark stock to a corporate income tax rate cut. The left (right) column plots responses estimated via direct (Bayesian) local projections; see Section 2.2 for details on methodology and Appendix C for data description. Note that intangible investment is measured at annual frequency from Compustat data. Shadow areas show the 68% and 90% confidence intervals/central $68^{th}$ and $90^{th}$ credible sets.

### 3.2 Sensitivity Analysis

In this section, we report a wide range of sensitivity analyses showing that the medium-term effects of corporate tax changes on productivity and output are a robust feature of postwar U.S. data.

**Frequentist Estimates.** Frequentist estimates of the responses of GDP, TFP, and R&D to the tax shocks can be obtained using either the 'direct' model of Equation (1) or a LPIV specification.[7] In Appendix Figure K.1 we present the estimated IRFs using LPIV. While the two-stage least squares estimate produces erratic responses (in grey), their pattern broadly aligns with the smooth LPIV of Barnichon and Brownlees (2019) (in dotted red). The effects of corporate tax cuts on GDP and TFP are evident after about four years and continue out to 40 quarters. The effects of corporate tax changes on R&D spending are evident at medium horizons.

**Weak Instruments.** Instrument strength is tested using a robust F-test for the regression of the endogenous variable on the instrument and controls. For the narrative corporate tax instrument, this delivers a test statistic of 11.38 if a correction for heteroscedasticity is used and 30.33 if a HAC covariance is employed.[8] For the corporate tax shock derived from the SVAR, we obtain 45.37 and 24.01, respectively, under the two assumptions. These statistics exceed the Stock and Yogo (2005) threshold, and are larger than the Montiel-Olea and Pflueger (2013) critical value of 23.1 in most cases. Given the test's sensitivity to the method used to account for contemporaneous correlation between the narrative proxies and the properties of the residuals, we follow Anderson and Rubin (1949) to compute weak instrument robust error bands for the LPIVs in Figure K.2. Corporate tax shocks are confirmed to have a significant medium-term impact on GDP, productivity, and R&D.[9]

**Alternative Estimators.** In Appendix Figure K.3, we present the impulse responses obtained using the mutually orthogonal structural shocks from the Mertens and Ravn (2013) VAR as instruments. The impact on output, productivity, and R&D expenditure from these LPIV models is very similar to the results from the Bayesian LPs. In Figure K.4, we use the estimator by Herbst and Johannsen (2020) that corrects the LP small-sample bias noted by Li et al. (2024). These responses are close to the OLS estimates. Finally, in Appendix Figure K.5, we report impulse responses to a corporate tax shock employing the same proxy-SVAR setup of Mertens and Ravn (2013) but

[7]In the direct model, both proxies are added as contemporaneous regressors. In the LPIV case, we account for the contemporaneous correlation among the narrative proxies of Mertens and Ravn (2013) using two strategies. First, we use the relevant narrative proxy as an instrument for the shock of interest, and then add the contemporaneous value of the proxy for the other tax shock as a control. It is worth noting that the identification of the shocks in this LPIV differs from the scheme used by Mertens and Ravn (2013) and therefore the responses from these regressions are not directly comparable to the results in Section 3.1. Second, we employ the mutually orthogonal structural shocks estimated from the Mertens and Ravn (2013) VAR as an instrument for the corresponding tax rate.

[8]Lags for the Newey and West (1987) correction are set to 1 plus the maximum impulse response horizon of 40.

[9]The test statistics for the personal tax instrument are 7.29 (heteroscedasticity) and 4.90 (serial correlation). In contrast, the VAR-derived personal tax shock appears to be a strong instrument with statistics of 78.51 and 104.14.

extended to very long lags (32), using Bayesian shrinkage as in Antolin-Diaz and Surico (2025) to draw reliable inference about medium-term effects. We obtain very similar results.

**Additional Specifications.** Finally, we implement a range of additional sensitivity analyses, detailed in Appendix K. In Figure K.6, we use Bayesian LPs with residuals modelled as an MA process. In Appendix Figure K.7, we (i) vary the lag length for the controls in $Z$, (ii) use the optimal prior strategy described in Giannone et al. (2015), (iii) include the defence news shock from Ramey (2011) as a further control, and (iv) change the causal ordering of the two taxes as in Mertens and Ravn (2013). The main takeaway from Appendix K and this section is that our main finding of significant medium-term effects of corporate income tax changes on TFP and GDP is not easily overturned.

# 4 A structural model with endogenous productivity

In the previous section, we documented that temporary corporate income tax cuts have significant medium-term effects on productivity and output, and that the response of aggregate TFP to a corporate tax shock is more persistent than the response of R&D expenditure. In this section, we develop a theoretical framework that blends elements of semi-endogenous growth and business-cycle analysis to account for these empirical results. In the next sections, we estimate this structural model by matching the empirical IRFs of Section 3 and then run counterfactual simulations to highlight the transmission mechanism of corporate income tax shocks to productivity and output.

## 4.1 The tax treatment of intangible assets and R&D

The distinction between tangible and intangible capital—and their different tax treatment—plays a central role in our analysis. Intangible assets are non-physical assets with quantifiable economic value: patents, copyrights, trademarks, and goodwill. These assets can be created internally or purchased externally. Under U.S. tax law, the costs of developing intangibles internally are typically expensed on the income statement and therefore deducted in full when calculating taxable profits. In contrast, the costs of externally purchased intangibles are capitalized on the balance sheet and deducted gradually over time. For example, expenditures on an internally developed innovation are recorded as R&D expenses, while the purchase of an existing patent is accounted for as an intangible asset on the balance sheet.

We model purchases of intangible assets as conceptually analogous to purchases of tangible capital. In analogy to the stock of physical capital, which can be produced internally or acquired from specialized good producers, firms can build intangible capital either through in-house investment

—such as R&D— or by purchasing intellectual property from outside sources. In this framework, purchased intangibles represent a form of investment whose market valuation determines the incentives for creating new ideas. Tax policy, therefore, matters for innovation through its effect on the market price of these assets.

Amortization—the gradual deduction of the cost of an intangible asset from taxable income—works similarly to depreciation for tangible capital. Under Section 197 of the Internal Revenue Code, enacted in 1993, purchased intangible assets, including goodwill, must be amortized over fifteen years, regardless of their actual economic life. Before Section 197, only intangibles with a well-defined life could be amortized under Section 167, which, for newly issued patents, implied a period of seventeen years. By contrast, since 1954, Section 174 allows firms to deduct the full amount of research and experimental expenditures in the year they are incurred, even when those expenditures do not yield a specific intangible asset.

Consistent with these provisions, in our model, we assume that R&D spending is fully and immediately expensed (and that innovators receive R&D tax credits). In contrast, purchased intangibles are amortized over fifteen years. This long amortization period implies that corporate taxation creates a distortion in the market price of ideas and, consequently, in innovation incentives. We discuss the institutional background and historical details of these tax rules in Appendix L.[10]

### 4.2 Endogenous productivity: basic and applied research

Our model blends elements of endogenous growth theory and business-cycle analysis as in Anzoategui et al. (2019).[11] We introduce innovation as a two-stage process consisting of 'basic' and 'applied' research. 'Basic research' refers to activities that uncover fundamental truths about the world in the form of new ideas and technologies. Innovation, however, is not just about new ideas or technologies; effort and expenditure are also required to turn those ideas into new products and processes. We refer to this type of innovation activity as 'applied research' (Akcigit et al., 2020, Jones, 2022), or 'adoption' (Comin and Gertler, 2006).

In the economy, there exists a continuum of measure $A_t$ of monopolistically competitive intermediate goods firms. As we explain below, potential entrants compete to buy technologies that enable them to become monopolistic producers of a differentiated good. $A_t$ is therefore both the measure of intermediate goods firms and the stock of adopted technologies. Each firm manufactures

[10]In line with the U.S. tax code, we also model depreciation allowances for physical capital. As for personal income taxes, we introduce a proportional tax on workers' labor income.

[11]Growth in our model is semi-endogenous rather than fully endogenous. In our context, this is a more "conservative" approach because it does not build in permanent level effects from transitory changes. Furthermore, a semi-endogenous model is consistent with the observation that the trend in U.S. GDP growth has been relatively stable even as the average corporation tax rate has trended consistently lower in the postwar era.

a differentiated product using capital and labor with a standard production function. In Appendix O, we show that aggregate output is given by:

$$Y_t = A_t^{\theta-1}(U_t K_{g,t})^{\alpha}(L_{g,t})^{1-\alpha}, \tag{3}$$

where $Y$ is aggregate output; $K_g$ and $U$ are the capital stock in the final goods sector and its utilization rate, respectively; and $L_g$ is labor in the final goods sector, measured in efficiency units. In this section, we describe how R&D and adoption drive the dynamics of the endogenous TFP term, $A_t$. Let $Z_t$ be the total stock of known technologies. Since $A_t$ is both the measure of intermediate goods firms and the stock of adopted technologies, $(Z_t - A_t)$ is the *un*adopted technology stock. Basic research expenditure (R&D for short) increases $Z_t$ while applied research expenditure (adoption) increases $A_t$.

**Basic Research.** There is a continuum measure 1 of innovators who hire R&D-specific labor and capital to discover new technologies. Let $X_{z,j,t} = L_{z,j,t}^{\gamma} K_{z,j,t}^{1-\gamma}$ be R&D expenditure by innovator $j$, where $L_{z,j,t}$ and $K_{z,j,t}$ are labor and capital hired by innovator $j$, and $\gamma$ is the labor share in innovation expenditure. The number of new technologies created by a unit of R&D expenditure (equivalently, total factor productivity in R&D), $\varphi_t$, is given by:

$$\varphi_t = Z_t^{1+\zeta} X_{z,t}^{\rho_z - 1}, \tag{4}$$

where $X_{z,t}$ is aggregate R&D spending and $Z_t$ is the stock of technology, both of which an individual innovator takes as given. Following Romer (1990), the presence of $Z_t$ reflects public learning-by-doing in the R&D process; as in Jones (1995), the degree of returns is parameterized by $\zeta$.[12] In the next section, we estimate $\rho_z < 1$, implying that higher aggregate R&D spending reduces R&D efficiency at the individual level.

Let $P_{z,t}$ denote the market price of an unadopted technology. As explained below, the relationship between the market price of an idea and the present value of ownership is determined by the tax treatment of intellectual property. Denoting $r_{z,t}$ and $w_{z,t}$ the rental rates of R&D capital and labor, respectively, we can express innovator $j$'s decision problem as choosing $L_{j,z,t}$ and $K_{j,z,t}$ to

[12] The existence of a balanced growth path requires $\zeta = -\rho_z \left(\frac{\theta-1}{1-\alpha}\right)\left(\frac{g_y}{g_y - g_n} - \gamma\right)$, where $g_y$ and $g_n$ are the growth rates of GDP and the population, and the other parameters are described in the text. In estimating the model, we use average GDP and population growth rates over our sample period and estimate or calibrate the remaining parameters. See Tables 1 and 2 for the estimated value of $\zeta$ and other parameters.

maximize period $t$ after-tax profit:

$$\max_{L_{z,j,t},K_{z,j,t}} (1-\tau_{c,t}) \left( P_{z,t}\varphi_t L_{z,j,t}^{\gamma} K_{z,j,t}^{1-\gamma} - w_{z,t}L_{z,j,t} - r_{z,t}K_{z,j,t} \right), \tag{5}$$

where the first term inside the brackets is innovator $j$'s period $t$ revenue, given by the product of the market price of technology ($P_{z,t}$) and the number of technologies produced ($\varphi_t X_{z,j,t}$). Innovator $j$ pays corporate income tax $\tau_{c,t}$ on profits, given by revenues minus the costs of hiring workers and R&D-specific capital. Note that taxes are paid on revenues net of all costs (i.e., the wage and rental bills) so that, consistent with the U.S. tax code in the sample period we study, R&D expenses are fully tax deductible.[13]

The optimality conditions for R&D (aggregated over the unit measure of innovators) equate the marginal cost and product of each factor:

$$w_{z,t} = \gamma P_{z,t}\varphi_t \frac{X_{z,t}}{L_{z,t}} \tag{6}$$

for labor and $r_{z,t} = (1-\gamma) P_{z,t}\varphi_t \frac{X_{z,t}}{K_{z,t}}$ for capital. In aggregate, $\varphi X_{z,t}$ new technologies are discovered in period $t$. Denoting by $\phi$ the one-period survival rate for any given technology, we can express the evolution of the stock of technologies as:

$$Z_{t+1} = \varphi_t X_{z,t} + \phi Z_t \tag{7}$$

Combining equations (7) and (4) yields the following expression for the growth of new technologies:

$$\frac{Z_{t+1}}{Z_t} = Z_t^{\zeta} X_{z,t}^{\rho_z} + \phi. \tag{8}$$

**Applied Research.** We next describe how unadopted technologies become adopted, and thus enter productive use. There is a competitive group of "adopters", indexed by $j$, who buy the rights to the (still unadopted) technology from the innovator at the competitive price $P_{z,t}$ and convert it into use by employing adoption-specific labor and capital. This process takes time on average, and the conversion rate may vary endogenously. In particular, the rate of adoption depends positively on the level of resources devoted: an adopter succeeds in making a product usable in any period $t$ with probability $\lambda_t$, which is an increasing and concave function of expenditure, $X_{a,j,t} = L_{a,j,t}^{\gamma} K_{a,j,t}^{1-\gamma}$,

[13]To fully capture the tax treatment of R&D in the U.S. during our sample period, our estimated model also includes a static proportional R&D tax credit $\tau_z$, which adds the term $\tau_z \tau_{c,t} (w_{z,t}L_{z,j,t} + r_{z,t}K_{z,j,t})$ to Equation 5, and corresponding terms to the first order conditions for R&D inputs. For empirically plausible values of $\tau_z$, (5%-7% for the U.S. per OECD calculations, Appelt et al., 2019), the effect of this static R&D credit on first-order dynamics conditional on a corporate tax cut is negligible, and we therefore omit it from the discussion to economize on notation.

according to the following function:

$$\lambda_t = \lambda \left( \frac{Z_t}{N_t^{\gamma} \Psi_t^{1-\gamma}} X_{a,j,t} \right), \tag{9}$$

where $\lambda' > 0$, $\lambda'' < 0$, $L_{a,j,t}$ and $K_{a,j,t}$ are labor and capital hired by innovator $j$, and $\gamma$ is the labor share in innovation expenditure.

To ensure the existence of a balanced growth path, we multiply $X_{a,j,t}$ by a spillover effect coming from the total stock of technologies $Z_t$ (implying that the adoption process becomes more efficient as the technological state of the economy improves) and $N_t^{\gamma} \Psi_t^{1-\gamma}$, where $\Psi_t$ is a scaling factor that grows at the same rate of GDP on the balanced growth path; $N_t$ refers to the population. Once in usable form, the adopter sells the rights to the technology at price $P_{a,t}$, determined in a competitive market, to a monopolistically competitive intermediate goods producer that makes the new product using a Cobb-Douglas production function (described in Appendix Equation (46)). Letting $\Pi_{i,t}$ be the profits that an intermediate goods firm makes from producing a good under monopolistically competitive pricing, the present value of after-tax monopolistic profits is given by:

$$V_t = (1 - \tau_{c,t}) \Pi_{i,t} + \beta \phi \mathbb{E}_t \left[ \Lambda_{t,t+1} V_{t+1} \right], \tag{10}$$

where $\tau_{c,t}$ is the tax rate on corporate income. An adopter's problem is choosing inputs to maximize the value $J_t$ of an unadopted technology, namely:

$$J_t = \max_{L_{a,j,t}, K_{a,j,t}} \mathbb{E}_t \left[ (1 - \tau_{c,t}) \left( \lambda_t P_{a,t} - w_{a,t} L_{a,j,t} - r_{a,t} K_{a,j,t} \right) + \phi \beta \left( 1 - \lambda_t \right) \Lambda_{t,t+1} J_{t+1} \right], \tag{11}$$

where $\lambda_t$ is as in Equation (9), $P_{a,t}$ is the market price of an adopted technology, and $w_{a,t}$ and $r_{a,t}$ are the rental rates of adoption-specific labor and capital, respectively. The first term in the Bellman equation reflects expected after-tax profits (expected revenues $\lambda_t P_{a,t}$ minus the costs of hiring adoption-specific labor and capital), while the second term stands for the discounted expected continuation value: $(1 - \lambda_t)$ times the discounted continuation value. As with R&D expenditure, we assume that the costs of technological adoption are fully tax-deductible. The first-order conditions for labor and capital are:

$$(1 - \tau_{c,t}) w_{a,t} = \frac{\partial \lambda_t}{\partial L_{a,j,t}} \beta \phi \mathbb{E}_t \left[ (1 - \tau_{c,t}) P_{a,t} - \Lambda_{t,t+1} J_{t+1} \right], \tag{12}$$

and $(1 - \tau_{c,t}) r_{a,t} = \frac{\partial \lambda_t}{\partial K_{a,j,t}} \beta \phi \mathbb{E}_t \left[ (1 - \tau_{c,t}) P_{a,t} - \Lambda_{t,t+1} J_{t+1} \right]$. The terms on the right are the marginal benefits of adoption expenditures: the increase in the adoption probability, $\lambda_t$, times the discounted difference between the value of an adopted and an unadopted technology. The left side is the marginal cost. Since $\lambda_t$ does not depend on adopter-specific characteristics, we can sum across adopters to obtain the following law of motion for the aggregate evolution of adopted technologies:

$$A_{t+1} = \lambda_t \phi \left[ Z_t - A_t \right] + \phi A_t \tag{13}$$

which crucially depends on $Z_t - A_t$, the stock of unadopted technologies.

### 4.3 Corporate taxes and the market price of intellectual property

The price of (un)adopted technologies (which we refer to as intellectual property, IPP) is determined in competitive markets and, as in the model of Hall and Jorgenson (1967), is given by the sum of the present value of after-tax service flows plus the tax deductions associated with IPP ownership. Consistent with the U.S. tax code over our sample, we assume that the value of purchased IPP assets is amortized over time, resulting in future tax deductions. Following Auerbach (1989), we model amortization as a geometric process: in every period, an owner of an IPP asset can deduct a fraction $\hat{\delta}_{IP}$ of the purchase price of the asset from taxable profits. The remaining portion (1-$\hat{\delta}_{IP}$) is carried into the next period.

With this assumption, the present value of profits, net of the purchase price $P_{a,t}$, for an entrant monopolist that buys a newly adopted technology at time $t$ and starts production at $t + 1$ is:

$$\Pi_t^M = -P_{a,t} + \mathbb{E}_t \left[ \beta \phi \Lambda_{t,t+1} V_{t+1} + \sum_{s=0}^{\infty} \beta^s \Lambda_{t,t+s} \hat{\delta}_{IP}^{s+1} \left( 1 - \hat{\delta}_{IP} \right)^s \tau_{c,t+s} P_{a,t} \right] \tag{14}$$

The first term on the right-hand side is negative because the entrant monopolist is purchasing the technology from an adopter. The second term captures the present value of after-tax monopolistic profits starting in period $t + 1$, as per Equation (10). The third term is the present value of amortization allowances. Potential monopolists compete to buy adopted technologies and therefore, in equilibrium, lifetime profits are zero ($\Pi_t^M = 0$). Rearranging terms and exploiting the zero-profit condition, we can express the price of an adopted technology as:

$$P_{a,t} \left( 1 - d_{IP,t} \right) = \phi \beta \mathbb{E}_t \Lambda_{t,t+1} V_{t+1}, \tag{15}$$

where the present value of amortization allowances is denoted by:

$$d_{IP,t} = \sum_{s=0}^{\infty} \beta^s \Lambda_{t,t+s} \hat{\delta}_{IP}^{s+1} \left( 1 - \hat{\delta}_{IP} \right)^s \tau_{c,t+s} \tag{16}$$

As adopters compete to buy unadopted technologies and unadopted technology purchases are amortized in the same way, analogous derivations yield the market price of an unadopted technology:

$$P_{z,t}\left(1-d_{IP,t}\right)=\phi\beta\mathbb{E}_t\Lambda_{t,t+1}J_{t+1}. \tag{17}$$

According to equations (10), (11), (15) and (17), changes in current and expected future corporate tax rates generate variation in the present value of both after-tax service flows and the amortization allowances associated with the IPP purchase. This leads to price fluctuations in $P_{z,t}$ and $P_{a,t}$, which in turn directly affect incentives to discover new technologies and adopt existing ones. As we show in Section 6, the tax amortization rate (which corresponds to the time span over which amortization is allowed in the tax code) is crucial for the ability of the structural model to generate fluctuations in the market price of IPP in response to corporate tax changes, and thereby to account for the estimated responses of output and productivity to a corporate tax cut.[14]

### 4.4 Labor supply and the rest of the model

**Labor supply.** Variable labor utilization is modelled as an effort choice, following Galí and van Rens (2020). The household chooses hours one period in advance and faces a quadratic adjustment cost (increasing in the change in hours) in doing so. After observing the period wage, the household chooses the effort per hour, and the effective labor supply is given by hours times the effort. The first order condition for labor effort of type $j$ labor ($j\in$ goods, R&D, adoption) is standard and given by $-\bar{e}_j e_{j,t}^{\chi_j}+u_{c,t}\left(\left(1-\tau_{p,t}\right)w_{j,t}\right)=0$, where $\bar{e}_j$ is a constant, $\chi_j$ is the inverse elasticity of effort, $u_{c,t}$ is the marginal utility of consumption, $\tau_{p,t}$ is the personal income tax rate and $w_{j,t}$ is the wage rate per unit of effort. Labor effort is unobserved in the data, such that variation in effort per hour explains the response of labor productivity (output per observed hour) to a cut in personal income tax. Although our focus is on the effect of corporate income tax cuts, to reduce our degrees of freedom in estimating the model, we match simultaneously the responses to corporate and personal income tax cuts, and therefore we require this additional complexity in the labor supply block to match the muted empirical response of hours to the personal tax cut (see Figure I.1). We provide a detailed description of the household optimization problem in the Appendix.

**Rest of the model.** The remaining block of our framework is relatively standard and described in Appendix O. Several features are common to many existing models: quadratic adjustment costs

[14] As in the canonical model of Hall and Jorgenson (1967), if all margins of corporate expenditure (on both physical capital and intellectual property) were fully tax deductible (i.e., $\hat{\delta}_{IP}=\hat{\delta}_K=1$), permanent cuts in corporate income taxes would only affect the government budget constraint but have no real effect on output at either short or long horizons. See Abel (2007) for an intuitive explanation of this neutrality result in a general equilibrium setting.

on capital (used in R&D, adoption, and goods production), sticky prices à la Calvo, an interest rate rule, and habits in consumption. We model depreciation allowances for physical capital following Winberry (2021) (with tax depreciation parameter $\hat{\delta}_K$). The definitions of corporate income and taxable corporate income are in the Appendix. The government budget constraint is balanced in every period, with lump-sum taxes adjusting to balance out any difference between exogenous government consumption and the revenues raised by corporate and personal income taxation.

# 5 Structural estimation

In this section, we describe the estimation of the structural model of Section 4 using a limited-information Bayesian approach and show that it can rationalize the evidence in Section 3 on the joint responses of TFP, R&D, and GDP to narratively-identified income tax changes. In the next section, we will shed light on the mechanism behind our results by decomposing the output and productivity responses into the contributions of the various channels at play in our model.

## 5.1 Econometric framework

We estimate the structural model in Section 4 using the limited-information Bayesian approach described in Christiano et al. (2010). We refer to the vector of structural parameters in the theoretical model as $\Upsilon$ and to the associated impulse responses as $\Phi(\Upsilon)$. The structural parameters are estimated by minimizing the distance between the theoretical model impulse responses, $\Phi(\Upsilon)$, and the median of the empirical LP impulse response posterior distributions to both tax shocks, which we denote by $\hat{\Phi}$.

The limited-information approach fulfills our desire to focus on the responses of the economy to corporate and personal tax cuts jointly, and to isolate the theoretical mechanism(s) that are most likely to drive the empirical evidence of Section 3. It is therefore important that the estimated parameters maximize the likelihood that the structural model generates the data not only conditional on both income tax shocks, but also across short and long horizons. In the next section, we will conduct a series of counterfactual experiments in which we artificially change the value of one set of structural parameters at a time to evaluate the importance of different channels. To implement this approach, we first set up the quasi-likelihood function:

$$F(\hat{\Phi}|\Upsilon) = \left(\frac{1}{2\pi}\right)^{\frac{N}{2}} |V|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\left(\hat{\Phi} - \Phi(\Upsilon)\right)' V^{-1} \left(\hat{\Phi} - \Phi(\Upsilon)\right)\right)$$

where $N$ denotes the number of elements in $\hat{\Phi}$, and $V$ is a diagonal weighting matrix with posterior variance of $\hat{\Phi}$. Denoting by $p(\Upsilon)$ the prior distributions, the quasi-posterior distribution is then:

$$F\left(\Upsilon|\hat{\Phi}\right) \propto F(\hat{\Phi}|\Upsilon)p(\Upsilon)$$

We use a random walk Metropolis-Hastings algorithm to approximate the posterior distribution. The number of iterations is set to 1,100,000, and we save every 50th draw after a burn-in of 100,000.[15] The vectors $\hat{\Phi}$ —which is based on the LPs of Section 3— and the vector $\Phi(\Upsilon)$ —which is based on the theoretical model of Section 4— contain the IRFs (to both shocks) of the following variables: R&D, investment, consumption, GDP, hours worked and (utilization-adjusted) TFP. It is worth emphasizing that, by simultaneously targeting the effects of both corporate and personal taxes, we seek to match several key moments jointly, across both shocks *and* forecast horizons.

### 5.2 Calibrated parameters and prior distributions

We partition the structural parameters into calibrated (Table 1) and estimated sets (Table 2). The discount factor, capital depreciation, and the capital share are set at 0.99, 0.02, and 0.35. The markup is calibrated to target the steady-state share of profits in GDP. The coefficients of the Taylor interest rate rule for monetary policy are borrowed from Anzoategui et al. (2019). Following Wen (2004), the employment adjustment cost for the three types of labor is set to $\psi = 0.35$ (whereas the elasticities of labor effort are estimated). The government spending share and the steady state tax rates are set to their sample averages. To calibrate the tax depreciation rate for capital ($\hat{\delta}_K$), we average the estimated present value of depreciation deductions employed by Hall and Jorgenson (1967) and House and Shapiro (2008), since those two sets of estimates bookend the time period covered by our data. We calibrate the tax depreciation for purchased intangible assets ($\hat{\delta}_{IP}$) to match the 15-year amortization period allowed by the U.S. tax code. Turning to the technological parameters, we calibrate the steady technology adoption rate $\bar{\lambda}$ to 0.05 (quarterly), implying an average diffusion lag of five years, in line with the evidence in Comin and Hobijn (2010); the rate of technological obsolescence, $(1-\phi)$, is 0.08 based on the estimates in Li and Hall (2020); and the labor share of production in R&D and adoption, $\gamma$, is set to 0.9, consistent with R&D expenditure data from the NSF.

In Table 2, we report the prior distributions of the estimated parameters, along with posterior moments that will be discussed in the next section. Priors are chosen to be diffuse and centered

[15] The starting values of the parameters are obtained by maximizing the log posterior using the covariance matrix adaption algorithm (CMA-ES). Then, an initial run of the Metropolis algorithm is used to approximate var $(\Upsilon)$. A scaled version of var $(\Upsilon)$ is used to calibrate the variance of the proposal distribution for the main run of the Metropolis algorithm. We choose the scaling so that the acceptance rate is about 20%.

Table 1: Calibrated Parameters

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\beta$ | Discount factor | 0.99 | |
| $\psi$ | Employment adjustment | 0.35 | Wen (2004) |
| $g_y$ | 100*SS GDP growth rate | 0.91 | Sample average |
| $g_n$ | 100*SS population growth rate | 0.35 | Sample average |
| GY | Government spending/GDP | 0.16 | Sample average |
| $\alpha$ | Capital share | 0.35 | |
| $\delta$ | Capital depreciation | 0.02 | |
| $\varsigma$ | Markup | 1.087 | Profits/GDP=8% |
| $\bar{\lambda}$ | SS technology adoption rate | 0.05 | Anzoategui et al. (2019) |
| $1-\phi$ | Technology obsolescence | 0.08 | Li and Hall (2020) |
| $\gamma$ | R&D expenditure labor share | 0.9 | NSF data |
| $\bar{\tau}_c$ | SS Corp. Tax | 0.19 | Sample average |
| $\bar{\tau}_p$ | SS Lab. Tax | 0.3 | Sample average |
| $\hat{\delta}_K$ | Tax depreciation (capital) | 0.0165 | Hall and Jorgenson (1967), House and Shapiro (2008) |
| $\hat{\delta}_{IP}$ | Tax depreciation (IP) | 0.0285 | US tax code (15y amortization period) |
| $\rho_r$ | Smoothing | 0.83 | Anzoategui et al. (2019) |
| $\phi_y$ | Output | 0.385 | Anzoategui et al. (2019) |
| $\phi_\pi$ | Inflation | 1.638 | Anzoategui et al. (2019) |

Table 2: Estimated Parameters

| Parameter | Description | Prior | | | Posterior | |
|---|---|---|---|---|---|---|
| | | Distr | Mean | Std. Dev. | Median | 90% int. |
| $h$ | Consumption habit | beta | 0.5 | 0.2 | 0.34 | [0.12, 0.59] |
| $\chi_g$ | Inverse effort elasticity (goods) | gamma | 1 | 0.5 | 0.47 | [0.22, 0.93] |
| $\chi_a$ | Inverse effort elasticity (adoption) | gamma | 1 | 0.5 | 0.67 | [0.29, 1.4] |
| $\chi_z$ | Inverse effort elasticity (R&D) | gamma | 1 | 0.5 | 2.04 | [1.37, 3.04] |
| $f''_a$ | Adoption adjustment | normal | 4 | 1.5 | 3.86 | [1, 6.4] |
| $f''_z$ | R&D adjustment | normal | 4 | 1.5 | 3.33 | [0.82, 5.87] |
| $f''_I$ | Investment adjustment | normal | 4 | 1.5 | 0.36 | [0.05, 0.94] |
| $\nu''$ | Capital utilization adjustment | beta | 0.6 | 0.15 | 0.74 | [0.66, 0.82] |
| $\xi_p$ | Calvo prices | beta | 0.5 | 0.2 | 0.2 | [0.07, 0.33] |
| $\theta$-1 | Dixit-Stiglitz parameter | gamma | 0.15 | 0.1 | 0.58 | [0.43, 0.79] |
| $\rho_\lambda$ | Adoption elasticity | beta | 0.5 | 0.2 | 0.78 | [0.66, 0.87] |
| $\rho_Z$ | R&D elasticity | beta | 0.5 | 0.2 | 0.2 | [0.12, 0.29] |
| $\zeta$ | R&D returns to scale | product | -0.08 | 0.07 | -0.13 | [-0.17, -0.09] |
| $\rho_{\tau,c}$ | Corporate taxes AR | beta | 0.85 | 0.07 | 0.95 | [0.95, 0.96] |
| $\rho_{\tau,p}$ | Labour taxes AR | beta | 0.85 | 0.07 | 0.83 | [0.8, 0.85] |

on values typically found in the literature. For conventional parameters —habit formation, price stickiness, and investment adjustment costs— the prior means align with estimates and priors in earlier empirical studies (e.g., Smets and Wouters, 2007, Justiniano et al., 2010). The prior distributions for the tax processes follow Leeper et al. (2010), imposing smooth adjustment of the tax rates over time.

A number of parameters are specific to our R&D, adoption, and utilization mechanisms, and therefore, we discuss them here in more detail. Estimates of the elasticity of patenting to R&D expenditures, analogous to $\rho_Z$ in the model, vary widely in the empirical literature (Danguy et al., 2013) but are typically below 1. Accordingly, we use a beta prior distribution centered at 0.5. We employ the same prior for the elasticity of adoption with respect to adoption spending, $\rho_\lambda$. The prior mean for the Dixit-Stiglitz parameter $\theta$ implies an elasticity of substitution across goods of 7.6, consistent with the estimates provided by Broda and Weinstein (2006). While we do not directly estimate $\zeta$ (footnote 12), we do compute and report moments of its implied prior distribution. To avoid tilting the balance in favor of any particular adjustment cost mechanism, we use the same prior for capital investment adjustment costs across all sectors. We are not aware of existing estimates of the (inverse) elasticity of effort, $\chi$. Consequently, we choose a relatively uninformative prior centered at 1.

In Appendix M, we report the distributions of the impulse response functions for output, productivity, R&D expenditure, investment, and consumption, implied by our prior distributions. The goal of this prior predictive analysis is to check whether any of the prior choices made in this section may build in a tendency for our posterior estimates to detect significant effects at long horizons spuriously. As shown in Appendix Figure M.1, our prior distributions for the structural parameters are centered around values that imply: (i) income tax changes have no long-term effects on the economy; (ii) productivity does not move much after a corporate income tax shock.

### 5.3 Posterior distributions

In this section, we discuss the posterior distributions of the model structural parameters, which are estimated by minimising the difference between the IRFs of the theoretical model, $\Phi(\Upsilon)$, and the IRFs of Section 3 LPs, $\hat{\Phi}$, to the tax shocks. The posterior median and central 90% credible set of the key parameters of interest are reported in the last two columns of Table 2. The model IRF (evaluated at the posterior medians of Table 2) are shown in Appendix Figures N.1 and N.2 as blue lines with circles. The estimates of the parameters on R&D and technological adoption in the third block of Table 2 are broadly consistent with the available evidence. All these parameters are inputs to the three external validation exercises we present below, which jointly provide a useful way to relate our estimates to the existing literature. The inverse effort elasticity is close to the value of 0.3 that Galí and van Rens (2020) calibrate to match second moments of the U.S. labor market. The estimation places a modest weight on investment adjustment costs, habit persistence, and price stickiness. In particular, adjustment costs associated with investment in physical capital are estimated to be significantly lower than the values reported by Christiano et al. (2005), Smets and Wouters (2007), Justiniano et al. (2010). Unlike conventional medium-scale business cycle models, however, our framework incorporates additional sources of endogenous persistence: the estimation appears to favor much larger adjustment costs on R&D and technological adoption than on physical capital investment, consistent with the evidence from aggregate data in Bianchi et al. (2019) and from firm-level data in Bernstein and Nadiri (1989), Bond et al. (2005), Chiavari and Goraya (2023), and Bloesch and Weber (2024). Finally, we also estimate a restricted version of our structural model in which we switch off all the endogenous growth mechanisms (Appendix Table R.1). The estimates of physical capital investment adjustment costs in this restricted specification become significantly larger, aligning with those reported in earlier studies. We interpret this as suggestive evidence that the omission of R&D spending and technological adoption from business-cycle models routinely used for policy analyses may distort inferences on the importance of physical capital investment and its adjustment costs for business-cycle fluctuations.

### 5.4 External validation of the estimated model

In this section, we provide external validation of our estimated structural model relative to three influential studies: Atkeson and Burstein (2019), Akcigit et al. (2021), and Bloom et al. (2013).

**Statistics from Atkeson and Burstein (2019).** Using a framework that nests a range of growth models, Atkeson and Burstein (2019) (AB19) show that two statistics are crucial in shaping the response of productivity and other aggregates to policy-induced changes in the economy's innovation intensity: (i) the degree of intertemporal knowledge spillovers in research, $1 + \zeta$ in our notation; and, (ii) the impact elasticity of aggregate productivity with respect to innovative investment. Our parameter estimates imply a 90% posterior interval for $\zeta$ of $[-0.17, -0.09]$ which is within the range of values considered by AB19[16].

AB19 provide a detailed analysis of the impact elasticity of productivity with respect to innovative investment, $\Theta$ in their notation, in a large class of models. Their framework does not nest our

[16] Our estimate of $\zeta$ is, by construction, consistent with average real GDP per capita growth over the estimation period, but does not directly map to the calibrated values in AB19 due to the presence in our model of i) congestion externalities ($\rho_z < 1$), ii) reproducible capital in the ideas production function ($\gamma < 1$).

expanding varieties model with a two-stage innovation investment process, so we cannot directly apply the formulas in the paper. However, we can use our estimated model to compute a conditional estimate of $\Theta$ based on the first-order approximation in Equation (16) of AB19:

$$(\theta - 1)\left(\log \tilde{A}_{t+1} - \log \tilde{A}_t\right) \approx \Theta\left(\log \tilde{X}_{z,t} - \log \bar{X}_z\right), \tag{18}$$

where tildes denote detrended variables; the left-hand side (expressed in our notation) is the change in aggregate productivity between $t$ and $t+1$, and the right-hand side is the log deviation of R&D investment from the steady state. Note that, for the case of a corporate tax cut, the right-hand side of Equation (18) is exactly the IRF for R&D investment from our estimated structural model, whereas the left-hand side is the (differenced) IRF for TFP. We can therefore estimate $\Theta$ conditional on a corporate income tax shock, by a linear regression of the (first differenced) IRF of TFP on the IRF of R&D expenditure (the second and third rows in the left column of Figure N.1). As our model has two margins of innovation, we apply the same approach to the IRF for adoption expenditure, $X_{a,t}$, and for total innovation expenditure, $X_{a,t} + X_{z,t}$. In Table 3, we compare the calibrated $\Theta$ in AB19 to our estimated values.

Table 3: $\Theta$ from Atkeson and Burstein (2019) and $\hat{\Theta}$ implied by model IRFs

| | R&D Investment | Adoption Investment | R&D + Adoption |
|---|---|---|---|
| Atkeson–Burstein $\Theta$ (with business stealing) | 0.01 | | |
| Atkeson–Burstein $\Theta$ (no business stealing) | 0.026 | | |
| $\hat{\Theta}$ Estimated from Model IRFs | 0.0293 | 0.0220 | 0.0284 |

All estimated $\hat{\Theta}$ in the last row are remarkably close to the calibration by AB19 for the case of no business stealing.[17] We conclude that the sizable effects of corporate income tax cuts on productivity and output—both in the data and in our model—do not arise from assuming implausibly large elasticities of productivity with respect to innovation. Instead, they are driven by the magnitude of the innovative investment response itself. This supports our thesis that corporate taxes impose significant distortions on innovative activity.

**Long-run elasticity of innovation to corporate taxes.** The analysis so far has focused on the effects of temporary corporate tax cuts, as in Section 3. However, our estimated model can also be used to study permanent tax changes. Accordingly, we compute the model-implied elasticities of innovation and compare them with those reported by Akcigit et al. (2021). Their study exploits historical variation in corporate and personal income tax rates across individual inventors and U.S.

[17] We also estimate $\hat{\Theta}$ using our empirical estimates of model (2) by drawing from the posterior distribution of the empirical IRFs of TFP and R&D and find a mean estimate of 0.014 with a 95% interval of $[-0.017, 0.049]$.

states to estimate the long-run effects of taxation on patenting, controlling for state and time fixed effects and other confounding factors. They report a 95% confidence interval of $[1.5, 2.46]$ for the elasticity of patenting with respect to corporate taxes, but emphasize that their estimates partly reflect reallocation of innovative activity across states rather than changes in aggregate innovation. When we compute the model-implied long-run elasticity of the stock of knowledge ($Z$) with respect to the corporate tax rate (see Appendix P for details), we obtain an elasticity of 1.71 in response to a permanent corporate income tax cut. This value falls within the 95% confidence interval reported by Akcigit et al. (2021).[18] Our empirical and theoretical analysis captures aggregate effects rather than cross-state reallocation, indicating that the aggregate elasticity to federal tax changes is of similar magnitude to the state-level responses.

**Social returns to R&D.** An additional instructive way to benchmark our structural model is to compute the social returns to investment in innovation that are implied by our estimates. To this end, we follow the variational approach of Jones and Williams (1998), modified to account for the two margins of innovation expenditure featured in our model (as detailed in Appendix Q). The 95% credible interval for the social return to investment in innovation implied by our model spans 20.8% to 74.5%. This estimate, based on changes in U.S. federal taxes over time, aligns closely with the 55% reported by Bloom et al. (2013) using cross-state and time variation in R&D tax credits.

# 6 Inspecting the transmission of corporate income tax changes

A key finding from the previous sections is that temporary corporate tax changes generate persistent effects on productivity and output, extending well beyond business-cycle horizons. In this section, we unpack the central mechanism underlying this result, in both the data and the model. We first provide firm-level evidence on differential effects across more and less innovative firms. We then use the estimated model to conduct counterfactual simulations, highlighting the role of endogenous productivity and the tax amortization of purchased intangible assets.

## 6.1 Firm-level evidence

In Figure 3, we illustrate the mechanism that links corporate taxes to innovation using CRSP and Compustat firm-level data. A lower corporate tax rate raises the present value of after-tax cash flows from owning intellectual property products (IPP) by more than the decrease in tax allowances, which rises the market price of IPP and strengthens incentives for R&D and adoption. We evaluate

[18] The model-implied elasticities with respect to personal tax cuts, reported in Appendix P, also fall within the confidence intervals reported by Akcigit et al. (2021)

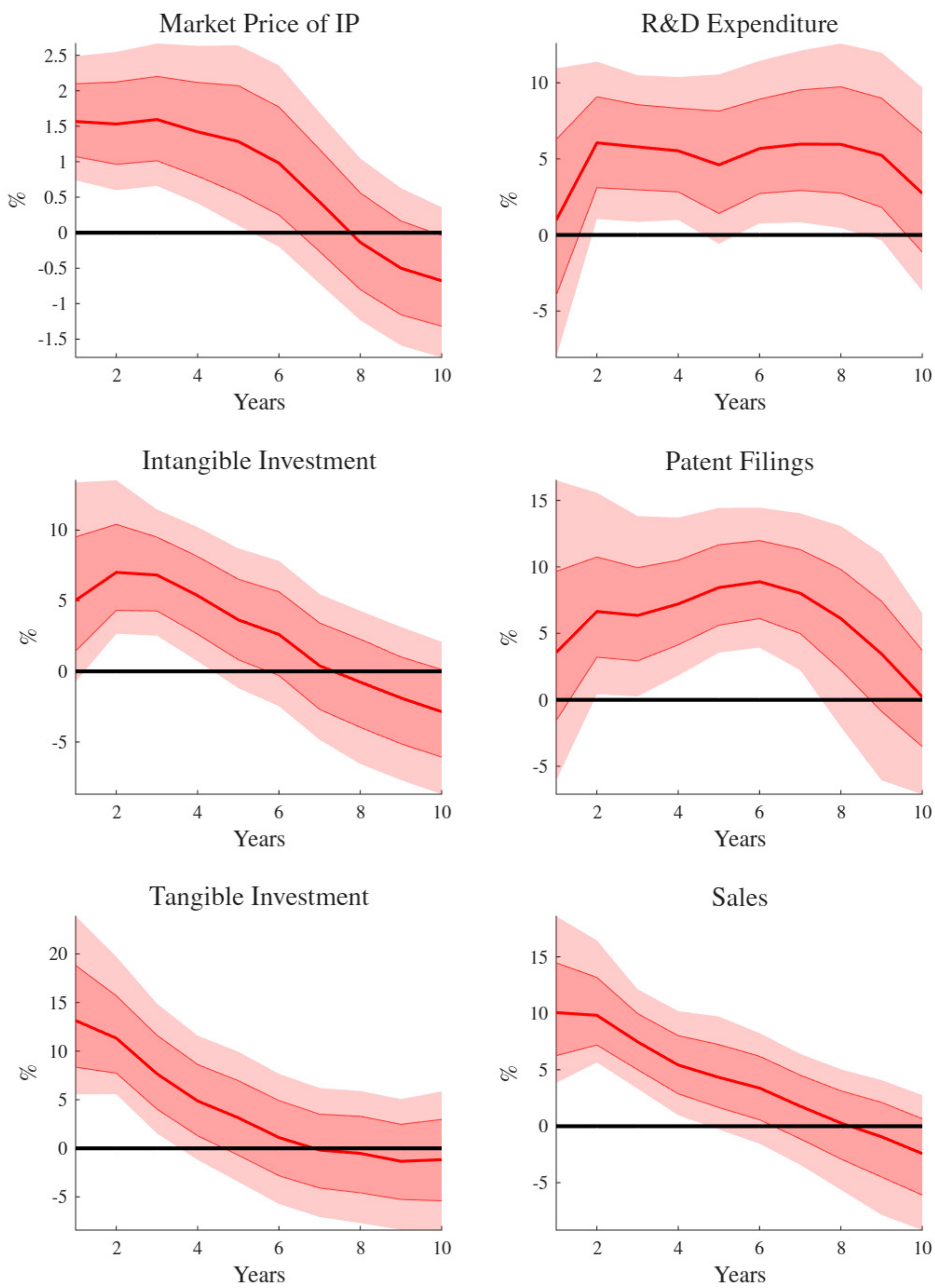
this channel in two complementary ways. First, we construct stock market portfolios sorted by ex-ante IPP intensity and track the relative performance of high- versus low-IPP firms following corporate tax cuts. Second, using the same ranking, we aggregate firm-level flows and stocks within IPP-intensity groups to compare how innovation inputs, outputs, and broader economic activity respond across firms with different IPP intensity. Details of data sources and variable construction are in Appendix C.

The top-left panel of Figure 3 employs CRSP stock returns. For each firm-year, we compute annual returns by aggregating monthly returns. In each year, firms are sorted by lagged IPP intensity, defined as the sum of patent portfolio value and intangible capital stock scaled by market capitalization. Patent portfolios are valued with the perpetual inventory method following Kogan et al. (2017), while intangible capital is constructed by accumulating a sector-specific share of SG&A as recommended by Ewens et al. (2023). To isolate IPP intensity from firm size, we scale by market capitalization. Within each IPP quartile, we form market-cap-weighted annual return chain-linked indices; the figure reports the IRF of the top-minus-bottom quartile index spread. The top-quartile index rises sharply relative to the bottom quartile on impact, and the high–low spread remains positive and persistent. This pattern shows that corporate tax cuts immediately reprice existing intangible assets by capitalizing the new tax environment, consistent with the theoretical model mechanism.[19]

The remaining panels use Compustat firm-year accounts merged with the same measures of patents and intangibles that we have presented above to study the response of quantities. Intangible investment is constructed following Ewens et al. (2023) as a sector-specific fraction of SG&A. We also compile R&D outlays, patent filings, tangible investment, and sales. All series are expressed in real per-capita terms. Each year, firms are ranked by lagged IPP intensity, and we compute aggregates for the top and bottom quartiles. As in other panels, we estimate the relative effect as the IRFs of the difference between top- and bottom-quartile groups. Two regularities emerge. First, innovation inputs and innovation outputs —such as R&D, intangible investment, and patent filings— rise gradually and persistently for the most IPP-intensive firms. In contrast, tangible investment and sales increase immediately. These dynamics mirror the aggregate evidence reported in Figures 1 and 2, and align with our theoretical mechanism. The tax change first operates through the asset-pricing margin: the market value of IPP jumps on impact, captured by the stock market response. Because idea creation and adoption face high adjustment costs, innovation responses are

[19] While the numerator of our IPP intensity index is closer to a book-value measure of IPP, our interpretation holds as long as the tax cut-induced revaluation of IPP assets scales with book value. Consistent with our findings, a high-frequency event study around the announcement of a global minimum corporate tax in 2021 finds that intangible-intensive firms exhibit significantly negative stock price responses (Gómez-Cram and Olbert, 2022).

Figure 3: Firm-Level Evidence on the Mechanism




Notes: this figure plots the responses of the market price of IP, R&D expenditure, intangible investment, patent filings, tangible investment, and sales for the top versus bottom quartile of firms sorted by intangibility to a 1% cut in the average rate of corporate income taxes. Red shadow bands represent central posterior $68^{th}$ and $90^{th}$ credible sets. Responses are estimated using the Bayesian local projection model described in Section 2, with the quarterly shocks aggregated to annual frequency. Data sources and definitions are described in Appendix C.

delayed and hump-shaped relative to prices, intangible investment, and sales.

### 6.2 Endogenous productivity

In the next two sections, we use the estimated model to conduct counterfactual simulations that isolate the role of endogenous growth (this section) and the amortization period of tax benefits on intangible assets (next section). Specifically, we compare the GDP response in the baseline model with that in an otherwise identical specification that excludes the endogenous productivity block.[20] Figure 4 reports the responses of log GDP in both models, decomposed into the contributions of TFP, capital and capital utilization, and labor and labor utilization, using the final-goods production function (Equation 3):

$$\Delta \log Y = (\theta - 1) \Delta \log A + \alpha (\Delta \log U + \Delta \log K_g) + (1 - \alpha) (\Delta \log e_g + \Delta \log H_g) . \tag{19}$$

In the baseline model (left panel), TFP accounts for the bulk of the medium-term effects, with the remainder explained by capital accumulation. A corporate tax cut raises after-tax profits, which increases the market value of IPP and strengthens incentives to both discover new technologies and adopt existing ones. Higher adoption effort raises the probability of success and shortens the expected time to market, further amplifying innovation incentives. In general equilibrium, this surge of innovation also promotes capital accumulation by increasing the marginal product of capital. By contrast, the counterfactual model with exogenous productivity (right panel of Figure 4) fails to reproduce the medium-term persistence of GDP observed in Figure 1, underscoring that endogenous productivity drives the majority of the medium-term response of GDP to corporate tax changes.

### 6.3 The amortization period of tax benefits on intangible investment

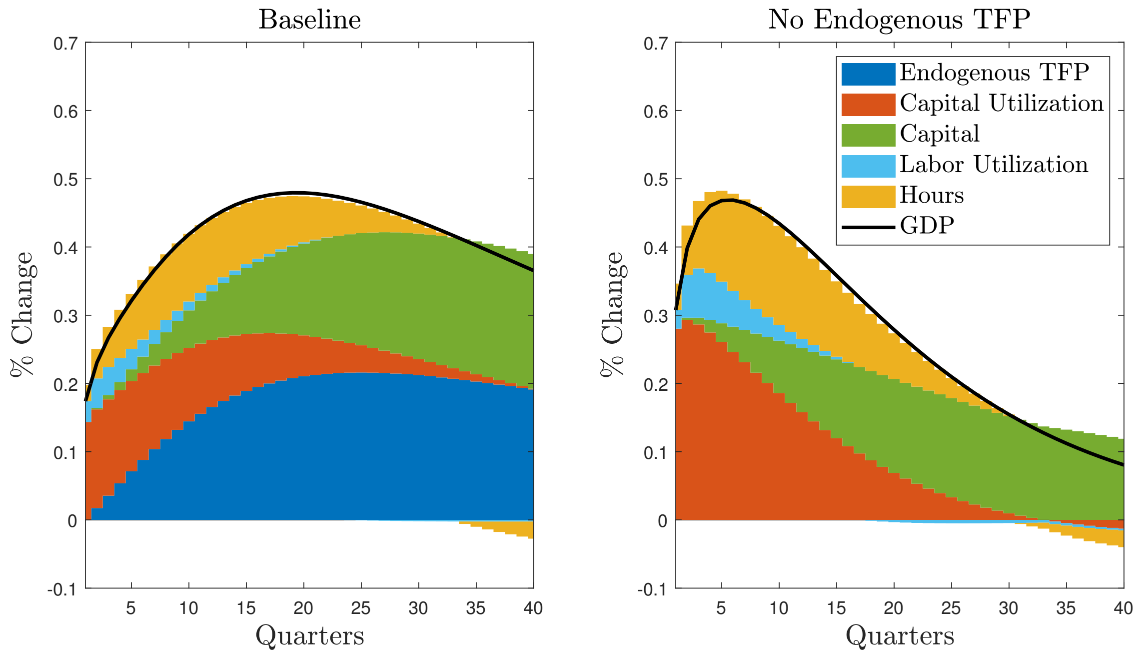
In Section 5, we set the tax amortization period for IPP to 15 years ($\hat{\delta}_{IP} = 0.0285$), consistent with Section 197 of the U.S. IRS Code, which mandates straight-line amortization of intellectual property over 15 years.[21] Here, we examine how the tax treatment of IPP shapes the effects of corporate income taxes by varying the amortization horizon from full expensing to no deductibility. Using the estimated model, we compute the long-run GDP response and the impact response of IPP prices to a temporary tax cut.

In Figure 5, both responses rise monotonically with the amortization period. Short horizons yield

[20] To ensure comparability, we re-estimate the exogenous productivity model by matching the same variables as in the baseline, except for R&D expenditure, which plays no role in the exogenous productivity case. Parameter estimates for this latter model are reported in the last two columns of Table R.1.

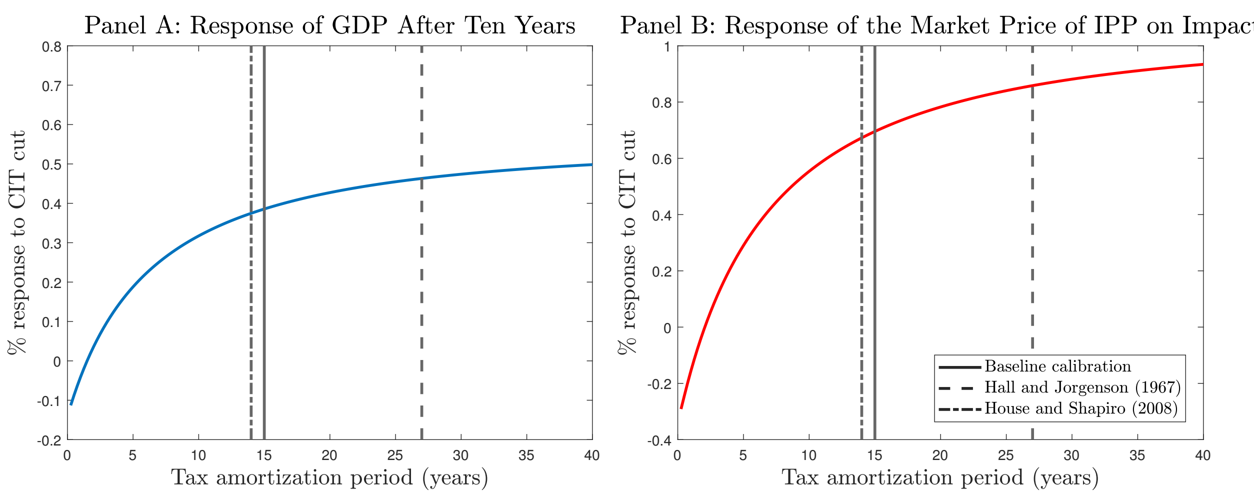
[21] In our model, using straight-line or a geometric approximation as in Auerbach (1989) produces very similar results.

Figure 4: GDP Decomposition and Counterfactual Analyses




Notes: this figure plots the model impulse responses of aggregate output and its components (see Equation 3) to a corporate income tax shock. The left panel shows the response of the baseline model, and the right panel that of a model with no innovation. To construct the counterfactual plots, we re-estimate the restricted model following the procedure described in Section 5. Parameter estimates for the restricted model are in Appendix R.

Figure 5: GDP and price of IPP response as a function of the tax amortization period on IPP




Notes: this figure shows the responses of GDP at the 10 year horizon (Panel A) and of the market price of IPP on impact (Panel B) to a 1% cut in the average rate of corporate income taxes as a function of the tax amortization period on intangible capital purchases, implied by the estimates of the structural model presented in Section 4. Vertical lines represent the value of the tax amortization period used in Hall and Jorgenson (1967) and House and Shapiro (2008) for tangible assets.

modest or negative long-run effects, while non-deductibility maximizes the impact.[22] The steepest changes occur between 1 and 10 years; then, the curve flattens: values implied by Hall and Jorgenson (1967), House and Shapiro (2008) for tangible capital yield similar results. In Equations (15) and (17), the present value of deductions, $d_{IP}$, enters as a wedge that falls with longer amortization. With full expensing, $d_{IP}$=$\tau_c$, after-tax and pre-tax profits coincide; with no amortization, $d_{IP}$=0, the wedge disappears. In other words, shorter amortization boosts steady-state innovation and GDP, but longer amortization increases the sensitivity of GDP to tax changes off steady-state.

## 7 Discussion

In this section, we provide some intuition for the drivers of the mechanism highlighted by the structural model. For the sake of exposition and of eliciting the different moving parts, we take the unusual (but hopefully clarifying) step of structuring the discussion in the form of a Q&A.

**Q:** Why do corporate income tax cuts have positive medium-term effects?
**A:** Because they foster intangible investment, which is characterized by increasing aggregate returns.

**Q:** Why does R&D respond at all to corporate tax changes if R&D is subject to full expensing?
**A:** Corporate tax changes can exert direct and indirect effects on R&D. The tax treatment of R&D expenditure governs the direct effect: with full and immediate deductibility, as in our model and over most of the post-WWII U.S. sample we consider, this direct effect is zero (the corporate tax rate does not appear in the FOCs for R&D inputs, see Equation 6). But, in general equilibrium, corporate tax cuts also influence the market price of intangible assets: a main indirect effect of a corporate tax cut is to increase the market price of intangibles, which stimulates R&D spending.

**Q:** Why does the market price of intangibles respond to corporate tax changes?
**A:** The market price of intangibles is made of two components: the Present Value (PV) of after-tax profits and tax amortization benefits (Equation 17). A cut in the corporate tax rate *increases* the PV of after-tax profits, but *decreases* the PV of amortization benefits. Whenever intangible purchases are not subject to full expensing, the change in the PV of profits is larger than the change in the PV of tax amortization benefits, leading to a response in the market price of intangible assets.

**Q:** Since capital investment is not fully expensed, why does a corporate tax cut not lead to large

[22] The negative values for the responses of GDP and the market price of IP near full expensing (zero years) are due to other distortions in the model (notably less than full expensing of capital investment). Allowing for full expensing of all investment, the response of GDP and the market price of IPP to a permanent tax cut are exactly zero.

medium-term effects on GDP through capital accumulation?

**A:** Because physical capital investment is characterized by a diminishing marginal product.

**Q:** Is increasing aggregate returns versus diminishing marginal product the only difference between the role of intangible and physical capital investment in the transmission of corporate tax changes?

**A:** No: in our estimated structural model, the direct effect dominates physical capital response whereas the indirect effect drives the R&D response. The reason is that the effects of tax changes on asset prices depend on the supply elasticity of the asset, which in turn is a function of the adjustment costs associated with its accumulation. According to the estimates in Table 2, the adjustment costs on intangibles are an order of magnitude larger than the adjustment costs on physical capital investment, consistent with the firm-level evidence in Bernstein and Nadiri (1989), Bond et al. (2005), Chiavari and Goraya (2023), and Bloesch and Weber (2024). This implies that the elasticity of supply of intellectual property is much lower than the capital supply elasticity, in line with the findings that the effects of corporate income tax changes are significant on the market price of IPP (Figure 3) but are insignificant on the price of capital (House and Shapiro, 2008).[23]

**Q:** Why do personal income tax changes have no medium-term effects?

**A:** In theory, personal income tax changes could also have medium-term effects, working (to a first order) through the response of the scientists' labor supply. However, our estimates do not reveal significant medium-term effects of personal taxes on productivity or GDP. Using the estimated structural model, we have verified that this is due to the combination of two factors in our sample: personal tax shocks are short-lived, and scientists' labor supply is relatively inelastic.

## 8 Conclusions

This paper identifies an overlooked channel through which fiscal policy affects innovation and productivity. We show that temporary corporate income tax cuts, far from being short-lived stimulus, generate sizable and persistent increases in innovation, productivity, and output. The key mechanism is the tax treatment of intangible assets: the long amortization horizon in the U.S. tax code for purchased patents, trademarks, and other intellectual property amplifies the medium-term effects of corporate taxation.

The policy implications are immediate. Just as bonus depreciation has become a standard instrument to stimulate tangible investment, our findings point to tax amortization allowances on

[23]It should be noted that, in the endogenous productivity model, the indirect effects of corporate tax changes on physical capital investment are boosted by the presence of increasing aggregate returns from innovation, as can be seen by comparing the contribution of capital investment in the two panels of Figure 4.

intangibles as a powerful and underused lever for productivity growth. Accelerated amortization of intangible capital would reduce corporate tax distortions and provide a new, targeted tool for stimulating productivity growth in advanced economies over the long-run.

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# Online Appendix

"Short-Term Tax Cuts, Long-Term Stimulus"

by James Cloyne (UC Davis), Joseba Martinez (LBS), Haroon Mumtaz (QMUL) and Paolo Surico (LBS)

# A Tax amortization of Intangible Assets around the World

In Table A.1, we report the legal tax amortization periods (in years) for the main types of intangible assets in selected countries as of 2016. The tax treatment of intangible assets varies widely across jurisdictions. Interestingly, advanced economies typically have longer tax amortization periods on intellectual property products than developing countries.

Table A.1: An International Perspective on Tax amortization of Intangible Assets

| **Country** | **Patents** | **Technology** | **Trademark** |
|---|---|---|---|
| Australia | 20 | 5 | no TAB |
| Austria | RUL | RUL | 15 |
| Canada | 20 | 20 | 20 |
| China | RUL (≥10) | RUL (≥10) | RUL (≥10) |
| France | RUL (≥5) | RUL (≤5) | no TAB |
| Germany | 15 | RUL (≤3) | 25 |
| Greece | RUL (≤5) | 5 | 20 |
| Hungary | RUL | 5 | 10 |
| India | 10 | RUL (≤3) | 10 |
| Indonesia | 10 | 10 | 10 |
| Ireland | 20 | 15 | no TAB |
| Italy | RUL (≥3) | 5 | RUL (≤5) |
| Japan | RUL | RUL | 20 |
| Malaysia | 20 | 20 | no TAB |
| Mexico | 20 | 20 | 10 |
| Netherlands | 20 | 5 | no TAB |
| New Zealand | 15 | 5 | no TAB |
| Norway | 20 | RUL | 10 |
| Poland | RUL | 5 | 5 |
| Portugal | RUL (≤5) | RUL (≤5) | no TAB |
| Romania | 20 | 5 | 15 |
| Russia | 15 | 15 | 10 |
| Singapore | 5 | 5 | no TAB |
| Slovakia | 15 | 4 | no TAB |
| Slovenia | RUL | 5 | no TAB |
| South Africa | 20 | 5 | no TAB |
| Spain | RUL (≥5) | RUL (≤5) | RUL (≤5) |
| Sweden | 10 | 10 | 10 |
| Switzerland | 20 | 5 | no TAB |
| Taiwan | 20 | 15 | no TAB |
| Thailand | 20 | 5 | 20 |
| Turkey | 20 | 10 | no TAB |
| UK | 25 | 20 | 20 |
| USA | 15 | 15 | 15 |
| Vietnam | 10 | 10 | 10 |

Notes: RUL: for Remaining Useful Lifetime; TAB: tax amortization benefit. The table reports the legal tax amortization life time in years of the main types of intangible assets across selected countries in 2016. Source: http://www.taxamortization.com/tax-amortization-benefit.html

# B Narrative Identified Exogenous Tax Changes 2007–19

The original Mertens and Ravn (2013) narrative identified corporate and personal income tax shocks were derived from the Romer and Romer (2010) dataset and span the period 1950 to 2006. Our paper considers the sample period up to 2019. We therefore construct an extended version of the Mertens and Ravn (2013) shocks by drawing on two sources. For the period 2007-2017 we use the analysis of legislated U.S. tax reforms from Liu and Williams (2019). Between 2007 and 2017, they identify two Acts that can be regarded as "exogenous" following Romer and Romer (2010) and Mertens and Ravn (2013). Specifically:

- Tax Relief, Unemployment Insurance Reauthorization and Job Creation Act 2010. This contained a payroll tax cut amounting to \$67.239 billion. The implementation date is assigned to 2011Q1. Liu and Williams (2019) provide evidence that this tax cut was motivated by long-run considerations and is exogenous following the Romer and Romer (2010) classification.

- American Taxpayer Relief Act 2012: This included an exogenous reduction in personal income taxes of \$5.901bn and a reduction in corporate income taxes of \$63.033 billion. These are assigned to 2013Q1. Liu and Williams (2019) argue that this was motivated by concerns about the inherited deficit, and is exogenous but "deficit driven" according to the Romer and Romer (2010) classification.

Over the period 2017 to 2019, we include one exogenous tax reform: the Tax Cuts and Jobs Act 2017. Liu and Williams (2019) note "Exogenous for sure, but not in our estimation time frame" (Online Appendix p.5) and their paper therefore does not include any further analysis of the TCJA. We therefore use the estimates and analysis from Mertens (2018). Specifically:

- We treat the TCJA as exogenous following Mertens (2018): "Since almost all of the provisions in TCJA become effective in the 2018 tax year, the Act clearly fits into the category of reforms with short implementation lags included in the Mertens and Ravn (2012) version of [the exogenous tax changes]. The motivation for the 2017 Act also seems predominantly ideological, such that it appears reasonable to make use of the estimated effects derived from the exogenous Romer and Romer (2010) tax reforms" (Mertens (2018), p.5).

- In keeping with the usual Romer and Romer (2010) approach, Mertens (2018) reports the revenue estimates for the TCJA. From Mertens (2018) Table 1 we use -\$75 billion as the estimate of the personal income tax change and -\$129 billion as the estimate of the corporate income tax change. The Act also included various changes to international corporate taxation, which are listed separately in Mertens (2018) Table 1 and in the original Joint Committee on Taxation budget effects table (JCT, December 18 2017 JCX-16-17). These reforms were estimated to raise \$69 billion. As a robustness check (see Figure K.8 in Appendix K) we therefore consider a broader measure of the TCJA corporate income tax shock by summing the two categories (-\$129 billion and \$69 billion). The Act was passed in December 2017 and most measures were effective after December 31, 2017. Following Mertens (2018) we use 2018Q1 as the implementation date.

As in Mertens and Ravn (2013), all revenue estimates for corporate and personal income taxes are scaled by corporate profits and personal taxable income in the previous quarter. As discussed below, the macroeconomic data are updated versions of the series described in Mertens and Ravn (2013).

# C Data Appendix

## C.1 Macroeconomic data

Table C.1: Macroeconomic variables definitions

| Variable | Description | Source |
|---|---|---|
| Consumption | Real personal consumption expenditure per-capita | U.S. BEA, Real Personal Consumption Expenditures divided by population |
| Investment | Real Non-residential investment per-capita | NIPA 1.1.3 line 9 divided by population |
| Productivity | Output per hour (Non-Farm business sector) | U.S. BLS, Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Workers |
| R&D spending | Investment in Research and Development | U.S. BEA, Gross Private Domestic Investment: Fixed Investment: Nonresidential: Intellectual Property Products: Research and Development divided by IPP deflator and population |
| TFP | Utilization Adjusted TFP | Fernald (2012) |
| Employment | Total economy employment per-capita | U.S. BLS, All Employees, Total Nonfarm seasonally adjusted and divided by population |
| Population | Total Population over age 16 | Data from Francis and Ramey (2009) spliced with 8 Qtr moving average of data from U.S. BLS, Civilian noninstitutional population |

The main macroeconomic variables are updated versions of the series described in Mertens and Ravn (2013): (1) $APITR_t$, (2) $ACITR_t$, (3) $\ln\left(B_t^{PI}\right)$, (4) $\ln\left(B_t^{CI}\right)$, (5) $\ln\left(G_t\right)$, (6) $\ln\left(GDP_t\right)$, (7) $\ln(DEBT_t)$. The personal and corporate tax rates are denoted by $APITR_t$ and $ACITR_t$, respectively while $\ln\left(B_t^{PI}\right)$ and $\ln\left(B_t^{CI}\right)$ are the corresponding tax bases in real per-capita terms. $\ln\left(G_t\right)$ denotes real per-capita government spending, while $\ln(DEBT_t)$ is real per-capita federal debt. Real per-capita GDP is denoted by $\ln\left(GDP_t\right)$. For a detailed description of these series and data sources, see the appendix of Mertens and Ravn (2013). The table above provides a list of the additional macroeconomic data used in our analysis and provides links to the appropriate series in the FRED database.

Data on R&D intensity is obtained from the Business Enterprise Research and Development Survey of the National Science Foundation for the period 1999 to 2007. R&D intensity is defined as funds for industrial R&D as a percent of net sales of companies. The R&D intensity data from this survey can be matched to 28 industries in the Gross output data set. These 28 industries are used in the sectoral analysis presented below.

## C.2 Data and definitions for Figures 2 and 3

### C.2.1 Figure 2

**Intangible Investment.** We estimate intangible investment at the firm level at annual frequency using data on Selling, General and Administrative expenses (Compustat variable xsga) and the industry-level parameters provided by Ewens et al. (2023). We aggregate this measure at annual frequency and divide by population and the GDP deflator from FRED. Sources: Compustat, Ewens et al. (2023), FRED.

**Stock of Patents.** We aggregate real patent values from the extended Kogan et al. (2017) database at quarterly frequency and the perpetual inventory method with 8% depreciation (Li and Hall (2020)) and divide by population. Sources: Kogan et al. (2017) database, Li and Hall (2020).

**Stock of Trademarks.** We aggregate trademark values from the Desai et al. (2025) (kindly provided by the authors) and the perpetual inventory method with 8% depreciation (Li and Hall (2020)), deflated using the GDP deflators, and divide by population. Sources: Desai et al. (2025), Li and Hall (2020).

**Stock Market.** Dow Jones Industrial Average data from WRDS. The model response is the aggregate value of assets (IPP and the capital stock). Source: WRDS.

**Trade in IPP.** Count of trademark transactions from USPTO Trademark Transactions Database. Source: USPTO.

**IPP Investment (excluding R&D).** Intellectual property products investment (excluding R&D) from the national accounts. Source: BEA.

### C.2.2 Figure 3

**Market Price of IP** We construct portfolios sorted by firm-level intangibility to study differences in cumulated returns between high- and low-intangibility firms. The firm-level measure of intangibility is the sum of intangible capital plus patent stock value divided by market capitalization. Intangibility is computed at the firm level following Ewens et al. (2023) by capitalizing an industry-specific part of SG&A from Compustat (xsga), depreciated at 20%. Patent stock values are computed at the firm level from the extended Kogan et al. (2017) database, computed using the perpetual inventory method with an 8% depreciation rate (Li and Hall (2020)). Market capitalization data is from CRSP. At each point in time, firms are sorted into quartiles based on their ratio of intangible assets plus patent stock value to market capitalization. We form two market capitalization–weighted portfolios corresponding to the top and bottom quartiles of this distribution and compute their cumulative return indices using CRSP data. The empirical response plotted in the top left panel of Figure 3 is the log difference between the cumulative return indices of the high- and low-intangibility portfolios, which captures the differential market performance of intangible-intensive firms. Sources: Center for Research in Security Prices (CRSP), Compustat, Kogan et al. (2017), Li and Hall (2020), Ewens et al. (2023).

**R&D, Sales, and Tangible Investment.** We merge CRSP–Compustat at the gvkey–year level and build a gvkey–permno bridge (monthly links collapsed to year) to align accounting and market data. Each year, firms are sorted by the intangibility intensity metric defined in the previous paragraph. R&D, sales and tangible investment correspond to the Compustat variables xrd, sale and capx+acqppe, respectively. We aggregate by year within each group (sum across firms), construct cumulative indices, and take the empirical response as the log difference between the top– and bottom–quartile aggregates. Sources: CRSP, Compustat, Kogan et al. (2017).

**Intangible Investment.** We estimate intangible investment at the firm level at annual frequency using data on Selling, General and Administrative expenses (Compustat variable xsga) and the industry-level parameters provided by Ewens et al. (2023). After forming the same top– and bottom–quartile intangibility groups, we sum intangible investment within each group. Sources: Compustat, Ewens et al. (2023), FRED.

**Patent Filings.** We pull patent–event microdata from the extended Kogan et al. (2017) dataset and construct firm–day counts of filings, then collapse to gvkey–year using the CRSP–Compustat link. After forming the same top– and bottom–quartile intangibility groups, we sum annual filing counts within each group. Sources: CRSP, Compustat, Kogan et al. (2017).

### C.3 Sectoral Data

Gross output (GO) by industry and Gross Value added (GVA) by industry is obtained from the Bureau of Economic Analysis (BEA) and is provided at annual frequency from 1947 to 1997 (available at the following link). We deflate Gross output by its deflator. This historical data is combined with the more recent data real GO and GVA to produce an annual time series for 87 sectors from 1950-2019. The series are divided by population.

Data on R&D intensity is obtained from the Business Enterprise Research and Development Survey of the National Science Foundation for the period 1999 to 2019. R&D intensity is defined as funds for industrial R&D as a percent of net sales of companies. The R&D intensity data from this survey can be matched to 28 industries in the GO/GVA data set. These 28 industries are used in the sectoral analysis presented below, in Appendix S.

## D Specification of the Benchmark Bayesian Local Projection

The benchmark Bayesian Local Projection (following Equation 2) is defined as:

$$Z_{t+h} = c^{(h)} + B_1^{(h)} Z_{t-1} + \sum_{j=2}^{P} b_j^{(h)} Z_{t-j} + d^h x_{t-1} + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{20}$$

Note that following Jordà (2005), the model is estimated jointly for the all the variables in the vector $Z_t$. As noted in the main text, in the benchmark case $Z_t$ includes 7 variables: $(i)$ $APITR_t$, $(ii)$ $ACITR_t$, $(iii)$ $\ln\left(B_t^{PI}\right)$, $(iv)$ $\ln\left(B_t^{CI}\right)$, $(v)$ $\ln\left(G_t\right)$, $(vi)$ $\ln\left(GDP_t\right)$, $(vii)$ $\ln(DEBT_t)$. We add additional variables of interest to this set of benchmark variables one by one. For example, the response of TFP is estimated from a LP that includes 8 variables-i.e. TFP in addition to the 7 variables listed above. $x_t$ denotes two additional controls included in the model:

1. An initial estimation of the structural tax shocks for $h = 0$ reveals that the estimated personal tax rate shock can be predicted by the lags of a principal component obtained from a large quarterly data set of macro and financial variables for the U.S. economy, which extends the panel used in Mumtaz and Theodoridis (2020). To implement the "structuralness" test of Forni and Gambetti (2014), we use up to 4 lags of the first 5 principal components obtained from this data set. The personal tax shock can be predicted by the first lag of the third principal component which is highly correlated with interest rates included in the panel. Detailed test results are presented in Appendix E. Following Forni and Gambetti (2014), we add one lag of

the third principal component as a control variable in our LPs to ameliorate concerns about information insufficiency.

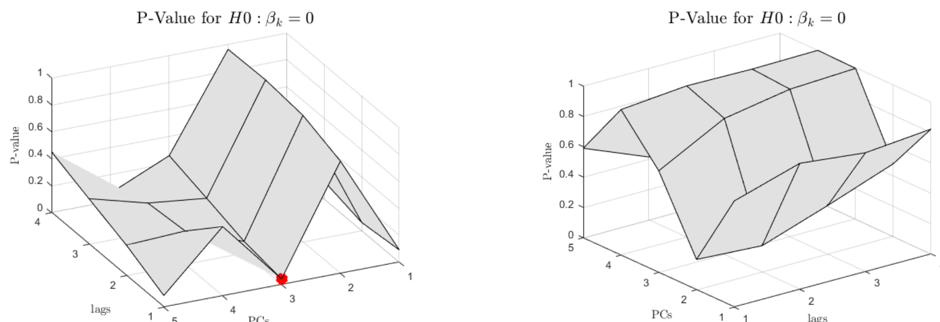
2. Finally, we also include a dummy variable that equals 1 from 2008 Q3-2009 Q1 to account for volatility associated with the Great Financial Crisis.

# E Structural shocks and controls in the benchmark model

Figure E.1: Test for information sufficiency

(a) Personal tax shock (b) Corporate tax shock

k




Notes: this figure shows P-value that the coefficients on the lags of the principal components are jointly equal to zero. P-values less than 0.05 are denoted by red dots

To select additional controls for the benchmark model we implement the following steps

1. We estimate a Bayesian VAR (i.e. a local projection at horizon 0 using the 7 endogenous variables of Mertens and Ravn (2013) and identify the corporate and personal tax shocks using the benchmark scheme. We obtain the estimated structural disturbances.

2. Following Forni and Gambetti (2014), we regress the structural shocks on up to 4 lags of the first 5 principal components taken from a data set of 83 macroeconomic and financial variables for the U.S.. The data set covers real activity, inflation, employment, production, lending, interest rates, exchange rates and stock prices. The regressions take the following form for $m = 1, \ldots, 5$:

$$\epsilon_{it} = c + \sum_{k=1}^{4} \beta_k F_{m,t-k} + v_t$$

where $\epsilon_i$ is the structural shock to personal and corporate taxes respectively and $F_{m,t}$ denotes the *mth* principal component. As shown in figure E.1, the third principal component has a significant lagged impact on the personal tax shock. This component has the highest correlation with the 2 year government bond yield. In contrast, the corporate tax shock is not predicted by the lagged principal components.

3. We include the first lag of the third principal component as an additional control in the benchmark model. This eliminates this problem and the structural shocks from this model are not predicted by the principal components.

# F Monte-Carlo evidence on Local Projections estimates of impulse response functions at medium and long-run horizons

In this section, we investigate the ability of LPs and VARs to estimate impulse response functions at medium and long-run horizons. Our Monte-Carlo analysis complements that of Jordà et al. (2020) as we consider the performance of multi-variate models.

## F.1 Data Generating Process and models

The data generating process is designed to mimic the broad features of the impulse responses of key variables to corporate tax shocks. The estimated response of variables such as GDP, consumption and productivity to corporate shocks is characterised by small increases at short horizons with larger positive changes arriving after about 20 periods. We replicate this shape by generating data from a bi-variate VAR(20)

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_{20} Y_{t-20} + A_0 E_t, E_t \sim N(0,1) \tag{21}$$

We assume that $B_1 = \begin{pmatrix} 0.7 & 0 \\ 0 & 0.75 \end{pmatrix}$ and $B_{20} = \begin{pmatrix} 0.1 & 0.1 \\ 0.1 & 0 \end{pmatrix}$ while $B_2 = B_3 = ... = B_{19} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$. The contemporaneous impact matrix is fixed at $A_0 = \begin{pmatrix} 1 & 0 \\ 0.05 & 1 \end{pmatrix}$ We generate $T_1 = T + T_0$ observations from this model where $T_0 = 50$ and $T = 280$. The first $T_0$ observations are discarded to account for initial values. We estimate two models using this artificial data: (i) A VAR(4) and (ii) A LP that includes 4 lags of the two variables as controls. The models are used to estimate the response to the first shock. Note that we do not attempt to estimate $A_0$ which is kept fixed at the true value for both models.

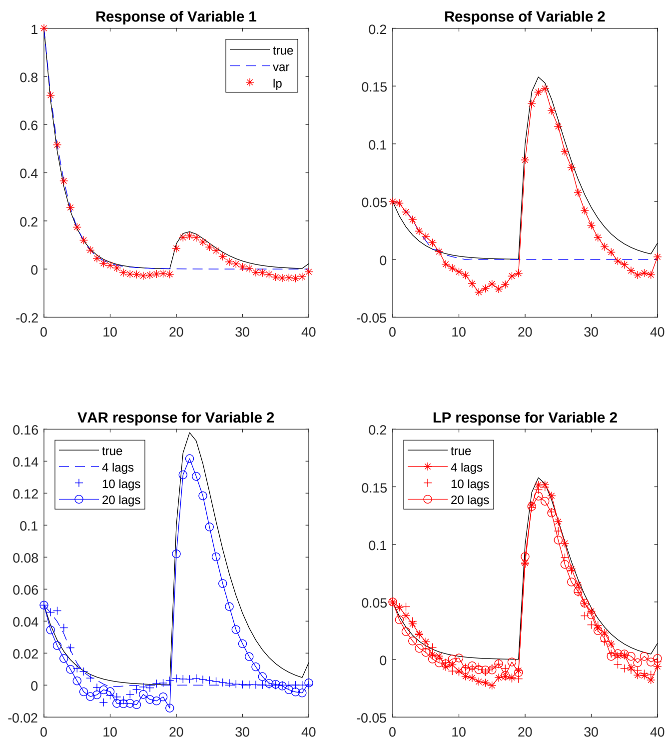
## F.2 Results

The top panel of Figure F.1 displays the main results. Consider first the true impulse response of Variable 2. The features of this function are similar to those reported in our empirical analysis for variables such as GDP, consumption and productivity. That is, a distinctive feature of this response is that the main effect occurs in the medium run rather than immediately. The VAR(4) model captures the short-run impact well. However, it completely misses the increase in the variables at horizon 20. In contrast, the LP that includes the same number of lags captures both the initial increase in the variables and the subsequent rise at horizon 20. The bottom panel of Figure F.1 shows the effect of increasing the lag length. Even with 10 lags, the VAR response of the second variable is far from the truth at long horizons. When the lag length is increased to 20, the performance of the VAR improves substantially. In the case of the LP, increasing the lag length does not materially affect the response after horizon 20. However, there is some evidence that longer lags reduce the discrepancy between the LP response and truth between horizons 10 and 20. In short, this simple stylised simulation demonstrates that VARs with a small number of lags are likely to be unreliable in estimating responses where the bulk of the movement occurs at long horizons. The LP appears to be more robust to lag truncation.

# G Estimation of the Local Projections

We estimate the local projections in Equation(2) via Bayesian methods. The Bayesian approach offers three main advantages in our setting. First, the error bands incorporate uncertainty regarding

Figure F.1: Monte-Carlo results




Notes: Monte-Carlo estimates of impulse responses of the two variables in $Y$ to the first shock. In the bottom panel, the experiment is repeated for different lag lengths

the $A_0$ matrix. Second, the Markov chain Monte-Carlo approach allows us to easily compute joint posterior distributions that can be used to assess statistical differences across shocks and horizons. Third, in Section 5, we use the IRFs produced by LPs to estimate the structural parameters of an endogenous growth model via IRF matching, for which Bayesian methods are routinely used.

The local projections in Equation (2) can be written compactly as:

$$Z_{t+h} = \beta^h X_t + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{22}$$

where $X_t = (1, Z_{t-1}, .., Z_{t-P})$ collects all the regressors and $\beta^h = \left(c^h, B_1^h, b_1^h, .., b_P^h\right)$ is the coefficient matrix. When the horizon is $h = 0$, the model reduces to a Bayesian VAR. Given a Normal prior for $\beta_0$ and an inverse Wishart *prior* for $\Omega_0$, the conditional posterior distributions of these parameters are known in closed form and the posterior distribution can be approximated via Gibbs sampling. We use the draws of these parameters to construct the posterior for the contemporaneous impact matrix $A_0$.

For longer horizons, the estimation of the model is more complex. As discussed in Jordà (2005), the residuals $u_{t+h}$ are nonspherical when $h > 0$. We deal with this issue in two ways. In the benchmark specification, we allow elements of $u_{t+h}$ to have a non-normal distribution. Following Chiu et al. (2017), we define $u_{t+h} = A^{-1}e_{t+h}$ where $A^{-1}$ is a lower triangular matrix. The vector $e_{t+h} = (e_{1,t+h}, .., e_{M,t+h})$ denotes the orthogonalised residuals that follow Student's t-distributions with degrees of freedom $\nu_j$ and variances $\sigma_j^2$ for $j = 1, .., M$. As discussed in Geweke (1993) and Koop (2003), this assumption is equivalent to allowing for heteroscedasticity of an unknown form. In the frequentist case, Montiel Olea and Plagborg-Møller (2021) show that heteroscedasticity robust confidence intervals for LPs that control for lags of the regression variables deliver satisfactory coverage rates. In Appendix F, we report a simple Monte-Carlo experiment showing that: (i) the results in Montiel Olea and Plagborg-Møller (2021) extend to the Bayesian LPs with Student's t-disturbances, and (ii) the estimated error bands display reasonably good coverage rates even at long-horizons. We provide details of the estimation algorithms in Appendix G below.

Furthermore, we attempt to account for autocorrelation in $u_{t+h}$ by modelling it directly. In a recent study, Lusompa (2021) show that the $u_{t+h}$ follows an $MA(h)$ process. Therefore, we consider the following extended model:

$$Z_{t+h} = \beta^h X_t + u_{t+h} \tag{23}$$

$$u_{t+h} = \epsilon_{t+h} + \theta_1 \epsilon_{t+h-1} + .. + \theta_q \epsilon_{t+h-q}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{24}$$

where we allow $q$ to grow with the horizon. As $\epsilon_t$ is unobserved, the estimation of this model is computationally intensive. In Appendix K, we show that the IRFs estimated using (23) and (24) corroborate our main findings.

Finally, in the benchmark specification, the prior for $\beta_h$ is centred on a mean that implies that each variable in $Z_{t+h}$ follows an AR(1) process. The prior variance follows the Minnesota prior, with tightness set to a large number. As discussed in Appendix G, we use a non-informative prior for the free elements of $A$ and $\sigma_j^2$.[1]

As for the 'Direct' model in (1) that is used in one of the sensitivity analyses of Section 3.2, we present frequentist estimates based on OLS. In the robustness checks we also consider LPIV models as used in Jordà and Taylor (2015):

$$Z_{i,t+h} = c^{(h)} + \beta_i^{(h)} \tau_{j,t} + \theta^{(h)} \epsilon_{k,t} + b^{(h)} X_{t-1} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{25}$$

where $\tau_{j,t}$ for $j{=}ct, pt$ denotes the tax rate, which is instrumented by the narrative measure $\epsilon_{j,t}$. The regression also includes the narrative measure for the other tax rate $\epsilon_{k,t}, k \neq j$ as a contemporaneous control.

The LPIV in (25), is estimated using the ridge estimator of Barnichon and Brownlees (2019) with smoothing parameter set via cross-validation.[2]

## G.1 Estimation of the Benchmark Bayesian LP model

The model used to produce the benchmark Bayesian LP results (Equation 2) is defined as:

$$Z_{t+h} = \beta^h X_t + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{26}$$

where $X_t = (1, Z_{t-1}, .., Z_{t-P}, x_{t-1})$ collects all the regressors and $\beta^h = \left(c^{(h)}, B_1^{(h)}, b_1^{(h)}, .., b_P^{(h)}, d^{(h)}\right)$ is the coefficient matrix. For $h = 0$, the model is a Bayesian VAR and estimation is standard (see for e.g. Bańbura et al. (2010)). When $h > 0$, we allow for non-normal disturbances. The covariance matrix $\Omega_h$ is decomposed as $\Omega_h = A^{-1} H_t A^{-1\prime}$ where $A$ is a lower triangular matrix while $H_t = diag\left(\frac{\sigma_1^2}{\lambda_{1t}}, \frac{\sigma_2^2}{\lambda_{2t}}, \ldots, \frac{\sigma_M^2}{\lambda_{Mt}}\right)$. Note that $\frac{1}{\lambda_{it}}$ for $i = 1, \ldots, M$ denotes the time-varying volatility of the orthogonal disturbances $e_{t+h} = Au_{t+h}$ Geweke (1993) shows that assuming a Gamma prior for

[1]Following Bańbura et al. (2010), we set the prior mean for $\beta_h$ by running AR(1) regressions for each endogenous variable. The diagonal elements of the prior variance matrix corresponding to own lags $p$ are defined as $\frac{\mu_1^2}{p^2}$ and as $\frac{s_i}{s_j}\frac{\mu_1^2}{p^2}$ for coefficients on lags of other variables. The variances $\frac{s_i}{s_j}$ account for the differences in scale between variables and are obtained as residual variance from the preliminary AR(1) regressions. We set the tightness parameter $\mu_1$ to 10 which implies a loose prior belief.

[2]Plagborg-Møller and Wolf (2021) show that smooth local projections imply a reduction in the variance while leading to only a small increase in the bias of LPs. We present the unsmoothed 2SLS estimate in Appendix K. Our main findings of a significant response of GDP and TFP at longer horizons are unaffected by these modifications.

$\lambda_{it}$ of the form $P(\lambda_i) = \prod_{t=1}^{T} P(\lambda_{it}) = \prod_{t=1}^{T} \Gamma(1, \nu_i)$ leads to scale mixture of normal distributions for the orthogonal residuals ($\Gamma(a, b)$ denotes a Gamma distribution with mean a and degrees of freedom b). As shown in Geweke (1993), this is equivalent to assuming that each orthogonal residual $e_{it}$ follows a Student's T-distribution with degrees of freedom equal to $\nu_i$. This setup is used for VAR models in Chiu et al. (2017).

### G.1.1 Priors

We employ the following prior distributions:

- We set a hierarchical prior for $\lambda_{it}$ and $\nu_i$ (see Koop (2003)):

$$P(\lambda_{it}) = \Gamma(1, \nu_i) \tag{27}$$

$$P(\nu i) = \Gamma(\nu_0, 2) \tag{28}$$

  Note that the prior for $\nu$ is an exponential distribution, which is equivalent to a Gamma distribution with 2 degrees of freedom. We set $\nu_0 = 10$ which gives prior weight to the possibility of fat tails in the distribution of $e_{it}$

- The prior for $\sigma_i^2$ is inverse Gamma : $IG(T_0, D_0)$. We assume a flat prior setting the scale and degrees of freedom to 0.

- The free elements of each row of $A$ have an independent prior of the form: $P(A_k) \sim N(a_{k,0}, s_{k,0})$ where $A_k$ is the $k_{th}$ row of this matrix. We set the mean of the prior to zero and the diagonal elements of $s_{k,0}$ to 1000

- We set a Minnesota type prior for the coefficients $\tilde{\beta^h} = vec(\beta^h)$: $P(\tilde{\beta^h}) \sim N(\beta_0, S_0)$. The mean $\beta_0$ implies that each variable in $Z_{t+h}$ follows an $AR(1)$ process. The diagonal elements of the variance matrix $S_0$ corresponding to own lags are defined as $\frac{\mu_1^2}{p^2}$ and as $\frac{s_i}{s_j}\frac{\mu_1^2}{p^2}$ for coefficients on lags of other variables. Here $p$ denotes the lag length while the ratio of variances $\frac{s_i}{s_j}$ accounts for differences in scale across variables. We set the tightness parameter $\mu_1$ to 10 which implies a loose prior belief.

### G.1.2 Gibbs Sampler

We use a Gibbs sampling algorithm to approximate the posterior distribution. The algorithm is based on the samplers presented in Geweke (1993), Koop (2003) and Chiu et al. (2017). In each iteration, the algorithm samples from the following conditional posterior distributions ($\Xi$ denotes all other parameters):

- $G(\lambda_{it}|\Xi)$. Given a draw for $A$, the orthogonal residuals are constructed as $e_t = Au_t$. The conditional posterior distribution for $\lambda_{i,t}$ derived in Geweke (1993) applies to each column of $e_t$. As shown in Koop (2003) this posterior density is a gamma distribution with mean $(\nu_i + 1) / \frac{1}{\sigma_i} e_{i,t}^2 + \nu_i$ and degrees of freedom $\nu_i + 1$. Note that $e_{i,t}$ is the $ith$ column of the matrix $e_t$.

- $G(\nu_i|\Xi)$. The conditional posterior distribution of $\nu_i$ is non-standard (see Koop (2003)) and given by:

$$G(\nu_i|\Xi) \propto \left(\frac{\nu_i}{2}\right)^{\frac{T\nu_i}{2}} \Gamma\left(\frac{\nu_i}{2}\right)^{-T} \exp\left(-\left(\frac{1}{\nu_0} + 0.5 \sum_{t=1}^{T} \left[\ln\left(\lambda_{i,t}^{-1}\right) + \lambda_{i,t}\right]\right) \nu_i\right) \tag{29}$$

As in Geweke (1993) we use the Random Walk Metropolis-Hastings Algorithm to draw from this conditional distribution. More specifically, for each of the $M$ equations of the VAR, we draw $\nu_i^{new} = \nu_i^{old} + c^{1/2}\epsilon$ with $\epsilon \sim N(0,1)$. The draw is accepted with probability $\frac{G(\nu_i^{new}|\Xi)}{G(\nu_i^{old}|\Xi)}$ with $c$ chosen to keep the acceptance rate around 40%.

- $G(A|\Xi)$: Given a draw for the coefficients $\beta^h$ the model can be written as: $Au_{t+h} = e_{t+h}$ where $e_{i,t+h} \sim N(0, \frac{\sigma_i^2}{\lambda_{it}})$ for $i = 1,..,M$. This is a system of $K$ linear regressions with known error variances. The first equation is an identity $u_{1,t+h} = e_{1,t+h}$. The second equation is: $u_{2,t+h} = A_2(-u_{1,t+h}) + e_{2,t+h}$, the k$th$ equation is $u_{k,t+h} = x_u A_k + e_{k,t+h}$ and so on, where $x_u = (-u_{1,t+h}, \ldots, -u_{k-1,t+h})$. By dividing both sides of the equations by the respective error standard deviation, i.e. $(\frac{\sigma_k^2}{\lambda_{kt}})^{(0.5)}$, the residual variance is normalised to 1. Given the normal prior for $A_k$, the conditional posterior is also normal with variance $v = \left(s_{0,k}^{-1} + \tilde{x_u}'\tilde{x_u}\right)^{-1}$ and mean $v\left(s_{0,k}^{-1}a_{0,k} + \tilde{x_u}'\tilde{u}_{k,t+h}\right)$ where $\tilde{x_u}$ and $\tilde{u}_{k,t+h}$ denote the regressors and the dependent variable after the GLS transformation described above.

- $G(\sigma_i^2|\Xi)$: The orthogonal residuals $e_{t+h}$ can be transformed as follows: $\tilde{e_{t+h}} = e_{t+h}\lambda_{i,t}^{0.5}$. The conditional posterior for $\sigma_i^2$ is inverse Gamma with scale parameter $\tilde{e_{t+h}}'\tilde{e_{t+h}} + D_0$ and degrees of freedom $T + T_0$

- $G(\beta^h|\Xi)$ We use the algorithm of Carriero et al. (2022) to draw from this conditional posterior distribution. Carriero et al. (2022) show that the system can be re-written as:

$$AZ_{t+h} = A\beta^h X_t + e_{t+h}, \qquad e_{it,t+h} \sim N\left(0, \frac{\sigma_i^2}{\lambda_{i,t}}\right) \tag{30}$$

  Given the lower triangular structure of $A$, the coefficients of the j$th$ equation can be sampled using blocks of the last $M - j + 1$ equations, conditional on the remaining blocks. Carriero et al. (2022) show that these conditional posterior distributions are normal and they provide expressions for the mean and variance. This algorithm is substantially faster that drawing the coefficients of all equations in the model, jointly.

We employ 51000 iterations and drop the first 1000 as burn-in. We keep every 5$th$ draws of the remainder for inference.

### G.1.3 Lag augmentation and coverage

Following Montiel Olea and Plagborg-Møller (2021), we carry out a Monte-Carlo experiment to check the coverage properties of the error bands produced the Bayesian LP described above. We generate data from a 4-variable VAR(4) model. The coefficients and variance-covariance of the error terms is set equal to the OLS estimates of a VAR(4) model using data on 4 variables employed in our benchmark LP: (1) $ACITR$, (2) $B^{CI}$, (3) $ln(G)$ and (4) $ln(GDP)$. We generate 280 observations after discarding an initial sample of 100 observations to account for starting values. Using this artificial data, we estimate two Bayesian LPs: (1) a model with 4 lags of all 4 variables included as controls and (2) a model that is not lag-augmented and only the first lag that is required to generate the IRF is included. We employ 51000 Gibbs iterations and drop the first 1000 as burn-in. We keep every 5$th$ draw of the remainder for inference. The experiment is repeated 1000 times and we compute coverage probabilities using the estimated 90 percent highest posterior density intervals. Figure G.1 Panel A shows that the benchmark model produces reasonably good coverage rates with distortions that remain below 10% even at long horizons. In contrast, when the lag augmentation is removed, the performance deteriorates substantially and coverage rates fall below 50% for all variables.

#### G.1.4 Convergence

To assess convergence of the Gibbs algorithm, we examine the inefficiency factors calculated using the impulse responses from the benchmark model. These estimates are below 20 for all variables and horizons (see Figure G.1 Panel B) providing support for convergence of the algorithm.

### G.2 Bayesian LP with MA residuals

Our alternative specification directly models the autocorrelation in the residuals. In a recent paper Lusompa (2021) has shown that the $u_{t+h}$ follows an $MA(h)$ process. We therefore consider the following extended model:

$$Z_{t+h} = \beta^h X_t + u_{t+h} \tag{31}$$

The residuals of each equation follow the MA process:

$$u_{t+h} = \epsilon_{t+h} + \theta_1 \epsilon_{t+h-1} + .. + \theta_q \epsilon_{t+h-q}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{32}$$

As noted in Chan (2020), this type of model can be re-written as:

$$Z_{t+h} = \beta^h X_t + \tilde{H}\epsilon_{t+h}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{33}$$

where $\tilde{H}$ is $T \times T$ banded matrix with ones on the main diagonal and the MA coefficients appearing below the main diagonal. For example, the process $u_{t+h} = \epsilon_{t+h} + \theta_1 \epsilon_{t+h-1}$ can be written as $u_{t+h} = \tilde{H}\epsilon_{t+h}$ where $\tilde{H} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ \theta_1 & 1 & \dots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & \theta_1 & 1 \end{pmatrix}$

The model is estimated using a Gibbs sampling algorithm that is based on the methods described in Chan (2020).

#### G.2.1 Priors

We employ the following prior distributions:

- The prior for $\Omega$ is inverse Wishart: $IW(\Omega_0, T_0)$. We employ a flat prior and set both the scale matrix and degrees of freedom to 0.
- We set a Minnesota type prior for the coefficients $\tilde{\beta^h} = vec(\beta^h)$: $P(\tilde{\beta^h}) \sim N(\beta_0, S_0)$. The mean $\beta_0$ implies that each variable in $Z_{t+h}$ follows an $AR(1)$ process. The diagonal elements of the variance matrix $S_0$ corresponding to own lags are defined as $\frac{\mu_1^2}{p^2}$ and as $\frac{\sigma_i}{\sigma_j}\frac{\mu_1^2}{p^2}$ for the coefficients on the lags of other variables. Here $p$ denotes the lag length while the ratio of variances $\frac{\sigma_i}{\sigma_j}$ accounts for differences in scale across variables. We set the tightness parameter $\mu_1$ to 10 which implies a loose prior belief.
- The prior for MA coefficients $\tilde{\Theta} = (\theta_1, \dots, \theta_q)$ is normal: $N(\Theta_0, V_0)$. The mean of the prior is set to 0. The variance is set using the Minnesota procedure (described above) with the coefficients on higher MA terms shrunk to 0 more quickly. We set the tightness parameter of the prior to 0.1

### G.2.2 Gibbs Sampler

The Gibbs sampling algorithm for this model samples from the following conditional posterior distributions ($\Xi$ denotes all other parameters):

- $G(\tilde{\beta^h}|\Xi)$: Given a draw for $\tilde{\Theta}$, the model can be written as

$$\tilde{Z}_{t+h} = \beta^h \tilde{X}_t + \epsilon_{t+h}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{34}$$

$$\tilde{Z}_{t+h} = \tilde{H}^{-1} Z_{t+h} \tag{35}$$

$$\tilde{X}_t = \tilde{H}^{-1} X_t \tag{36}$$

  This is simply a system of linear equations with iid residuals. Let $\tilde{Z}$ and $\tilde{X}$ denote the matrices holding the transformed dependent and covariates, respectively. The conditional posterior is normally distributed with mean $M$ and variance $V$:

$$V = \left(S_0^{-1} + \Omega_h^{-1} \otimes \tilde{X}'\tilde{X}\right)^{-1} \tag{37}$$

$$M = V\left(S_0^{-1}\beta_0 + \left(\Omega_h^{-1} \otimes \tilde{X}'\tilde{X}\right)\beta_{ols}\right) \tag{38}$$

$$\beta_{ols} = vec\left(\left(\tilde{X}'\tilde{X}\right)^{-1}\left(\tilde{X}'\tilde{Z}\right)\right) \tag{39}$$

- $G(\Omega_h|\Xi)$: Given a draw for $\beta_h$, the residuals $\epsilon_{t+h}$ can be easily calculated. The conditional posterior of $\Omega_h$ is inverse Wishart with scale matrix $\epsilon'_{t+h}\epsilon_{t+h} + \Omega_0$ and degrees of freedom $T + T_0$.

- $G(\tilde{\Theta}|\Xi)$: The model can be written in state-space form:

$$Z_{t+h} = \beta^h X_t + \begin{pmatrix} I_m & I_m \times \theta_1 & \dots & I_m \times \theta_q \end{pmatrix} \begin{pmatrix} \epsilon_t \\ \epsilon_{t-1} \\ \vdots \\ \epsilon_{t-q} \end{pmatrix} \tag{40}$$

$$\begin{pmatrix} \epsilon_t \\ \epsilon_{t-1} \\ \vdots \\ \epsilon_{t-q} \end{pmatrix} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & \dots & \dots \end{pmatrix} \begin{pmatrix} \epsilon_{t-1} \\ \epsilon_{t-2} \\ \vdots \\ \epsilon_{t-q-1} \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \\ \vdots \\ 0 \end{pmatrix} \tag{41}$$

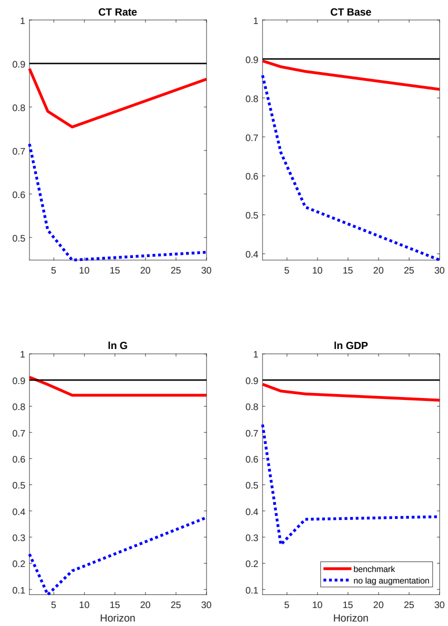
$$var\left(\begin{pmatrix} \epsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}\right) = \begin{pmatrix} \Omega & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & \dots & \dots \end{pmatrix} \tag{42}$$

  We use a random walk Metropolis-Hastings step to draw $\tilde{\Theta}$. We generate a candidate draw using $\tilde{\Theta}_{new} = \tilde{\Theta}_{old} + e, e \sim N(0, \tau)$. The draw is accepted with probability $\alpha = \frac{F\left(Z_{t+h}|\tilde{\Theta}_{new}, \Xi\right) \times P\left(\tilde{\Theta}_{new}\right)}{F\left(Z_{t+h}|\tilde{\Theta}_{old}, \Xi\right) \times P\left(\tilde{\Theta}_{old}\right)}$ where the likelihood function $F\left(Z_{t+h}|\tilde{\Theta}, \Xi\right)$ is calculated using the Kalman filter and the Normal prior $P\left(\tilde{\Theta}\right)$ is evaluated directly. We adjust the variance $\tau$ to ensure an acceptance rate between 20 and 40%.

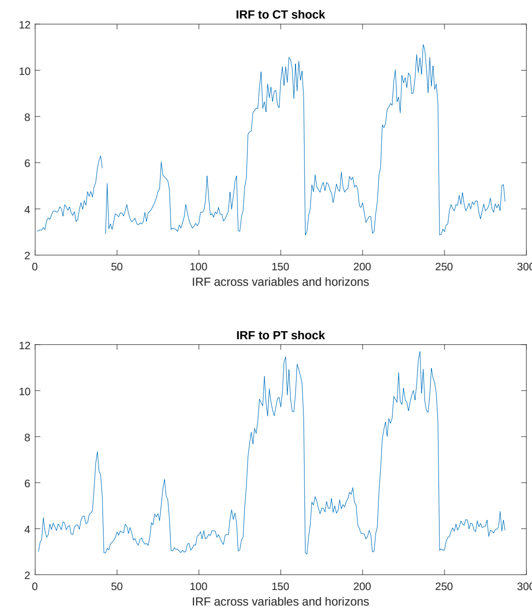
We employ 51000 Gibbs iterations and drop the first 1000 as burn-in. We keep every $5th$ draw of the remainder for inference.

Figure G.1: Coverage probabilities and inefficiency factors

(a) Coverage Probabilities




(b) Inefficiency Factors




Notes: this figure shows the coverage probabilities for the Bayesian LP with and without lag augmentation (Panel A) and inefficiency factors calculated using the MCMC draws of the impulse responses from the benchmark model (Panel B).

# H Forecast Error Variance Decomposition

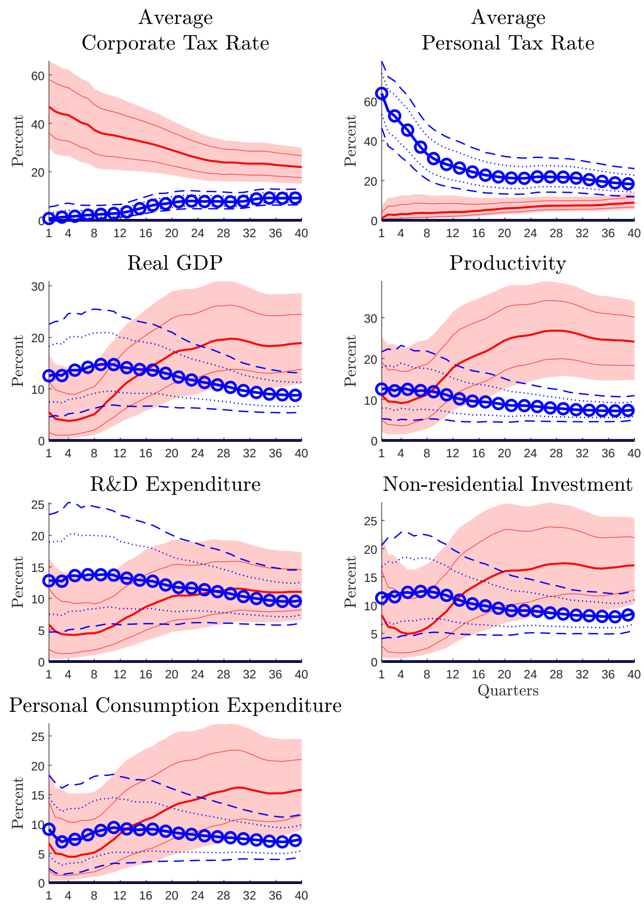
In this section, we use the LP estimates of Section 3 to assess the contribution of each shock to the variance of endogenous variables at different forecast horizons. The results of this exercise are summarised in Figure H.1, which reports the median estimates and 90% central credible sets of the forecast error variance decomposition for the corporate income tax shock (in red) and the personal income tax shock (in blue).[3]

Two main results emerge. First, at the shorter horizon of one year, the contribution of the corporate shock is smaller relative to the personal shock, accounting for around 5 % of the variance of GDP, as well as the variation in productivity and R&D spending. In general, the short-run contribution of the personal tax shock is larger, estimated to be about 10% for these variables. But as the forecast period increases, and especially at longer horizons, the contribution of the corporate income tax shock becomes dominant, peaking around year 9 and accounting for around 20% of the variance of GDP and investment, and 30% for productivity. In contrast, the contribution of personal income tax changes to longer-term fluctuations tends to be lower.[4]

[3]By estimating the Mertens and Ravn (2013) VAR-type structure using local projections, we sidestep practical issues associated with computing forecast error variance decompositions using local projection IV methods (see Plagborg-Møller and Wolf, 2022).

[4]These findings also echo results in earlier studies that focused more on short-term impact. Mertens and Ravn (2012) find that Romer and Romer (2010) tax shocks explain around 20% of the output fluctuations at business cycle frequencies, consistent with the short-term results in Appendix Figure H.1. Cloyne (2013) finds that narrative-identified tax shocks in the U.K. account for around 25% of productivity variation, 20% of GDP, 15% of investment and consumption at the ten-year horizon. McGrattan (1994) finds that labor taxes account for around 25% of the in-sample variance of output and capital taxes around 5% at business cycle frequencies, using a completely different VAR-based identification approach.

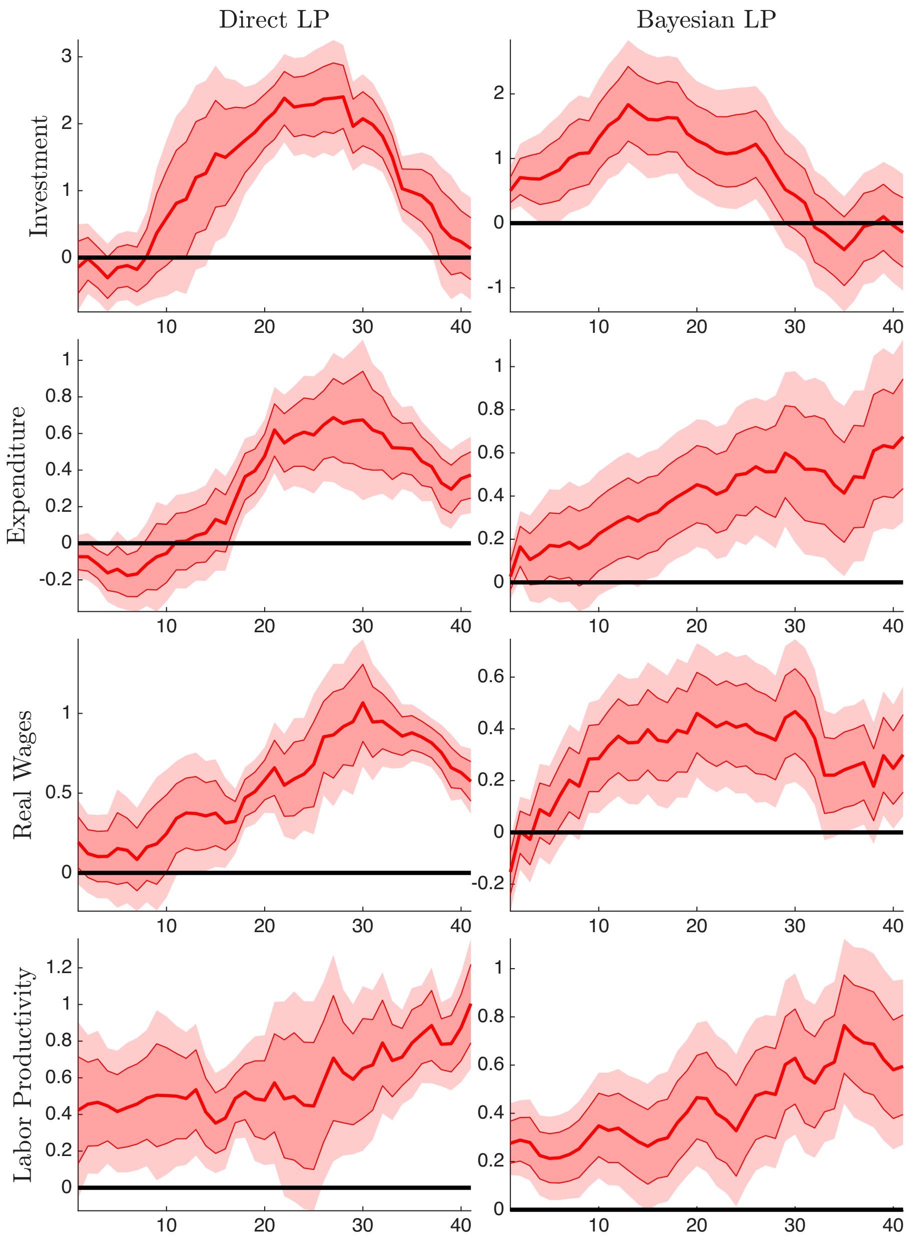
Figure H.1: Forecast Error Variance decomposition




Notes: contribution of corporate and personal tax changes to the variance of each variable in the figure. The contribution of corporate tax changes are shown in the red lines (posterior median and 68 percent band) and the shaded area (90% band). The line with circles shows the contribution of the personal tax shock, with the posterior 68 % (90 %) bands shown by the dotted (dashed) lines.

# I Response of Consumption, Investment and labor market

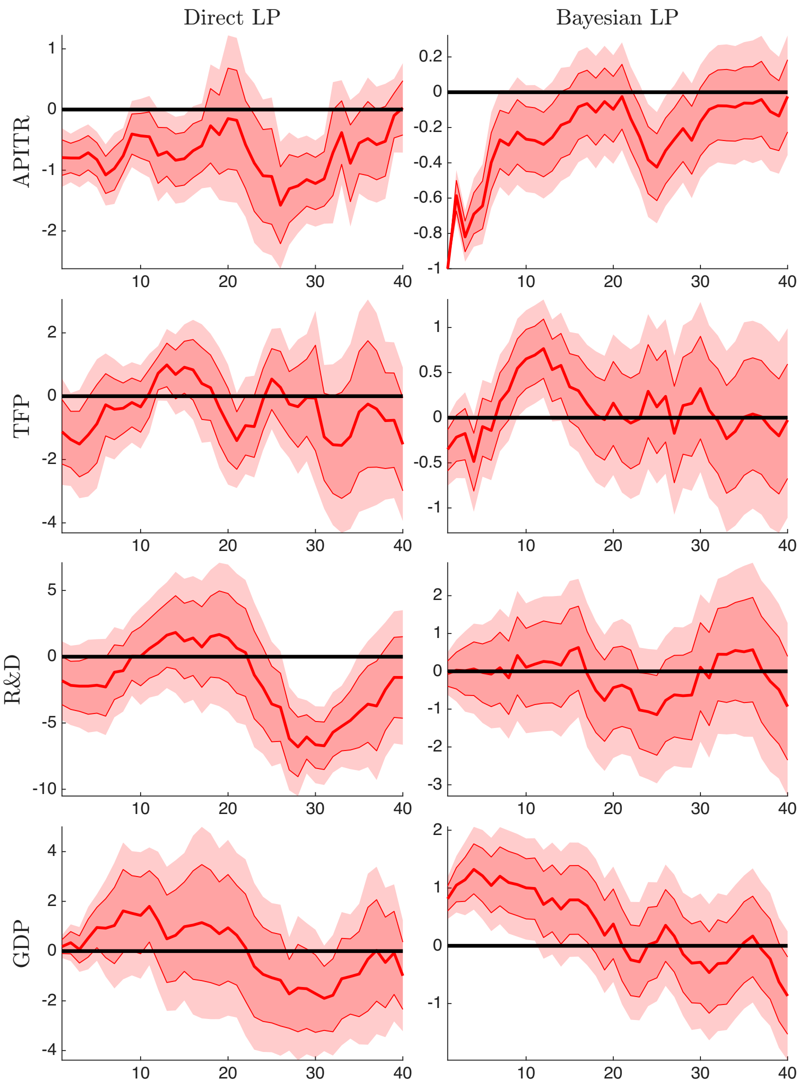
Figure I.1: Response of Investment, Consumption Expenditure, Real Wages and Labour Productivity to a Corporate Tax Shock




Notes: responses to a 1% cut in the corporate income tax. Shadow areas show the 68% and 90% confidence intervals/central $68^{th}$ and $90^{th}$ credible sets.

# J The Effects of Personal Income Tax shocks

Figure J.1: Response of Tax Rate, TFP, R&D spending and GDP to a Personal Income Tax Cut



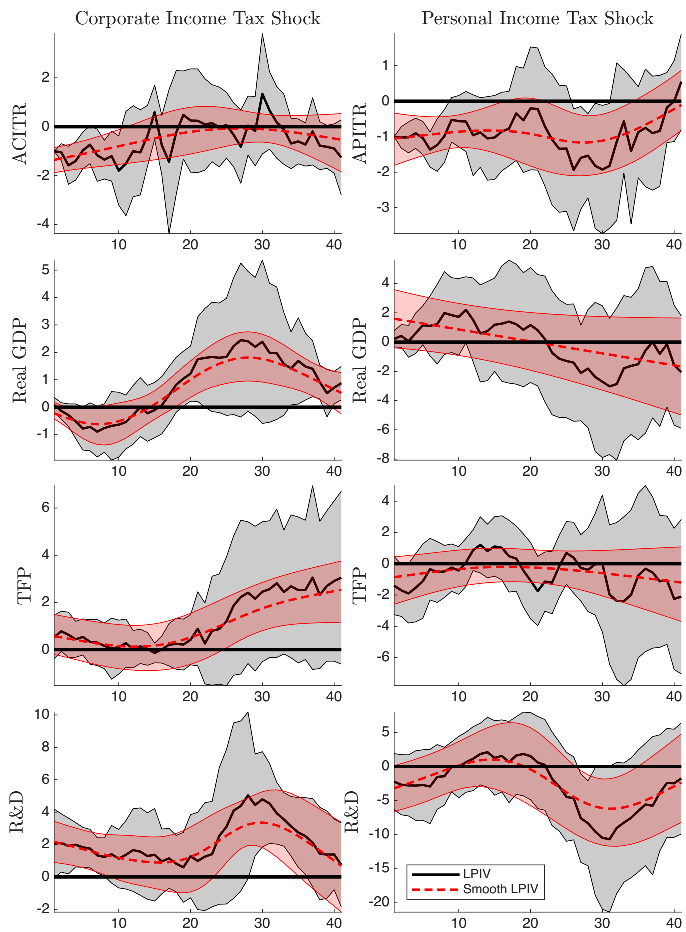

Notes: responses of the average tax rate, TFP, R&D expenditure, and GDP to a personal income tax rate cut. The left (right) column plots responses estimated via direct (Bayesian) local projections; see Section 2.2 for details on methodology and Appendix C for data description. Shadow areas show the 68% and 90% confidence intervals/central $68^{th}$ and $90^{th}$ credible sets.

# K Robustness checks

**Frequentist estimates of the Direct model and LPIV.** We present two cases:

1. **using narrative measures as instruments.** In Figure K.1, we present impulse responses estimated using the frequentist approach. The figure shows estimates obtained using the standard (2SLS) and the smoothed version of LPIV (Barnichon and Brownlees (2019)). As noted in the text, these regressions use the narrative measures of Mertens and Ravn (2013) as regressors/instruments.

Figure K.1: Responses of GDP, TFP and R&D expenditure to Corporate and Personal Tax Changes using alternative local projection models

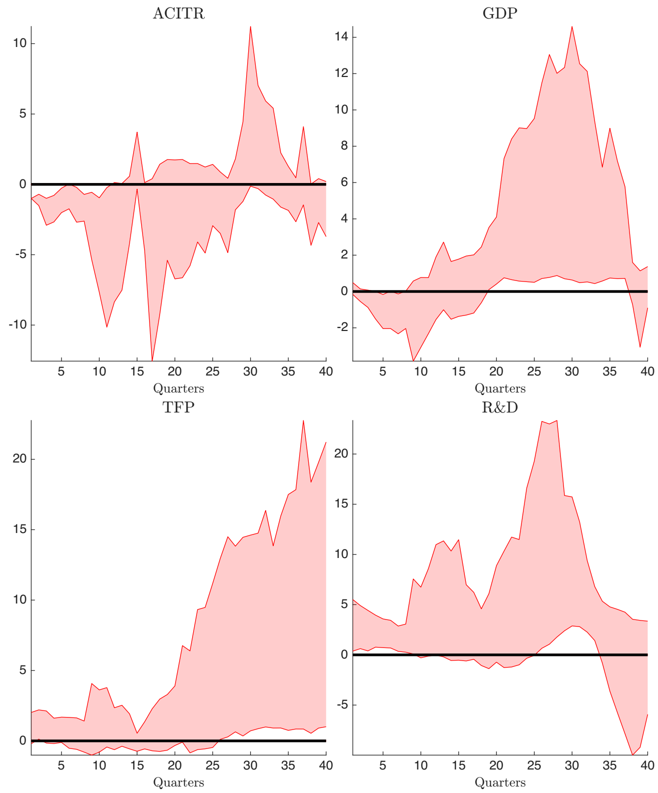



Notes: responses of the average tax rates, real GDP, and TFP to a 1% cut in the average rate of corporate income taxes (left column) and the average rate of personal income taxes (right column). Red and grey shadow bands represent 90 percent confidence intervals using robust standard errors.

**Weak instrument robust error bands.** Figure K.2 shows LPIV estimates with error bands constructed by inverting the Anderson and Rubin (1949) test statistic. While these error bands are generally wider, the medium-term effects of corporate tax shocks are still significant.

2. **using VAR shocks as instruments.** In this exercise, we use the structural tax shocks estimated by the VAR of Mertens and Ravn (2013) as instruments. One advantage of this approach is that the VAR shocks are orthogonal by construction and each of them can be used to instrument the two tax rates separately. We proceed in the following steps:

Figure K.2: LPIV estimates with Anderson and Rubin (1949) error bands




Notes: Impulse responses using IV estimates of local projections. The shaded areas are the Anderson and Rubin (1949) 90% error bands, respectively.

(a) estimate Mertens and Ravn (2013) VAR and obtain the estimates of structural corporate and personal tax shocks ($z_{ct}$ and $z_{pt}$, respectively), which are orthogonal by construction.

(b) we then estimate the following regression:

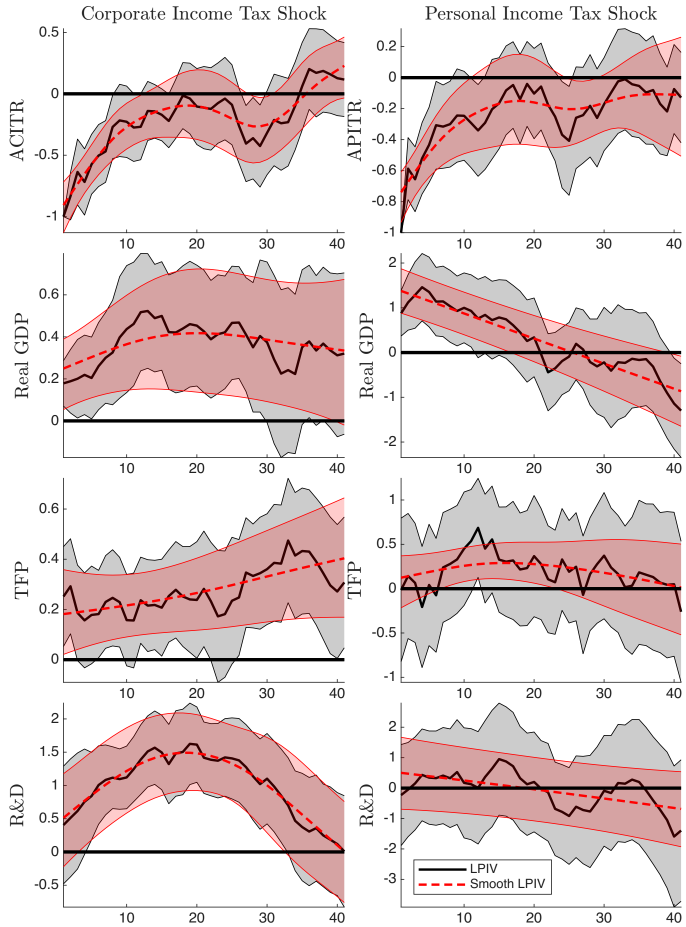
$$Z_{i,t+h} = c^{(h)} + B_1^{(h)} x_t + \sum_{j=1}^{L} b_j^{(h)} Z_{t-j} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{43}$$

where $x_t$ is the endogenous variable (i.e. either the corporate or the personal tax rate) which is instrumented by the appropriate shock obtained in step 1. As the instruments are orthogonal by construction, the remaining shock does not need to be included as a contemporaneous control. The matrix $Z$ denotes the 8 variables considered in the benchmark specification and $L$ is set equal to 1.

The IRFs are given by $B_1^{(h)}$; error bands use Robust standard errors. Figure K.3 reveals that the LPIV estimates broadly support the benchmark results. We reach similar conclusions when we employ the smooth local projections (SLP) of Barnichon and Brownlees (2019).

**Bias correction and control lags in the frequentist Direct model.** In small sample, OLS estimates of impulse responses from LPs can be biased (Herbst and Johannsen, 2020, Li et al., 2024). In this Appendix, we also report the IRFs from model (1) using the bias correction proposed by Herbst and Johannsen (2020) and different lag lengths. Appendix Figure K.4 below shows that the responses of the average tax rate, TFP, R&D and GDP are close to those reported in Figure 1 and virtually never outside their 90% confidence intervals.

Figure K.3: LPIV estimates using Mertens and Ravn (2013) VAR shocks as instruments




Notes: Impulse responses using IV estimates of local projections.The black lines show TSLS estimates, while the dotted red lines are smoothed local projections. The shaded areas are the the 90% error bands, respectively. These are constructed using robust standard errors.

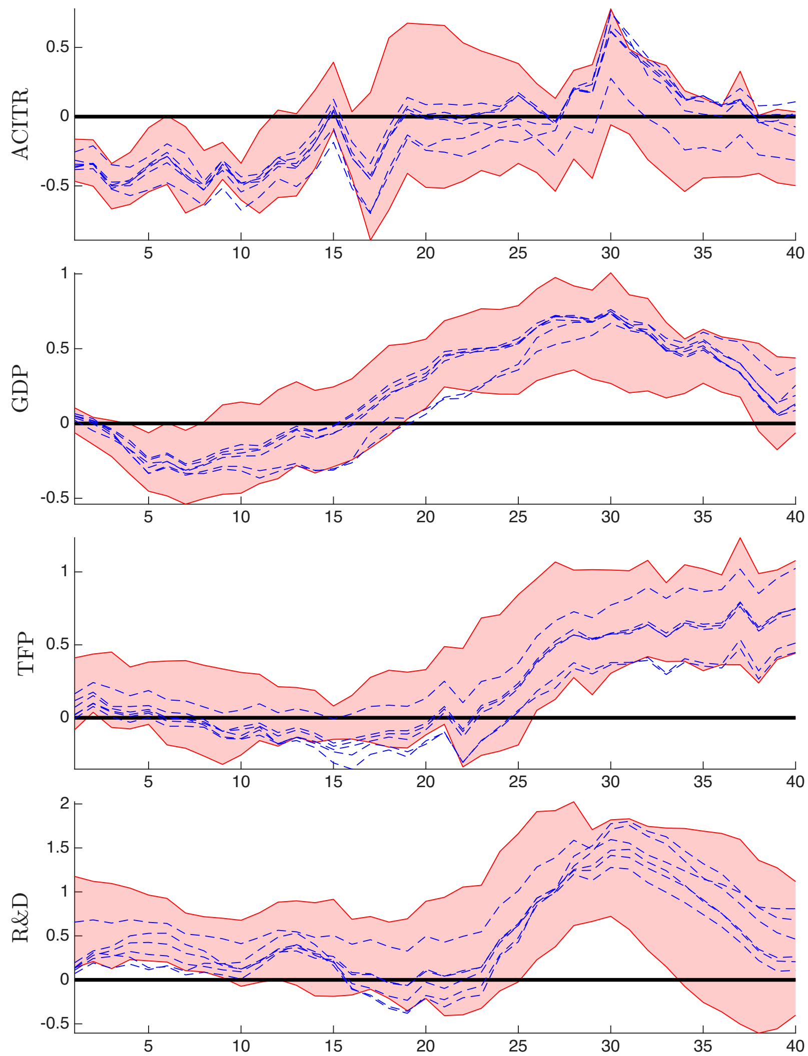
**Impulse response from a BVAR with long-lags** In this section we present impulse responses from a Bayesian VAR model that includes 32 lags. The choice of the lag length reflects our interest in the response at medium/long-run horizons (see Baumeister (2025), Antolin-Diaz and Surico (2025)). The VAR model is defined as:

$$Z_t = c + \sum_{l=1}^{32} B_l Z_{t-l} + A_0 \epsilon_t \tag{44}$$

where $Z_t$ denotes matrix of endogenous variables that includes the following 5 variables in our basic model: $(i)$ $APITR_t$, $(ii)$ $ACITR_t$, $(iii)$ $\ln(G_t)$, $(iv)$ $\ln(GDP_t)$, $(iv)$ $\ln(DEBT_t)$. We successively add $R\&D$ and $TFP$ to this basic model to obtain the response of these additional variables. We follow Antolin-Diaz and Surico (2025) and use a Minnesota prior on the VAR coefficients along with the dummy initial observation prior of Sims (1993). The parameters governing the tightness of these priors are assumed to be unknown and estimated along with the VAR parameters (see Giannone et al. (2015)). We show exactly the same identification scheme as in the benchmark Bayesian LP, using the narrative proxies and the approach of Mertens and Ravn (2013) to obtain the relevant columns of the $A_0$ matrix.

Figure K.5 shows that the VAR responses are qualitatively similar to the benchmark LP. Importantly, they support the assertion that that the corporate tax shock has a persistent and long-lasting

Figure K.4: Response of real GDP, TFP and R&D to corporate tax shocks using Herbst and Johannsen (2020)'s bias correction and up to six lags of control variables



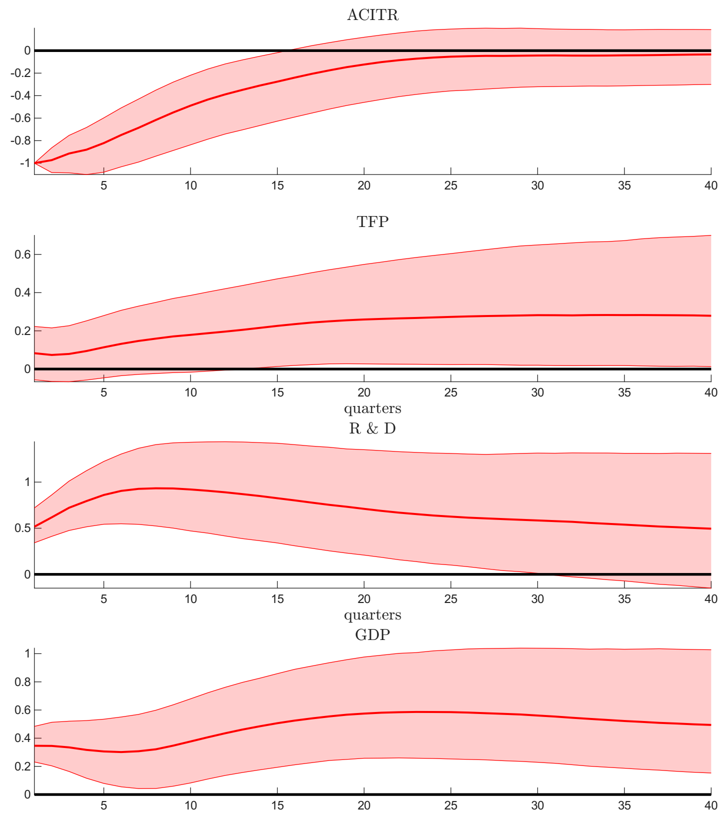

Notes: shaded areas and solid red lines are point estimates and 90% bands of the Direct LP estimates in Figure 1.

impact on real GDP, TFP and R&D.

**Bayesian LP with MA residuals.** In Figure K.6, we use the Bayesian LPs described in section G.2. While the response of GDP, TFP and R&D to corporate shocks is more volatile than the benchmark, the results confirm that this shock has long-lasting effects on output and productivity. In contrast, the estimated impact of personal tax shocks is short-lived.

**Alternative Specifications.** In Figure K.7, we show that our main findings of persistent effects of corporate tax changes on GDP and TFP are also robust to varying the number of lags, using optimal priors, adding the measure of government spending shocks proposed by Ramey (2011), and changing the ordering of the tax shocks.

Figure K.5: Response of real GDP, TFP and R&D to corporate tax shocks using a BVAR(32)




Notes: 90% bands are shown in the shaded area

# L Accounting and Tax Treatment of Intangibles and R&D

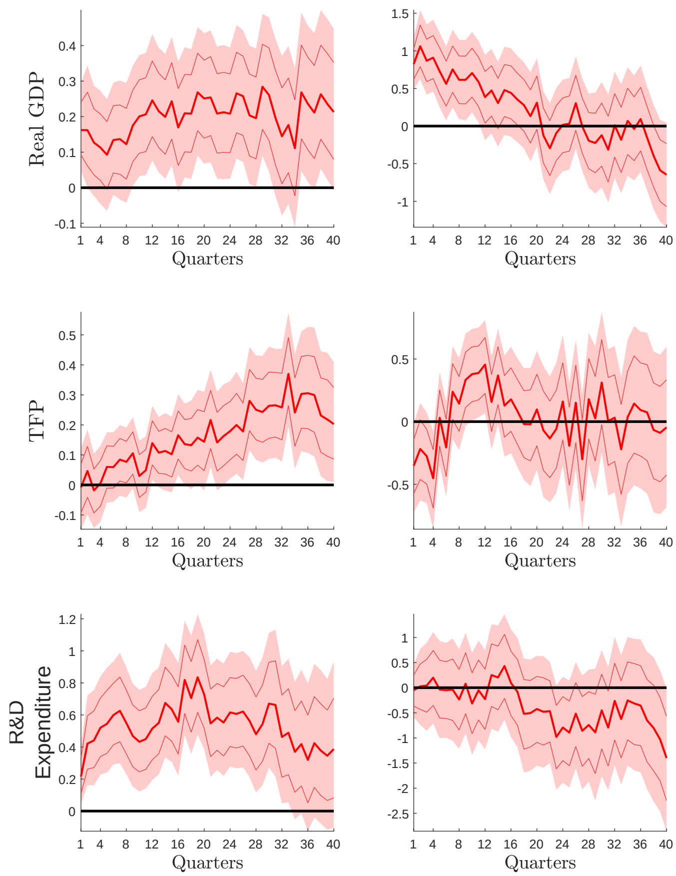
**The treatment of intangible assets in U.S. GAAP.** Intangible assets are non-physical assets that have a quantifiable economic value and are expected to generate future benefits for a company. Examples include patents, copyrights, trademarks, goodwill, and brand recognition. U.S. GAAP (Generally Accepted Accounting Principles) distinguish between internally created and externally purchased intangible assets (Ernst & Young (2024)):

- Internally created intangible assets: in most cases, the cost of developing these assets is expensed on the income statement as it is incurred. This reflects the difficulty of reliably measuring the value of internally generated intangibles.

- Externally purchased intangible assets: these assets are usually capitalised on the balance sheet, meaning their cost is recorded as an asset. This occurs when a company acquires these assets through a purchase or merger.

**Amortization of purchased intangibles.** Amortization refers to the systematic allocation of the cost of an intangible asset over its estimated useful life. It's a way of recognising the gradual

Figure K.6: IRFs using Bayesian LP with MA residuals

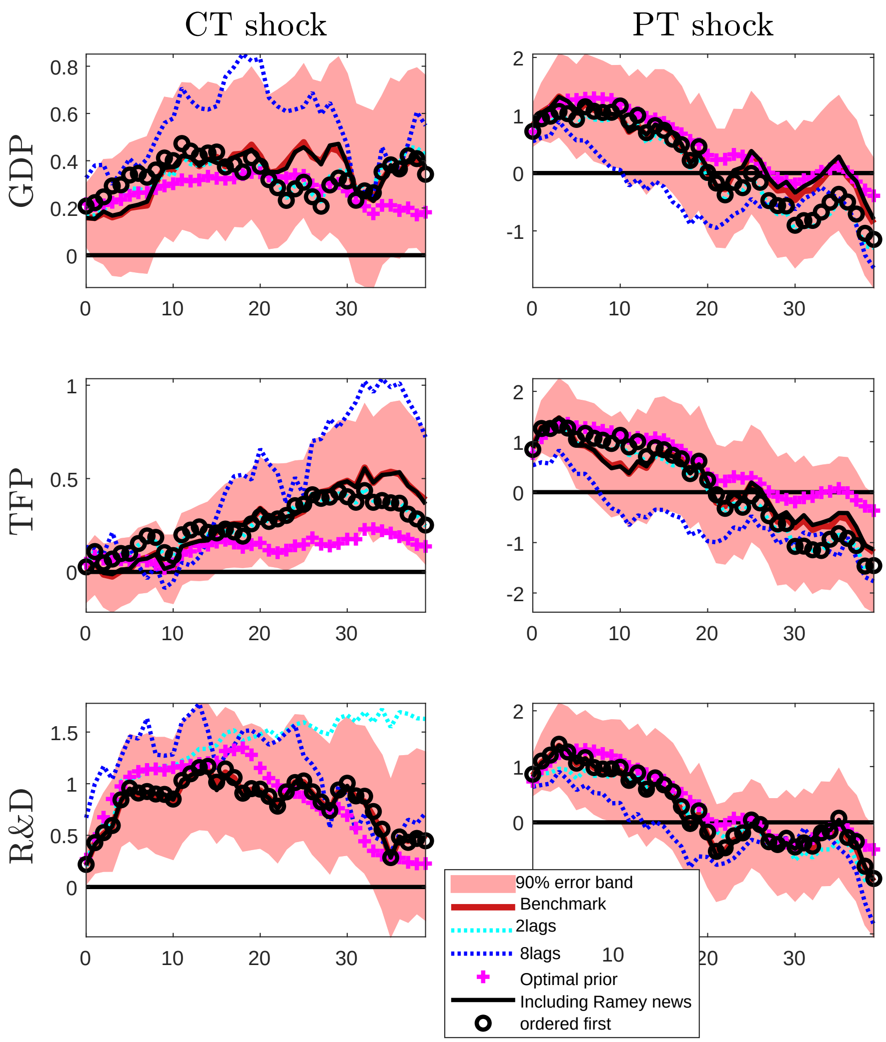



Notes: this figure shows impulse responses estimated using the Bayesian LP with residuals modelled as an MA process. The thin lines and shaded areas are the 68% and 90% error bands.

decline in the value of an intangible asset over time, similar to how depreciation works for tangible assets. Under Section 197 of the U.S. Internal Revenue Code (IRC), enacted as part of the Omnibus Budget Reconciliation Act of 1993, purchased intangible assets, including goodwill, are amortized over a 15-year period. This applies regardless of the actual estimated useful life of the asset. For example, even if a patent has a legal life of 20 years, it will be amortized over 15 years for tax purposes. In practice, this means that firms deduct a constant fraction of the cost of purchasing the intangible asset from their taxable profits over 15 years. This 15-year amortization rule aims to simplify the tax treatment of intangible assets and prevent disputes over their useful lives. Before 1993, the tax code did not contain specific provisions for the amortization of intangible assets. Still, intangibles that had a well-defined useful life could be amortized under Section 167 of the IRC (Douglass (1994)), which, for newly issued patents, implied an amortization period of 17 years.

**Tax treatment of R&D expenditures pre-TCJA.** Prior to the Tax Cuts and Jobs Act (2017) (TCJA), IRC Section 174(a), enacted in the Internal Revenue Code of 1954, allowed companies to deduct the full amount of Research and Experimental Expenditures (REE) in the year when they were incurred, even if the R&D activities did not lead to the creation of a specific, identifiable intangible asset. Prior to 1954, the U.S. tax code did not have specific provisions addressing R&D expenditures (Guenther (2022)).

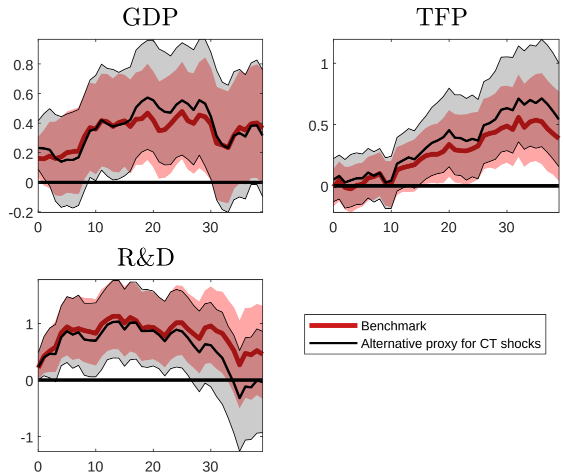
Figure K.7: Response of real GDP, TFP and R&D: Different Specifications




Notes: 90% bands for the Bayesian local projection model described in section 2 are shown in pink, together with the point estimates from various alternative specifications. These include: (i) changing the number of lags used as control variables, (ii) adjusting the prior, (iii) including the Ramey (2011) defence news shock as a control, (iv) changing the ordering of the tax shocks. See text for more discussion.

**Changes introduced by the TCJA.** The TCJA introduced a major change to the tax treatment of REEs, effective for tax years beginning after December 31, 2021 (i.e., after the end of our sample). The key change was the repeal of the option to expense REEs. Companies are now required to capitalise all REEs and amortize them over a specified period: 5 years for domestic research expenditures and 15 years for foreign research expenditures. The TCJA did not make any significant changes to the tax treatment of acquired intangibles. These assets continue to be amortized over 15 years under Section 197 of the IRC. The changes to the REE expensing regime were reversed (for domestic R&D) with the passage of P.L. 119-21 in July 2025.

Figure K.8: Response of real GDP, TFP and R&D to corporate tax shocks using alternative instrument



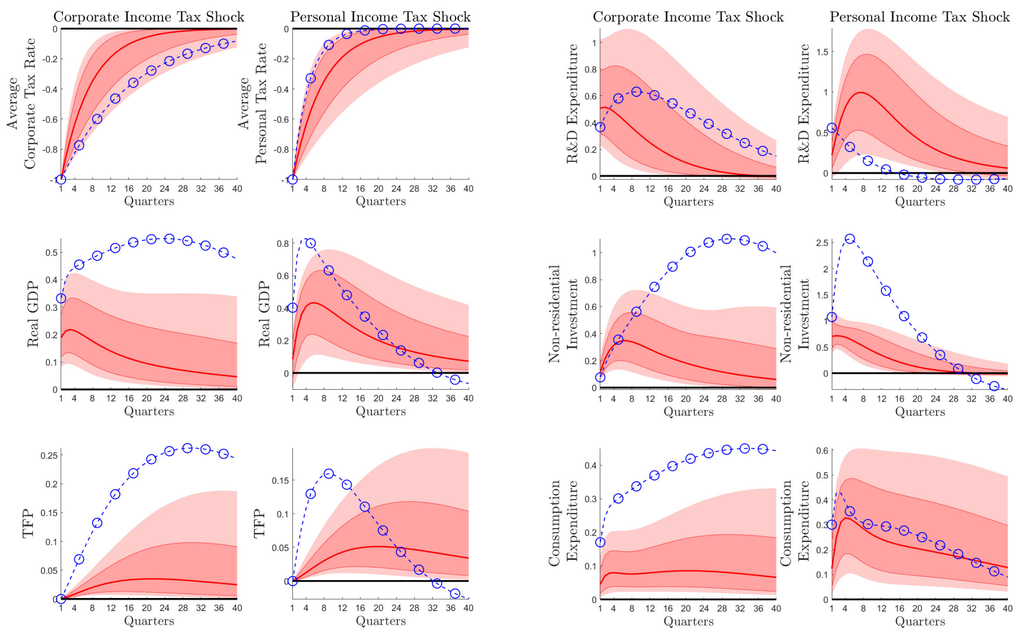

Notes: 90% bands for the baseline empirical real GDP result are shown in pink. The error bands for the alternative model are in Grey See text for more discussion.

# M Prior Predictive Analysis

Prior predictive analysis involves drawing a candidate $\Upsilon_i$ from the marginal prior distributions of the parameters. For each candidate $\Upsilon_i$, the associated set of IRFs, $\Phi(\Upsilon_i)$, are computed. This is repeated 100,000 times, thereby generating a distribution of impulse responses.[5] Prior predictive analysis allows us to elicit a number of useful insights. First, we can see the range of different possible outcomes that the model is likely to generate given our prior distributions. Second, we can see what our priors imply about the shorter and longer-term effects of tax changes. In Appendix Figure M.1, we report the distributions of the model impulse responses implied by our prior distributions. The light and dark shaded red areas report the central 68% and 90% prior credible sets of the IRF *prior* distribution. The blue line with circles refers to the impulse responses of the model evaluated at the estimated *posterior* median of the parameters. The main takeaway from this exercise is that our prior distributions give far more weight to an economy in which the effects of both personal and corporate income taxes are quite short-lived and productivity is virtually a-cyclical. As shown in Section 5, however, the posterior distributions paint a quite different picture.

[5]For more details on prior predictive analysis, we refer interested readers to Leeper et al. (2017).

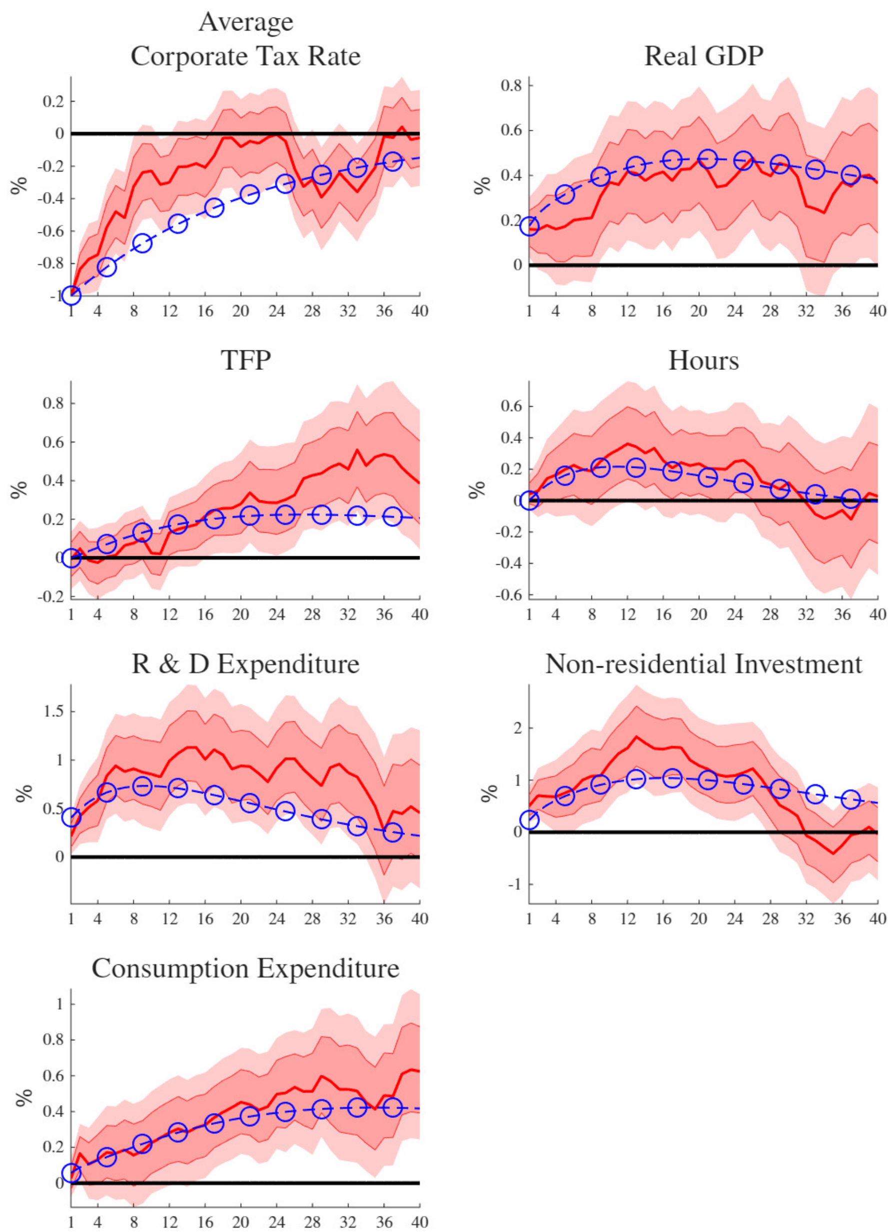
Figure M.1: Prior and Posterior Distributions of the response of the main variables in the model




Notes: this figure shows the response of the average tax rates, real GDP, productivity, consumption, investment, and R&D to a 1% cut in the average tax rate of corporate income taxes (left column) and the average tax rate of personal income taxes (right column). Red shadow bands and solid lines represent the $90^{th}$ and $68^{th}$ percentiles of the prior distribution of impulse response functions. Blue lines with circles represent the impulse responses of the model in Section 4 evaluated at the posterior median of estimated model parameters.

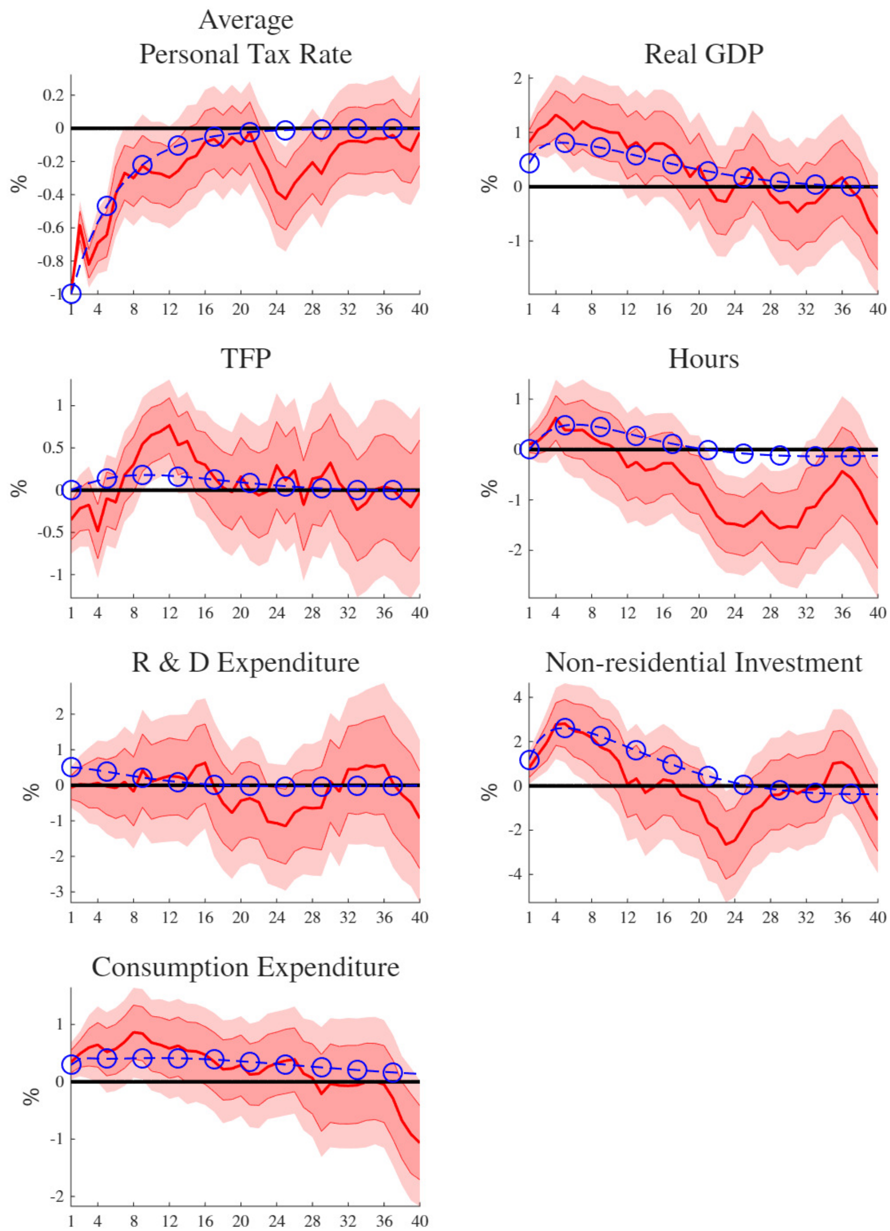
# N The Effects of Income Tax Changes in the Estimated Model

Figure N.1: Responses to Corporate Income Tax Changes




Notes: responses to a 1% cut in the corporate income tax rate. Red shadow bands represent central posterior credible sets. Blue lines with circles represent the estimated structural model impulse responses.

Figure N.2: Responses to Personal Income Tax Changes




Notes: responses to a 1% cut in the personal income tax rate. Red shadow bands represent central posterior credible sets. Blue lines with circles represent the estimated structural model impulse responses.

In Figure N.2, we report that personal income tax changes are typically short-lived and their significant effects on GDP and TFP tend to disappear by the time the shock reverts to zero, after about three to four years. The response of R&D expenditure is modest and insignificant at all times.

# O Model Appendix

## O.1 Production Sector and Endogenous Productivity

There exists a continuum of measure $A_t$ of monopolistically competitive intermediate goods firms. Each of them manufactures a differentiated product: intermediate goods firm $i$ produces output

$Y_{i,t}$. The endogenous state variable $A_t$ is the mass of intermediate goods adopted in production (equivalently, the stock of adopted technologies). As detailed in the text, $A_t$ grows as a result of expenditures on applied research, which we call adoption. The final goods composite is the following CES aggregate of individual intermediate goods, with $\theta > 1$:

$$Y_t = \left( \int_0^{A_t} (Y_{i,t})^{\frac{1}{\theta}} \, di \right)^{\theta} \tag{45}$$

Let $K_{g,i,t}$ be the stock of capital that firm $i$ uses, $U_t$ denotes capital utilization (described below), and $L_{g,i,t}$ represents the stock of labor employed. Firm $i$ produces output $Y_{i,t}$ according to the following Cobb-Douglas technology:

$$Y_{i,t} = (U_t K_{i,t})^{\alpha} (L_{i,t})^{1-\alpha} . \tag{46}$$

Given a symmetric equilibrium for intermediate goods, the aggregate production function is:

$$Y_t = A_t^{\theta-1} \cdot (U_t K_{g,t})^{\alpha} (L_{g,t})^{1-\alpha}. \tag{47}$$

$L_{g,t}$ and $K_{g,t}$ are aggregate capital and labor employed in the goods production sector.

## O.2 Households and the Corporate Sector

The representative household consumes, supplies labor, saves and receives dividends from the corporate sector (described below). There is habit formation in consumption. The model differs from the standard setup in the specification of labor supply. There are three types of labor: goods production ($g$), R&D ($z$) and adoption labor ($a$). Households supply the three types of labor competitively but choose hours $H_{j,t+1}$ one period in advance, and face a quadratic adjustment cost when changing hours. Following the realization of uncertainty in period $t$, the household chooses effort, $e_{j,t}$, and we assume that the effective labor supply is given by $L_{j,t} = H_{j,t} e_{j,t}$. The household's maximization problem and budget constraint are:

$$\max_{C_t, S_{t+1}, H_{j,t+1}, e_{j,t}} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left\{ \log \left( \frac{C_t}{N_t} - b \frac{C_{t-1}}{N_{t-1}} \right) - \sum_{j \in \{g,a,z\}} \frac{1 + \bar{e}_j e_{j,t}^{1+\chi_j}}{1 + \chi_j} \frac{H_{j,t}}{N_t} \right\}, \tag{48}$$

and

$$C_t + P_{S,t} S_{t+1} = \sum_{j \in \{g,a,z\}} \left[ (1 - \tau_{p,t}) \, w_{j,t} e_{j,t} H_{j,t} - \frac{\psi_j}{2} \left( \frac{H_{j,t+1}}{(1 + g_n) \, H_{j,t}} - 1 \right)^2 \Psi_t \right] + T_t + S_t \left( P_{S,t} + D_t \right), \tag{49}$$

where $C_t$ is consumption, $S_t$ are shares in the corporate sector (which trade at price $P_{S,t}$), $D_t$ are dividends from the corporate sector, $w_{j,t}$ are real wages, and $T_t$ are government transfers.[6] The symbol $\Psi_t$ denotes a scaling factor that grows at the same rate as aggregate output, required to ensure that labor adjustment costs do not vanish along the balanced growth path. The household's investment decisions are managed on their behalf by a representative investment fund that invests in the physical capital stock (with associated quadratic adjustment cost), rents capital to intermediate goods firms, finances innovation costs, and chooses the rate of capital utilization in the goods sector, $U_t$, with associated cost $\nu(U_t) K_{g,t}$, where $\nu(U)$ is increasing and convex. The objective is to maximize lifetime dividends to households, discounted using the household's discount factor,

[6] Changes in dividend taxes are a small part of the personal income tax measure in the Mertens and Ravn (2013) data set. As a result, we abstract from explicitly modelling dividend taxes.

$\Lambda_{t,t+1}$. The investment fund owns all firms in the economy. Individual firms and innovators make the specific production, R&D and technological adoption decisions, as described earlier.

Dividends in period $t$ are given by overall corporate sector income minus corporate taxes due:

$$D_t = CI_t - \tau_{c,t} CI_t^{TAX}, \tag{50}$$

where $CI_t$ is net corporate income, which is GDP net of wages, investment and utilization:

$$CI_t = Y_t - \sum_{j \in \{g,a,z\}} \left[ w_{j,t} L_{j,t} + I_{j,t} \left( 1 + f_j \left( \frac{I_{j,t}}{(1+g_y) I_{j,t-1}} \right) \right) \right] - \nu (U_t) K_{g,t} \tag{51}$$

$\tau_{c,t}$ is the corporate income tax rate and $CI^{TAX}$ is corporate income minus deductions for depreciation and amortization. As with intellectual property assets (described above), we follow Auerbach (1989), Mertens and Ravn (2011) and Winberry (2021) in modelling depreciation allowances for the capital stock as a geometric process: in every period, a fraction $\hat{\delta}$ of investment can be deducted from taxable profits, with the remaining portion 1-$\hat{\delta}$ carried into the next period. Details of the derivation of amortization allowances and taxable corporate income are in Appendix O.3.

**Factor demands.** Intermediate goods firm $i$ chooses capital services $U_t K_{i,t}$, and labor $L_{i,t}$ to minimize costs, given the rental rate $r_t^k$, the real wage $w_t$ and the desired markup $\varsigma$. Expressed in aggregate terms, the first-order conditions from firms' cost minimization problem are given by:

$$\alpha \frac{MC_t Y_t}{U_t K_{g,t}} = r_{g,t}, \tag{52}$$

$$(1-\alpha) \frac{MC_t Y_t}{L_{g,t}} = w_{g,t}, \tag{53}$$

where $MC_t$ is the real marginal cost of production. We allow the actual markup $\varsigma$ to be smaller than the optimal unconstrained markup $\theta$ due to the threat of entry by imitators, as is common in the literature (e.g Aghion and Howitt, 1998, Anzoategui et al., 2019).

**Investment good producers.** There are three types of capital goods in the economy, used in the goods-producing, R&D and adoption sectors. Competitive producers use final output to produce these goods which they sell to the investment fund, which in turn rents capital to firms. Following Christiano et al. (2005), we assume flow adjustment costs of investment for the three types of capital goods. The adjustment cost functions (for $j \in \{g,z,a\}$)are $f_j \left( \frac{I_{j,t}}{(1+g_y) I_{j,t-1}} \right)$, with each function increasing and concave, with $f_x(1) = f_x^{'}(1) = 0$ and $f_x^{''}(1) > 0$; and $I_{j,t}$ is new capital of type $i$ produced in period $t$. The first-order conditions are:

$$\begin{aligned} Q_{j,t} = 1 + f_j \left( \frac{I_{j,t}}{(1+g_y) I_{j,t-1}} \right) + \frac{I_{j,t}}{(1+g_y) I_{j,t-1}} f_j' \left( \frac{I_{j,t}}{(1+g_y) I_{j,t-1}} \right) \\ -\beta \mathbb{E}_t \Lambda_{t,t+1} \left( \frac{1-\tau_{c,t+1}}{1-\tau_{c,t}} \right) (1+g_y) \left( \frac{I_{j,t+1}}{(1+g_y) I_{j,t}} \right)^2 f_j' \left( \frac{I_{j,t+1}}{(1+g_y) I_{j,t}} \right), \end{aligned} \tag{54}$$

where $Q_{j,t}$ is the price of type $j$ capital.

**Price Setting.** Nominal prices are set on a staggered basis following the Calvo adjustment rule. Denoting by $\xi_p$ the probability that a firm cannot adjust its price, by $\hat{\pi}_t$ the inflation rate and by $\widehat{mc}_t$ the marginal cost in log-deviation from steady state, the Phillips curve reads $\hat{\pi}_t = \kappa_p \widehat{mc}_t + \beta \mathbb{E}_t[\hat{\pi}_{t+1}]$ with slope $\kappa_p = \frac{(1-\xi_p \beta)(1-\xi_p)}{\xi_p}$.

**Fiscal Policy.** The government's budget constraint is given by:

$$\bar{G}\left(1+g_{y}\right)^{t}-T_{t}=\tau_{p,t}\left(\sum_{j\in\{g,a,z\}}w_{j,t}L_{j,t}\right)+\tau_{c,t}CI_{t}^{TAX}, \tag{55}$$

For simplicity, the government finances consumption using personal and corporate income taxes; lump sum taxes adjust to balance the budget every period. The process of tax rates $\tau_{c,t}$ and $\tau_{p,t}$

$$\log\left(\tau_{t}^{x}\right)=\left(1-\rho_{\tau x}\right)\bar{\tau}^{x}+\rho_{\tau x}\log\left(\tau_{t-1}^{x}\right)+\varepsilon_{t}^{\tau x}, \tag{56}$$

follows an AR(1) process in logs for $x\in\{c,p\}$, with $\rho_{\tau x}\in(0,1)$, and $\varepsilon_{t}^{\tau x}\sim N(0,1)$ is i.i.d..

**Monetary Policy.** The nominal interest rate $R_{n,t+1}$ is set according to a Taylor rule $R_{n,t+1}=\left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi}\left(\frac{L_t}{\bar{L}}\right)^{\phi_y}R_n\right)^{1-\rho^R}\left(R_{n,t}\right)^{\rho^R}$ where $R_n$ is the steady state nominal rate, $\bar{\pi}$ the target rate of inflation, $L_t$ total effective labor supply and $\bar{L}$ steady-state labor supply; $\phi_\pi$ and $\phi_y$ are the feedback coefficients on, respectively, the inflation gap and the capacity utilization gap, measured as in Anzoategui et al. (2019).

**Resource Constraint.** Finally, the aggregate resource constraint is given by:

$$Y_t=C_t+\sum_{j\in\{g,a,z\}}\left[\left(1+f_j\left(\frac{I_{j,t}}{(1+g_y)I_{j,t-1}}\right)\right)I_{j,t}+\frac{\psi_j}{2}\left(\frac{H_{j,t+1}}{(1+g_n)H_{j,t}}-1\right)^2\Psi_t\right]+\nu\left(U_t\right)K_t+\bar{G}\left(1+g_y\right)^t. \tag{57}$$

## O.3 Derivation of Taxable Corporate Income

Taxable corporate income is corporate income minus amortization and depreciation allowances for capital and intellectual property assets. To derive this, we start by defining corporate income:

$$\begin{aligned}CI_t=&\underbrace{Y_t-w_{g,t}L_{g,t}-r_{g,t}K_{g,t}-P_{a,t}\Delta A_t}_{\text{Goods-producing firms}}+\underbrace{\sum_{j\in\{g,a,z\}}\left(r_{j,t}K_{j,t}-Q_{j,t}I_{j,t}\right)-\nu\left(U_t\right)K_t}_{\text{Investment firm}}\\&+\underbrace{\sum_{j\in\{g,a,z\}}\left(Q_{j,t}I_{j,t}-I_{j,t}\left(1+f_j\left(\frac{I_{j,t}}{(1+g_y)I_{j,t-1}}\right)\right)\right)}_{\text{Capital-producing firms}}+\underbrace{P_{z,t}\Delta Z_t-w_{z,t}L_{z,t}-r_{z,t}K_{z,t}}_{\text{R\&D firms}}\\&+\underbrace{P_{a,t}\Delta A_t-w_{a,t}L_{a,t}-r_{a,t}K_{a,t}-P_{z,t}\Delta Z_t}_{\text{Adoption firms}},\end{aligned} \tag{58}$$

where $\Delta A_t\equiv A_{t+1}-\phi A_t$ and $\Delta Z_t\equiv Z_{t+1}-\phi Z_t$ are the measures of newly adopted and discovered technologies, respectively, such that the terms in red are the aggregate entry costs in the goods-producing and adoption sectors (which are equal to the aggregate revenues of the adoption and R&D sectors). Netting out terms, corporate income is given by:

$$CI_t=Y_t-\sum_{j\in\{g,a,z\}}\left[w_{j,t}L_{j,t}-I_{j,t}\left(1+f_j\left(\frac{I_{j,t}}{(1+g_y)I_{j,t-1}}\right)\right)\right]-\nu\left(U_t\right)K_{g,t}, \tag{59}$$

which is real output minus wages and the cost of investment in each of the goods-producing, adoption and R&D sectors, and utilization cost in the goods-producing sector. Consistent with the U.S. tax code, in the model firms deduct depreciation and amortization from taxable profits to arrive at taxable income. We model these allowances as a geometric process in which a fraction $\hat{\delta}$ of the value of investments can be deducted from profits each period. Denoting amortization allowances by $\Xi$, the laws of motion for aggregate allowances in capital and intellectual property products are given respectively by:

$$\Xi_{IP,t+1} = \left(1 - \hat{\delta}_{IP}\right)\left(\Xi_{IP,t} + P_{Z,t}\Delta Z_t + P_{A,t}\Delta A_t\right) \tag{60}$$

$$\Xi_{K,t+1} = \left(1 - \hat{\delta}_K\right)\left(\Xi_{K,t} + \sum_{j\in\{g,a,z\}} Q_{j,t} I_{j,t}\right) \tag{61}$$

Depreciation allowances at $t+1$ are $1 - \hat{\delta}_\bullet$ times the sum of depreciation allowances at $t$ and the value of new investments in the three types of capital and the two types of intellectual property products. Using this notation, taxable corporate income is:

$$CI_t^{TAX} = CI_t + \nu\left(U_t\right) K_{g,t} - \hat{\delta}_K \left(\Xi_{K,t} + \sum_{j\in\{g,a,z\}} Q_{j,t} I_{j,t}\right) - \hat{\delta}_{IP}\left(\Xi_{IP,t} + P_{Z,t}\Delta Z_t + P_{A,t}\Delta A_t\right) \tag{62}$$

To arrive at taxable corporate income, we add back a non-deductible expense (capital utilization) and subtract the depreciation allowances that reduce the corporate sector tax liabilities.

# P Long-run elasticities

In the paper, we study responses to *temporary* tax changes. In this Appendix, we examine the model's ability to generate plausible magnitudes in response to *permanent* tax changes. For this purpose, we use our estimated model (Table 2) to compute the elasticities of the stock of knowledge ($Z$) to a 1% permanent change in the marginal rates on corporate and personal taxes, and compare them to the estimates reported in Akcigit et al. (2021).

Table P.1: Long-run elasticity of innovation to permanent tax rate changes

| | Estimated Model | Literature |
|---|---|---|
| Corporate Income Tax | 1.71 | 1.98*** [1.50,2.46] |
| Top Personal Income Tax | 1.34 | 1.452*** [1.22,1.68] |
| Bottom Personal Income Tax | -0.17 | 1.668 [-0.69,4.03] |

Note: This table compares the effects of permanent tax shocks on the stock of unadopted technology ($Z$) in our estimated structural model to the effects on patents reported in Akcigit et al. (2021), Table 3, panel A (corporate – corp. MTR – and top personal income tax – MTR90) and Table C8 (bottom personal income tax – MTR50). Innovation workers pay the highest personal income tax in the model, while workers in the goods production sector pay the bottom personal income tax. The first column reports elasticities implied by the estimated model (see Table 2). The second column reports the estimates in Akcigit et al. (2021). As in that paper, elasticities are computed with respect to the 'keep' rate (1-tax rate).

Our findings are reported in Table P.1. The first row reports elasticities to a 1% permanent change in the marginal corporate tax rate, whereas the second (third) row refers to a 1% permanent change in the marginal personal tax rate at the top (bottom) of the income distribution. The first column refers to the elasticities implied by the estimated model, where scientists (workers) exemplify top (non-top) earners. The second column reports the elasticities of patents in Akcigit et al. (2021), who exploit historical variation across U.S. states to estimate the effects of permanent changes in marginal tax rates.

For the marginal tax rates on corporate income and top personal incomes (the first two rows), our baseline structural model generates elasticities of the stock of knowledge that are within the 95% intervals for patent elasticities estimated by Akcigit et al. (2021). The model also predicts that patents should not move much following a tax rate change at the bottom of the income distribution, which is consistent with the insignificant coefficient estimated by Akcigit et al. (2021).

# Q Social Returns to R&D

The social returns to innovation are calculated as the return in additional units of consumption relative to the balanced growth path of reallocating one unit of output from consumption to R&D today, and consuming the proceeds in the future. In our model, the future proceeds from an increase in R&D today are the sum of the two components in the Jones and Williams (1998) calculation, plus a novel dimension due to the adoption margin: (i) the additional output generated, (ii) the future reduction in R&D such that the subsequent stock of unadopted technologies is unchanged, and (iii) the future reduction in adoption expenditure such that the subsequent stock of adopted technologies is unchanged.

Following Jones and Williams (1998), the production function for new unadopted technologies is given by a function $G$ of research efforts and the stock of unadopted technologies:

$$Z_{t+1} - \phi Z_t = G\left(X_{z,t}, Z_t\right) = Z_t^{1+\zeta} X_{z,t}^{\rho_z}$$

The increase in technology associated with a marginal change in research effort is

$$\nabla Z_{t+1} = \left(\frac{\partial G}{\partial X_z}\right)_t,$$

where $\nabla$ denotes the change relative to the balanced growth path. Note that $X_{z,t}$ is in units of the R&D good, which is produced using R&D labor and capital. Denoting by $P_{Xz,t}$ the price of this composite good, 1 unit of consumption yields $P_{Xz,t}^{-1}$ units of the R&D good. Since we are computing the return in terms of consumption, the relative prices of R&D and adoption will be used in the calculation.

To determine how much consumption is gained in time $t+1$ from the reduction in R&D that returns $Z$ to its balanced growth path, note that $Z_{t+2} - \phi Z_{t+1} = G\left(X_{z,t+1}, Z_{t+1}\right)$ and that the deviation of $Z$ from its balanced growth path is given by:

$$\nabla Z_{t+2} = \nabla Z_{t+1} + \left(\frac{\partial G}{\partial X_z}\right)_{t+1} \nabla X_{z,t+1} + \left(\frac{\partial G}{\partial Z}\right)_{t+1} \nabla Z_{t+1}$$

where the terms are, respectively: the deviation in $Z$ occasioned by the increase in research effort; the reduction in $Z$ from a cut in research effort; and the change in research efficiency as a result of additional technologies. The gain in consumption from returning $Z$ to its balanced growth path is found by setting $\nabla Z_{t+2} = 0$:

$$\nabla X_{z,t+1} = -\frac{\left(\frac{\partial G}{\partial X_z}\right)_t}{\left(\frac{\partial G}{\partial X_z}\right)_{t+1}}\left(\left(\frac{\partial G}{\partial Z}\right)_{t+1} + 1\right).$$

Following the same logic, the change in adopted technologies at $t+1$, which determines the change in output, is given by $A_{t+2} - \phi A_{t+1} = \phi \lambda_t (Z_{t+1} - A_{t+1})$.

Note that, because there is a one period delay between when technologies are discovered and when adopters can start working to adopt them, the initial change in R&D affects the stock of adopted technologies, and therefore output, at time $t+2$. Defining $\nabla A_{t+2}$ as the deviation in adopted technologies from the balanced growth path,

$$\nabla A_{t+2} = \nabla Z_{t+1}\frac{\partial A_{t+2}}{\partial Z_{t+1}} = \nabla Z_{t+1}\left(\phi\left((Z_{t+1} - A_{t+1})\left(\frac{\partial \lambda}{\partial Z}\right)_{t+1} + \lambda\right)\right).$$

The change in technologies has two components: (i) an increase in $Z_t$ increases adoption efficiency, so any technology is more likely to be adopted; (ii) $\lambda \nabla Z_{t+1}$ extra technologies are adopted. At $t+2$, the contribution to output of these additional technologies is given by $\nabla Y_{t+2} = \left(\frac{\partial Y}{\partial A}\right)_{t+2} \nabla A_{t+2}$ Furthermore, at $t+2$, the deviation in the stock of adopted technologies is given by:

$$\nabla A_{t+3} = \nabla A_{t+2} + \left(\frac{\partial \lambda}{\partial X_a}\right)_{t+2} \nabla X_{a,t+2},$$

and as with R&D, we compute the reduction in adoption expenditure that returns the economy to the balanced growth path by solving for the value of $\nabla X_{a,t+2}$ such that $\nabla A_{t+3} = 0$:

$$\nabla X_{a,t+2} = -\frac{\nabla A_{t+2}}{\left(\frac{\partial \lambda}{\partial X_a}\right)_{t+2}}$$

Grouping all terms, the social return to R&D is given by

$$1 + \tilde{r}_{RD} = \beta^2 \left(\frac{\partial Y}{\partial A}\right)_{t+2} \frac{\nabla A_{t+2}}{P_{Xz,t}} + \beta^2 \frac{P_{Xa,t+2}}{P_{Xz,t}} \frac{\nabla A_{t+2}}{\left(\frac{\partial \lambda}{\partial X_a}\right)_{t+2}} + \beta \frac{P_{Xz,t+1}}{P_{Xz,t}} \frac{\left(\frac{\partial G}{\partial X_z}\right)_t}{\left(\frac{\partial G}{\partial X_z}\right)_{t+1}} \left(\left(\frac{\partial G}{\partial Z}\right)_{t+1} + 1\right),$$

where $\beta$ and $\beta^2$ terms appear because the gains happen at different times, and each of the terms is scaled by the relative price of the R&D goods at $t$ and $t+1$ or the adoption good at $t+2$, which converts all terms into units of consumption in the given time period, relative to price of R&D goods at time $t$. Defining the social cost of a new idea in units of consumption as $\tilde{P}_{Z,t} = \left(\frac{\nabla Z_{t+1}}{P_{Xz,t}}\right)^{-1}$, and $g_{\tilde{P}Z}$ as the growth rate of the social cost, and $\tilde{d}_t = \frac{\beta}{\tilde{P}_{Z,t}}\left(\beta \frac{\partial A_{t+2}}{\partial Z_{t+1}}\left(\left(\frac{\partial Y}{\partial A}\right)_{t+2} + \frac{P_{Xa,t+2}}{\left(\frac{\partial \lambda}{\partial X_a}\right)_{t+2}}\right) + \tilde{P}_{Z,t+1}\left(\frac{\partial G}{\partial Z}\right)_{t+1}\right)$, we obtain the expression in the main text,

$$\tilde{r}_{RD} = \frac{\tilde{d}_t}{\tilde{P}_{Z,t}} + g_{\tilde{P}Z}. \tag{63}$$

The "social dividend" of R&D has three components: the increase in output, the decrease in adoption expenditures, and the change in the efficiency of R&D. The social return on R&D is a function of (i) model parameters, namely $g_n$ (the population growth rate) and $\beta$ (the discount factor), plus the parameters of the endogenous growth block of the model ($\theta$, $\rho_z$, $\rho_\lambda$, $\phi$, $\zeta$, $\bar{\lambda}$; see Tables 1 and 2 for definitions); and (ii) the expenditure shares of R&D and adoption, which are in turn also functions of parameters, including the tax parameters ($\hat{\tau}_c$, $\hat{\delta}_{IP}$, and to a lesser extent $\hat{\tau}_p$ and $\hat{\delta}_K$).

Endowed with Equation (63), we use the posterior distributions in Table 2 to calculate the social returns to R&D implied by our structural model. We estimate that the social returns to investment in innovation, $\tilde{r}_{RD}$, range from 20.8% to 74.5% (95% confidence level), with a posterior median of 35.9%. Excluding the consumption gains to adoption from the social dividend lowers this interval to [14.9%,40%] with a median value of 22%, highlighting the importance of the complementarity between R&D and adoption in determining the social returns to innovation.

# R Estimates of the model with no endogenous growth

This section reports the prior and posterior distributions of the parameters in the structural model's restricted specification, excluding technological adoption and R&D expenditure. The main difference relative to Table 2 is that the investment adjustment cost parameter is significantly higher than the estimates based on the model with endogenous growth. Furthermore, and in sharp contrast to Table 2, the estimate of this parameter in Table R.1 is in line with the available estimates in the business cycle literature on DSGE model (see for instance Smets and Wouters, 2007, Justiniano et al., 2010), which typically assume an exogenous growth path.

Table R.1: Estimated Parameters - No technological adoption or R&D spending

| Parameter | Description | Prior | | | Baseline | | No Adoption | | No R&D | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Distr | Mean | Std. Dev. | Median | 90% int. | Median | 90% int. | Median | 90% int. |
| **Preference & HHs** | | | | | | | | | | |
| $h$ | Consumption habit | beta | 0.5 | 0.2 | 0.34 | [0.12, 0.59] | 0.41 | [0.15, 0.66] | 0.48 | [0.2, 0.72] |
| $\chi_g$ | Inverse effort elasticity (goods) | gamma | 1 | 0.5 | 0.47 | [0.22, 0.93] | 0.44 | [0.19, 0.89] | 0.47 | [0.22, 0.96] |
| $\chi_a$ | Inverse effort elasticity (adoption) | gamma | 1 | 0.5 | 0.67 | [0.29, 1.4] | - | - | - | - |
| $\chi_z$ | Inverse effort elasticity (R&D) | gamma | 1 | 0.5 | 2.04 | [1.37, 3.04] | 0.2 | [0.06, 0.56] | - | - |
| **Frictions & Production** | | | | | | | | | | |
| $f_a''$ | Adoption adjustment | normal | 4 | 1.5 | 3.86 | [1, 6.4] | - | - | - | - |
| $f_z''$ | R&D adjustment | normal | 4 | 1.5 | 3.33 | [0.82, 5.87] | 4.59 | [2.13, 6.96] | - | - |
| $f_I''$ | Investment adjustment | normal | 4 | 1.5 | 0.36 | [0.05, 0.94] | 0.31 | [0.04, 0.84] | 1.62 | [0.88, 2.66] |
| $\nu''$ | Capital utilization adjustment | beta | 0.6 | 0.15 | 0.74 | [0.66, 0.82] | 0.65 | [0.56, 0.75] | 0.52 | [0.44, 0.6] |
| $\xi_p$ | Calvo prices | beta | 0.5 | 0.2 | 0.2 | [0.07, 0.33] | 0.18 | [0.06, 0.31] | 0.16 | [0.06, 0.3] |
| **Endogenous Technology** | | | | | | | | | | |
| $\theta$-1 | Dixit-Stiglitz parameter | gamma | 0.15 | 0.1 | 0.58 | [0.43, 0.79] | 0.39 | [0.23, 0.65] | - | - |
| $\rho_\lambda$ | Adoption elasticity | beta | 0.5 | 0.2 | 0.78 | [0.66, 0.87] | - | - | - | - |
| $\rho_Z$ | R&D elasticity | beta | 0.5 | 0.2 | 0.2 | [0.12, 0.29] | 0.67 | [0.48, 0.86] | - | - |
| **Shocks** | | | | | | | | | | |
| $\rho_{\tau,c}$ | Corporate taxes AR | beta | 0.85 | 0.07 | 0.95 | [0.95, 0.96] | 0.94 | [0.93, 0.95] | 0.95 | [0.94, 0.95] |
| $\rho_{\tau,p}$ | Labour taxes AR | beta | 0.85 | 0.07 | 0.83 | [0.8, 0.85] | 0.83 | [0.81, 0.85] | 0.86 | [0.84, 0.88] |

## S Sectoral Evidence

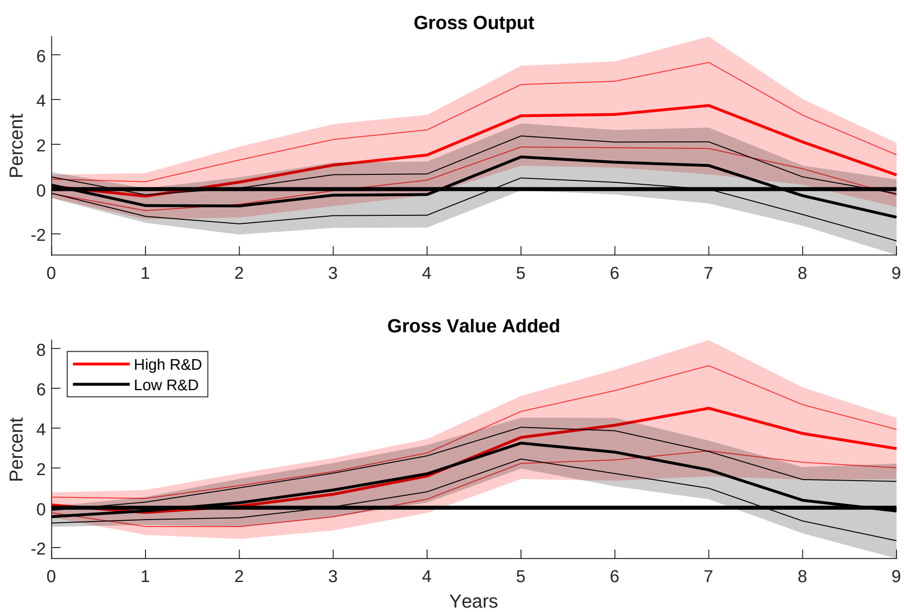
We consider the impact of corporate income tax shocks on Gross Output and Gross value added in 28 industries using BEA sectoral annual data. Our goal is to investigate whether the effects of corporate taxes are different for industries classified as R&D intensive. We adopt a simple approach and estimate the following frequentist panel LPIV model for high- and low-R&D intensive sectors:

$$Z_{i,t+h}^{K} = c_i^{(h)} + \beta^{(h)}\tau_{ct,t} + \theta^{(h)}\epsilon_{pt,t} + b^{(h)}X_{t-1} + u_{i,t+h}$$

where $K$ denotes either the low- or high-R&D intensity group of industries. High R&D intensity is defined as sectors where the time-average of R&D intensity is above the median across all industries. $i = 1, \dots, N$ indexes the $N$ sectors in each group and $t$ denotes the time dimension. The model allows for fixed effects and uses the narrative measure of Mertens and Ravn (2013) of corporate tax changes to instrument the tax rate $\tau_{ct}$. We control for personal tax shocks by adding the narrative measure for personal tax shocks $\epsilon_{pt,t}$ as a contemporaneous control. We add a lag of the dependent variable, real GDP, debt to GDP ratio, the two tax rates and aggregated version of the principal component as lagged controls $X$. The model also includes a dummy variable that equals 1 in 2008 and 2009 to account for the Great Financial Crisis. The confidence intervals are based on Driscoll and Kraay (1998) standard errors. Solid lines refers to median estimates while shaded areas represent 68% and 90% confidence intervals.

In Figure S.1, we report the dynamic effects of a corporate tax cut on Gross Output (top panel) and Gross Value Added (bottom panel) in the two groups of industries. The medium-term response of the high-R&D sectors, in red, is larger and more persistent than the change among low-R&D industries, in black, at horizons beyond 5 years.

Figure S.1: GO and GVA responses to corporate tax shocks by high- and low-R&D intensity sectors




Notes: 68% (90%) bands are shown as the lines and shaded area, respectively. The response to a 1% cut in the average corporate tax rate is displayed in red for high-R&D intensity sectors and in black for low-R&D intensity industries.