***Internet Appendix to*:**

Institutional Investors, Households and the Time-Variation in Expected Stock Returns

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Internet Appendix

A. Simulation Methodology

Equation (5) implies that the error terms of regressions (1) to (3) must also be related. Deducting the conditional time t expectation from each side of Equation (4) yields

$$r_{t+1} - E_t[r_{t+1}] \approx k_0 - k_0 - k_1\left(dp_{t+1} - E_t\left[dp_{t+1}\right]\right) + \Delta d_{t+1} - E_t\left[\Delta d_{t+1}\right] + dp_t - dp_t \tag{C.1}$$

$$\Leftrightarrow u_{t+1} \approx w_{t+1} - k_1 v_{t+1}. \tag{C.2}$$

Under the null of no return predictability, the data are generated by

$$r_{t+1} = \mu_r + w_{t+1} - k_1 v_{t+1} \tag{C.3}$$

$$\Delta d_{t+1} = \mu_d + (k_1\rho - 1)dp_t + w_{t+1} \tag{C.4}$$

$$pd_{t+1} = \alpha + \rho\ dp_t + v_{t+1}. \tag{C.5}$$

Analogously, under the null of no dividend-growth predictability, the data are generated by

$$r_{t+1} = \mu_r - (k_1\rho - 1)dp_t + u_{t+1} \tag{C.6}$$

$$\Delta d_{t+1} = \mu_d + u_{t+1} + k_1 v_{t+1} \tag{C.7}$$

$$pd_{t+1} = \alpha + \rho\ dp_t + v_{t+1}. \tag{C.8}$$

The simulated data are generated using the parameter estimates from the actual data but imposing the null. E.g. μ_r in (C.3) is given by $\hat{\mu}_r = \frac{1}{T-1}\sum_{t=1}^{T-1} r_{t+1}$.[32] The simulated error terms are drawn from a multivariate normal distribution, the covariance matrix of which is estimated under the respective null hypotheses. Using bootstrapped residuals according to the procedure in Goyal and Welch (2008) instead does not alter the

[32] Using instead $\rho = 0.99$ or $\rho = 0.975$ for all portfolios gives qualitatively similar, albeit more extreme rejections of either null hypothesis (not tabulated).

results qualitatively. Results are also robust to using a vector autoregression (VAR) specification (both not tabulated). I simulate 10,000 data sets, each consisting of a dividend-price ratio, return and dividend-growth time series.

B. Weighted Regressions

Rather than inferring long-run coefficients by imposing the structure of the vector autoregression (1) to (3), one can run direct regressions of weighted returns and dividend growth:

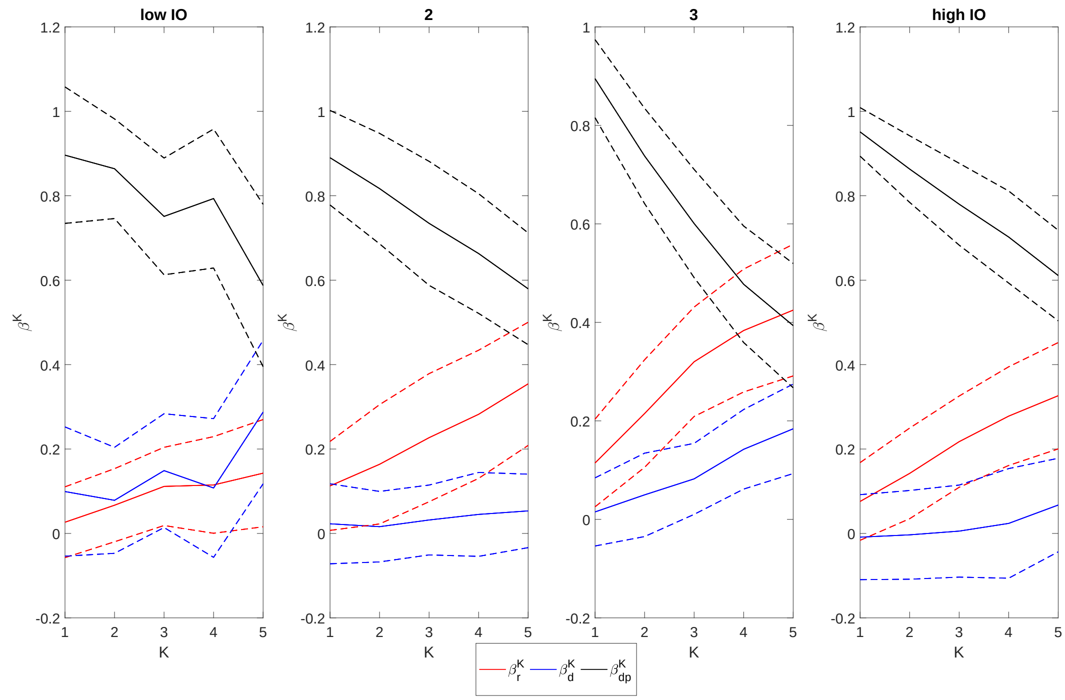
$$\sum_{j=1}^{K} k_1^{j-1} r_{t+j} = \mu_r^K + \beta_r^K \; dp_t + u_{t+1} \tag{C.9}$$

$$\sum_{j=1}^{K} k_1^{j-1} \Delta d_{t+j} = \mu_d^K + \beta_d^K \; dp_t + w_{t+1} \tag{C.10}$$

$$k_1^j dp_{t+j} = \alpha^K + \beta_{dp}^K \; dp_t + v_{t+1}. \tag{C.11}$$

It holds that $\beta_r^K - \beta_d^K + \beta_{dp}^K \approx 1$. The coefficients with horizon K are plotted in Figure C.1 below. While these results should be treated with caution due to the even shorter sample (in order to have the same measure of k_1, I only go from 1980 to 2009 in terms of formation periods), the results from Section III are confirmed: Dominance of dividend-growth predictability in the low IO portfolio, somewhat mixed results for portfolios 2 and 3, and overwhelming dominance of return predictability in portfolio 4. The left figure is somewhat at odds with the characterization of the low IO dividend yield as a fairly low persistence AR(1) process. This is due to the cumulative weighted 4-year return. Specifically, this result is driven by two years, 1984 and 1988.The stocks that constituted the low IO portfolio in 1984 had fairly low valuations. Four years later, these stocks (that are not to be confused with the stocks in the low IO portfolio in 1988) had huge dividend growth, as opposed to low dividend growth as would be expected from low valuations. One reason for this is the October 1987 crash. For a thorough discussion of this effect, see Chen (2009). This massively drove down the estimate for β_d^4. If they did not predict dividend growth, the low valuations in 1984 were supposed to predict high returns in 1988. However, stocks did not do particularly well that year. In particular, the stocks that had made up the low IO portfolio in 1984 actually had very low returns of about -7%, leading

Figure C.1: **Multi-period coefficients, direct estimate**
Multi-period regression coefficients as in Equations C.9 to C.11 for different horizons K. Dashed lines are 10% confidence intervals. The formation period sample is from 1980 to 2009.



to no increase in β_r^4 and consequently to an estimate of a very persistent dp transition over four years. For horizons with $K > 4$, the general picture of fairly low dp persistence resumes.

C. Priced and Unpriced Exposure to Liquidity Risk

Section IV.C.3 shows that CH, a proxy for liquidity risk, predicts returns for the high-IO portfolio but not for the low-IO portfolio. The rationale behind this test is that if household direct investors care in the exact same way about liquidity risks and are in just the same way affected by it, then one would expect that a proxy for liquidity transformation risk also positively predicts returns on households' directly-held stocks. Unless, of course, low IO stocks simply have no innate exposure to time-varying risks independent of who holds them. Expressed more formally, when there is an institutionally-held portfolio i and a household-held portfolio h where expected returns are governed by

$$E_t[R^i_{t+1}] = \alpha_i + \beta_{i,j}\lambda^i_{j,t} \tag{C.12}$$

$$E_t[R^h_{t+1}] = \alpha_h + \beta_{h,j}\lambda^h_{j,t}, \tag{C.13}$$

a lacking time variation in $E_t[R^h_{t+1}]$ is due to zero exposure, $\beta_{h,j} = 0$ with time-varying identical market prices of risk $\lambda^h_{j,t} = \lambda^i_{j,t} \neq 0$ rather than $\lambda^h_{j,t} = 0$ in the applicable SDF.

Assume a monotonic relationship $\beta_j(x)$ between stock characteristics x and the exposure of a stock β_j to a (risk) factor j with market price $\lambda^{\cdot}_{j,t}$ where $\beta_j(x)$ does not depend on stock ownership. Then, a stock characteristic x that is linked to liquidity risk exposure (and hence predictability by CH) in the high-IO portfolio should also be related to exposure (and predictability) in the low-IO portfolio. Varying $\beta_{i,j}$ or $\beta_{h,j}$ by varying characteristic x would consequently elicit variation in predictability within both, portfolios h and i – *if* the SDFs that price both portfolios are the same.

To test this, I divide portfolios of stocks with below and above 30% IO into terciles according to their Amihud (2002) liquidity measure, ILLIQ. The relatively high cutoff point in IO ensures sufficiently large portfolios. To have comparable levels and spreads of ILLIQ within the groups of stocks with below or above 30% IO despite its correlation with IO, I restrict the overall sample to stocks with ILLIQ between the 1/3 and 2/3 quantiles. Table C.2, Panel A shows that this yields portfolios that are comparable in terms of the relevant characteristics such as the number of stocks or the spreads between and levels of ILLIQ and cash-flow duration. The results of predictive regressions of the returns of those portfolios are presented in Table C.2, Panel B. Start with the high-IO stocks in Panel B.2. In line with the findings of Scholes (2000); Coval and Stafford (2007); Berger (2019) that institutions prefer to reduce their holdings in liquid stocks in the event of outflows and similar to a recent finding by Ma, Xiao, and Zeng (2020) about treasuries, liquid stocks also have higher exposure to liquidity transformation risk as proxied by ΔCH. Their slope coefficients are comparably large. As liquidity goes down, so does the predictive power of ΔCH. This is also what one would expect for low IO stocks – *if* they were indeed priced by the same SDF. Panel B.1 shows that this is not the case: The slope coefficients of the predictive regressions are very similar across ILLIQ terciles within the portfolio with

IO$<$ 30%. This is in line with the notion that risk proxided by CH is not priced in low IO portfolios, i.e. λ_j^h = const. = 0, rather than their exposure being constantly zero ($\beta_{i,j} = 0$).

Table C.2: **Priced and Unpriced Exposure**

Panel A shows characteristics of the double-sorted portfolios. Panel B shows slope coefficients of the predictive regression of year $t+1$ returns (normalized by sample means) on portfolios sorted into Amihud (2002) illiquidity measure (ILLIQ) terciles within the low and high IO portfolios on changes in average mutual fund cash-holdings (CH) at the end of year t. Returns are normalized by the sample mean as in Haddad and Muir (2021). Simulated $p-$values p. computed in the exact same way as described in Table 5. CFD is Dechow et al. (2004) cash-flow duration

Panel A: Portfolio characteristics

	IO $<$ 30%			IO $\geq$ 30%		
	low ILLIQ	2	high ILLIQ	low ILLIQ	2	high ILLIQ
ILLIQ $\times 10^3$ e.w.	0.0159	0.0397	0.0856	0.0121	0.0246	0.0659
IO e.w.	0.16	0.15	0.13	0.53	0.50	0.47
CFD e.w.	17.53	17.50	17.10	16.16	15.72	15.17
Return v.w. %	11.14	14.78	16.26	13.82	15.27	16.79
number of stocks	254.11	254.96	255.00	201.68	201.00	202.39

Panel B: Regression $\frac{R_{t+1}}{\bar{R}} = \alpha + b \cdot \Delta CH_t$

	Panel A.1: IO $<$ 30	Panel A.2: IO $\geq$ 30%
	b	b
low ILLIQ	0.0607 p. 0.3605	0.1254 p. 0.1715
2	0.0990 p. 0.2665	0.0327 p. 0.4043
high ILLIQ	0.0520 p. 0.3673	0.0166 p. 0.4520

D. Internet Appendix: Tables and Figures

Table D.1: **Predictive Regressions, no Reinvestment**

Slope coefficients from the predictive regressions of log returns on log dividend growth on the dividend-price ratio and dividend-price ratio autoregression for each of the four IO-sorted portfolios and the CRSP market portfolio (Mkt.). The long-run coefficients are defined as $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $\beta_d^{LR} = \frac{\beta_d}{1-k_1\rho}$. The frequency is yearly. Numbers in brackets are Newey and West (1987) (NW)-t-statistics with 10 lags. For long-run coefficients, standard errors are computed according to the delta method using the NW covariance matrix of residuals. *, ** and *** for one-period slope estimates indicate significance at the ten, five and one percent level, respectively. Formation periods 1980 to 2012.

		low IO	2	3	high IO
r_{t+1}	β_r	-0.01	0.08***	0.11***	0.14***
		(-0.25)	(3.15)	(3.00)	(2.97)
	β_r^{LR}	-0.04	0.35**	0.92**	1.71**
		(-0.25)	(2.39)	(2.09)	(2.12)
	R^2	0.00	0.08	0.12	0.10
Δd_{t+1}	β_d	-0.28***	-0.14**	-0.01	0.06
		(-2.81)	(-2.21)	(-0.36)	(1.32)
	β_d^{LR}	-1.04***	-0.65**	-0.08	0.71
		(-3.64)	(-2.23)	(-0.19)	(1.18)
	R^2	0.31	0.12	0.00	0.03
dp_{t+1}	ρ	0.75***	0.80***	0.90***	0.94***
		(7.52)	(3.00)	(21.95)	(13.45)

Table D.2: **Simulation Inference, Excess Returns and Dividend Growth**

Slope coefficients and long-run slope coefficients from the predictive regressions of log excess returns on log excess dividend growth on the dividend-price ratio and dividend-price ratio autoregression as defined in (1) to (3) for each of the four IO-sorted portfolios and simulated inference based on 10,000 simulations, yearly regression. The long-run coefficients are defined as $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $\beta_d^{LR} = \frac{\beta_d}{1-k_1\rho}$. $p.$ denotes the estimated probability of observing a more extreme estimate then in the data under the respective nulls H_0^r and H_0^d. Q_p denotes the p-quantile of the simulated distribution. The rows labeled "$p.$ joint hyp." show the estimated probability of the event $\beta_r^{LR} \leq \hat{\beta}_r^{LR} \wedge \beta_d^{LR} \leq \hat{\beta}_d^{LR}$ occuring given that the respective null hypothesis is true. *, ** and *** indicate that the respective probability is below 10, 5 or 1 percent, respectively. The autocorrelation coefficients of dp in the respective portfolios are 0.86, 0.80, 0.92 and 0.91.

			H_0^r: $\beta_r = 0, \rho = \hat{\rho}$			H_0^d: $\beta_d = 0, \rho = \hat{\rho}$		
Portfolio		est.	$p.$	$Q_{0.05}$	$Q_{0.95}$	$p.$	$Q_{0.05}$	$Q_{0.95}$
1: low IO	β_r	-0.05	0.8716	-0.08	0.18	0.0057	0.04	0.34
	β_r^{LR}	-0.32	0.8896	-0.55	0.61	0.0045***	0.19	1.73
	β_d	-0.20	0.5350	-0.41	-0.06	0.1267	-0.28	0.09
	β_d^{LR}	-1.33	0.8941	-1.54	-0.39	0.0043***	-0.81	0.72
	$p.$ joint hyp.		0.8894			0.0043***		
2	β_r	0.03	0.3044	-0.10	0.11	0.0115**	0.09	0.35
	β_r^{LR}	0.14	0.2443	-0.37	0.36	0.0214**	0.23	1.64
	β_d	-0.19	0.1944	-0.58	-0.12	0.2311	-0.37	0.11
	β_d^{LR}	-0.87	0.2600	-1.37	-0.63	0.0194**	-0.76	0.63
	$p.$ joint hyp.		0.2437			0.0194**		
3	β_r	0.09	0.2859	-0.07	0.23	0.2194	0.03	0.33
	β_r^{LR}	0.81	0.0524*	-0.72	0.82	0.5069	0.20	1.67
	β_d	-0.02	0.0408*	-0.32	-0.03	0.5750	-0.21	0.07
	β_d^{LR}	-0.19	0.0540*	-1.73	-0.18	0.5060	-0.80	0.68
	$p.$ joint hyp.		0.0520*			0.5023		
4: high IO	β_r	0.08	0.3941	-0.11	0.33	0.2399	-0.01	0.42
	β_r^{LR}	0.75	0.2091	-1.30	1.29	0.3693	-0.08	2.02
	β_d	-0.03	0.1665	-0.30	0.05	0.4305	-0.19	0.15
	β_d^{LR}	-0.26	0.2140	-2.30	0.29	0.3604	-1.08	1.03
	$p.$ joint hyp.		0.2087			0.3602		

Table D.3: **Predictive Regressions, Quartile Portfolios**

Slope coefficients and long-run slope coefficients from the predictive regressions of log returns on log dividend growth on the dividend-price ratio and dividend-price ratio autoregression as defined in (1) to (3) for each of the four IO quartile portfolios. The long-run coefficients are defined as $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $\beta_d^{LR} = \frac{\beta_d}{1-k_1\rho}$. The frequency is yearly. Numbers in brackets are Newey and West (1987) (NW)-t-statistics with 10 lags. For long-run coefficients, standard errors are computed according to the delta method using the NW covariance matrix of residuals. *, ** and *** for one-period slope estimates indicate significance at the ten, five and one percent level, respectively. "NW t-stat" in Panel D denotes the t-statistic computed with Newey and West (1987) standard errors with three lags. Formation periods 1980 to 2012.

		1^{st} quartile	2	3	4^{th} quartile
	Panel A: Raw returns and dividend growth				
r_{t+1}	β_r	0.06**	0.07***	0.12**	0.07**
		(2.08)	(4.01)	(2.43)	(2.19)
	β_r^{LR}	0.26***	0.53***	0.85***	0.94***
		(1.62)	(1.77)	(2.31)	(1.64)
	R^2	2.55%	6.48%	12.86%	5.14%
Δd_{t+1}	β_d	-0.17	-0.06*	-0.02	-0.01
		(-1.45)	(-1.32)	(-0.70)	(-0.24)
	β_d^{LR}	-0.76***	-0.47***	-0.16	-0.09
		(-1.40)	(-2.39)	(-1.38)	(-0.16)
	R^2	4.44%	4.68%	0.92%	0.04%
	Panel B: Excess returns and excess dividend growth				
$r_{t+1} - r_{f,t+1}$	β_r	0.02	0.04**	0.08	0.03
		(0.52)	(2.21)	(1.37)	(0.7)
	β_r^{LR}	0.08	0.28**	0.55***	0.36
		(0.43)	(1.00)	(1.42)	(0.58)
	R^2	0.22%	1.92%	5.32%	0.7%
$\Delta d_{t+1} - r_{f,t+1}$	β_d	-0.22*	-0.09**	-0.07**	-0.05
		(-1.80)	(-2.38)	(-2.26)	(-1.49)
	β_d^{LR}	-0.95***	-0.72***	-0.46***	-0.67**
		(-1.67)	(-1.79)	(-1.74)	(-1.05)
	R^2	6.61%	9.79%	6.65%	2.12%
	Panel C: Dividend-price ratio autoregression				
dp_{t+1}	ρ	0.79***	0.89***	0.88***	0.95***
		(5.46)	(21.19)	(18.77)	(38.45)
	Panel D: Descriptive statistics				
IO	mean, %	6.49	25.17	47.41	73.29
return	mean, %	11.63	11.74	13.01	13.07
	NW t-stat	6.19	4.94	4.32	4.88
	std, %	19.76	15.36	17.72	18.10
div. growth	mean, %	16.45	0.32	4.66	7.49
	NW t-stat	1.07	0.13	2.48	2.84
	std, %	88.85	14.66	12.90	21.24
PD-ratio	mean	62	44	40	65
	std	24	24	20	36

Table D.4: **Simulation Inference, Quarterly Frequency**

Slope coefficients and long-run slope coefficients from the predictive regressions of log returns on log dividend growth on the dividend-price ratio and dividend-price ratio autoregression as defined in (1) to (3) for each of the four IO-sorted portfolios and simulated inference based on 10,000 simulations, quarterly regression. The long-run coefficients are defined as $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $\beta_d^{LR} = \frac{\beta_d}{1-k_1\rho}$. $p.$ denotes the estimated probability of observing a more extreme estimate then in the data under the respective nulls H_0^r and H_0^d. Q_p denotes the p-quantile of the simulated distribution. The rows labeled "$p.$ joint hyp." show the estimated probability of the event $\beta_r^{LR} \leq \hat{\beta}_r^{LR} \wedge \beta_d^{LR} \leq \hat{\beta}_d^{LR}$ occuring given that the respective null hypothesis is true. *, ** and *** indicate that the respective probability is below 10, 5 or 1 percent.

Portfolio		est.	H_0^r: $\beta_r = 0, \rho = \hat{\rho}$ $p.$	$Q_{0.05}$	$Q_{0.95}$	H_0^d: $\beta_d = 0, \rho = \hat{\rho}$ $p.$	$Q_{0.05}$	$Q_{0.95}$
1: low IO	β_r	0.01	0.1983	-0.02	0.03	0.0000***	0.10	0.15
	β_r^{LR}	0.12	0.1301	-0.17	0.16	0.0000***	0.52	1.44
	β_d	-0.11	0.2091	-0.23	-0.08	0.0481*	-0.11	0.04
	β_d^{LR}	-0.89	0.1525	-1.16	-0.84	0.0000***	-0.48	0.44
	$p.$ joint hyp.		0.1301			0.0000***		
2	β_r	0.03	0.0100**	-0.02	0.02	0.0000***	0.11	0.16
	β_r^{LR}	0.25	0.0011***	-0.13	0.13	0.0000***	0.54	1.44
	β_d	-0.10	0.0870*	-0.24	-0.09	0.0673*	-0.11	0.04
	β_d^{LR}	-0.75	0.0013***	-1.13	-0.87	0.0000***	-0.46	0.44
	$p.$ joint hyp.		0.0011***			0.0000***		
3	β_r	0.04	0.0490**	-0.02	0.04	0.0039***	0.05	0.11
	β_r^{LR}	0.48	0.0049***	-0.29	0.31	0.0584*	0.46	1.46
	β_d	-0.04	0.0174**	-0.16	-0.05	0.2375	-0.08	0.03
	β_d^{LR}	-0.52	0.0051***	-1.29	-0.69	0.0580*	-0.54	0.46
	$p.$ joint hyp.		0.0049***			0.0580***		
4: high IO	β_r	0.05	0.0661*	-0.03	0.05	0.0432	0.05	0.12
	β_r^{LR}	0.62	0.0032***	-0.37	0.40	0.1664	0.47	1.45
	β_d	-0.03	0.0042***	-0.15	-0.05	0.3039	-0.08	0.03
	β_d^{LR}	-0.38	0.0034***	-1.37	-0.60	0.1625	-0.53	0.45
	$p.$ joint hyp.		0.0032***			0.1625		

Table D.5: **Predictive Regressions, Quartile Portfolios, Dividend Payers**

Slope coefficients and long-run slope coefficients from the predictive regressions of log returns on log dividend growth on the dividend-price ratio and dividend-price ratio autoregression as defined in (1) to (3) for each of the four IO quartile portfolios, restricted to stocks that paid dividends in the formation period. The long-run coefficients are defined as $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $\beta_d^{LR} = \frac{\beta_d}{1-k_1\rho}$. The frequency is yearly. "t.s." indicates moments computed along the time-series dimension at portfolio level, "e.w." and "v.w." denote time-series moments of cross sectional means computed equally (value-) weighted. "std." denotes usual standard deviations. AC(1) denotes the first order autocorrelation coefficient. Numbers in brackets are Newey and West (1987) (NW)-t-statistics with 10 lags. For long-run coefficients, standard errors are computed according to the delta method using the NW covariance matrix of residuals. *, ** and *** for one-period slope estimates indicate significance at the ten, five and one percent level, respectively. Formation periods 1980 to 2012.

Panel A: Descriptive statistics

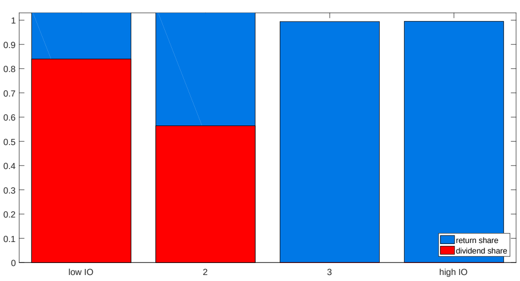
IO	ew. mean	0.1105	0.3357	0.5394	0.7488
return	t.s. mean	0.1311	0.1214	0.1262	0.1336
	std.	0.1461	0.1597	0.1608	0.1773
	AC(1)	-0.1757	0.0029	0.0346	-0.1263
div. growth	t.s. mean	-0.0418	-0.0022	0.0731	0.0475
	std.	0.2001	0.1265	0.1488	0.1821
	AC(1)	-0.2918	-0.2211	-0.1621	-0.3631
D/P	t.s. mean	0.0394	0.0403	0.0319	0.0255
	std.	0.0143	0.0176	0.0129	0.0107

Panel B: Predictive regression slope coefficients

		1^{st} quartile	2	3	4^{th} quartile
r_{t+1}	β_r	0.04	0.14^{***}	0.11^{**}	0.11^{***}
		(1.82)	(5.80)	(2.65)	(3.49)
	β_r^{LR}	0.18	0.71^{***}	0.87^{*}	1.21^{*}
		(0.68)	(2.60)	(1.73)	(1.88)
	R^2	0.88%	14.4%	8.33%	6.45%
Δd_{t+1}	β_d	-0.19	-0.06	-0.02	0.02
		(-1.24)	(-1.30)	(-0.03)	(0.67)
	β_d^{LR}	-0.83^{*}	-0.30	-0.14	0.20
		(-1.80)	(-1.26)	(-0.41)	(0.32)
	R^2	7.4%	3.39%	0.29%	0.16%
dp_{t+1}	ρ	0.8044^{***}	0.8369^{***}	0.8941^{***}	0.9303^{***}
		(5.42)	(13.65)	(16.98)	(17.80)

Figure D.1: **Share of Variation, Two- and Three-Year Predictive Regressions**

Share of variation due to either dividend growth or returns as computed with long-run coefficients $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $|\beta_d^{LR}| = \frac{|\beta_r|}{1-k_1\rho}$, respectively, for each of the four IO-sorted portfolios with two (left) and three (right) year horizons.



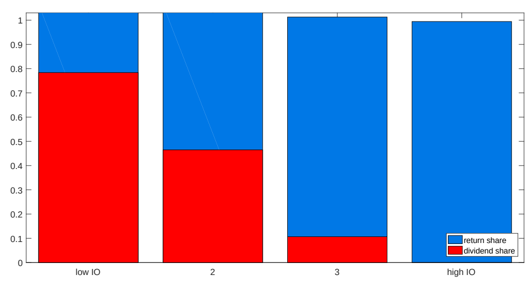


Figure D.2: **Share of Return and Dividend Growth Variation for Alternative Sorts**
Share of variation due to either dividend growth or returns as computed with long-run coefficients $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $|\beta_d^{LR}| = \frac{|\beta_r|}{1-k_1\rho}$, respectively, for each of the portfolios split along the median for the 13(f) subcategories and by S&P 500 index inclusion, respectively. Missing observations for a subcategory are treated as having zero holdings by that subcategory.

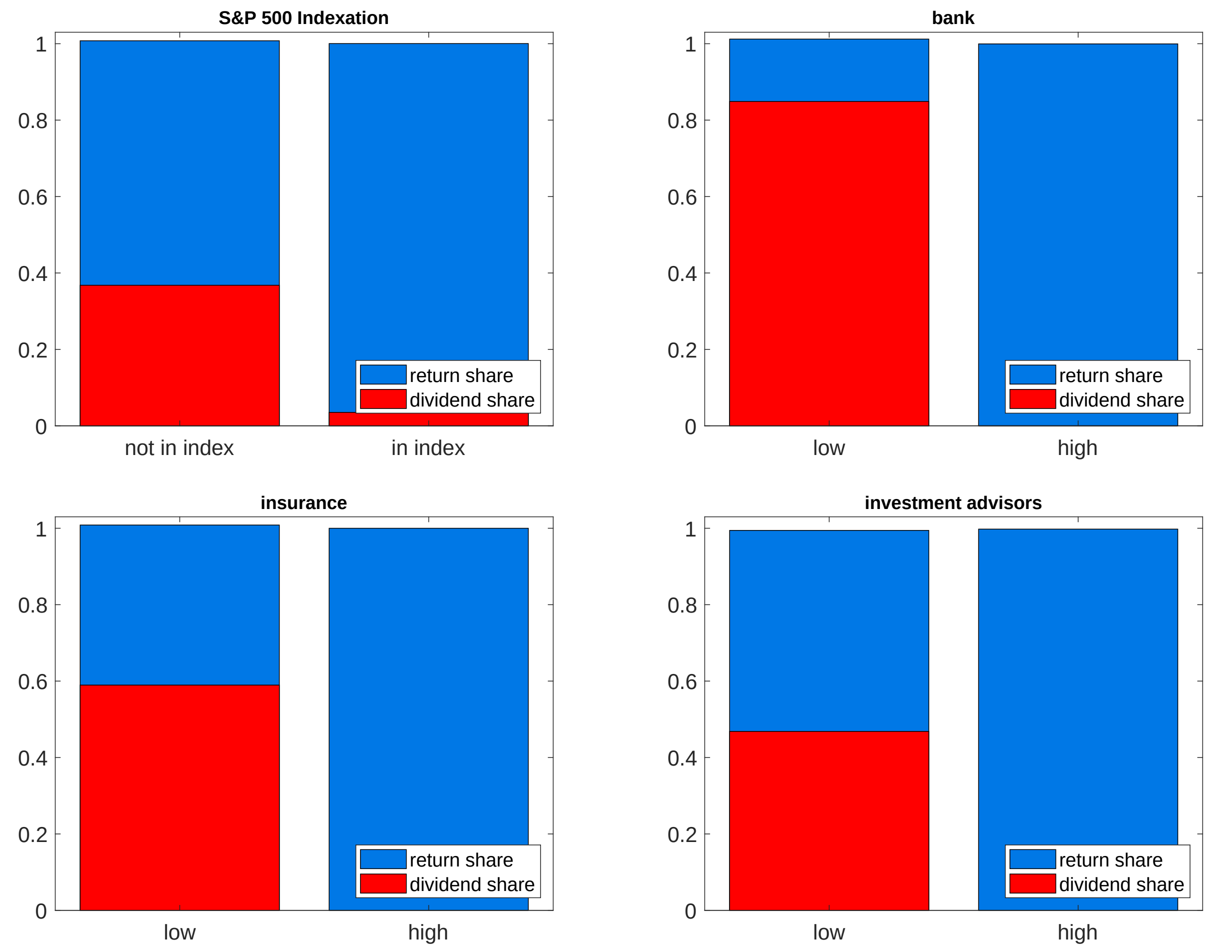


Table D.6: **Predictive Regressions Using the Earnings-Price Ratio**

Slope estimates of predictive regressions of log earnings growth log and returns on the log earnings-price ratio *ep* for each of the four portfolios. Number is parentheses are Newey-West t-statistics. R^2 is given in %. The sample period is 1980 to 2013. Stocks with negative earnings are discarded for the computation of EP to ensure defined log values.

	Panel A		Panel B	
	$\Delta e_{t+1} = \alpha + \beta_e \; ep_t$		$r_{t+1} = \mu + \beta_r \; ep_t$	
	β_E	R^2	β_r	R^2
low IO	0.13	1.81	0.04	0.86
	(1.16)		(0.81)	
2	0.18**	1.55	0.06	1.24
	(2.04)		(1.31)	
3	0.10	0.62	0.10**	5.30
	(0.93)		(2.25)	
high IO	-0.06	0.12	0.21***	12.38
	(-0.49)		(3.42)	

Table D.7: **Predictive Regressions using cay, the Market DP and SVIX**

Slope estimates of predictive regressions of returns R on predictor variables *cay* (from Martin Lettau's website), the market dividend price ratio (Mkt. DP) and the SVIX divided by the risk-free rate risk ($R_{f,t}^{-1}SVIX^2$). The regression in Panel C is on quarterly frequency with sample period 1996 to 2012. $R_{f,t}^{-1}SVIX^2$ is from Ian Martin's website. For the other predictors it is 1980 to 2012. p. indicates the probability under the null of observing a slope coefficient larger than in the data. *, ** and *** indicate that the respective probability is below 10, 5 or 1 percent, respectively. It is computed using 5,000 artificial data sets generated under the null of no predictability:

$$Y_{t+1} = \bar{Y} + \epsilon_{t+1}^{Y}$$
$$X_{t+1} = \rho X_t + \epsilon_{t+1}^{X},$$

where $\bar{Y}$, ρ and $Cov(\epsilon^Y, \epsilon^r)$ are as estimated from the data. $E[\epsilon^Y] = E[\epsilon^x] = 0$.

	Panel A:		Panel B:		Panel C:	
	cay	R^2	Mkt. DP	R^2	$R_{f,t}^{-1}SVIX^2$	R^2
	β		β		β	
low IO	-6.1891	0.24	6.2077	0.5	0.6035	2.98
	p. 0.6897		p. 0.4498		p. 0.1451	
2	23.008	6.07	19.0961	4.69	0.4498	2.44
	p. 0.0885		p. 0.3437		p. 0.1729	
3	22.4524	6.39	18.0429	4.19	0.7278*	5.80
	p. 0.1148		p. 0.464		p. 0.0677	
high IO	20.5939	5.66	22.5351	6.54	0.6736	4.39
	p. 0.1072		p. 0.3511		p. 0.1041	

Table D.8: **Regression coefficients, high and low valuation**

Slope coefficients from predictive regressions of returns on the dividend yield from Equation (1). The sample is divided by above (high dp) or below (low dp) median dividend yield. Quarterly frequency. Numbers in brackets are standard $t-$statistics computed under the assumption that the estimators for the respective β_r^{high} and β_r^{low} are uncorrelated. Formation periods Q1-1980 to Q2-2013.

	β_r^{high}	β_r^{low}	$\Delta\beta_r$
low IO	0.026	0.022	0.004
	(0.60)	(0.82)	(0.42)
2	0.122	0.026	0.096
	(2.90)	(1.09)	(11.71)
3	0.058	0.097	-0.040
	(1.62)	(2.35)	(-4.20)
high IO	0.118	0.101	0.017
	(2.30)	(2.05)	(1.37)

Table D.9: **Predictive Regressions of Returns on the Average Degree of IO**

Slope estimates b of predictive regressions of aggregate sample returns normalized by their sample mean on the detrended average degree of institutional ownership in the overall sample. The sample period is 1981 to 2013. p. indicates the probability of observing a slope coefficient smaller than in the data. It is computed using 5,000 artificial data sets generated under the null of no predictability:

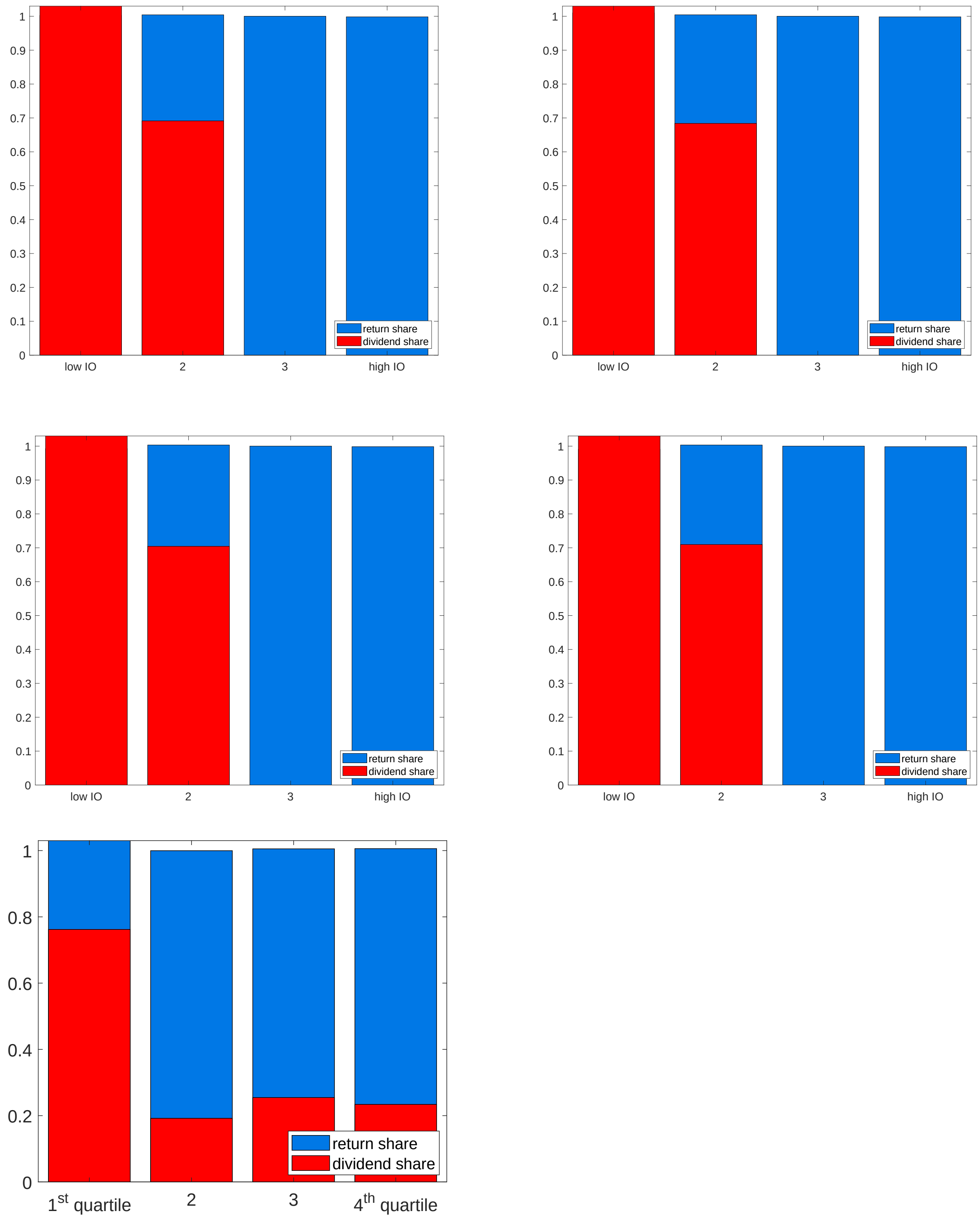
$$Y_{t+1} = \bar{Y} + \epsilon_{t+1}^{Y}$$
$$X_{t+1} = \rho X_t + \epsilon_{t+1}^{X},$$

where $\bar{Y}$, ρ and $Cov(\epsilon^Y, \epsilon^r)$ are as estimated from the data. $E[\epsilon^Y] = E[\epsilon^x] = 0$.

	b	R^2
low IO	-0.7640	0.0003
	p. 0.5536	
2	-0.9224	0.0008
	p. 0.5525	
3	0.2607	0.0001
	p. 0.4527	
high IO	0.6250	0.0005
	p.0.4594	
Mkt.	0.5694	0.0003
	p. 0.4410	

Figure D.3: **Share of Return and Dividend Growth Variation for Subsamples**

Share of variation due to either dividend growth or returns as computed with long-run coefficients $\beta_r^{LR} = \frac{\beta_r}{1-k_1\rho}$ and $|\beta_d^{LR}| = \frac{|\beta_r|}{1-k_1\rho}$, excluding microcaps (stocks in bottom 20% of market capitalization) (upper left), prices below one dollar (upper right), five dollars (mid left) or microcaps and prices below five dollars (mid right) or with quartile portfolios excluding microcaps (bottom), respectively.



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