Online Appendix for "Customer Capital, Talents and Stock Returns"

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A Numerical Algorithm

The coupled PDEs involve free boundary conditions as the dividend payout boundary, the financing boundary, and the turnover boundary are endogenous. We convert PDEs in continuous time to recursive formulations in discrete time, and implement a dynamic programming algorithm to solve the model.

A.1 Discretization of the Original Problem

Let Δ be the unit of time grid. To formulate the recursive problem, we assume that decisions in period t are made after the realization of lumpy capital shocks $\mathrm{d}M_t$ but before the realization of shocks $a_{t+\Delta}$, $f_{t+\Delta}$, $\mathrm{d}Z_t$, and $\xi_{t+\Delta}$. As long as the time grid is sufficiently small, whether decisions are made before or after shock realization would not affect the results. We adopt this timing assumption because (1). it ensures that the firm can issue equity immediately after the realization of lumpy cash flow shocks to avoid dealing with the case of negative cash holdings;

(2). it ensures that each state corresponds to a specific set of decisions that are independent of the realized shocks $a_{t+\Delta}$, $f_{t+\Delta}$, $\mathrm{d}Z_t$, and $\xi_{t+\Delta}$. See Figure A.1 for the detailed timing of events.

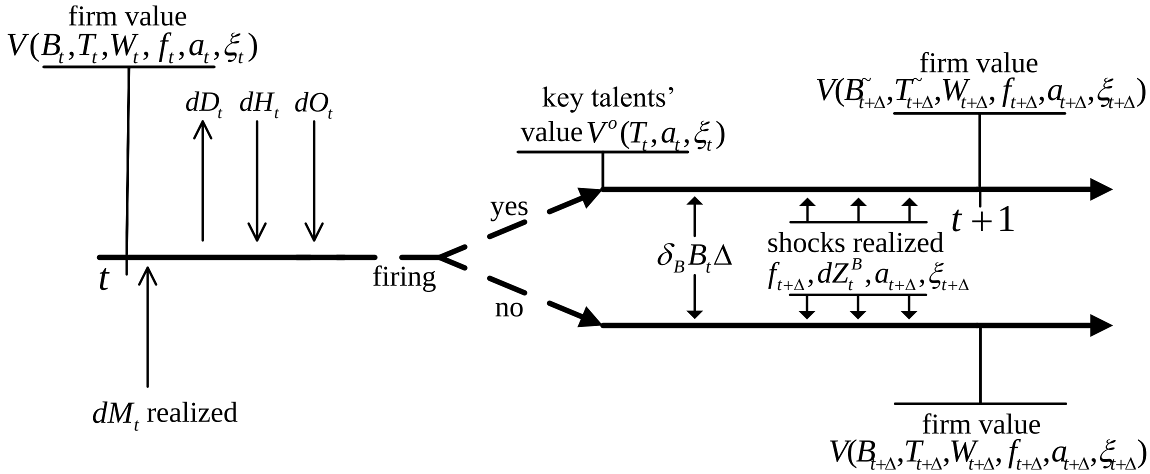

Figure A.1: Timing of events.

The firm solves the following recursive problem in discrete time

$$
\begin{aligned}
&V(B_t, T_t, W_t, f_t, a_t, \xi_t) = \max_{\tau_t, s_t, \mathrm{d}D_t, \mathrm{d}H_t, \overline{\tau_t}, \overline{s_t}, \overline{\mathrm{d}D_t}, \overline{\mathrm{d}H_t}} \\
&(1-\xi_t\Delta)\left[\mathrm{d}D_t - \mathrm{d}H_t - \mathrm{d}X_t + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(B_{t+\Delta}, T_{t+\Delta}, W_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right. \\
&\left. +\vartheta\Delta\max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(B_{t+\Delta}, T_{t+\Delta}, W_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(B^{\sim}_{t+\Delta}, T^{\sim}_{t+\Delta}, W_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\right] \\
&\xi_t\Delta\left[\overline{\mathrm{d}D_t} - \overline{\mathrm{d}H_t} - \overline{\mathrm{d}X_t} + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{B_{t+\Delta}}, \overline{T_{t+\Delta}}, \overline{W_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right. \\
&\left. +\vartheta\Delta\max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{B_{t+\Delta}}, \overline{T_{t+\Delta}}, \overline{W_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{B^{\sim}_{t+\Delta}}, \overline{T^{\sim}_{t+\Delta}}, \overline{W_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\right]
\end{aligned}
\tag{A.1}
$$

In the objective function, shareholders' consumption in the current period is given by dividend $\mathrm{d}D_t$ net of equity issuance $\mathrm{d}H_t$ and issuance costs $\mathrm{d}X_t$. With probability $1-\vartheta\Delta$, the replacement shock does not arrive, in which case the continuation value is $V(B_{t+\Delta}, T_{t+\Delta}, W_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})$. With probability $\vartheta\Delta$, the replacement shock arrives, in which case the firm optimally decides whether to fire key talents. The continuation value of firing key talents is given by $V(B^{\sim}_{t+\Delta}, T^{\sim}_{t+\Delta}, W_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})$. Expectation is taken with respect to aggregate liquidity shock $\xi_{t+\Delta}$, aggregate productivity shock $a_{t+\Delta}$, customer capital transformation shocks f_t, and cash flow shocks $\mathrm{d}Z_t^B$. As the firm makes decisions after the realization of lumpy cash flow shocks $\mathrm{d}M_t$, there are two cases happening with probabilities $1-\xi_t\Delta$ and $\xi_t\Delta$.

The budget constraint is given by

$$
\begin{aligned}
W_{t+\Delta} =& (1+r\Delta-\rho\Delta)W_t - \mathrm{d}D_t + \mathrm{d}H_t + uB_t\Delta + \sigma_B B_t \mathrm{d}Z_t^B - \phi(s_t)T_t\Delta - \Gamma_t\Delta \\
& - \frac{B_t}{e^{a_t}}\left[\mu(\tau_t, s_t)m_t - \delta_B + \delta_K + \mu_a(a_t-\overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}B_t\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.2}
$$

$$
\begin{aligned}
\overline{W_{t+\Delta}} =& (1+r\Delta-\rho\Delta)W_t - \overline{\mathrm{d}D_t} + \overline{\mathrm{d}H_t} + uB_t\Delta + \sigma_B B_t \mathrm{d}Z_t^B - \zeta B_t - \phi(\overline{s_t})T_t\Delta - \overline{\Gamma_t}\Delta \\
& - \frac{B_t}{e^{a_t}}\left[\mu(\overline{\tau_t}, \overline{s_t})m_t - \delta_B + \delta_K + \mu_a(a_t-\overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}B_t\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.3}
$$

If the firm does not fire key talents, the evolution of talent-based customer capital is

$$T_{t+\Delta} = (1-\delta_B\Delta)T_t + (1-f_t)\mu(\tau_t, s_t)T_t\Delta. \tag{A.4}$$

$$\overline{T_{t+\Delta}} = (1-\delta_B\Delta)T_t + (1-f_t)\mu(\overline{\tau_t}, \overline{s_t})T_t\Delta. \tag{A.5}$$

The evolution of customer capital is given by

$$B_{t+\Delta} = (1-\delta_B\Delta)B_t + \mu(\tau_t, s_t)T_t\Delta. \tag{A.6}$$

$$\overline{B_{t+\Delta}} = (1-\delta_B\Delta)B_t + \mu(\overline{\tau_t}, \overline{s_t})T_t\Delta. \tag{A.7}$$

If the firm fires key talents successfully, the current talent-based customer capital is reduced by a fraction ω. and the next-period talent-based customer capital is given by

$$T_{t+\Delta}^{\sim} = (1-\omega)(1-\delta_B\Delta)T_t + (1-f_t)\mu(\tau_t, s_t)T_t\Delta. \tag{A.8}$$

$$\overline{T_{t+\Delta}^{\sim}} = (1-\omega)(1-\delta_B\Delta)T_t + (1-f_t)\mu(\overline{\tau_t}, \overline{s_t})T_t\Delta. \tag{A.9}$$

The evolution of customer capital is given by

$$B_{t+\Delta}^{\sim} = (1-\delta_B\Delta)B_t - \omega(1-\delta_B\Delta)T_t + \mu(\tau_t, s_t)T_t\Delta. \tag{A.10}$$

$$\overline{B_{t+\Delta}^{\sim}} = (1-\delta_B\Delta)B_t - \omega(1-\delta_B\Delta)T_t + \mu(\overline{\tau_t}, \overline{s_t})T_t\Delta. \tag{A.11}$$

The compensation to key talents is determined to honor the continuation value of key talents

$$(\Gamma_t + hB_t)\Delta = V^o(T_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t} V^o(T_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{A.12}$$

$$(\overline{\Gamma_t} + bB_t)\Delta = V^o(T_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t} V^o(\overline{T_{t+\Delta}}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{A.13}$$

In addition, the firm's decisions are constrained by

$$\tau_t, \overline{\tau_t} \in [0, \overline{\tau}]; \quad s_t, \mathrm{d}D_t, \mathrm{d}H_t, \overline{s_t}, \overline{\mathrm{d}D_t}, \overline{\mathrm{d}H_t}, \in [0, \infty). \tag{A.14}$$

A.2 Normalized Problem

Because the model is homogeneous of degree zero with respect to the firm's customer capital. We normalize the firm's problem by customer capital B_t to eliminate one state variable. Let $w_t = \frac{W_t}{B_t}$, $m_t = \frac{T_t}{B_t}$, , $\mathrm{d}\tilde{D}_t = \frac{\mathrm{d}D_t}{B_t}$, $\mathrm{d}\tilde{H}_t = \frac{\mathrm{d}H_t}{B_t}$, $\mathrm{d}\tilde{X}_t = \frac{\mathrm{d}X_t}{B_t} = [\gamma + \varpi v^o(m_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t > 0} + \varphi \mathrm{d}\tilde{H}_t$, and $\tilde{\Gamma}_t = \frac{\Gamma_t}{B_t}$.

The new state variables are m_t, w_t, f_t, a_t, ξ_t. Let $v(m_t, w_t, f_t, a_t, \xi_t)$ denote the normalized firm value, thus $v(m_t, w_t, f_t, a_t, \xi_t) = \frac{V(B_t, T_t, W_t, f_t, a_t, \xi_t)}{B_t}$.

The normalized firm value is derived from

$$\begin{aligned}
&v(m_t, w_t, f_t, a_t, \xi_t) = \max_{\tau_t, s_t, \mathrm{d}\tilde{D}_t, \mathrm{d}\tilde{H}_t, \overline{\tau_t}, \overline{s_t}, \overline{\mathrm{d}\tilde{D}_t}, \overline{\mathrm{d}\tilde{H}_t}} \\
&(1 - \xi_t\Delta)\Bigg[\mathrm{d}\tilde{D}_t - \mathrm{d}\tilde{H}_t - [\gamma + \varpi v^o(m_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t > 0} - \varphi \mathrm{d}\tilde{H}_t \\
&+ (1 - \vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\tau_t, s_t)m_t\Delta\right) v(m_{t+\Delta}, w_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
&+ \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\tau_t, s_t)m_t\Delta\right) v(m_{t+\Delta}, w_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
&\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left[(1 - \omega m_t)(1 - \delta_B\Delta) + \mu(\tau_t, s_t)m_t\Delta\right] v(m_{t+\Delta}^{\sim}, w_{t+\Delta}^{\sim}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg] \\
&\xi_t\Delta\Bigg[\overline{\mathrm{d}\tilde{D}_t} - \overline{\mathrm{d}\tilde{H}_t} - [\gamma + \varpi v^o(m_t, a_t, \xi_t)]\mathbb{1}_{\overline{\mathrm{d}\tilde{H}_t} > 0} - \varphi \overline{\mathrm{d}\tilde{H}_t} \\
&+ (1 - \vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\overline{\tau_t}, \overline{s_t})m_t\Delta\right) v(\overline{m_{t+\Delta}}, \overline{w_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
&+ \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\overline{\tau_t}, \overline{s_t})m_t\Delta\right) v(\overline{m_{t+\Delta}}, \overline{w_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
&\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left[(1 - \omega m_t)(1 - \delta_B\Delta) + \mu(\overline{\tau_t}, \overline{s_t})m_t\Delta\right] v(\overline{m_{t+\Delta}^{\sim}}, \overline{w_{t+\Delta}^{\sim}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg],
\end{aligned} \tag{A.15}$$

subject to the budget constraints,

$$
\begin{aligned}
&[1-\delta_B\Delta+\mu(\tau_t,s_t)m_t\Delta]\,w_{t+\Delta}=(1+r\Delta-\rho\Delta)w_t-\mathrm{d}\tilde{D}_t+\mathrm{d}\tilde{H}_t+u\Delta+\sigma_B\mathrm{d}Z_t^B\\
&-\alpha s_t^\eta m_t\Delta-\tilde{\Gamma}_t\Delta-\frac{1}{e^{a_t}}\left[\mu(\tau_t,s_t)m_t-\delta_B+\delta_K+\mu_a(a_t-\bar{a})+\frac{1}{2}\sigma_a^2a_t\right]+\frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.16}
$$

$$
\begin{aligned}
&[1-\delta_B\Delta+\mu(\overline{\tau_t},\overline{s_t})m_t\Delta]\,\overline{w_{t+\Delta}}=(1+r\Delta-\rho\Delta)w_t-\overline{\mathrm{d}\tilde{D}_t}+\overline{\mathrm{d}\tilde{H}_t}+u\Delta+\sigma_B\mathrm{d}Z_t^B-\zeta\\
&-\alpha \overline{s_t}^\eta m_t\Delta-\overline{\tilde{\Gamma}}_t\Delta-\frac{1}{e^{a_t}}\left[\mu(\overline{\tau_t},\overline{s_t})m_t-\delta_B+\delta_K+\mu_a(a_t-\bar{a})+\frac{1}{2}\sigma_a^2a_t\right]+\frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.17}
$$

$$
\begin{aligned}
&[(1-\omega m_t)(1-\delta_B\Delta)+\mu(\tau_t,s_t)m_t\Delta]\,w_{t+\Delta}^{\sim}=(1+r\Delta-\rho\Delta)w_t-\mathrm{d}\tilde{D}_t+\mathrm{d}\tilde{H}_t+u\Delta+\sigma_B\mathrm{d}Z_t^B\\
&-\alpha s_t^\eta m_t\Delta-\tilde{\Gamma}_t\Delta-\frac{1}{e^{a_t}}\left[\mu(\tau_t,s_t)m_t-\delta_B+\delta_K+\mu_a(a_t-\bar{a})+\frac{1}{2}\sigma_a^2a_t\right]+\frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.18}
$$

$$
\begin{aligned}
&[(1-\omega m_t)(1-\delta_B\Delta)+\mu(\tau_t,s_t)m_t\Delta]\,\overline{w_{t+\Delta}^{\sim}}=(1+r\Delta-\rho\Delta)w_t-\overline{\mathrm{d}\tilde{D}_t}+\overline{\mathrm{d}\tilde{H}_t}+u\Delta+\sigma_B\mathrm{d}Z_t^B-\zeta\\
&-\alpha \overline{s_t}^\eta m_t\Delta-\overline{\tilde{\Gamma}}_t\Delta-\frac{1}{e^{a_t}}\left[\mu(\overline{\tau_t},\overline{s_t})m_t-\delta_B+\delta_K+\mu_a(a_t-\bar{a})+\frac{1}{2}\sigma_a^2a_t\right]+\frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{A.19}
$$

the evolution of m_t,

$$m_{t+\Delta}=\frac{(1-\delta_B\Delta)m_t+(1-f_t)\mu(\tau_t,s_t)m_t\Delta}{1-\delta_B\Delta+\mu(\tau_t,s_t)m_t\Delta}, \tag{A.20}$$

$$\overline{m_{t+\Delta}}=\frac{(1-\delta_B\Delta)m_t+(1-f_t)\mu(\overline{\tau_t},\overline{s_t})m_t\Delta}{1-\delta_B\Delta+\mu(\overline{\tau_t},\overline{s_t})m_t\Delta}, \tag{A.21}$$

$$m_{t+\Delta}^{\sim}=\frac{(1-\omega)(1-\delta_B\Delta)m_t+(1-f_t)\mu(\tau_t,s_t)m_t\Delta}{(1-\omega m_t)(1-\delta_B\Delta)+\mu(\tau_t,s_t)m_t\Delta}, \tag{A.22}$$

$$\overline{m_{t+\Delta}^{\sim}}=\frac{(1-\omega)(1-\delta_B\Delta)m_t+(1-f_t)\mu(\overline{\tau_t},\overline{s_t})m_t\Delta}{(1-\omega m_t)(1-\delta_B\Delta)+\mu(\overline{\tau_t},\overline{s_t})m_t\Delta}, \tag{A.23}$$

the compensation to key talents,

$$(\tilde{\Gamma}_t+h)\Delta=v^o(m_t,a_t,\xi_t)-\mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta+\mu(\tau_t,s_t)m_t\Delta\right)v^o(m_{t+\Delta},a_{t+\Delta},\xi_{t+\Delta})\right], \tag{A.24}$$

$$(\overline{\tilde{\Gamma}}_t+h)\Delta=v^o(m_t,a_t,\xi_t)-\mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta+\mu(\overline{\tau_t},\overline{s_t})m_t\Delta\right)v^o(\overline{m_{t+\Delta}},a_{t+\Delta},\xi_{t+\Delta})\right], \tag{A.25}$$

The normalized continuation value $v^o(m_t, a_t, \xi_t) = \frac{V^o(T_t, a_t, \xi_t)}{B_t}$ is given by

$$v^o(m_t, a_t, \xi_t) = v^n(m_t, a_t, \xi_t) + \gamma(\omega + \ell)m_t + \varphi W_0^*(\omega + \ell)m_t, \tag{A.26}$$

where $v^n(m_t, a_t, \xi_t)$ is derived from equation (A.27) and W_0^* is the optimal solution to equation (A.27),

$$v^n(m_t, a_t, \xi_t) = \max_{W_0}(\omega + \ell)m_t \left[-\gamma - (1 + \varphi)W_0 + \mathbb{E}[v\left(1 - f', W_0, f', a_t, \xi_t\right)]\right]. \tag{A.27}$$

As we explain in subsection A.3, implementing our numerical algorithms also require solving two special cases of the normalized problem, one with zero financing costs and one with no new customer flows. We write down their formulations below.

Zero Financing Costs When the financing costs are zero, the firm does not hold cash. The firm's state variable are m, f, a, and ξ. Given our calibration, the firm does not fire key talents because the expected cash inflows generated by key talents are larger than their compensation. Thus the firm solves the following problem to maximize shareholder value:

$$\begin{aligned}
&v(m_t, f_t, a_t, \xi_t) = \max_{\tau_t, s_t, \overline{\tau_t}, \overline{s_t}} \\
&(1 - \xi_t\Delta)\left[u\Delta - \alpha s_t^\eta m_t\Delta - \tilde{\Gamma}_t\Delta - \frac{1}{e^{a_t}}\left(\mu(\tau_t, s_t)m_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right)\right. \\
&\left. + \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\tau_t, s_t)m_t\Delta\right)v(m_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right] \\
&+ \xi_t\Delta\left[u\Delta - \zeta - \alpha\overline{s_t}^\eta m_t\Delta - \overline{\tilde{\Gamma}}_t\Delta - \frac{1}{e^{a_t}}\left(\mu(\overline{\tau_t}, \overline{s_t})m_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right)\right. \\
&\left. + \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \mu(\overline{\tau_t}, \overline{s_t})m_t\Delta\right)v(\overline{m_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right],
\end{aligned} \tag{A.28}$$

subject to the evolution of m_t,

$$m_{t+\Delta} = \frac{(1 - \delta_B\Delta)m_t + (1 - f_t)\mu(\tau_t, s_t)m_t\Delta}{1 - \delta_B\Delta + \mu(\tau_t, s_t)m_t\Delta}, \tag{A.29}$$

$$\overline{m_{t+\Delta}} = \frac{(1 - \delta_B\Delta)m_t + (1 - f_t)\mu(\overline{\tau_t}, \overline{s_t})m_t\Delta}{1 - \delta_B\Delta + \mu(\overline{\tau_t}, \overline{s_t})m_t\Delta}, \tag{A.30}$$

the compensation to key talents,

$$\tilde{\Gamma}_t\Delta = v^o(m_t, a_t, \xi_t) - E_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta+\mu(\tau_t,s_t)m_t\Delta\right)v^o(m_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{A.31}$$

$$\overline{\tilde{\Gamma}_t}\Delta = v^o(m_t, a_t, \xi_t) - E_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta+\mu(\overline{\tau_t},\overline{s_t})m_t\Delta\right)v^o(\overline{m_{t+\Delta}}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{A.32}$$

where the normalized continuation value $v^o(m_t, a_t, \xi_t) = \frac{V^o(T_t, a_t, \xi_t)}{B_t}$ is given by

$$v^o(m_t, a_t, \xi_t) = (\omega+\ell)m_t\mathbb{E}_t\left[v\left(1-f', f', a_t, \xi_t\right)\right]. \tag{A.33}$$

No New Customer Flows When we set $\psi = 0$, there are no new customer flows. Thus the firm's hiring and discount decisions are trivially determined by $\tau_t = s_t = \overline{\tau_t} = \overline{s_t} = 0$. The normalized firm value can be written as

$$\begin{aligned}
&v(m_t, w_t, f_t, a_t, \xi_t) = \max_{\mathrm{d}\tilde{D}_t, \mathrm{d}\tilde{H}_t, \overline{\mathrm{d}\tilde{D}_t}, \overline{\mathrm{d}\tilde{H}_t}} \\
&(1-\xi_t\Delta)\Bigg[\mathrm{d}\tilde{D}_t - \mathrm{d}\tilde{H}_t - [\gamma+\varpi v^o(m_t,a_t,\xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t>0} - \varphi\mathrm{d}\tilde{H}_t \\
&+(1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta\right)v(m_{t+\Delta}, w_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
&+\vartheta\Delta\max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta\right)v(m_{t+\Delta}, w_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right),\right. \\
&\left.\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)(1-\omega m_t)v(m^{\sim}_{t+\Delta}, w^{\sim}_{t+\Delta}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\Bigg] \\
&\xi_t\Delta\Bigg[\overline{\mathrm{d}\tilde{D}_t} - \overline{\mathrm{d}\tilde{H}_t} - [\gamma+\varpi v^o(m_t,a_t,\xi_t)]\mathbb{1}_{\overline{\mathrm{d}\tilde{H}_t}>0} - \varphi\overline{\mathrm{d}\tilde{H}_t} \\
&+(1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta\right)v(\overline{m_{t+\Delta}}, \overline{w_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
&+\vartheta\Delta\max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta\right)v(\overline{m_{t+\Delta}}, \overline{w_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right),\right. \\
&\left.\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)(1-\omega m_t)v(\overline{m^{\sim}_{t+\Delta}}, \overline{w^{\sim}_{t+\Delta}}, f_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\Bigg],
\end{aligned} \tag{A.34}$$

subject to the budget constraints,

$$\begin{aligned}
(1-\delta_B\Delta)w_{t+\Delta} =& (1+r\Delta-\rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_B\mathrm{d}Z_t^B - \tilde{\Gamma}_t\Delta \\
&-\frac{1}{e^{a_t}}\left[-\delta_B+\delta_K+\mu_a(a_t-\overline{a})+\frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned} \tag{A.35}$$

$$
\begin{aligned}
(1-\delta_B\Delta)\overline{w_{t+\Delta}} =& (1+r\Delta-\rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_B \mathrm{d}Z_t^B - \overline{\tilde{\Gamma}}_t\Delta - \zeta \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t-\bar{a}) + \frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned} \tag{A.36}
$$

$$
\begin{aligned}
(1-\omega m_t)(1-\delta_B\Delta)w_{t+\Delta}^{\sim} =& (1+r\Delta-\rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_B \mathrm{d}Z_t^B - \tilde{\Gamma}_t\Delta \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t-\bar{a}) + \frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned} \tag{A.37}
$$

$$
\begin{aligned}
(1-\omega m_t)(1-\delta_B\Delta)\overline{w_{t+\Delta}^{\sim}} =& (1+r\Delta-\rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_B \mathrm{d}Z_t^B - \overline{\tilde{\Gamma}}_t\Delta - \zeta \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t-\bar{a}) + \frac{1}{2}\sigma_a^2 a_t\right] + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned} \tag{A.38}
$$

the evolution of m_t,

$$
m_{t+\Delta} = \overline{m_{t+\Delta}} = m_t, \tag{A.39}
$$

$$
m_{t+\Delta}^{\sim} = \overline{m_{t+\Delta}^{\sim}} = \frac{1-\omega}{1-\omega m_t} m_t, \tag{A.40}
$$

the compensation to key talents,

$$
\tilde{\Gamma}_t\Delta = v^o(m_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v^o(m_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{A.41}
$$

$$
\overline{\tilde{\Gamma}}_t\Delta = v^o(m_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v^o(\overline{m_{t+\Delta}}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{A.42}
$$

The normalized continuation value $v^o(m_t, a_t, \xi_t) = \frac{V^o(T_t, a_t, \xi_t)}{B_t}$ is given by

$$
v^o(m_t, a_t, \xi_t) = v^n(m_t, a_t, \xi_t) + \gamma(\omega+\ell)m_t + \varphi W_0^*(\omega+\ell)m_t, \tag{A.43}
$$

where $v^n(m_t, a_t, \xi_t)$ is derived from equation (A.44) and W_0^* is the optimal solution to equation (A.44),

$$
v^n(m_t, a_t, \xi_t) = \max_{W_0}(\omega+\ell)m_t\left[-\gamma-(1+\varphi)W_0 + \mathbb{E}[v(1-f', W_0, f', a_t, \xi_t)]\right]. \tag{A.44}
$$

A.3 Implementation

We discretize the cash flow shocks based on 11 grids spanning from $-3\sigma_B$ to $3\sigma_B$ and the aggregate productivity shocks based on 5 grids spanning from $-3\sigma_a$ to $3\sigma_a$ using the method of Tauchen (1986). We use collocation methods to solve the firm's problem (A.15). Let

$S = S_m \times S_w \times S_f \times S_a \times S_\xi$ be the grid of collocation nodes, where $S_m = \{s_{m_1}, s_{m_2}, ..., s_{m_l}\}$, $S_w = \{s_{w_1}, s_{w_2}, ..., s_{w_k}\}$, $S_f = \{s_{f_1}, s_{f_2}\}$, $S_a = \{s_{a_1}, ..., s_{a_5}\}$ and $S_\xi = \{s_{\xi_1}, s_{\xi_2}\}$. Our solution indicates the model is highly nonlinear in w, thus we set $w_k = 101$ and use 100 equi-spaced nodes from 0 to 0.6 to construct S_w. The lower bound s_{w_1} is set to be zero because we restrict the firm to have non-zero cash holdings in our model. The firm's dividend payout boundary increases with m and the arrival rate of lumpy cash flow shocks. We thus choose the upper bound s_{w_k} so that even when the arrival rate is high (i.e. $\xi = \xi_H$), the dividend payout boundary $\overline{w}$ is below s_{w_k} for the firm with $m = 1$. Our solution indicates that the firm's decisions are approximately linear in m, thus we set $m_l = 11$ and use 10 equi-spaced nodes from 0 to 1 to construct S_m. The states $s_{a_1}, ..., s_{a_5}$ correspond to the five levels of aggregate productivity shocks. The states s_{f_1}, s_{f_2} correspond to the two levels of pure-brand-based transformation rate $f_{(1)}, f_{(2)}$. The states s_{ξ_1} and s_{ξ_2} correspond to the arrival rates of lumpy cash flow shocks, ξ_L and ξ_H. When solving continuous time models in discrete time, it is important to choose the time grid consistent with the state space. This is because if the time grid is too dense relative to the state grid, the solution of the value functions tend to be non-smooth. If the time grid is too sparse relative to the state grid, computing power is wasted without increasing accuracy. By trial and error, we set our time grid $\Delta = 1/365$, which implies that one period in our discretized model represents one day.

We approximate the firm's value function $v(m, w, f, a, \xi)$ on S using a linear spline with coefficients corresponding to each grid point. We first form a guess for the spline's $m_l \times w_k \times 2 \times 5 \times 2$ coefficients, then we iterate to obtain a vector that solves the system of $m_l \times w_k \times 2 \times 5 \times 2$ Bellman equations. Below we detail the procedures of forming initial guess and calculating iterations.

Initial Guess The major difficulty of implementing a dynamic programming algorithm to solve a continuous-time value function is that the convergence of value functions requires tens of thousands of iterations. When solving the model, we find that the marginal value of liquidity, $v_w(m, w, f, a, \xi)$ converges to the true value much faster than the convergence of the value function $v(m, w, f, a, \xi)$. In many macroeconomics and finance models, the absolute value of value functions would not matter for the decisions made by economic agents. However, in our model, the cost of firing key talents is captured by a reduction in the firm's customer capital. In the normalized problem (A.15), the cost of firing key talents increases with the absolute value of $v(m, w, f, a, \xi)$. Therefore, in order to get the firm's firing decisions right, we have to accurately solve the absolute value of $v(m, w, f, a, \xi)$.

In principle, we can start with any initial guess of the value function $v(m, w, f, a, \xi)$ and do a sufficiently large number of iterations to reach convergence, which is guaranteed by the contraction mapping theorem. However, this is very costly as each iteration takes several minutes to finish given that our model has two endogenous state variables and four decision variables. To form an initial guess that is close to the final solution, we solve the model in three step.

First, we solve the firm's problem (A.28) in a perfect financial market. This problem is much easier to solve because m is the only endogenous state variable. We iterate the value functions for about 60,000 times to reach a convergence until the level of accuracy satisfies $max_{(m,f,a,\xi)\in\{S_m\times S_f\times S_a\times S_\xi\}}|V^1_{n^1-1}(m,f,a,\xi) - V^1_{n^1}(m,f,a,\xi)| < 10^{-16}$ at the n^1th iteration.

Second, we use the value functions $V^1(m,f,a,\xi)$ from the perfect financial market to initialize the firm's value functions in problem (A.34) with no new customer flows. Specifically, we initialize the value of $V^2(m,w,f,a,\xi)$ at collocation nodes $S_m \times S_w \times S_f \times S_a \times S_\xi$ by setting $V^2_0(m,w,f,a,\xi) = V^1_{n^1}(m,f,a,\xi) + w$. We start with the first iteration with perfect financial market, i.e. $\gamma = \varphi = 0$, and linearly increase the financing costs to the calibrated values of γ and φ in the first 100 iterations. This is to ensure that the value and policy functions move smoothly from the perfect financial market to the frictional financial market. We then continue iterating the value functions $V^2(m,w,f,a,\xi)$ for another 6,000 times to reach a convergence until the level of accuracy satisfies $max_{(m,w,f,a,\xi)\in\{S_m\times S_w\times S_f\times S_a\times S_\xi\}}|V^2_{n^2-1}(m,w,f,a,\xi) - V^2_{n^2}(m,w,f,a,\xi)| < 10^{-7}$ at the n^2th iteration.

Third, we use the value functions $V^2(m,w,f,a,\xi)$ to initialize the firm's value functions in problem (A.15) by setting $V^3_0(m,w,f,a,\xi) = V^2_{n^2}(m,w,f,a,\xi)$. Then we iterate the value functions $V^3_0(m,w,f,a,\xi)$ for about 6,000 times to reach a convergence until the level of accuracy satisfies $max_{(m,w,f,a,\xi)\in\{S_m\times S_w\times S_f\times S_a\times S_\xi\}}|V^3_{n^3-1}(m,w,f,a,\xi) - V^3_{n^3}(m,w,f,a,\xi)| < 10^{-7}$ at the n^3th iteration.

Calculating Iterations Given the value functions from the previous iteration, we use golden section search to find the optimal financing, payout, discounts, and sales decisions. The way to search for the optimal discounts and sales decisions are straight forward because both decision variables are continuous. When searching for the discount decision, we set the initial upper bound to be $\overline{\tau}$ and the the initial lower bound to be 0. When searching for the optimal sales decision, we set the initial lower bound to be zero and the initial upper bound is set to guarantee a non-negative cash ratio in the next period even when the worst idiosyncratic cash flow shock occurs.

Searching for the optimal financing and payout decisions are more involved because they only happen at the boundaries when time is continuous. There are two complications when solving this continuous-time model in discrete time. First, the firm starts to issue equity in advance before cash ratio exactly hits the zero lower bound. Second, the discretized cash flow shocks may drive the next period cash ratio to a negative number even when the firm's current period cash ratio is strictly positive. We deal with the first problem by choosing a fine time grid $\Delta = 1/365$. This ensures a reasonably good approximation as the firm issues equity when cash ratio drops below 0.01, the smallest cash ratio grid we consider. To deal with the second issue, we impose a sufficiently large penalty on the firm's value (in the code, we subtract the firm's value by 10) whenever the next-period cash ratio drops below zero. This is to ensure that the firm would issue equity whenever there is a chance to have a negative cash ratio in the next period given our discretization of cash flow shocks. The large penalty is important to guarantee the convergence of the value functions. If the penalty is not large enough, then the firm may wait for a bit longer before issuing equity, and as a result, the optimal financing boundary is not correctly solved at this level of discretization.

Having dealt with the two issues above, we search for optimal financing and payout boundaries separately using golden section search. Regarding the financing boundary, we set the initial lower bound to be zero and the initial upper bound to be the highest cash ratio grid, s_{w_k}. If the search algorithm returns zero, it means that the firm does not issue equity in that state. Otherwise, the search algorithm returns some positive number, which is the optimal amount of equity issued by the firm. Therefore, the golden section search allows us to simultaneously find the financing boundary and the amount of financing. Regarding the payout boundary, we set the initial lower bound to be zero and the initial upper bound to be the firm's current cash ratio. Then similarly, the golden section search allows us to find both the payout boundary and the amount of dividend.

B Mimicking Portfolio Analysis

We construct the mimicking portfolio for BTR by projecting the BMT portfolio returns onto the space of excess returns of asset pricing factors and industry portfolios. Specifically, we run the following regression:

$$\begin{aligned}\mathrm{BMT}_t = a + b'[&\mathrm{BL}, \mathrm{BM}, \mathrm{BH}, \mathrm{SL}, \mathrm{SM}, \mathrm{SH}, \mathrm{Mom}, \mathrm{RMW}, \mathrm{CMA}, \mathrm{Ind}_{cnsmr}, \mathrm{Ind}_{manuf}, \\ &\mathrm{Ind}_{hitec}, \mathrm{Ind}_{hlth}, \mathrm{Ind}_{other}, \mathrm{PS}, \mathrm{HKM}, \mathrm{LS\_}\beta_{AEM}, \mathrm{LS\_}\beta_{VXO}]_t + \varepsilon_t.\end{aligned} \tag{B.1}$$

Here, BMT_t is the value-weighted returns of the BMT portfolio. BL, BM, BH, SL, SM and SH are the excess returns of the six Fama-French benchmark portfolios on size (*S*mall and *B*ig) and book-to-market (*L*ow, *M*edium, and *H*igh) in excess of the risk-free rate. Mom is the momentum factor, RMW and CMA are the profitability factor and the investment factor from the Fama-French five factor model. Ind_{cnsmr}, Ind_{manuf}, Ind_{hitec}, Ind_{hlth}, and Ind_{other} are the Fama-French five industry returns in excess of the risk-free rate. PS is the Pástor-Stambaugh market liquidity factor.

In the projection space of the excess returns, we also include three measures of the aggregate liquidity condition. HKM is the intermediary capital risk factor in He, Kelly and Manela (2017). LS_β_{AEM} is the returns of the long-short portfolio of the betas, estimated by regressing the returns of individual stocks on the broker-dealer leverage ratio (see Adrian, Etula and Muir, 2014).[1] LS_β_{VXO} is the returns of the long-short portfolio of the betas, estimated by regressing the returns of individual stocks on the changes of the monthly CBOE S&P 100 volatility index (VXO).[2] We show the correlation matrix between BMT and the three aggregate liquidity measures in Table B.1. The BTR mimicking portfolio return is given by:

$$\begin{aligned}\mathrm{MP}_t = \hat{b}'[&\mathrm{BL}, \mathrm{BM}, \mathrm{BH}, \mathrm{SL}, \mathrm{SM}, \mathrm{SH}, \mathrm{Mom}, \mathrm{RMW}, \mathrm{CMA}, \mathrm{Ind}_{cnsmr}, \mathrm{Ind}_{manuf}, \\ &\mathrm{Ind}_{hitec}, \mathrm{Ind}_{hlth}, \mathrm{Ind}_{other}, \mathrm{PS}, \mathrm{HKM}, \mathrm{LS\_}\beta_{AEM}, \mathrm{LS\_}\beta_{VXO}]_t.\end{aligned} \tag{B.2}$$

We next estimate two sets of mimicking portfolio betas for firm i in month t. We estimate the first set of mimicking portfolio betas with the controls of the Fama-French three factors and use them in the asset pricing tests.[3] The second set of mimicking portfolio betas are estimated without the controls of asset pricing factors. We use these univariate mimicking portfolio betas to study their relation with key talent turnovers and corporate financial policies, where the outcome variables are not asset returns; the usage of asset pricing factors as controls does not have theoretical underpinnings.

$$\mathrm{ret}_{i,t} = \alpha_{i,\tilde{t}} + \beta_{i,t}\mathrm{MP}_{\tilde{t}} + \gamma_{i,t}\mathrm{MktRf}_{\tilde{t}} + \delta_{i,t}\mathrm{SMB}_{\tilde{t}} + \eta_{i,t}\mathrm{HML}_{\tilde{t}} + \varepsilon_{i,\tilde{t}},\ where\ \tilde{t} \in [t-36, t-1]. \tag{B.3}$$

$$\mathrm{ret}_{i,t} = \alpha_{i\tilde{t}} + \beta_{i,t}\mathrm{MP}_{\tilde{t}} + \varepsilon_{i,\tilde{t}},\ where\ \tilde{t} \in [t-36, t-1]. \tag{B.4}$$

The estimated coefficients $\hat{\beta}_{i,t}$ are the mimicking portfolio betas for firm i in month t. We compute the average values of $\hat{\beta}_{i,t}$ at yearly frequency (denoted as β_{mp}) to reduce the noise of the estimated results. Table B.2 shows the summary statistics of the extended sample. [4]

We use the mimicking portfolio betas as a proxy for BTR and repeat our empirical analyses.

[1] We do not project the BMT returns directly onto the broker-dealer leverage ratio and the changes of VXO index because the vectors in the projection space should be tradable returns.

[2] VXO index is available from 1986 onward. We follow Bloom (2009) and extend the VXO times series back to 1926. Prior to 1986, VXO is calculated as the monthly standard deviation of the daily S&P 500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward.

[3] Pastor and Stambaugh (2003) use the same approach to study the asset pricing implications of the market liquidity betas.

[4] The HKM factor is available from 1970. When there are less than 36 monthly historical returns, we require at least 12 monthly returns (1-year data) to estimate the mimicking portfolio beta. After we estimate the monthly mimicking portfolio betas, we take the yearly average to reduce noise. We then sort stocks into quintiles based on their lagged annual mimicking portfolio beta to perform asset pricing tests. Thus, the sample for the mimicking portfolio analyses starts from 1972.

We find that the firms with higher mimicking portfolio betas are associated with lower alphas (see Table B.3). We then study the relation between the mimicking portfolio betas and firms' cash flow volatilities, key talent turnovers, and financial policies. To mitigate the errors-in-variable problem, we use the quintiles of the mimicking portfolio betas (denoted as β_{mp}^{Q}) as the independent variables in the regressions. We find that the firms with higher β_{mp}^{Q} have lower cash flow volatilities (see Table B.4) and higher turnover rates of CEOs and innovators (see Table B.5). Moreover, these firms are less likely to adopt precautionary financial policies (see Table B.6). They hold less cash, issue less equity, and pay out more dividends. In summary, the role of the mimicking portfolio betas in the extended sample is very similar to the role of BTR in the BAV sample, strongly supporting our model's predictions.

Table B.1: Correlation among BMT and aggregate liquidity measures.

	BMT	HKM	LS_β_{AEM}	LS_β_{VXO}
BMT	1			
HKM	-0.103	1		
LS_β_{AEM}	0.194	-0.130	1	
LS_β_{VXO}	0.566	-0.382	0.265	1

Note: This table shows the correlation among BMT and three aggregate liquidity measures. The first measure HKM is the intermediary capital risk factor in He, Kelly and Manela (2017). The second measure, LS_β_{AEM}, is the returns of the long-short portfolio of the beta with the broker-dealer leverage ratio (see Adrian, Etula and Muir, 2014). The last measure, LS_β_{VXO}, is the returns of the long-short portfolio of the beta with the changes of the monthly CBOE S&P 100 volatility index (VXO). VXO index is available from 1986 onward. We follow Bloom (2009) and extend the VXO times series back to 1926. Prior to 1986, VXO is calculated as the monthly standard deviation of the daily S&P 500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward.

Table B.2: Summary statistics for the mimicking portfolio samples.

Variables	Mean	Median	10%	90%	S.D.	# of obs.
Firm Characteristics						
lnsize	4.73	4.57	1.81	8.75	2.32	122,610
lnBEME	−0.47	−0.41	−1.64	0.65	0.95	119,279
lnlev	−0.16	−0.13	−1.51	1.09	1.11	119,875
ln(OC/Asset)	−0.41	−0.20	−1.67	0.72	1.25	117,525
Cash Flow Volatility						
Vol(Daily Ret) (%)	3.64	2.98	1.55	6.44	2.59	123,919
Vol(Sales_Gr) (%)	30.63	14.58	4.44	48.71	74.04	113,399
Vol(Net Income/Asset) (%)	9.70	4.19	1.03	22.87	16.11	114,063
Vol(EBITDA/Asset) (%)	6.92	3.96	1.23	14.44	9.70	113,897
Key Talent Compensation						
Administrative Expenses/Sales (%)	24.55	20.65	7.27	47.53	16.63	111,763
R&D/Sales (%)	21.86	4.24	0.55	32.46	30.51	59,110
Execucomp/Sales (%)	0.93	0.54	0.12	2.42	1.02	27,995
CEO Turnover						
$\text{Turnover}_t^{(1)} \times 100$	4.15	0	0	0	19.95	26,974
$\text{Turnover}_t^{(2)} \times 100$	4.76	0	0	0	21.30	26,974
Innovator Turnover						
$ln(1 + \text{leavers})$	0.24	0	0	1.1	0.58	32,550
$ln(1 + \text{new hires})$	0.23	0	0	0.69	0.55	32,550
Corporate Financial Policy						
Cash/Lagged Asset (%)	16.76	7.95	1.00	44.50	22.63	123,365
ΔCash/Net Income (%)	12.02	0	−73.05	117.22	209.96	88,236
ΔEquity/Lagged Asset (%)	4.82	0.22	0	7.72	17.27	123,366
Payout/Lagged Asset (%)	2.45	0.68	0	6.82	4.40	123,366
Dividend/Lagged Asset (%)	1.09	0	0	3.25	1.91	123,366
Repurchases/Lagged Asset (%)	1.26	0	0	4.03	3.29	123,366

Note: This table shows the summary statistics for the mimicking portfolio sample. We explain the details of constructing the mimicking portfolio beta in the main text. Briefly, we project the returns of the BMT portfolio on asset pricing factors to obtain the mimicking portfolio for BMT. We then regress stock returns of individual firms on the returns of the mimicking portfolio to find their mimicking portfolio beta. We then merge the mimicking portfolio beta with Compustat, Execucomp, and the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014). The mimicking portfolio betas are derived from CRSP and the sample period is 1972 to 2016. CEO turnover variables are derived from Execucomp and the sample period is 1992 to 2016. Innovator turnover variables are derived from the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), and the sample period is 1975 to 2010. Corporate financial policy variables and control variables are derived from Compustat and the sample period is 1972 to 2016. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We explain the definition of the variables in Appendix Table **??**.

Table B.3: Excess portfolio returns sorted on mimicking portfolio betas

β_{mp} Portfolios	1 (Low)	2	3	4	5 (High)	$5-1$
			Panel A: Average Excess Returns			
E[R]-r_f (%)	14.23***	11.53***	10.78***	11.49***	12.50***	-1.74
	[3.93]	[4.22]	[4.17]	[4.45]	[4.15]	[-0.88]
			Panel B: Carhart Four-Factor Model			
α (%)	8.33***	5.10***	3.97***	4.47***	4.44***	-3.89^{**}
	[6.17]	[6.71]	[5.44]	[5.97]	[3.43]	[-2.09]
β_{mkt}	1.18***	1.04***	1.03***	1.03***	1.09***	-0.09^{**}
	[45.48]	[71.63]	[73.55]	[71.73]	[43.75]	[-2.58]
β_{smb}	0.60***	0.27***	0.17***	0.18***	0.40***	-0.20^{***}
	[16.47]	[13.23]	[8.53]	[8.80]	[11.57]	[-3.91]
β_{hml}	-0.31^{***}	0.01	0.09***	0.11***	0.09**	0.40***
	[-7.89]	[0.29]	[4.23]	[5.16]	[2.35]	[7.36]
β_{mom}	-0.18^{***}	-0.11^{***}	-0.08^{***}	-0.07^{***}	-0.02	0.16***
	[-7.17]	[-7.85]	[-5.61]	[-4.68]	[-1.02]	[4.50]
R^2	0.874	0.930	0.928	0.924	0.833	0.197
			Panel C: Pástor-Stambaugh Five-Factor Model			
α (%)	8.10***	4.93***	3.95***	4.22***	3.88***	-4.21^{**}
	[5.97]	[6.47]	[5.37]	[5.65]	[3.02]	[-2.26]
β_{mkt}	1.18***	1.04***	1.03***	1.03***	1.08***	-0.09^{***}
	[45.52]	[71.84]	[73.47]	[72.27]	[44.31]	[-2.60]
β_{smb}	0.60***	0.27***	0.17***	0.18***	0.40***	-0.20^{***}
	[16.45]	[13.22]	[8.51]	[8.80]	[11.64]	[-3.95]
β_{hml}	-0.32^{***}	0.00	0.09***	0.11***	0.08**	0.40***
	[-7.96]	[0.20]	[4.21]	[5.06]	[2.21]	[7.30]
β_{mom}	-0.18^{***}	-0.11^{***}	-0.08^{***}	-0.07^{***}	-0.02	0.16***
	[-7.17]	[-7.86]	[-5.60]	[-4.69]	[-1.00]	[4.52]
β_{ps}	5.02	3.80**	0.53	5.42***	12.02***	7.00
	[1.59]	[2.14]	[0.31]	[3.11]	[4.02]	[1.61]
R^2	0.874	0.930	0.928	0.925	0.838	0.201

Note: This table shows the asset pricing tests for portfolios sorted on mimicking portfolio beta. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive consumer survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. In June of year t, we sort firms into five quintiles based on firms' mimicking portfolio beta in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We compute the value-weighted portfolio returns and report the average excess returns of the individual portfolios and the long/short portfolio. We also report the portfolio alphas and betas estimated by the Carhart four-factor model and the Pástor-Stambaugh five-factor model. Data on SMB, HML, and MOM are from Kenneth French's website. The liquidity factor is from L'uboš Pástor's website. The sample of this table is the CRSP monthly data from Jan. 1972 to Dec. 2016. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table B.4: Mimicking portfolio betas and cash flow volatilities.

	(1) Vol(Daily Ret)$_t$ (%)	(2) Vol(Sales_Gr)$_t$ (%)	(3) Vol($\frac{\text{NI}}{\text{Asset}}$)$_t$ (%)	(4) Vol($\frac{\text{EBITDA}}{\text{Asset}}$)$_t$ (%)
$\beta^{Q}_{mp,t-1}$	-0.106^{***}	-0.819^{**}	-0.635^{***}	-0.305^{***}
	[-3.698]	[-2.662]	[-4.795]	[-4.816]
$ln(\text{OC}/\text{Asset})_{t-1}$	0.058^{***}	-5.057^{***}	0.072	-0.009
	[4.501]	[-7.040]	[0.566]	[-0.108]
$ln\text{size}_{t-1}$	-0.576^{***}	-7.326^{***}	-2.198^{***}	-1.578^{***}
	[-16.006]	[-19.389]	[-24.124]	[-27.758]
$ln\text{BEME}_{t-1}$	-0.132^{***}	-12.843^{***}	-2.956^{***}	-2.715^{***}
	[-2.900]	[-14.005]	[-11.558]	[-18.153]
$ln\text{lev}_{t-1}$	0.196^{***}	-6.395^{***}	-0.388^{***}	-0.740^{***}
	[8.193]	[-8.842]	[-2.848]	[-9.792]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	114172	104225	104731	104605
R-squared	0.369	0.092	0.154	0.196

Note: This table shows the relation between mimicking portfolio beta and firms' cash flow volatility. Our analysis is performed based on the mimicking portfolio beta (denoted as β_{mp}) for BTR. The dependent variables are the volatility of daily stock returns in current year (t), volatility of the forward-looking growth rates of sales (standard deviation of the six yearly growth rates of sales over the period t through $t+5$), volatility of the forward-looking net-income-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$), volatility of the forward-looking EBITDA-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$). These dependent variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. The main independent variable is the quintile of the mimicking portfolio beta (β^{Q}_{mp}). The sorting of mimicking portfolio beta is performed at yearly basis based on the average mimicking portfolio beta of the firms in the previous year. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio $ln(\text{OC}/\text{Asset})$, the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), and the 12-month stock returns in the previous year (StockRet). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1972 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table B.5: Mimicking portfolio betas and key talent turnovers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEOs				Innovators			
	$\text{Turnover}_t^{(1)} \times 100$		$\text{Turnover}_t^{(2)} \times 100$		$ln(1+\text{leavers})_t$		$ln(1+\text{new hires})_t$	
$\beta^Q_{mp,t-1}$	-0.528^{***}	-0.451^{***}	-0.600^{***}	-0.522^{***}	-0.020^{***}	-0.014^{**}	-0.020^{***}	-0.013^{***}
	[−6.212]	[−4.915]	[−6.186]	[−4.862]	[−3.278]	[−2.714]	[−3.328]	[−2.833]
$ln(\text{OC/Asset})_{t-1}$	0.328^{***}	0.357^{***}	0.386^{***}	0.404^{***}	0.020	0.016	0.015	0.010
	[3.699]	[3.478]	[4.202]	[3.676]	[2.280]	[1.595]	[2.612]	[2.297]
$ln\text{size}_{t-1}$	−0.097	−0.061	−0.138	−0.095	0.125^{***}	0.138^{***}	0.117^{***}	0.131^{***}
	[−0.995]	[−0.591]	[−1.341]	[−0.876]	[9.322]	[9.562]	[9.032]	[9.266]
$ln\text{BEME}_{t-1}$	−0.044	0.136	0.056	0.272	0.045^{***}	0.075^{***}	0.014	0.039^{***}
	[−0.220]	[0.625]	[0.246]	[1.105]	[4.388]	[6.695]	[1.675]	[4.406]
$ln\text{lev}_{t-1}$	0.111	0.151	0.036	0.104	0.048^{***}	0.065^{***}	0.021^{***}	0.036^{***}
	[0.998]	[1.197]	[0.272]	[0.699]	[5.654]	[7.533]	[2.751]	[4.968]
StockRet_{t-1}	-2.321^{***}	-2.308^{***}	-2.985^{***}	-2.964^{***}	0.012	0.013	0.035^{***}	0.037^{***}
	[−6.091]	[−5.873]	[−7.089]	[−6.918]	[1.241]	[1.467]	[2.957]	[3.317]
Female	0.469	−0.017	0.355	−0.145				
	[0.715]	[−0.024]	[0.530]	[−0.206]				
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25242	25242	25242	25242	30499	30498	30499	30498
R-squared	0.007	0.011	0.008	0.012	0.244	0.288	0.243	0.282

Note: This table shows the relation between mimicking portfolio beta and key talent turnovers. Our analysis is performed based on the mimicking portfolio beta (denoted as β_{mp}) for BTR. CEO turnover data come from Execucomp. In Column (1) and (2), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) and (4), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise. Innovator turnover data come from the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), which provides the names of the innovator and their affiliations from 1975 to 2010. Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year. In Column (5) and (6) , the dependent variables are the natural log of one plus the number of leavers. In Column (7) and (8), the dependent variables are the natural log of one plus the number of new hires. The main independent variable is the quintile of the mimicking portfolio beta (β^Q_{mp}). The sorting of mimicking portfolio beta is performed at yearly basis based on the average mimicking portfolio beta of the firms in the previous year. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), and a dummy variable for the gender of the executives (Female). SIC-2 industry fixed effects and year fixed effects are included in the regressions as indicated by the table. The sample for CEO turnovers span 1992 and 2016 while the sample for innovator turnover span 1975 to 2010. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table B.6: Mimicking portfolio betas and firms' financial policies.

	(1) $\frac{\text{Cash}_t}{\text{Asset}_{t-1}}$ (%)	(2) $\frac{\Delta\text{Cash}_t}{\text{NI}_t}$ (%)	(3) $\frac{\Delta\text{Equity}_t}{\text{Asset}_{t-1}}$ (%)	(4) $\frac{\text{Payout}_t}{\text{Asset}_{t-1}}$ (%)	(5) $\frac{\text{Dividend}_t}{\text{Asset}_{t-1}}$ (%)	(6) $\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$ (%)
$\beta^Q_{mp,t-1}$	-1.105^{***}	-2.487^{***}	-0.245^{***}	0.057^{*}	0.053^{**}	0.006
	[−5.614]	[−3.336]	[−2.802]	[1.843]	[2.672]	[0.355]
$ln(\text{OC/Asset})_{t-1}$	-0.364^{**}	0.621	0.032	0.309^{***}	0.117^{***}	0.185^{***}
	[−2.123]	[0.910]	[0.365]	[8.817]	[6.308]	[7.638]
$ln\text{size}_{t-1}$	-1.640^{***}	-2.547^{***}	-1.542^{***}	0.638^{***}	0.296^{***}	0.341^{***}
	[−14.803]	[−4.567]	[−11.673]	[16.627]	[16.008]	[7.903]
$ln\text{BEME}_{t-1}$	-8.628^{***}	-9.574^{***}	-6.672^{***}	-0.489^{***}	-0.164^{***}	-0.245^{***}
	[−18.207]	[−4.994]	[−13.655]	[−6.827]	[−4.151]	[−6.343]
$ln\text{lev}_{t-1}$	-7.060^{***}	0.956	-0.987^{***}	-0.579^{***}	-0.284^{***}	-0.240^{***}
	[−30.545]	[0.928]	[−6.685]	[−14.079]	[−7.496]	[−8.971]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114049	82605	114049	114049	114049	114049
R-squared	0.320	0.008	0.163	0.173	0.228	0.119

Note: This table shows the relation between mimicking portfolio beta and firms' financial policies. Our analysis is performed based on the mimicking portfolio beta (denoted as β_{mp}) for BTR. The dependent variables are the amount of cash holdings (% of lagged asset), the change of cash holdings (% of contemporaneous net income), the amount of equity issuance (% of lagged asset), the amount of total payout (% of lagged asset), the amount of dividend issuance (% of lagged asset), and the amount of share repurchases (% of lagged asset). The outcome variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. In Column (2), we only include observations with positive net income. The main independent variable is the quintile of the mimicking portfolio beta (β^Q_{mp}). The sorting of mimicking portfolio beta is performed at yearly basis based on the average mimicking portfolio beta of the firms in the previous year. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio $ln(\text{OC/Asset})$, the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME) and the natural log of the debt-to-equity ratio (lnlev). We include SIC-2 industry fixed effects and year fixed effects in the regressions. The sample for the analysis of this table is the Compustat yearly data from 1972 to 2016. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

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