Internet Appendix

"The Short Duration Premium"

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This Internet Appendix is organized as follows. Section A contains technical derivations required to support the results in the paper, Section B details data sources and measurement for the analysis, Section C explains how I estimate the ICAPM, and Section D describes some further results that supplement the main findings in the paper.

A Technical Derivations

This section omits firm's subscript, j, to simplify the notation during the derivations.

A.1 Using VAR to get $\mathbb{E}_t[PO_{t+h}]/BE_t$

From Eq. 3 and the conditional normality imposed by the VAR process in Eq. 4, we have:

$$\begin{aligned}
\frac{\mathbb{E}_t\left[PO_{t+h}\right]}{BE_t} &= \mathbb{E}_t\left[\left(e^{CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}} - e^{\sum_{\tau=1}^{h}BEg_{t+\tau}}\right)\right] \\
&= e^{\mathbb{E}_t[CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}]+0.5\cdot Var_t\left[CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&\quad - e^{\mathbb{E}_t[\sum_{\tau=1}^{h}BEg_{t+\tau}]+0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&= \left(e^{\mathbb{E}_t[CSprof_{t+h}-BEg_{t+h}]+0.5\cdot Var_t[CSprof_{t+h}-BEg_{t+h}]+Cov_t\left[CSprof_{t+h}-BEg_{t+h},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} - 1\right) \\
&\quad \times e^{\mathbb{E}_t[\sum_{\tau=1}^{h}BEg_{t+\tau}]+0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&= \left[e^{(\mathbf{1}_{CSprof}-\mathbf{1}_{BEg})'\Gamma^h s_t+v_1(h)} - 1\right]\cdot e^{\mathbf{1}'_{BEg}(\sum_{\tau=1}^{h}\Gamma^{\tau})\cdot s_t+h\cdot v_2(h)}
\end{aligned}$$

which is Eq. 5 in Subsection 2.1 with:

$$v_1(h) \;=\; 0.5\cdot Var_t\left[CSprof_{t+h}-BEg_{t+h}\right] + Cov_t\left[CSprof_{t+h}-BEg_{t+h},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]$$

and

$$h\cdot v_2(h) = 0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right] = 0.5\cdot Cov_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]$$

a) Deriving $v_1(h)$

Define $po = CSprof - BEg$ and $\mathbf{1}_{po} = \mathbf{1}_{CSprof} - \mathbf{1}_{BEg}$. Then, from the VAR structure, it is straightforward to get:

$$Var_t\left[CSprof_{t+h}-BEg_{t+h}\right] = Var_t\left[CSprof_{t+h-1}-BEg_{t+h-1}\right] + \mathbf{1}'_{po}\Gamma^{h-1}\Sigma\Gamma'^{h-1}\mathbf{1}_{po} \qquad \text{(IA.1)}$$

with boundary condition $Var_t\left[CSprof_{t+1}-BEg_{t+1}\right] = \mathbf{1}'_{po}\Sigma\mathbf{1}_{po}$.

For the other term in $v_1(h)$, which I label $Cov_1(h)$ for simplicity, we have $Cov_1(1) = Cov_t[po_{t+1}, BEg_{t+1}] = \mathbf{1}'_{po}\Sigma\mathbf{1}_{BEg}$ and then:

$$
\begin{aligned}
Cov_1\left(2\right) &= Cov_t\left[po_{t+2}, BEg_{t+1} + BEg_{t+2}\right] \\
&= Cov_t\left[po_{t+2}, BEg_{t+1}\right] + Cov_t\left[po_{t+2}, BEg_{t+2}\right] \\
&= Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}_{BEg}^{'} u_{t+1}\right] + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}_{BEg}^{'}(\Gamma u_{t+1} + u_{t+2})\right] \\
&= \mathbf{1}_{po}^{'}\Gamma\Sigma\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Gamma\Sigma\Gamma^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}_{po}^{'}\Gamma\Sigma(\Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + Cov_1\left(1\right)
\end{aligned}
$$

and

$$
\begin{aligned}
Cov_1\left(3\right) &= Cov_t\left[po_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}\right] \\
&= Cov_t\left[po_{t+3}, BEg_{t+1}\right] + Cov_t\left[po_{t+3}, BEg_{t+2}\right] + Cov_t\left[po_{t+3}, BEg_{t+3}\right] \\
&= Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'} u_{t+1}\right] \\
&\quad + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'}(\Gamma u_{t+1} + u_{t+2})\right] \\
&\quad + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3})\right] \\
&= \mathbf{1}_{po}^{'}\Gamma^2\Sigma(\Gamma^2 + \Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Gamma\Sigma(\Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}_{po}^{'}\Gamma^2\Sigma(\Gamma^2 + \Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + Cov_1\left(2\right)
\end{aligned}
$$

which generalizes to:

$$
Cov_1\left(h\right) = \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma F_1(h)^{'}\mathbf{1}_{BEg} + Cov_1\left(h-1\right) \tag{IA.2}
$$

where $F_1(h) = F_1(h-1)\Gamma + \mathrm{I}$ with I representing an identity matrix.

Putting all terms together, we have:

$$
v_1(h) = v_1(h-1) + 0.5 \cdot \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma\Gamma^{'h-1}\mathbf{1}_{po} + \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma F_1(h)^{'}\mathbf{1}_{BEg} \tag{IA.3}
$$

with boundary condition $v_1(1) = 0.5 \cdot \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{po} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg}$.

b) Deriving $v_2(h)$

Letting $Cov_t\left(BEg_{t+\tau}, BEg_{t+h}\right) = Cov_{\tau,h}^{BEg}$, we have $1 \cdot v_2(1) = 0.5 \cdot Cov_{1,1}^{BEg}$ and then:

$$
\begin{aligned}
2 \cdot v_2\,(2) = 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2}, BEg_{t+1} + BEg_{t+2}\right] \\
= \; 0.5{\cdot}(Cov_{1,1}^{BEg} + Cov_{2,2}^{BEg}) + Cov_{1,2}^{BEg}
\end{aligned}
$$

and

$$
\begin{aligned}
3 \cdot v_2\,(3) = 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2} + BEg_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}\right] \\
= \; 0.5{\cdot}(Cov_{1,1}^{BEg} + Cov_{2,2}^{BEg} + Cov_{3,3}^{BEg}) + \left[Cov_{1,2}^{BEg} + Cov_{2,3}^{BEg} + Cov_{1,3}^{BEg}\right]
\end{aligned}
$$

which generalizes to:

$$
h \cdot v_2\,(h) = (h-1) \cdot v_2\,(h-1) + 0.5 \cdot Cov_{h,h}^{BEg} + \sum_{i=1}^{h-1} Cov_{h-i,h}^{BEg} \tag{IA.4}
$$

with boundary condition $v_2(1) = 0.5 \cdot Cov_{1,1}^{BEg}$

Hence, all we need is an expression for $Cov_{\tau,h}^{BEg}$ with $\tau = 1, 2, ..., h$. However, note that $BEg_{t+h} = u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1} + \Gamma^h s_t$, and thus:

$$
\begin{aligned}
Cov_{\tau,h}^{BEg} &= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1}\right) \\
&= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, \Gamma^{h-\tau} u_{t+\tau} + \Gamma^{h-\tau+1} u_{t+\tau-1} + ... + \Gamma^{h-1} u_{t+1}\right) \\
&= \mathbf{1}_{BEg}^{'}\left[\mathrm{I}\Sigma\Gamma'^{h-\tau} + \Gamma\Sigma\Gamma'^{h-\tau+1} + \Gamma^2\Sigma\Gamma'^{h-\tau+2} + ... + \Gamma^{\tau-1}\Sigma\Gamma'^{h-1}\right]\mathbf{1}_{BEg} && \text{(IA.5)} \\
&= \mathbf{1}_{BEg}^{'} F_2(\tau, h) \mathbf{1}_{BEg} && \text{(IA.6)}
\end{aligned}
$$

with $F_2(\tau, h) = \Gamma F_2(\tau - 1, h) + \mathrm{I}\Sigma\Gamma^{h-\tau}$ and boundary condition $F_2(0, h) = 0$

c) An Adjustment

The VAR implied long-term variance and covariance terms needed for $v_1(h)$ and $v_2(h)$ can be very noisy because a small estimation error in Γ or Σ can induce a substantial estimation error in such terms. As such, when estimating $v_1(h)$ and $v_2(h)$, I replace Γ with $\Gamma_{adj} = \theta \cdot \Gamma + (1-\theta) \cdot \Gamma_{ss}$, where $0 < \theta < 1$ and the intercepts in Γ_{ss} are the steady state values and all slopes being zero. This specification shrinks Γ towards the steady state to speed up the convergence of the variance/covariance terms. I choose θ such that $\theta^{10} = 0.1$ as this specification solves all numerical problems I encountered during the estimation of $v_1(h)$ and $v_2(h)$.[35]

A.2 Infinite Sums

While in principle the valuation identity in Eq. 6 accounts for the present value of cash flows going to infinity, in practice (numerically) we need some approximation to deal with very long-term cash flows. I assume that cash flow growth has reached its limiting behavior at a maturity of $H = 1,000$ years. This means that (for $h \geq H$):

$$\frac{e^{-(h+1)\cdot dr_t} \cdot \mathbb{E}_t \left[PO_{t+h+1} \right] / BE_t}{e^{-h \cdot dr_t} \cdot \mathbb{E}_t \left[PO_{t+h} \right] / BE_{i,t}} = e^{\overline{BEg} + \overline{v}_2 - dr_t} \tag{IA.7}$$

so that we can split the valuation equation into two terms:

$$\begin{aligned}
\frac{ME_t}{BE_t} &= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{t+h}/BE_t \right] \cdot e^{-h \cdot dr_t} \right) + \left(\sum_{h=H+1}^{\infty} \mathbb{E}_t \left[PO_{t+h}/BE_t \right] \cdot e^{-h \cdot dr_t} \right) \\
&= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{t+h}/BE_{i,t} \right] \cdot e^{-h \cdot dr_t} \right) + \mathbb{E}_t \left[PO_{t+H}/BE_t \right] \cdot e^{-H \cdot dr_{i,t}} \cdot \sum_{h=1}^{\infty} e^{h \cdot (\overline{BEg} + \overline{v}_2 - dr_t)} \\
&= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{t+h}/BE_t \right] \cdot e^{-h \cdot dr_t} \right) + \mathbb{E}_t \left[PO_{t+H}/BE_t \right] \cdot e^{-H \cdot dr_t} \cdot \frac{e^{\overline{BEg} + \overline{v}_2 - dr_t}}{1 - e^{\overline{BEg} + \overline{v}_2 - dr_t}}
\end{aligned}$$

where $\overline{BEg}$ represents the steady-state growth in (log) book-equity (obtained from the VAR) and $\overline{v}_2 \equiv \lim_{h \to \infty} v_2(h)$, which we approximate with $v_2(H)$.

[35] I find very similar results with $\theta = 1$, except that I could not find $dr_{j,t}$ for some firm/year observations, which had to be dropped from the analysis. The main results are also similar with the log-linear duration measure introduced in Subsection 5.1, which does not require a shrinkage factor as it does not depend on any variance/covariance term.

Similarly, when calculating equity duration, I relied on:

$$
\begin{aligned}
Dur_t &= \left(\sum_{h=1}^{H} w_t^{(h)} \cdot h\right) + \left(\sum_{h=H+1}^{\infty} w_t^{(h)} \cdot h\right) \\
&= \left(\sum_{h=1}^{H} w_t^{(h)} \cdot h\right) + H \cdot \left(1 - \sum_{h=1}^{H} w_t^{(h)}\right) + w_t^{(H)} \cdot \sum_{h=1}^{\infty} h \cdot e^{h \cdot (\overline{BEg} + \overline{v}_2 - dr_t)} \\
&= \left(\sum_{h=1}^{H} w_t^{(h)} \cdot h\right) + H \cdot \left(1 - \sum_{h=1}^{H} w_t^{(h)}\right) + w_t^{(H)} \cdot \frac{e^{\overline{BEg} + \overline{v}_2 - dr_t}}{(1 - e^{\overline{BEg} + \overline{v}_2 - dr_t})^2}
\end{aligned}
$$

A.3 Deriving $llDur$

Consider the following first order (bivariate) Taylor expansion around $\mathbb{E}_t[mb_{t+h}]$ and $\mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]$:

$$
log\left(e^{mb_{t+h}} + e^{CSprof_{t+h} - BEg_{t+h}} - 1\right) \approx k_{1,t}^{(h)} + k_{2,t}^{(h)} \cdot mb_{t+h} + k_{3,t}^{(h)} \cdot (CSprof_{t+h} - BEg_{t+h}) \quad \text{(IA.8)}
$$

with:

$$
\begin{aligned}
k_{1,t}^{(h)} &= log\left(e^{\mathbb{E}_t[mb_{t+h}]} + e^{\mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]} - 1\right) - \left\{k_{2,t}^{(h)} \cdot \mathbb{E}_t[mb_{t+h}] + k_{3,t}^{(h)} \cdot \mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]\right\} \\
k_{2,t}^{(h)} &= e^{\mathbb{E}_t[mb_{t+h}]} / (e^{\mathbb{E}_t[mb_{t+h}]} + e^{\mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]} - 1) \\
k_{3,t}^{(h)} &= e^{\mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]} / (e^{\mathbb{E}_t[mb_{t+h}]} + e^{\mathbb{E}_t[CSprof_{t+h} - BEg_{t+h}]} - 1)
\end{aligned}
$$

Now, note that gross stock returns are given by:

$$
\begin{aligned}
R_{t+1} &= (P_{t+1} + D_{t+1}) / P_t \\
&= (N_{t+1} \cdot P_{t+1} + N_t \cdot D_{t+1} - \Delta N_{t+1} P_{t+1}) / (N_t \cdot P_t) \\
&= (ME_{t+1} + PO_{t+1}) / ME_t \qquad \text{(IA.9)}
\end{aligned}
$$

Then, using the definition of clean surplus earnings, $CSE_t = PO_t + \Delta BE_t$, we can get:

$$
R_{t+1} = \frac{BE_{t+1}}{BE_t} \left[\frac{ME_{t+1}}{BE_{t+1}} + \left(\frac{CSE_{t+1}}{BE_t} + 1\right) \cdot \left(\frac{BE_{t+1}}{BE_t}\right)^{-1} - 1\right] / \frac{ME_t}{BE_t} \qquad \text{(IA.10)}
$$

which in logs becomes:

$$r_{t+1} = BEg_{t+1} + log\left(e^{mb_{t+1}} + e^{CSprof_{t+1} - BEg_{t+1}} - 1\right) - mb_t \tag{IA.11}$$

$$\Downarrow$$

$$mb_t \approx k_{1,t}^{(1)} + k_{3,t}^{(1)} \cdot CSprof_{t+1} + [1 - k_{3,t}^{(1)}] \cdot BEg_{t+1} - r_{t+1} + k_{2,t}^{(1)} \cdot mb_{t+1} \tag{IA.12}$$

where the approximation follows from the Taylor expansion in Eq. IA.8.

For mb_{t+1}, we can use the Taylor expansion on $log\left(e^{mb_{t+2}} + e^{CSprof_{t+2} - BEg_{t+2}} - 1\right)$ to get:

$$\begin{aligned} mb_t \approx\ & k_{1,t}^{(1)} + k_{2,t}^{(1)} \cdot k_{1,t}^{(2)} \\ & + \left(k_{3,t}^{(1)} \cdot CSprof_{t+1} + [1 - k_{3,t}^{(1)}] \cdot BEg_{t+1}\right) + k_{2,t}^{(1)} \cdot \left(k_{3,t}^{(2)} \cdot CSprof_{t+2} + [1 - k_{3,t}^{(2)}] \cdot BEg_{t+2}\right) \\ & - \left(r_{t+1} + k_{2,t}^{(1)} r_{t+2}\right) + k_{2,t}^{(1)} \cdot k_{2,t}^{(2)} \cdot mb_{t+2} \end{aligned} \tag{IA.13}$$

and apply recursive substitution to obtain:

$$\begin{aligned} mb_t \approx\ & \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot k_{1,t}^{(h)} \\ & + \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot \left(k_{3,t}^{(h)} \cdot CSprof_{t+h} + [1 - k_{3,t}^{(h)}] \cdot BEg_{t+h}\right) \\ & - \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot r_{t+h} + \lim_{h \to \infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot mb_{t+h} \end{aligned} \tag{IA.14}$$

Then, taking expectation and applying the transversality (no rational bubble) condition, we have:

$$\begin{aligned} mb_t \approx\ & \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot k_{1,t}^{(h)} \\ & + \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot \left(k_{3,t}^{(h)} \cdot \mathbb{E}_t[CSprof_{t+h}] + [1 - k_{3,t}^{(h)}] \cdot \mathbb{E}_t[BEg_{t+h}]\right) \\ & - \sum_{h=1}^{\infty} \left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right) \cdot \mathbb{E}_t[r_{t+h}] \end{aligned} \tag{IA.15}$$

which implies $llDur_t = -\partial log(ME_t)/\partial dr_t = \sum_{h=1}^{\infty}\left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right)$ after replacing all $\mathbb{E}_t[r_{t+h}]$ components by dr_t as done when defining equity duration in general.

In terms of the log-linear valuation equation, note that if we had approximated around the unconditional mean, then we would recover:

$$\begin{aligned} mb_t \approx\ & k_1/(1-k_2) \\ & + \sum_{h=1}^{\infty} k_2^{h-1} \cdot (k_3 \cdot \mathbb{E}_t[CSprof_{t+h}] + [1-k_3] \cdot \mathbb{E}_t[BEg_{t+h}]) \\ & - \sum_{h=1}^{\infty} k_2^{h-1} \cdot \mathbb{E}_t[r_{t+h}] \end{aligned} \tag{IA.16}$$

which is a generalization of the approximation in Vuolteenaho (2002). In his case, $k_3 = 1$ (expected growth is irrelevant) because the approximation is around $ME/BE = 1$ or $mb = 0$.

This unconditional log-linear approximation has an equity duration that is constant across firms and over time: $\sum_{h=1}^{\infty} k_2^{h-1}$. Hence, this approximation is not useful for the purpose of this paper. I adjust it by changing the expansion point to incorporate firm- and time-specific information so that $llDur_t = \sum_{h=1}^{\infty}\left(\prod_{\tau=0}^{h-1} k_{2,t}^{(\tau)}\right)$ varies across firms and over time.

B Data Sources and Measurement

B.1 Constructing Returns on the Short-term Dividend Claim

Fig. 1(c) and 5(c) use a short duration asset, which I proxy for with a S&P500 dividend claim with maturity between 1 and 2 years. This subsection describes the construction of this dividend claim.

I obtain daily prices on S&P500 dividend futures from two sources: (i) a proprietary dataset of over-the-counter quoted prices for dividend futures (from 03-Jan-2005 to 14-Oct-2016) that Goldman Sachs uses firm-wide both as a pricing source and to mark the internal trading books to the market and (ii) Bloomberg (from 15-Oct-2016 to 30-June-2018).[36]

To get dividend futures monthly prices, $F_{d,t}^{(h)}$, I use the last trading day of each month as the end of month price except that I use the quoted price as of the first trading day of 2005 as the end of month price for Dec-2004.

Dividend futures mature every December so that to obtain constant-maturity dividend futures prices at the monthly frequency I follow Binsbergen et al. (2013) and linearly interpolate between the two closest maturities. For instance, to get $F_d^{(2)}$ at the end of July-2010, I interpolate between the contracts with maturities of 17 and 29 months (expiring in Dec-2011 and Dec-2012). I use this approach to get $F_{d,t}^{(h)}$ and $F_{d,t}^{(h-1/12)}$ with $h = 1$ and 2 years.

Following Binsbergen and Koijen (2017), I avoid using prices of contracts that are close to maturity because they trade infrequently. Consequently, the shortest constant maturity strip I construct has 1.25 years. For simplicity, I still refer to it as the 1-year contract and use notation with $h = 1$. Goldman's data does not include the contract that matures in Dec-2005, which is needed to get $F_t^{(1)}$ from Dec-2004 to Sept-2005. I use the Dec-2006 contract for $F_{d,t}^{(1)}$ over these first months so that the maturity of the contract effectively starts at 2 years (in Dec-2004) and declines to 1.25 years by Oct-2005.

I calculate prices of dividend claims, $P_{d,t}^{(h)}$ and $P_{d,t}^{(h-1/12)}$, using a non-arbitrage condition,

[36] I thank Christian Mueller-Glissmann at Goldman Sachs International for providing me with the over-the-counter data.

$P_{d,t}^{(h)} = F_{d,t}^{(h)} \cdot e^{-h \cdot y_t^{(h)}}$, with zero coupon bond yields, $y_t^{(h)}$, obtained from the parameters of the Svensson (1994) fit to bond yields provided by the FED (see Gürkaynak, Sack, and Wright, 2007). I then calculate monthly returns by $R_{d,t}^{(h)} = P_{d,t}^{(h-1/12)} / P_{d,t-1/12}^{(h)}$ and form the short-maturity claim based on a equal-weighted portfolio of $R_{d,t}^{(1)}$ and $R_{d,t}^{(2)}$. To avoid potential illiquidity/microstructure issues, I follow the recommendation in Boguth et al. (2012) and use annual log returns on this short-maturity claim.

The entire procedure described above provides annual returns on the short-term dividend claim from December/2005 to June/2018. For the earlier period, I use monthly returns on a S&P500 dividend strategy (with average maturity of 1.6 years) based on S&P500 option contracts (data made available by Binsbergen, Brandt, and Koijen, 2012) to construct annual returns from June/1997 to November/2005. Combining the two periods, I have a full time series of annual returns from June/1997 to June/2018 (22 years), which I use to construct Fig. 1(c) and 5(c).

B.2 Variables used to Measure Risk Factors

This subsection details the data sources and measurement for variables used in the estimation of the risk factors in Section 4. The final dataset is a multivariate time series of monthly observations in which flow variables have annual measurement; this dataset extends from Dec/1952 to June/2018.

a) Equity Returns (r_e), Dividend Growth (Δd), and Dividend Yield (dp)

Equity returns (r_e) and dividend growth (Δd) are based on a value-weighted portfolio containing all common stocks available in the CRSP dataset and their measurement accounts for M&A paid in cash (as suggested in Allen and Michaely, 2003). I do not use the CRSP value-weighted index because it includes all issues listed on NYSE, NASDAQ and AMEX with, on average, 5.3% of the market capitalization in the index referring to non common stock issues (see Sabbatucci, 2015). Moreover, accounting for M&A activity requires a "bottom-up" approach.

I construct returns based on a value-weighted equity portfolio. I start by selecting all common shares (share codes 10 and 11) listed on NYSE, NASDAQ or AMEX (exchange code 1, 2, and 3) and then calculate value-weighted cum- and ex-dividend monthly returns ($R^{cum}_{m,t}$ and $R^{ex}_{m,t}$).

I also construct a monthly "M&A yield" ($M\&Ay = M\&A_t/P_{t-1}$) at the aggregate level. Specifically, each month I sum all proceeds from distributions that can be classified as originating from an M&A paid in cash (distribution code between 3000 and 3400) across all firms that have lagged market equity available and I divide this value by the sum of the lagged market equity for these firms.

To get dividends that incorporate M&A activity, I first adjust aggregate ex-dividend monthly returns by $\widehat{R}^{ex}_{m,t} = R^{ex}_{m,t} - M\&Ay$ and calculate a normalized aggregate price series, $\widehat{P}_t$, by cumulating $\widehat{R}^{ex}_{m,t}$. I then calculate dividends from cum- and ex-dividend returns as is standard the literature (see Koijen and Nieuwerburgh, 2011), but relying on the adjusted ex-dividend return so that $\widehat{D}_{m,t} = \left(R^{cum}_{m,t} - \widehat{R}^{ex}_{m,t}\right) \cdot \widehat{P}_{t-1}$.[37]

The monthly series of annual dividends ($\widehat{D}_t$) is based on the sum of the monthly dividends ($\widehat{D}_{m,t}$) over the respective period. I sum the dividend as opposed to reinvesting them into the stock market to avoid introducing properties of returns into dividend growth (see Binsbergen and Koijen, 2010; Chen, 2009).

Dividend growth is given by $\Delta d = log(\widehat{D}_t/\widehat{D}_{t-12})$ and dividend yield by $dy = log(\widehat{D}_t/\widehat{P}_t)$. To get annual returns that are consistent with the assumption of no dividend reinvestment, I use $r_{e,t} = log((\widehat{P}_t + \widehat{D}_t)/\widehat{P}_{t-12})$ as opposed to compounding $R^{cum}_{m,t}$ (but the return series is almost identical either way). Finally, I subtract annual (log) inflation from r_e and Δd using the CPI index to get real quantities.

[37] It is important to note that the somewhat natural approach of calculating M&A based on $\widehat{D}_{m,t} = (R^{cum}_{m,t} - R^{ex}_{m,t}) \cdot P_{t-1} + M\&Ay \cdot P_{t-1}$ in which P_t is constructed from by cumulating $R^{ex}_{m,t}$ is incorrect as it produces price and dividend series that are inconsistent with the cum return provided: $R^{cum}_{m,t} \neq (P_t + \widehat{D}_{m,t})/P_{t-1}$. The method I develop ensures that $R^{cum}_{m,t} = (\widehat{P}_t + \widehat{D}_{m,t})/\widehat{P}_{t-1}$, which is important because accounting for M&A activity in dividend payments should not affect the cum-dividend return delivered by equities. It simply affects the split between how much of that return comes from dividends and price appreciation.

Sabbatucci (2015) and Gonçalves (2020) both show that including M&A activity in the dividend measurement changes the dynamics of Δd and dy and helps alleviating non-stationarity concerns with dividend yield.

b) Aggregate Predictive Variables ($z_t = [dp \quad poy \quad ty \quad TS \quad CS \quad VS]$)

Sources and measurement for the dividend yield (dp) were detailed above. Following Boudoukh et al. (2007), aggregate equity payout yield is $poy_t = log(0.1 + e^{dp_t} - NI_t/ME_t)$. To get the annual aggregate net issuances yield, NI_t/ME_t, I first calculate monthly aggregate net issuances yield, $NI_{m,t}/ME_{m,t} = \Sigma_j(ME_{j,t} - ME_{j,t-1} \cdot R^{ex}_{j,t})/\Sigma_j ME_t$, based on firms that have $ME_{j,t}$, $ME_{j,t-1}$, and $R^{ex}_{j,t}$ available. Then, I get the normalized market equity series $\widehat{ME}_t = \widehat{P}_t \cdot N_t$, where the normalized aggregate number of shares outstanding, N_t, comes from dividing the cumulative $\Sigma_j ME_{j,t}/\Sigma_j ME_{j,t-1}$ by the cumulative $R^{ex}_{m,t}$. Finally, $NI_t/ME_t = [\Sigma^{\tau=t}_{\tau=t-11}\widehat{ME}_\tau \cdot (NI_{m,\tau}/ME_{m,\tau})]/\widehat{ME}_t$.

The treasury yield (ty) is the one year log Treasury yield and comes from CRSP Fama-Bliss discount bond file. The term spread (TS) is the difference between the ten year log Treasury yield and ty with the former coming from Global Financial Data until Mar-1953 and from the Federal Reserve of St. Louis website after that. The credit spread (CS) is the difference between Moody's corporate BAA and AAA log yields with both coming from the Federal Reserve of St. Louis website. The value spread is the difference between the log book-to-market ratios of the value and growth portfolios formed based on small stocks with an adjustment to account for within year movements in market equity. Data comes from Kenneth French's data library and the measurement follows Campbell and Vuolteenaho (2004).

C ICAPM Estimation and Inference

The relative risk premium between assets j and i in the ICAPM is given by:

$$\mathbb{E}\left[R_{j,t} - R_{i,t}\right] = \gamma \cdot Cov(r_{j,t} - r_{i,t}, \tilde{r}_{e,t}) \ + \ \lambda_{\mathbb{E}r} \cdot Cov(r_{j,t} - r_{i,t}, \widetilde{\mathbb{E}}_t r) \tag{IA.17}$$

$$\Downarrow$$

$$R_{j,t} - R_{i,t} = \gamma \cdot Cov(r_{j,t} - r_{i,t}, \tilde{r}_{e,t}) \ + \ \lambda_{\mathbb{E}r} \cdot Cov(r_{j,t} - r_{i,t}, \widetilde{\mathbb{E}}_t r) \ + \ \epsilon_{j,t} \tag{IA.18}$$

where $\lambda_{\mathbb{E}r} = (\gamma - 1) \cdot (1 - \phi_r^{H-1})/(1 - \phi_r)$, with γ, H, and ϕ_r representing relative risk aversion, investor's horizon, and expected return persistence.

The model is estimated using Eq. IA.18 with different restrictions: $\gamma \geq 0$ and $\lambda_{\mathbb{E}r} = 0$ for the CAPM; $\gamma \geq 0$ and $0 \leq \lambda_{\mathbb{E}r}/(\gamma - 1) \leq (1 - \phi^{49})/(1 - \phi)$ for the ICAPM; and no restriction for the ICAPM$_{\text{U}}$.[38] However, the estimation method is identical (except for the restrictions imposed) in all three cases.

Specifically, I use as excess returns the spreads between each duration portfolio (from decile 2 to decile 10) relative to the shortest duration portfolio (decile 1) and estimate the covariances $Cov(r_{j,t} - r_{i,t}, \tilde{r}_{e,t})$ and $Cov(r_{j,t} - r_{i,t}, \widetilde{\mathbb{E}}_t r)$. I then estimate Eq. IA.18 by regressing the respective excess returns on the covariances (which are fixed over time). To impose the relevant restrictions, I estimate risk prices using least squares with the respective equality and inequality restrictions (often called "order restricted linear regression"). Inference is done by repeating the estimation procedure for each cross-section to obtain a time series of parameter estimates and then getting the covariance matrix of parameter estimates from Newey and West (1987, 1994) applied to this time series. For specifications designed to match the equity premium, I also impose the constraint $\mathbb{E}[R_e - R_f] = \gamma \cdot Cov(r_{e,t} - r_{f,t}, \tilde{r}_{e,t}) \ + \ \lambda_{\mathbb{E}r} \cdot Cov(r_{e,t} - r_{f,t}, \widetilde{\mathbb{E}}_t r)$.

The entire estimation/inference procedure is identical to Fama and MacBeth (1973) (with

[38]For the ICAPM specification, I simplify the restrictions to keep the restriction set linear in γ and $\lambda_{\mathbb{E}r}$, which decreases the computational cost of estimating the model. Specifically, I impose $\gamma \geq 1$ (instead of $\gamma \geq 0$) because in this case the $0 \leq \lambda_{\mathbb{E}r}/(\gamma - 1) \leq (1 - \phi^{49})/(1 - \phi)$ restriction reduces to $0 \leq \lambda_{\mathbb{E}r} \leq (\gamma - 1) \cdot (1 - \phi^{49})/(1 - \phi)$. This adjustment has no effect on my results as the fully unconstrained model yield parameter estimates that are identical to the constrained one.

Newey and West, 1987, 1994 standard errors) in the absence of parameter restrictions. However, parameter restrictions break the equivalence between pooled panel regressions and Fama and MacBeth (1973) cross-sectional regressions even when the restrictions do not bind for the final parameter estimates. This happens because restrictions can bind for specific cross-sections in the Fama and MacBeth (1973) procedure, which affects the final Fama and MacBeth (1973) estimates and standard errors. As such, I use panel regressions with coefficient restrictions as they are standard in empirical work. I still obtain standard errors using Fama and MacBeth (1973) because they are analogous to the typical bootstrap procedure used in many papers.

D Supplementary Empirical Results

D.1 Robustness: Firm-level State Vector

This subsection details a robustness analysis to the state variables included in the firm-level VAR used to construct equity duration. Specifically, I remove state variables from $s_{j,t}$ one at a time before estimating the VAR used to calculate equity duration.

Table IA.3 provides results for portfolio regressions analogous to the ones used in Table 3. The first row in each column reports univariate results (i.e., the raw short duration premium). The other rows provide results controlling for the different characteristics. Column 1 shows that the value and profitability premia are strong when we do not control for Dur (they are 14.1% and 12.8% respectively). Column 2 shows the baseline result that there is a short duration premium that subsumes the value and profitability premia. The other columns remove state variables one at a time from $s_{j,t}$ and show that there is a short duration premium in all specifications studied. The smallest premium is 6.6% and happens when we remove gross profitability from $s_{j,t}$, which is an important predictor of future cash flows. Similarly, controlling for $Dur_{j,t}$ substantially weakens the value and profitability premia, which become insignificant in all specifications.

D.2 Robustness: ICAPM Specification

This subsection details a robustness analysis to the ICAPM results. Specifically, I reestimate the ICAPM that matches the equity premium and imposes $\gamma \geq 0$ and $0 \leq \lambda_{\mathbb{E}r}/(\gamma - 1) \leq (1 - \phi^{49})/(1 - \phi)$ after changing several aspects of the baseline empirical specification. Results are provided in Table IA.5.

Column 1 changes the measurement of expected returns. In particular, the OLS estimation of $\mathbb{E}_t r = b' z_t$ (which is the baseline specification) does not use information on dividend growth predictability. However, Campbell-Shiller decomposition implies $B_r \cdot \mathbb{E}_t r = (dp_t - \overline{dp}) + B_g \cdot g_t$ where $B_g = 1/(1 - \rho \cdot \phi_g)$ and $B_r = 1/(1 - \rho \cdot \phi_r)$, and Chen and Zhao (2009) argue that it is important to account for both return and dividend growth predictability when estimating

ICAPM risk factors. To address this issue, Column 1 shows that the baseline results are similar if we estimate $b_r' z_t$ and $b_g' z_t$ by projecting returns and dividend growth onto z_t (using OLS) and set $\mathbb{E}_t r$ to the average of $b_r' z_t$ and $[(dp_t - \overline{dp}) + B_g \cdot b_g' z_t]/B_r$.

Column 2 provides results that are similar to the baseline specification when dividends are measured without accounting for M&A paid in cash. However, the dividend yield in this case shows signs of non-stationarity (see Gonçalves (2020) and Sabbatucci (2015)).

Columns 3 to 8 change the state variables used in $\mathbb{E}_t r = b' z_t$. Specifically, Columns 3 to 7 drop each of the state variables from the analysis (except for dp since the AR(1) specification for $\mathbb{E}_t r$ and g_t automatically implies dp is a state variable) and Column 8 adds dividend growth as a state variable. Alphas for the short duration premium are small and insignificant in all cases.

Columns 9 and 10 replace Dur with the two alternative duration measures, EPP and $llDur$, I explore in the main text. The ICAPM captures the short duration premium obtained from both of these equity duration measures.

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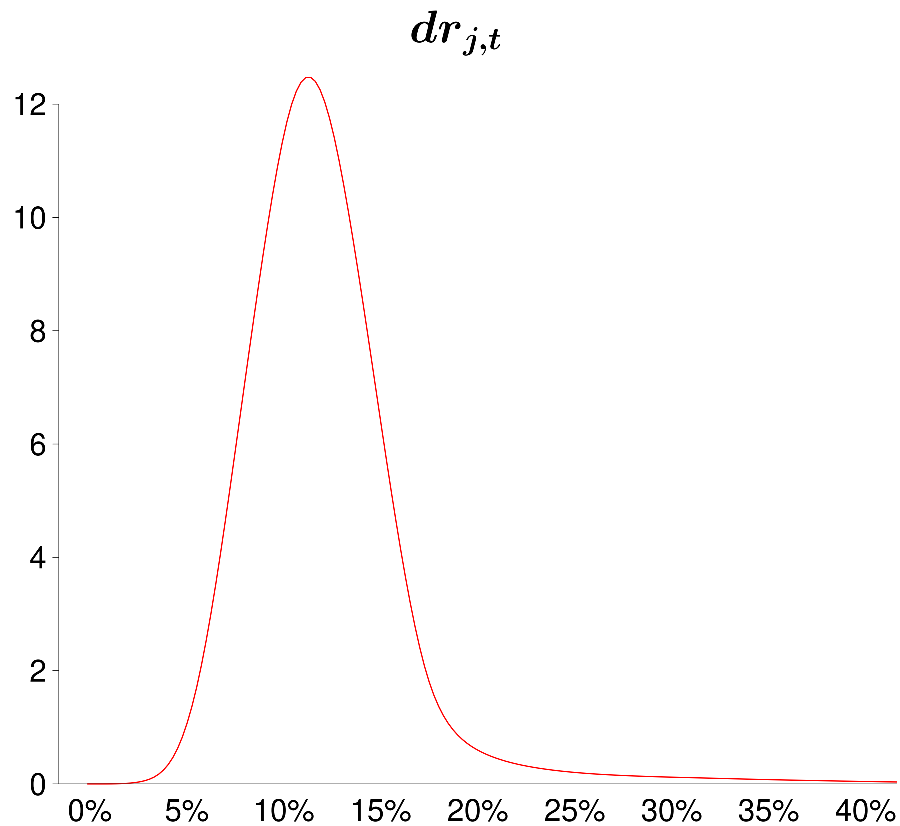

Figure IA.1
Density Function of Firm Implied Discount Rates

The graph reports the empirical density function (estimated with a quadratic kernel) of $dr_{j,t}$ obtained by solving the valuation Eq. 6 for each firm-year observation from 1973 to 2017. Empirical details are provided in Section 2.

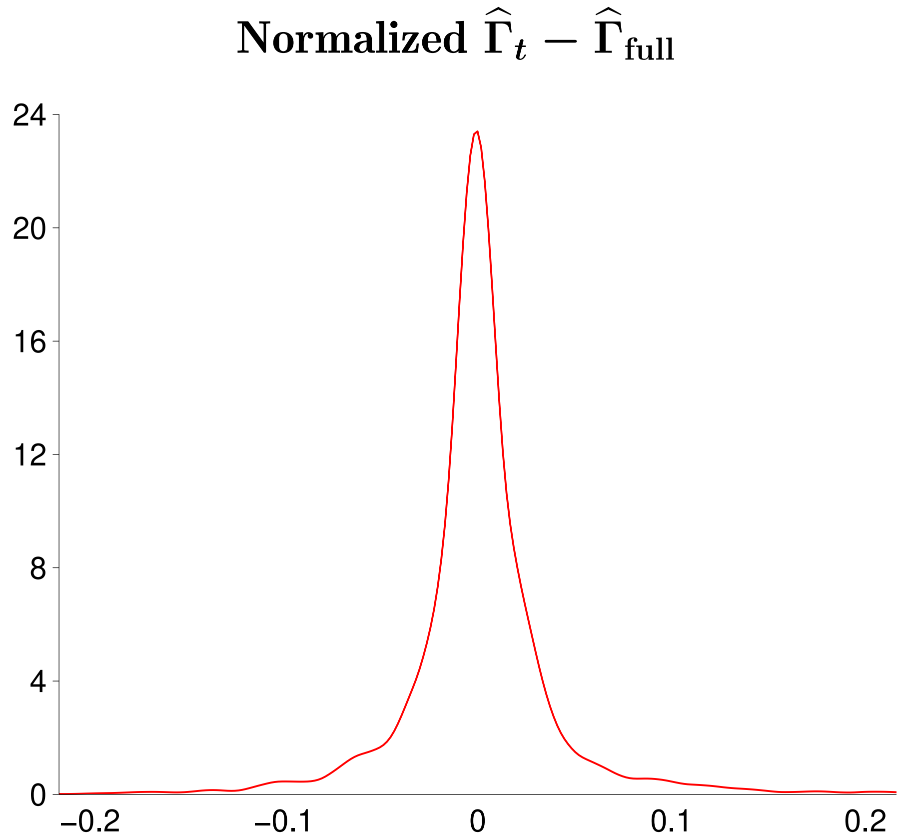

Figure IA.2
Density Function of VAR Parameters Relative to their Full Sample Estimates

The graph reports the empirical density function (estimated with a quadratic kernel) of VAR out-of-sample parameter estimates relative to their full sample estimates. Specifically, for each parameter in the Γ matrix (except for intercepts), I obtain the full sample estimate (using data from 1962 to 2017) as well as the out-of-sample estimates obtained each year from 1973 to 2017. I then normalize each parameter by multiplying it by the full-sample $\sigma(s_x)/\sigma(s_y)$ (s_x represents the respective explanatory variable and s_y the respective dependent variable) so that they are all in standard deviation units. Finally, I obtain the difference between each out-of-sample estimate and its respective full-sample estimate and plot the resulting empirical density function. Empirical details on the VAR estimation can be found in Section 2.

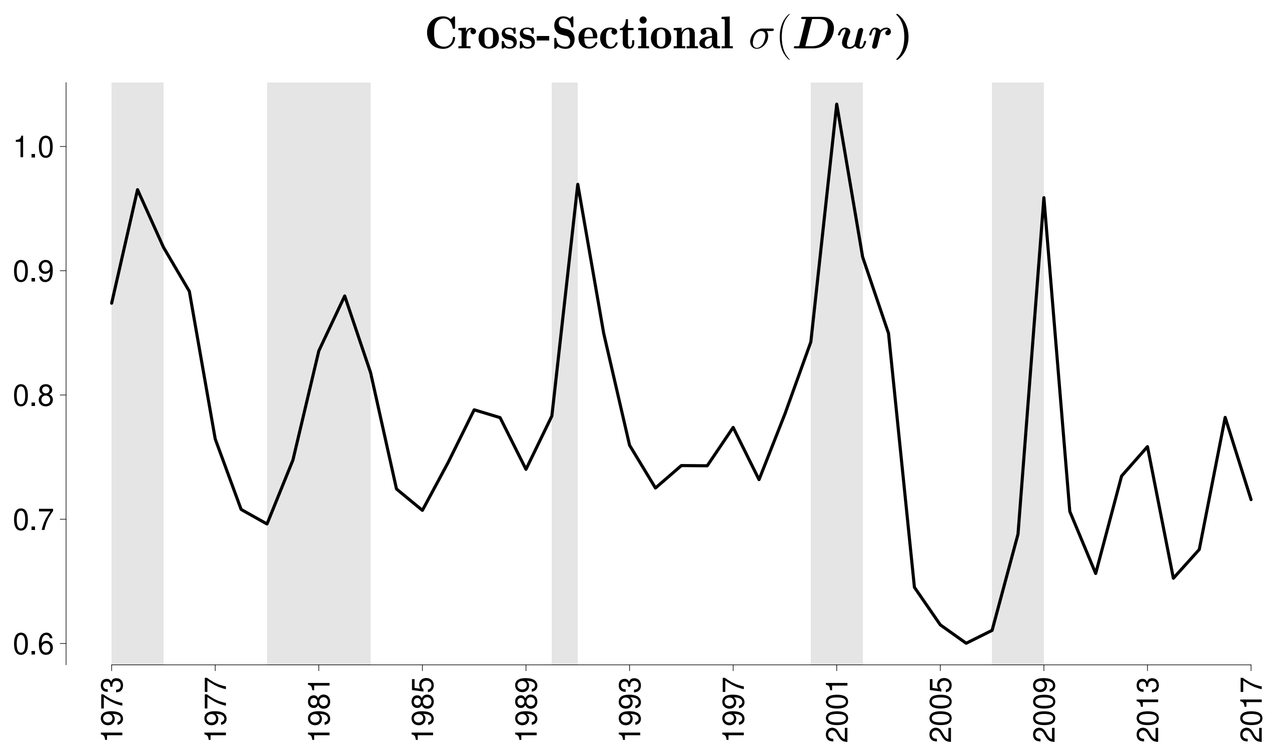

Figure IA.3
Time Series of Cross-Sectional Dispersion in Duration

The graph reports the time variation in the cross-sectional standard deviation of $log(Dur)$, with Dur measured from Eq. 7 (empirical details in Section 2). Specifically, at June of year t, I select all firms with Dur calculated based on accounting information with fiscal year ending in December of $t-1$ (to align all accounting information) and measure the standard deviation of $log(Dur_t)$ at that point in time. The logarithm transformation is used to decrease the large asymmetry in duration and the potential influence of outliers. Shaded regions represent recessionary periods (as defined by the National Bureau of Economic Research - NBER). I classify the Dur available in June of year t as being measured in a recessionary period if there is any recession from July of year $t-1$ to June of year t.

Table IA.1
Rank Correlations Between Firm-level Characteristics

The table reports time series averages of cross-sectional rank correlations (Spearman's correlations) for the firm-level characteristics using the full sample of firms included in the duration portfolios. Characteristics are evaluated at June of each year from 1973 to 2017. All variables are defined in Section 2.

	Dur	***Size***	***BE/M***	***PO/M***	***Y/M***	***BEg***	***Ag***	***Yg***	***CSprof***	***Roe***	***Gprof***	***Mlev***	***Blev***	***Cash***
Dur	1													
Size	0.21	1												
BE/M	-0.58	-0.38	1											
PO/M	-0.28	0.23	0.13	1										
Y/M	-0.45	-0.32	0.64	0.17	1									
BEg	0.07	0.24	-0.29	-0.29	-0.23	1								
Ag	0.15	0.24	-0.29	-0.17	-0.24	0.66	1							
Yg	0.18	0.16	-0.29	-0.19	-0.21	0.43	0.55	1						
CSprof	-0.02	0.39	-0.34	0.11	-0.20	0.80	0.55	0.38	1					
Roe	-0.08	0.43	-0.37	0.21	-0.16	0.63	0.44	0.31	0.85	1				
Gprof	-0.34	0.02	-0.24	0.06	0.09	0.23	0.19	0.16	0.34	0.39	1			
Mlev	0.02	-0.09	0.43	0.05	0.58	-0.18	-0.12	-0.11	-0.19	-0.20	-0.27	1		
Blev	0.24	0.03	0.11	-0.01	0.32	-0.08	-0.01	-0.01	-0.07	-0.09	-0.24	0.89	1	
Cash	-0.02	-0.03	-0.21	-0.10	-0.37	0.07	0.04	0.03	0.03	0.02	0.07	-0.53	-0.51	1

Table IA.2
Firm-Level Cross-Sectional Regressions

The table reports results from Fama and MacBeth (1973) cross-sectional regressions of stock returns on firm characteristics (from July/1973 to June/2018) where all predictive variables are measured in log units and each cross-section is weighted based on the number of firms to avoid overweighting earlier observations (results are similar either way). I transform independent variables into z-scores and multiply coefficients by twelve to facilitate interpretation. This means that a coefficient of 1% implies that one cross-sectional standard deviation increase in the respective characteristic predicts a 1% higher average return on an annual basis. Columns 1.1 to 1.8 winsorize all independent variables at 1% and 99% while columns 2.1 to 2.8 also winsorize returns at the same levels. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West, 1987, 1994) with t_{stat} in parentheses.

Sorting	**PANEL A - No Winsorization on Returns**							
Variable	**[1.1]**	**[1.2]**	**[1.3]**	**[1.4]**	**[1.5]**	**[1.6]**	**[1.7]**	**[1.8]**
Dur	-4.3%	-3.2%	-4.2%	-3.9%	-3.7%		-2.7%	-2.6%
	(-6.33)	(-4.37)	(-6.28)	(-5.99)	(-4.83)		(-3.36)	(-3.54)
BE/M	3.4%	1.4%				3.7%	1.9%	1.0%
	(4.44)	(1.70)				(4.63)	(1.89)	(1.01)
$Gprof$	1.8%		0.4%			2.3%	1.0%	0.8%
	(3.60)		(0.89)			(4.37)	(1.67)	(1.51)
Ag	-3.1%			-2.3%				-2.0%
	(-5.62)			(-4.44)				(-4.54)
$Size$	-1.7%				-1.0%			-0.5%
	(-1.92)				(-1.07)			(-0.56)
Sorting	**PANEL B - Returns Winsorized at 1% and 99%**							
Variable	**[2.1]**	**[2.2]**	**[2.3]**	**[2.4]**	**[2.5]**	**[2.6]**	**[2.7]**	**[2.8]**
Dur	-4.2%	-3.6%	-4.1%	-4.0%	-4.0%		-3.3%	-3.0%
	(-6.53)	(-5.21)	(-6.31)	(-6.30)	(-5.41)		(-4.26)	(-4.28)
BE/M	2.9%	0.7%				3.1%	1.0%	0.9%
	(3.84)	(0.95)				(4.09)	(1.05)	(0.94)
$Gprof$	2.0%		0.6%			2.4%	0.7%	0.8%
	(4.17)		(1.28)			(4.91)	(1.28)	(1.46)
Ag	-2.4%			-1.7%				-1.6%
	(-4.60)			(-3.33)				(-3.76)
$Size$	-0.2%				0.6%			1.0%
	(-0.21)				(0.65)			(1.02)

Table IA.3
Short Duration Premium: Removing State Variables from *Dur*

Portfolios are formed every June (1973 to 2017) from deciles based on the respective characteristics, which are described in Section 2. Monthly portfolio returns span the subsequent twelve months (from July/1973 to June/2018). The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 3.4 provides details on the methodology. The first column shows results without controlling for duration and the second column controls for the *Dur* obtained in the baseline analysis. The other columns remove state variables from the firm-level VAR one at a time. The first row in each column provides the coefficient on duration in a univariate specification. The other rows provide coefficients from a multivariate specification with the respective covariates included. All specifications are based on the deciles from the firm-level characteristics included in the regression. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting			Removing from $s_{j,t}$									
Variable	*No Dur*	Baseline	*bm*	*POy*	*Yy*	*Ag*	*Yg*	*Roe*	*Gprof*	*Mlev*	*Blev*	*Cash*
Dur		-8.6%	-8.5%	-8.9%	-8.8%	-8.7%	-8.8%	-8.1%	-6.6%	-9.0%	-9.2%	-8.0%
		(-3.85)	(-3.84)	(-4.00)	(-3.90)	(-3.80)	(-3.90)	(-3.62)	(-2.70)	(-4.08)	(-4.31)	(-3.51)
Dur		-14.4%	-15.4%	-14.7%	-14.9%	-13.5%	-14.9%	-14.1%	-9.6%	-18.6%	-17.0%	-13.9%
		(-2.44)	(-2.38)	(-2.48)	(-2.51)	(-2.35)	(-2.51)	(-2.12)	(-1.99)	(-2.67)	(-2.54)	(-2.65)
BE/ME	14.1%	-2.5%	-3.9%	-2.6%	-3.2%	-1.2%	-3.2%	-3.3%	3.5%	-8.3%	-4.9%	-2.6%
	(2.57)	(-0.37)	(-0.54)	(-0.38)	(-0.46)	(-0.18)	(-0.46)	(-0.41)	(0.59)	(-1.12)	(-0.66)	(-0.46)
Gprof	12.8%	-1.8%	-2.6%	-2.2%	-2.2%	-0.8%	-2.2%	-1.1%	5.9%	-5.1%	-3.9%	-2.0%
	(2.77)	(-0.31)	(-0.42)	(-0.37)	(-0.37)	(-0.13)	(-0.37)	(-0.18)	(1.18)	(-0.83)	(-0.62)	(-0.39)
Ag	-3.5%	-3.3%	-3.5%	-3.3%	-3.1%	-4.3%	-3.1%	-3.3%	-3.4%	-3.0%	-3.3%	-3.2%
	(-1.22)	(-0.94)	(-0.99)	(-0.91)	(-0.87)	(-1.23)	(-0.87)	(-0.92)	(-0.94)	(-0.85)	(-0.92)	(-0.87)
Size	-1.3%	-2.8%	-2.9%	-2.9%	-2.9%	-2.9%	-2.9%	-2.1%	-2.7%	-3.5%	-3.1%	-3.2%
	(-0.44)	(-0.97)	(-1.00)	(-1.01)	(-1.01)	(-1.00)	(-1.01)	(-0.71)	(-0.92)	(-1.25)	(-1.07)	(-1.13)

PANEL B: Equal-Weighted Portfolios

Sorting			Removing from $s_{j,t}$									
Variable	*No Dur*	Baseline	*bm*	*POy*	*Yy*	*Ag*	*Yg*	*Roe*	*Gprof*	*Mlev*	*Blev*	*Cash*
Dur		-9.1%	-9.0%	-9.0%	-9.1%	-8.6%	-9.1%	-9.3%	-7.9%	-9.3%	-9.2%	-8.9%
		(-4.40)	(-4.45)	(-4.35)	(-4.34)	(-4.25)	(-4.34)	(-4.69)	(-3.75)	(-4.51)	(-4.61)	(-4.15)
Dur		-8.4%	-8.4%	-8.3%	-8.0%	-8.3%	-8.0%	-7.6%	-5.7%	-9.5%	-9.4%	-8.2%
		(-1.78)	(-1.77)	(-1.76)	(-1.73)	(-1.84)	(-1.73)	(-1.57)	(-1.52)	(-1.92)	(-1.93)	(-1.72)
BE/ME	9.5%	2.2%	2.0%	2.3%	2.4%	2.1%	2.4%	2.4%	4.5%	0.8%	1.3%	2.2%
	(3.20)	(0.42)	(0.38)	(0.44)	(0.46)	(0.42)	(0.46)	(0.45)	(1.02)	(0.14)	(0.24)	(0.42)
Gprof	9.0%	2.0%	2.0%	2.0%	2.4%	1.9%	2.4%	2.9%	5.9%	1.3%	1.0%	2.0%
	(3.71)	(0.44)	(0.44)	(0.43)	(0.53)	(0.44)	(0.53)	(0.67)	(1.81)	(0.28)	(0.21)	(0.42)
Ag	-3.9%	-3.9%	-4.0%	-3.9%	-3.9%	-4.3%	-3.9%	-3.7%	-4.0%	-4.0%	-3.9%	-3.9%
	(-2.62)	(-2.47)	(-2.58)	(-2.47)	(-2.47)	(-2.74)	(-2.47)	(-2.43)	(-2.49)	(-2.51)	(-2.51)	(-2.41)
Size	0.0%	-0.2%	-0.2%	-0.2%	-0.2%	-0.2%	-0.2%	0.1%	-0.1%	-0.4%	-0.1%	-0.2%
	(0.02)	(-0.07)	(-0.08)	(-0.08)	(-0.09)	(-0.09)	(-0.09)	(0.03)	(-0.06)	(-0.16)	(-0.03)	(-0.10)

Table IA.4

Correlations Between Shocks to Risk Factors and State Variables

The table reports correlations between shocks to risk factors and state variables. The risk factors are equity market realized returns (r_e) and expected returns ($\mathbb{E}r$). The state variables are the dividend yield (dp), equity payout yield (poy), one year Treasury yield (ty), term spread (TS), credit spread (CS), and value spread (VS). Measurement details are provided in Subsection 4.1.

	r_e	$\mathbb{E}r$	dp	poy	ty	TS	CS	VS
r_e	1							
$\mathbb{E}r$	-0.41	1						
dp	-0.55	0.47	1					
poy	-0.47	0.61	0.68	1				
ty	-0.14	-0.38	0.27	0.12	1			
TS	-0.07	0.60	-0.17	-0.02	-0.73	1		
CS	-0.41	0.29	0.30	0.15	-0.13	0.25	1	
VS	0.28	-0.56	-0.22	-0.37	-0.16	-0.02	0.04	1

Table IA.5
ICAPM Estimation and Pricing Errors: Alternative Specifications

Equity duration portfolios are formed every June (1973 to 2017) from deciles based on Dur, which is measured from Eq. 7 (empirical details in Section 2). The table reports risk prices and pricing errors (αs) for the estimation of Eq. 13 using as testing assets excess returns of (value- and equal-weighted) duration portfolios relative to the shortest duration portfolio ($R^{(h)}_{Dur} - R^{(1)}_{Dur}$). The estimation further requires the model to perfectly match the equity premium, $\mathbb{E}[R_e - R_f]$, and satisfy the ICAPM pricing restrictions $\gamma \geq 0$ and $0 \leq \lambda_{\mathbb{E}r}/(\gamma - 1) \leq (1 - \phi^{49})/(1 - \phi)$. Each column changes one empirical decision relative to the baseline specification reported in the main text (see Section D for details). Subsection 4.1 explains the construction of risk factors and Section C provides details for the model estimation and inference. t_{stat} are in parentheses and statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West, 1987, 1994).

		$\mathbb{E}_t[R_e]$ w/ Δd Pred	D_t w/o $M\&A$	s_t w/o poy_t	s_t w/o ty_t	s_t w/o TS_t	s_t w/o CS_t	s_t w/o VS_t	s_t w/ Δd_t	Dur = EPP_t	Dur = $llDur_t$
	$\lambda_m = \gamma$	11.1	11.5	12.0	10.0	10.2	10.4	14.9	10.6	9.5	9.6
		(6.26)	(6.43)	(6.21)	(6.73)	(6.48)	(6.64)	(6.82)	(6.58)	(6.51)	(7.63)
	$\lambda_{\mathbb{E}r}$	37.9	27.2	33.8	24.4	26.0	24.8	61.8	23.6	21.2	21.5
		(4.30)	(4.32)	(4.34)	(4.22)	(4.18)	(4.25)	(5.22)	(4.25)	(3.96)	(4.67)
	implied H	6	4	5	4	4	4	7	4	4	4
	implied δ	0.87	0.74	0.83	0.80	0.81	0.79	0.90	0.78	0.78	0.78
	$\mathbb{E}[R_e - R_f]$	7.3%	7.4%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%
VW	α_{2-1}	0.4%	-2.2%	-2.0%	0.3%	-1.3%	-0.6%	-3.8%	-1.2%	0.2%	1.5%
VW	α_{3-1}	1.5%	-1.9%	-1.3%	0.8%	-0.2%	-0.1%	-5.6%	-0.7%	-1.0%	0.3%
VW	α_{4-1}	-1.0%	-4.3%	-4.3%	-1.4%	-2.5%	-2.5%	-8.3%	-3.0%	-4.1%	-3.4%
VW	α_{5-1}	3.2%	-0.6%	-0.5%	2.7%	1.8%	1.8%	-3.0%	1.0%	-1.2%	-1.6%
VW	α_{6-1}	1.6%	-2.3%	-1.5%	0.9%	-0.4%	-0.1%	-4.4%	-0.7%	-0.5%	-0.6%
VW	α_{7-1}	3.6%	0.6%	2.0%	2.9%	2.0%	2.7%	2.2%	1.9%	-1.1%	0.1%
VW	α_{8-1}	0.8%	-3.7%	-2.2%	0.0%	-1.5%	-0.6%	-1.5%	-1.8%	-1.4%	-0.2%
VW	α_{9-1}	-0.3%	-2.6%	-0.8%	-0.9%	-1.3%	-0.8%	-2.8%	-1.4%	-1.7%	2.6%
VW	α_{10-1}	-3.4%	-4.2%	-1.8%	-3.2%	-4.3%	-2.9%	-2.3%	-3.7%	-0.3%	-1.9%
VW	(t^{α}_{10-1})	(-1.17)	(-1.43)	(-0.61)	(-1.10)	(-1.47)	(-0.97)	(-0.80)	(-1.25)	(-0.10)	(-0.66)
EW	α_{2-1}	2.3%	3.4%	2.6%	2.9%	2.6%	2.7%	0.8%	2.9%	3.0%	0.3%
EW	α_{3-1}	1.5%	3.2%	2.1%	2.3%	2.2%	2.1%	-1.9%	2.5%	2.4%	-1.6%
EW	α_{4-1}	0.7%	1.4%	0.4%	1.0%	1.8%	0.8%	-3.5%	1.2%	0.7%	-0.4%
EW	α_{5-1}	-0.1%	0.4%	-0.2%	0.1%	0.6%	0.1%	-5.2%	0.4%	-0.4%	-0.2%
EW	α_{6-1}	0.3%	1.3%	0.5%	0.8%	1.6%	0.8%	-4.8%	1.2%	1.4%	0.1%
EW	α_{7-1}	-0.7%	-0.3%	-1.5%	-0.4%	0.3%	-0.5%	-6.7%	0.1%	-2.2%	-0.2%
EW	α_{8-1}	-0.4%	-0.2%	-0.5%	-0.7%	0.8%	-0.4%	-5.5%	0.4%	0.4%	-0.3%
EW	α_{9-1}	-2.9%	-1.3%	-0.8%	-2.5%	-1.6%	-1.8%	-5.6%	-1.7%	-1.0%	0.6%
EW	α_{10-1}	-1.5%	2.8%	1.6%	-0.1%	0.9%	0.8%	-3.4%	1.7%	1.2%	0.1%
EW	(t^{α}_{10-1})	(-0.49)	(0.92)	(0.53)	(-0.04)	(0.30)	(0.26)	(-1.12)	(0.56)	(0.42)	(0.04)

Table IA.6
Correlations Between Equity Duration Measures

Panel A reports time series averages of cross-sectional rank correlations (Spearman's correlations) for the firm-level characteristics using the full sample of firms included in the duration portfolios (from 1973 to 2017). All variables are defined in Section 2. Panels B and C report return correlations between value- and equal-weighted High-Low portfolios constructed based on the different equity duration proxies (from July of 1973 to June of 2018).

PANEL A - Firm-level Characteristics

	Dur	***EPP***	***llDur***	***DSS Dur***
Dur	1			
EPP	0.99	1		
llDur	0.83	0.87	1	
DSS Dur	0.66	0.66	0.56	1
BE/ME	-0.58	-0.61	-0.57	-0.64

PANEL B - VW Returns on High-Low Portfolio

	Dur	***EPP***	***llDur***	***DSS Dur***
Dur	1			
EPP	0.96	1		
llDur	0.83	0.88	1	
DSS Dur	0.53	0.59	0.55	1
BE/ME	-0.49	-0.53	-0.50	-0.73

PANEL C - EW Returns on High-Low Portfolio

	Dur	***EPP***	***llDur***	***DSS Dur***
Dur	1			
EPP	0.98	1		
llDur	0.91	0.94	1	
DSS Dur	0.80	0.83	0.77	1
BE/ME	-0.56	-0.61	-0.57	-0.76

Table IA.7
Performance of Duration Portfolios Based on *DSS Dur*: Keep Microcaps, no NYSE Breakpoints, and Winsorize Returns

Equity duration portfolios are formed every June (1973 to 2017) from deciles based on *DSS Dur*, which is measured from Eq. 16 (empirical details in Section 5.3). Portfolio returns are measured monthly and constructed without using NYSE breakpoints, keeping microcaps in equal-weighted portfolios, and winsorizing returns at 1% and 99%. Panel A shows annualized average excess returns ($\times 12$) and Sharpe Ratios ($\times\sqrt{12}$). $\overline{r}_{t+j\rightarrow t+h}$ indicates the portfolio is implemented j years after the Dur measurement and is held for $h-j$ years. Moreover, $\overline{r}^{Large}$ indicates the portfolio is based on firms with market equity above the 80% NYSE quantile and $\overline{r}^{dlst\ adj}$ indicates returns are adjusted for delistings. Panel B reports βs and annualized αs ($\times 12$) from factor regressions. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West, 1987, 1994) with t_{stat} in parentheses and p-value in brackets.

PANEL A: Average Returns and Sharpe Ratios

Duration	**Value-Weighted Portfolios**						**Duration**	**Equal-Weighted Portfolios**					
Decile	$\overline{r}_{t\rightarrow t+1}$	$\overline{r}_{t\rightarrow t+5}$	$\overline{r}_{t+4\rightarrow t+5}$	$\overline{r}^{Large}_{t\rightarrow t+1}$	$\overline{r}^{dlst\ adj}_{t\rightarrow t+1}$	$\overline{r}/\sigma$	**Decile**	$\overline{r}_{t\rightarrow t+1}$	$\overline{r}_{t\rightarrow t+5}$	$\overline{r}_{t+4\rightarrow t+5}$	$\overline{r}^{Large}_{t\rightarrow t+1}$	$\overline{r}^{dlst\ adj}_{t\rightarrow t+1}$	$\overline{r}/\sigma$
Short	10.7%	11.4%	9.2%	9.8%	10.5%	0.53	**Short**	14.4%	15.4%	14.2%	11.2%	14.0%	0.71
2	11.9%	10.2%	9.8%	8.5%	11.9%	0.67	**2**	14.2%	14.5%	14.2%	9.6%	14.0%	0.72
3	10.3%	9.8%	9.9%	8.3%	10.3%	0.60	**3**	13.1%	14.0%	14.3%	9.7%	13.0%	0.68
4	10.7%	9.8%	8.9%	7.7%	10.7%	0.65	**4**	12.5%	13.7%	13.5%	9.2%	12.4%	0.65
5	8.2%	8.9%	8.8%	7.9%	8.3%	0.52	**5**	11.5%	12.5%	12.6%	8.9%	11.4%	0.61
6	8.8%	8.6%	9.1%	7.8%	8.8%	0.53	**6**	11.1%	12.1%	12.1%	8.9%	11.1%	0.57
7	8.1%	7.9%	7.1%	6.9%	8.1%	0.52	**7**	10.3%	11.6%	11.5%	7.8%	10.2%	0.52
8	7.9%	7.4%	8.0%	6.3%	7.9%	0.47	**8**	8.7%	10.7%	11.2%	6.9%	8.6%	0.40
9	8.0%	8.1%	10.6%	6.0%	8.0%	0.36	**9**	5.4%	9.7%	11.6%	6.9%	4.8%	0.21
Long	-0.7%	2.9%	6.3%	5.4%	-0.8%	-0.03	**Long**	3.5%	9.8%	11.5%	5.1%	1.7%	0.12
L-S	-11.4%	-8.5%	-2.9%	-4.4%	-11.3%	-0.56	**L-S**	-10.9%	-5.6%	-2.7%	-6.1%	-12.3%	-0.76
(t_{L-S})	(-3.50)	(-3.54)	(-1.10)	(-1.31)	(-3.50)	[0.00]	**(t_{L-S})**	(-4.26)	(-2.56)	(-1.17)	(-2.15)	(-4.83)	[0.00]

PANEL B: Risk-Adjusted Performance Based on Factor Models

Duration	**CAPM**		Fama and French (2015) **5-Factors**						Hou, Xue, and Zhang (2015) **q-Factors**				
Decile	α_{CAPM}	β_{MKT}	α_{FF}	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	α_q	β_{MKT}	β_{SIZE}	β_{INV}	β_{ROE}
						Value-Weighted Portfolios							
Short	2.7%	1.02	-1.2%	1.06	0.45	0.70	-0.20	0.07	1.7%	1.02	0.32	0.48	-0.31
2	4.5%	0.97	0.0%	1.06	0.27	0.42	0.11	0.28	1.5%	1.03	0.18	0.55	-0.02
3	3.1%	0.97	-0.8%	1.06	0.21	0.40	0.06	0.27	0.6%	1.03	0.13	0.48	-0.01
4	3.9%	0.94	0.3%	1.02	0.17	0.22	0.20	0.26	1.7%	0.99	0.08	0.38	0.02
5	1.7%	0.91	-1.8%	1.00	0.11	0.12	0.28	0.30	-0.8%	0.97	0.03	0.39	0.08
6	1.9%	0.95	-0.9%	1.02	0.09	0.02	0.16	0.39	-0.4%	1.00	0.02	0.22	0.18
7	1.4%	0.93	0.3%	0.96	0.03	-0.18	0.23	0.19	0.2%	0.95	0.02	0.00	0.18
8	0.5%	1.00	0.6%	1.00	-0.04	-0.31	0.14	0.18	0.4%	0.99	-0.03	-0.20	0.21
9	-1.3%	1.25	2.8%	1.11	0.04	-0.48	-0.18	-0.20	4.0%	1.13	-0.01	-0.74	-0.13
Long	-11.0%	1.41	-8.1%	1.25	0.34	-0.30	0.12	-0.59	-6.4%	1.28	0.28	-0.22	-0.52
L-S	-13.7%	0.38	-6.9%	0.19	-0.11	-1.01	0.32	-0.67	-8.1%	0.26	-0.04	-0.70	-0.21
(t_{L-S})	(-3.60)	(2.72)	(-2.36)	(1.88)	(-0.61)	(-5.83)	(1.22)	(-2.62)	(-2.66)	(2.20)	(-0.26)	(-2.47)	(-0.71)
						Equal-Weighted Portfolios							
Short	7.1%	0.96	2.9%	0.92	0.92	0.47	0.03	-0.03	5.6%	0.88	0.78	0.51	-0.43
2	6.8%	1.00	2.4%	0.97	0.87	0.42	0.02	0.08	4.9%	0.93	0.73	0.46	-0.32
3	5.7%	1.01	1.4%	0.97	0.88	0.34	0.05	0.13	3.5%	0.93	0.76	0.37	-0.23
4	5.0%	1.03	0.9%	0.99	0.83	0.32	0.01	0.17	3.1%	0.95	0.69	0.31	-0.20
5	3.9%	1.05	0.5%	1.00	0.78	0.21	0.00	0.16	2.3%	0.97	0.66	0.19	-0.14
6	3.1%	1.08	-0.1%	1.03	0.77	0.15	0.05	0.15	1.6%	1.00	0.65	0.17	-0.12
7	2.1%	1.12	0.5%	1.02	0.71	0.02	-0.01	0.02	2.2%	1.00	0.61	-0.05	-0.17
8	-0.3%	1.21	-0.4%	1.07	0.71	-0.09	-0.06	-0.13	1.5%	1.06	0.61	-0.23	-0.27
9	-4.6%	1.35	-1.9%	1.08	0.88	-0.31	-0.01	-0.64	0.6%	1.09	0.79	-0.45	-0.64
Long	-6.3%	1.32	-5.8%	1.09	1.09	-0.05	0.15	-0.70	-1.8%	1.08	0.94	-0.02	-0.90
L-S	-13.4%	0.35	-8.7%	0.17	0.18	-0.52	0.12	-0.67	-7.4%	0.20	0.16	-0.53	-0.48
(t_{L-S})	(-4.81)	(4.51)	(-4.27)	(3.81)	(2.35)	(-4.56)	(0.66)	(-6.00)	(-2.45)	(2.75)	(2.08)	(-2.68)	(-2.58)

Table IA.8

Performance of Duration Portfolios Based on Dur Keep Microcaps, no NYSE Breakpoints, and Winsorize Returns

Equity duration portfolios are formed every June (1973 to 2017) from deciles based on Dur, which is measured from Eq. 7 (empirical details in Section 2). Portfolio returns are measured monthly and constructed without using NYSE breakpoints, keeping microcaps in equal-weighted portfolios, and winsorizing returns at 1% and 99%. Panel A shows annualized average excess returns ($\times 12$) and Sharpe Ratios ($\times\sqrt{12}$). $\overline{r}_{t+j\to t+h}$ indicates the portfolio is implemented j years after the Dur measurement and is held for $h-j$ years. Moreover, $\overline{r}^{Large}$ indicates the portfolio is based on firms with market equity above the 80% NYSE quantile and $\overline{r}^{dlst\ adj}$ indicates returns are adjusted for delistings. Panel B reports βs and annualized αs ($\times 12$) from factor regressions. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West, 1987, 1994) with t_{stat} in parentheses and p-value in brackets.

PANEL A: Average Returns and Sharpe Ratios

Duration	**Value-Weighted Portfolios**						**Duration**	**Equal-Weighted Portfolios**					
Decile	$\overline{r}_{t\to t+1}$	$\overline{r}_{t\to t+5}$	$\overline{r}_{t+4\to t+5}$	$\overline{r}^{Large}_{t\to t+1}$	$\overline{r}^{dlst\ adj}_{t\to t+1}$	$\overline{r}/\sigma$	**Decile**	$\overline{r}_{t\to t+1}$	$\overline{r}_{t\to t+5}$	$\overline{r}_{t+4\to t+5}$	$\overline{r}^{Large}_{t\to t+1}$	$\overline{r}^{dlst\ adj}_{t\to t+1}$	$\overline{r}/\sigma$
Short	12.4%	12.0%	12.1%	10.3%	12.4%	0.59	**Short**	16.5%	16.5%	15.4%	11.0%	16.1%	0.77
2	12.2%	11.3%	12.5%	10.1%	12.3%	0.68	**2**	14.2%	15.6%	14.8%	9.8%	13.9%	0.72
3	12.1%	10.9%	9.3%	9.9%	12.1%	0.69	**3**	14.6%	14.8%	13.3%	11.3%	14.5%	0.74
4	12.2%	11.1%	10.4%	11.8%	12.2%	0.72	**4**	13.3%	14.0%	13.7%	11.7%	13.2%	0.68
5	10.6%	9.9%	8.2%	5.5%	10.6%	0.64	**5**	12.3%	13.2%	13.2%	7.7%	12.2%	0.63
6	9.6%	8.7%	7.4%	6.7%	9.6%	0.62	**6**	10.8%	12.3%	12.4%	8.4%	10.6%	0.55
7	8.6%	7.9%	7.9%	6.0%	8.6%	0.52	**7**	9.7%	11.5%	11.9%	7.3%	9.5%	0.47
8	6.4%	6.8%	8.2%	6.9%	6.4%	0.38	**8**	7.8%	10.4%	11.5%	6.9%	7.6%	0.37
9	5.3%	6.5%	8.2%	3.8%	5.4%	0.27	**9**	4.8%	8.6%	10.1%	4.9%	4.4%	0.21
Long	2.3%	3.7%	5.8%	3.7%	2.3%	0.10	**Long**	0.6%	7.1%	10.0%	5.3%	-0.9%	0.02
L-S	-10.1%	-8.3%	-6.3%	-6.6%	-10.0%	-0.56	**L-S**	-15.9%	-9.5%	-5.4%	-5.7%	-17.0%	-1.07
(t_{L-S})	(-3.48)	(-3.92)	(-2.48)	(-2.31)	(-3.47)	[0.00]	**(t_{L-S})**	(-6.96)	(-4.37)	(-2.33)	(-2.18)	(-7.46)	[0.00]

PANEL B: Risk-Adjusted Performance Based on Factor Models

Duration	**CAPM**		Fama and French (2015) **5-Factors**						Hou, Xue, and Zhang (2015) **q-Factors**				
Decile	α_{CAPM}	β_{MKT}	α_{FF}	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	α_q	β_{MKT}	β_{SIZE}	β_{INV}	β_{ROE}
							Value-Weighted Portfolios						
Short	4.4%	1.02	-0.9%	1.04	0.80	0.40	0.19	0.16	1.5%	0.98	0.68	0.52	-0.21
2	5.1%	0.93	1.1%	0.95	0.56	0.24	0.17	0.20	2.9%	0.90	0.47	0.32	-0.08
3	5.1%	0.96	2.2%	0.96	0.46	0.17	0.05	0.18	3.1%	0.93	0.39	0.16	0.03
4	5.3%	0.94	2.2%	0.97	0.33	0.16	0.08	0.28	3.4%	0.93	0.28	0.15	0.08
5	3.5%	0.95	1.6%	0.99	0.10	0.07	0.07	0.22	2.0%	0.98	0.07	0.13	0.13
6	3.3%	0.90	1.2%	0.94	0.13	-0.18	0.40	0.17	1.7%	0.91	0.11	0.10	0.12
7	1.2%	0.98	0.6%	0.99	0.03	-0.07	0.03	0.17	0.8%	0.99	0.00	-0.01	0.10
8	-1.0%	1.01	-0.7%	1.01	-0.03	-0.14	0.10	0.00	0.5%	1.00	-0.07	-0.09	-0.06
9	-3.2%	1.16	-3.3%	1.14	0.08	-0.06	-0.09	0.13	-2.6%	1.14	0.03	-0.15	0.06
Long	-7.4%	1.33	-4.6%	1.22	0.14	-0.22	-0.07	-0.36	-3.8%	1.24	0.12	-0.31	-0.27
L-S	-11.8%	0.31	-3.7%	0.18	-0.66	-0.62	-0.26	-0.52	-5.3%	0.26	-0.56	-0.83	-0.06
(t_{L-S})	(-3.20)	(3.31)	(-1.55)	(2.32)	(-4.59)	(-3.69)	(-1.50)	(-3.59)	(-1.88)	(3.82)	(-3.93)	(-4.14)	(-0.32)
							Equal-Weighted Portfolios						
Short	9.2%	0.96	4.9%	0.90	1.05	0.41	0.10	-0.07	7.7%	0.85	0.91	0.47	-0.45
2	7.0%	0.98	3.1%	0.91	0.95	0.31	0.04	0.05	5.7%	0.87	0.80	0.32	-0.33
3	7.2%	1.02	4.0%	0.94	0.92	0.29	-0.03	0.01	6.0%	0.91	0.80	0.23	-0.28
4	5.6%	1.05	2.7%	0.97	0.85	0.20	0.00	0.04	4.4%	0.94	0.75	0.14	-0.20
5	4.5%	1.08	1.7%	1.01	0.79	0.17	0.02	0.04	3.7%	0.97	0.68	0.13	-0.22
6	2.8%	1.09	0.5%	1.01	0.74	0.15	-0.03	0.05	2.6%	0.99	0.63	0.07	-0.22
7	1.2%	1.15	-0.5%	1.05	0.74	0.10	-0.07	-0.01	1.5%	1.03	0.62	0.00	-0.24
8	-0.9%	1.18	-2.7%	1.09	0.73	0.06	0.03	-0.04	-0.4%	1.07	0.61	0.04	-0.29
9	-4.5%	1.26	-5.3%	1.12	0.78	-0.04	0.04	-0.18	-3.1%	1.12	0.66	-0.03	-0.38
Long	-9.5%	1.36	-8.1%	1.14	0.88	-0.15	0.11	-0.65	-5.0%	1.15	0.76	-0.12	-0.77
L-S	-18.7%	0.40	-13.0%	0.25	-0.17	-0.56	0.01	-0.58	-12.7%	0.30	-0.16	-0.59	-0.32
(t_{L-S})	(-7.00)	(4.68)	(-5.94)	(4.42)	(-1.16)	(-2.85)	(0.08)	(-4.12)	(-5.26)	(4.69)	(-1.10)	(-3.31)	(-1.55)