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Mariano Croce,
University of North Carolina at Chapel Hill

Thien Nguyen,
The Ohio State University

Steve Raymond,
University of North Carolina at Chapel Hill

Lukas Schmid,
Duke University

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M. Croce T. Nguyen S. Raymond L. Schmid*

Abstract

Elevated levels of government debt raise concerns about their effects on long-term growth prospects. Using the cross section of US stock returns, we show that (i) high-R&D firms are more exposed to government debt and pay higher expected returns than low-R&D firms; and (ii) higher levels of the debt-to-GDP ratio predict higher risk premia for high-R&D firms. Furthermore, rises in the cost of capital for innovation-intensive firms predict declines in subsequent R&D activity and economic growth. We study these findings in a production-based asset pricing model with endogenous innovation as in Comin and Gertler (2006). By accounting for fiscal and political risk, our model reproduces several aspects of the empirical evidence.

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*Croce is affiliated with the University of North Carolina at Chapel Hill, Kenan-Flagler Business School. Nguyen is affiliated with the Ohio State University, Fisher College of Business. Raymond is a PhD student in the Economics Department of the University of North Carolina at Chapel Hill. Schmid is affiliated with Duke University, Fuqua School of Business, and CEPR. We are grateful for feedback from Diego Comin, Joao Gomes, Timothy Johnson, Dana Kiku, Amir Yaron, and Joshua Pollet. We thank the seminar participants at the Wharton School, the Finance Department at the Erasmus University, the UIUC College of Business, the Kenan-Flagler Business School (UNC), the Fuqua School of Business (Duke University), the Fisher College of Business (OSU), Olin Business School (Washington University), Scheller College of Business (Georgia Institute of Technology), the SED Conference, the Econometric Society Meetings, the RCEF Conference, and The University of St. Gallen Conference on Growth.

1 Introduction

Fiscal stabilization policies implemented in response to the recent great recession have led to a surge in government debt across the globe. A common concern is that the budget consolidation processes required by this debt will come at the cost of dimmer long-run growth prospects. Such concerns are based on expectations of either higher future tax pressure or raises in average inflation through attempts to inflate debt away, as well as on the political uncertainty surrounding the restoration of a balanced budget. While these adverse effects of debt and fiscal policy on economic growth are well grounded in economic theory, the empirical evidence in their support in cross-country tests has been weak or ambiguous, perhaps because of short samples and small cross sections.

In this paper, we propose a different perspective based on a large cross section of US firms. We highlight a novel and distinct mechanism shaping the link between public debt and future growth, namely a *risk* channel. More specifically, we identify innovations to government indebtedness as a risk factor priced in both the cross section and the time series of stock returns. By affecting their cost of capital, movements in government debt impact firms' investment and, critically, innovation decisions. Empirically, we implement powerful tests of this link on the entire cross-section of US stock returns, and interpret and quantify them through the lens of a production-based asset pricing model with endogenous innovation and growth in the spirit of Comin and Gertler (2006).

Our analysis starts from the empirical observation that the government debt–to–GDP ratio, $DGDP$ for short, significantly predicts higher future aggregate stock returns at longer horizons, even after we control for standard predictors such as the price-dividend ratio and market volatility. In other words, investors perceive episodes of high government debt as bad times. This finding suggests that news to government debt is a risk factor priced in the cross section of stock returns, as investors are hesitant to incur losses on stocks in times of rising debt. Indeed, we find that about one third of the well documented premium of R&D-intensive stocks over less innovative stocks—hereafter, the return on what we call the

HML-R&D portfolio—can be attributed to exposure to fiscal variables. In the time series, we show that this premium rises when government debt increases. In other words, our asset pricing tests suggest that rises in government debt increase the cost of capital, especially for innovative firms, as measured by Lin (2012).

Critically, we document that movements in the cost of capital of innovative firms in response to surges in government debt predict slowdowns in innovative activity and declines in growth prospects at longer horizons. For example, an increase in the expected excess return of the *HML-R&D* portfolio forecasts a significant decline in output growth over a horizon of 20 quarters. This is because rises in $DGDP$ are accompanied by subsequent declines in corporate investment and R&D. At the same time, a reallocation towards investment in physical capital occurs, as innovation is depressed relatively more.

To interpret our findings and provide guidance on further empirical tests, we develop a quantitative model of a stochastic production economy in which endogenous innovation drives growth prospects and the Ricardian equivalence does not hold (Barro (1974, 1979)). Specifically, we focus on an economy with two capital stocks, one of which is comprised of intangible innovations (for a complementary approach with more firm heterogeneity, see Gomes, Michaelides, and Polkovnichenko (2010, 2012)). The government finances expenditures by issuing debt and levying distortionary taxes on corporate profits according to fiscal rules that determine the extent of fiscal stabilization through tax smoothing (i.e., the persistence and the volatility of the tax rate). Movements in government debt drive the dynamics of tax rates, which affect corporate investment and innovation and thus equilibrium growth.

We find that the model quantitatively rationalizes our empirical evidence on return predictability well when we allow for shocks to productivity, government expenditures, and government financing. Financing shocks alter the government's stance regarding deficit spending. In our general equilibrium setting, all of these three shocks are reflected in the stochastic discount factor and hence give rise to a three-factor asset pricing model. More specifically, we show that our general equilibrium model predicts nearly constant negative market prices of debt policy and government expenditure risks, and exposures of returns to fundamental shocks that are nearly affine in $DGDP$. As a result, the reduced form of our equilibrium model is a three-factor model with conditional betas that can be expressed as a linear function of $DGDP$. In our setting, a rising $DGDP$ level elevates the exposure of returns to the underlying risks and forces firms to cope with a higher cost of capital.

Our model also predicts that excess returns on *HML-R&D* are forecastable by $DGDP$ because the sensitivity of the cost of capital of innovative firms with respect to $DGDP$ is higher than that of low R&D-intensity firms. The mechanism behind this result can be explained as follows. As $DGDP$ increases, uncertainty about future tax rates rises endogenously and trickles down to all quantities in general equilibrium. Since the value of innovative firms is crucially driven by the present value of volatile monopolistic rents, R&D firms are more exposed to spikes in cash-flow uncertainty than non-R&D firms.

From the perspective of the representative household, such elevated exposure triggers a reallocation of investment towards tangible capital. With adjustment costs, the market value of low R&D-intensity firms falls less, so that they emerge as a hedge through this reallocation. This channel is stronger when the economy has higher values of $DGDP$.

As a result, less innovative firms are unconditionally less risky than R&D-intensive firms (e.g., our model-impled *HML-R&D* is positive as in the data) and relatively safer in high debt episodes (e.g., the model-implied *HML-R&D* grows with $DGDP$). Within the context of the model, this premium predominantly reflects elevated exposure to debt policy shocks. We view these shocks as arising from the budget negotiation process or from shifts in the political composition of the administration. Our model thus highlights the role of political risk in the determination of risk premia, in the spirit of Kelly, Pastor, and Veronesi (2015) and Pastor and Veronesi (2012, 2013).

We provide further evidence supporting our cost of capital mechanism by running standard cross-sectional asset pricing tests based on the conditional three-factor model implied by our production economy. This cross-sectional estimation is based on both R&D-sorted

test assets as well as the twenty-five Fama-French size and book-to-market double-sorted portfolios. Our estimation results confirm significantly negative risk prices for fiscal risks, implying that sudden rises in $DGDP$ are indeed bad states for investors.

Moreover, in line with our model predictions, the expected excess return on *HML-R&D* is increasing in $DGDP$ so that high-R&D firms are more exposed to government debt and pay higher expected returns than low-R&D firms. Notably, these results hold even after controlling for standard financial risk factors, confirming a distinct role for fiscal factors both in the cross-section of innovation-sorted returns and for aggregate investment and growth.

Related Literature. Our paper contributes to several strands of literature. First, our study highlights the role of political risk in determining the cost of capital across innovation-sorted firms. In this regard, our analysis is related to the growing literature on policy uncertainty and asset markets (see, among others, Kelly, Pastor, and Veronesi (2015); Pastor and Veronesi (2012, 2013); Bloom (2009); Baker, Bloom, and Davis (2016); Manela and Moreira (2016); Gomes, Michaelides, and Polkovnichenko (2010, 2012); Gomes, Kotlikoff, and Viceira (2011); Glover, Gomes, and Yaron (2010); Belo, Gala, and Li (2013); Belo and Yu (2013); Sialm (2009); Croce, Kung, Nguyen, and Schmid (2012); Brogaard and Detzel (2015); and Fernandez-Villaverde, Guerrn-Quintana, Kuester, and Rubio-Ramrez (2015)). Lustig, Sleet, and Yeltekin (2008) and Lustig, Berndt, and Yeltekin (2012) examine the nature of fiscal risks. In contrast to these studies, we examine the role of uncertainty about the fiscal stance in both the cross section and the time series of stock returns. Our results on the link between government borrowing and the cost of equity of innovation-intensive firms complements those found by Graham, Leary, and Roberts (2014) in the corporate bonds market.

Our empirical asset pricing tests are in the spirit of recent and classic work emphasizing return predictability in the cross section and the time series. A nonexhaustive list of classic papers on cross-sectional return predictability includes Fama and French (1992, 1993);

Cochrane (1996); and Pastor and Stambaugh (2003). These papers establish a number of important tradable and macroeconomic factors priced in the cross section of stock returns. Recent work by Hou, Xue, and Zhang (2015a, b) and Fama and French (2015) adds novel factors related to corporate policies to that list, such as investment and profitability factors. We contribute to this literature by introducing a simple and economically meaningful predictor in both the cross section and the time series, namely our $DGDP$ factor.

Time-series predictability has been explored by Campbell and Shiller (1988), Cochrane (2008), Lettau and Ludvigson (2005), and Koijen, Lustig, and Van Nieuwerburgh (2010), among others. We document the relevance of $DGDP$ in this regard. In independent recent work, Bai (2016) and Liu (2016) empirically confirm that the government $DGDP$ ratio significantly predicts aggregate stock returns over longer horizons. In addition, we show that our $DGDP$ factor predicts not only aggregate stock returns, but also spreads between innovation-sorted portfolios in the time series and cross section. Furthermore, we explicitly link fiscal uncertainty, innovation, and growth, adding new insights to the findings of Easterly and Rebelo (1993); Mendoza, Milesi-Ferretti, and Asea (1997); Mendoza and Tesar (1998); and Barro and Redlick (2011).

Methodologically, our theoretical work builds on recent papers by Comin and Gertler (2006); Comin, Gertler, and Santacreu (2009); Kung and Schmid (2015); Corhay, Kung, and Schmid (2015); and Gavazzoni and Santacreu (2015). Following on the seminal work of Romer (1990) and Grossman and Helpman (1991), these papers integrate innovation-based endogenous growth models into the workhorse real business cycle model of macroeconomics. In contrast, our paper focuses on the role of government debt and taxation on investment, growth, and returns. In this sense, our paper is related to that of Croce, Nguyen, and Schmid (2012), who introduce fiscal policy into a simple stochastic endogenous growth model.

More broadly, our paper shares its focus with the growing literature on asset pricing in general equilibrium models with production. We adopt recursive preferences, in the more recent spirit of Tallarini (2000); Campanale, Castro, and Clementi (2010); Kuehn (2008, 2009);

Kaltenbrunner and Lochstoer (2010), as they all explore the relevance of priced endogenous consumption news shocks. Gourio (2012, 2013) examines disaster risks, a dimension which we consider relevant for future analysis on fiscal policy, but that is not part of our current analysis.

This paper is structured as follows. In section 2, we provide motivating empirical evidence linking movements in the government debt–to–GDP ratio to time-series patterns in stock returns. We develop a model to rationalize these findings in section 3. We calibrate the model in section 4 and provide novel predictions on the cross-sectional determinants of stock returns. We provide direct cross-sectional tests in the data in section 5. Section 6 concludes.

2 Empirical Analysis

In this section, we provide novel empirical evidence on the link between government debt and R&D-sorted stock returns. We begin by describing our data sources, and then we discuss the results from our empirical asset-pricing tests.

2.1 Data Sources

We use stock return data from CRSP and fundamental accounting data from COMPUSTAT to construct a combined panel at a quarterly frequency from 1966:Q2–2013:Q4. For each calendar year, we construct stock return portfolios by sorting firms based on their R&D intensity. Our benchmark measure of intensity is the ratio of R&D expenses to total assets, as reported on COMPUSTAT. Our results are confirmed also when we measure intensity as the ratio of R&D and capital expenditures (CAPEX), as in Lin (2012).

We group firms into ten portfolios based on approximately even market capitalization. Each portfolio constitutes at least 10% of the total market capitalization; hence, our results are not based on a small number of illiquid stocks. We rebalance these portfolios once for each year based on the previous year's R&D intensity and record the equally-weighted (EW) return performance for the subsequent year. We work on equally-weighted returns so that our asset pricing results are not driven by large firms. Our results are preserved and often enhanced when working with value-weighted returns. Table A1 in the appendix gives a flavor of the industry composition of these portfolios. Our results are consistent with prior studies in the literature.

Summary statistics of our extreme portfolios are reported in table 1. Consistent with prior findings, our R&D-intensive firms feature higher average excess returns, lower financial leverage, and lower sales-to-assets ratios then firms in our low-R&D-intensity firms. In the appendix, table A2, we report the corresponding results when we restrict our sample to firms with positive R&D, as often customary in empirical work on firm-level innovation (Chan, Lakonishok, and Sougiannis (2001)). In table A2, we group portfolios 2–9 into a single portfolio called "Middle". In this case, our results arguably are even stronger, as the excess return spread on innovative firms almost doubles.

In the second part of our empirical procedure, we employ the q-factors of Hou, Xue, and Zhang (2015a, b) and the Fama and French (2015) five factors (FF5). Fama-French factors and portfolio returns are from Kenneth French's website, and price-dividend data are from Robert Shillers website.[1] Quarterly market volatility is defined as the sum of squared monthly returns for a given quarter. Our quarterly macroeconomic data are from the Federal Reserve Bank of St. Louis. Productivity is utilization-adjusted as in Fernald et al. (2012) (San Francisco FED). All measures are seasonally adjusted. In what follows, $DGDP$ denotes US quarterly debt-output ratio.

2.2 Time-Series Asset Pricing Tests

In tables 2 and 3, we report results from predictive return regressions at various horizons. We show results both at the market level and for our cross section of portfolios sorted on firms' innovation intensity. Specifically, we report summary results for our bottom-10 (*Low-R&D*)

[1]We thank Hou, Xue, Zhang as well as Fama and French and Shiller for sharing their data for use in this study.

Table 1: Data Summary Statistics

	Low	High	*HML-R&D*
	Portfolio Returns		
Mean	17.21***	23.57***	6.14**
	(3.80)	(4.47)	(2.99)
Standard Deviation	26.27	30.91	20.65
Sample Size	191	191	191
	Portfolio Characteristics		
Market Capital Share	10.49	11.20	21.69
R&D/Assets	0.14	77.25	38.70
Sales/Assets	2.73	0.14	1.43
Equity/Assets	41	55	48
Average Number of Firms	403	589	

Notes: This table shows summary statistics for two R&D-sorted portfolios and the implied *HML-R&D* portfolio. Returns are equally-weighted and presented in annualized percentages. The average market capital share, R&D/Assets, Sales/Assets, and Equity/Assets are presented in percentages. R&D/Assets is defined as annual research & development expenses divided by total assets and is used as our benchmark measure of R&D intensity. Our two extreme portfolio cover at least 10% of market capitalization. Sales/Assets is defined as annual net sales divided by total assets. Equity/Assets is defined as total shareholders' equity divided by total assets. Our quarterly sample starts in 1966:Q2 and ends in 2013:Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

and top-10 (*High-R&D*) portfolios, the entire market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). In addition to $DGDP$, we use standard predictors such as price-dividend ratios and market volatility. In this exercise, we do not include aggregate productivity growth because it plays no role in our forecasting regressions.

Consistent with Bai (2016) and Liu (2016), we find that government debt predicts aggregate market returns significantly with a positive sign. This suggests that times of high government indebtedness correspond to times of high aggregate risk premiums and are thus viewed as bad states of the world from the perspective of investors.

Most importantly, we are the first to show that $DGDP$ is an important predictor for the entire cross section of innovation intensity–sorted stocks, and especially so for innovation-intensive firms. As a result, high levels of government debt also forecast higher expected

Table 2: *DGDP* and Predictability of Returns to Innovation

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.12***	0.22**	0.39**	0.52	0.62
	(0.05)	(0.09)	(0.19)	(0.37)	(0.95)
R^2	0.07	0.15	0.16	0.15	0.15
High-R&D	0.16***	0.31***	0.59***	1.05**	3.14***
	(0.05)	(0.10)	(0.21)	(0.41)	(1.19)
R^2	0.05	0.11	0.15	0.19	0.33
HML-R&D	0.04	0.09	0.20*	0.53**	2.51***
	(0.03)	(0.06)	(0.12)	(0.23)	(0.54)
R^2	0.02	0.02	0.03	0.07	0.42
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return; $DGDP$ and PD denote debt-to-output and aggregate price-dividend ratio, respectively; and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equally weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

returns for our *HML-R&D* portfolio. These findings are robust across all forecast horizons and become more significant for longer holding periods.

In the appendix, we report a detailed series of robustness tests which suggests that our baseline empirical results may be interpreted as conservative. When we use value-weighted returns (see tables A3 and A4), the predictability of our *HML-R&D* returns is enhanced as it is statistically significant also over short horizons of one and two quarters. When we restrict our samples to positive R&D firms, our predictability results continue to be significant, regardless of whether we use equally-weighted returns (see tables A5 and A6)

Table 3: ***PD, MV*** **and Predictability of Returns to Innovation**

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	−0.0008	−0.0013	−0.0020	−0.0015	0.0024
	(0.0007)	(0.0012)	(0.0022)	(0.0036)	(0.0049)
High-R&D	−0.0006	−0.0010	−0.0017	−0.0014	−0.0030
	(0.0009)	(0.0016)	(0.0027)	(0.0036)	(0.0042)
HML-R&D	0.0002	0.0003	0.0003	0.0000	−0.0054**
	(0.0005)	(0.0010)	(0.0021)	(0.0000)	(0.0026)
Market	−0.0011***	−0.0021***	−0.0043***	−0.0081***	−0.0147***
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	1.10**	2.46***	3.61***	4.69***	6.21***
	(0.46)	(0.50)	(0.90)	(1.37)	(1.62)
High-R&D	0.84*	2.07***	3.57***	4.90***	6.27**
	(0.45)	(0.44)	(0.91)	(1.54)	(2.58)
HML-R&D	−0.26	−0.39*	−0.04	0.21	0.06
	(0.18)	(0.21)	(0.36)	(0.70)	(1.19)
Market	0.31	0.88*	1.12**	1.54**	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equally-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

or value-weighted returns (see A7 and A8). In addition, our results are confirmed when we focus on a sample starting in 1975 (see tables A9 and A10), when the Financial Accounting Standards Board (FASB) introduced new accounting standards regarding the expensing of R&D costs.

We note that our predictability results hold after controlling for both price-dividend ratio and market volatility; thus, we are using a distinct predictor which is meaningful both statistically and economically. For completeness, we report the predictability results for these two canonical factors in table 3. We find that the price-dividend ratio predicts future market returns with a significant negative coefficient, consistent with many prior studies. This negative impact is statistically relevant for *HML-R&D* only over the long-run. Market volatility is a significant predictor for expected returns, but it has no significant impact on *HML-R&D*, in sharp contrast to government debt.

To summarize, our asset pricing tests show that innovative firms earn a time varying premium that rises with government indebtedness. In other words, the cost of capital for innovative firms increases with government debt, and more so than for less innovative firms. To the extent that innovative firms are engines of growth, rises in government debt may have implications for the real economy through its impact on their cost of capital. We examine this intuition in the next section.

2.3 Government Debt, R&D, and Growth

In this section we provide evidence on the effects of government debt on real economic activity both in the cross section of R&D intensity–sorted firms and in the aggregate.

***DGDP* and Investments.** In table 4, we show several relevant results regarding the link between $DGDP$ and investment decisions both in the aggregate and for firms in our top-10 portfolio (High R&D). To facilitate comparisons, all variables are standardized. First, we document that an increase in government debt is indeed associated with a decline in firms' future investment growth both in R&D and in fixed assets.

As documented in the rightmost column, the drop in R&D investment dominates the reduction in capital expenditure both in the aggregate and for high-R&D-intensive firms.[2] Equivalently, when $DGDP$ increases there exists a strong reallocation effect away from R&D as firms reduce their total investment but increase their relative investment in fixed assets. In the theoretical part of this manuscript, we show that this reallocation effect can explain

[2] We first compute the difference of the raw investment growth rates and then standardize the resulting series.

Table 4: Predicting Investment with $DGDP$

	$\Delta R\&D_{t+1}$	ΔI_{t+1}	$\Delta I_{t+1} - \Delta R\&D_{t+1}$
Panel A: Aggregate Data			
θ^{A}_{DGDP}	-0.24^{**}	-0.05	1.13^{***}
	(0.12)	(0.06)	(0.35)
Panel B: Micro Data			
$\theta^{\text{High}}_{DGDP}$	-0.22^{***}	-0.25^{***}	0.20^{***}
	(0.06)	(0.06)	(0.06)

Notes: Panel A shows results from the following predictive regressions:

$$y_{t+1} = \theta_0 + \theta^{A}_{DGDP} \cdot \Delta DGDP_t + \text{controls}_t + \epsilon_{t+1}$$

where y_{t+1} is either aggregate R&D investment growth ($\Delta R\&D_t$), private domestic investment growth (ΔI_{t+1}), or the difference of these growth rates. $\Delta DGDP_t$ denotes debt-to-output ratio growth. Our control variables are the growth rates of aggregate TFP and government spending. Our quarterly sample starts in 1947:Q1 and ends in 2013:Q4.
Panel B reports results from the following predictive regressions:

$$y^{\text{High}}_{t+1} = \theta^{\text{High}}_0 + \theta^{\text{High}}_{DGDP} \cdot \Delta DGDP_t + \text{controls}^{\text{High}}_t + \epsilon_{t+1}$$

where 'High' refers to our top-10 (High-R&D) portfolio, and y^{High}_{t+1} is either portfolio-level R&D investment growth, physical investment growth, or the difference of these growth rates. We control for average portfolio-level Tobin's Q. Our COMPUSTAT quarterly sample starts in 1966:Q2 and ends in 2013:Q4. In both panels, Newey-West (1987) standard errors are in parentheses. All variables are standardized. In the rightmost column, we first compute the difference of the raw investment growth rates and then standardize the resulting series. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

the link between *HML-R&D* and $DGDP$.

We note that our aggregate results are obtained after controlling for productivity and government expenditure changes, i.e., two key exogenous variables in the context of the model that we introduce in the next section. Through the lens of our model, an adjustment in $DGDP$ uncorrelated to productivity and government expenditure news can be interpreted as a pure shock to public financing, i.e., to the mix of taxation and deficits. When working with firm data aggregated to a portfolio level, we control for measured Tobin's Q, a standard proxy for growth opportunities. Equivalently, our channel is economically and statistically relevant even after we account for a key firm characteristic used to predict investment growth.

***DGDP* and Output.** It takes time for R&D investment to generate innovation and be manifested in observable GDP growth. For this reason, in order to assess the impact of government debt on future growth, we forecast output growth over long horizons and report the results in table 5. In panel A, we report our findings from a simple univariate regression. Across all possible horizons, the debt-to-GDP ratio forecasts output growth with a negative coefficient. This coefficient is statistically significant over a two-year and even a five-year horizon.

In panel B, we corroborate these results further by connecting future output growth to our results on the cost of capital of R&D-intensive firms. Specifically, Croce, Nguyen, and Schmid (2012) show that the free-entry condition of a stochastic version of the Romer (1990) model implies a negative link between growth and cost of capital. The contemporaneous connection between current growth and unexpected productivity shocks, in contrast, should be positive. In the context of our empirical investigation, these statements apply to the returns of *HML-R&D*, as this portfolio has a short position in low-innovation stocks, that is, firms that are essentially out of the R&D segment of the economy.

Our empirical results are consistent with the aforementioned theoretical insights on the free-entry condition in the innovation sector. When we forecast returns with the predictive variables discussed in the previous section, we find that $DGDP$-induced rises in expected *HML-R&D* predict lower growth going forward. Unexpected good shocks to *HML-R&D* returns, conversely, are associated with contemporaneous improvements in growth. These results are significant at medium horizons, consistent with Comin and Gertler (2006). Furthermore, our findings hold regardless of whether we use equally-weighted or value-weighted results (see panel C of table 5).

These patterns linking debt, innovation, and returns motivate us to develop a formal R&D-based production economy model in order to link fiscal policy risks and growth and provide a structural interpretation of our empirical results.

Table 5: *DGDP* and GDP Growth Predictability

Horizon J	1	2	4	8	20
		Panel A: Forecasts based on *DGDP*			
DGDP	-0.003	-0.007	-0.015^{*}	-0.032^{**}	-0.101^{***}
	(0.003)	(0.005)	(0.009)	(0.014)	(0.032)
R^2	0.006	0.009	0.014	0.023	0.070
		Panel B: Forecasts based on *HML-R&D* Return Decomposition-EW			
$\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right)$	0.0001	-0.0332	-0.0714^{*}	-0.0591^{**}	-0.0328^{**}
	(0.0621)	(0.0450)	(0.0415)	(0.0274)	(0.0161)
$\widehat{\epsilon_{t+J}}$	0.0061	0.0055	0.0057	0.0034	0.0063
	(0.0057)	(0.0052)	(0.0053)	(0.0071)	(0.0100)
R^2	0.0044	0.0060	0.0171	0.0213	0.0303
		Panel C: Forecasts based on *HML-R&D* Return Decomposition-VW			
$\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right)$	-0.0226	-0.0227	-0.0298	-0.0306^{*}	-0.0270^{**}
	(0.0370)	(0.0259)	(0.0212)	(0.0166)	(0.0135)
$\widehat{\epsilon_{t+J}}$	0.0037	0.0113^{**}	0.0191^{***}	0.0267^{***}	0.0034
	(0.0057)	(0.0057)	(0.0069)	(0.0083)	(0.0081)
R^2	0.0038	0.0184	0.0406	0.0511	0.0289

Notes: We forecast excess returns cumulated over J quarters using the following predictive regression:

$$R^{HML-R\&D}_{t\to t+J} = \beta^J_0 + \beta^J_{DGDP}\cdot DGDP_t + \beta^J_{PD}\cdot PD_t + \beta^J_{MV}\cdot MV_t + \epsilon_{t+J},$$

and obtain expected returns as in table 2,

$$\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right) = \widehat{\beta^J_0} + \widehat{\beta^J_{DGDP}}\cdot DGDP_t + \widehat{\beta^J_{PD}}\cdot PD_t + \widehat{\beta^J_{MV}}\cdot MV_t.$$

Portfolios are formed based on innovation intensity, measured as R&D investment expenses divided by total value of assets. Panel A shows the results from the following predictive regression:

$$\Delta GDP_{t\to t+J} = d^J_0 + d^J_1\cdot Debt_t/GDP_{t-1} + w_{t+J}.$$

Panel B shows the results from the following predictive regression:

$$\Delta GDP_{t\to t+J} = c^J_0 + c^J_1\cdot \widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right) + c^J_2\cdot\widehat{\epsilon_{t+J}} + v_{t+J},$$

where $\Delta GDP_{t\to t+J}$ denotes J-period cumulative output growth. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

3 An Asset-Pricing Model with Debt and Innovation

We link public debt and innovation by developing a stochastic endogenous growth model in which a government finances exogenous expenditures by issuing public debt and taxing firms. Our baseline framework adds fiscal policy rules in the spirit of Croce, Nguyen, and Schmid (2012) to the Comin and Gertler (2006) model with recursive preferences proposed by Kung and Schmid (2015).

In the model, there is no exogenous technological progress, since sustained growth arises endogenously through the accumulation of patented intermediate goods (henceforth patents) that facilitate the production of a final consumption good. New patents are created through innovation requiring investment in research and development and can be stored. In this model, therefore, patents represent an endogenous stock of intangible capital. The model also features physical capital and can be used to study a cross section of returns sorted according to R&D intensity.

We start by introducing the government's fiscal stance. We proceed by describing in detail the production sector and the innovation process in our economy, after which we present the household sector and define the general equilibrium.

3.1 Government

We assume that the government faces an exogenous and stochastic expenditure stream, G_t, that evolves as follows:

$$\frac{G_t}{GDP_t} = \frac{1}{1 + e^{-gy_t}}, \tag{1}$$

where

$$gy_t = (1 - \rho_G)\overline{gy} + \rho_G gy_{t-1} + \epsilon_{G,t}, \quad \epsilon_{G,t} \sim N(0, \sigma_G^2). \tag{2}$$

This specification ensures that $G_t \in (0, GDP_t)$ for all date t, and it enables us to replicate key features of the expenditure-to-output ratio observed in the US data. In most of our analysis, we focus only on the expenditure component of total public liabilities and abstract away from entitlements. GDP_t arises endogenously from the production process, and we describe its components in detail below.

We assume that the government can finance these expenditures by raising public debt or by levying distortionary profit taxes on corporations, at a possibly time-varying rate τ_t. When doing so, the government is subject to the following budget constraint:

$$B_t = (1 + r_{f,t-1})B_{t-1} + G_t - T_t, \tag{3}$$

where $T_t = \tau_t \cdot tax\, base_t$ denotes its total tax income. We specify the components of the tax base below.

The government chooses the mix of taxation and deficit by means of simple, implementable, and plausible fiscal rules, in the spirit of Favero and Monacelli (2005), Schmitt-Grohe and Uribe (2007), Bi and Leeper (2010), and Leeper, Plante, and Traum (2010). In this paper we focus on a tax rule that allows for tax smoothing and lets the government adjust its fiscal stance according to prevailing macroeconomic conditions. We focus on two aspects of tax smoothing, namely the persistence and intensity of swings in the tax rate. We specify the government's policy in terms of a debt management rule, with tax rates implied by the budget constraint, as follows:

$$\frac{B_t}{GDP_t} = (1 - \rho_B)\mu_B + \rho_B \frac{B_{t-1}}{GDP_{t-1}} + \epsilon_t^B, \tag{4}$$

$$\epsilon_t^B = A_\omega \epsilon_{\omega,t} + A_G \epsilon_{G,t} + A_\phi \epsilon_{\phi,t}, \tag{5}$$

where A_ω, A_G and A_ϕ are constant parameters that determine both the intensity and cyclicality of the government response to shocks; $\epsilon_{\omega,t}$ is a productivity shock; and $\epsilon_{\phi,t} \sim i.i.d.N(0,1)$ is a pure policy shock. In what follows, we show that policy shocks are relevant in bringing the model closer to the data. The parameter μ_B captures the long-run level of debt, and $\rho_B \in (0,1)$ is a measure of the speed of repayment of debt: the higher the value of ρ_B, the slower the repayment of debt relative to output.

This parsimonious specification has two main advantages. First, the condition $\rho_B < 1$ guarantees that the debt-output ratio remains stationary, consistent with the evidence in

Bohn (1998). In the language of Bi and Leeper (2010), our rule in equation (4) anchors expectations about future debt and rules out unstable paths. Second, this specification replicates key empirical properties of the US debt-output ratio.

3.2 Production

The production process involves three sectors. The final consumption good is produced in a competitive sector, namely the final-goods sector, using physical capital, labor, and patents. Stationary shocks drive stochastic fluctuations in the production of the final consumption good. Patents are produced in the intangible sector, where firms have monopoly power. New patents are created by means of innovation through R&D in the competitive innovation sector, which determine the speed of growth.

Regarding taxation, we assume that profits in both the final-goods sector and the intangible sector are taxed at the rate τ_t. In this setup, taxes distort firms' investment and innovation decisions, and hence the rate and the dynamics of growth.

Final-Goods Sector. There is a representative firm that uses capital K_t, labor L_t, and a composite of patents Γ_t to produce the final (consumption) good according to the production technology

$$Y_t = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\Gamma_t^{\xi}, \tag{6}$$

where the composite Γ_t is defined as

$$\Gamma_t \equiv \left[\int_0^{N_t} X_{i,t}^{\nu}\, di\right]^{\frac{1}{\nu}}, \tag{7}$$

and $X_{i,t}$ is the quantity of patents $i \in [0, N_t]$. N_t is the measure of patents in use at date t, α is the physical capital share, ξ is the intangible capital share, and the elasticity of substitution between patents is $\frac{1}{1-\nu}$ with $\nu < 1$. We interpret N_t as the stock of intangible capital.

We introduce uncertainty into the model by means of an exogenous stochastic process Ω_t affecting the level of output. Importantly, we assume that Ω_t follows a stationary Markov process by specifying that $\Omega_t = e^{a_t}$, and $a_t = \rho a_{t-1} + \epsilon_{\omega,t}$, with $\epsilon_{\omega,t} \sim N(0, \sigma^2)$ and $\rho < 1$. Because the forcing process is stationary, sustained growth arises endogenously from the development of new patents. We describe how new patents are developed by means of innovation below.

The firm's objective is to maximize shareholder value. This can be formally stated as

$$\max_{\{I_t, L_t, K_{t+1}, X_{i,t}\}_{t \geq 0, i \in [0, N_t]}} E_0 \left[\sum_{t=0}^{\infty} M_t D_t \right],$$

where the firm's dividends are

$$D_t = (1 - \tau_t) \left[Y_t - W_t L_t - \int_0^{N_t} P_{i,t} X_{i,t} \, di \right] - I_t. \tag{8}$$

Here, M_t is the stochastic discount factor, I_t is investment in physical capital, W_t is the wage rate, and $P_{i,t}$ is the price per unit of patent i at time t. Prices $P_{i,t}$ are set by patent producers in the intangible sector, while the stochastic discount factor and the wage rate are determined in the general equilibrium and are all taken as given by the final-goods firm. The final-goods firm's profits are taxed at the rate τ_t.

In line with the literature on production-based asset pricing, we assume that investment is subject to convex capital adjustment costs, so that the physical capital stock evolves as

$$K_{t+1} = (1 - \delta) K_t + \Lambda \left(\frac{I_t}{K_t} \right) K_t. \tag{9}$$

Here, δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ the capital adjustment cost function. We specify $\Lambda(\cdot)$ as in Jermann (1998), $\Lambda\left(\frac{I_t}{K_t}\right) \equiv \frac{\alpha_1}{\zeta} \left(\frac{I_t}{K_t}\right)^{\zeta} + \alpha_2$, where $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters α_1 and α_2 are set so that there are no adjustment costs in the deterministic steady state.

Intangible Sector. Patents are produced in the intangible sector. Patent producers have monopoly power. Given the demand schedules set by the final-good firm, monopolists producing the patents set the prices $P_{i,t}$ in order to maximize their after-tax profits $(1-\tau_t)\Pi_{i,t}$. Patent producers transform one unit of the final good into one unit of their patent. This fixes the marginal cost of producing one patent at unity. Further, production is "roundabout" in that monopolists take final-goods production as given, as they are tiny themselves.

Thus, monopolists solve the following static profit-maximization problem each period:

$$\max_{P_{i,t}}(1-\tau_t)\Pi_{i,t} \equiv \max_{P_{i,t}}(1-\tau_t)(P_{i,t} \cdot X_{i,t}(P_{i,t}) - X_{i,t}(P_{i,t})).$$

The value $V_{i,t}$ of owning exclusive rights to produce patent i is equal to the present discounted value of the current and future monopoly net profits,

$$V_{i,t} = (1-\tau_t)\Pi_{i,t} + (1-\phi)E_t[M_{t+1}V_{i,t+1}], \tag{10}$$

where ϕ is the probability that a patent becomes obsolete. This asset price is important in our model, as it provides the payoff for creating new patents by means of innovation. Indeed, thanks to monopoly power, the associated profits provide the rents required to support innovation.

Innovation Sector. Innovators develop new patents used in the production of final output. They do so by conducting research and development, using the final good as input at unit cost. These newly developed patents can be sold to patent producers. Assuming that this market is competitive, the price of a new patent will equal its value to the patent producer, namely $V_{i,t}$.

We link the evolution of the intangible capital stock N_t, to innovation as follows:

$$N_{t+1} = \vartheta_t S_t + (1-\phi)N_t, \tag{11}$$

where S_t denotes R&D expenditures (in terms of the final good) and ϑ_t represents the productivity of the R&D sector that is taken as exogenous by the R&D sector. In the spirit of Comin and Gertler (2006), we assume that this technology coefficient involves a congestion externality effect

$$\vartheta_t = \frac{\chi \cdot N_t}{S_t^{1-\eta} N_t^{\eta}}, \tag{12}$$

where $\chi > 0$ is a scale parameter and $\eta \in [0,1]$ is the elasticity of new patents with respect to R&D. This specification captures the notion that concepts already discovered make it easier to come up with new ideas, $\partial\vartheta/\partial N > 0$, and that R&D investment has decreasing marginal returns, $\partial\vartheta/\partial S < 0$.[3]

3.3 Household

The household sector is standard. The representative household has Epstein-Zin preferences defined over consumption:

$$U_t = \left\{(1-\beta)C_t^{\theta} + \beta(E_t[U_{t+1}^{1-\gamma}])^{\frac{\theta}{1-\gamma}}\right\}^{\frac{1}{\theta}}, \tag{13}$$

where γ is the coefficient of relative risk aversion and $\psi \equiv \frac{1}{1-\theta}$ is the intertemporal elasticity of substitution. When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects. We assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes shocks to long-run expected growth rates.

The household maximizes utility by participating in financial markets and by supplying labor. Specifically, the household can take positions $\mathcal{Z}_t$ in the stock market, which pays an aggregate dividend $\mathcal{D}_t$, and positions B_t in the bond market. Accordingly, the budget

[3]Similarly, this congestion externality can be thought of as giving rise to adjustment costs to investment in intangible capital, that is, R&D. We will later see that the optimality condition for R&D is $\frac{1}{\vartheta_t} = E_t[M_{t+1}V_{t+1}]$. Absent the congestion externality, this becomes $1 = E_t[M_{t+1}V_{t+1}]$, a result analogous to q-theory, in which case the absence of adjustment cost fixes marginal Q at unity.

constraint of the household becomes

$$C_t + \mathcal{Q}_t \mathcal{Z}_{t+1} + B_{t+1} = W_t L_t + (\mathcal{Q}_t + \mathcal{D}_t)\mathcal{Z}_t + (1 + r_{f,t})B_t,$$

where $\mathcal{Q}_t$ is the stock price, $r_{f,t}$ is the risk-free rate, W_t is the wage, and L_t denotes hours worked.

We assume that stocks are claims to all the production sectors, namely the final-goods sector, the intangible sector, and the R&D sector. Accordingly, we define the aggregate dividend as the net payout from all production sectors:

$$\mathcal{D}_t = D_t + \int_0^{N_t} (1 - \tau_t)\Pi_{i,t}\, di - S_t. \tag{14}$$

3.4 Equilibrium and Asset Prices

An equilibrium is a set of sequences of prices and quantities such that (i) quantities solve producers' and the household's optimization problems, and (ii) prices are such that the markets clear. We focus on a symmetric equilibrium in which all patent producers are identical. In the following, we describe the most important equilibrium conditions.

The final-good firm's optimality conditions are mostly standard. Denoting by $q_t = \frac{1}{\Lambda_t'}$ the shadow value of physical capital, the first-order condition for investment in physical capital implies

$$\begin{aligned} R_{t+1} &:= \frac{1}{q_t}\left((1 - \tau_{t+1})\alpha(1 - \xi)\frac{Y_{t+1}}{K_{t+1}} + q_{t+1}(1 - \delta) - \frac{I_{t+1}}{K_{t+1}} + q_{t+1}\Lambda_{t+1}\right), \\ 1 &= E_t\left[M_{t+1}R_{t+1}\right]. \end{aligned} \tag{15}$$

On the other hand, the final-good firm's demand for patent i is determined by

$$P_{i,t} = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\frac{\xi}{\nu}\left[\int_0^{N_t} X_{i,t}^{\nu}\, di\right]^{\frac{\xi}{\nu}-1} \nu X_{i,t}^{\nu-1},$$

where it takes the price $P_{i,t}$ as given. The latter is set by the monopolistically competitive producer of patent i. In a symmetric equilibrium, the Dixit and Stiglitz (1977) monopolistically competitive characterization of the intangible sector implies

$$X_{i,t} \equiv X_t, \quad \text{and} \quad P_{i,t} \equiv P_t = \frac{1}{\nu}. \tag{16}$$

That is, each patent producer charges a markup $\frac{1}{\nu} > 1$ over unit marginal cost, so that profits are

$$\Pi_{i,t} \equiv \Pi_t = \left(\frac{1}{\nu} - 1\right) X_t, \tag{17}$$

with $X_t = \left(\xi\nu \left(K_t^{\alpha}(\Omega_t L_t)^{1-\alpha}\right)^{1-\xi} N_t^{\frac{\xi}{\nu}-1}\right)^{\frac{1}{1-\xi}}$. Profits are thus procyclical.

Discounted future profits on patents are the payoff for innovation, so that, since the R&D sector is competitive, the optimality condition for R&D investment becomes

$$E_t[M_{t+1}V_{t+1}](N_{t+1} - (1-\phi)N_t) = S_t, \tag{18}$$

in which case the expected sales revenues equals costs, or equivalently, at the margin,

$$\frac{1}{\vartheta_t} = E_t[M_{t+1}V_{t+1}].$$

This condition is crucial in this model, as it sets the equilibrium amount of R&D investment and ultimately determines the equilibrium growth rate of the economy. Importantly, R&D investment inherits the procyclicality of profits.

The stochastic discount factor in the economy is given by

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{\theta-1} \left(\frac{U_{t+1}}{E_t(U_{t+1}^{1-\gamma})^{\frac{1}{1-\gamma}}}\right)^{1-\gamma-\theta}, \tag{19}$$

where the second term involves continuation utilities and captures concerns about long-run growth prospects. Optimality implies the following asset pricing conditions:

$$\begin{aligned} \mathcal{Q}_t &= E_t[M_{t+1}(\mathcal{Q}_{t+1} + \mathcal{D}_{t+1})] \\ \frac{1}{1+r_{f,t}} &= E_t[M_{t+1}]. \end{aligned} \tag{20}$$

In equilibrium, the representative agent holds the entire supply of both bonds and equities. The latter is normalized to be one, that is, $\mathcal{Z}_t = 1 \ \forall t$.

Finally, since the agent has no disutility for labor, she will supply her entire endowment, which we normalize to unity.

Resource Constraint. Final output is used for consumption and investment in physical capital and is used as a factor input in R&D, the production of patents, and government expenditures:

$$\begin{aligned} Y_t &= C_t + I_t + N_t X_t + S_t + G_t \\ &= C_t + I_t + N_t^{1-\frac{1}{\nu}} \Gamma_t + S_t + G_t, \end{aligned}$$

where the second equality exploits the optimality conditions and the term $N_t^{1-\frac{1}{\nu}}\Gamma_t$ captures the costs of patent production. Given that $\nu < 1$ reflects monopolistic competition, it follows that a growing intangible capital stock increases the efficiency of patent production, since the costs fall as N_t grows.

Given the resources used in the production of patents, in our economy measured GDP_t is obtained as follows:

$$GDP_t \equiv Y_t - N_t X_t. \tag{21}$$

Finally, the tax base is given by taxable profits in both final-goods and intangible sectors, so that

$$\begin{aligned} tax\,base_t &= Y_t - W_t L_t - N_t \nu^{-1} X_t + N_t \Pi_t \\ &= GDP_t - W_t L_t. \end{aligned}$$

Stock Market and Cross Section. According to equation (20), the ex-dividend value of the stock market value, $\mathcal{Q}_t$, is the discounted sum of future net payouts of all production sectors. In our symmetric equilibrium, we have

$$\mathcal{D}_t = (1 - \tau_t)\left[GDP_t - W_t L_t\right] - S_t - I_t.$$

The existence of two capital stocks, namely those of physical and intangible capital, gives rise to a cross section of stock returns in our model. For empirical purposes, we associate the return on tangible (intangible) capital, with the empirical returns of Low-R&D (High-R&D) firms. In the model, the return of intangible capital is

$$R_t^{rd} = \frac{V_t}{V_{t-1} - (1 - \tau_t)\Pi_t},$$

and that of physical capital is defined in equation (15). While clearly not unique, we view this mapping as natural and economically meaningful.

3.5 Aggregate Productivity and Fiscal Policy

The previous paragraphs have outlined a stochastic equilibrium model in which innovation through firms' R&D drives long-term growth rates. Let us briefly describe how, in the context of the model, government debt and fiscal policy affect innovation and thus growth. Following Kung and Schmid (2015), it can be shown that under the parameteric restriction $\alpha + \frac{\frac{\xi}{\nu} - \xi}{1 - \xi} = 1$, which we impose in the following, the model is equivalent to a real business cycle model with a standard neoclassical production function of the form $Y_t = Z_t K_t^{\alpha} L_t^{1-\alpha}$, where

$$Z_t \equiv \overline{A}(\Omega_t N_t)^{1-\alpha}, \tag{22}$$

is an endogenous productivity process, with $\overline{A} \equiv (\xi\nu)^{\frac{\xi}{(1-\xi)}} > 0$. In other words, our model can be seen as a real business cycle model in which productivity is endogenously driven by the accumulation of intangible capital via innovation. Taxation thus directly affects growth and its dynamics through its effects on the demand for intangible capital.

Two channels shape the accumulation of intangible capital. First, the final-good firm's demand for patents, $P_{i,t} = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\frac{\xi}{\nu}\left[\int_0^{N_t} X_{i,t}^{\nu}\,di\right]^{\frac{\xi}{\nu}-1}\nu X_{i,t}^{\nu-1}$, depends positively on the capital stock, whose accumulation itself is affected by taxation. By slowing down capital accumulation, taxation also depresses innovation and growth. Second, taxation affects the valuation of patents, as the value of a patent is given by $V_{i,t} = (1-\tau_t)\Pi_t + (1-\phi)E_t[M_{t+1}V_{i,t+1}]$. Higher taxes thus depress patent valuations, and this lowers the incentives to engage in innovation, as the value of patents is the payoff for R&D.

To summarize, in our model with stochastic endogenous growth, higher taxes and the expectation of an elevated tax burden going forward depress firms' incentives to engage in innovation, thereby curtailing growth prospects. Since tax rates in our model reflect both the government's expenditures and its indebtedness through its budget constraint, we expect the model to generate predictions regarding the links between debt, growth, and innovation. We examine these predictions quantitatively in the next section.

4 Quantitative Analysis

In this section we calibrate our model and explore its predictions regarding key links between debt, innovation, and stock returns in the cross section and the time series. In particular, we show that the model predicts a reallocation effect across the R&D and non-R&D sectors that is sensitive to the level of the debt-to-output ratio, and it helps in interpreting the time-varying *HML-R&D* spread documented empirically.

4.1 Calibration

We report our baseline quarterly calibration in table 6. The preference parameters are standard in the literature. The risk aversion (γ) is calibrated to 10 in line with reasonable upper bounds (see Mehra and Prescott (1985), among others). The intertemporal elasticity of substitution (ψ) is set to 1.2, a choice consistent with the empirical results in the long-run risk literature. The household's subjective discount rate is chosen to target both the average historical level of the risk-free and the consumption return premium documented by Lustig, Van Nieuwerburgh, and Verdelhan (2013).

In the R&D sector, we set the quarterly survival rate ϕ of a patent to 0.96, consistent with the Bureau of Economic Analysis annual depreciation rate for R&D capital of 16%. The elasticity of new intermediate goods with respect to R&D (η) is set to the value reported in Croce, Nguyen, and Schmid (2012). χ is a scale parameter that is set to match an average annual consumption growth of 2.0%.

As shown in our empirical analysis, low-R&D firms command a lower risk premium than R&D-intensive firms. In order to reproduce this fact, we set the elasticity of the adjustment cost function (ζ) to 13.3. The elasticity of substitution between intermediate goods (ν) is set to capture the fact that the level of productivity in the final-goods sector is increasing. The parameter α determines the average income share of physical capital. The annualized depreciation rate of physical capital (δ) is set to 8%.

Since R&D data became available only in 1953, we target specific moments in the US sample for the period 1953 to 2014. Specifically, we set the volatility of our productivity shocks to match an annual volatility of consumption growth of about 2%. The persistence of productivity is chosen so as to have a positive but small autocorrelation in consumption growth.

In a similar spirit, the average level, the volatility, and the persistence of the ratio of

Table 6: Benchmark Calibration

Parameter	Symbol	Value
Preferences:		
Subjective Discount Factor	β	0.996
Intertemporal Elasticity of Substitution	ψ	1.2
Relative Risk Aversion	γ	10.0
Technology:		
Labor Income Subshare	α	0.42
Intangible Capital Income Share	ξ	0.47
Intangible Capital Congestion, Scale Parameter	χ	0.45
Intangible Capital Congestion, Elasticity	η	0.83
Patent Survival Rate	ϕ	0.96
Physical Capital Depreciation	δ	0.02
Physical Capital Adjustment Costs, Elasticity	ζ	13.30
Elasticity of Substitution Across Goods	ν^{-1}	1.65
Exogenous Processes:		
Productivity Shock, Volatility	σ_ω	0.02
Productivity Shock, Persistence	ρ	0.99
Average Expenditure-Output Ratio	$1/(1+e^{-\overline{gy}})$	0.20
Expenditure Shock, Volatility	σ_G	0.08
Expenditure Shock, Persistence	ρ_G	0.98
Policy Parameters:		
Average Quarterly Debt-GDP Ratio	μ_B	2.40
Persistence of Debt-GDP	ρ_B	0.99
Policy Response to Productivity Shock	A_ω	-0.56
Policy Response to Expenditure Shock	A_G	0.45
Policy Response to Policy Shock	A_ϕ	0.07

	Model		Data	
	$\mu_B/4$ =60%	$\mu_B/4$ =30%	Est.	Std. Err.
a_2	-0.13	-0.13	-0.17^{*}	0.10
a_3	0.16	0.16	0.19^{***}	0.05
$\sigma(\epsilon_t^{DGDP})$	0.02	0.02	0.01^{***}	0.001

Notes: This table reports our benchmark quarterly calibration. In the bottom portion, we report results from the following auxiliary regression:

$$DGDP_t = a_0 + a_1 DGDP_{t-1} + a_2 \widehat{\epsilon_t^{\Delta TFP}} + a_3 \widehat{\epsilon_{G,t}} + \epsilon_t^{DGDP},$$

where $\widehat{\epsilon_t^{\Delta TFP}}$ is the fitted residual from the regression $\Delta TFP_t = b_0 + b_1 \Delta TFP_{t-1} + \epsilon_t^{\Delta TFP}$, and $\widehat{\epsilon_{G,t}}$ is obtained by estimating equations (1)–(2). Our quarterly sample starts in 1966:Q2 and ends in 2013:Q4. In the model, *TFP* is measured as in equation (22).

government expenditure to output are set to replicate US quarterly data from 1966:Q2 to 2013:Q4. Specifically, we transform the US measured government-output ratio according to equation (1) and estimate equation (2), with the following results:

$$gy_t = -\underset{(0.05)}{1.32} \cdot [1 - 0.96] + \underset{(0.02)}{0.96} gy_{t-1} + \underset{(0.02)}{0.06} \epsilon_{G,t}.$$

Numbers in parentheses are standard errors. Our parameter values are within our empirical confidence intervals.

Turning our attention to the the fiscal policy rule, the average annual debt-to-output ratio is set to 60%, as in the data. In the next section we also consider a fiscal regime with an average debt-to-output ratio of 30%. The parameter ρ_B is set to mimic the well-known high persistence of the debt-to-output ratio in the US.

The other parameters of the systematic part of our fiscal rule, A_ϕ and A_G, are chosen so that the government expands its debt financing in response to either negative technology or positive government spending shocks. Thus, our government implements a countercyclical debt policy in an attempt to attenuate the tax burden on corporations in downturns.

In order to have quantitative guidance on these parameters, we project innovations in the US debt-output ratio on innovations to both TFP growth and government expenditure–to–output. In the model, the correct counterpart of measured TFP is obtained by simulating equation (22). By running our auxiliary regression in the model exactly as we do in the data, we mitigate concerns about identification of pure exogenous fiscal shocks. As shown in the bottom portion of table 6, our calibration is consistent with our auxiliary regression, that is, it captures the right amount of coutercyclicality.

Since the standard deviation of the fiscal policy shocks is normalized to one, the parameter A_ϕ determines the magnitude of the policy shocks, and it is set to replicate the volatility of the debt-to-output ratio.

Table 7: Model Summary Statistics

	60% Debt/GDP Case			30% Debt/GDP Case		
	Mean	Std. Dev.	AR(1)	Mean	Std. Dev.	AR(1)
Unconditional Moments						
Δs	1.95	10.56	−0.01	2.17	10.20	−0.01
Δi	1.95	8.73	0.06	2.17	8.53	0.06
Δc	1.95	2.07	0.38	2.17	2.06	0.38
r_f	1.10	1.05	0.98	1.22	1.04	0.98
$r^{rd} - r$	3.32	4.03	0.07	2.67	3.71	0.07
$r_c - r_f$	3.82	3.15	−0.01	3.89	3.19	−0.01
$Govt/GDP$	20.96	6.10	0.98	20.96	6.10	0.98
$DGDP$	59.84	17.22	0.99	29.84	17.22	0.99
τ	35.44	17.33	0.34	35.98	17.00	0.34
Predictability						
$\frac{\partial E_t(r^{rd}_{t+1} - r_{t+1})}{\partial DGDP_t}$	1.37			1.27		

Notes: This table shows annualized model statistics for the scenarios in which the debt-to-GDP ratio is on average either 60% or 30%. All growth and return statistics are in logs. The tax rate (τ), government spending–to–GDP ($Govt/GDP$), and debt-to-GDP ratio ($DGDP$) variables are in levels. Means and standard deviations have been multiplied by 100. Statistics are obtained from a long-sample simulation. The excess return of the R&D sector over that of the physical capital sector in log units is denoted by $r^{rd} - r$. This excess return is levered by a factor of three. The excess return of the claim to the consumption stream in log units is $r_c - r_f$.

4.2 Findings

We start by evaluating the overall fit of the model in regard to stylized facts about economic growth, cycles, and asset returns, and we then turn to a more detailed discussion of the cross-sectional and time-series links between debt, innovation, and returns, motivated by our empirical evidence.

Unconditional Moments. In table 7 we report basic moments from model simulations, both for quantities and for returns. We show results from our benchmark calibration and from an alternative calibration in which the average debt-to-output ratio is set to 30%.

Our model is broadly quantitatively consistent with basic patterns of real aggregates, such as output, consumption, and investment, as well as innovation and endogenous growth. Consumption is realistically smooth with low autocorrelation, implying that our model does not generate an implausibly high variation in long-run growth, consistent with the data. As in the data, both investment in R&D and physical capital are more volatile than output. These results are relevant, because models with innovation-driven endogenous growth face additional challenges in matching the average growth rate, above and beyond those in a standard real business cycle model.

Through the government budget constraint, our calibration implies an average tax rate of 35% and a volatility of about 17% percent, in line with the estimates in McGrattan and Prescott (2005) after we include pre–World War II data.

Our model yields a realistic spread between the excess returns on intangible and tangible capital, that is, the counterpart of our *HML-R&D* return. As in the data, R&D-intensive firms earn a positive premium relative to physical capital–intensive firms. The claim to aggregate consumption commands a significant premium, and our risk-free rate is low and smooth, consistent with the data.

Fiscal Policy Regimes. Inspection of the rightmost panel of table 7 paves the way to interpreting our empirical results through the lens of our model. Specifically, we explore the sensitivity of our results with respect to a long-run annual debt-to-output level ($\mu_B/4$) of 30%. We view this exercise as a comparison of economies with different fiscal regimes due to different tolerance for long-run public debt. Equivalently, we can see this counterfactual exercise as a way to assess the economic significance of the link between public debt and growth.

When we consider the calibration in which average debt is 30% of output, the unconditional average of *HML-R&D* decreases by 20%, i.e., 65 annual basis points. Not surprisingly, because of the lower cost of capital for R&D-intensive firms, there is more investment in innovation and the growth rate of GDP increases by 23 basis points, i.e., 12% in relative terms. In other words, higher steady state debt comes with a relatively higher cost of capital for innovative firms and lower growth.

In the next section, we show that our results on the link between expected *HML-R&D* returns, growth, and differential levels of steady-state government debt carry over to the time-series, that is, persistent increases in $DGDP$ depress future expected growth, much as our empirical results suggest.

4.2.1 Debt and Innovation Returns

We now examine the evidence linking $DGDP$, expected returns to innovative firms and growth, uncovered in our initial empirical analysis, through the lens of our model. We start by verifying that our model gives rise to similar time series patterns and then proceed to inspect the underlying model mechanism, along with further empirical tests.

Quantifying Predictability. Table 8 reports the results of predictive regressions of (i) future GDP growth rates (panel A) and (ii) future stock returns (panel B) at various horizons on the current debt-to-GDP ratio. Consistent with our time-series evidence, rises in $DGDP$ forecast a slowdown in future growth accompanied with higher future expected stock returns. This holds both for the aggregate market return as well as the return on *HML-R&D*, so that the average cost of capital rises, and especially so for innovative firms. Our model therefore produces endogenous predictability. Even though the extent of predictability is not identical to that in the data, we consider our results significant, as (i) they are obtained without assuming any exogenous time-varying volatility process, and (ii) they are not too distant from their empirical counterpart.

In unreported results, we point out that absent fiscal policy shocks, ϵ_ϕ, debt-to-output has half of the volatility measured in our baseline model and accordingly, removing these shocks weakens the quantitative predictability results.

In general, our predictable risk premia could result from either endogenous time-varying conditional volatility of the stochastic discount factor, or time-varying exposure of returns, or a combination of the two. Figure 1 sheds light on the mechanism at work in the model. The

Table 8: Predictive Regressions–Debt/GDP

Horizon J		1	2	4	8	20
	Panel A: $\Delta GDP_{t\to t+J} = d_0^J + d_1^J \cdot Debt_t/GDP_{t-1} + w_{t+J}$					
Data	d_1^J	-0.003	-0.007	-0.015^{*}	-0.032^{**}	-0.101^{***}
		(0.003)	(0.005)	(0.009)	(0.014)	(0.032)
	R^2	0.006	0.009	0.014	0.023	0.070
Model	d_1^J	-0.017	-0.033	-0.065	-0.124	-0.279
	R^2	0.047	0.074	0.102	0.121	0.126
	Panel B: $R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J}$					
	HML-R&D					
Data	β^J_{DGDP}	0.10^{**}	0.10^{**}	0.16^{***}	0.26^{***}	0.65^{***}
		(0.04)	(0.04)	(0.04)	(0.05)	(0.13)
	R^2	0.01	0.02	0.03	0.7	0.43
Model	β^J_{DGDP}	0.13	0.18	0.24	0.30	0.37
	R^2	0.02	0.03	0.06	0.09	0.14
	Market					
Data	β^J_{DGDP}	0.13^{***}	0.18^{***}	0.27^{***}	0.33^{***}	0.32
		(0.04)	(0.04)	(0.04)	(0.05)	(0.22)
	R^2	0.02	0.05	0.13	0.19	0.35
Model	β^J_{DGDP}	0.06	0.08	0.11	0.15	0.20
	R^2	0.01	0.01	0.01	0.02	0.04

Notes: Our quarterly data sample is from the period 1966:Q2–2013:Q4. In panel B, all variables are standardized by their respective standard deviations. *HML-R&D* is measured using equally-weighted returns from portfolios sorted on R&D-to-Assets. We adopt the Stambaugh (1999) OLS bias correction method for β^J_{DGDP} in panel B. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

leftmost panel verifies that expected excess returns on stock portfolios conditional on $DGDP$ indeed are increasing, as is the spread between high and low R&D portfolios. Moreover, conditional risk premia are approximately linear in $DGDP$, which implies that the overall sensitivity of the cost of capital of different firms to $DGDP$, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$, is roughly constant. The bottom-right row of table 7 shows that the sensitivity of *HML-R&D* to $DGDP$ is more pronounced when the steady state government indebtedness is higher.

Intriguingly, as the rightmost panel of figure 1 shows, the movements in conditional expected returns are only marginally affected by changes in the conditional volatility of the SDF, as this conditional volatility is roughly flat across $DGDP$ levels. This suggests that

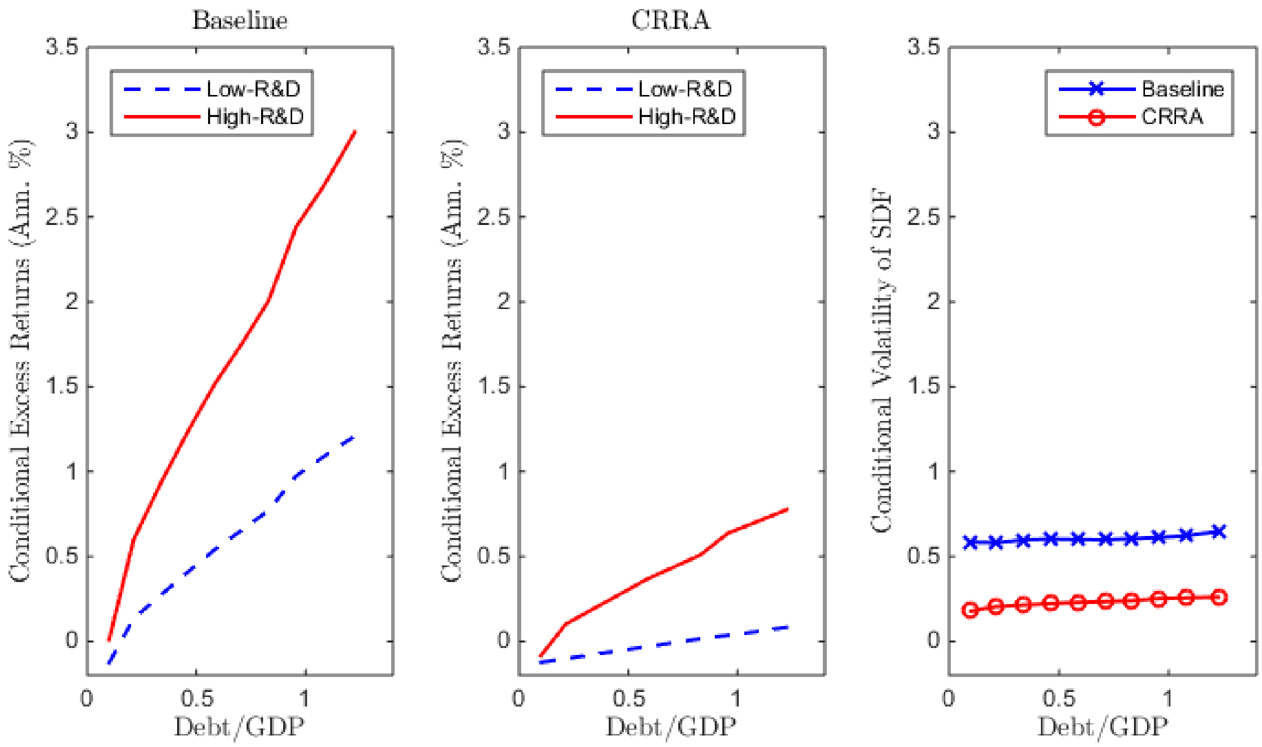

Fig. 1: Conditional Risk Premia (annualized, %)

Notes – This figure shows the unlevered conditional excess returns of the *Low-R&D* and *High-R&D* from a long simulation of the model. Conditional excess returns are sorted into deciles based on their corresponding *DGDP* and plotted. All parameters are calibrated as in table 6.

our predictability results are driven by time-varying exposure of returns to *DGDP*.

A Conditional Three-factor Model Representation. The lack of significant heteroskedasticity of the SDF, documented in figure 1, suggests that the reduced form of our model corresponds to a conditional three-factor model with nearly constant market prices of risk and time-varying betas. Excess returns in our model can be approximated by the following reduced-form system of equations

$$
\begin{aligned}
E_t[R^{ex}_{i,t+1}] &= \sum_{j=1}^{J} \beta^i_{j,t}\lambda_j \\
R^{ex}_{i,t+1} &= a^i + \sum_{j=1}^{J} \beta^i_{j,t} Factor_{j,t+1} + \epsilon^i_{t+1} \\
\beta^i_{j,t} &\approx \beta^{0i}_j + \beta^{1i}_j DGDP_t,
\end{aligned}
\tag{23}
$$

where our J factors refer to government financing shocks, government spending-to-output shocks, and productivity shocks. We let $\lambda_j, j \in \{1, 2, 3\}$ denote the implied market prices of risk for our exogenous shocks.

Consistent with the model, the exposures of the returns to the underlying factors, $\beta^i_{j,t}$, are allowed to be time-varying. Clearly, conditional betas in the model are affected by $DGDP$, as well as by productivity and government expenditures-to-output ratio. Quantitatively, the last two exogenous state variables play a negligible role once we use $DGDP$. Hence we abstract away from them for the sake of parsimony and without loss of generality. The linearity of the conditional risk premia with respect to $DGDP$ depicted in the left panel of figure 1 suggests that conditional betas are affine in $DGDP$.

According to the model detailed in the system of equations (23),

$$
\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta^{1i}_j \lambda_j, \tag{24}
$$

i.e., the sensitivity of the cost of capital for stock i is a composite of both the extent of time-variation of the betas, β^{1i}_j, and the market price of risk associated to our factors, λ_j. The signs of the model implied market prices of risk for the factors can be recovered by the impulse responses of the SDF to negative realizations of our fundamental shocks. Figure 2 shows the results. Consistent with intuition, the model predicts a positive price of risk for productivity, and negative ones for government expenditure and fiscal policy shocks. Indeed,

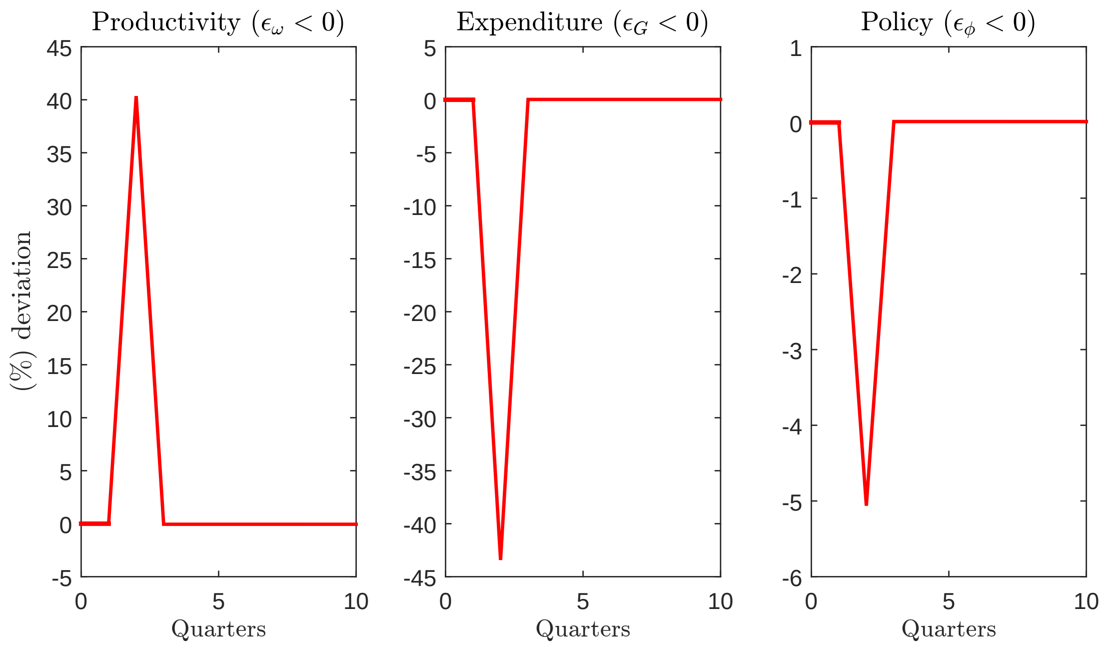

Fig. 2: SDF Impulse Responses to Fundamental Shocks

Notes – This figure shows the impulse response of the stochastic discount factor (SDF) in our DSGE model with respect to negative shocks. Responses are in quarterly percentages. All parameters are calibrated as in table 6.

a sudden reduction in $DGDP$ is a good state for households.

In this setting, movements in expected returns on *HML-R&D* need to be driven by differential sensitivity of the respective betas to $DGDP$. Specifically, the following must hold,

$$\frac{\partial E_t(R^{ex}_{rd,t+1})}{\partial DGDP_t} - \frac{\partial E_t(R^{ex}_{t+1})}{\partial DGDP_t} > 0,$$

so that a higher debt-to-output ratio increases the spread in the expected returns of intangible and tangible capital, in line with the left panel of figure 1.

Under our data-driven calibration, policy shocks, $\epsilon_{\phi,t}$, emerge as a critical driver of the conditional exposure coefficients. Intuitively, our way to model political uncertainty in the government budget process allows for sizeable variation in the debt-to-output ratio independent from productivity and expenditure shocks. In what follows, we document that fiscal policy shocks give rise to endogenous tax uncertainty, to which tangible and intangible assets exhibit differential exposure because of a reallocation motive.

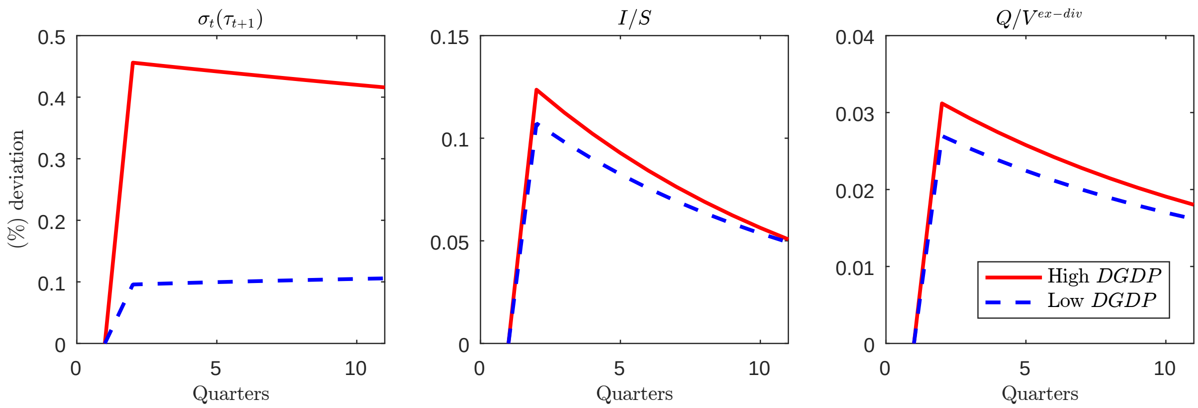

Fig. 3: Conditional Tax Risk, Investment Reallocation and Asset Prices

Notes – This figure shows the conditional average impulse responses to a positive one-standard-deviation shock to $\epsilon_{\phi,t}$. $\sigma_t(\tau_{t+1})$ is the conditional volatility of the tax rate, I/S is the ratio of tangible capital investment to R&D investment, and Q/V^{ex-div} is the ex-dividend price ratio of tangible to intangible capital. The impulse responses are conditional with respect to the model being in 'High $DGDP$' states and 'Low $DGDP$' states. We define 'High $DGDP$' states as the top 5% of $DGDP$ values from a simulated stationary distribution from the model after a burn-in of 100 periods. Equivalently, we define 'Low $DGDP$' states as the bottom 5% of $DGDP$ values from the same stationary distribution. The model is then shocked from the respective states (conditional on $DGDP$), and impulse responess are averaged over the respective $DGDP$ bins. All parameters are calibrated as in table 6.

Endogenous Time-Varying Tax Uncertainty. In figure 3, we depict the response of variables of interest with respect to a positive debt policy shock, $\epsilon_\phi > 0$. This shock is useful to understand the mechanism behind our model because it is a pure public financing shock that affects neither government expenditures nor R&D productivity. In the first panel on the left, we show two important features of the tax rate implied by the government's budget constraint in equilibrium. First, expansionary fiscal shocks increase tax rate uncertainty, as measured by the conditional volatility of the tax rate going forward. Second, this response is more pronounced when the debt-to-output ratio in the economy is above average.

Before proceeding, we confirm and gauge the magnitude of this effect in the data. Specifically, both in the model and in the data we estimate the volatility of the tax rate, σ_t^τ, from the following system of equations:

$$\tau_t = \mu_t^\tau + \sigma_t^\tau \epsilon_t^\tau$$
$$\mu_t^\tau = \mu^\tau + \rho^\tau \mu_{t-1}^\tau$$
$$(\sigma_t^\tau)^2 = \omega + \alpha^\tau (\sigma_{t-1}^\tau)^2 + \beta^\tau (\epsilon_{t-1}^\tau)^2.$$

In the data, we obtain the following results:

$$(\sigma_t^\tau)^2 - \overline{\sigma^\tau}^2 = \underset{(0.002)}{0.006} \cdot DGDP_{t-1} + \epsilon_{\sigma,\tau},$$

which are almost exactly replicated by simulated data:

$$(\sigma_t^\tau)^2 - \overline{\sigma^\tau}^2 = 0.005 \cdot DGDP_{t-1} + \epsilon_{\sigma,\tau}.$$

Thus, both in the data and in the model, rises of the debt-to-GDP ratio come with higher tax uncertainty going forward. Further, the data support the notion that policy shocks are a relevant driver of the time variation of tax volatility. More precisely, we find that in the data fiscal policy shocks drive fiscal uncertainty going forward in that :

$$(\sigma_t^\tau)^2 = \underset{(0.000)}{0.001} + \underset{(0.025)}{0.095} \cdot (\sigma_{t-1}^\tau)^2 + \underset{(0.003)}{0.006} \cdot \widehat{\epsilon_{t-1}^{DGDP}} + \epsilon_{\sigma,\tau},$$

where $\widehat{\epsilon_{t-1}^{DGDP}}$ is the fitted residuals from the regression

$$DGDP_t = a_0 + a_1 DGDP_{t-1} + a_2 \cdot gy_t + a_3 TFP_t + \epsilon_t^{DGDP},$$

used to calibrate the model. Hence, as in Croce, Nguyen, and Schmid (2012), fiscal uncertainty is an endogenously time-varying determinant of risk which becomes more relevant as the debt-to-output ratio increases.[4] Given this observation, the results depicted in the

[4] In appendix B, we reproduce the Croce, Nguyen, and Schmid (2012) intuition for this result through

left panel of figure 1 should not appear surprising: as the debt-to-output ratio increases, uncertainty increases as well, and all capital stocks must pay a higher expected return.

Endogenous Time-Varying Reallocation. The novel insight of our model points to the existence of an important reallocation channel, consistent with that documented in table 4. As already noted in other studies (see, among others, Bocola and Gornemann 2013 and Bianchi and Kung 2014), the present value of monopoly rents is very sensitive to fundamental shocks. As a result, the innovation sector is more sensitive to debt policy shocks and is subject to more severe fluctuations in investment. Equivalently, upon the arrival of an expansionary public debt shock, the household cuts down total investment but simultaneously increases its share of investment in tangible capital stock (figure 3, middle panel). As a result, this reallocation aggravates the capital loss for the R&D sector, whereas it works as a valuable hedge for firms that are tangible-capital intensive (figure 3, rightmost panel).

Since this reallocation effect is more pronounced when the debt-to-output ratio is higher, the hedging motive manifests itself as a more sizable spread across the exposure coefficients of our two stocks exactly when debt is greater. Consistent with this intuition, the difference in the conditional risk premia of the two capital stocks increases in $DGDP$, as shown in the left panel of figure 1.[5]

4.2.2 Sensitivity

CRRA. To quantify the role played by preferences, we solve our model under a configuration with CRRA preferences by setting $\gamma = 1/\psi = 10$. This calibration confirms a positive link between expected returns and the debt-to-output ratio, and it also predicts that intangible capital should be more sensitive to the size of government debt than tangible capital.

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a simple example that enables us to have closed-form solutions. Intuitively, in production economies with random productivity, future tax rates are uncertain because the government faces uncertainty on the future tax base. When debt-to-output is high, tax-base uncertainty turns into more pronounced tax rate volatility.

[5] A small part of this increase is also due to the larger volatility of the stochastic discount factor (SDF) (figure 1, rightmost panel). The discount rate channel is expected in general equilibrium, as consumption inherits the time-varying volatility of the tax rate. Quantitatively, however, this channel is negligible in our model.

From a quantitative point of view, this formulation of the model is unsatisfactory. As shown in the middle panel of figure 1, the implied spread in the expected excess returns across tangible and intangible capital is modest and further from the data.

No Government Risks. To quantify the role of fiscal shocks, we solve our model under a calibration that differs from that reported in table 6 because we impose $A_{\phi} = \sigma_G = 0$. Under this configuration, TFP shocks are active whereas all other exogenous fiscal risks are muted. We find that $E_t[HML - R\&D]$ declines to 1.45%, implying that in the model about 65% of the total *HML-R&D* is driven by fiscal shocks. No surprisingly, the unconditional growth rate increases as well, by about 8 basis points per year.

Furthermore, $\frac{\partial E_t(R^{rd}_{t+1} - R_{t+1})}{\partial DGDP_t}$ becomes nearly null, meaning that the model fails to produce predictability. This result is consistent with our previous observation: since our exogenous R&D productivity process does not produce any relevant reallocation motive, the conditional exposures of our returns are constant with respect to productivity.

5 Cross-Sectional Asset Pricing Tests

In this section, we provide direct empirical evidence supporting the cross-sectional asset pricing implications of our model documented in the previous section. These tests are important as they provide the links between government debt and growth emphasized through our risk-based mechanism.

Conditional model with time-varying betas. We estimate the pricing model detailed in the system of equations (23) in the data using our three empirical macroeconomic factors, namely, the log difference of government spending-to-output (ΔGY), TFP (ΔTFP), and debt-to-GDP ratio ($\Delta DGDP$). We choose changes in DGDP as empirical proxy for fiscal shocks to confirm that our results are broad and do not depend on a specific choice of the fiscal policy rule. Untabulated results confirm that our main findings continue to hold when we work with our filtered policy shocks, $\widehat{\epsilon_t^{DGDP}}$, as opposed to $\Delta DGDP$.

We expand our cross section of test assets to keep our inference sharp. Specifically, in addition to the market and our cross section of R&D-intensity sorted portfolios, we consider the 25 portfolios constructed by Fama and French (FF25) using size and book-to-market, and the entire market. We also add SMB and HML to study the link between $DGDP$, size, and book-to-market. We use GMM to estimate all coefficients simultaneously and report our main results in table 9.

We are interested in assessing the sensitivity of the cost of capital of different firms to movements in $DGDP$, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$, as specified in the model in (24). We report our estimates in the top portion of table 9 together with standard errors computed using the delta method. The estimates of the market price of risk are in the middle of the table, followed by the results for the J-test associated to our GMM.

We have three observations. First of all, this cross-sectional estimation both confirms and sharpens the results obtained through our predictability regressions. The variations that we obtain for the market and *HML-R&D* are very similar to those obtained in table 2 over a 1-quarter horizon. Furthermore, the adverse effect of public debt on the cost of capital is a very pervasive phenomenon as it is also present in the extreme FF25 portfolios.

Interestingly, SMB and HML feature no significant sensitivity to DGDP. The relevance of this outcome is twofold, as it suggests that (i) our results are not a restatement of size or book-to-market effects, and (ii) our strategy of sorting firms according to their R&D intensity is essential for the correct assessment of the impact of public debt on the cross section of equity returns.

Second, these results hold regardless of whether we use equally-weighted or value-weighted returns for our R&D-sorted portfolios. We also conduct our estimation using a different measure of R&D intensity to form our cross-section. Specifically, we sort firms according to their expenditures in R&D relative to capital expenditure, as in Lin (2012), and obtain very similar results (see table A11). We find it reassuring that our results are robust to different

Table 9: **Conditional Macro Factors Model**

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.05***	0.10***
	(0.01)	(0.03)
High–R&D	0.13***	0.16***
	(0.01)	(0.03)
HML–R&D	0.08***	0.06***
	(0.01)	(0.02)
Market	0.11***	0.18***
	(0.01)	(0.05)
Small–Low B/M	0.14***	0.21***
	(0.01)	(0.06)
Small–High B/M	0.13***	0.21***
	(0.01)	(0.04)
Big–Low B/M	0.11***	0.17***
	(0.02)	(0.05)
Big–High B/M	0.08***	0.15***
	(0.01)	(0.04)
SMB	0.02	0.02
	(0.01)	(0.03)
HML	−0.01	−0.02
	(0.01)	(0.02)

	EW			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.002**	0.008***	−0.017***	−0.014***	0.009***	−0.021***
	(0.001)	(0.0004)	(0.001)	(0.004)	(0.002)	(0.005)
J-Test		7.09			7.09	
p-value		1.00			1.00	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (23). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i}\lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; the Fama-French SMB and HML factors; and the full market portfolio. Newey-West (1987) standard errors are in parentheses. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 29 degrees of freedom.

ways of measuring innovation intensity across firms. In the appendix, we show that our results also hold when we focus only on positive-R&D firms (see table A12), and when we use a shorter sample starting in 1975 (see table A13).

Third, the estimated signs of the market prices of risk of our three factors are consistent with the predictions of our DSGE model about the responses of the SDF to our fundamental shocks depicted in figure 2. Specifically, the SDF implied by the system of equations (23) can be written as $m_t = \overline{m} - bF_t$, in which $b = -E(FF')^{-1}\lambda$, F comprises our three macroeconomic risk factors, and λ is the vector of the market prices of risk.

In our data, the implied SDF loadings have opposite sign with respect to our estimated market prices of risk. As a result, both in the model and in the data, states with low productivity are associated to high marginal utility. This is a very common result in production economies. In contrast, government expenditure has a positive loading in the SDF. In our model, this is true because government expenditure is wasteful. According to our estimates, shocks that produce a lower levels of debt-to-output should decrease marginal utility. This is true in our model as well, as unexpected reductions of debt result in lower future tax uncertainty and represent good news.

Macroeconomic and Financial Factors. Fama and French (2015) and Hou, Xue, and Zhang (2015a, b) have recently proposed sets of financial factors that have proven successful in explaining the cross-section of equity returns. It is natural to wonder whether our macroeconomic factors are related to the above mentioned financial factors. We address this question by projecting each one of our macroeconomic factors on either the FF5 factors or the q-Factors. The results reported in table 10 suggest that our macroeconomic factors are nearly completely disconnected from these financial factors. As shown in table A14, our conditional pricing model continues to confirm our results about the role of $DGDP$ even after simultaneously controlling for both the FF5 and the q-Factors.

Table 10: Macroeconomic and Financial Factors

	q-Factors					Fama-French Five Factors					
	MKT	ME	I2A	ROE	R^2	$R_m - R_f$	SMB	HML	RMW	CMA	R^2
$\Delta DGDP$	0.02	−0.01	0.02	−0.01	0.01	0.00	−0.01	−0.01	−0.03	0.01	0.01
	(0.02)	(0.03)	(0.04)	(0.03)		(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	
ΔTFP	0.01	0.00	−0.01	−0.03**	0.05	0.00	0.00	−0.01	0.00	0.03	0.01
	(0.01)	(0.01)	(0.02)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	
ΔGY	−0.01	0.04	0.01	0.00	0.01	0.02	−0.03	0.04	−0.05	−0.05	0.03
	(0.02)	(0.03)	(0.05)	(0.03)		(0.02)	(0.03)	(0.04)	(0.03)	(0.05)	

Notes: Let i index macroeconomic factors (MacroF) and j index financial factors (FinF). For each macroeconomic factor, we run the following regression:

$$MacroF_{i,t} = a^i + \sum_{j=1}^{J} \beta^i_j FinF_{j,t} + \epsilon^i_t.$$

Our macro factors are log differences of debt-to-GDP ratio ($\Delta DGDP$), government spending-to-GDP (ΔGY), and TFP (ΔTFP). The Fama-French Five Factors are from Ken French's data library, and the q-Factors are from Hou, Xue, and Zhang (2015a, b). We thank the authors for sharing their data. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusion

We present novel empirical evidence that government debt, as measured for example by the debt-to-output ratio, is a determinant of risk in stock markets. In the time series, the debt-to-output ratio significantly predicts higher future aggregate stock returns at longer horizons, even when we control for standard predictors such as price-dividend ratios and market volatility.

The sensitivity of expected returns to debt-to-output is higher for R&D intensive firms, implying that their cost of equity increases more when public debt grows. Simultaneously, we find that high levels of debt-to-output forecast both lower tangible and intangible investment, as well as lower output growth over the medium term.

We interpret our empirical results in the context of an equilibrium production economy in which endogenous innovation drives long-term growth. Corporate investment and innovation depend on the fiscal policy stance of the government, which resorts to taxation to ensure a balanced budget in the long run. Unexpected movements in the government's debt policy give rise to an endogenous time-varying exposure to macroeconomic shocks priced in the cross-section of returns.

We find that agents require a premium increasing in debt-to-output in order to hold innovative stocks due to this time-varying exposure. We test this hypothesis in the cross-section of equity returns and fail to reject it. High levels of public debt are then associated with slow downs in innovation and growth. Both the model and our empirical investigation thus highlight the role of political and fiscal uncertainty in shaping future aggregate growth. Future work should explore our results in alternative settings like those of Farhi and Gabaix (2015).

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A Additional Statistics and Tests

In table A1, we provide the most frequent industries in both our high and low R&D-intensity sorted portfolios.

Table A1: Top 10 Industries in R&D Intensity Sorted Portfolio

Panel A: All Firms

Low-R&D		High-R&D	
Category	% Count	Category	% Count
Eating Places	9.9	Prepackaged Software	12.9
Crude Petroleum and Natural Gs	3.6	Pharmaceutical Preparations	11.5
Grocery Stores	3.5	Biological Pds, Ex Diagnstics	10.2
Misc Amusement and Rec Service	3.0	Semiconductor,Related Device	6.8
Variety Stores	2.6	Electromedical Apparatus	3.7
Hotels and Motels	2.5	In Vitro,In Vivo Diagnostics	3.4
Women's Clothing Stores	2.5	Cmp Integrated Sys Design	3.3
Real Estate Investment Trust	2.2	Computer Communications Equip	3.3
Department Stores	2.0	Radio, TV Broadcast, Comm Eq	3.0
Computers and Software-Whsl	1.8	Tele and Telegraph Apparatus	2.9
Total	33.4	Total	61.2

Panel B: Positive R&D Firms

Low-R&D		High-R&D	
Category	% Count	Category	% Count
Petroleum Refining	5.4	Prepackaged Software	12.8
Crude Petroleum and Natural Gs	3.3	Pharmaceutical Preparations	11.6
Steel Works and Blast Furnaces	3.1	Biological Pds, Ex Diagnstics	10.4
Phone Comm Ex Radiotelephone	2.8	Semiconductor,Related Device	6.7
Mng, Quarry Nonmtl Minerals	1.8	Electromedical Apparatus	3.7
Metal Mining	1.8	In Vitro,In Vivo Diagnostics	3.5
Indl Inorganic Chemicals	1.6	Computer Communications Equip	3.3
Radiotelephone Communication	1.4	Cmp Integrated Sys Design	3.3
Paper Mills	1.3	Radio, TV Broadcast, Comm Eq	3.0
Paperboard Mills	1.2	Tele and Telegraph Apparatus	2.9
Total	23.7	Total	61.3

Notes: This table shows the top-10 industries in our baseline high and low R&D-sorted portfolios. We count SIC codes across time and firms in each portfolio and report the most frequent industries within each portfolio. In Panel A, we include all firm. In Panel B, we only consider firms with positive R&D expense.

In table A2, we report basic statistics on a restricted sample, in which we consider only firms with positive R&D expenditures.

Table A2: Data Summary Statistics – Positive R&D Firms

	Low	Middle	High	*HML-R&D*
Panel A: Equally-Weighted Portfolio Returns				
Mean	13.97***	16.07***	23.81***	10.39***
	(3.74)	(3.56)	(4.51)	(3.19)
Standard Deviation	25.81	24.57	31.15	22.04
Sample Size	191	191	191	191
Panel B: Value-Weighted Portfolio Returns				
Mean	5.65**	7.93***	14.86***	9.41***
	(2.87)	(2.66)	(3.67)	(3.08)
Standard Deviation	19.80	18.37	25.33	21.31
Sample Size	191	191	191	191

Notes: This table shows summary statistics for three R&D-sorted portfolios and the implied *HML-R&D* portfolio. We only include firms with positive R&D expense in our cross-section. Equally-weighted returns are presented in Panel A and value-weighted returns are presented in Panel B. All returns are presented in annualized percentages. Our quarterly sample starts in 1966:Q2 and ends in 2013:Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In tables A3 and A4, we show that when we use value-weighted returns, high levels of government debt forecast higher expected returns for our *HML-R&D* portfolio. This result is consistent with that of the baseline forecasting exercise in the main text. Furthermore, it is statistically significant also over short horizons of one and two quarters.

Table A3: $DGDP$ and Predictability of Returns to Innovation (VW)

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.12***	0.22***	0.42***	0.72***	0.86*
	(0.03)	(0.05)	(0.11)	(0.24)	(0.51)
R^2	0.06	0.12	0.19	0.20	0.11
High-R&D	0.21***	0.41***	0.82***	1.59***	3.82***
	(0.03)	(0.06)	(0.13)	(0.22)	(0.57)
R^2	0.08	0.13	0.23	0.37	0.53
HML-R&D	0.09***	0.19***	0.40***	0.87***	2.96***
	(0.03)	(0.07)	(0.14)	(0.28)	(0.57)
R^2	0.02	0.04	0.07	0.18	0.50
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4: ***PD, MV*** **and Predictability of Returns to Innovation (VW)**

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	-0.0009^{***}	-0.0017^{***}	-0.0032^{***}	-0.0049^{***}	-0.0048
	(0.0003)	(0.0005)	(0.0010)	(0.0017)	(0.0031)
High-R&D	-0.0011^{***}	-0.0022^{***}	-0.0045^{***}	-0.0075^{***}	-0.0119^{***}
	(0.0004)	(0.0007)	(0.0011)	(0.0019)	(0.0030)
HML-R&D	-0.0002	-0.0005	-0.0013	-0.0025	-0.0071^{**}
	(0.0004)	(0.0007)	(0.0013)	(0.0019)	(0.0028)
Market	-0.0011^{***}	-0.0021^{***}	-0.0043^{***}	-0.0081^{***}	-0.0147^{***}
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	0.73^{**}	1.56^{**}	2.28^{**}	2.91^{**}	3.35^{***}
	(0.48)	(0.75)	(1.00)	(1.37)	(0.86)
High-R&D	0.55^{*}	1.13^{**}	1.76^{**}	2.33^{*}	3.06^{**}
	(0.30)	(0.49)	(0.80)	(1.31)	(1.29)
HML-R&D	-0.18	-0.43	-0.52	-0.58	-0.30
	(0.36)	(0.57)	(0.67)	(0.92)	(1.04)
Market	0.31	0.88^{*}	1.12^{**}	1.54^{**}	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In tables A5 and A6, we show that even when we restrict our sample to firms with positive R&D expenditures, high levels of government debt forecast higher expected returns for our *HML-R&D* portfolio. In this case, returns are equally-weighted. Tables A7–A8 are based on value-weighted results.

Table A5: $DGDP$ and Predictability of Returns to Innovation (Positive R&D Firms-EW)

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.13***	0.23***	0.44***	0.72**	1.26
	(0.04)	(0.08)	(0.16)	(0.35)	(0.94)
R^2	0.07	0.14	0.17	0.18	0.13
High-R&D	0.16***	0.30***	0.57***	1.00**	3.12***
	(0.05)	(0.11)	(0.21)	(0.41)	(1.20)
R^2	0.05	0.10	0.15	0.19	0.33
HML-R&D	0.03	0.07	0.13	0.28	1.86**
	(0.04)	(0.08)	(0.14)	(0.25)	(0.77)
R^2	0.03	0.04	0.07	0.15	0.35
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equal-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A6: ***PD, MV*** **and Predictability of Returns to Innovation (Pos. R&D Firms-EW)**

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	-0.0011^{***}	-0.0021^{***}	-0.0040^{***}	-0.0063^{***}	-0.0077^{*}
	(0.0004)	(0.0007)	(0.0012)	(0.0021)	(0.0046)
High-R&D	-0.0005	-0.0008	-0.0014	-0.0008	-0.0022
	(0.0009)	(0.0016)	(0.0029)	(0.0041)	(0.0043)
HML-R&D	0.0007	0.0013	0.0026	0.0056	0.0055
	(0.0007)	(0.0014)	(0.0025)	(0.0039)	(0.0041)
Market	-0.0011^{***}	-0.0021^{***}	-0.0043^{***}	-0.0081^{***}	-0.0147^{***}
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	1.00^{*}	2.03^{***}	2.86^{***}	3.69^{***}	4.17^{**}
	(0.58)	(0.60)	(0.92)	(1.19)	(1.72)
High-R&D	0.83^{*}	2.08^{***}	3.60^{***}	4.96^{***}	6.29^{**}
	(0.45)	(0.43)	(0.90)	(1.53)	(2.60)
HML-R&D	-0.16	0.05	0.74	1.27	2.12^{*}
	(0.35)	(0.45)	(0.68)	(0.97)	(1.09)
Market	0.31	0.88^{*}	1.12^{**}	1.54^{**}	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equal-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A7: $DGDP$ **and Predictability of Returns to Innovation (Pos. R&D Firms-VW)**

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.13***	0.26***	0.54***	1.09***	2.34***
	(0.03)	(0.06)	(0.14)	(0.28)	(0.60)
R^2	0.04	0.09	0.17	0.28	0.29
High-R&D	0.21***	0.40***	0.81***	1.58***	4.02***
	(0.03)	(0.06)	(0.13)	(0.23)	(0.58)
R^2	0.08	0.13	0.23	0.38	0.58
HML-R&D	0.08***	0.14***	0.27***	0.50***	1.68***
	(0.02)	(0.04)	(0.07)	(0.11)	(0.31)
R^2	0.08	0.13	0.23	0.38	0.58
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A8: *PD, MV* and Predictability of Returns to Innovation (Pos. R&D Firms-VW)

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	-0.0010^{***}	-0.0020^{***}	-0.0043^{***}	-0.0087^{***}	-0.0151^{***}
	(0.0003)	(0.0006)	(0.0011)	(0.0019)	(0.0040)
High-R&D	-0.0010^{**}	-0.0019^{***}	-0.0040^{***}	-0.0066^{***}	-0.0117^{***}
	(0.0004)	(0.0007)	(0.0012)	(0.0018)	(0.0034)
HML-R&D	0.0000	0.0001	0.0003	0.0021^{*}	0.0034^{*}
	(0.0000)	(0.0006)	(0.0009)	(0.0012)	(0.0019)
Market	-0.0011^{***}	-0.0021^{***}	-0.0043^{***}	-0.0081^{***}	-0.0147^{***}
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	0.15	0.64	1.00	1.87	2.13
	(0.31)	(0.49)	(0.81)	(1.31)	(1.33)
High-R&D	0.53^{*}	1.08^{**}	1.70^{**}	2.50^{**}	3.20^{**}
	(0.29)	(0.49)	(0.78)	(1.27)	(1.31)
HML-R&D	0.38^{**}	0.45	0.70	0.63	1.07^{*}
	(0.18)	(0.35)	(0.55)	(0.77)	(0.57)
Market	0.31	0.88^{*}	1.12^{**}	1.54^{**}	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In addition, our results are confirmed when we focus on a sample starting in 1975 (see tables A9 and A10), when novel accounting standards introduced by the Financial Accounting Standards Board (FASB).

Table A9: $DGDP$ **and Predictability of Returns to Innovation (Post-1975-EW)**

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.07*	0.12	0.17	0.19	0.33
	(0.04)	(0.07)	(0.14)	(0.23)	(0.50)
R^2	0.06	0.13	0.15	0.13	0.25
High-R&D	0.11*	0.20*	0.36*	0.66*	3.06***
	(0.06)	(0.10)	(0.20)	(0.35)	(0.84)
R^2	0.04	0.08	0.11	0.14	0.42
HML-R&D	0.04	0.09	0.19	0.48*	2.73***
	(0.04)	(0.07)	(0.14)	(0.29)	(0.68)
R^2	0.01	0.02	0.03	0.06	0.46
Market	0.09***	0.18***	0.35***	0.71***	1.35***
	(0.02)	(0.03)	(0.07)	(0.15)	(0.51)
R^2	0.04	0.09	0.17	0.33	0.48

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equal-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1975:Q1–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A10: $DGDP$ and Predictability of Returns to Innovation (Post-1975-VW)

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.09***	0.18***	0.34***	0.65***	0.84
	(0.02)	(0.04)	(0.09)	(0.20)	(0.55)
R^2	0.06	0.10	0.20	0.23	0.14
High-R&D	0.20***	0.39***	0.78***	1.61***	4.07***
	(0.04)	(0.07)	(0.14)	(0.26)	(0.81)
R^2	0.08	0.13	0.22	0.42	0.54
HML-R&D	0.10***	0.21***	0.44***	0.98***	3.23***
	(0.04)	(0.07)	(0.15)	(0.29)	(0.59)
R^2	0.03	0.05	0.09	0.23	0.59
Market	0.09***	0.18***	0.35***	0.71***	1.35***
	(0.02)	(0.03)	(0.07)	(0.15)	(0.51)
R^2	0.04	0.09	0.17	0.33	0.48

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1975:Q1–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In table A11 we sort portfolios according to the Lin (2012) measure of innovation intensity, i.e., the ratio of R&D and capital expenditure. As in the analysis presented in the main text, we find that *DGDP* predicts higher *HML-R&D*.

Table A11: Conditional Macro Factors Model (II)

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.05***	0.14***
	(0.02)	(0.03)
High–R&D	0.15***	0.22***
	(0.03)	(0.03)
HML–R&D	0.10***	0.09***
	(0.01)	(0.02)
Market	0.11***	0.20***
	(0.02)	(0.03)
Small–Low B/M	0.15***	0.24***
	(0.03)	(0.04)
Small–High B/M	0.14***	0.23***
	(0.03)	(0.03)
Big–Low B/M	0.12***	0.20***
	(0.02)	(0.04)
Big–High B/M	0.07***	0.15***
	(0.02)	(0.03)

	EV			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.002	0.008***	−0.020***	−0.016***	0.010***	−0.028***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.005)
J-Test		8.54			8.54	
p-value		1.00			1.00	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (23). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i}\lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. Our portfolio are sorted on R&D-to-capital expenditure (capx) as in Lin (2012). The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; and the full market portfolio. Newey-West (1987) standard errors are in parentheses. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 27 degrees of freedom.

In table A12, we confirm that our predictability results also hold when we focus only on positive-R&D firms.

Table A12: Conditional Macro Factors Model – Positive R&D Firms

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.10***	0.07***
	(0.03)	(0.02)
High–R&D	0.16***	0.16***
	(0.04)	(0.03)
HML–R&D	0.05**	0.08***
	(0.02)	(0.02)
Market	0.14***	0.16***
	(0.03)	(0.03)
Small–Low B/M	0.17***	0.19***
	(0.03)	(0.04)
Small–High B/M	0.16***	0.19***
	(0.03)	(0.04)
Big–Low B/M	0.13***	0.15***
	(0.03)	(0.04)
Big–High B/M	0.10***	0.13***
	(0.03)	(0.03)
SMB	0.02	0.02
	(0.02)	(0.02)
HML	−0.02	−0.01
	(0.02)	(0.02)

	EW			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.006*	0.008***	−0.020***	−0.012***	0.009***	−0.019***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.004)
J-Test		31.80			38.80	
p-value		1.00			0.99	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (23). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i} \lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; and the full market portfolio. We only include firms with positive R&D expense in our cross-section. Newey-West (1987) standard errors are in parentheses. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 29 degrees of freedom.

Table A13 shows our estimation results for the conditional 3-factor model detailed in the system of equations (23) when we use a shorter sample starting in 1975.

Table A13: Conditional Macro Factors Model – Post-1975

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.01	0.03
	(0.05)	(0.04)
High–R&D	0.07	0.06
	(0.05)	(0.05)
HML–R&D	0.06**	0.03
	(0.03)	(0.03)
Market	0.11**	0.11
	(0.05)	(0.04)
Small–Low B/M	0.12**	0.10
	(0.06)	(0.06)
Small–High B/M	0.10*	0.08
	(0.06)	(0.06)
Big–Low B/M	0.13***	0.14***
	(0.04)	(0.05)
Big–High B/M	0.08	0.06
	(0.05)	(0.06)

	EW			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.006	0.007***	−0.020***	−0.019***	0.006*	−0.030***
	(0.003)	(0.001)	(0.003)	(0.007)	(0.003)	(0.007)
J-Test		5.96			7.15	
p-value		1.00			1.00	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (23). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i} \lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; and the full market portfolio. Newey-West (1987) standard errors are in parentheses. Data are from 1975:Q1 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 27 degrees of freedom.

In table A14, we use the residual component of our macroeconomic factors orthogonal to both the FF5 and the q-Factors. As in the analysis presented in the main text, we find that *DGDP* predicts higher *HML-R&D*.

Table A14: Conditional Macro Factor Residuals Model

			$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$
HML–R&D			0.04^{*}
			(0.03)
Market			0.05^{*}
			(0.03)
	Macro Factor Residuals		
	$\widehat{\Delta DGDP}$	$\widehat{\Delta TFP}$	$\widehat{\Delta GY}$
Price of risk, λ	0.003	0.015^{***}	-0.047^{***}
	(0.003)	(0.002)	(0.003)
J-Test (df=27)			2.82
p-value			1.00

Notes: This table shows results from our GMM estimation of the conditional factor model detailed in the system of equations (23) in which our macroeconomic factors are the residuals of the regressions presented in table A14. We simultaneously project our macroeconomic factors on both the FF5 and the q-Factors. Returns for the R&D-sorted portfolios are equally-weighted. All other conditions reported in table 9 apply.

B Tax Rate Dependence on the Debt-to-Output Ratio

Let $BY_t = \frac{B_t}{Y_t}$ denote the debt-to-output ratio in the economy at time t, and assume that authorities are planning to bring this ratio from an initial level of BY_0 to $BY_0 - \delta$ in T periods. Assume that output grows at a constant average rate of g, $Y_t = Y_0(1+g)^t$.

Given an initial level of debt B_0, the law of motion for the debt level is

$$B_t = B_{t-1}(1+r) - \tau Y_{t-1},\ t \geq 1,$$

where τ is the average tax rate over T periods and r is the constant interest rate on the government's debt. We abstract away from additional expenditures without loss of generality. Iterating this equation forward, we obtain

$$B_t = B_0(1+r)^t - \tau Y_0 \left[\sum_{i=0}^{t-1} (1+r)^i (1+g)^{(t-1)-i}\right]. \tag{25}$$

Given the target of the authorities, $B_T = (BY_0 - \delta)Y_0(1+g)^T$, the implied equilibrium τ is

$$\tau = \frac{B_0(1+r)^T - B_T}{Y_0\left[\sum_{i=0}^{T-1}(1+r)^i(1+g)^{(T-1)-i}\right]}, \tag{26}$$

and it simplifies further if we assume that $r = 0$:

$$\tau \quad = \quad \left[\frac{\delta(1+g)^T}{(1+g)^T - 1} - G_0\right] g.$$

As a result, we obtain the following conditions:

$$\frac{\partial^2 \tau}{\partial g \partial G_0} < 0$$
$$\frac{\partial \left|\frac{\partial \tau}{\partial g}\right|}{\partial |G_0|} > 0,$$

which imply that higher levels of the debt-to-output ratio increase the volatility of the tax rate under uncertainty about the growth rate of the economy. Below we report the change in average tax rate when growth ranges from −3% to +3% for both a high (50%) and a low (20%) initial ratio of debt to output with a targeted reduction δ of 20%. The range of the implied τ captures the extent of tax rate volatility.

Table B1: Avg. Tax Rate in High and Low Debt/GDP Environments

	Target Debt/GDP	
	50%–30%	20%–0%
−3% Growth	3.18%	2.28%
3% Growth	0.84%	1.75%
Tax Rate Range	2.34%	0.54%
	Change in Range	**1.80%**