Government Debt and the Returns to Innovation

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Online Appendix

Appendix 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 provide predictability regressions based on five portfolios sorted on R&D intensity. Each portfolio comprises an equal number of firms.

Table A2: $DGDP$ and Predictability of Returns to Innovation (II)

Horizon (J)	1	2	4	8	20
HML-R&D (EW)	0.06	0.11	0.26**	0.61***	2.61***
	(0.05)	(0.09)	(0.11)	(0.16)	(0.70)
R^2	0.02	0.03	0.04	0.09	0.48
HML-R&D (VW)	0.14***	0.29***	0.59***	1.21***	2.91**
	(0.05)	(0.08)	(0.09)	(0.15)	(1.16)
R^2	0.06	0.09	0.14	0.25	0.33

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

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

where $R_{t \to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ is the debt-to-output ratio. We report results for the portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*), where returns are either equal-weighted (EW) or value-weighted (VW). The underlying portfolios are constructed by sorting firms based on innovation intensity into five portfolios, each with an equal number of firms. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1975:Q1–2013:Q4. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In table A3, we report basic statistics on a restricted sample, in which we consider only firms with positive R&D expenditures.

Table A3: 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. Equal-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.

Table A4 shows summary statistics for both equal- and value-weighted portfolio returns.

Table A4: Portfolio Summary Statistics – Allocated by Number of Firms

	Low	High	*HML-R&D*
	Equally-Weighted Returns		
Mean	22.95***	36.55***	13.61***
	(3.96)	(5.98)	(4.52)
Standard Deviation	24.75	37.36	28.26
Sample Size (number of quarters)	156	156	156
	Value-Weighted Returns		
Mean	17.81***	35.33***	17.52***
	(4.12)	(6.09)	(5.45)
Standard Deviation	25.75	38.04	34.03
Sample Size (number of quarters)	156	156	156
	Portfolio Characteristics		
Market Capital Share	6.59	1.49	8.08
R&D/Assets	0.01	32.07	16.04
Sales/Assets	0.59	0.02	0.31
Leverage	60	45	53
Average Number of Firms	205	205	

Notes: This table shows summary statistics for two R&D-sorted portfolios and the implied *HML-R&D* portfolio. We present results for returns in annualized percentages that are both equal-weighted and value-weighted. The average market capital share, R&D/Assets, Sales/Assets, and Leverage 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 portfolios cover at least 10% of the number of firms. Sales/Assets is defined as annual net sales divided by total assets. Book leverage is defined as 1 - Tot. Equity/Tot. Assets. Our quarterly sample starts in 1975:Q1 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.

Table A5 shows sensitivity of our baseline estimates with respect to the lag chosen in the Newey-West estimator.

Table A5: Tstat by Newey-West Lags – HML R&D Returns

	Lag (quarters)				
Point estimate	2	4	6	8	24
2.76	5.19	4.29	3.92	3.76	4.09

Notes: This table shows sensitivity results from varying the lags for computing Newey-West (1987) standard errors in our univariate predictive return regressions. The estimate is performed without adjusting for the Stambaugh bias correction (in table 2, the adjusted estimate is 2.31). We report results from the *HML-R&D* equal-weighted returns for the predictive regression at 20 quarters horizon using our baseline portfolios. Data are from 1975:Q1 to 2013:Q4.

Table A6 documents sensitivity of our baseline estimates with respect to additional return predictors. Table A7 presents results from predictive regressions based on characteristic-adjusted returns.

Table A6: Predictive Regression for HML-R&D – Additional Factors

	β^J_{DGDP}	t-stat
First 2 principle components	2.96	2.44
First 3 principle components	2.94	2.39
First 2 principle components plus PD and MV	1.99	2.00
First 3 principle components plus PD and MV	1.99	2.00

Notes: This table shows predictive return regressions using principle components from the panel of regressors used in Welch and Goyal (2008) (WG). We report results for our equal-weighted *R&D-HML* portfolio at a horizon of 20 quarters by estimating $R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta'^J_W WG_t + \epsilon_{t+J}$, where WG_t represents either the first two or three principle components from a panel of the Goyal and Welch regressors. We also control for integrated market returns volatility (MV) and price-dividends (PD) ratio.

Table A7: Predictive Regressions - HML-R&D Adjusted Returns

	Univariate–β_{DGDP}					Multivariate–β_{DGDP}				
Horizon J	1	2	4	8	20	1	2	4	8	20
Asset/Book Equity	0.13	0.15	0.19**	0.27***	0.73***	0.06**	0.12**	0.25**	0.59***	2.97***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.20)	(0.03)	(0.06)	(0.11)	(0.21)	(0.57)
R^2	0.02	0.03	0.04	0.09	0.53	0.03	0.04	0.06	0.12	0.52
Asset/Market Equity	0.10	0.11	0.16**	0.23***	0.70***	0.03	0.08	0.15	0.33*	2.21***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.19)	(0.03)	(0.05)	(0.10)	(0.20)	(0.62)
R^2	0.01	0.02	0.03	0.06	0.48	0.02	0.03	0.03	0.08	0.40
KZ Index	0.13	0.15	0.19**	0.28***	0.75***	0.06*	0.14*	0.29*	0.73**	4.01***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.19)	(0.04)	(0.08)	(0.17)	(0.37)	(0.55)
R^2	0.02	0.03	0.04	0.09	0.55	0.03	0.05	0.08	0.18	0.63
SA Index	0.06	0.06	0.10	0.16**	0.63***	0.02	0.05	0.11	0.32	2.73***
	(0.12)	(0.11)	(0.08)	(0.08)	(0.21)	(0.04)	(0.07)	(0.14)	(0.29)	(0.82)
R^2	0.02	0.03	0.03	0.06	0.39	0.01	0.02	0.02	0.05	0.40

Notes: This table predictive return regressions with characteristic adjusted equal-weighted returns for the HML-R&D portfolio. We separately adjust for asset/book equity, asset/market equity, KZ index, and SA index. The KZ index is constructed following Kaplan and Zingales (1997) and the SA index is constructed following Hadlock and Pierce (2010). We follow the methods in Titman et al. (2004) to form characteristic adjusted returns. Univariate refers to the following regression $R_{t\rightarrow t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J}$. In the multivariate regressions, we control for integrated market volatility (MV) and the aggregate price-dividends (PD) ratio.

In Table A8 we use the growth rate of the debt-to-output ratio, $\Delta DGDP$, as a return predictor. Panel A shows that our model predicts that $\Delta DGDP$ has no predictive power for the *HML-R&D* portfolio and for market excess returns, and panel B verifies that this prediction is true in our data sample.

Table A8: *DGDP* and Predictability of Returns to Innovation

Horizon (J)	1	2	4	8	20
Panel A: Model					
			Using $DGDP$ as Predictor		
HML-R&D	0.13	0.18	0.24	0.30	0.37
R^2	0.02	0.03	0.06	0.09	0.14
Market	0.06	0.08	0.11	0.15	0.20
R^2	0.01	0.01	0.01	0.02	0.04
			Using $\Delta DGDP$ as Predictor		
HML-R&D	−0.01	−0.01	0.00	0.00	0.01
R^2	0.00	0.00	0.00	0.00	0.00
Market	−0.00	−0.00	0.00	0.00	0.00
R^2	0.00	0.00	0.00	0.00	0.00
Panel B: Data					
			Using $\Delta DGDP$ as Predictor		
HML-R&D	−0.46	−0.17	−0.42	0.48	4.78
	(1.10)	(2.03)	(3.81)	(6.26)	(10.13)
R^2	0.00	0.00	0.00	0.00	0.01
Market	0.98	2.15	3.68	6.74	14.93**
	(0.80)	(1.38)	(2.29)	(3.85)	(5.92)
R^2	0.01	0.03	0.04	0.09	0.14

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

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

and

$$R_{t\to t+J} = \beta_0 + \beta^J_{\Delta DGDP} \Delta DGDP_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ denotes the debt-to-output ratio. In Panel A, all results are based on a long sample simulation of our benchmark model. In panel B, we run the regressions described in table 2 using $\Delta DGDP$ as predictor, as opposed to $DGDP$. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In tables A9 and A10, 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 equal-weighted. Tables A11–A12 are based on value-weighted results.

Table A9: $DGDP$ **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 A10: *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 A11 $DGDP$ **and Predictability of Returns to Innovation (Positive 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 A12: *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 table A13 we form equally weighted portfolios and compute their returns assuming that no further rebalancing of the holdings takes place for the next four quarters. For the sake of completeness, we consider both the case in which dividends are reinvested and the case in which dividends are not reinvested. The latter case corresponds to keeping fixed the number of shares in our portfolios throughout the year. Our main predictability results hold also in these settings over the 2-year and 5-year horizons.

Table A13: ***DGDP* and Predictability with Annual Re-balance**

Horizon (J)	1	2	4	8	20
	With Quarterly Dividends Reinvestment				
HML-R&D	0.04	0.05	0.19	0.54**	2.79***
	(0.07)	(0.12)	(0.14)	(0.21)	(0.95)
R^2	0.01	0.01	0.02	0.05	0.33
	No Dividends Reinvestment				
HML-R&D	0.04	0.05	0.17	0.50**	2.59***
	(0.07)	(0.11)	(0.14)	(0.21)	(0.98)
R^2	0.01	0.01	0.02	0.05	0.29

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

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

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ denotes the debt-to-output ratio. We report results for a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Innovation intensity is measured as the ratio of R&D expenses to total assets. Returns are from a buy-and-hold strategy of portfolios formed once a year with equal weights. We consider both the case with and without dividends reinvestment. Our quarterly sample is 1975:Q1–2013:Q4. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In table A14 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 A14: 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 (25). 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 equal-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 A15, we confirm that our predictability results also hold when we focus only on positive-R&D firms.

Table A15: 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 (25). 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 equal-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 A16 uses financial constraints adjusted returns to evaluate the conditional 3-factor macro model.

Table A16 Conditional Macro Factors Model – Financially Constrained Adjusted Returns

	KZ Index Price of risk, λ				SA Index Price of risk, λ			
	TWX		OLS		TWX		OLS	
	Est	SE	Est	SE	Est	SE	Est	SE
$DGDP$	-0.012^{***}	0.002	-0.013^{***}	0.003	-0.009^{***}	0.002	-0.011^{***}	0.002
TFP	0.006^{***}	0.001	0.007^{***}	0.001	0.006^{***}	0.001	0.006^{***}	0.001
GY	-0.027^{***}	0.004	-0.026^{***}	0.004	-0.026^{***}	0.004	-0.027^{***}	0.003
	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$				$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$			
	Est	SE	Est	SE	Est	SE	Est	SE
HML-R&D	0.070^{**}	0.034	0.073^{**}	0.031	0.069^{***}	0.024	0.072^{***}	0.019

Notes: This table shows the main macro model when we use financially constrained adjusted returns in our R&D portfolios. The model is estimated using characteristic adjusted returns from Titman et al. (2004) (TWX) as well as residuals (OLS) from returns regressed contemporaneously on the financial constraint indices. The KZ index is constructed following Kaplan and Zingales (1997) and the SA index is constructed following Hadlock and Pierce (2010). We present Newey-West (1987) standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Data are from 1975:Q1 to 2013:Q4.

Appendix 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

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

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

$$\tau = \frac{B_0(1+r)^T - B_T}{Y_0 \left[\sum_{i=0}^{T-1} (1+r)^i (1+g)^{(T-1)-i} \right]}, \tag{2}$$

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%**

Appendix C. Empirical specifications

C.1. Parameterized β regressions

We decompose the coefficient β^J_{DGDP} defined in the following regressions,

$$R_{i,t\to t+J} = \beta_{i,0} + \beta^J_{i,DGDP} DGDP_t + \epsilon_{i,t+J}, \tag{3}$$

as follows

$$\beta^J_{i,DGDP} = \beta(J)[1 + \gamma(rd_i - \bar{rd})], \tag{4}$$

where rd_i is the time-series average of the R&D intensity of portfolio i; $\bar{rd}$ is the overall average of R&D intensity; and $\beta(J)$ is a horizon-specific coefficient. We then jointly estimate $\theta = (\beta(1), \beta(2), \beta(4), \beta(8), \beta(20), \gamma)$ in a GMM setting with the appropriate orthogonality restrictions implied by equation (3).[1]

The multivariate case is analogous, where $X_{i,J}$ is now the OLS design matrix related to Equation equation (5).

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J}. \tag{5}$$

[1] We focus on the following quadratic objective function:

$$Q_n(\theta) = \sum_{i,J} [\iota_2'(X_{i,J}'X_{i,J})^{-1}(X_{i,J}'R_{i,J}) - \beta(J)[1 + \gamma(rd_i - \bar{rd})]]^2,$$

where $X_{i,J}$ is the OLS design matrix related to Equation equation (3) and $R_{i,J}$ is the stacked cumulative returns, both for portfolio i and horizon J. We define ι_2 to be a conformable zeros column vector with a one in the 2nd position.

C.2. TFP construction

We use the following Solow residual method to create the TFP series used in the predictive regressions for TFP growth:

$$\Delta TFP_t = \Delta GDP_t - \alpha \Delta L_t - (1-\alpha)\Delta K_t. \tag{6}$$

Labor growth is the log difference of the FRED series "Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing". We use real physical investment excluding R&D expenditures ($I = Inv - R\&D$) to create our physical capital series. Nominal series are transformed to real using the GDP deflator. Physical capital evolves using the law of motion $K_t = (1-\delta)K_{t-1} + I$, where δ is the quarterly capital depreciation rate. We initialize the capital series in 1975:Q1 using the perpetuity formula $K_{1975:Q1} = \frac{I_{1975:Q1}}{\delta}$. We set the parameters $\delta = 0.02$ and $\alpha = 0.58$ as in our calibration.

C.3. Look-ahead bias correction

We first estimate the following equation using a rolling window size of 32 quarters,

$$R^{HML-R\&D}_{t\to t+J} = \beta^J_0 + \beta^J_{DGDP} \cdot DGDP_t + \beta^J_{PD} \cdot PD_t + \beta^J_{MV} \cdot MV_t + \epsilon_{t+J}. \tag{7}$$

From this estimation, we store the end-period fitted values for $\{\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right), \widehat{\epsilon_{t+J}}\}$, where

$$\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right) = \widehat{\beta^J_0} + \widehat{\beta^J_{DGDP}} \cdot DGDP_t + \widehat{\beta^J_{PD}} \cdot PD_t + \widehat{\beta^J_{MV}} \cdot MV_t \tag{8}$$

$$\widehat{\epsilon_{t+J}} = R^{HML-R\&D}_{t\to t+J} - \widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right). \tag{9}$$

This method guarantees that only information up to time t was used to construct fitted values for periods $t+J$. We then use this sequence of $\{\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right), \widehat{\epsilon_{t+J}}\}$ to estimate the following regression:

$$\Delta GDP_{t\to t+J} = c^J_0 + c^J_1 \cdot \widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right) + c^J_2 \cdot \widehat{\epsilon_{t+J}} + v_{t+J}. \tag{10}$$

C.4. Stambaugh bias correction

We follow the methods in Stambaugh (1999) and use the sample counterpart of his equation (18) to correct for bias in our univariate predictive return regressions. The method is also explained in Stambaugh (1986), equation 11. We report bootstrapped standard errors for this procedure, and use a block bootstrap with a block size of $T/4$.

C.5. Characteristic-adjusted returns

We follow Titman et al. (2004) in constructing returns adjusted for the impact of both financial constraints and financial leverage (secondary sorting characteristic).

Each year, we first sort firms by their secondary sorting characteristic into three portfolios whereby both the low and high portfolios are guaranteed to contain firms totaling 10% of the overall market capitalization. These portfolios are re-formed each year. Quarterly stock returns are then adjusted by taking each firm's quarterly return and subtracting the cross-sectional average quarterly returns of the secondary sorting characteristic portfolio that the firm is a member of. Firms are then sorted according to our baseline procedure based on R&D intensity.

C.6. Monte Carlo evidence

To assess the potential for spurious inference in our predictive regressions with a highly persistent regressor, namely $DGDP$, we perform a Monte Carlo analysis with simulated data under the null of no predictability. Since our benchmark sample spans 156 quarters, we simulate 10,000 samples with 156 observations of the following system of equations:

$$DGDP_t = (1 - \rho_{DGDP})\mu_{DGDP} + \rho_{DGDP} DGDP_{t-1} + \epsilon_{DGDP,t} \tag{11}$$

$$r_t = (1 - \rho_r)\mu_r + \rho_r r_{t-1} + \epsilon_{r,t} \tag{12}$$

$$\begin{bmatrix} \epsilon_{DGDP,t} \\ \epsilon_{r,t} \end{bmatrix} \overset{iid}{\sim} N(\mathbf{0}, \Sigma) \tag{13}$$

$$\Sigma = \begin{bmatrix} \sigma^2_{DGDP} & \beta\sigma_{DGDP}\sigma_r \\ \beta\sigma_{DGDP}\sigma_r & \sigma^2_r \end{bmatrix} \tag{14}$$

In each repetition, consistent with our empirical methodology, we adopt a Stambaugh bias correction and estimate the following regression

$$R_{t \to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J}, \tag{15}$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return. By doing so, we recover the short-sample distribution of both β^J_{DGDP} and its own $t-stat$ under then null hypothesis that $DGDP$ has no forecasting power for future excess returns. The $t-stats$ are computed exactly as in the empirical section, that is, in each sample we compute the standard error of the corrected β^J_{DGDP} with a block-bootstrap procedure.

To be consistent with our quarterly data for public debt (1975:Q1-2013:Q4), we set $\rho_{DGDP} = 0.98$, $\mu_{DGDP} = 0.56$, and $\sigma_{DGDP} = 0.97\%$. Focusing on returns, we set $\mu_r = 1.96\%$, and $\sigma_r = 0.10$. In our benchmark specification, we set $\rho_r = 0$ so that under the null returns are $i.i.d.$. Since in the data the point estimate of this coefficient is 0.35, we also show results for the case in which we consider persistence in excess returns. Finally, we set $\beta = 0$, as in the data we recover an insignificant value of -6%.[2]

We report summary results across repetitions in Table C2. Even though the distribution of β^J_{DGDP} has slightly fatter tails than the one used in the empirical investigation, we continue to reject the null of no predictability for horizons longer than two quarters.

[2]On the basis of tabulated sensitivity analysis, β plays no major role.

Table C2: Montecarlo Results for β^J_{DGDP}

	$\rho_r = 0$					$\rho_r = 0.35$				
Horizon (J)	1	2	4	8	20	1	2	4	8	20
Mean	0.00	0.00	0.00	0.01	0.02	-0.01	-0.01	-0.01	-0.00	0.02
95%	0.12	0.22	0.44	0.86	2.11	0.17	0.33	0.67	1.32	3.25
5%	-0.11	-0.22	-0.43	-0.85	-2.06	-0.18	-0.35	-0.68	-1.33	-3.21
$t - stat$	1.00	1.00	2.10	3.06	3.79	1.00	1.00	2.10	3.06	3.79
$prob(x > t - stat)$	0.20	0.21	0.06	0.02	0.02	0.19	0.20	0.06	0.02	0.02

Notes: This table shows the average, the 95^{th}, and the 5^{th} percentile of β^J_{DGDP}, as defined by the following predictive regression

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

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ denotes the debt-to-output ratio. All results are based on 10,000 Montecarlo simulations of the system of equations (11)–(14) under the null hypothesis that $DGDP$ does not predict returns. The row $t - stat$ reports the t-statistics obtained from our real data for equally-weighted returns. The last row reports the percentage of repetitions that generated t-statistics greater than those obtained from real data.

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