APPENDIX – FOR ONLINE PUBLICATION

A Appendix Material for Section 2

The firm-level optimization problem is a standard dynamic programming one. While it admits no closed form solution, it can be solved numerically by discretizing the state space and using value function iteration. This gives us a numerical estimate for the optimal investment-borrowing policy function. Given, we simulate a large panel of firms whose cash-flows we discount at a rate $r^\star$. This gives us estimates for the value of a firm using the wrong discount rate, which we use to compute the value us.

Calibration. Table A.1 summarizes our calibration. The one parameter that is important is the elasticity of demand φ, which we set to 6.7 in our baseline calibration as in Midrigan and Xu (2014). We also try a larger value 10 which corresponds to some estimates in Broda and Weinstein (2006) but is admittedly in the upper part of the acceptable range. The other parameters take standard values.[6]

Discretization. We work with a discretized version of the state space. For the productivity process, we implement the method in Tauchen (1986) to create a grid with 30 points for log TFP. We use bounds of -3 and 3 standard deviations. We then create a 50×30 grid for capital and debt. For capital, we form an equally spaced grid from $\log k_{\min}$ to $\log k_{\max}$, where

$$k_{\min} = \frac{1}{2}\left(\frac{(1-\tau)\theta e^{\rho z_{\min}+\frac{\sigma}{2}}}{r_f(1-\tau M)+(1-\tau)\delta}\right)^{\frac{1}{1-\theta}} \quad ; \quad k_{\max} = \left(\frac{(1-\tau)\theta e^{\rho z_{\max}+\frac{\sigma}{2}}}{r_f(1-\tau M)+(1-\tau)\delta}\right)^{\frac{1}{1-\theta}}.$$

For debt, we use an equally spaced grid for the debt-to-capital ratio ranging from $-m = -0.25$ to $M = 0.4$. Finally, we use an equally spaced grid with 41 points for discount rates ranging from 0.05 to 0.15.

Solution method. For each r in the grid, we solve for the value function, policy function, and stationary distribution.

1. Starting from a guess for the value function $\widehat{V}_0$, iterate on the Bellman equation until convergence. To do so, we use a grid search to solve, for every $n > 0$,

$$\left(\widehat{\kappa}_n(z,k,d;r), \widehat{\Delta}_n(z,k,d;r)\right) = \arg\max_{k',d'} \Pi(z,k,d,k',d') + \frac{1}{1+r}\mathbb{E}\left[\widehat{V}_{n-1}(z,k,d;r) \mid z\right],$$

   and update the value function accordingly. To speed-up convergence, we use 30 steps of policy function iteration for each step of value function iteration. We assess convergence by checking

$$\max\left|\log \widehat{V}_n(z,k,d;r) - \log \widehat{V}_{n-1}(z,k,d;r)\right| \leq 10^{-5}.$$

   Denote $\widehat{V}(\cdot;r)$, $\widehat{\kappa}(\cdot;r)$, and $\widehat{\Delta}(\cdot;r)$ the value and policy functions at the end of the procedure.

2. Simulate N firms over T periods using the estimated policy $\widehat{\kappa}(\cdot;r)$ and $\widehat{\Delta}(\cdot;r)$ starting from an arbitrary state. Discard the first T_0 periods for each firm, and define

$$\widehat{\mu}(S;r) = \frac{1}{N(T-T_0+1)}\sum_{i=1}^{N}\sum_{t=T_0}^{T}\mathbf{1}\{S_{it}=S\},$$

   where $S = (z,k,d)$, i denotes a firm, and t denotes time. We use $N = 10^5$, $T = 500$, and $T_0 = 300$. We ensure that those values are sufficient to attain convergence by checking that we obtain results

[6] For the constraints on leverage and cash, we roughly use the third quartile for the book leverage ratio and cash ratio in our sample. Moreover, the parameters ρ and σ reported the scaled log TFP process z.

similar to the 10^{-3} using different seeds and uniformly drawn initial states.

To estimate the valuation loss from discounting at the wrong loss, we use the following method.

1. For each $r^\star$ in the grid, draw initial states from the estimated stationary distribution $\widehat{\mu}(\cdot; r^\star)$.
2. Using these initial states, for each r in the grid, simulate N firms over T periods using the estimated policy functions $\widehat{\kappa}(\cdot; r)$ and $\widehat{\Delta}(\cdot; r)$. We use $N = 10^5$ and $T = 300$.
3. Using the simulated cash-flows compute the present value

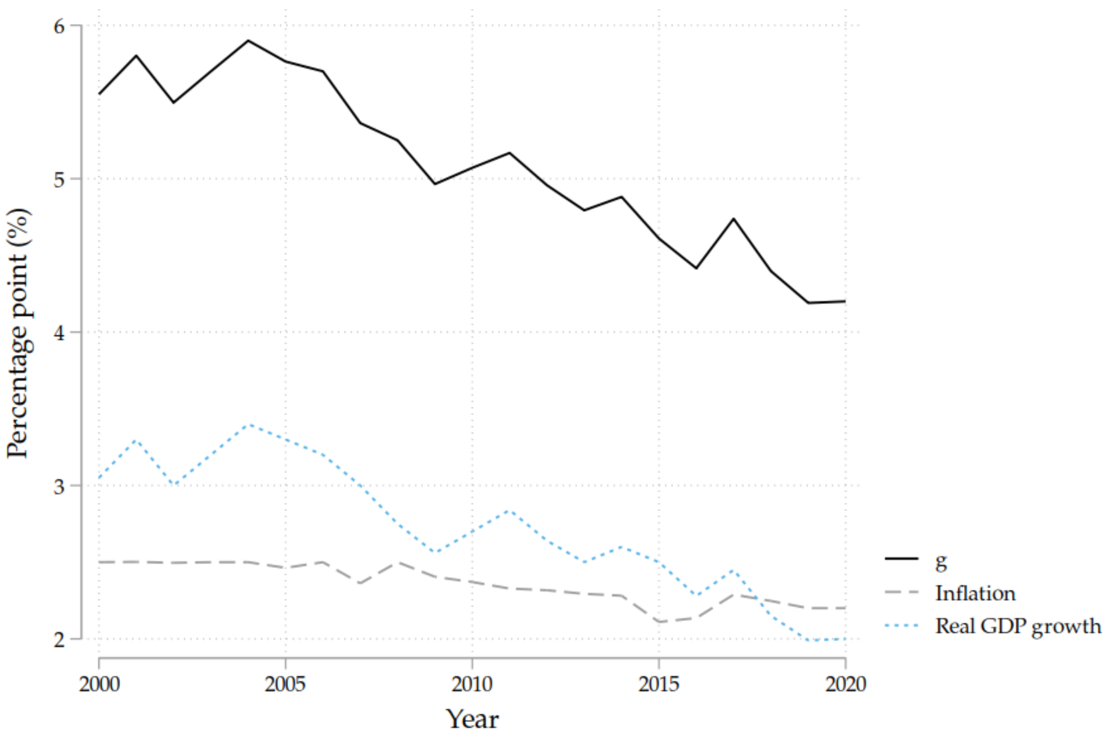
$$\widehat{W}(r, r^\star) = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T-1} \frac{\Pi\left(z_{it}, k_{it}, d_{it}, \widehat{\kappa}(z_{it}, k_{it}, d_{it}; r), \widehat{\Delta}(z_{it}, k_{it}, d_{it}; r)\right)}{(1 + r^\star)^t}.$$

   The estimated value loss is

$$\frac{\widehat{W}(r^\star, r^\star) - \widehat{W}(r, r^\star)}{\widehat{W}(r^\star, r^\star)}.$$

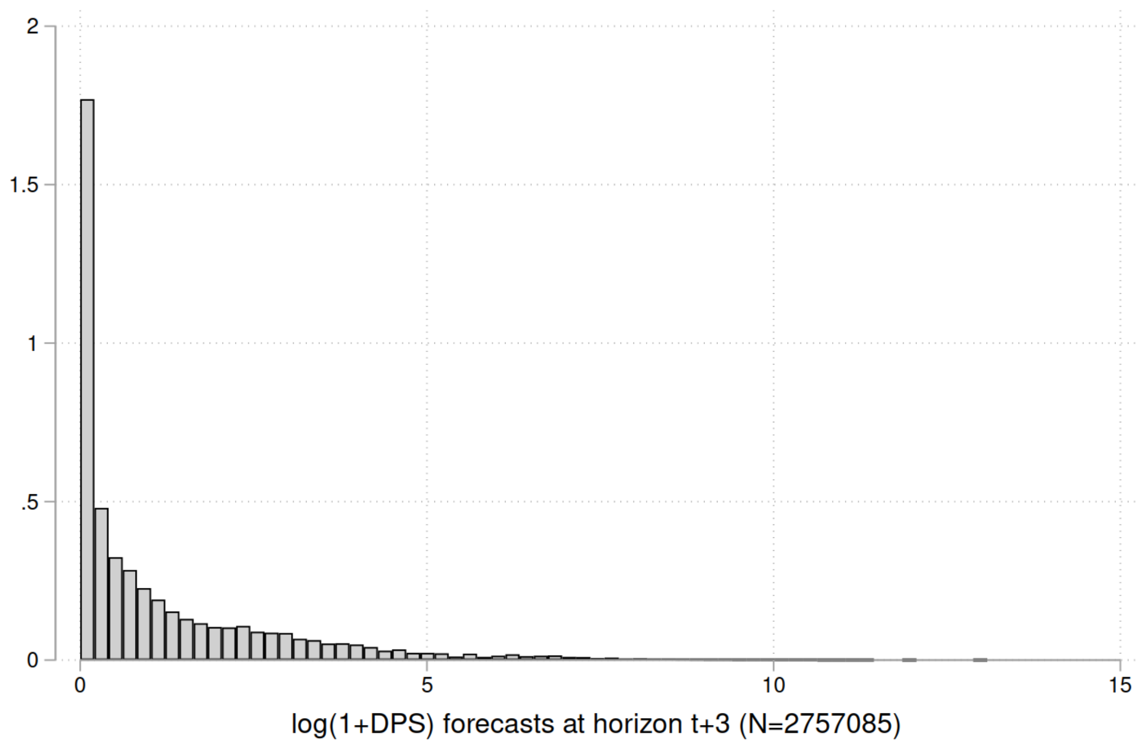
B Appendix Figures

Figure A.1: Time series of long-run nominal GDP forecasts



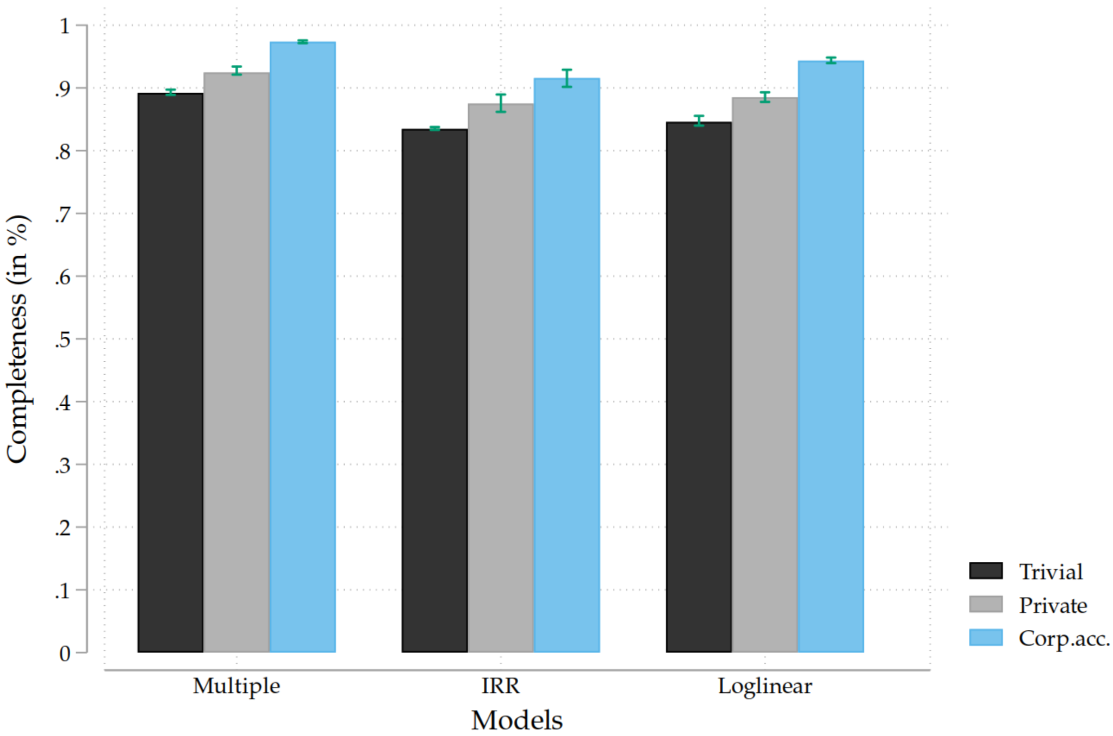
Note. We add 10-year real GDP growth forecasts to the 10-year horizon inflation forecasts. For both variables, we use the median consensus forecast from the Survey of Professional Forecasters maintained by the Philadelphia Federal Reserve.

FIGURE A.2: Distribution of (log) DPS forecasts



Note. We use the median consensus firm-level 3 years ahead DPS forecast from the IBES Summary files. Out of the 2,700,000 observations, over 500,000 (about 19%) are exactly zero.

Figure A.3: Completeness of predictive models using statistical forecasts

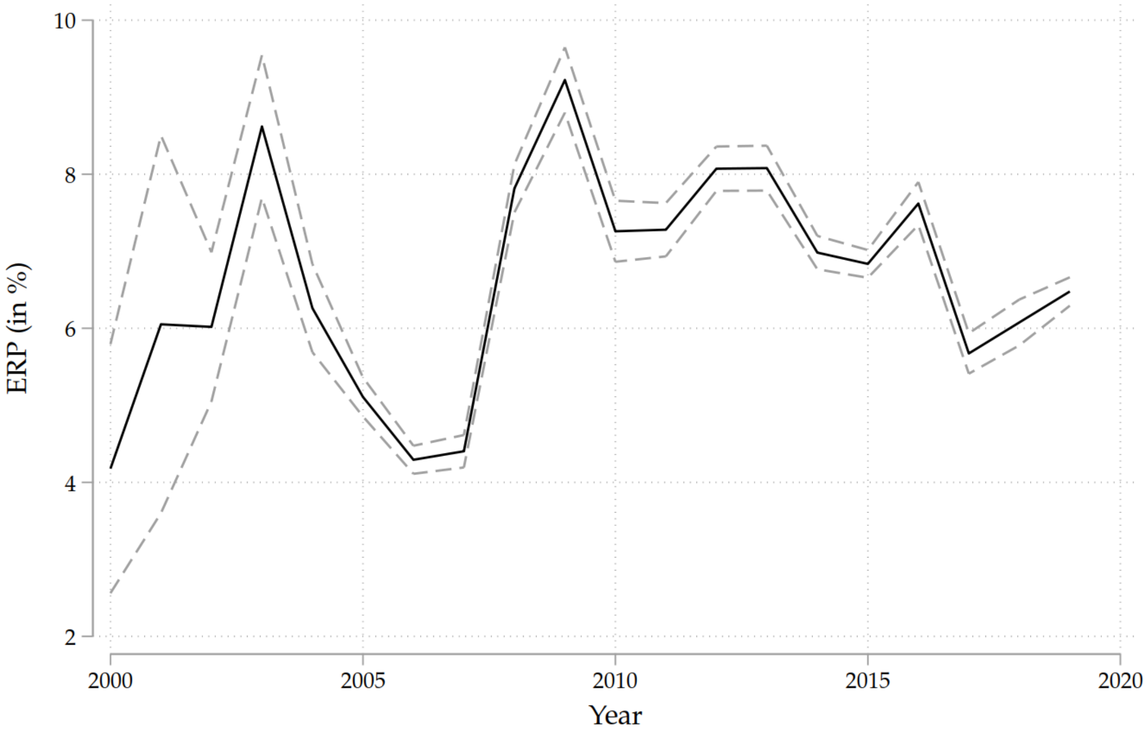


Note. This figure reports the median of the completeness metric of Fudenberg et al. (2022) over 100 train-test splits using statistical forecasts. Confidence intervals at the 90% level are displayed. Completeness is defined as

$$\frac{\text{MSE}_{\text{benchmark}} - \text{MSE}_{\text{model}}}{\text{MSE}_{\text{benchmark}} - \text{MSE}_{\text{irreducible}}}$$

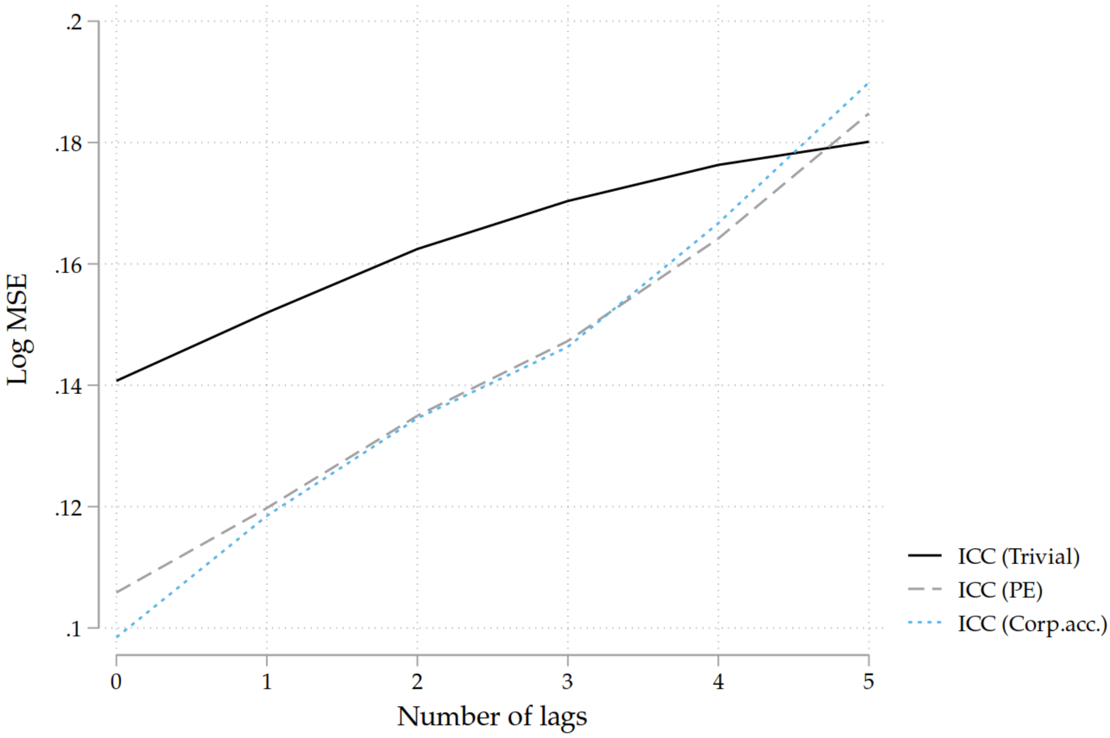
where MSE_m denotes the mean-squared error of model m. The irreducible error is proxied by the error of the local linear forest model trained using corporate accounts information. The benchmark model is the CAPM.

FIGURE A.4: Optimal equity risk-premium for the CAPM



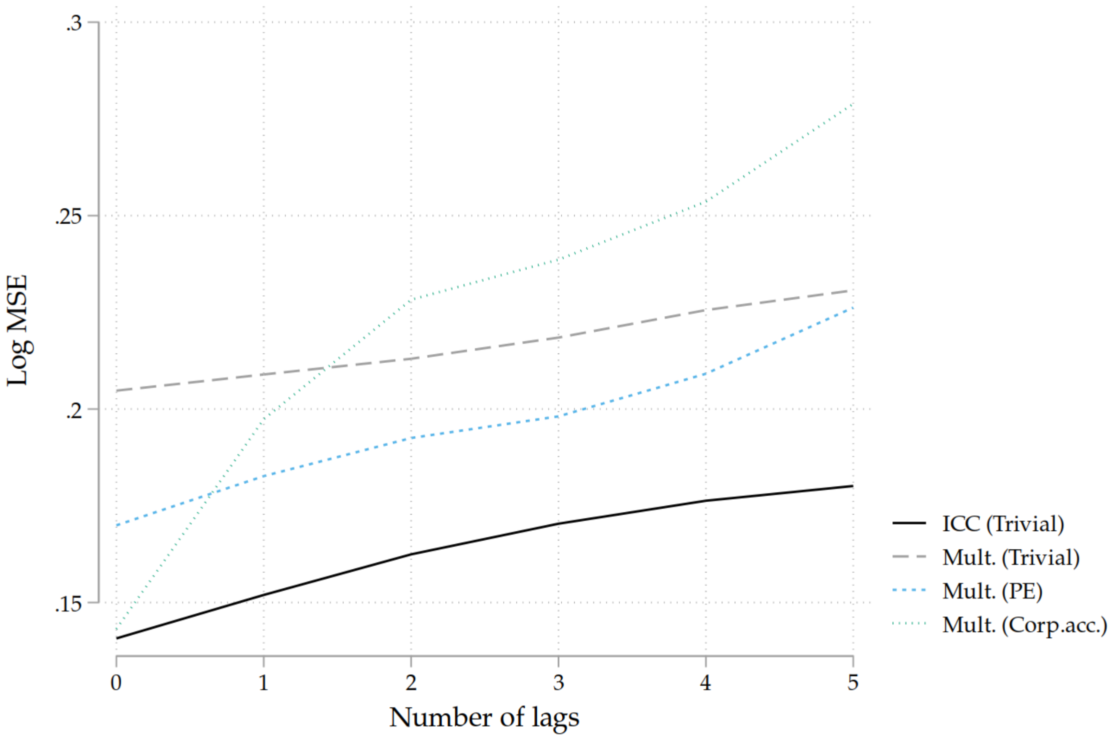
Note. For each year, we estimate the risk-premium that minimizes the in-sample mean-squared error of the CAPM using nonlinear least squares. The dotted line shows pointwise bootstrapped confidence intervals at the 95% level.

Figure A.5: Performance of the IRR when using lagged information



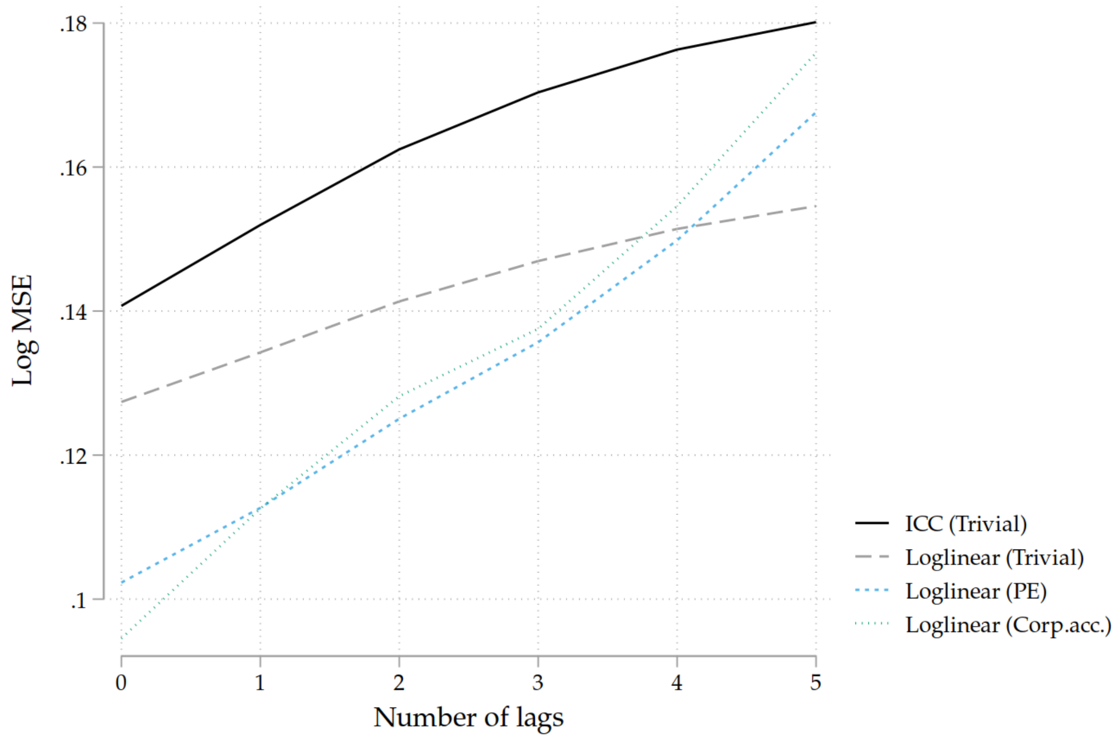
Note. This figure plots the out-of-sample MSE obtained by using the lagged discount rate $\widehat{\text{ICC}}_{it-h}$ to discount the cash-flows of firm i at time t. We compute the MSE using only those observations for which all three models (ICC, multiple, and loglinear) are available for all lags h.

FIGURE A.6: Performance of the multiple when using lagged information



Note. This figure plots the out-of-sample MSE obtained by using the predicted multiple $\widehat{\text{Multiple}}_{it-h}$ lagged by h years to compute the price of firm i at time t. We also plot the corresponding MSE using a lagged discount rate predicted using a trivial information set for comparison. We compute the MSE using only those observations for which all three models (ICC, multiple, and loglinear) are available for all lags h.

Figure A.7: Performance of the loglinear model when using lagged information



Note. This figure plots the out-of-sample MSE obtained by using the predicted loglinear discount rate term $\widehat{\text{DR}}_{it-h}$ lagged by h years to compute the price of firm i at time t. We also plot the corresponding MSE using a lagged discount rate predicted using a trivial information set for comparison. We compute the MSE using only those observations for which all three models (ICC, multiple, and loglinear) are available for all lags h.

C Appendix Tables

Table A.1: Calibration summary

Parameter	Description	Value	Source
α	Capital expenditure share	0.33	Bartelsman et al. (2013)
φ	Demand elasticity	6.7	Broda and Weinstein (2006)
θ	Production curvature	0.65	$\frac{\alpha(\varphi-1)}{1+\alpha(\varphi-1)}$
ρ	Persistence of TFP	0.85	Catherine et al. (2022)
σ	Volatility of TFP innovations	0.30	–
γ	Investment costs	0.10	Catherine et al. (2022)
δ	Depreciation rate	0.06	Midrigan and Xu (2014)
r_f	Risk-free borrowing rate	0.03	Catherine et al. (2022)
M	Maximum leverage	0.40	Compustat
m	Maximum cash	0.25	Compustat
τ	Tax rate	0.33	Statutory tax rate
λ	Equity issuance cost	0.10	Catherine et al. (2022)

Table A.2: List of predictive variables

Variable	(1)	(2)	(3)	(4)	Construction
Industry		✓	✓		`gind`
Size (assets)		✓	✓		Log `at`
EPS_t			✓		From IBES Actuals
F_tEPS_{t+1}			✓		Median EPS forecast from IBES
F_tEPS_{t+2}			✓		Median EPS forecast from IBES
F_tEPS_{t+3}			✓		Median EPS forecast from IBES
ROA			✓		`ebitda` divided by `at`
Book leverage			✓		Total debt (`dltt` plus `dlc`) over `at`
Age			✓		2019 minus year of entry in Compustat
Cash ratio			✓		`che` over `at`
Assets growth			✓	✓	`at` growth rate
IVOL			✓	✓	Idiosyncratic volatility from FFC model
Tangibility			✓	✓	`ppent` over `at`
CAPEX				✓	`capx`
Size (market cap.)				✓	Log market cap
Net issue				✓	Log difference of `shrout`
Dividend payout				✓	`dvc` over market cap
Book to market				✓	`ceq` over market cap
Amihud ratio				✓	See Appendix D
Market leverage				✓	Debt plus market cap over market cap

Note. Column (1) describes the trivial information set, column (2) the "PE" information set, column (3) the corporate accounts information set, and column (4) the variables used for predicting returns.

Table A.3: Summary statistics

	Final Sample ($N = 19416$)				
	Mean	S.d.	Med.	Min	Max
Variable	(1)	(2)	(3)	(4)	(5)
Age	31.72	16.90	27.00	2.00	69.00
Amihud ratio	–7.43	1.99	–7.66	–10.31	3.65
Assets growth	1.12	0.27	1.06	0.60	2.76
Book leverage	0.23	0.17	0.22	0.00	0.87
Book to market	4.83	3.83	3.91	0.39	36.36
Capital expenditures	4.38	1.94	4.42	–6.21	8.00
Cash ratio	0.14	0.16	0.09	0.00	0.99
Dividend payout ratio	0.01	0.02	0.01	0.00	0.90
EPS	2.24	1.99	1.78	–2.87	8.69
EPS forecast at $t + 1$	1.57	1.42	1.20	0.03	9.77
EPS forecast at $t + 2$	1.80	1.55	1.39	0.09	10.63
EPS forecast at $t + 3$	2.02	1.71	1.57	0.13	11.88
Idiosyncratic volatility	1.85	0.93	1.65	0.45	12.75
Log market capitalization	14.95	1.63	14.90	8.07	20.98
Log sale	7.64	1.65	7.62	0.85	13.15
Net issue	–0.04	0.15	–0.00	–0.84	0.18
ROA	0.13	0.08	0.12	–0.66	0.39
Tangibility ratio	0.24	0.23	0.16	0.00	0.88

Note. Columns (1) to (5) report summary statistics for the final sample.

Table A.4: In-sample predictive regressions of models

	(1) Mult.	(2) ICC	(3) DR	(4) Mult.	(5) ICC	(6) DR	(7) Mult.	(8) ICC	(9) DR
Log assets				-0.09	0.08	-0.03	-0.05	0.11	-0.02
				(0.01)	(0.03)	(0.01)	(0.01)	(0.04)	(0.01)
EPS for. $t+1$							-0.32	0.14	-0.01
							(0.05)	(0.16)	(0.03)
EPS for. $t+2$							0.15	-0.88	0.15
							(0.05)	(0.22)	(0.04)
EPS for. $t+3$							0.16	0.57	-0.09
							(0.03)	(0.14)	(0.03)
EPS							-0.08	0.27	-0.07
							(0.02)	(0.06)	(0.01)
ROA							-1.56	0.20	-0.28
							(0.19)	(0.60)	(0.14)
IVOL							-0.07	0.80	-0.13
							(0.02)	(0.10)	(0.02)
Tangibility							0.37	-0.75	0.21
							(0.08)	(0.25)	(0.06)
Assets growth							0.01	-0.22	0.06
							(0.03)	(0.12)	(0.03)
Book lvg.							-0.34	1.85	-0.35
							(0.06)	(0.26)	(0.05)
Age							0.00	0.00	-0.00
							(0.00)	(0.00)	(0.00)
Cash							0.89	-2.23	0.63
							(0.09)	(0.31)	(0.07)
Constant	3.43	9.52	-1.71						
	(0.03)	(0.17)	(0.03)						
Observations	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863
R^2	-0.00	0.00	-0.00	0.19	0.22	0.22	0.38	0.34	0.32
Fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table shows in-sample predicting regressions for one particular train-test split. We show estimates using the entirety of the training sample although predicting regressions are estimated on rolling windows using available information only. Columns (1) to (3) reports estimates for the "trivial" information set, while columns (4) to (6) report estimates for the "PE" information set and columns (7) to (9) for the "corporate accounts" information set. When included, fixed effects are year and industry dummies. Standard errors are two-way clustered by firm and year.

Table A.5: In-sample predictive regressions of the ICC

	(1) ICC	(2) ICC	(3) ICC	(4) ICC	(5) ICC	(6) ICC	(7) ICC	(8) ICC
Beta	0.24	-0.10	0.07	-0.04	0.26	-0.31	-0.04	0.16
	(0.17)	(0.15)	(0.13)	(0.11)	(0.22)	(0.20)	(0.21)	(0.17)
IVOL		0.57	0.37	0.20		0.77	0.57	0.32
		(0.10)	(0.05)	(0.06)		(0.20)	(0.10)	(0.11)
Dividend yield			1.72	3.65			0.19	5.37
			(1.65)	(1.80)			(3.12)	(4.58)
Net issue			-0.02	0.04			0.16	-0.03
			(0.23)	(0.16)			(0.25)	(0.15)
Book-to-market			0.13	0.11			0.16	0.18
			(0.02)	(0.01)			(0.03)	(0.03)
ROA			3.44	2.43			2.69	2.06
			(0.60)	(0.72)			(0.60)	(0.69)
Amihud ratio			0.11	0.08			0.30	0.38
			(0.05)	(0.04)			(0.11)	(0.12)
Market leverage			0.40	0.52			0.55	0.71
			(0.07)	(0.08)			(0.14)	(0.13)
Assets growth			0.16	0.11			-0.65	-0.71
			(0.08)	(0.08)			(0.13)	(0.13)
Capex			-0.53	-0.45			-0.56	-0.41
			(0.08)	(0.07)			(0.09)	(0.07)
Size			0.35	0.34			0.18	0.02
			(0.10)	(0.09)			(0.14)	(0.14)
Tangibility			-2.49	-2.08			-2.48	-1.89
			(0.29)	(0.31)			(0.44)	(0.41)
Observations	9,553	9,553	9,553	9,553	4,671	4,671	4,671	4,670
R^2	0.00	0.07	0.29	0.40	0.00	0.08	0.31	0.44
Fixed effects	No	No	No	Yes	No	No	No	Yes

Note. Note. This table shows in-sample predicting regressions for one particular train-test split. In columns (1) to (4), we use the ICC computed from IBES forecasts. In columns (5) to (8), we use the ICC computed from statistical forecasts. When included, fixed effects are year and industry dummies. Standard errors are two-way clustered by firm and year.

Table A.6: Performance of various models in predicting log prices with shrinkage of factor models towards 10%

	Performance			
Model	Trivial	PE	Corp.acc.	Factor
CAPM				0.245
				(0.008)
CAPM (including a term-structure)				0.245
				(0.008)
CAPM (flexible ERP)				0.164
				(0.003)
CAPM (LW)				0.219
				(0.006)
Fama-French-Carhart				0.480
				(0.004)
Characteristics-based predicted returns				0.676
				(0.012)
Multiple	0.206	0.187	0.142	
	(0.006)	(0.005)	(0.003)	
ICC	0.126	0.105	0.097	
	(0.004)	(0.007)	(0.005)	
Loglinear model	0.121	0.104	0.092	
	(0.003)	(0.005)	(0.003)	
Local linear forest		0.099	0.086	
		(0.003)	(0.003)	

Note. This table reports the average MSE across models and information sets. We shrink the returns predicted by factor models towards 10%. Given a train-test split, we restrict our sample to observations for which the log price prediction of every model is available. The MSE of model m is defined as

$$MSE^m = \frac{1}{N} \sum_{(i,t)} \left(\log P_{it} - \log \widehat{P}_{it}^m \right)^2$$

We repeat this procedure 100 times on different train-test splits and report the average MSE across all splits along with standard deviations. On average, there are 3,872 observations in this restriction of the validation sample.
Each line corresponds to a different model and each column corresponds to a different information set. Column (1) uses a constant only, column (2) uses industry dummies and log total assets ("PE" information set) and column (3) a large set of firm-level characteristics. In all models, expected cash-flows are given by analyst forecasts up to year 3 and then a perpetual growth assumption.

Table A.7: Performance of various models in predicting log prices with and without leverage

	Subjective		Statistical		Four-stage	
Model	PE	LVG	PE	LVG	PE	LVG
Multiple	0.187	0.186	0.140	0.136	0.187	0.186
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
ICC	0.105	0.105	0.176	0.176	0.139	0.138
	(0.007)	(0.005)	(0.014)	(0.016)	(0.002)	(0.003)
Loglinear model	0.104	0.102	0.169	0.166	0.126	0.125
	(0.005)	(0.004)	(0.009)	(0.009)	(0.002)	(0.002)

Note. This table reports the average MSE across models and information sets. Given a train-test split, we restrict our sample to observations for which the log price prediction of every model is available. The MSE of model m is defined as

$$MSE^m = \frac{1}{N} \sum_{(i,t)} \left(\log P_{it} - \log \widehat{P}_{it}^m \right)^2$$

We repeat this procedure 100 times on different train-test splits and report the average MSE across all splits along with standard deviations. On average, there are 3,872 observations in this restriction of the validation sample.
Each line corresponds to a different model and each column corresponds to a different information set. The "PE" columns use industry and year dummies, along with log total assets ("PE" information set). The "LVG" column also includes book leverage.
We compare the performance of models across three sets of forecast: subjective IBES forecasts, statistical forecasts, and forecasts constructed according to a four-stage growth model.

Table A.8: Predicting FCFF and FCFE using a linear model

Horizon	$t+1$	$t+2$	$t+3$
Panel A: Mean forecast error			
Free cash-flows to the firm	-0.05	-0.08	-0.01
Free cash-flows to equity	-0.06	0.05	0.22
Panel B: s.d. of forecast error			
Free cash-flows to the firm	2.12	2.31	2.37
Free cash-flows to equity	4.25	4.54	4.74
Panel C: R^2_{OOS}			
Free cash-flows to the firm	0.44	0.36	0.36
Free cash-flows to equity	0.80	0.77	0.77
Observations	5471	5471	5471

Note. We compute the out-of-sample forecasting error $\text{FCF}_{it+h} - \widehat{\text{FCF}}_{it+h}$ for free cash-flows to the firm and free cash-flows to equity, where $\widehat{\text{FCF}}_{it+h}$ is computed using a linear model trained in-sample. Panels A and B report the means and s.d. of these errors, by rule and horizon. Panel C shows the OOS R^2 measured as:

$$R^2_{OOS} = 1 - \frac{\sum_{it}\left(\text{FCF}_{it+h} - \widehat{\text{FCF}}_{it+h}\right)^2}{\sum_{it}\left(\text{FCF}_{it+h} - \overline{\text{FCF}}_{t+h}\right)^2}$$

where $\overline{\text{FCF}}_{t+h}$ is the constant forecast, so the statistic R^2_{OOS} represents the MSE gain of the forecasting rule relative to the average of past realizations.

Table A.9: Performance of various models in predicting log prices using free cash-flows

Model	Performance			
	Trivial	PE	Corp.acc.	Factor
Panel A – Analyst forecasts				
CAPM				0.919
				(0.015)
CAPM (including a term-structure)				0.967
				(0.016)
CAPM (LW)				1.093
				(0.015)
Fama-French-Carhart				1.555
				(0.016)
ICC	0.178	0.154	0.138	
	(0.005)	(0.005)	(0.005)	
Panel B – FCFF forecasts				
CAPM				2.113
				(0.060)
CAPM (including a term-structure)				2.548
				(0.068)
CAPM (LW)				2.438
				(0.066)
Fama-French-Carhart				2.581
				(0.068)
ICC	0.508	0.417	0.327	
	(0.029)	(0.025)	(0.017)	
Panel C – FCFE forecasts				
CAPM				1.520
				(0.059)
CAPM (including a term-structure)				1.584
				(0.061)
CAPM (LW)				1.929
				(0.073)
Fama-French-Carhart				2.451
				(0.092)
ICC	0.311	0.279	0.251	
	(0.018)	(0.017)	(0.016)	

Note. This table reports the average MSE across models and information sets. Given a train-test split, we restrict our sample to observations for which the log price prediction of every model is available. The MSE of model m is defined as

$$MSE^m = \frac{1}{N} \sum_{(i,t)} \left(\log P_{it} - \log \widehat{P}_{it}^m \right)^2$$

We repeat this procedure 100 times on different train-test splits and report the average MSE across all splits along with standard deviations.
Panel A is taken from Table 3, which is computed on a different subsample as Panels B and C. This is only to simplify presentation, as computing all MSEs on the sample subsample would not alter the results.

Table A.10: Comparison of model performance in the training sample and the testing sample

	Performance			
Model	Trivial	PE	Corp.acc.	Factor
CAPM				–0.9
				(–2.7)
CAPM (including a term-structure)				–0.9
				(–2.6)
CAPM (flexible ERP)				0.6
				(1.6)
CAPM (LW)				–0.8
				(–3.0)
Fama-French-Carhart				–0.3
				(–1.5)
Characteristics-based predicted returns				–0.1
				(–0.4)
Multiple	–1.0	12.4	16.4	
	(–1.5)	(17.0)	(21.0)	
ICC	–0.2	14.4	15.9	
	(–0.4)	(20.6)	(21.4)	
Loglinear model	–0.3	15.7	18.4	
	(–0.5)	(23.0)	(24.0)	
Random forest		142.3	158.4	
		(95.3)	(100.7)	
Local linear forest		71.1	254.1	
		(65.5)	(107.9)	

Note. This table reports the performance loss coming from out-of-sample prediction, measured as

$$\left(\frac{\text{MSE}_{\text{In-sample}}}{\text{MSE}_{\text{Out-of-sample}}} - 1\right) \times 100.$$

We compute this measure for 100 different train-test splits and report its average across all splits. The t-statistic for the test that the average performance loss is zero is in parentheses.

D Data appendix

In this section, we describe our methodology in more details. Variable definitions are summarized in Table A.2, which also contains which variable is used in which predictive regression. We report summary statistics for the final dataset in Table A.3.

Sample selection steps. In our baseline results, we use the following procedure:

1. keep observations between year 1980 and 2019 (for predictive regressions) and between 2000 and 2019 (for the final sample).
2. keep observations whose share code (`shrcd` in CRSP) is 10 or 11, and whose exchange code (`exchcd` in CRSP) is 1, 2, or 3.
3. drop observations whose price per share (`prc` in CRSP) is below 1 or above 5,000.
4. drop observations for which any of the following variable is negative: long-term debt (`dltt`), debt in current liabilities (`dlc`), total assets (`at`), shares outstanding (`shrout`)
5. drop observations when the `permno` appears twice in the same fiscal year in Compustat, or when the IBES ticker appears twice in the same fiscal year in the IBES Unadjusted Summary Files.
6. drop observations which cannot be merged across all datasets: CRSP, Compustat, CAPM loadings and Fama–French–Carhart loadings from the WRDS beta suite, Fama–Bliss discount bonds, IBES Unadjusted Summary Files, and IBES Actuals.
7. drop observations for which any variable used in predictive regressions, or used to construct such variable, is missing (see Table A.2 for a complete list).
8. drop observations for which EPS forecasts at horizons $t+1$, $t+2$, or $t+3$ are not available.
9. drop observations for which EPS forecasts are negative.
10. drop observations for which the predicted log price of any model is below zero or above seven.

For robustness results only, we add the following steps

9a drop observations for which the long-term growth forecast from IBES is missing.

9b drop observations for which actual earnings at time $t+1$, $t+2$, or $t+3$ are missing.

9c drop observations for which earnings as predicted by the statistical model are negative.

For the results using free cash-flows only, we add the following steps

9a drop observations for which FCFF or FCFE are missing.

9b drop observations for which the forecasted FCFF or FCFE at horizon $t+3$ is negative.

Definition of variables.

- CRSP–Compustat variables.
  - Returns. We use the CRSP Monthly Stock File to compute returns over the year

$$\text{Future returns}_m = \prod_{k=0}^{11} \texttt{ret}_{m-k},$$

where m denotes a monthly time period.

  - Market capitalization is defined as the product of `prc` and `shrout`.
  - Illiquidity measure of Amihud (2002). Using daily data from CRSP, we compute the absolute value of returns (`ret`) divided by the volume traded in dollars (`prc` times `vol`). We drop penny stocks (`prc` $<$ 1) and observations for which the volume traded is negative. We compute the average of this variable by month, and keep those observations for which there are at least 7 daily trading days in a month. Then, we winsorize the illiquidity measure at the 1% and 99% levels. Finally, we rescale the it and take logs.
  - Asset growth is $\texttt{at}_t/\texttt{at}_{t-1}$.
  - Book leverage is debt (see below) over `at`
  - Book to market is `ceq` over market capitalization.
  - Capital expenditures (capex) are `capx`.
  - Cash is defined as `che` over equity `ceq`.
  - Debt is the sum of long-term debt `dltt` and current liabilities `dlc`.
  - Dividend payout is `dvc` over market capitalization.
  - Industry-level payout ratio. We compute the firm-level payout ratio including stock repurchases, which we define as `dvc` plus `prstkc` minus `pstkrv` over `ni`. We winsorize this ratio at 0 and 1. We then compute its mean at the sector level (`gsec`) on a 5-year rolling window.
  - Free cash flows to the firm (FCFF) are `oancf` minus `capx` over `shrout`.
  - Free cash flows to equity (FCFE) are FCFF $-(1-\tau)\cdot\texttt{intpn}+\Delta$Debt over `shrout`, where τ is the corporate tax rate. We use a tax rate of 35% throughout the sample.
  - Industry is `gind`.
  - Market leverage is debt plus market capitalization over market capitalization.
  - Returns on assets (ROA) are `ebitda` over `at`.
  - Returns on equity (ROE) are net income `ni` over equity `ceq`.
  - Sector is `gsec`.
  - Size (assets) is defined as $\log \texttt{at}$, and size (market cap) is defined as $\log \texttt{prc} + \log \texttt{shrout}$.
  - Tangibility is `ppent` over `at`.

- Macroeconomic variables.
  - Long-run inflation forecasts are taken from the SPF (median CPI10 series).
  - Long-run real GDP growth forecasts are taken from the SPF (median RGDP10 series).
  - Nominal GDP growth forecasts are the sum of long-run inflation and real GDP forecasts.
  - 5-year treasury bonds are taken from FRED (DGS5 series at the monthly frequency).
  - AA corporate yields are taken from FRED (BAMLC0A2CAAEY series at the monthly frequency).

- WRDS Factor Suite variables.
  - Loadings for the CAPM and the Fama–French–Carhart models are estimated at the stock level using daily returns. We take our estimates from the WRDS Beta Suite, and we use the monthly average of those daily betas.

Winsorization steps. We winsorize variables at the 1% and 99% levels to minimize the influence of outliers, except CRSP variables (`prc`, `shrout`, and `ret`). We implement this step before constructing new variables. After constructing a variable, we also winsorize it at the 1% and 99% levels.