# Online Appendix for "Customer Capital, Financial Constraints, and Stock Returns"

## === *Not for Publication* ===

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## Contents

# A Micro Foundation for Customer Capital

We use competitive search (see Moen, 1997; Gourio and Rudanko, 2014) to micro found the creation and maintenance of customer capital. The firm's existing customers $B_t$ can purchase goods directly, while new customers have to incur flow search costs $x\mathrm{d}t$ before meeting with the firm's sales representatives. Following Gourio and Rudanko (2014), we assume that each agent has constant willingness to pay, denoted as $u$, and that the firm cannot commit to future product prices. Thus, the firm charges constant price $u$ to existing customers to fully exploit their consumer surplus. The firm offers initial discounts $f_t \in [0, \overline{f}]$ to attract new customers. In other words, the price is $u - f_t$ over $[t, t + \mathrm{d}t]$ for the agents not in $B_t$. The upper bound $\overline{f}$ for initial discounts ensures that the price is at least as high as the average cost per unit of goods.

In the following, we describe the firm's selling problem, the consumer's buying problem, the equilibrium matching, and customer capital growth.

**The Firm's Selling Problem.** The firm hires sales representatives to build new customer capital. The cost of hiring $s_t$ units of sales representatives over $[t, t + \mathrm{d}t]$ is $\phi(s_t)B_t\mathrm{d}t$ with

$$\phi(s_t) \equiv \alpha s_t^{\eta}, \text{ with } \alpha > 0 \text{ and } \eta > 1. \tag{A.1}$$

The specification of an increasing and convex hiring cost function follows Gourio and Rudanko (2014), which guarantees a decreasing-return-to-scale profit function for hiring sales representatives. By modeling the hiring cost proportional to $B_t$, we ensure that the firm does not grow out of the cost. Thus, the firm's effective number of sales representatives is $s_t B_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$.

**Agents' Buying Problem.** Agents are aware of the discounts $f_t$ offered by all firms and decide where to direct their search for goods. Denote $b(f_t, s_t; B_t)\mathrm{d}t$ as the number of agents who plan to shop at the firm over $[t, t + \mathrm{d}t]$. Purchases are made when agents meet with the firm's sales representatives. Due to search and matching frictions, meetings happen with some probability $\lambda(\theta_t)$ depending on the firm's market tightness $\theta_t$:

$$\theta_t = \frac{s_t B_t}{b(f_t, s_t; B_t)}. \tag{A.2}$$

From agents' perspective, a tighter market is associated with a greater chance of meeting with the firm's sales representatives. Assuming a Cobb-Douglas matching function, we can derive $\lambda(\theta_t)$ as:

$$\lambda(\theta_t) = \left(\overline{\psi}\theta_t\right)^{1/\chi}, \tag{A.3}$$

where $\overline{\psi} > 0$ denotes the matching efficiency and $\chi > 1$ denotes the matching elasticity.

**Equilibrium Matching.** The market tightness $\theta_t$ is pinned down by the free entry condition. The firm's existing customers $B_t$ have two options. They can either purchase the firm's goods at price $u$ and obtain zero consumer surplus, or they can incur the flow search costs $x\mathrm{d}t$ to purchase other firms' goods with initial discounts $f_t$ and probability $\lambda(\theta_t)$. In the latter case, the expected consumer surplus net of search costs is $[f_t\lambda(\theta_t) - x]\,\mathrm{d}t$. In equilibrium, we have

$$[f_t\lambda(\theta_t) - x]\mathrm{d}t = 0. \tag{A.4}$$

Intuitively, this is because the firm offering greater discounts or hiring more sales representatives will attract more potential buyers. The free entry condition ensures that the firm-specific market tightness will adjust until the expected consumer surplus is equalized across all firms. As a result, in equilibrium, agents are indifferent about where to purchase goods. In particular, the firm's existing customers have no incentive to purchase goods from other firms, implying that the customer relationship is long-term in nature.[1]

Substituting equations (A.2) and (A.3) into equation (A.4), we obtain

$$b(f_t, s_t; B_t) = \overline{\psi} f_t^{\chi} s_t B_t. \tag{A.5}$$

The number of agents meeting with the firm's sales representatives is $b(f_t, s_t; B_t)\lambda(\theta_t)\mathrm{d}t$ over $[t, t + \mathrm{d}t]$. Thus, the flow rate of new customers per unit of $B_t$ is

$$\overline{\mu}(f_t, s_t) = \overline{\psi} f_t^{\chi-1} s_t. \tag{A.6}$$

Equation (A.6) implies that offering greater discounts and hiring more sales representatives increase the flow rate of new customers, increasing future profits. However, the firm has to pay the hiring cost $\phi(s_t)$ at present, which is costly when the firm's current marginal value of liquidity is high. Therefore, the optimal hiring decision crucially depends on the firm's cash holdings $W_t$. On the other hand, optimal discounts are trivially set at the upper bound, $f_t = \overline{f}$, to maximize the flow rate of new customers. This is because discounts are only offered to new customers $\overline{\mu}(f_t, s_t)B_t\mathrm{d}t$ for the initial instant $\mathrm{d}t$. The loss of revenue due to offering greater discounts is of second-order importance.

Thus what matters for the flow rate of new customers is the effective matching efficiency, $\psi$, defined as

$$\psi \equiv \overline{\psi}\overline{f}^{\chi-1}, \tag{A.7}$$

and we define

$$\mu(s_t) \equiv \overline{\mu}(\overline{f}, s_t) = \psi s_t. \tag{A.8}$$

# B Numerical Algorithm

The coupled PDEs involve free boundary conditions because 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.

## B.1 Discretization of the Original Problem

Let $\Delta$ 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 $\mathrm{d}Z_t^a$, $\mathrm{d}Z_t^c$, $\mathrm{d}Z_t^\omega$, and $\xi_{t+\Delta}$. As long as the time grid is sufficiently small, whether decisions are made before or after shocks' 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 $\mathrm{d}Z_t^a$, $\mathrm{d}Z_t^c$, $\mathrm{d}Z_t^\omega$, and $\xi_{t+\Delta}$. See Figure OA.1 for the detailed timing of events.

The firm solves the following recursive problem in discrete time

[1] The sticky customer base endows the firm with pricing power, which has been well recognized in the macroeconomics and industrial organization literature as an important source of imperfect competition (see, e.g. Phelps and Winter, 1970; Rotemberg and Woodford, 1991; Klemperer, 1995; Ravn, Schmitt-Grohe and Uribe, 2006; Gourio and Rudanko, 2014; Gilchrist et al., 2017).

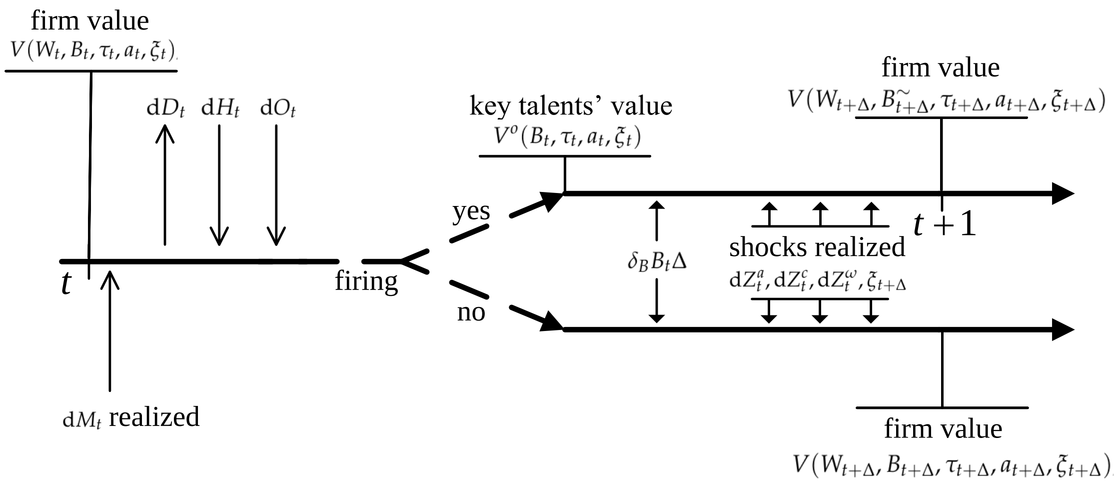


Figure OA.1: Timing of events.

$$
\begin{aligned}
&V(W_t, B_t, \tau_t, a_t, \xi_t) = \max_{s_t, dD_t, dH_t, \overline{s_t}, \overline{dD_t}, \overline{dH_t}} \\
&(1-\xi_t\Delta)\left[dD_t - dH_t - dX_t + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(W_{t+\Delta}, B_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right. \\
&+ \vartheta\Delta \max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(W_{t+\Delta}, B_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right),\right. \\
&\left.\left.\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(W_{t+\Delta}, B_{t+\Delta}^{\sim}, \tau_{t+\Delta}^{\sim}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\right] \\
&+ \xi_t\Delta\left[\overline{dD_t} - \overline{dH_t} - \overline{dX_t} + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{W_{t+\Delta}}, \overline{B_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right. \\
&+ \vartheta\Delta \max\left\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{W_{t+\Delta}}, \overline{B_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right),\right. \\
&\left.\left.\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}V(\overline{W_{t+\Delta}}, \overline{B_{t+\Delta}^{\sim}}, \tau_{t+\Delta}^{\sim}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right\}\right]. \qquad \text{(B.1)}
\end{aligned}
$$

In the objective function, shareholders' consumption in the current period is given by dividend $dD_t$ net of equity issuance $dH_t$ and issuance costs $dX_t$. With probability $1-\vartheta\Delta$, the replacement shock does not arrive, in which case the continuation value is
$V(W_{t+\Delta}, B_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})$. 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 $V(W_{t+\Delta}, B_{t+\Delta}^{\sim}, \tau_{t+\Delta}^{\sim}, a_{t+\Delta}, \xi_{t+\Delta})$. Expectation is taken with respect to financial constraints risk shocks $\xi_{t+\Delta}$, aggregate productivity shock $a_{t+\Delta}$, TBR $\tau_{t+\Delta}$ ($\tau_{t+\Delta}^{\sim}$), and cash flow shocks $dZ_t^c$. As the firm makes decisions after the realization of lumpy cash flow shocks $dM_t$, there are two cases happening with probabilities $1-\xi_t\Delta$ and $\xi_t\Delta$.

The budget constraint is given by

$$
\begin{aligned}
W_{t+\Delta} =& (1 + r\Delta - \rho\Delta)W_t - dD_t + dH_t + uB_t\Delta + \sigma_c B_t dZ_t^c - \phi(s_t)T_t\Delta - \Gamma_t\Delta \\
&- \frac{B_t}{e^{a_t}}\left[\mu(s_t) - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}B_t dZ_t^a}{e^{a_t}}, \qquad \text{(B.2)}
\end{aligned}
$$

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

If the firm does not fire key talents, the evolution of customer capital and TBR is given by

$$B_{t+\Delta} = (1 - \delta_B\Delta)B_t + \mu(s_t)B_t\Delta. \tag{B.4}$$

$$\overline{B_{t+\Delta}} = (1 - \delta_B\Delta)B_t + \mu(\overline{s_t})B_t\Delta. \tag{B.5}$$

$$\frac{\tau_{t+\Delta} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z_t^\omega. \tag{B.6}$$

If the firm fires key talents successfully, the current customer capital is reduced by a fraction $m\tau_t$. The evolution of customer capital and TBR is given by

$$B_{t+\Delta}^{\sim} = (1 - m\tau_t)(1 - \delta_B\Delta)B_t + \mu(s_t)B_t\Delta. \tag{B.7}$$

$$\overline{B_{t+\Delta}^{\sim}} = (1 - m\tau_t)(1 - \delta_B\Delta)B_t + \mu(\overline{s_t})B_t\Delta. \tag{B.8}$$

$$\frac{\tau_{t+\Delta}^{\sim} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z_t^\omega + \ln\left(\frac{1-m}{1-m\tau_t}\right). \tag{B.9}$$

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

$$(\Gamma_t + hB_t)\Delta = V^o(B_t, \tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}V^o(B_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{B.10}$$

$$(\overline{\Gamma_t} + hB_t)\Delta = V^o(B_t, \tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}V^o(\overline{B_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{B.11}$$

In addition, the firm's decisions are constrained by

$$s_t, \mathrm{d}D_t, \mathrm{d}H_t, \overline{s_t}, \overline{\mathrm{d}D_t}, \overline{\mathrm{d}H_t} \in [0, \infty). \tag{B.12}$$

## B.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 $w_t = \frac{W_t}{B_t}$, $\mathrm{d}\tilde{D}_t = \frac{\mathrm{d}D_t}{B_t}$, $\mathrm{d}\tilde{H}_t = \frac{\mathrm{d}H_t}{B_t}$, $\mathrm{d}\tilde{X}_t = \frac{\mathrm{d}X_t}{B_t} = [\gamma + \varphi\mathrm{d}\tilde{H}_t + \varpi v^o(\tau_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t>0}$, and $\tilde{\Gamma}_t = \frac{\Gamma_t}{B_t}$.

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

The normalized firm value is derived from

$$
\begin{aligned}
& v(w_t, \tau_t, a_t, \xi_t) = \max_{s_t, \mathrm{d}\tilde{D}_t, \mathrm{d}\tilde{H}_t, \overline{s_t}, \overline{\mathrm{d}\tilde{D}_t}, \overline{\mathrm{d}\tilde{H}_t}} \\
& (1-\xi_t\Delta)\Bigg[\mathrm{d}\tilde{D}_t - \mathrm{d}\tilde{H}_t - [\gamma + \varphi \mathrm{d}\tilde{H}_t + \varpi v^o(\tau_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t>0} \\
& + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi s_t\Delta\right) v(w_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
& + \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi s_t\Delta\right) v(w_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
& \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left[(1-m\tau_t)(1-\delta_B\Delta) + \psi s_t\Delta\right] v(w^{\sim}_{t+\Delta}, \tau^{\sim}_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg] \\
& + \xi_t\Delta\Bigg[\overline{\mathrm{d}\tilde{D}_t} - \overline{\mathrm{d}\tilde{H}_t} - [\gamma + \varphi\overline{\mathrm{d}\tilde{H}_t} + \varpi v^o(\tau_t, a_t, \xi_t)]\mathbb{1}_{\overline{\mathrm{d}\tilde{H}_t}>0} \\
& + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi \overline{s_t}\Delta\right) v(\overline{w_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
& + \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi \overline{s_t}\Delta\right) v(\overline{w_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
& \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left[(1-m\tau_t)(1-\delta_B\Delta) + \psi \overline{s_t}\Delta\right] v(\overline{w^{\sim}_{t+\Delta}}, \tau^{\sim}_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg],
\end{aligned} \tag{B.13}
$$

subject to the budget constraints,

$$
\begin{aligned}
& (1-\delta_B\Delta + \psi s_t\Delta)\, w_{t+\Delta} = (1 + r\Delta - \rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_c \mathrm{d}Z^c_t \\
& - \alpha s_t^{\eta}\Delta - \tilde{\Gamma}_t\Delta - \frac{1}{e^{a_t}}\left[\psi s_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z^a_t}{e^{a_t}},
\end{aligned} \tag{B.14}
$$

$$
\begin{aligned}
& (1-\delta_B\Delta + \psi \overline{s_t}\Delta)\, \overline{w_{t+\Delta}} = (1 + r\Delta - \rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_c \mathrm{d}Z^c_t - \varsigma \\
& - \alpha \overline{s_t}^{\eta}\Delta - \overline{\tilde{\Gamma}}_t\Delta - \frac{1}{e^{a_t}}\left[\psi \overline{s_t} - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z^a_t}{e^{a_t}},
\end{aligned} \tag{B.15}
$$

$$
\begin{aligned}
& [(1-m\tau_t)(1-\delta_B\Delta) + \psi s_t\Delta]\, w^{\sim}_{t+\Delta} = (1 + r\Delta - \rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_c \mathrm{d}Z^c_t \\
& - \alpha s_t^{\eta}\Delta - \tilde{\Gamma}_t\Delta - \frac{1}{e^{a_t}}\left[\psi s_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z^a_t}{e^{a_t}},
\end{aligned} \tag{B.16}
$$

$$
\begin{aligned}
& [(1-m\tau_t)(1-\delta_B\Delta) + \psi s_t\Delta]\, \overline{w^{\sim}_{t+\Delta}} = (1 + r\Delta - \rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_c \mathrm{d}Z^c_t - \varsigma \\
& - \alpha \overline{s_t}^{\eta}\Delta - \overline{\tilde{\Gamma}}_t\Delta - \frac{1}{e^{a_t}}\left[\psi \overline{s_t} - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z^a_t}{e^{a_t}},
\end{aligned} \tag{B.17}
$$

$$
\frac{\tau_{t+\Delta} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z^\omega_t, \tag{B.18}
$$

$$
\frac{\tau^{\sim}_{t+\Delta} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z^\omega_t + \ln\left(\frac{1-m}{1-m\tau_t}\right), \tag{B.19}
$$

and the compensation to key talents,

$$(\tilde{\Gamma}_t + h)\Delta = v^o(\tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \psi s_t\Delta\right) v^o(\tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{B.20}$$

$$(\bar{\tilde{\Gamma}}_t + h)\Delta = v^o(\tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \psi \overline{s_t}\Delta\right) v^o(\tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{B.21}$$

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

$$v^o(\tau_t, a_t, \xi_t) = v^n(\tau_t, a_t, \xi_t) + \gamma(m+\ell)\tau_t + \varphi w_0^*(m+\ell)\tau_t, \tag{B.22}$$

where $v^n(\tau_t, a_t, \xi_t)$ is derived from equation (B.23) and $w_0^*$ is the optimal solution to equation (B.23),

$$v^n(\tau_t, a_t, \xi_t) = \max_{w_0}(m+\ell)\tau_t\left[-\gamma - (1+\varphi)w_0 + \mathbb{E}^{\tilde{\tau}}[v(w_0, \tilde{\tau}, a_t, \xi_t)]\right]. \tag{B.23}$$

As we explain in Section B.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 $\tau$, $a$, and $\xi$. Given our calibration, the firm does not fire key talents because the expected cash inflows generated by key talents are greater than their compensation. Thus the firm solves the following problem to maximize shareholder value:

$$\begin{aligned}
&v(\tau_t, a_t, \xi_t) = \max_{s_t, \overline{s_t}} \\
&(1-\xi_t\Delta)\left[u\Delta - \alpha s_t^\eta\Delta - \tilde{\Gamma}_t\Delta - \frac{1}{e^{a_t}}\left(\psi s_t - \delta_B + \delta_K + \mu_a(a_t - \bar{a}) + \frac{1}{2}\sigma_a^2 a_t\right)\Delta\right. \\
&\left.+\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi s_t\Delta\right) v(\tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right] \\
&+\xi_t\Delta\left[u\Delta - \varsigma - \alpha\overline{s_t}^\eta\Delta - \bar{\tilde{\Gamma}}_t\Delta - \frac{1}{e^{a_t}}\left(\psi\overline{s_t} - \delta_B + \delta_K + \mu_a(a_t - \bar{a}) + \frac{1}{2}\sigma_a^2 a_t\right)\Delta\right. \\
&\left.+\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1-\delta_B\Delta + \psi\overline{s_t}\Delta\right) v(\tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\right],
\end{aligned} \tag{B.24}$$

subject to the compensation to key talents,

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

$$(\bar{\tilde{\Gamma}}_t + h)\Delta = v^o(\tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}\left(1 - \delta_B\Delta + \psi \overline{s_t}\Delta\right) v^o(\overline{\tau_{t+\Delta}}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{B.26}$$

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

$$v^o(\tau_t, a_t, \xi_t) = (m+\ell)\tau_t\mathbb{E}^{\tilde{\tau}}\left[v(\tilde{\tau}, a_t, \xi_t)\right]. \tag{B.27}$$

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

$$
\begin{aligned}
& v(w_t, \tau_t, a_t, \xi_t) = \max_{\mathrm{d}\tilde{D}_t, \mathrm{d}\tilde{H}_t, \overline{\mathrm{d}\tilde{D}_t}, \overline{\mathrm{d}\tilde{H}_t}} \\
& (1-\xi_t\Delta)\Bigg[\mathrm{d}\tilde{D}_t - \mathrm{d}\tilde{H}_t - [\gamma + \varphi \mathrm{d}\tilde{H}_t + \varpi v^o(\tau_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}\tilde{H}_t > 0} \\
& + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v(w_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
& + \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v(w_{t+\Delta}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
& \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)(1-m\tau_t)v(w^{\sim}_{t+\Delta}, \tau^{\sim}_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg] \\
& + \xi_t\Delta\Bigg[\overline{\mathrm{d}\tilde{D}_t} - \overline{\mathrm{d}\tilde{H}_t} - [\gamma + \varphi \overline{\mathrm{d}\tilde{H}_t} + \varpi v^o(\tau_t, a_t, \xi_t)]\mathbb{1}_{\overline{\mathrm{d}\tilde{H}_t} > 0} \\
& + (1-\vartheta\Delta)\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v(\overline{w_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right) \\
& + \vartheta\Delta \max\Bigg\{\mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v(\overline{w_{t+\Delta}}, \tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right), \\
& \mathbb{E}_t\left(\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)(1-m\tau_t)v(\overline{w^{\sim}_{t+\Delta}}, \tau^{\sim}_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right)\Bigg\}\Bigg],
\end{aligned}
\tag{B.28}
$$

subject to the budget constraints,

$$
\begin{aligned}
(1-\delta_B\Delta)w_{t+\Delta} = & (1 + r\Delta - \rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_c \mathrm{d}Z_t^c - \tilde{\Gamma}_t\Delta \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{B.29}
$$

$$
\begin{aligned}
(1-\delta_B\Delta)\overline{w_{t+\Delta}} = & (1 + r\Delta - \rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_c \mathrm{d}Z_t^c - \overline{\tilde{\Gamma}}_t\Delta - \varsigma \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{B.30}
$$

$$
\begin{aligned}
(1-m\tau_t)(1-\delta_B\Delta)w^{\sim}_{t+\Delta} = & (1 + r\Delta - \rho\Delta)w_t - \mathrm{d}\tilde{D}_t + \mathrm{d}\tilde{H}_t + u\Delta + \sigma_c \mathrm{d}Z_t^c - \tilde{\Gamma}_t\Delta \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{B.31}
$$

$$
\begin{aligned}
(1-m\tau_t)(1-\delta_B\Delta)\overline{w^{\sim}_{t+\Delta}} = & (1 + r\Delta - \rho\Delta)w_t - \overline{\mathrm{d}\tilde{D}_t} + \overline{\mathrm{d}\tilde{H}_t} + u\Delta + \sigma_c \mathrm{d}Z_t^c - \overline{\tilde{\Gamma}}_t\Delta - \varsigma \\
& - \frac{1}{e^{a_t}}\left[-\delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\Delta + \frac{\sigma_a\sqrt{a_t}\mathrm{d}Z_t^a}{e^{a_t}},
\end{aligned}
\tag{B.32}
$$

$$
\frac{\tau_{t+\Delta} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z_t^\omega,
\tag{B.33}
$$

$$
\frac{\tau^{\sim}_{t+\Delta} - \tau_t}{\tau_t} = -\mu_\omega(\ln\tau_t + \overline{\omega})\mathrm{d}t - \sigma_\omega\sqrt{-\ln\tau_t}\mathrm{d}Z_t^\omega + \ln\left(\frac{1-m}{1-m\tau_t}\right),
\tag{B.34}
$$

and the compensation to key talents,

$$(\tilde{\Gamma}_t + h)\Delta = v^o(\tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v^o(\tau_{t+\Delta}, a_{t+\Delta}, \xi_{t+\Delta})\right], \tag{B.35}$$

$$(\overline{\tilde{\Gamma}}_t + h)\Delta = v^o(\tau_t, a_t, \xi_t) - \mathbb{E}_t\left[\frac{\Lambda_{t+\Delta}}{\Lambda_t}(1-\delta_B\Delta)\, v^o(\overline{\tau_{t+\Delta}}, a_{t+\Delta}, \xi_{t+\Delta})\right]. \tag{B.36}$$

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

$$v^o(\tau_t, a_t, \xi_t) = v^n(\tau_t, a_t, \xi_t) + \gamma(m+\ell)\tau_t + \varphi w_0^*(m+\ell)\tau_t, \tag{B.37}$$

where $v^n(\tau_t, a_t, \xi_t)$ is derived from equation (B.38) and $w_0^*$ is the optimal solution to equation (B.38),

$$v^n(\tau_t, a_t, \xi_t) = \max_{w_0}(m+\ell)\tau_t\left[-\gamma - (1+\varphi)w_0 + \mathbb{E}^{\tilde{\tau}}[v(w_0, \tilde{\tau}, a_t, \xi_t)]\right]. \tag{B.38}$$

## B.3 Implementation

We discretize the cash flow shocks based on 11 grids spanning from $-3\sigma_c$ to $3\sigma_c$, the TBR shocks based on 11 grids spanning from $-3\sigma_\omega$ and $3\sigma_\omega$, and the aggregate productivity shocks based on 5 grids spanning from $-3\sigma_a$ to $3\sigma_a$ using the method of Tauchen (1986). In particular, using the discretization of productivity shocks as an example,

$$a_{t+\Delta} = (1-\mu_a\Delta)a_t + \mu_a\bar{a}\Delta + \sigma_a\sqrt{a_t\Delta}z^a, \tag{B.39}$$

where $z^a \sim N(0,1)$. The unconditional standard deviation of $a_t$ can be approximated as

$$\sigma_a\sqrt{\frac{\bar{a}\Delta}{1-(1-\mu_a\Delta)^2}}. \tag{B.40}$$

We select the maximum value $s_{a_5}$ as $\bar{a}$ plus three unconditional standard deviations, i.e.

$$s_{a_5} = \bar{a} + 3\sigma_a\sqrt{\frac{\bar{a}\Delta}{1-(1-\mu_a\Delta)^2}}. \tag{B.41}$$

Let $s_{a_1} = 2 * \bar{a} - s_{a_5}$ because the unconditional mean of $a_t$ is $\bar{a}$. Let $\{s_{a_2}, s_{a_3}, s_{a_4}\}$ be located in an equispaced manner over the interval $[s_{a_1}, s_{a_5}]$. Denote $d = s_{a_2} - s_{a_1}$ as the distance between successive points in the productivity grid.

The generic transition probability $\pi_{jk}$ is given by

$$\begin{aligned}
\pi_{jk} &= \Pr\left\{a_{t+1} = s_{a_k} | a_t = s_{a_j}\right\} \\
&= \Pr\left\{s_{a_k} - d/2 < (1-\mu_a\Delta)s_{a_j} + \mu_a\bar{a}\Delta + \sigma_a\sqrt{s_{a_j}\Delta}z^a \le s_{a_k} + d/2\right\} \\
&= \Pr\left\{\frac{s_{a_k} - d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}} < z_a \le \frac{s_{a_k} + d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}}\right\}.
\end{aligned} \tag{B.42}$$

Then, if $1 < k < 5$, for each $j$ choose

$$\pi_{jk} = \Phi\left(\frac{s_{a_k} + d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}}\right) - \Phi\left(\frac{s_{a_k} - d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}}\right), \tag{B.43}$$

while for the boundaries of the interval $k = 1$ and $k = 5$, choose

$$\pi_{j1} = \Phi\left(\frac{s_{a_1} + d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}}\right),$$

$$\pi_{j5} = 1 - \Phi\left(\frac{s_{a_5} - d/2 - (1-\mu_a\Delta)s_{a_j} - \mu_a\bar{a}\Delta}{\sigma_a\sqrt{s_{a_j}\Delta}}\right). \tag{B.44}$$

We use collocation methods to solve the firm's problem (B.13). Let $S_w \times S_\tau \times S_a \times S_\xi$ be the grid of collocation nodes, where $S_w = \{s_{w_1}, s_{w_2}, ..., s_{w_k}\}$, $S_\tau = \{s_{\tau_1}, s_{\tau_2}, ..., s_{\tau_{11}}\}$, $S_a = \{s_{a_1}, ..., s_{a_5}\}$ 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 $\tau$ 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 $\tau = \tau_{11}$. The states $s_{\tau_1}, ..., s_{\tau_{11}}$ correspond to the eleven levels of TBR. The states $s_{a_1}, ..., s_{a_5}$ correspond to the five levels of aggregate productivity shocks. The states $s_{\xi_1}$ and $s_{\xi_2}$ correspond to the arrival rates of lumpy cash flow shocks, $\xi_L$ and $\xi_H$. 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 $v(w, \tau, a, \xi)$ on $S$ using a linear spline with coefficients corresponding to each grid point. We first form a guess for the spline's $w_k \times 11 \times 5 \times 2$ coefficients, then we iterate to obtain a vector that solves the system of $w_k \times 11 \times 5 \times 2$ 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, $v_w(w, \tau, a, \xi)$ converges to the true value much faster than the convergence of the value function $v(w, \tau, a, \xi)$ itself. 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 replacing key talents is captured by a reduction in the firm's customer capital. As shown in the normalized problem (B.13), the cost of replacing key talents increases with the absolute value of $v(w, \tau, a, \xi)$. Therefore, in order to obtain the correct solution for the firm's talent turnover decisions, we need to accurately solve the absolute value of $v(w, \tau, a, \xi)$.

In principle, we can start with any initial guess of the value function $v(w, \tau, a, \xi)$ and iterate a sufficient number of times to reach convergence, which is guaranteed by the contraction mapping theorem. However, this is very costly as each iteration takes several minutes to finish because 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 steps.

First, we solve the firm's problem (B.24) in a perfect financial market. This problem is much easier to solve because

$\tau$ 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 $max_{(\tau,a,\xi)\in\{S_\tau\times S_a\times S_\xi\}}|V^1_{n^1-1}(\tau,a,\xi)-V^1_{n^1}(\tau,a,\xi)|<10^{-16}$ at the $n^1th$ iteration.

Second, we use the value functions $V^1(\tau,a,\xi)$ from the perfect financial market to initialize the firm's value functions in problem (B.28) with no new customer flows. Specifically, we initialize the value of $V^2(w,\tau,a,\xi)$ at collocation nodes $S_w\times S_\tau\times S_a\times S_\xi$ by setting $V^2_0(w,\tau,a,\xi)=V^1_{n^1}(\tau,a,\xi)+w$. 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 $\gamma$ and $\varphi$ 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 $V^2(w,\tau,a,\xi)$ for another 6,000 times to reach a convergence until the level of accuracy satisfies $max_{(w,\tau,a,\xi)\in\{S_w\times S_\tau\times S_a\times S_\xi\}}|V^2_{n^2-1}(w,\tau,a,\xi)-V^2_{n^2}(w,\tau,a,\xi)|<10^{-7}$ at the $n^2th$ iteration.

Third, we use the value functions $V^2(w,\tau,a,\xi)$ to initialize the firm's value functions in problem (B.13) by setting $V^3_0(w,\tau,a,\xi)=V^2_{n^2}(w,\tau,a,\xi)$. Then we iterate the value functions $V^3_0(w,\tau,a,\xi)$ for about 6,000 times to reach a convergence until the level of accuracy satisfies $max_{(w,\tau,a,\xi)\in\{S_w\times S_\tau\times S_a\times S_\xi\}}|V^3_{n^3-1}(w,\tau,a,\xi)-V^3_{n^3}(w,\tau,a,\xi)|<10^{-7}$ 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 sales decisions is straight forward because it is a continuous decision variable. We set the initial lower bound to be zero. 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 the cash ratio 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, i.e. $\Delta=1/365$. 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.

# C Examples of Creating and Maintaining Customer Capital

In this section, we elaborate on how key talents and pure brand recognition create and maintain a firm's customer capital in different ways. Key talents are the essential employees of a firm, and they mainly include managers and innovators. Key talents' unique contributions can create new customer capital. For example, managers frequently bring in new businesses and customer relationships through personal connections and specialized skills; meanwhile, innovators in R&D teams often develop products with creative features that attract new customers. Key talents and pure brand recognition can also jointly create new customer capital. For example, new customers can be attracted by marketing campaigns designed and executed by firm managers. Finally, pure brand recognition alone can also bring in new customers. For example, consumers may purchase the firm's products upon friends' recommendations, a marketing approach referred to as *word-of-mouth marketing*. Besides creating new customer capital, both key talents and pure brand recognition also maintain the existing customer capital. When customers are brought into the firm, some become loyal to the firm's talents, whereas others become loyal to the firm's pure brand. Customers brought by personal connections or innovations are more likely to be loyal to the firm's talents and thus become part of talent-based customer capital, whereas customers brought by advertisements and friends' recommendations are more likely to be loyal to the firm's pure brand.

# D Construct Firm-Level Brand Metrics

The BAV Group conducts consumer surveys at the brand-level. The fraction of firm-year observations that contain one/two/three/four/five or more brands is 58%/15%/8%/4%/15%. For the firm-year observations that contain more than one brand, we assign the average brand stature and brand strength across all brands to the corresponding firm-year observations. Our results are robust to aggregation methods based on the median (or maximal) brand stature and brand strength among the brands that the firm owns. Moreover, the results are robust to an alternative method in which we identify the brands with the same names to the companies and assign the metrics of these brands to the firms. For example, The Coca-Cola Company owns Coca-Cola, Dasani, Fanta, and other brands. We assign the brand metrics of Coca-Cola to the Coca-Cola Company.

# E Sample Characteristics and Summary Statistics

In this section, we provide additional details on the industry distribution of our merged BAV-Compustat-CRSP sample. We also show the distribution of TBR and the summary statistics of the main variables in our analyses.

As Table OA.1 shows, our merged sample covers a wide range of industries and represent all the major sectors. Compared to the Compustat-CRSP data, our sample contains more observations from the consumer non-durables and retail sectors. This pattern is not surprising, because most of the firms in these sectors are business-to-consumer firms. Financial firms (SIC classification between 6000 and 6999) and utility firms (SIC classification between 4000 and 4999) are under-represented in the merged sample. Given that we exclude financial firms and utility firms from our analyses, the underrepresentation of these two industries does not affect us. The distribution of the remaining segments in the merged sample is comparable to the distribution in the Compustat-CRSP universe.

Table OA.2 tabulates the distribution of the merged sample across GICS industries. Although the merged sample is biased towards final consumption goods firms, the data also provide a significant amount of coverage for the investment goods firms. Final consumption goods firms are firms in the following GICS industries: (1) automobiles & components, (2) consumer durables & apparel, (3) consumer services, (4) media, (5) retailing, (6) food & staples retailing, (7) food, beverages & tobacco, and (8) household & personal products. In the merged sample, 55.9% of

Table OA.1: Fama-French 12 Industry distribution of the merged BAV-Compustat-CRSP sample.

| FF12 industry name | # Firm-year observations | | % Firm-year observations | |
|---|---|---|---|---|
| | Merged sample | Compustat-CRSP | Merged sample | Compustat-CRSP |
| Consumer non-durables | 1,290 | 4,411 | 17.72 | 4.66 |
| Consumer durables | 222 | 2,116 | 3.05 | 2.24 |
| Manufacturing | 633 | 9,297 | 8.70 | 9.82 |
| Energy | 138 | 3,418 | 1.90 | 3.61 |
| Chemicals | 322 | 2,193 | 4.42 | 2.32 |
| Business equipment | 920 | 17,776 | 12.64 | 18.78 |
| Telecommunications | 441 | 2,584 | 6.06 | 2.73 |
| Utilities | 19 | 2,743 | 0.26 | 2.90 |
| Shops | 1,600 | 8,591 | 21.98 | 9.08 |
| Healthcare | 240 | 11,060 | 3.30 | 11.68 |
| Money | 838 | 19,935 | 11.51 | 20.06 |
| Other | 615 | 10,538 | 8.45 | 11.13 |

Note: This table presents the distribution of the merged BAV-Compustat-CRSP sample and CRSP-Compustat universe by industry for the period 1993-2016. Industries are defined according to the Fama-French 12-industry classification. We report the total number of firm-year observations and the proportion (in percentage) of the number of observations in each industry in both the merged sample and the Compustat-CRSP universe. We include the observations from financial firms and utility firms in this table, but we exclude them in the analyses of our paper.

firm-year observations come from final consumption good firms, compared to 21.0% in the Compustat/CRSP data.

Table OA.2: GICS industry distribution of the BAV-Compustat-CRSP sample.

| GICS inudstry group | Industry code | # Firm-year obs. | % Firm-year obs. |
|---|---|---|---|
| Energy | 1010 | 162 | 2.22 |
| Materials | 1510 | 218 | 2.99 |
| Capital goods | 2010 | 390 | 5.35 |
| Commercial services & supplies | 2020 | 74 | 1.02 |
| Transportation | 2030 | 268 | 3.68 |
| Automobiles & components | 2510 | 128 | 1.76 |
| Consumer durables & apparel | 2520 | 753 | 10.34 |
| Consumer services | 2530 | 556 | 7.63 |
| Media | 2540 | 369 | 5.07 |
| Retailing | 2550 | 1,105 | 15.17 |
| Food & staples retailing | 3010 | 203 | 2.79 |
| Food, beverage & tobacco | 3020 | 669 | 9.18 |
| Household & personal products | 3030 | 271 | 3.72 |
| Health care equipment & services | 3510 | 146 | 2.00 |
| Pharmaceuticals, biotechnology & life sciences | 3520 | 200 | 2.75 |
| Banks | 4010 | 189 | 2.59 |
| Diversified financials | 4020 | 294 | 4.04 |
| Insurance | 4030 | 168 | 2.31 |
| Software & services | 4510 | 555 | 7.62 |
| Technology hardware & equipment | 4520 | 281 | 3.86 |
| Semiconductors & semiconductor equipment | 4530 | 73 | 1.00 |
| Telecommunication services | 5010 | 186 | 2.55 |
| Utilities | 5510 | 15 | 0.21 |
| Real estate | 6010 | 12 | 0.16 |

Note: This table presents the distribution of the BAV-Compustat-CRSP data by GICS industry for the period 1993-2016. We report the total number and the percent of firm-year observations in each industry. Our sample includes the firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We include the observations from financial firms and utility firms in this table, but we exclude them in the analyses of our paper.

We follow Gomes, Kogan and Yogo (2009) and classify each SIC industry into categories (durables, non-durables, services, domestic investment, government, and net exports) based on the durability of firms' output. Table OA.3 tabulates the distribution of durability categories within each TBR quintile. We find that the distribution of industries across durability categories is not significantly different across TBR quintiles, suggesting that the TBR sorting is not simply a sorting based on the durability of firms' output.

Panel A of Figure OA.2 shows that brand stature and brand strength are positively correlated, with the correlation

Table OA.3: Sample distribution across durability industry categories and TBR quintiles.

| Portfolios sorted on TBR | Q1 (Low) | Q2 | Q3 | Q4 | Q5 (High) |
|---|---|---|---|---|---|
| Durables | 167 | 107 | 73 | 30 | 85 |
| Non-durables | 303 | 414 | 417 | 362 | 279 |
| Services | 241 | 137 | 169 | 215 | 172 |
| Private domestic investment | 121 | 129 | 101 | 84 | 111 |
| Government | 89 | 94 | 166 | 202 | 297 |
| Net exports | 29 | 15 | 14 | 13 | 9 |
| Others | 286 | 326 | 282 | 316 | 278 |

Note: This table presents the sample distribution across durability industry categories and TBR quintiles. The durability industry categories come from Gomes, Kogan and Yogo (2009), who classify each SIC industry into six categories (durables, non-durables, services, private domestic investment, government, and net exports) according to the durability of firms' output. Wholesale and retail firms (SIC 5000-5999) are not classified in Gomes, Kogan and Yogo (2009) due to data availability. We label wholesale and retail firms as "others" in the table. Our sample includes the firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude utility firms and financial firms in the analysis. Our sample spans 1993 to 2016.

coefficient being 0.4. However, the relation between brand stature and brand strength is far from a one-to-one mapping. Panel B of Figure OA.2 shows that lnTBR has a good amount of variation and its distribution is close to normal.

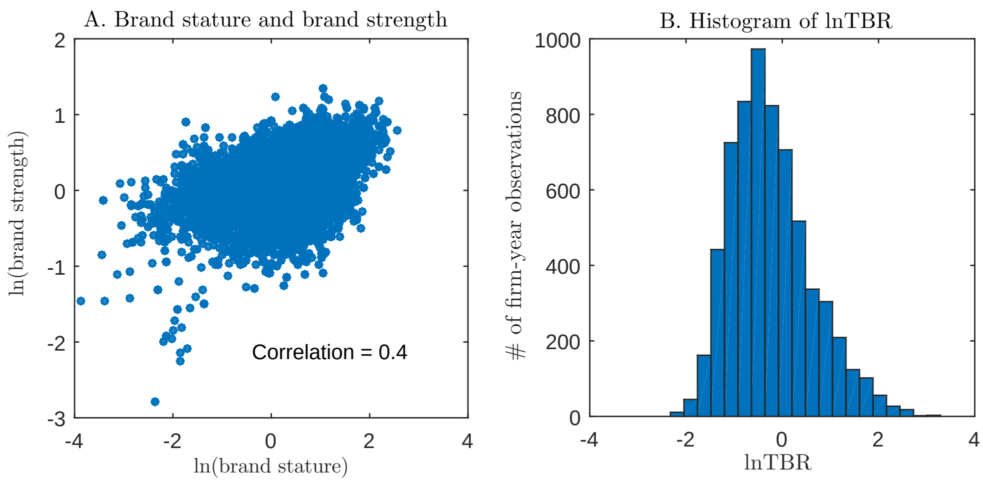


Figure OA.2: The distribution of brand stature, brand strength, and lnTBR.

Table OA.4 shows the summary statistics of the main variables in our analyses. We explain the detailed definition of the variables in the table note of Table OA.4.

# F TMBWW Is An Asset Pricing Factor

In the main text of our paper, we have shown that TMB is an asset pricing factor that comoves with the WW factor. Here, we show that the average between TMB and WW, denoted as TMBWW, is also priced in the cross section of all U.S. public firms. Specifically, we estimate the betas with respect to TMBWW (denoted as $\beta_{TMBWW}$) for all U.S. public firms using a rolling-estimation-window approach. We sort firms into quintiles based on $\beta_{TMBWW}$, and find that the firms with higher $\beta_{TMBWW}$ have significantly higher average excess returns and alphas (see Table OA.5), suggesting that TMBWW is an asset pricing factor.

Table OA.4: Summary statistics.

| Variables | Mean | Median | 10% | 90% | S.D. | # of observations |
|---|---|---|---|---|---|---|
| **BAV variables** | | | | | | |
| ln(strength) | 0.09 | 0.12 | −0.45 | 0.59 | 0.42 | 6,420 |
| ln(stature) | 0.32 | 0.48 | −1.00 | 1.36 | 0.92 | 6,420 |
| lnTBR (unstandardized) | −0.23 | −0.35 | −1.21 | 0.96 | 0.84 | 6,420 |
| **Firm characteristics** | | | | | | |
| lnsize | 8.47 | 8.50 | 5.97 | 10.99 | 1.92 | 6,254 |
| lnBEME | −1.01 | −0.99 | −2.04 | 0.05 | 0.92 | 6,004 |
| lnlev | 0.24 | 0.20 | −0.97 | 1.41 | 1.01 | 6,004 |
| ln(OC/asset) | −0.36 | −0.05 | −1.46 | 0.75 | 1.55 | 6,089 |
| **Cash flow volatility** | | | | | | |
| Vol(daily returns) (%) | 2.45 | 2.09 | 1.21 | 4.03 | 1.40 | 6,399 |
| Vol(sales growth) (%) | 12.96 | 8.05 | 2.66 | 24.98 | 24.84 | 5,962 |
| Vol(net income/asset) (%) | 5.05 | 2.74 | 0.81 | 11.07 | 8.07 | 5,971 |
| Vol(EBITDA/asset) (%) | 3.40 | 2.41 | 0.84 | 6.80 | 3.88 | 5,967 |
| **Key-talent compensation** | | | | | | |
| Administrative expenses/sales (%) | 22.81 | 21.04 | 7.55 | 40.03 | 13.16 | 5,690 |
| R&D/sales (%) | 7.07 | 2.98 | 0.57 | 17.50 | 11.24 | 2,763 |
| Executive compensation/sales (%) | 0.47 | 0.26 | 0.06 | 1.06 | 0.61 | 5,171 |
| **Executive turnover** | | | | | | |
| Turnover × 100 | 11.77 | 0 | 0 | 0 | 32.22 | 25,989 |
| **Innovator turnover** | | | | | | |
| ln(1 + leavers) | 1.43 | 1.10 | 0 | 3.71 | 1.46 | 1,865 |
| ln(1 + new hires) | 1.44 | 1.10 | 0 | 3.69 | 1.47 | 1,865 |
| **Corporate financial policy** | | | | | | |
| Cash/lagged asset (%) | 15.38 | 9.21 | 1.29 | 36.47 | 18.03 | 6,253 |
| ΔCash/net income (%) | 15.32 | 4.50 | −73.45 | 111.70 | 185.79 | 5,380 |
| ΔEquity/lagged asset (%) | 1.80 | 0.48 | 0 | 2.84 | 7.79 | 6,253 |
| Payout/lagged asset (%) | 5.91 | 3.62 | 0 | 16.04 | 6.64 | 6,253 |
| Dividend/lagged asset (%) | 1.91 | 1.07 | 0 | 5.28 | 2.48 | 6,253 |
| Repurchases/lagged asset (%) | 3.77 | 1.28 | 0 | 12.19 | 5.20 | 6,253 |

Note: This table presents the summary statistics for the main variables of our analyses. We merge BAV brand survey data with Compustat and CRSP data to construct a firm-year panel. Firm characteristics and cash flow volatility variables are derived from Compustat and CRSP. Key-talent compensation variables are derived from Execucomp and Compustat. The executive turnover variable is derived from Execucomp and BoardEx. Innovator turnover variables are derived from the Harvard Business School patent and innovator database. Corporate financial policy variables are derived from Compustat. Our sample spans the period 1993-2016 and includes the firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analyses. The definition of the variables is listed below: TBR is the natural log of the ratio between brand strength and brand stature. lnsize is the natural log of the market cap (in million dollars). lnBEME is the natural log of the book-to-market ratio. lnlev is the natural log of the debt-to-equity ratio. ln(OC/asset) is the natural log of the organization capital normalized by assets. Following Eisfeldt and Papanikolaou (2013), we construct the organization capital from SG&A expenditures using the perpetual inventory method. Vol(daily returns) is the volatility of daily stock returns in a given year. Vol(sales growth) is the volatility of forward-looking growth rates of sales (standard deviation of yearly growth rates of sales over the period $t$ through $t+5$). Vol(net income/asset) is the volatility of forward-looking net-income-to-asset ratio (standard deviation of yearly ratios from period $t$ through $t+5$). Vol(EBITDA/asset) is the volatility of forward-looking EBITDA-to-asset ratio (standard deviation of yearly ratios from period $t$ through $t+5$). Administrative expenses/sales is the administrative-expenses-to-sales ratio. We take out advertisement costs, R&D expenses, commissions, and foreign currency adjustments from SG&A to estimate the talent compensation. R&D/sales is the R&D-to-sales ratio. Execucomp/sales is the executive-compensation-to-sales ratio. The executive compensation is the summation of the total pay (*tdc*1) for the top five executives in the Execucomp data. Turnover is a dummy variable that equals one if an executive leaves the firm at age 59 or younger for reasons other than death, and it is 0 otherwise. 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. Cash/lagged asset is the amount of cash holding (*che*) normalize by lagged total assets (*at*). ΔCash/net income is the change in cash holding (*chech*) normalized by the contemporaneous net income (*ni*). ΔEquity/lagged asset is the amount of equity issuance (*sstk*) normalized by lagged total assets (*at*). Payout/lagged asset is the amount of total payout (*dv* + *prstkc*) normalized by lagged total assets (*at*). Dividend/lagged asset is the amount of dividend issuance (*dv*) normalized by lagged total assets (*at*). Repurchases/lagged asset is the amount of share repurchases (*prstkc*) normalized by lagged total assets (*at*).

# G TBR and Financial Constraints

Our model implies that there exist nonlinear interactions between TBR and financial constraints. In particular, the effect of TBR is greater among financially constrained firms. To provide some evidence on this prediction, we conduct a split-sample analyses based on three measures of financial constraints: the HP index (see Hadlock and Pierce, 2010), the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007), and firm size measured by the market capitalization of equity (see, e.g. Gilchrist and Himmelberg, 1995; Livdan, Sapriza and Zhang, 2009; Hadlock and

Table OA.5: TMBWW is an asset pricing factor.

| | Excess returns and alphas for portfolios sorted on $\beta_{TMBWW}$ | | | | | |
|---|---|---|---|---|---|---|
| Portfolios sorted on $\beta_{TMBWW}$ | 1 (Low) | 2 | 3 | 4 | 5 (High) | 5 − 1 |
| Excess returns (%) | 11.74*** | 11.60*** | 11.27*** | 13.49*** | 18.58*** | 6.85* |
| | [2.72] | [3.37] | [3.28] | [3.24] | [3.14] | [1.89] |
| Fama-French three-factor $\alpha$ (%) | 2.39 | 4.27*** | 4.29*** | 5.74*** | 9.49*** | 7.10*** |
| | [1.33] | [3.58] | [3.85] | [4.07] | [4.28] | [2.74] |
| Carhart four-factor $\alpha$ (%) | 2.64 | 4.52*** | 4.98*** | 6.37*** | 10.99*** | 8.35*** |
| | [1.42] | [3.65] | [4.74] | [4.55] | [5.18] | [3.23] |
| Pástor-Stambaugh five-factor $\alpha$ (%) | 1.92 | 4.21*** | 4.76*** | 5.79*** | 10.74*** | 8.82*** |
| | [1.04] | [3.39] | [4.64] | [4.46] | [5.12] | [3.40] |
| Hou-Xue-Zhang $q$-factor $\alpha$ (%) | 0.78 | 2.65** | 4.20*** | 7.22*** | 13.55*** | 12.77*** |
| | [0.43] | [2.15] | [4.03] | [5.00] | [5.44] | [4.33] |
| Fama-French five-factor $\alpha$ (%) | 0.20 | 1.68 | 3.07*** | 6.04*** | 12.43*** | 12.22*** |
| | [0.11] | [1.61] | [2.86] | [3.94] | [5.68] | [4.87] |

Note: This table shows the value-weighted excess returns and alphas for portfolios sorted on the beta with respect to TMBWW ($\beta_{TMBWW}$). In each month, we estimate $\beta_{TMBWW}$ for all U.S. public firms by regressing their monthly stock returns on the returns of TMBWW and the returns of the Fama-French three factors in the preceding 36 months. In the beginning of the sample, when less than 36 monthly historical returns of TMBWW are present, we require at least 12 monthly returns to estimate $\beta_{TMBWW}$. We then average the monthly $\beta_{TMBWW}$ into yearly $\beta_{TMBWW}$ for each stock and sort the stocks into quintiles based on their lagged yearly $\beta_{TMBWW}$. The sample period of this table is from 1995 to 2016, because we use the first two years' data to compute the lagged yearly $\beta_{TMBWW}$. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Pierce, 2010; Li, 2011). The firms with higher HP index, higher WW index, and smaller size are more likely to be financially constrained.

Table OA.6: Excess returns and alphas for the long-short portfolios sorted on TBR across subsamples split by financial constraints.

| Low HP | Medium HP | High HP | Low WW | Medium WW | High WW | Big Size | Medium Size | Small Size |
|---|---|---|---|---|---|---|---|---|
| | | | Panel A: Average excess returns (%) | | | | | |
| 2.64 | −0.21 | 8.46** | 1.82 | 1.86 | 9.79** | 2.11 | 6.80** | 8.80** |
| [1.48] | [−0.07] | [2.44] | [0.72] | [0.62] | [1.99] | [0.65] | [2.05] | [2.01] |
| | | | Panel B: Fama-French three-factor $\alpha$ (%) | | | | | |
| 3.31* | −0.11 | 7.51** | 2.46 | 2.66 | 10.32** | 1.25 | 8.40*** | 9.89** |
| [1.85] | [−0.04] | [2.28] | [1.05] | [0.96] | [2.18] | [0.47] | [2.77] | [2.06] |
| | | | Panel C: Carhart four-factor $\alpha$ (%) | | | | | |
| 3.19* | 0.16 | 7.27** | 2.79 | 3.24 | 10.24** | 2.79 | 7.10** | 11.43** |
| [1.76] | [0.05] | [2.09] | [1.18] | [1.15] | [2.14] | [1.06] | [2.34] | [2.37] |
| | | | Panel D: Pástor-Stambaugh five-factor $\alpha$ (%) | | | | | |
| 2.99 | −0.52 | 7.20** | 2.59 | 2.88 | 9.32* | 2.59 | 6.56** | 11.28** |
| [1.64] | [−0.17] | [2.06] | [1.09] | [1.02] | [1.94] | [0.97] | [2.16] | [2.32] |
| | | | Panel E: Hou-Xue-Zhang q-factor $\alpha$ (%) | | | | | |
| 3.35* | 2.50 | 12.09*** | 5.47** | 6.21** | 16.13*** | 8.05*** | 10.29*** | 12.86** |
| [1.81] | [0.81] | [3.00] | [2.23] | [2.17] | [3.18] | [3.22] | [3.08] | [2.53] |
| | | | Panel F: Fama-French five-factor $\alpha$ (%) | | | | | |
| 3.25* | 2.34 | 11.49*** | 4.56* | 5.62** | 14.03*** | 7.16*** | 9.55*** | 10.85** |
| [1.76] | [0.79] | [2.96] | [1.89] | [1.98] | [2.87] | [2.87] | [3.01] | [2.17] |

Note: This table shows the excess returns and alphas for the long-short portfolios sorted on TBR across subsamples split by financial constraints. In June of year $t$, we sort firms into three groups based on the finanical constraint measures: the HP index (see Hadlock and Pierce, 2010), the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007), and the firm size measured by the market capitalization of equity. We then sort firms in each group into five quintiles based on firms' TBRs 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 portfolio that longs Q5 (high TBR) firms and shorts Q1 (low TBR) firms. We also report the portfolio alphas estimated by the Fama-French three-factor model, the Carhart four-factor model, the Pástor-Stambaugh five-factor model, the Hou-Xue-Zhang q-factor model and the Fama-French five-factor model. Our sample includes the firms 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 spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

In June of year t, we sort firms into three groups based on each financial constraint measure. We further sort firms in each group into five quintiles based on firms' TBRs in year $t-1$. We then compute the value-weighted portfolio returns and estimate the portfolios' alphas using various factor models. Table OA.6 presents the average excess returns and alphas of the long-short portfolios sorted on TBR. We find that the average excess returns and alphas of the long-short portfolios sorted on TBR are positive in all groups, and importantly, their magnitudes are much larger among financially constrained firms. This pattern is robust to the choices of financial constraint measures and factor models.

# H Double-Sort Analyses

In this section, we show that the asset pricing implications of TBR we have documented in the main text are robust and cannot be explained by other related factors or firm characteristics. In Table OA.7, we show that other measures of customer capital (brand stature, brand strength, and firms' product market fluidity) are either not priced in the cross section or their association with stock returns can be explained away by TBR. On the other hand, TBR remains priced in the cross section after controlling for the three customer capital measures (see Table OA.8). We further verify that the average excess returns and alphas of the long-short portfolio sorted on TBR remain significantly positive after controlling for the measures of hum capital importance (see Table OA.9) and industry classifications (see Table OA.10).

# I TBR and Tunovers

We have examined the relation between TBR and the turnovers of top executivies covered by the Execucomp data in the main text of our paper. Here, we replicate the analyses using two different samples: (1) only CEOs, and (2) all managers covered by the BoardEx data. We find that the patterns we document in the main text are robust in these two samples.

## I.1 TBR and CEO Tunovers

In the main text, we show that TBR is positively related to the turnover rates of the top executives. Consistent with that finding, we find CEO turnover rates are significantly higher in the firms with higher TBRs (see columns 1 and 2 of Table OA.11). This result is robust to the inclusion of the SIC-2 industry fixed effects.

In the main text, we also show that the positive relation between TBR and executive turnovers is more pronounced conditional on heightened financial constraints risk (i.e., when the TMB factor becomes more negative). We find similar results for CEO turnovers (see columns 3 and 4 of Table OA.11). The coefficients for the interaction term between TBR and TMB are negative and statistically significant, suggesting that the difference in CEO turnover rates between high TBR firms and low TBR firms is indeed larger conditional on heightened financial constraints risk.

## I.2 TBR and Managerial Turnovers in the BoardEx Data

Next, we repeat the turnover analyses by including all managers from the BoardEx (see Table OA.12). Consistent with our previous analyses using CEOs and top five executives, we find that managerial turnovers are positively associated with TBR. Moreover, this positive relation is more pronounced conditional on heightened financial constraints risk.

Table OA.7: Long-short portfolio returns associated with various customer capital measures.

| Long-short Portfolios | High brand stature - Low brand stature | High brand strength - Low brand strength | High product fluidity - Low product fuidity |
|---|---|---|---|
| Panel A: Excess returns of the long-short portfolios (%) | | | |
| Single sort | −4.61** | 1.21 | 0.14 |
| | [−2.48] | [0.53] | [0.05] |
| Double sort | −0.89 | 1.06 | 2.45 |
| (First sort on TBR) | [−0.50] | [0.51] | [1.03] |
| Panel B: Fama-French three-factor $\alpha$ of the long-short portfolios (%) | | | |
| Single sort | −4.63** | 0.78 | −0.63 |
| | [−2.54] | [0.39] | [−0.26] |
| Double sort | −1.10 | 0.54 | 1.74 |
| (First sort on TBR) | [−0.63] | [0.29] | [0.84] |
| Panel C: Carhart four-factor $\alpha$ of the long-short portfolios (%) | | | |
| Single sort | −4.14** | 1.69 | 0.08 |
| | [−2.25] | [0.84] | [0.03] |
| Double sort | −0.29 | 1.44 | 2.71 |
| (First sort on TBR) | [−0.17] | [0.78] | [1.21] |
| Panel D: Pástor-Stambaugh five-factor $\alpha$ of the long-short portfolios (%) | | | |
| Single sort | −3.87** | 2.00 | −0.07 |
| | [−2.09] | [0.99] | [−0.03] |
| Double sort | −0.15 | 1.55 | 2.58 |
| (First sort on TBR) | [−0.09] | [0.83] | [1.12] |
| Panel E: Hou-Xue-Zhang $q$-factor $\alpha$ of the long-short portfolios (%) | | | |
| Single sort | −4.53** | 2.50 | 2.91 |
| | [−2.34] | [1.38] | [1.44] |
| Double sort | 1.51 | 2.76 | 3.74 |
| (First sort on TBR) | [0.88] | [1.54] | [1.45] |
| Panel F: Fama-French five-factor $\alpha$ of the long-short portfolios (%) | | | |
| Single sort | −4.10** | 2.84 | 3.17 |
| | [−2.15] | [1.46] | [1.30] |
| Double sort | 1.53 | 2.78 | 3.94 |
| (First sort on TBR) | [0.88] | [1.58] | [1.56] |

Note: This table shows long-short portfolio returns associated with three customer capital measures: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). We sort stocks into quintiles based on the customer capital measures and then compute the average excess returns and alphas for the value-weighted long-short portfolios. We also perform a double-sort analysis in which we first sort firms into three groups based on TBR and then sort the firms in each group into five quintiles based on the customer capital measures. The fluidity measure, as developed in Hoberg, Phillips and Prabhala (2014), measures how intensively the product market around a firm is changing in each year. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. 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 OA.8: Excess returns and alphas of the long-short portfolio sorted on TBR controlling for customer capital measures.

| First sort variables | Brand stature | Brand strength | Product fluidity |
|---|---|---|---|
| Excess returns (%) | 2.90 | 6.02** | 5.15** |
| | [1.45] | [2.50] | [2.19] |
| Fama-French three-factor $\alpha$ (%) | 3.18* | 5.94*** | 5.57*** |
| | [1.81] | [2.85] | [2.84] |
| Carhart four-factor $\alpha$ (%) | 3.94** | 6.06*** | 5.92*** |
| | [1.99] | [2.87] | [2.99] |
| Pástor-Stambaugh five-factor $\alpha$ (%) | 3.94** | 5.74*** | 5.66*** |
| | [1.97] | [2.71] | [2.84] |
| Hou-Xue-Zhang $q$-factor $\alpha$ (%) | 7.62*** | 8.74*** | 9.34*** |
| | [3.90] | [3.93] | [4.66] |
| Fama-French five-factor $\alpha$ (%) | 7.60*** | 7.80*** | 8.70*** |
| | [4.12] | [3.63] | [4.50] |

Note: This table shows the excess returns and alphas of the value-weighted long-short portfolio sorted on TBR controlling for customer capital measures using a double-sort approach. In June of year $t$, we sort firms into three groups based on three measures of customer capital: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). We then sort firms within each group into five quintiles based on firms' TBRs in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year $t$ to June of year $t+1$. The fluidity measure, as developed in Hoberg, Phillips and Prabhala (2014), measures how intensively the product market around a firm is changing in each year. It is downloaded from the Hoberg-Phillips data library. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. 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 OA.9: Excess returns and alphas of the long-short portfolio sorted on TBR controlling for key-talent compensation.

| First sort variables | Administrative expenses | R&D expenditure | Managerial compensation | Organization capital |
|---|---|---|---|---|
| Excess returns (%) | 5.24** | 5.01** | 4.26** | 5.16* |
| | [2.30] | [2.08] | [2.01] | [1.95] |
| Fama-French three-factor $\alpha$ (%) | 5.05*** | 5.39*** | 4.68*** | 5.28** |
| | [2.72] | [2.76] | [2.61] | [2.45] |
| Carhart four-factor $\alpha$ (%) | 5.55*** | 5.99*** | 4.56** | 5.32** |
| | [2.96] | [3.05] | [2.51] | [2.43] |
| Pástor-Stambaugh five-factor $\alpha$ (%) | 5.22*** | 5.72*** | 4.31** | 5.17** |
| | [2.78] | [2.90] | [2.36] | [2.34] |
| Hou-Xue-Zhang $q$-factor $\alpha$ (%) | 8.67*** | 9.59*** | 7.20*** | 9.56*** |
| | [4.48] | [4.83] | [3.81] | [4.29] |
| Fama-French five-factor $\alpha$ (%) | 7.47*** | 8.74*** | 6.86*** | 8.83*** |
| | [3.97] | [4.58] | [3.79] | [4.13] |

Note: This table shows the excess returns and alphas of the value-weighted long-short portfolio sorted on TBR controlling for key-talent compensation using a double-sort approach. In June of year $t$, we first sort firms into three groups based on four measures of key-talent compensation: administrative expenses, R&D expenditure, managerial compensation, and organizational capital. We then sort firms within each group into five quintiles based on firms' TBRs in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year $t$ to June of year $t+1$. Administrative expenses are computed from SG&A by taking out advertisement costs, R&D expenses, commissions, and foreign currency adjustments. R&D expenditure comes from Compustat. Managerial compensation is the summation of the total pay ($tdc1$) for the top five executives in the Execucomp data. Administrative expenses, R&D expenditure, and managerial compensation are normalized by sales. Organization capital is constructed from SG&A expenditures using the perpetual inventory method, following Eisfeldt and Papanikolaou (2013). The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table OA.10: Excess returns and alphas of the long-short portfolio sorted on TBR controlling for industry classifications.

| Industry classifications | SIC-2 | FF5 | FF10 | FF12 | FF17 | FF48 | Durability |
|---|---|---|---|---|---|---|---|
| Excess returns (%) | 3.88** | 5.43*** | 5.49*** | 5.38*** | 4.86** | 5.04*** | 4.66** |
| | [2.48] | [3.09] | [3.17] | [3.08] | [2.24] | [3.08] | [2.00] |
| Fama-French three-factor $\alpha$ (%) | 3.30** | 5.06*** | 4.54*** | 4.37*** | 4.37** | 4.19*** | 4.37** |
| | [2.33] | [2.95] | [2.73] | [2.60] | [2.44] | [2.69] | [2.25] |
| Carhart four-factor $\alpha$ (%) | 3.46** | 5.14*** | 4.70*** | 4.55*** | 4.75*** | 4.26*** | 4.58** |
| | [2.40] | [2.96] | [2.79] | [2.67] | [2.62] | [2.70] | [2.33] |
| Pástor-Stambaugh five-factor $\alpha$ (%) | 3.24** | 4.74*** | 4.37** | 4.24** | 4.51** | 3.97** | 4.32** |
| | [2.24] | [2.73] | [2.59] | [2.48] | [2.47] | [2.51] | [2.19] |
| Hou-Xue-Zhang $q$-factor $\alpha$ (%) | 4.43*** | 5.80*** | 5.56*** | 5.41*** | 7.92*** | 5.11*** | 7.71*** |
| | [2.99] | [3.27] | [3.24] | [3.13] | [4.36] | [3.20] | [3.87] |
| Fama-French five-factor $\alpha$ (%) | 4.31*** | 5.54*** | 5.39*** | 5.27*** | 7.43*** | 5.09*** | 7.45*** |
| | [2.94] | [3.13] | [3.15] | [3.05] | [4.22] | [3.16] | [3.90] |

Note: This table shows the excess returns and alphas of the value-weighted long-short portfolio sorted on TBR controlling for industry classifications using a double-sort approach. In June of year $t$, we group firms into different industries based on various industry classifications. We then sort firms within each industry into five quintiles based on firms' TBRs in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year $t$ to June of year $t+1$. SIC-2 is the two-digit SIC industry. FF5, FF10, FF12, FF17, and FF48 are corresponding Fama-French industry classifications. The durability industry classification comes from Gomes, Kogan and Yogo (2009), who classify each SIC industry into six categories (durables, non-durables, services, private domestic investment, government, and net exports) based on its contributions to final demand. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. 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 OA.11: TBR and CEO turnovers

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Turnover$_t$ × 100 | | | |
| lnTBR$_{t-1}$ | 0.902*** | 0.870*** | 1.099*** | 1.076*** |
| | [3.948] | [3.240] | [4.343] | [3.486] |
| lnTBR$_{t-1}$ × TMB$_{t-1}$ | | | −6.100*** | −6.305*** |
| | | | [−3.549] | [−3.656] |
| ln(OC/Asset)$_{t-1}$ | 0.143 | 0.151 | 0.263 | 0.129 |
| | [0.629] | [0.539] | [1.072] | [0.439] |
| lnsize$_{t-1}$ | −0.110 | 0.144 | −0.193 | 0.046 |
| | [−0.560] | [0.570] | [−1.000] | [0.175] |
| lnBEME$_{t-1}$ | 0.105 | 0.674 | 0.498 | 1.007 |
| | [0.229] | [1.216] | [0.981] | [1.657] |
| lnlev$_{t-1}$ | 0.360 | 0.415 | 0.603 | 0.697 |
| | [1.244] | [1.003] | [1.682] | [1.497] |
| StockRet$_{t-1}$ | −4.258*** | −4.274*** | −4.355*** | −4.315*** |
| | [−3.505] | [−3.224] | [−2.979] | [−2.819] |
| Female | 0.259 | −0.534 | −0.027 | −0.908 |
| | [0.245] | [−0.480] | [−0.026] | [−0.811] |
| Industry FE | No | Yes | No | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 4875 | 4875 | 4931 | 4931 |
| R-squared | 0.012 | 0.028 | 0.015 | 0.030 |

Note: Columns (1) and (2) show the relation between CEO turnovers and TBR. Columns (3) and (4) show the relation between CEO turnovers and the interaction between TBR and the yearly TMB factor. We identify CEO turnovers based on the Execucomp and BoardEx data. Turnover$_t$ is a dummy variable that equals one for a given CEO-year observation if the CEO leaves the firm at age 59 or younger for reasons other than death, and 0 otherwise. TMB is the yearly returns for the long-short portfolio sorted on TBR. We standardize lnTBR to ease the interpretation of the coefficients. Control variables include the 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 CEOs (Female). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes the firms 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 spans 1993 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 OA.12: TBR and managerial turnovers in the BoardEx data

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Turnover$_t$ $\times$ 100 | | | |
| lnTBR$_{t-1}$ | 1.928$^{***}$ | 1.324$^{***}$ | 2.026$^{***}$ | 1.374$^{***}$ |
| | [6.154] | [3.378] | [6.444] | [3.481] |
| lnTBR$_{t-1}$ $\times$ TMB$_{t-1}$ | | | $-1.564^{**}$ | $-0.829^{**}$ |
| | | | [$-2.536$] | [$-2.218$] |
| ln(OC/Asset)$_{t-1}$ | 0.421$^{**}$ | 0.228 | 0.416$^{**}$ | 0.229 |
| | [2.685] | [1.123] | [2.661] | [1.101] |
| lnsize$_{t-1}$ | 0.939$^{***}$ | 0.589$^{***}$ | 0.945$^{***}$ | 0.597$^{***}$ |
| | [5.815] | [3.156] | [5.860] | [3.176] |
| lnBEME$_{t-1}$ | 1.467$^{***}$ | 1.830$^{***}$ | 1.509$^{***}$ | 1.862$^{***}$ |
| | [4.356] | [5.742] | [4.453] | [5.813] |
| lnlev$_{t-1}$ | 0.662 | 0.915$^{**}$ | 0.661 | 0.917$^{**}$ |
| | [1.693] | [2.783] | [1.695] | [2.782] |
| StockRet$_{t-1}$ | $-1.705^{***}$ | $-1.905^{***}$ | $-1.669^{**}$ | $-1.894^{***}$ |
| | [$-2.895$] | [$-3.636$] | [$-2.797$] | [$-3.639$] |
| Female | $-0.053$ | 0.092 | $-0.053$ | 0.094 |
| | [$-0.252$] | [0.424] | [$-0.251$] | [0.433] |
| Industry FE | No | Yes | No | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 421269 | 421269 | 419195 | 419195 |
| R-squared | 0.009 | 0.013 | 0.009 | 0.013 |

Note: Columns (1) and (2) of this table show the relation between managerial turnovers and TBR. Columns (3) and (4) of this table show the relation between managerial turnovers and the interaction between TBR and the yearly TMB factor. We identify managerial turnovers using the employment history data in BoardEx. The dependent variables are 100 for a given manager-year observation if the manager leaves the firm at age 59 or younger for reasons other than death, and 0 otherwise. TMB is the yearly returns for the long-short portfolio sorted on TBR. We standardize lnTBR to ease the interpretation of the coefficients. Control variables include the 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 managers (Female). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes the firms 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 spans 1993 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.

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