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ABSTRACT

Using a narrative identification of tax changes in the United States over the period 1950-2019, we document that a temporary cut in corporate income tax rates leads to a long-lasting increase in innovation and productivity. An estimated endogenous productivity model reveals that the long period of tax amortization for the purchases of Intellectual Property Products (IPP) featured in the US tax code over most of the sample is crucial to account for this finding. We provide direct evidence on the model mechanism by showing that a temporary corporate tax cut generates a more pronounced jump in the share prices of patent-rich firms, leading to a persistent increase in R&D expenditure, non-R&D IPP investment, patents and trademark assignments.

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1 Introduction

The last two decades have witnessed a dismal record of productivity growth in advanced economies. In response, many governments have pursued an array of policy interventions, from public spending on education, R&D subsidies, income tax cuts, and infrastructure investment to industrial policies. However, little is known about the effects of these policies on aggregate productivity in the data. This is all the more surprising given the large empirical literature on fiscal policy spurred by the 2007-2009 crisis, which mostly focuses on the ability of public spending and taxation to stimulate GDP in the short run.

This paper provides empirical evidence for the U.S. that corporate income tax cuts have medium-term effects on productivity through innovation. Corporate tax changes can exert direct and indirect effects on Research and Development (R&D). The direct effect is governed by the tax treatment of R&D expenditure: under full and immediate deductibility, as over most of our sample, the direct effect is zero. The indirect effect is driven by the tax treatment of Intellectual Property Purchases (IPP) such as patents, trademarks, and brands, which can be bought, sold, and licensed: under a long period of tax amortization, as during most of the post-WWII era, the indirect effect can be large. Whenever the law does not provide for full expensing of IPP purchases, corporate taxes depress the present value of after-tax profits accruing to IPP and thus lower their market value. However, a cut in corporate income taxes reduces this intertemporal distortion, thereby boosting the market value of firms' intangible assets. This encourages innovation, whose non-rivalrous nature triggers the increasing aggregate returns that eventually lead to significant medium term effects on productivity and output.

Our empirical analysis begins by revisiting the transmission of tax shocks in Romer and Romer (2010) and Mertens and Ravn (2013). We departure from these important studies along three main dimensions. First, we focus on productivity and innovation. Second, we look at horizons beyond business-cycle frequencies. Third, we extend their narrative sample to 2019, following the analyses in Liu and Williams (2019) and Mertens (2018). We find that a temporary cut in corporate income taxes triggers a sustained but transitory expansion in capital and R&D expenditure. This causes a medium-term increase in patenting, productivity and output, which lasts much longer than the corporate tax cut itself.

We interpret our empirical findings through the lens of an estimated endogenous productivity model. Counterfactual simulations reveal a novel channel for the transmission of tax shocks. Two ingredients appear essential to generate long-lasting effects of corporate income tax changes: (i) increasing aggregate returns (from innovation); (ii) a long period of tax amortization on Intellectual

Property Products (IPP) purchases. A cut in corporate income taxes leads to a jump in the market price of IPP, which, in turn, encourages firms to innovate more by investing in R&D. This is the case even though in the model R&D is subject to immediate and full expensing, consistent with the U.S. tax code over most of our sample. We provide direct firm-level evidence for the mechanism highlighted by our model. On impact, the share prices of the most patent-rich companies increase more than the share prices of firms with fewer patents. At business cycle frequencies, R&D spending, non-R&D IPP investment and firm-to-firm trade in intangibles all increase following a cut in corporate income taxes. This leads to significant medium-term effects on patenting, productivity and eventually output.

Our estimated effects are economically significant. A 1% cut in the corporate tax rate that reverts to zero after 4 years leads to a significant increase in productivity of 0.5% after 8 years. Using Compustat, we calculate that, in 2023, physical capital expenditures and depreciation accounted for 6.4% and 4.4% of GDP whereas intangible expenditures and amortization were 5.5% and 1.3%. In words, intangible investments and their overlooked tax amortization have a similar incidence on firms' balance sheets than physical capital expenditures and their well-understood tax depreciation. But while bonus depreciation is a popular tax policy tool, accelerated amortizations are rarely used, if ever, as fiscal stimulus.

The amortization of intangible assets is a salient feature of the tax system of many advanced and emerging economies (Appendix A). Furthermore, the tax amortization life of some of those assets, such as purchased patents, varies between 10 and 25 years, while for the U.S. is 15 years. This implies that the novel mechanism put forward in this paper might be not only at play around the world but also that the effects of international changes in corporate income taxes on innovation and productivity may be even larger than the one we estimate in this paper 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), and including many more recent studies in the macroeconomic and accounting tradition (e.g. Shevlin et al., 2019), estimate the short-term response of GDP to tax shocks. However, these contributions do not look at productivity and R&D expenditure, nor at the responses of macro variables at long 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) 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 a lack of full expensing encourages firms to invest more after a corporate tax cut. A key distinction, however, is that capital expenditure is associated with a diminishing marginal product, whereas intangible purchases generate increasing aggregate returns. This implies that if intangible investment was fully expensed but capital investment was not, corporate tax cuts would generate no medium-term effects. In contrast, if capital expenditure was fully expensed but intangible purchases were not, then corporate tax cuts would still have a significant medium-term impact. As we show below, this holds even if R&D is fully expensed for tax purposes.

Several recent studies focus on the link between tax changes and innovation. Jaimovich and Rebelo (2017) develop an endogenous growth model in which the effects of taxation on growth are non-linear. Jones (2022) studies optimal taxation for top earners in a model where innovation cannot be perfectly targeted by subsidies. Akcigit et al. (2022) 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 that changes in the tax incentives to R&D have a large impact on R&D and patenting. Cram and Olbert (2022) measure the impact of the 2021 global corporate tax reform on the stock prices of companies with different shares of intangible assets. We complement these studies by documenting the persistent effects of temporary corporate tax cuts on innovation and productivity.

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 (2022), Fieldhouse and Mertens (2023), examine the long-term effects of non-technology shocks working via hysteresis, financial frictions, monetary policy and government spending. A distinctive feature of our analysis 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 summarises the main findings and report an extensive sensitivity analysis in which we vary the sample, estimation method, specification and controls. In Section 4, we lay out an endogenous productivity model of the business-cycle with tax depreciation on physical capital, tax amortization on IPP and distortionary taxes on corporate and personal income. In Section 5, we estimate the structural model, while in Section 6 we provide further evidence on the novel mechanism highlighted by our analysis. Section 7 offers a discussion of our findings that aims to elicit 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 the data we use. Finally, we provide details of the estimation procedure.

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 tax 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 taxes 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 corporate/personal tax split 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 quasinatural experiments from historical episodes has a long tradition in macroeconomic research, as exemplified by Barro and Redlick (2011), Cloyne (2013), Mertens and Ravn (2012, 2014), Guajardo et al. (2014), Hayo and Uhl (2014), Cloyne and Surico (2017), Gunter et al. (2018), Nguyen et al. (2021), Hussain and Liu (2018), Cloyne et al. (2021).[1]

The literature on the effects of tax changes using narrative methods finds large effects on GDP, but typically these papers focus only on the shorter-term effects over 2 to 5 years and do not look at all at the response of productivity and innovation. A sizable part of the macroeconomic policy debate, however, has focused on the potential longer-term effects of tax reforms. Despite this, there is little direct evidence on whether fiscal policy can boost productivity, and policy recommendations often have to rely on inferring longer-term results from the short-run estimates in some of the papers referenced above.

The identification issue centres around the fact that the reduced form residuals are an unknown combination of all underlying structural shocks, ε_t, including the exogenous variation in tax policy. The goal is to identify the contemporaneous impact of a structural shock to taxes on the vector of reduced-form residuals u_t. The mapping from the reduced-form residuals in period t to the structural shocks can be written as:

$$u_t = A_0 \varepsilon_t \tag{1}$$

We follow Mertens and Ravn (2013) and use the narratively identified tax changes as proxies for the true structural variation in taxes. This is akin to using narrative shocks as instruments for observed tax policy changes. The identification restriction is that narrative shocks are uncorrelated with other structural shocks that may influence the economy, at least conditional on the lags of Z.[2] As discussed in Mertens and Ravn (2013), the two instruments are contemporaneously correlated (as corporate and personal 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. As in Mertens and Ravn (2013), we use a Cholesky factorization of the covariance matrix of the identified structural shocks and order last the tax rate being 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

[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 popularised 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] Stock and Watson (2018) call this lag-lead exogeneity. This is a form of weak exogeneity in which narrative shocks are identified as orthogonal to current and future economic shocks but can, in principle, reflect past events.

the ordering assumptions.

2.2 Econometric method

As for the empirical model, we need an econometric approach that allows us to draw inferences about medium-term effects. Recent work by Jordà et al. (2020) has shown that the longer-term effects of policy interventions tend to be incorrectly captured when impulse response functions (IRFs) are estimated using a traditional Vector Autoregression (VAR) approach with short lag lengths (as is common in the empirical macro literature on tax policies, which focuses on relatively short time series samples after WWII). This is because impulse responses are constructed as a projection from a fixed model using all the lags in the VAR. In finite samples, the lag structure has to be truncated and the VAR impulse response function at longer horizons will be sensitive to the number of lags included (as shown by Li et al., 2021). Jordà et al. (2020) recommend 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 afflict VAR methods in finite samples. For estimation, we use Bayesian methods, which provide an efficient way to compute and characterise joint and marginal posterior distributions.

One contribution of Mertens and Ravn (2013) is to introduce a methodology for treating the narratively identified tax changes derived from historical documents as potentially noisy "proxies" (or instruments) for the genuinely exogenous variation in tax policy (the "shock"). The Mertens and Ravn (2013) technology, however, is based on a vector autoregression framework. Accordingly, we begin from a structure close to Mertens and Ravn (2013) where the joint dynamics of a vector of observables Z can be described by a reduced form that includes all the lags of the variables in Z. This is the conventional starting point for a vector autoregression approach. To construct the impulse response function, however, we follow Jordà (2005) and estimate a sequence of local projections:

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

where Z_t denotes the M variables of interest described below, h is the impulse response horizon and u_{t+h} denote residuals. As discussed in Section 2.4, we allow for the possibility that the distribution of u_{t+h} is non-Gaussian.

Given the knowledge of the relevant elements of A_0, Jordà (2005) shows that the impulse response at horizon h can be calculated as $B_1^{(h-1)} A_0$. This has two main advantages for our purposes. First, the formulation 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. Second, the approach in Mertens and Ravn (2013) considers two types of tax changes using two instruments that are correlated. The two instruments identify a convolution of tax shocks, but we do not know the true causal relationship between the personal and the corporate income tax changes in the data. Mertens and Ravn (2013) consider different causal orderings when simulating their results from their proxy VAR. We implement the same approach here. This is our baseline model.[3]

However, several empirical studies do not estimate the contemporaneous impact matrix separately from the reduced form dynamics. Instead, the outcome variable is regressed directly on the instruments and control variables. In our setting, such a LP can be written as:

$$Z_{i,t+h} = c^{(h)} + \beta_{ct}^{(h)} \epsilon_{ct,t} + \beta_{pt}^{(h)} \epsilon_{pt,t} + b^{(h)} Z_{t-1} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{3}$$

where $\epsilon_{ct,t}$ ($\epsilon_{pt,t}$) denotes the narrative measure of corporate (personal) tax shocks of Mertens and Ravn (2013). We refer to Equation (3) as 'Direct' model because it treats the narrative measures as the structural shocks and the estimates of $\beta_{ct}^{(h)}$ ($\beta_{pt}^{(h)}$) provide the response to the corporate (personal) tax shock under the assumption that the contemporaneous impact on the personal (corporate) tax shock is zero.

One concern with this 'Direct' model is the fact that it does not take into account the possibility of measurement error in the narrative tax proxies. This can be dealt with by using an instrumental variable approach (LPIV) as in Jordà and Taylor (2015):

$$Z_{i,t+h} = c^{(h)} + \beta_i^{(h)} \tau_{j,t} + \theta^{(h)} \epsilon_{k,t} + b^{(h)} Z_{t-1} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{4}$$

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

[3] An alternative LP-IV setup would be: $\Delta^h Z_{t+h} = \alpha^h + \beta^h \Delta T_t + \Gamma^h X_{t-1} + u_{t+h}$ where Z are the same outcome variables of interest above, ΔT_t is the observed and potentially endogenous variation in tax policy (containing two tax variables) and X is a vector of controls, potentially including lagged values of Z. $\Delta^h Z_{t+h} = Z_{t+h} - Z_{t-1}$. ΔT_t would then be instrumented using the narrative "proxies" from Mertens and Ravn (2013). Because corporate and personal tax changes are correlated, we would need to be careful in comparing the coefficient estimates with those in Mertens and Ravn (2013) (who explicitly consider the relationship between the two taxes when simulating the IRFs). More generally, Stock and Watson (2018) and Plagborg-Møller and Wolf (2022) discuss the equivalence of LP-IV and proxy VAR methods. For transparency and completeness, we also implement a LP-IV approach in the robustness section.

control. In Section 3.2, we show that our results are robust to these alternative estimation strategies.

2.3 Data

In our benchmark specification, we use the data set in Mertens and Ravn (2013) extended to the sample 1950Q1-2019Q4. The control variables in the sequence of local projections (2) include four lags of the following seven 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)* $\ln(DEBT_t)$.[4] 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. Finally, $\ln\left(G_t\right)$ denotes government spending, $\ln(DEBT_t)$ stands for federal debt and GDP is represented by $\ln\left(GDP_t\right)$. All variables, except $APITR_t$ and $ACITR_t$, are expressed in real per capita terms.

An initial estimation of the structural tax shocks using the variables (i) to (vii) above for $h = 0$ reveals that the estimated personal tax rate shock can be predicted by the lags of a principal component (denoted PC_t) obtained from a large quarterly data set of macro and financial variables for the US economy.[5] Following Forni and Gambetti (2014), we add one lag of this principal component as a control variable in our LPs to ameliorate concerns about information insufficiency. We also include a dummy variable that equals 1 from 2008 Q3-2009 Q1 to account for volatility associated with the Great Financial Crisis. Note that, as in Mertens and Ravn (2013), any additional variables of interest (that we will consider below) are added one by one to the benchmark model. These are utilization-adjusted Total Factor Productivity (TFP), hours worked, Research and Development (R&D) expenditure, non-residential investment, personal consumption expenditures and real wages. In Appendix C, we provide a detailed description of the variables and data sources.

2.4 Estimation

We estimate the local projections in Equations (2) to (4) via Bayesian methods. The Bayesian approach offers three 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 LPs to estimate the structural

[4] Montiel Olea and Plagborg-Møller (2021) demonstrate that lag-augmented local projections are particularly well-suited to draw robust inference about impulse responses at long horizons. Furthermore, they show that lag augmentation obviates the need to correct standard errors for serial correlation in the regression residuals.

[5] The large data set is an extended version of 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 D

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:

$$Z_{t+h} = \beta^h X_t + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{5}$$

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 β_0 and an inverse Wishart *prior* for Ω_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 ν_j and variances σ_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 E, 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.[6]

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:

$$Z_{t+h} = \beta^h X_t + u_{t+h} \tag{6}$$

$$u_{t+h} = \epsilon_{t+h} + \theta_1 \epsilon_{t+h-1} + .. + \theta_q \epsilon_{t+h-q}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{7}$$

where we allow q to grow with the horizon. As ϵ_t is unobserved, the estimation of this model is computationally intensive. In Appendix J, we show that the IRFs estimated using (6) and (7)

[6] We provide details of the estimation algorithms in Appendix F.

corroborate our main findings.[7]

Finally, in the benchmark specification, the prior for β_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 F, we use a non-informative prior for the free elements of A and σ_j^2.[8]

As for the 'Direct' model in (3) that is used in one of the sensitivity analyses of Section 3.2, we present frequentist estimates based on OLS. For the LPIV in (4), we adopt instead the ridge estimator of Barnichon and Brownlees (2019) with smoothing parameter set via cross-validation.[9] In either case, we construct asymptotic confidence intervals using Newey and West (1987) HAC standard errors with the number of lags set so as to match the length of the IRF horizon.

3 Empirical results

In this section, we report the local projections estimates on the data described in the previous section. We begin by presenting novel evidence on the dynamic effects of a corporate income tax cut on productivity and R&D. Then, we revisit the evidence in Mertens and Ravn (2013) by extending their sample to 2019 and their forecast horizon of five years to a decade. Finally, we discuss further results and an extensive set of robustness exercises, which are reported in Appendices G to J.

3.1 Main findings

Using the approach outlined in Section 2, we present the estimates on productivity and R&D, before turning to the responses of GDP, investment, consumption and hours. Each additional variable is added to the benchmark vector Z one at a time to avoid a sharp increase in the number of estimated parameters. In Figure 1, we report the response of the corporate tax rate (left column), TFP (middle column) and R&D expenditure to a shock that reduces the corporate income tax rate by 1% on impact. The solid red lines are the posterior medians, and the shaded bands refer to 68% and 90% credible sets. Impulse response functions are computed using posterior draws of the coefficients

[7]Our results do not depend on the Bayesian approach. As we discuss in Section 3.2, frequentist LPs estimated via OLS or IV with confidence intervals based on HAC standard errors produce very similar results.

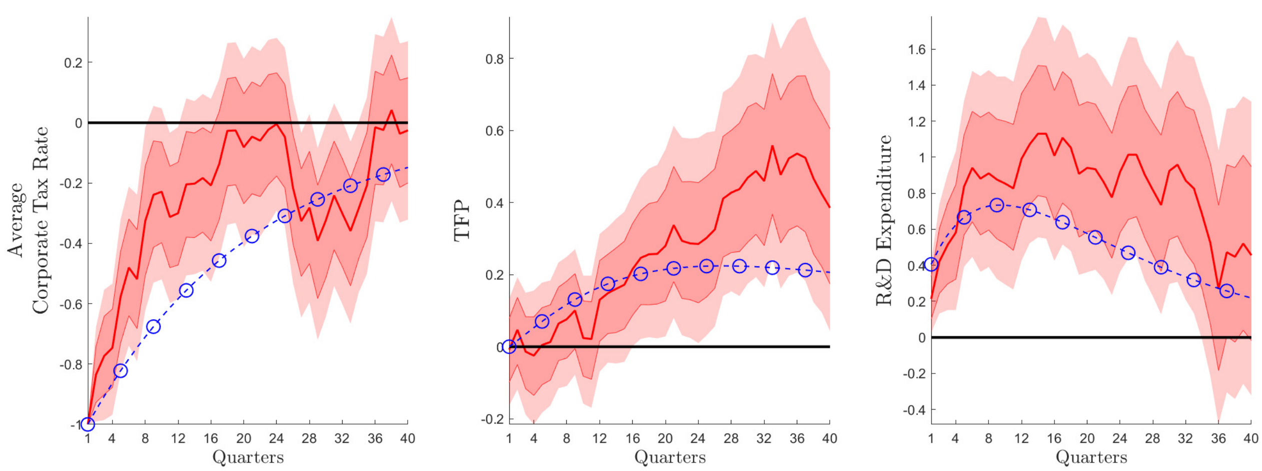
[8]Following Bańbura et al. (2010), we set the prior mean for β_h by running AR(1) regressions for each endogenous variable. The diagonal elements of the prior variance matrix corresponding to own lags p are defined as $\frac{\mu_1^2}{p^2}$ and as $\frac{s_i}{s_j}\frac{\mu_1^2}{p^2}$ for coefficients 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 μ_1 to 10 which implies a loose prior belief.

[9]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 J. Our main findings of a significant response of GDP and TFP at longer horizons are unaffected by these modifications.

A_0 and B_1. Solid blue lines come from the estimated structural model that will be presented and estimated in Section 5.

The left panel of Figure 1 reveals that the corporate tax shock is temporary and reverts to zero after a few years. In sharp contrast, the response of TFP is delayed: it is negligible for the first four years but then becomes significant and large, peaking at 0.5% after eight years. Finally, the effects on R&D are hump-shaped, as they start with a significant response, peak at 1.1% after four years and then revert to zero by the end of the decade. Two main findings emerge from Figure 1. First, although corporate income tax changes tend to be temporary, their effects on TFP are persistent and extend well beyond the duration of the tax change itself. Second, the responses of TFP and R&D are characterized by different dynamics: delayed for the latter and frontloaded for the former.

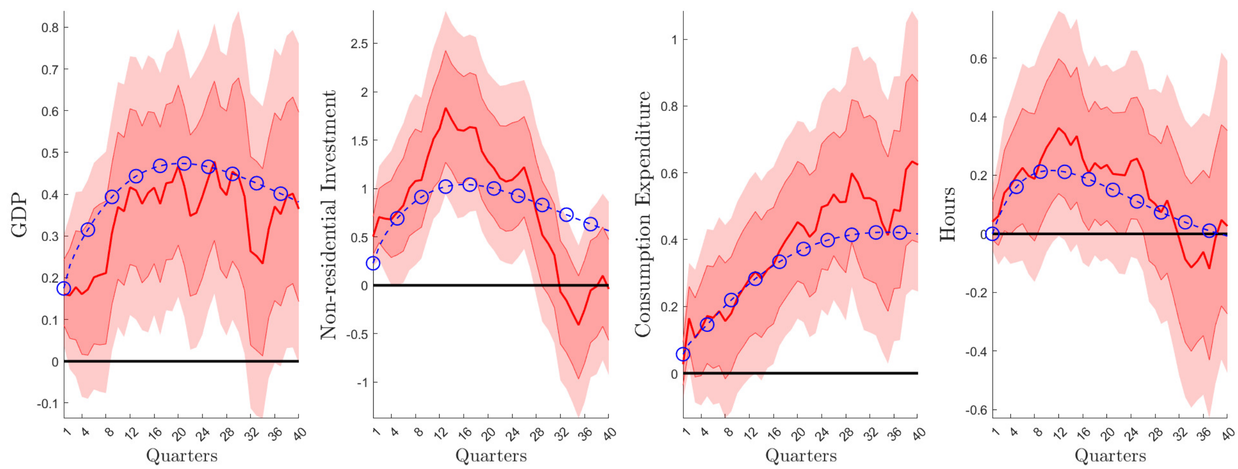
Figure 1: Response of the Tax Rate, TFP and R&D expenditure to a Corporate Income Tax Cut



Notes: this figure shows the responses of the average tax rates, TFP and R&D expenditure to a 1% cut in the corporate income tax rate. Red shadow bands represent central posterior 68^{th} and 90^{th} credible sets. Blue lines with circles represent the impulse responses of the model in Section 4 evaluated at the posterior median of estimated model parameters. These model-produced estimates will be discussed later in the text.

In Figure 2, we broaden the evidence in Figure 1 to GDP, investment, consumption and hours worked. This exercise is similar to Mertens and Ravn (2013), except that we extend their sample from 2006 to 2019 and their forecast horizon from 5 to 10 years, so as to study the effects of corporate tax changes over the medium-term. The left panels report the responses of GDP and investment whereas the last two columns refer to household expenditure and hours worked. Extending the horizon to a decade reveals that the effects of a temporary corporate tax cut on GDP are also long-lasting, with a significant estimate of 0.4% even after ten years. The response of investment in the second column resembles the one of R%D in Figure 1: it is hump-shaped, peaks after four years and revert to zero by the end of the horizon. The effects on consumption in the third column are also persistent and similar to GDP. In contrast, the response of hours worked is small and short-lived.

Figure 2: Responses of GDP, non-residential investment, household expenditure and hours worked



Notes: responses of R&D expenditure, non-residential investment and personal consumption expenditures 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 shadow bands represent central posterior 68^{th} and 90^{th} credible sets. Blue lines with circles represent the impulse responses of the model in Section 4 evaluated at the posterior median of estimated model parameters. These model-produced estimates will be discussed later in the text.

In Appendix G, we report a similar set of estimates for a personal income tax cut. The main finding is that, in sharp contrast to the effects of corporate tax changes, the responses of TFP and R&D expenditure are short-lived. As a result, the impact of a personal income tax cut on GDP, investment, hours worked and consumption is significant only during the first eight quarters after the shock and then becomes negligible, both statistically and economically, at horizons beyond three years. Given the lack of evidence for medium-term effects of personal tax changes, the estimates in Appendix G very much resembles the impulse responses by Mertens and Ravn (2013). Finally, in Appendix H, we show that corporate tax changes explain up to 25% of medium-term variation in productivity, 20% for GDP and 15% for investment and consumption.[10]

3.2 Sensitivity Analysis

In this section, we discuss the frequentist counterpart of the Bayesian IRFs of the previous section and provide evidence that these do not suffer from weak instruments. Then, we present the findings from a large range of sensitivity analyses where we alter the estimation method, the model specifications, details of the identification and the controls. None of our results is overturned by these

[10]In Appendix I, we report the IRFs to further labor market outcomes, fiscal deficit and public debt.

modifications.

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 (3) or the LPIV of equation (4). In the case of the LPIV, we account for the contemporaneous correlation amongst the narrative proxies of Mertens and Ravn (2013) using two strategies. First, we use the narrative proxy for the shock of interest as its instrument, and then add the contemporaneous value of the proxy for the other tax shock as a control.[11] Second, we employ the mutually orthogonal structural shocks estimated from the Mertens and Ravn (2013) VAR as instruments, by estimating the following regressions:

$$Z_{i,t+h} = c^{(h)} + \beta_i^{(h)} \tau_{j,t} + b^{(h)} Z_{t-1} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{8}$$

where $\tau_{j,t}$ for $j = ct, pt$ denotes the tax rate that is instrumented by the corresponding shock.

Frequentist Estimates. In Figure J.1, we present the estimated responses of GDP, TFP and R&D using either the Direct model or the LPIV. These two specifications employ the narrative proxies of Mertens and Ravn (2013) as exogenous regressors and instruments, respectively. While the "direct" regression of the instruments on the outcome variables produces responses (in solid grey) that are erratic, their pattern broadly matches those obtained via the smooth LPIV (in dotted red). The effects of corporate tax cuts on GDP are evident after about four years and continue up to 40 quarters ahead. The response of TFP is persistent, grows with the forecast horizon, and becomes significant over the longer term. In contrast, the effects of corporate tax changes on R&D spending occurs during the first 5 years after the shock. Regarding personal tax changes, we find little evidence of significant medium-term effects on output, productivity or R&D expenditure.

Weak Instruments. Instrument strength can be tested using a robust F-test for the regression of the endogenous variable on the instrument and controls. This delivers a statistic of 30.62 for the narrative corporate tax instrument and 49.44 when the SVAR corporate tax shock is used. Both values are above the Stock and Yogo (2005) threshold and greater than the critical values of Montiel-Olea and Pflueger (2013). The results are more varied when considering the personal tax instruments. While the personal tax shock from the Mertens and Ravn (2013) VAR appears to be highly relevant with a F-statistic of 109.57, the F-statistic for the narrative personal tax proxy is substantially lower at 4.86. Given the sensitivity of the test to the method used to account for

[11] 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. In the direct model, both proxies are added as contemporaneous regressors.

contemporaneous correlation between the narrative proxies, we follow Anderson and Rubin (1949) to compute weak instrument robust error bands for the LPIVs of Figure J.2. Corporate tax shocks are confirmed to have a significant medium-term impact on GDP, productivity and R&D.

Alternative Estimators. In recent contributions, Herbst and Johannsen (2020) and Li et al. (2024) show that OLS estimates of impulse responses from LPs can be biased in small samples. Accordingly, in Figure J.1, we also report the impulse responses from model (3) using the bias correction proposed by Herbst and Johannsen (2020). These responses are close to the OLS estimates suggesting that this bias is not a significant concern in our setting. In Appendix Figure J.3, we present the impulse responses obtained using the mutually orthogonal structural shocks from the Mertens and Ravn (2013) VAR as instruments. The impulse responses of output, productivity and R&D expenditure from these LPIV models are very similar to the results from the Bayesian LPs.

Additional Robustness Checks. In this final part, we briefly describe a range of additional analyses that we have performed to confirm the robustness of our results. Full details are reported in Appendix J. In Figure J.4, we use Bayesian LPs where the residuals are modelled as an MA process. The estimated responses of GDP, TFP and R&D to corporate tax cuts are positive and persistent. In contrast, the effects of personal tax shocks are shorter-lived. In Appendix Figure J.5, we show that the benchmark model is robust to a number of other changes in the model specification, namely to: (i) varying the lag length for the controls in Z, (ii) using the optimal prior strategy described in Giannone et al. (2015), (iii) including the defence news shock from Ramey (2011) as a further control, and (iv) changing the causal ordering of the two taxes as in Mertens and Ravn (2013). The solid red line and the shaded areas in Figure J.5 replicate the median estimate and 90% credible set of Figure 1. The results of each of the robustness checks mentioned above are overlayed. The main takeaway from Figure J.5, Appendix J and this section more generally is that our main finding of significant medium-term effects of corporate income tax changes on output and productivity is a very robust feature of post-WWII U.S. data.

4 A structural model with endogenous productivity

In the previous section, we have documented two main findings. First, corporate income tax changes have significant medium-term effects on productivity and output. Second, the response of aggregate TFP to a corporate tax shock is much more persistent than the response of R&D expenditure. In this section, we develop a theoretical framework that blends elements of 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.

4.1 The tax treatment of intangible assets and R&D

The distinction between tangible and intangible capital and the differential tax treatment of intangible expenditures play a crucial role in our analysis. Before outlining the model, we find it useful to clarify these differences.

Intangible assets are non-physical assets with a quantifiable economic value. Examples include patents, copyrights, trademarks, and goodwill. The US GAAP (Generally Accepted Accounting Principles) distinguish between internally created and externally purchased intangible assets. The costs of developing intangible assets internally is typically expensed on the income statement, meaning that these expenditures are fully and immediately subtracted from revenue when calculating a company's taxable profits.

As for externally purchased intangibles, these are usually capitalised on the balance sheet and their cost is recorded as an asset at the time of purchase. For instance, the costs of an internally developed innovation (patented or not) goes on the income statement under R&D expenditure, whereas the costs of purchasing a patent from another company is recorded on the balance sheet under intangible purchases.

Amortization refers to the systematic allocation of the cost of an intangible asset over its estimated useful life. It recognises the gradual decline in the value of an intangible asset over time and it is conceptually and quantitatively similar to the mechanics of how depreciation works for tangible assets expenditure.

Under Section 197 of the Internal Revenue Code (IRC) of the United States, enacted in 1993, purchased intangible assets, including goodwill, are amortized over a period of 15 years. This applies regardless of the actual estimated useful life of the asset, and allows firms to deduct a constant fraction of the cost of purchasing the intangible asset from their taxable profits over 15 years.[12] In contrast, over most of our sample, Section 174 of the IRC, enacted in 1954, allowed companies to deduct the full amount of research and experimental expenditures in the year in which they were incurred, even if the expenditures did not lead to the creation of a specific, identifiable intangible asset.

In our model, consistent with the U.S. tax code over most of our sample period, we assume that

[12]Before 1993, the US tax code did not explicitly allow for amortization of purchased intangibles.

R&D spending is subject to full and immediate expensing whereas intangible purchases are subject to a tax amortization period of 15 years. In Appendix K, we discuss these rules in more details.[13]

4.2 Endogenous productivity: basic and applied research

Our model blends elements of endogenous growth theory and business cycle analysis, following Anzoategui et al. (2019).[14] 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' (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. Each of them manufactures a differentiated product using capital and labor with a standard production function. In Appendix M, we show that aggregate output is given by:

$$Y_t = A_t^{\theta-1}(U_t K_{g,t})^{\alpha}(L_{g,t})^{1-\alpha}. \tag{9}$$

In this section, we describe how R&D and adoption drive the dynamics of A_t. Let Z_t be the total stock of known technologies. A_t is the stock of adopted technologies, so $(Z_t - A_t)$ is the *un*adopted technology stock. Basic research expenditure –or R&D for short– increases Z_t while applied research expenditure –or adoption for short – increases A_t.

Basic Research. There is a continuum measure 1 of innovators that 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 γ 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), φ_t, is given by:

$$\varphi_t = Z_t^{1+\zeta} X_{z,t}^{\rho_z - 1}, \tag{10}$$

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

[14]Growth in our model is semi-endogenous rather than fully endogenous as in Anzoategui et al. (2019). 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 US GDP growth has been relatively stable even as the average corporation tax rate has trended consistently lower in the postwar era.

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 ζ.[15] We estimate $\rho_z < 1$ (see below), which implies that higher aggregate R&D spending reduces the efficiency of R&D 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 maximimise period t after-tax profit:

$$\max_{L_{z,j,t}, K_{z,j,t}} (1 - \tau_{c,t}) \left(P_{z,t} \varphi_t L_{z,j,t}^{\gamma} K_{z,j,t}^{1-\gamma} - w_{z,t} L_{z,j,t} - r_{z,t} K_{z,j,t} \right), \tag{11}$$

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 ($\varphi X_{z,j,t}$). 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.

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

$$w_{z,t} = \gamma P_{z,t} \frac{X_{z,t}}{L_{z,t}} \tag{12}$$

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

$$Z_{t+1} = \varphi_t X_{z,t} + \phi Z_t \tag{13}$$

[15] 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 ζ and other parameters.

Combining equations (13) and (10) yields the following expression for the growth of new technologies:

$$\frac{Z_{t+1}}{Z_t} = Z_t^{\zeta} X_{z,t}^{\rho_z} + \phi. \tag{14}$$

Applied Research. We next describe how unadopted technologies become adopted, and therefore enter productive use. There is a competitive group of "adopters", indexed by j, who convert unadopted technologies into adopted ones. They buy the rights to the technology from the innovator at the competitive price $P_{z,t}$ and convert the technology into use by employing adoption-specific labor and capital as inputs. 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 to adoption: an adopter succeeds in making a product usable in any period t with probability λ_t, which is an increasing and concave function of expenditure, $X_{a,j,t} = L_{a,j,t}^{\gamma} K_{a,j,t}^{1-\gamma}$, according to the following function:

$$\lambda_t = \lambda \left(\frac{Z_t}{N_t^{\gamma} \Psi_t^{1-\gamma}} X_{a,j,t} \right), \tag{15}$$

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

To ensure the existence of a balanced growth path, we increase $X_{a,j,t}$ 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 Ψ_t is a scaling factor that grows at the same rate of GDP on the balanced growth path and N_t is 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:

$$V_t = (1 - \tau_{c,t}) \Pi_{i,t} + \beta \phi \mathbb{E}_t \left[\Lambda_{t,t+1} V_{t+1} \right], \tag{16}$$

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:

$$J_t = \max_{L_{a,j,t}, K_{a,j,t}} \mathbb{E}_t \left[(1 - \tau_{c,t}) \left(\lambda_t P_{a,t} - w_{a,t} L_{a,j,t} - r_{a,t} K_{a,j,t} \right) + \phi \beta \left(1 - \lambda_t \right) \Lambda_{t,t+1} J_{t+1} \right], \tag{17}$$

where λ_t is as in Equation (15), $P_{a,t}$ 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, we assume that the costs of technological adoption are fully tax-deductible. The first-order conditions for labor and capital are:

$$(1-\tau_{c,t})\, w_{a,t} = \frac{\partial \lambda_t}{\partial L_{a,j,t}} \beta \phi \mathbb{E}_t \left[(1-\tau_{c,t})\, P_{a,t} - \Lambda_{t,t+1} J_{t+1} \right] \tag{18}$$

and

$$(1-\tau_{c,t})\, r_{a,t} = \frac{\partial \lambda_t}{\partial K_{a,j,t}} \beta \phi \mathbb{E}_t \left[(1-\tau_{c,t})\, P_{a,t} - \Lambda_{t,t+1} J_{t+1} \right]. \tag{19}$$

The terms on the right are the marginal benefits of adoption expenditures: the increase in the adoption probability, λ_t, times the discounted difference between the value of an adopted versus an unadopted technology. The left side is the marginal cost. Since λ_t does not depend on adopter-specific characteristics, we can sum across adopters to obtain the following relation for the aggregate evolution of adopted technologies:

$$A_{t+1} = \lambda_t \phi \left[Z_t - A_t \right] + \phi A_t \tag{20}$$

where $(Z_t - A_t)$ measures 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 ownership of IPP. Consistent with the US tax code for the period we study, 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, inclusive of the purchase price $P_{a,t}$, for an entrant monopolist that buys a newly adopted technology at time t and starts production at time

$t+1$ is given by:

$$\Pi_t^M = -P_{a,t} + \mathbb{E}_t \left[\beta\phi\Lambda_{t,t+1}V_{t+1} + \sum_{s=0}^{\infty} \beta^s \Lambda_{t,t+s} \hat{\delta}_{IP}^{s+1} \left(1-\hat{\delta}_{IP}\right)^s \tau_{c,t+s} P_{a,t} \right] \tag{21}$$

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 monopolistic profits starting in period $t+1$ (as per Equation (16)). 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:

$$P_{a,t}\left(1 - d_{IP,t}\right) = \phi\beta\mathbb{E}_t\Lambda_{t,t+1}V_{t+1}, \tag{22}$$

where

$$d_{IP,t} = \sum_{s=0}^{\infty} \beta^s \Lambda_{t,t+s} \hat{\delta}_{IP}^{s+1} \left(1-\hat{\delta}_{IP}\right)^s \tau_{c,t+s} \tag{23}$$

is the present value of amortization allowances.

As adopters compete to buy unadopted technologies and the purchase price of unadopted technologies is amortised in the same way, the analogous derivation yields the market price of an unadopted technology:

$$P_{z,t}\left(1 - d_{IP,t}\right) = \phi\beta\mathbb{E}_t\Lambda_{t,t+1}J_{t+1}. \tag{24}$$

According to equations (16), (17), (22) and (24), 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 purchase of IPP. 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 account for the estimated responses of output and productivity to a corporate tax cut.

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, χ_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. We assume that 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 (see Figure I.1). We fully describe the household optimization problem in the Appendix.

Rest of the model. This is relatively standard and described in Appendix M. Several features are common to many existing models: quadratic adjustment costs on capital (used in R&D, adoption and goods production); sticky prices à la Calvo, an interest rate rule; 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 show that our set-up can rationalise all our empirical findings. To do so, we estimate the model of Section 4 using a limited-information Bayesian approach and show that it accounts jointly for the responses of TFP, R&D and GDP to corporate and personal 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 Υ and to the associated impulse responses as $\Phi\left(\Upsilon\right)$. The structural parameters are estimated by minimizing the distance between the theoretical model impulse responses, $\Phi\left(\Upsilon\right)$, and the median of the empirical LP impulse response posterior distributions from Section 3, denoted by $\hat{\Phi}$, to both tax shocks.

The limited-information approach fulfils 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 findings of Section 3. It is therefore important that the estimated parameters maximize the likelihood that the structural model generates the data not only conditional to both income tax shocks, but also across short and long horizons. We will then be able to conduct, in the next section, a series of counterfactual experiments where we artificially change the value of one set of structural parameters at a time to evaluate the importance of different channels for explaining the empirical evidence from LPs in Section 3. To implement this approach, we first set up the quasi-likelihood function as follows:

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

where N denotes the number of elements in $\hat{\Phi}$, and V is a weighting matrix. In our application, V is a diagonal matrix with the posterior variance of $\hat{\Phi}$ on the main diagonal. Denoting by $p\left(\Upsilon\right)$ the prior distributions, the quasi-posterior distribution is defined as:

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

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.[16] 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 are attempting to hit a number of key moments jointly, across shocks *and* across forecast horizons.

5.2 Calibrated parameters and prior distributions

We partition the structural parameters into a calibrated set (Table 1) and an estimated set (Table 2). The discount factor, capital depreciation and the capital share are set at 0.99, 0.02 and 0.35 respectively. 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

[16]The starting values of the parameters are obtained by maximising the log posterior using the covariance matrix adaption algorithm (CMA-ES). Then, an initial run of the Metropolis algorithm is used to approximate $\text{var}\left(\Upsilon\right)$. A scaled version of $\text{var}\left(\Upsilon\right)$ is used to calibrate the variance of 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
β	Discount factor	0.99	
ψ	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
α	Capital share	0.35	
δ	Capital depreciation	0.02	
ς	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)
γ	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)
ρ_r	Smoothing	0.83	Anzoategui et al. (2019)
ϕ_y	Output	0.385	Anzoategui et al. (2019)
ϕ_π	Inflation	1.638	Anzoategui et al. (2019)

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 intellectual property assets ($\hat{\delta}_{IP}$) to match the 15-year amortization period allowed by the US tax code.[17] 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, γ, is set to 0.9, consistent with R&D expenditure data from the NSF.

In Table 2, we collect the parameters that will be estimated and their prior distributions. The table also reports moments from the posterior distribution, which will be discussed in the next section. Prior distributions are chosen to be diffuse but centred on values typically found in the literature. The prior means for the more standard parameters, such as habit formation, the Calvo probability that governs price stickiness, and investment adjustment costs are consistent with common estimates and priors used in earlier empirical studies, such as Smets and Wouters (2007). The priors for the tax processes assume that the tax rates are adjusted smoothly over time and follow

[17] For robustness, we have also tried a version of the model in which an R&D subsidy is calibrated to the rate estimated by the OECD. We find that the inclusion of a static subsidy of empirically plausible magnitude has a very small effect on the conditional model dynamics, and thus we do not include it in the baseline model for parsimony.

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]
χ_g	Inverse effort elasticity (goods)	gamma	1	0.5	0.47	[0.22, 0.93]
χ_a	Inverse effort elasticity (adoption)	gamma	1	0.5	0.67	[0.29, 1.4]
χ_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]
ν''	Capital utilization adjustment	beta	0.6	0.15	0.74	[0.66, 0.82]
ξ_p	Calvo prices	beta	0.5	0.2	0.2	[0.07, 0.33]
θ-1	Dixit-Stiglitz parameter	gamma	0.15	0.1	0.58	[0.43, 0.79]
ρ_λ	Adoption elasticity	beta	0.5	0.2	0.78	[0.66, 0.87]
ρ_Z	R&D elasticity	beta	0.5	0.2	0.2	[0.12, 0.29]
ζ	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]

Leeper et al. (2010).

There are a number of parameters that are specific to our R&D, adoption and utilization mechanisms and therefore we discuss them here in more details. Estimates of the elasticity of patenting to R&D expenditures, analogous to ρ_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 centred at 0.5. We employ the same prior for the elasticity of adoption with respect to R&D spending, ρ_λ. The prior mean for the Dixit-Stiglitz parameter θ implies an elasticity of substitution across goods of 7.6, consistent with the estimates provided by Broda and Weinstein (2006). We do not directly estimate ζ (see footnote 15), but we compute and report moments of its implied prior distribution. To avoid tilting the balance in favour of any particular adjustment cost mechanism, in each of the sectors, we use the same prior as for capital investment adjustment costs. We are not aware of existing estimates of the (inverse) elasticity of effort, χ. Consequently, we choose a relatively uninformative prior centred at 1.

In Appendix L, 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 spuriously detect significant effects at long horizons. As shown in Appendix Figure L.1, our prior distributions for the structural parameters are centred 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 structural parameters of the model, which are estimated by minimising the difference between the IRFs of the theoretical model, $\Phi(\Upsilon)$, and the IRFs of the baseline LPs of Section 3, $\hat{\Phi}$, 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 impulse responses (evaluated at the posterior medians of Table 2) are shown in Figures 1 and 2 as blue lines with circles.

In the last two rows of Table 2, we report the processes for the tax rates: corporate income tax changes tend to be more persistent but, as shown in Figure 1, both tax rates return to zero by year four. The estimates of the parameters on R&D and technological adoption are reported in the third block of Table 2 and are largely consistent with the available evidence. All these parameters are included in the calculation of the social returns to R&D below, which provides a useful way to relate the implications of 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 (top of Table 2). Interestingly, by incorporating an endogenous growth mechanism, our estimates seem to downplay significantly these more 'traditional' ways of generating persistence and amplification. In particular, adjustment costs on investment in physical capital are estimated to be much 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 features a range of additional sources of endogenous persistence via research spending and innovation. More specifically, 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 (see appendix Table O.1). The estimates of physical capital investment adjustment costs in this restricted specification become much larger and in line with those reported by the earlier literature cited above. We interpret this finding as suggestive evidence that the omission of R&D spending and technological adoption in the business cycle models routinely used for policy analyses might distort inference on the importance of physical capital investment and its adjustment costs for business cycle fluctuations.

Social returns to R&D. An instructive way to summarise the estimates of our structural model is to revisit a fundamental question in growth theory: what are the social returns to investment in innovation? To this end, we follow the variational approach of Jones and Williams (1998), modified to account for the two margins of innovation featured in our model: R&D and adoption (see Appendix N for details). 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%. These estimates, which are based on US tax changes over time, are remarkably similar to those obtained by Bloom et al. (2013) exploiting variation in R&D tax credits across time and US states.

6 Inspecting the transmission of corporate income tax changes

A main novel empirical finding from the previous sections is that temporary corporate tax changes have persistent effects on aggregate productivity and output at horizons beyond business-cycle frequencies. In this section, we use the structural model to perform a set of counterfactual simulations that highlight the role of endogenous productivity, and the two main forces behind it: (i) innovation, and (ii) the tax amortization allowances on intellectual property. We present independent evidence that the responses of both patents and the share prices of the most patent-rich US firms, estimated with local projections, display a very similar pattern relative to the *untargeted* IRFs implied by our structural model. Finally, we show that the impact response of the market price of IPP (and thus the medium-term effects of corporate taxes on TFP and GDP) would be far smaller and less persistent in a counterfactual world with a shorter tax amortization period on intangible investment.

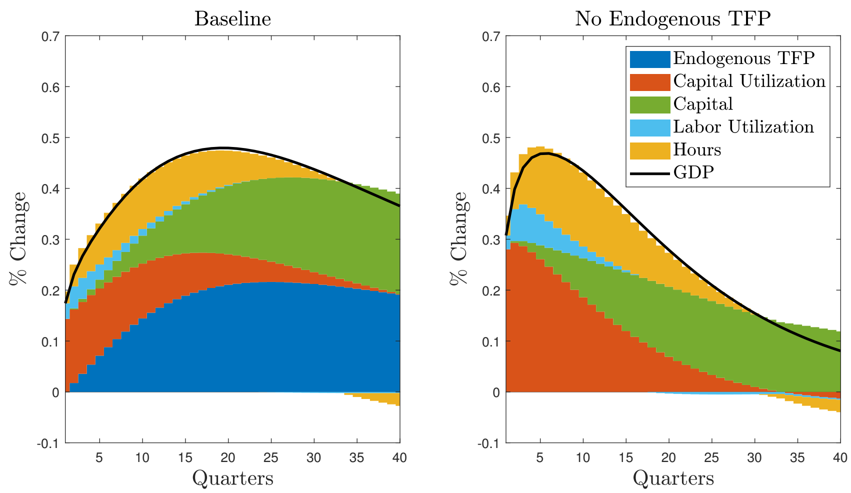
6.1 Endogenous productivity

The goal of this section is to elicit the role that endogenous productivity plays in accounting for the medium-term response of output to corporate tax changes. To this end, we compare the response of GDP in our baseline model with the response of a model with all of the features except for the endogenous productivity block. To ensure that we give this alternative model the best possible chance of matching the data, we estimate this alternative model to match the same variables, excluding R&D, which plays no role in the exogenous productivity model (we report parameter estimates for this restricted model in the last two columns of Table O.1).

Figure 3 plots the response of (log) GDP in the two models, decomposed into the contributions of TFP, capital and capital utilization, labor and labor utilization, using the final goods production function (Equation 9):

$$\Delta \log Y = (\theta - 1) \Delta \log A + \alpha (\Delta \log U + \Delta \log K) + (1 - \alpha) (\Delta \log e_g + \Delta \log H) . \tag{25}$$

Figure 3: GDP Decomposition and Counterfactual Analyses



Notes: this figure plots the model impulse responses of aggregate output and its components (see Equation 9) to a corporate income tax shock. From left to right, these are the responses of the baseline model, a model in which the diffusion rate of new technologies is constant ("No Applied Research") and a model with no innovation. To construct the counterfactual plots, we re-estimate the restricted models following the procedure described in Section 5. Parameter estimates for the restricted models are in Appendix O.

The left panel of Figure 3 plots the decomposition (25) implied by our baseline model. The black line is the response of GDP (as in Figure 1), and the shaded areas represent the contribution of each variable. TFP accounts for the largest share of the medium-term effects, with the rest explained by capital accumulation. A cut in corporate taxes boosts after-tax profits, which increases the market price of IPP and the incentive to discover new technologies and adopt existing ones. Moreover, the rise in adoption effort increases the adoption probability and reduces the expected 'time to market' of innovation, further raising the incentives to innovate. In general equilibrium, more innovation also fosters capital accumulation by boosting the marginal product of capital.

From the right panel of Figure 3, we get a clearer sense of the total contribution of innovation and endogenous TFP in accounting for the response of the economy to a corporate tax cut. This plots a similar decomposition to the left panel, except that it is based on a model without the endogenous productivity channel (akin to a RBC model with variable factor utilization). To give the restricted model the best chance to match the data, we re-estimate the parameters of this specification following the procedure described in Section 5. Without an endogenous productivity channel, the model is unable to reproduce the medium-term persistence of the GDP response reported in our empirical estimates. We conclude that endogenous productivity accounts for the vast majority of the medium-term response of GDP.

6.2 Innovation: price and quantities

At the heart of our model is a theory of investment in innovation. R&D and applied research firms allocate labor and capital as a function of the prices of inputs – wages and the rental rate of capital – and of the prices of outputs, the market prices of adopted and unadopted technologies. The first-order effect of a corporate income tax cut is a jump in the market price of IPP, which in turn stimulates investment in innovation (in the form of both higher R&D and applied research expenditure). Increased investments lead to larger stocks of unadopted and adopted technologies and, thereby, cause persistently higher productivity and GDP. We provide further empirical evidence for this transmission mechanism in Figure 4. In Panel A (left column), we plot both the empirical and model-implied responses for measures of quantities and prices of innovation, as well as the overall response of asset prices. Empirical IRFs based on LPs are shown as red lines and shaded areas whereas the model IRFs are displayed as blue lines with circles. It is important to emphasise that we do not target these impulse responses in estimation; instead, we use them as a validation for the empirical merits of the model mechanism. In Panel B, we provide further evidence on the response of investment in intangible assets for which, however, there is not a direct model counterpart. Descriptions of the variables are detailed in the Data Appendix C.

Patents. In Panel A top row of Figure 4, we record the empirical response of the aggregate stock of patents (red shaded areas) and the model response of the stock of technologies Z_t (blue line with circles). We construct a measure of the stock of patents based on the data set of estimated real patent values provided by Kogan et al. (2017). We first aggregate the real patent values for each firm within each quarter and calculate the cumulative stock of patent values at the firm level using the perpetual inventory method and a quarterly depreciation rate of 8% (in line with BEA estimates). Finally, we sum over firms to obtain our aggregate measure of the patent stock value. In the data and in the model, the stock of knowledge remains above its steady-state level ten years after the shock. A long-standing literature (exemplified by Griliches, 1990) has argued that patents are a useful measure of technological progress. While the IRFs levels are different (more below), the ability of the model to match the evolution of the response of patents and real variables (TFP, GDP, etc.) in the data represents further evidence that not only patents contain relevant information about technological progress, but also that our estimated model can replicate the joint dynamics of innovation effort, innovation output, and the medium-term productivity gains of innovation.

The market price of IPP. The middle row of Figure 4 Panel A displays the difference in the stock price responses of value-weighted stock portfolios that are computed by ranking companies according to the value of their patents, as described in the previous paragraph. The firm-level measure we compute is analogous to the 'book value' of patents and therefore does not directly measure the market value that we are interested in studying. However, because our theory implies that the market value of firms with a high book value of patents will respond more to a corporate tax cut as the market price of those patents increases, we provide evidence of this mechanism using stock portfolios. We compare this 'market price of IPP' to the model response of the difference between: (i) the price of a portfolio consisting of adopted and unadopted technologies; and (ii) the price of capital. The market price of IPP jumps on impact and smoothly returns to zero over the forecast horizon, consistent with the key mechanism in the model. In the bottom row of Panel A, we plot the response of the stock market (Dow Jones index) in red and the response of a value-weighted portfolio of all assets in the model economy (i.e. IPP and capital) in blue. In sharp contrast to the effects on the market price of IPP, both in the data and in the model, the stock market responds gradually to a change in corporate taxes as IPP and capital accumulate over time.[18]

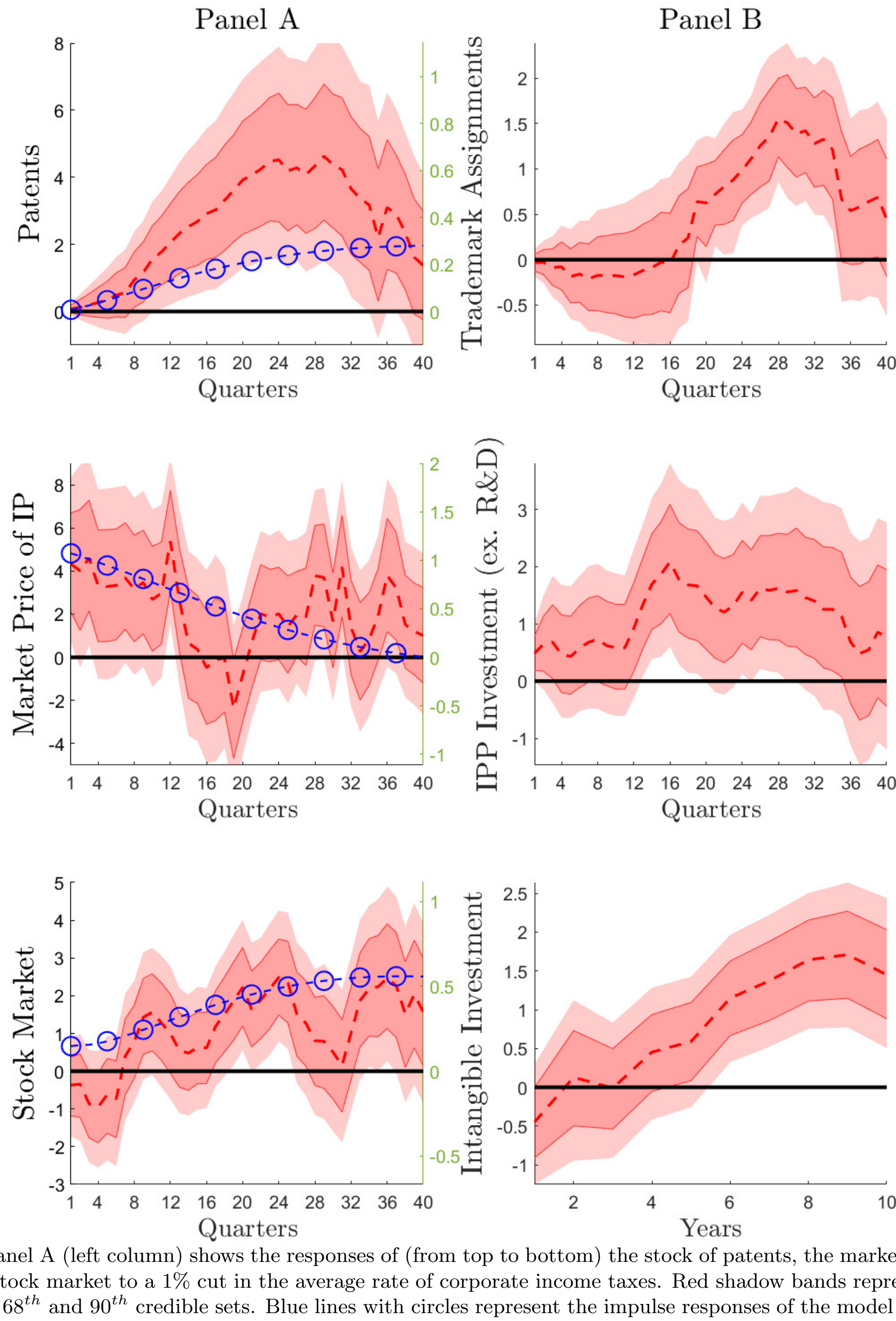
Trademark assignments. In Panel B top row of Figure 4, we report a measure of transactions in the market for IPP: the count of transactions in the secondary market for trademarks (assignments). These transactions are registered with the USPTO when this type of intellectual property - a trademark - changes ownership for any reason. Consistent with the model mechanism, where a corporate tax cut leads to a prolonged period of increased innovation activity, trademark assignments show a positive LP response, which is significant up to 34 quarters after the shock.

Intangible investment. The last two rows of Panel B refer to additional measures of intangibles: (i) investment in Intellectual Property Products (IPP) other than R&D (as measured in the national accounts), and (ii) the measure of (non R&D) intangible investment proposed by Ewens et al. (2023), estimated using Selling, General & Administrative expenditure data from Compustat. In line with the effects of corporate tax changes on other measures of investment in innovation, the response of IPP investment displays persistent dynamics that extend beyond the horizon of the shock itself.

In summary, the mechanism highlighted by the estimated structural model of Section 5 generates

[18]It should be noted that while the estimated structural model replicates well the *dynamics* of the patent value and stock market responses to corporate tax cuts over the forecast horizon, it does not match the *level* of the stock price responses, possibly because –by design– we have not included features that could potentially account for the stock price volatility observed in the data. Consequently, in Figure 4, the LP and model IRFs for panel A are plotted on different scales: on the left axes for the empirical LPs and on the right axes for the estimated stuctural model.

Figure 4: Evidence on the Mechanism



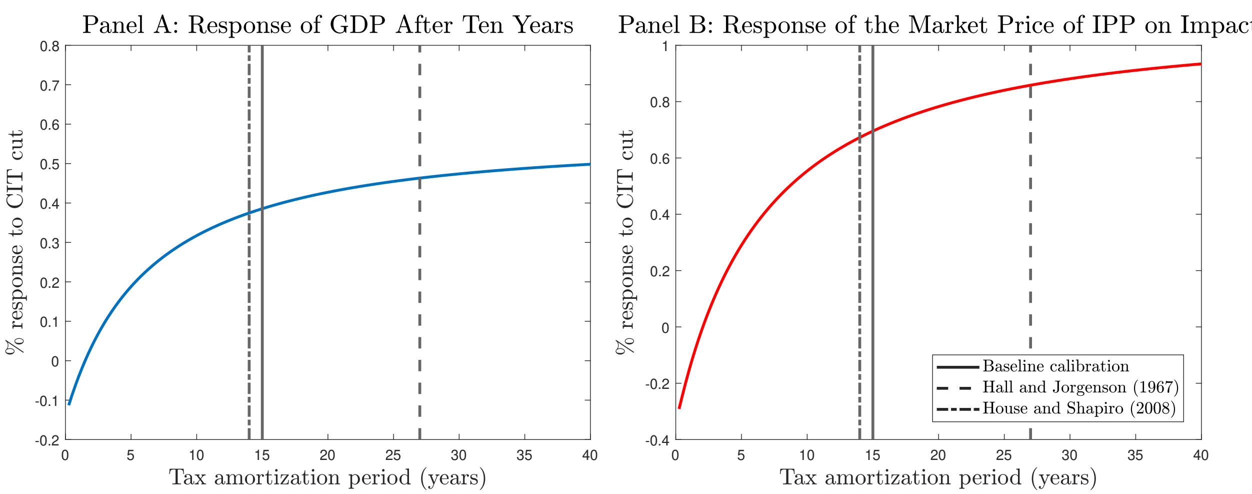
Notes: Panel A (left column) shows the responses of (from top to bottom) the stock of patents, the market price of IP and the stock market to a 1% cut in the average rate of corporate income taxes. Red shadow bands represent central posterior 68^{th} and 90^{th} credible sets. Blue lines with circles represent the impulse responses of the model in Section 4 evaluated at the posterior median of estimated model parameters. The blue lines with circles in Panel A are plotted on the right-hand axis. Panel B (right column) shows the responses of trademark transactions, intellectual property products investment (excluding R&D) and intangible investment. These variables are described in Section 6.2, and data sources are described in the Data Appendix C.

testable predictions that are strongly supported by the evidence in this section. A corporate tax cut leads to: (i) an increase in patents, trademark assignments and other non-R&D IPP purchases; (ii) a jump in the share price of more patent-rich companies; (iii) a delayed stock market boom. In Appendix P, we report independent evidence on BEA annual data that the medium-term effects of corporate tax changes on gross output are significantly larger in more R&D-intense sectors.

6.3 Tax allowances on the amortization of intellectual property

In Section 5, we have set the tax amortization period for IPP to 15 years, equivalent to $\hat{\delta}_{IP} = 0.0285$, consistent with Section 197 of the IRS Code which allows for straight-line amortization of intellectual property assets over a 15-year period. In Appendix A, we further show that: (i) tax amortization benefits on intangible assets are a salient feature of the tax codes of many countries around the world; (ii) the legal tax amortization periods for patents, technology and trademarks vary widely across countries; (iii) advanced economies tend to set a much longer tax amortization period than emerging markets.

Figure 5: GDP and price of IPP response as 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 allowance amortization period on intangible capital investment, 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.

In this section, we highlight the role played by the tax treatment of IPP. To do so, we calculate tax depreciation rates that equate the present value of tax deductions to straight-line amortization over different amortization periods. We use our estimated model to compute the effects of a corporate income tax cut on: (a) GDP at long horizons and (b) the market price of IPP on impact, as a function of the tax amortization period, ranging from 0 (i.e. fully amortised within the year) to 40 years (which we take as a proxy for codes in which purchases of intellectual property cannot be amortised at all).

The results from this exercise are summarized in Figure 5. A main finding from Panel A is that the medium-term response of output to a temporary corporate tax cut increases monotonically with the tax amortization period. For short amortization periods, corporate tax cuts would have a modest (negative) impact on GDP at long horizons. In contrast, if intangible assets were not deductible at all, at the far right of the chart, the medium-term effects on output would be maximized. In between these two extremes, the steeper increases occur between one and ten years. After that, the tax amortization benefits curve flattens and values of 12, 15, 20 or the number of years in the vertical lines implied by the calculations in Hall and Jorgenson (1967) and House and Shapiro (2008) for tangible capital would all produce similar medium-term effects on GDP. Panel B paints a similar picture: the *impact* response of the market price of IPP grows monotonically with the tax amortization horizon.

The findings of this section highlight the central role that the tax treatment of IPP plays in determining the output response to corporate income tax changes. In Equations (22) and (24), the present value of tax deductions, d_{IP}, appears as a wedge that decreases in the amortization length. This equals exactly τ_c for instant amortization and equals zero in the case of no amortization at all (which is equivalent to setting $\hat{\delta}_{IP}$ to 1 or 0 in equation 23, respectively). Because the right-hand sides of Equations (22) and (24) are the value functions of *after tax* profits, when $d_{IP} = \tau_c$ the tax rates cancel on both sides in steady state, and the market price of IPP is equal to the present value of pretax profits. Extending this logic to a dynamic setting, the closer is the value of the wedge to the tax rate itself (and hence the shorter the amortization window), the smaller is the response of the market price of IPP to changes in corporate taxes. This reduces additional incentives to engage in R&D and adoption, and, therefore, dampens the response of GDP after forty quarters. In other words, shortening the tax amortization period reduces the distortionary effects of the corporate income taxes on the market price of IPP, increasing steady-state innovation and GDP but reducing their sensitivity to the changes in the corporate tax rate.

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 changes have medium-term effects?
A: Because they stimulate R&D 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 12). 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 (see Equation 24). A cut in the corporate tax rate *increases* the PV of after-tax profits, but *decreases* the PV of amortization benefits. If 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 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 of corporate tax changes dominate the response of physical capital investment whereas the indirect effect drives the response of R&D. 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). This implies that the IPP elasticity of supply 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

4) but are insignificant on the price of capital (House and Shapiro, 2008).[19]

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

A: In theory, also personal income tax changes could have medium-term effects, working (to a first order) through the response of the scientists labor supply. However, in our estimates, we do not find 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 the scientists labor supply is relatively inelastic.

8 Conclusions

This paper provides empirical evidence for a novel transmission mechanism of fiscal policy: a temporary reduction in corporate income taxes generates a significant, sizable and persistent increase in innovation, productivity and output. An estimated structural model with endogenous productivity attributes the bulk of the medium-term responses of innovation, TFP and GDP to the long period of tax amortization on intangible asset purchases, even though R&D investment is subject to immediate expensing over most of our sample. We provide firm-level evidence on the mechanism highlighted by the structural model: a corporate tax rate reduction generates a large and significant share price appreciation for the most patent-rich firms, which — consistent with the predictons of the structural model— stimulates R&D expenditure, non-R&D IPP investment, patenting and trademark assignments.

As for policy implications, we note that a long-standing tradition in macroeconomics has convincingly made the case for the empirical and theoretical importance of *tax depreciation allowances* on physical capital expenditure in the transmission of tax policies over the short-run. Accordingly, governments around the world have frequently made use of 'bonus depreciation' as a tool to stimulate capital investment. Our analysis uncovers a crucial role for *tax amortization allowances* on intangible capital expenditure in the transmission of tax policies over the medium-term. This suggests that allowing firms to expense a greater portion of intangible asset costs through 'accelerated amortization' would reduce the distortionary effects of corporate income taxes and therefore might represent a new tax instrument in the lawmakers' toolkit to revert the ongoing challenges posed by slow productivity growth.

[19]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 3.

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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. As a robustness check (see Figure J.6 in Appendix J) we also consider a broader measure of corporate income tax changes: \$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 Figure 4

Stock of Patents. We compute firm-level patent stock values using patent values from the extended Kogan et al. (2017) database and the perpetual inventory method with 8% depreciation (Li and Hall (2020)). We aggregate these firm-level values at quarterly frequency and divide by population. The model plot is the IRF of Z_t. Sources: Kogan et al. (2017) database, Li and Hall (2020).

Market Price of IPP We then: (i) sort firms by their patent stock value, (ii) form two portfolios consisting of the top and bottom deciles of the patent stock value distribution, and (iii) calculate the capitalization-weighted average price of these portfolios. The empirical IRF is that of the log difference of the prices of the top minus bottom decile portfolios. The model response is the log difference between the value-weighted prices of a portfolio that holds all adopted and unadopted technologies minus a portfolio that holds all capital. Sources: Center for Research in Security Prices (CRSP), Kogan et al. (2017), 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.

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.

C.3 Sectoral Data

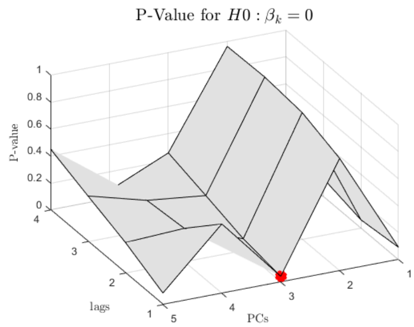
Gross output (GO) by industry and Gross Value added (GVA) by industry is obtained from the Bureau of Economic Analysis (BEA) and is provided at annual frequency from 1947 to 1997 (available at the following link). We deflate Gross output by its deflator. This historical data is combined with the more 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 P.

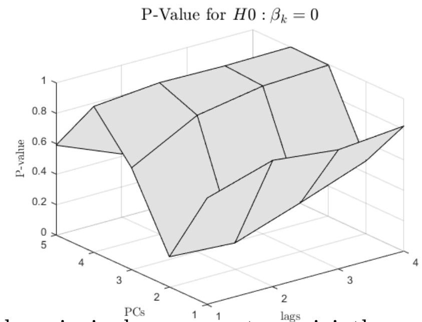
D Structural shocks and controls in the benchmark model

Figure D.1: Test for information sufficiency

(a) Personal tax shock



(b) Corporate tax shock



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 US. The data set covers real activity, inflation, employment, production, lending, interest rates, exchange rates and stock prices. The regressions take the following form:

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

   where ϵ_i is the structural shock to personal and corporate taxes respectively and F_K denote the $m = 1, \ldots, 5$ principal components. As shown in figure D.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.

E 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.

E.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)

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_{20} Y_{t-20} + A_0 E_t, E_t \sim N(0,1) \tag{26}$$

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.

E.2 Results

The top panel of Figure E.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 E.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.

F Estimation of the Bayesian Local Projection

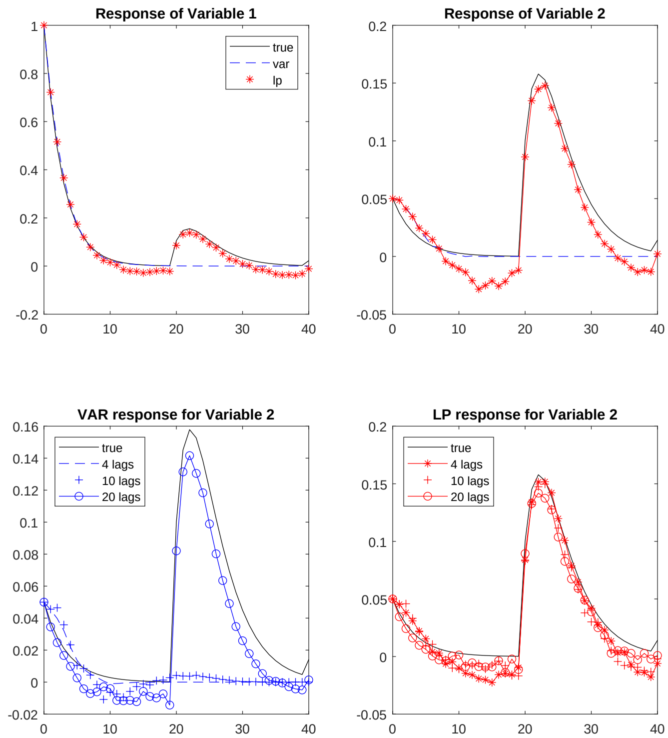
F.1 Benchmark model

The model used to produce the benchmark results is defined as:

$$Z_{t+h} = \beta^h X_t + u_{t+h}, \qquad var(u_{t+h}) = \Omega_h \tag{27}$$

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. 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 Ω_h is decomposed as $\Omega_h = A^{-1} H_t A^{-1\prime}$ where A is a lower triangular matrix while

Figure E.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

$H_t = diag\left(\frac{\sigma_1^2}{\lambda_{1t}}, \frac{\sigma_2^2}{\lambda_{2t}}, \ldots, \frac{\sigma_M^2}{\lambda_{Mt}}\right)$. 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 λ_{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 ν_i. This setup is used for VAR models in Chiu et al. (2017).

F.1.1 Priors

We employ the following prior distributions:

- We set a hierarchical prior for λ_{it} and ν_i (see Koop (2003)):

$$P(\lambda_{it}) = \Gamma(1, \nu_i) \tag{28}$$
$$P(\nu i) = \Gamma(\nu_0, 2) \tag{29}$$

  Note that the prior for ν 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 σ_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 β_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 μ_1 to 10 which implies a loose prior belief.

F.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 (Ξ 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 ν_i is non-standard (see Koop (2003)) and given by:

$$G(\nu_i|\Xi) \propto \left(\frac{\nu_i}{2}\right)^{\frac{T\nu_i}{2}} \Gamma\left(\frac{\nu_i}{2}\right)^{-T} \exp\left(-\left(\frac{1}{\nu_0} + 0.5\sum_{t=1}^{T}\left[\ln\left(\lambda_{i,t}^{-1}\right) + \lambda_{i,t}\right]\right)\nu_i\right) \tag{30}$$

  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 β^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 σ_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:

$$AZ_{t+h} = A\beta^h X_t + e_{t+h}, \qquad e_{it,t+h} \sim N\left(0, \frac{\sigma_i^2}{\lambda_{i,t}}\right) \tag{31}$$

  Given the lower triangular structure of A, the coefficients of the jth 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 $5th$ draws of the remainder for inference.

F.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 $5th$ 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 F.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.

F.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 F.1 Panel B) providing support for convergence of the algorithm.

F.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:

$$Z_{t+h} = \beta^h X_t + u_{t+h} \tag{32}$$

The residuals of each equation follow the MA process:

$$u_{t+h} = \epsilon_{t+h} + \theta_1\epsilon_{t+h-1} + .. + \theta_q\epsilon_{t+h-q}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{33}$$

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

$$Z_{t+h} = \beta^h X_t + \tilde{H}\epsilon_{t+h}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{34}$$

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).

F.2.1 Priors

We employ the following prior distributions:

- The prior for Ω 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 β_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 μ_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

F.2.2 Gibbs Sampler

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

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

$$\tilde{Z}_{t+h} = \beta^h \tilde{X}_t + \epsilon_{t+h}, \qquad \epsilon_{t+h} \sim N(0, \Omega_h) \tag{35}$$

$$\tilde{Z}_{t+h} = \tilde{H}^{-1} Z_{t+h} \tag{36}$$

$$\tilde{X}_t = \tilde{H}^{-1} X_t \tag{37}$$

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:

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

$$M = V\left(S_0^{-1}\beta_0 + \left(\Omega_h^{-1} \otimes \tilde{X}'\tilde{X}\right)\beta_{ols}\right) \tag{39}$$

$$\beta_{ols} = vec\left(\left(\tilde{X}'\tilde{X}\right)^{-1}\left(\tilde{X}'\tilde{Z}\right)\right) \tag{40}$$

- $G(\Omega_h|\Xi)$: Given a draw for β_h, the residuals ϵ_{t+h} can be easily calculated. The conditional posterior of Ω_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:

$$Z_{t+h} = \beta^h X_t + \begin{pmatrix} I_m & I_m \times \theta_1 & \dots & I_m \times \theta_q \end{pmatrix} \begin{pmatrix} \epsilon_t \\ \epsilon_{t-1} \\ \vdots \\ \epsilon_{t-q} \end{pmatrix} \tag{41}$$

$$\begin{pmatrix} \epsilon_t \\ \epsilon_{t-1} \\ \vdots \\ \epsilon_{t-q} \end{pmatrix} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & \dots & \dots \end{pmatrix} \begin{pmatrix} \epsilon_{t-1} \\ \epsilon_{t-2} \\ \vdots \\ \epsilon_{t-q-1} \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \\ \vdots \\ 0 \end{pmatrix} \tag{42}$$

$$var\left(\begin{pmatrix} \epsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}\right) = \begin{pmatrix} \Omega & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & \dots & \dots \end{pmatrix} \tag{43}$$

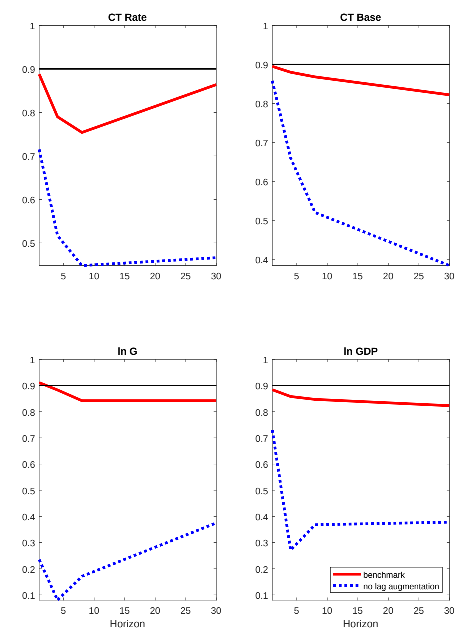
  We use a random walk Metropolis-Hastings step to draw $\tilde{\Theta}$. We generate a candidate draw using $\tilde{\Theta}_{new} = \tilde{\Theta}_{old} + e, e \sim N(0, \tau)$. The draw is accepted with probability $\alpha = \frac{F\left(Z_{t+h}|\tilde{\Theta}_{new},\Xi\right) \times P\left(\tilde{\Theta}_{new}\right)}{F\left(Z_{t+h}|\tilde{\Theta}_{old},\Xi\right) \times P\left(\tilde{\Theta}_{old}\right)}$ 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 τ 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.

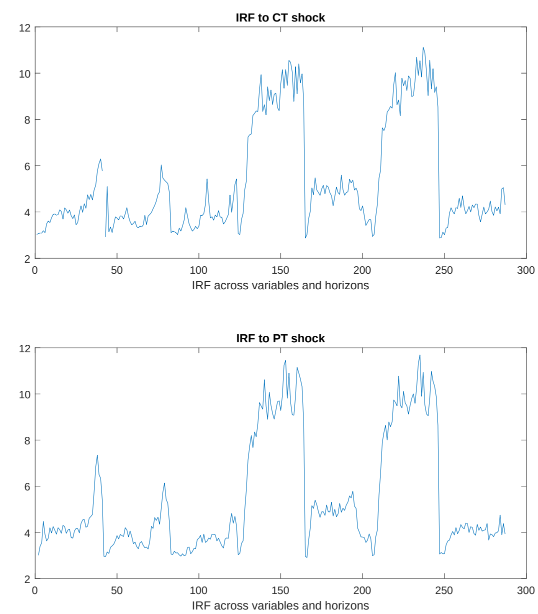
the US BEA. The first row show the average effect. The bottom row further split sectors into high R&D intensive and low R&D intensive.

Figure F.1: Coverage probabilities and inefficiency factors

(a) Coverage Probabilities



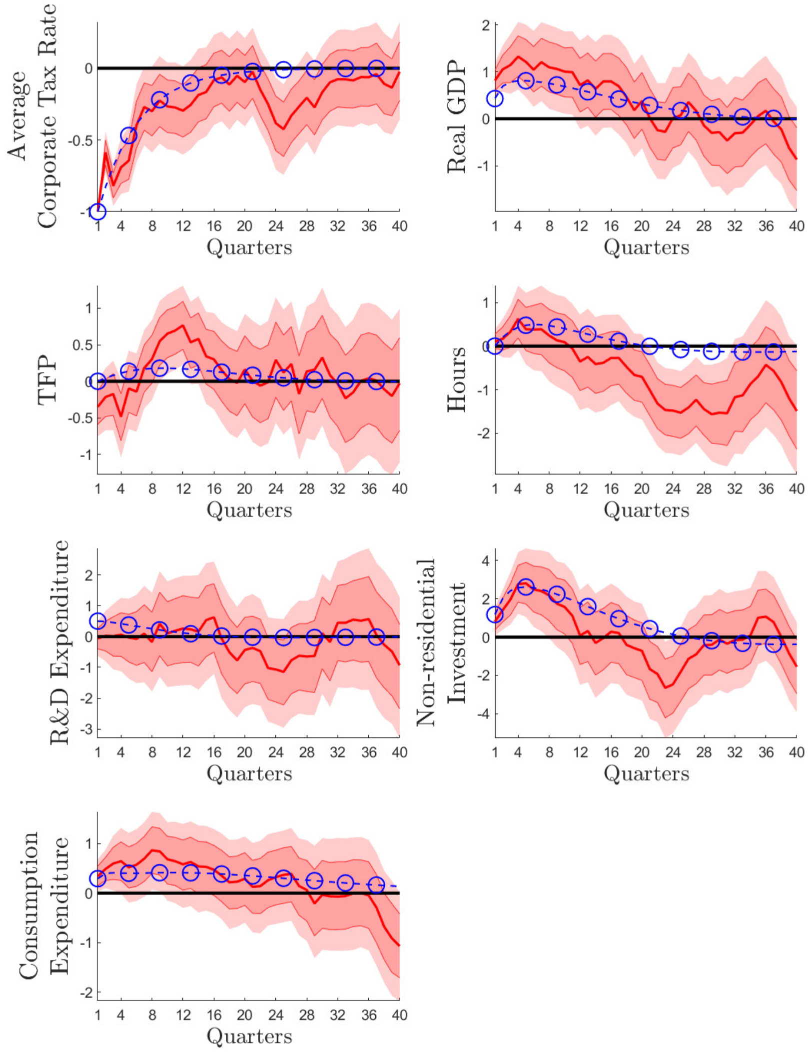
(b) Inefficiency Factors



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).

G The Dynamic Effects of Personal Income Tax Changes

Figure G.1: 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 G.1, 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 time.

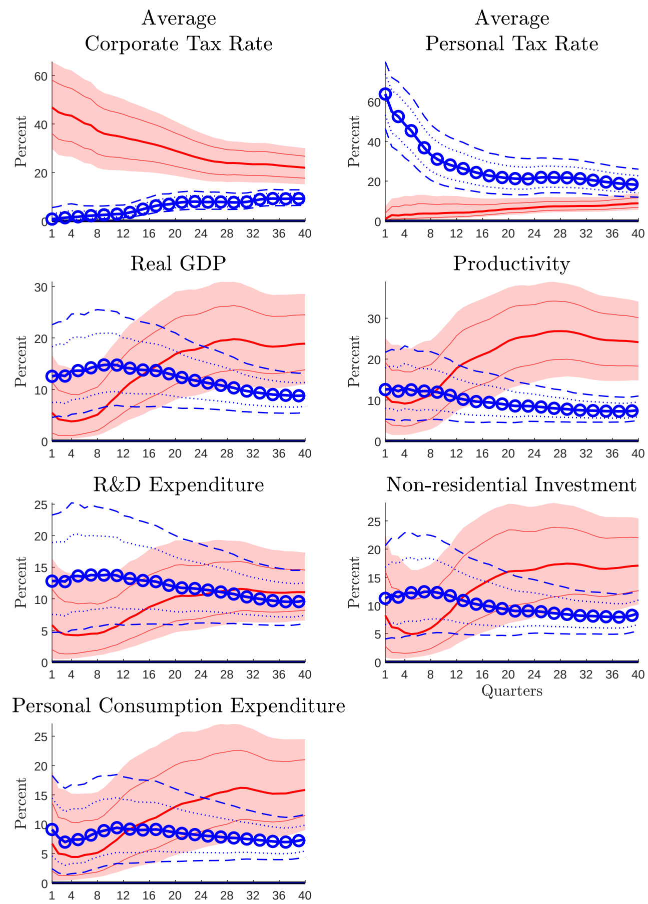
H Forecast Error Variance Decomposition

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).[1]

[1] 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).

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.[2]

Figure H.1: Forecast Error Variance decomposition

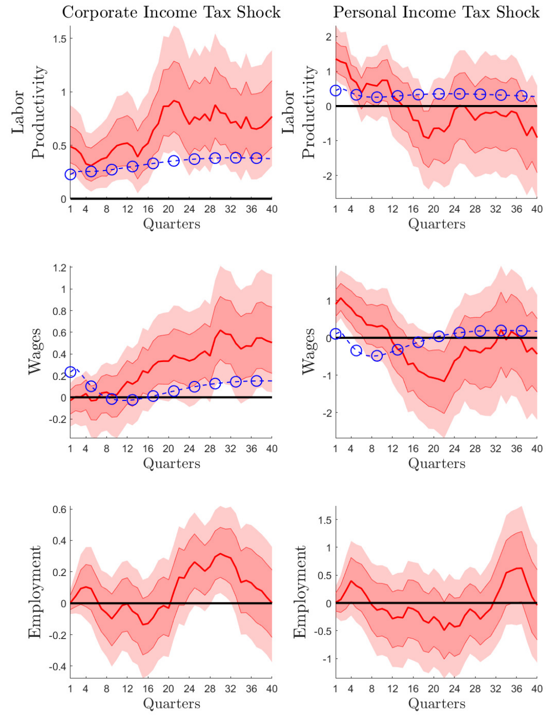


Notes: contribution of corporate and personal tax changes to the variance of each variable in the figure. The contribution of corporate tax changes are shown in the red lines (posterior median and 68 percent band) and the shaded area (90% band). The line with circles shows the contribution of the personal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

[2] 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.

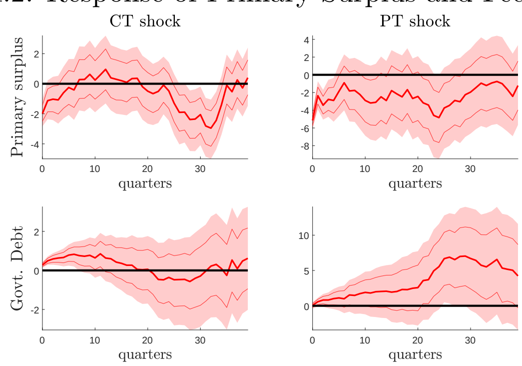
I The labor Market and Public Finance Responses

Figure I.1: Response of labor Productivity, Wages and Employment to Income Tax Changes



Notes: responses to a 1% cut in the corporate income (left column) and of personal income (right column) tax rate. Red shadow bands represent central posterior credible sets. Blue lines with circles represent the estimated structural model impulse responses. The structural model does not have an extensive employment margin, and so no model response is plotted for employment.

Figure I.2: Response of Primary Surplus and Federal Debt



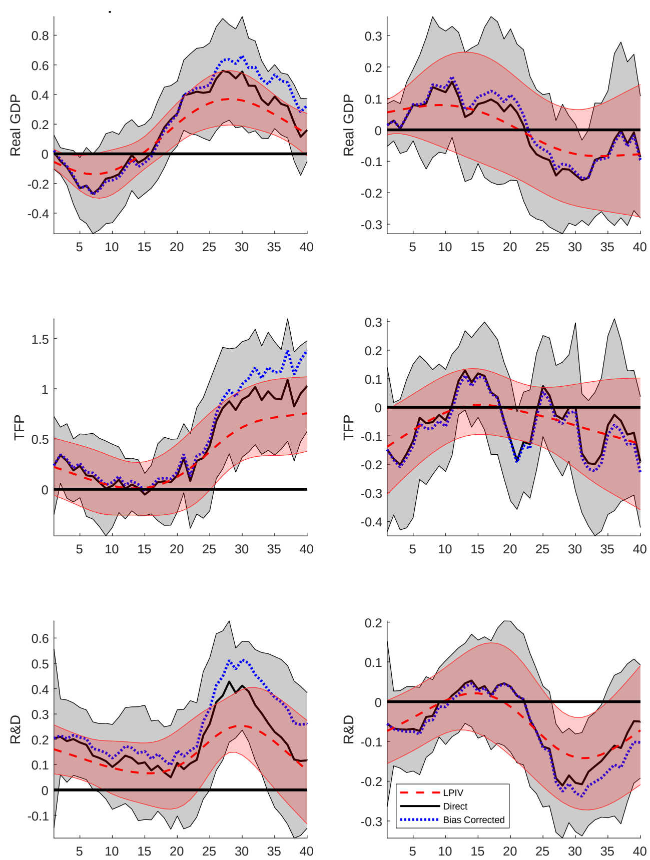
Notes: responses to a 1% cut in the corporate income (left column) and of personal income tax rate. Primary surplus is defined as Tax Revenues minus Government Spending. The revenue response is constructed as in footnote 9 of Mertens and Ravn (2013)

J Robustness checks

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

1. **using narrative measures as instruments.** In Figure J.1, we present impulse responses estimated using the frequentist approach discussed in Section 2.2. The figure shows estimates obtained using OLS and the smoothed version of LPIV (Barnichon and Brownlees (2019)). We also present the bias corrected OLS estimates of the impulse response using the method of Herbst and Johannsen (2020). As noted in the text, these regressions use the narrative measures of Mertens and Ravn (2013) as regressors/instruments. Following Mertens and Montiel Olea (2018), instrument relevance can be tested using a robust F-statistic for the regression of the endogenous variables on the instruments and controls. In our context, this delivers test statistic of 30.62 for the corporate tax instrument, a value above the Stock and Yogo (2005) threshold and greater than the critical values of Montiel-Olea and Pflueger (2013). The F-statistic is estimated to be 4.86 for the personal tax shock instrument in the LPIV.

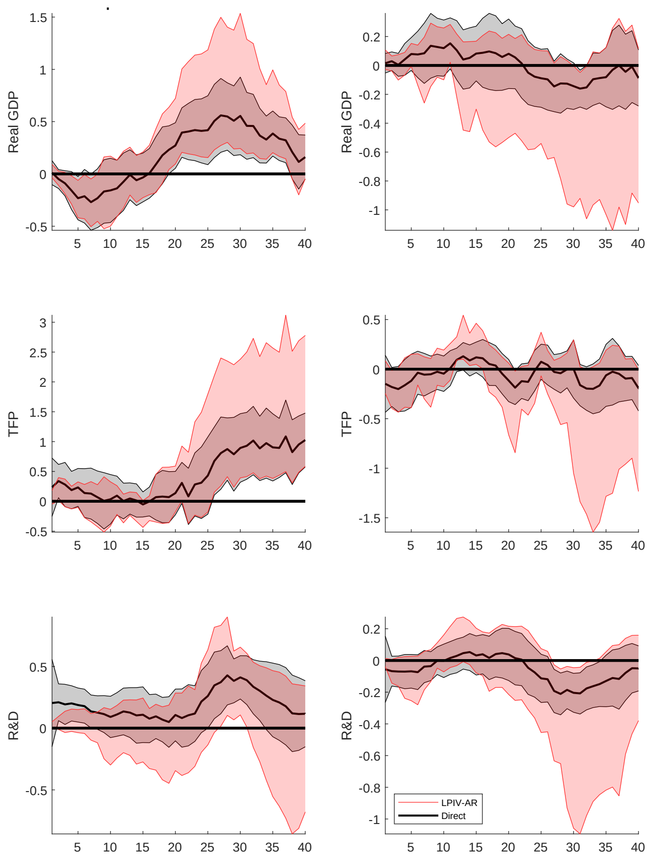
Figure J.1: Responses of GDP, TFP and R&D expenditure to Corporate and Personal Tax Changes using alternative local projection models



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 based on Newey and West (1987) standard errors. The blue dotted line presents the OLS point estimate corrected for bias using the method of Herbst and Johannsen (2020)

Weak instrument robust error bands. Figure J.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.

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



Notes: Impulse responses using IV estimates of local projections.The black lines show OLS estimates, while the dotted red lines are LPIV estimates. The shaded areas are the the 90% error bands, respectively. For LPIV, these are constructed by inverting the Anderson and Rubin (1949) statistic.

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:

   (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.

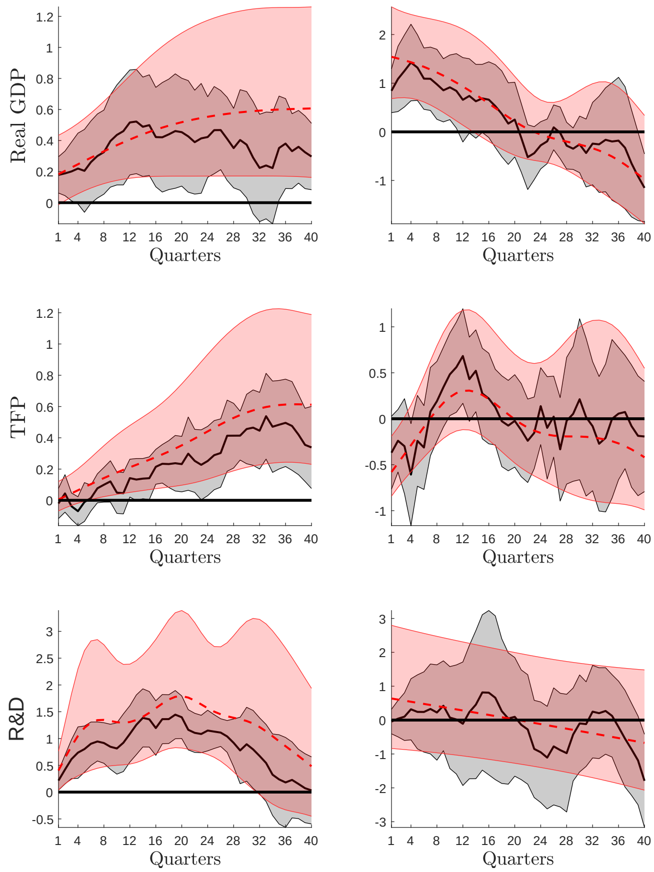
   (b) we then estimate the following regression:

$$Z_{i,t+h} = c^{(h)} + B_1^{(h)} x_t + \sum_{j=1}^{L} b_j^{(h)} Z_{t-j} + u_{t+h}, \qquad u_{t+h} \sim N(0, \sigma_h) \tag{44}$$

   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. 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 HAC standard errors. Figure J.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). Note that

Figure J.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 the Newey and West (1987) HAC estimator for the variance of the coefficients. The bandwidth parameter is set to the horizon of the impulse response

the F-statistic for the corporate tax instrument in this case is 49.44 while this statistic for the personal tax instrument is 109.57. Therefore the orthogonalised shocks from the Mertens and Ravn (2013) VAR seem stronger instruments.

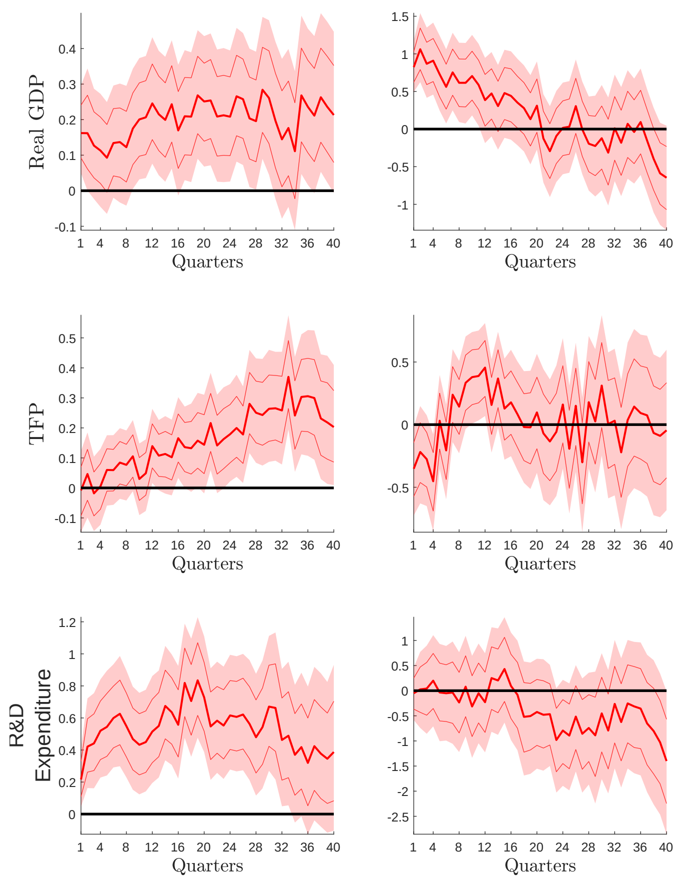
Bayesian LP with MA residuals. In Figure J.4, we use the Bayesian LPs described in section F.2. While the response of GDP, TFP and R&D to corporate shocks is more volatile than the benchmark, the results confirm that this shock has long-lasting effects on output and productivity. In contrast, the estimated impact of personal tax shocks is short-lived.

Alternative Specifications. In Figure J.5, we show that our main findings of very persistent effects of corporate tax changes on GDP and TFP are robust also 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.

K Accounting and tax treatment of intangibles and R&D

The treatment of intangible assets in US GAAP. Intangible assets are non-physical assets that have a quantifiable economic value and are expected to generate future benefits for a company.

Figure J.4: 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.

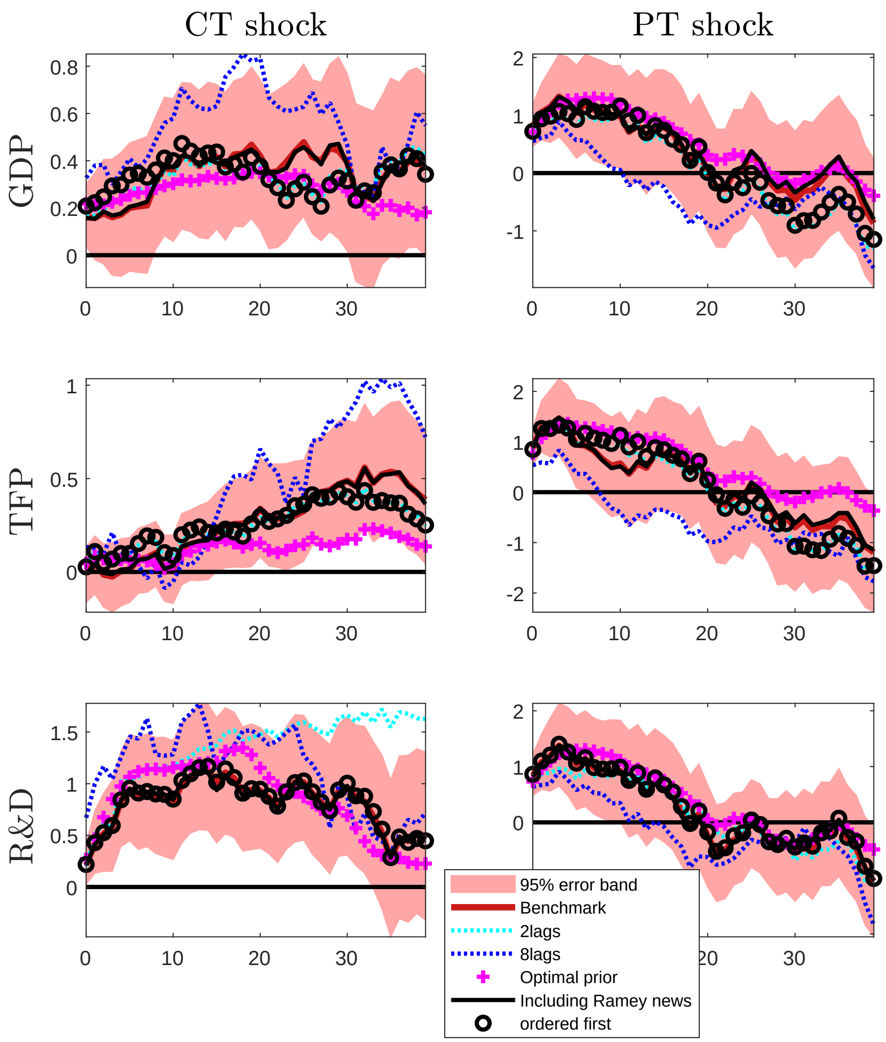
Examples include patents, copyrights, trademarks, goodwill, and brand recognition. US GAAP (Generally Accepted Accounting Principles) distinguish between internally created and externally purchased intangible assets (Ernst & Young (2024)):

- 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 decline in the value of an intangible asset over time, similar to how depreciation works for tangible assets. Under Section 197 of the US 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 amortised over 15 years for tax

Figure J.5: Response of real GDP, TFP and R&D: Different Specifications

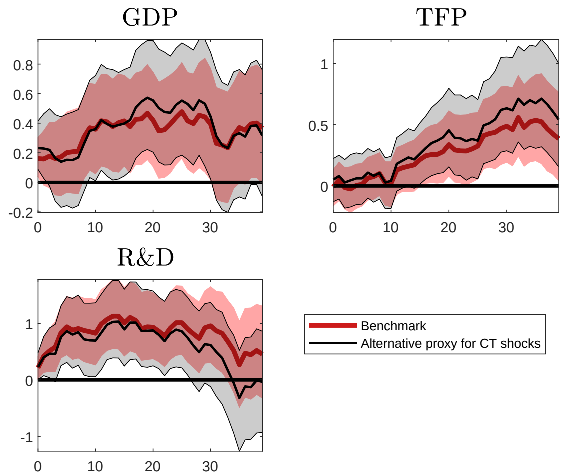


Notes: 90% bands for the baseline empirical real GDP result are shown in pink, together with the point estimates from various alternative specifications. These include: (i) changing number of lags used as control variables, (ii) adjusting the prior, (iii) including the Ramey (2011) defence news shock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

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 explicit provisions for the amortization of intangible assets (Douglass (1994)).

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 US tax code did not have specific provisions addressing R&D expenditures (Guenther (2022)).

Figure J.6: 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.

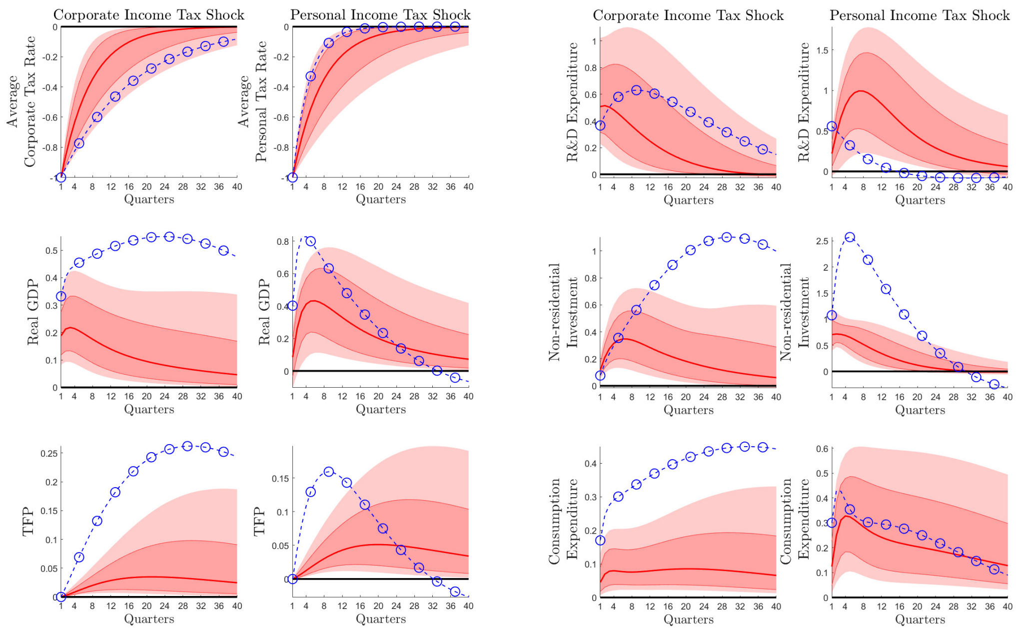
Changes introduced by the TCJA. The TCJA, enacted in 2017, introduced a major change to the tax treatment of REEs, effective for tax years beginning after December 31, 2021 (i.e. after the end of our sample). The key change was the repeal of the option to expense REEs. Companies are now required to capitalise all REEs and amortise 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 amortised over 15 years under Section 197 of the IRC.

L Prior Predictive Analysis

Prior predictive analysis involves drawing a candidate Υ_i from the marginal prior distributions of the parameters. For each candidate Υ_i, the associated set of IRFs, $\Phi(\Upsilon_i)$, are computed. This is repeated 100,000 times, thereby generating a distribution of impulse responses.[3] 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 L.1, we report the distributions of the model impulse responses implied by our prior distributions. The solid (shaded) red lines report the median and central 68% (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.

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

Figure L.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.

M Model Appendix

M.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.

M.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.[4] The symbol Ψ_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, $\Lambda_{t,t+1}$. 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:

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

$\tau_{c,t}$ 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 M.3.

[4] 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.

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 ς. 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 ς to be smaller than the optimal unconstrained markup θ 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 ξ_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:

$$\bar{G}(1+g_y)^t - T_t = \tau_{p,t}\left(\sum_{j\in\{g,a,z\}} w_{j,t} L_{j,t}\right) + \tau_{c,t} C I_t^{TAX}, \tag{55}$$

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 $\tau_{p,t}$

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

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 $R_{n,t+1} = \left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi}\left(\frac{L_t}{\bar{L}}\right)^{\phi_y} R_n\right)^{1-\rho^R} (R_{n,t})^{\rho^R}$ 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; ϕ_π and ϕ_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:

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

M.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:

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

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 US 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 Ξ, 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 depreciation allowances at t plus 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.

N 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 ∇ 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 $A_{t+2} - \phi A_{t+1} = \phi \lambda_t \left(Z_{t+1} - A_{t+1}\right)$.

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 ∇A_{t+2} as the deviation in adopted technologies from the balanced growth path,

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

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 β and β^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 β (the discount factor), plus the parameters of the endogenous growth block of the model (θ, ρ_z, ρ_λ, ϕ, ζ, $\bar{\lambda}$; 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.

O Estimates of the model with no endogenous growth

This section reports the prior and posterior distributions of the parameters of the structural model in the restricted specification with neither technological adoption nor 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 O.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 O.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]
χ_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]
χ_a	Inverse effort elasticity (adoption)	gamma	1	0.5	0.67	[0.29, 1.4]	-	-	-	-
χ_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]
ν''	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]
ξ_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										
θ-1	Dixit-Stiglitz parameter	gamma	0.15	0.1	0.58	[0.43, 0.79]	0.39	[0.23, 0.65]	-	-
ρ_λ	Adoption elasticity	beta	0.5	0.2	0.78	[0.66, 0.87]	-	-	-	-
ρ_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]

P Sectoral Evidence

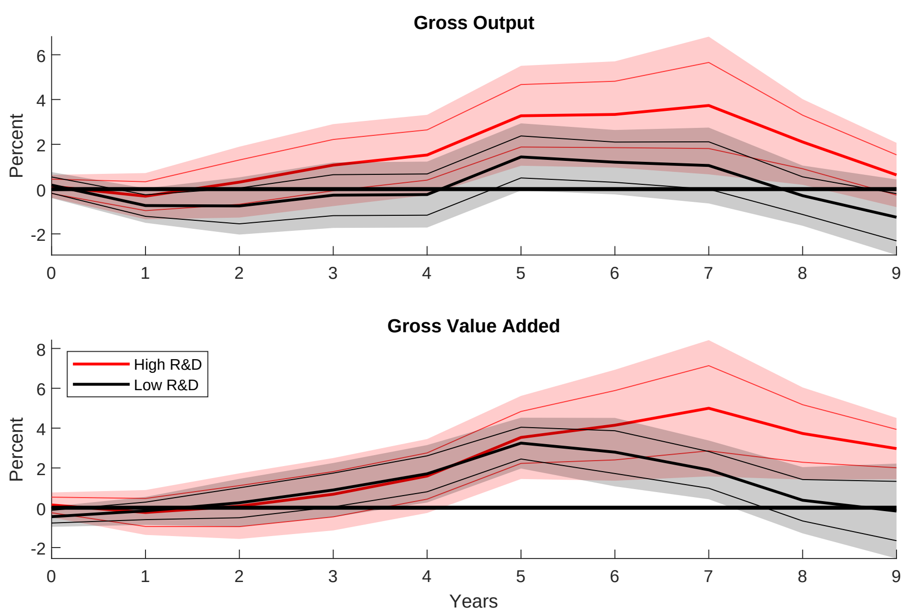
We consider the impact of corporate income tax shocks on Gross Output and Gross value added in 28 industries using BEA sectoral annual data. Our goal is to investigate whether the effects of corporate taxes are different for industries classified as R%D intensive. We adopt a simple approach and estimate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

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

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. $i = 1, \ldots, N$ 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 τ_{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% credible sets.

In Figure P.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 P.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.