Customer Capital, Financial Constraints and Stock Returns

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Abstract

We develop an asset pricing model in which part of customer capital depends on key talents' specialized contribution, while the rest is retained by customers' pure brand loyalty unrelated to current key talents. The former component is fragile to financial constraints risk, as key talents tend to escape from the financially constrained firm, damaging talent-based customer capital. Using granular proprietary brand perception survey data, we construct the firm-level brand-talent ratio (BTR) for customer capital and document new joint cross-sectional patterns: the firms with lower BTRs have higher (risk-adjusted) average returns, higher talent turnover rates, and more precautionary financial policies.

Keywords: Cross-sectional stock returns; Brand loyalty; Industrial organization and finance; Inalienable human capital; Robust firms; Financial Constraints Risk.

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1 Introduction

Customer capital – customers' brand loyalty to the firm – is one of the firm's most crucial assets, as it determines the capacity of stable demand flows for the firm. Creating and sustaining customer capital is essential for a firm's survivorship, growth, profitability, and thus its valuation, even though customer capital does not explicitly appear on the balance sheet.[1]

Existing studies have focused on the implications of customer capital and product market structure on corporate policies (see, e.g. Titman, 1984; Titman and Wessels, 1988; Chevalier and Scharfstein, 1996; Gourio and Rudanko, 2014; Gilchrist et al., 2017).[2] Our paper investigates the composition of customer capital and its interaction with financial constraints. We develop a quantitative structural model to analyze the implications of such interaction on asset prices, talents turnovers, and financial policies. As illustrated in Figure 1, the creation and maintenance of customer capital mainly depend on innovation, dynamic management, and product differentiation through the channel of key talents' unique contributions, as well as advertisement, (price-adjusted) product quality, and market structure through the channel of brand recognition. In principle, part of customer capital is maintained mainly by key talents' unique contributions, while the rest is retained only by customers' pure brand recognition unrelated to current key talents. We refer to the former component as *talent-based customer capital*, and the latter as *pure-brand-based customer capital*.

Talent-based customer capital is fundamentally linked to key talents' inalienable human capital as they can leave the firm, taking away or damaging talent-based customer capital, especially when the firm is financially constrained. Thus, talent-based customer capital is fragile to the firm's financial constraints risk, whereas pure-brand-based customer capital is immune to financial constraints risk. Our paper is the first to dissect total customer capital and highlight how different components of customer capital interact with financial constraints risk, generating important financial implications. Without differentiating the two components' fragility to financial constraints risk, the existing studies may inflate or overestimate the amount of customer capital robustly owned by the firm.

As a major empirical contribution, we use granular proprietary survey data on consumers' brand perception to decompose the firm-level customer capital and construct the brand-talent ratio (BTR) to capture the relative contributions of pure-brand-based customer capital and

[1]As emphasized by Rudanko (2017), customer capital is crucial for other assets of firms to be profitable. One example to demonstrate the necessity of customer capital is Iridium's bankruptcy case. The global satellite phone company backed by Motorola filed for bankruptcy in 1999 due to its failure to create and maintain customer capital. The system that cost Motorola more than $5 billion to build (the book value) was ultimately sold for $25 million, or about half a penny for every dollar it originally cost. In general, the risk of losing customer capital was rated as the most top business risk.

[2]Corporate policies include financial policies such as capital structure and payout policies, investment policies, and price-setting policies in product markets.

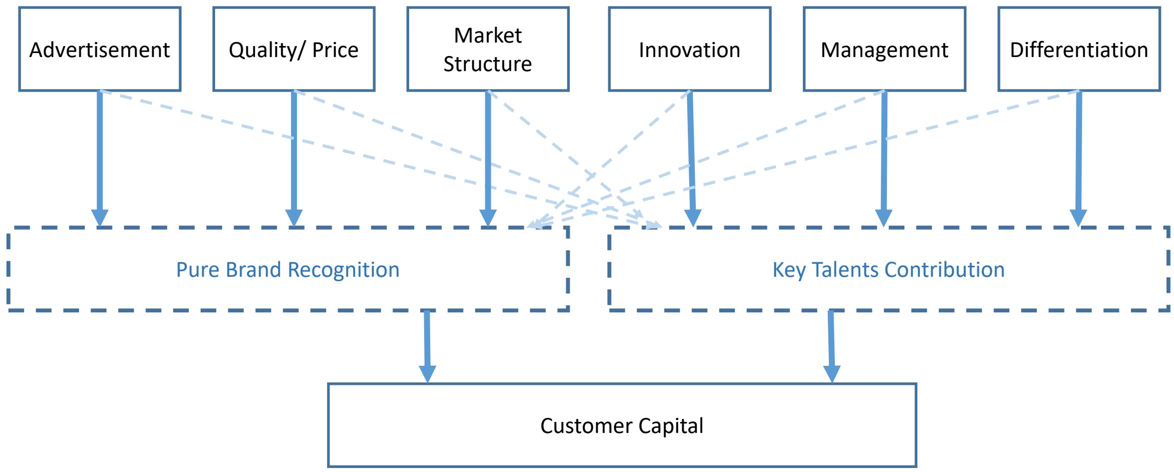


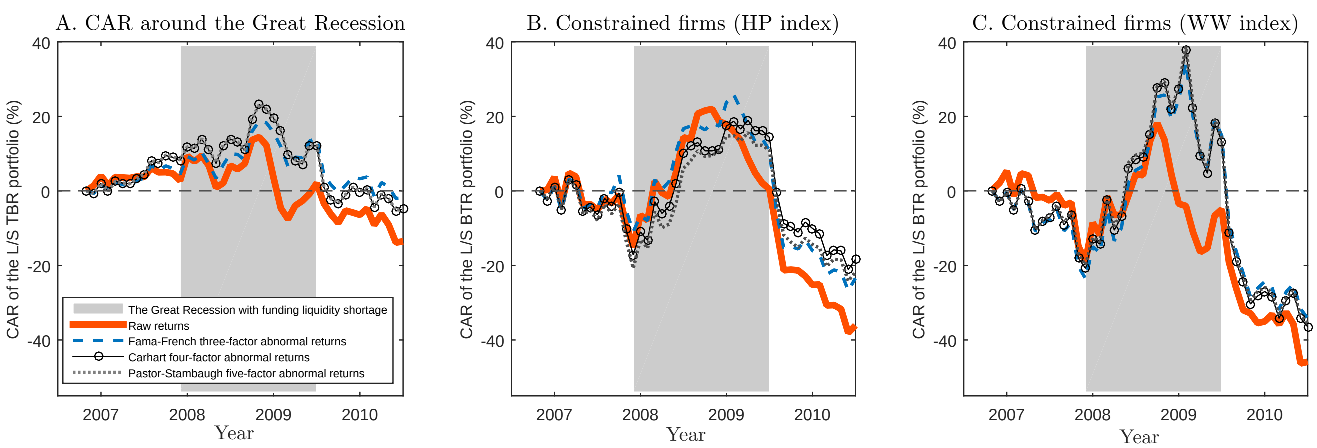
Figure 1: A conceptual illustration of customer capital composition.

talent-based customer capital. We document new cross-sectional patterns: the firms with lower BTRs have higher (risk-adjusted) average returns, even after controlling for various confounding factors. The return spread across firms' BTRs is highly correlated with the return spread across firms' financial conditions (Whited and Wu, 2006). Moreover, the firms with lower BTRs are associated with higher talent turnover rates, and this pattern is more pronounced in the periods with heightened financial constraints risk. These findings suggest that talent-based customer capital is more fragile to financial constraints risk because key talents tend to escape from the financially constrained firms and have the talent-based customer capital damaged. And thus, the firms with lower BTRs are riskier due to their higher exposure to financial constraints risk.

Identifying and empirically measuring the economic importance of the interaction between customer capital composition and financial constraints risk in explaining the cross-sectional patterns presents a challenge. Empirical identification requires exogenous variations in firm-level BTR and exogenous variations in the aggregate financial constraints risk factor. However, there are no obvious instruments. Therefore, evaluating the magnitude of the implications of customer capital components requires estimating or calibrating a dynamic structural model. We thus develop an asset pricing model featuring inalienable talent-based customer capital and endogenous marginal value of internal funds. Our calibrated model is consistent with the data and quantitatively explains the joint cross-sectional stock return and turnover patterns.

Our model itself has threefold theoretical contributions: first, it generates a testable prediction that the firm's exposure to the underlying financial constraints risk is simultaneously reflected in both of the cross-sectional variation in firms' BTRs and the cross-sectional variation in firms' financial conditions. In our model, the two cross-equation restrictions based on two different cross sections jointly identify the same underlying asset pricing factor in the similar spirits to Papanikolaou (2011). Second, it endogenizes talent turnovers driven by financial constraints risk, which differentiates our model from other dynamic models investigating the valuation effect of turnovers (see, e.g. Taylor, 2010; Eisfeldt and Papanikolaou, 2013; Berk, Stanton and Zechner, 2010). Third, it incorporates the idea of inalienable human capital (see, e.g. Hart and Moore, 1994; Lustig, Syverson and Nieuwerburgh, 2011; Bolton, Wang and Yang, 2016) into a dynamic model emphasizing endogenous marginal value of internal funds.

As a motivating fact, Figure 2 presents the cumulative abnormal returns for the long-short portfolio based on BTR sorting. The time series are displayed around the Great Recession, which featured poor liquidity conditions for U.S. firms. As shown by Figure 2, the firms with lower BTRs have lower abnormal returns during the period of poor liquidity condition, while this pattern reverses when aggregate liquidity condition improves due to economic recovery. This pattern is especially pronounced among financially constrained firms. These stylized facts suggest that high BTR firms are generally far more resilient than low BTR firms against adverse aggregate liquidity shocks.



Note: This figure plots CAR for the long-short portfolio (long Quintile 5 and short Quintile 1) of BTR around the Great Recession. We follow NBER and define the time period of the Great Recession as from Dec. 2007 to Jun. 2009. We compute the abnormal returns using the Fama-French three factor model, the Carhart four-factor model, and the Pástor-Stambaugh five-factor model using an event study approach. We estimate the model parameters using monthly returns of the long-short portfolio from Dec. 2003 to Nov. 2006. We then compute the cumulative abnormal returns for the time period that starts from Dec. 2006 and ends at July 2010. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ with share codes 10 or 11. We exclude financial firms and utility firms. Panel A includes both financially constrained firms and financially unconstrained firms. Panel B and C include only financially constrained firms, classified based on the HP index (see Hadlock and Pierce, 2010) and the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007), respectively. Firms whose HP or WW indexes are in the top tertile are classified as financially constrained firms.

Figure 2: Motivating facts for the importance of customer capital composition.

Inspired by the stylized facts in Figure 2, we develop a theoretical framework to shed light on the underlying mechanism. In our model, the firm's external financing is costly, motivating retained earnings; thus, it faces endogenous financial constraints risk. The level of internal funds determines the firm's marginal value of liquidity. The value of customer capital is the present value of the net profit attributed to the existing customer base during their entire relationship with the firm. It is coined *customer lifetime value* by Farris et al. (2010) in the marketing literature. Customer capital has two unique features that determine the firm's exposure to systematic financial constraints risk. First, key talents have limited commitment to the firm – they can leave the firm and take away a fraction of talent-based customer capital. To retain talent-based customer capital, the firm compensates key talents and thus is subject to operating leverage. Second, key talents enjoy non-pecuniary private benefits from the firm's customer capital, because high brand values with strong public recognition implicitly offer identity-based benefits, signaling values of human capital quality, and social status. As a result, pure-brand-based customer capital is robust against financial constraints risk; by contrast, talent-based customer capital is fragile particularly when the firm's liquidity condition is poor, as the effective cost of compensation increases with the firm's marginal value of liquidity. The fragility of talent-based customer capital is the essential feature that generates the spread in risk-adjusted returns across BTR portfolios. Quantitatively, our calibrated model implies that non-pecuniary private benefits contribute to the spread by about 20% as an amplification channel.

Our model highlights an intertemporal tradeoff between risks and returns when the firm decides whether to retain talent-based customer capital. Although retaining talent-based customer capital on average brings positive net cash flows, the associated operating leverage increases the firm's exposure to financial constraints risk. When the firm's liquidity condition is poor, key talents may find it optimal to *escape from a sinking ship* or *jump to a safer boat* (see, e.g. Brown and Matsa, 2016; Baghai et al., 2017; Babina, 2017)[3]; alternatively, firms may find it optimal to conduct *deleveraging of fixed costs* by replacing incumbent talents with less-cash-compensated new talents (see, e.g. Gilson and Vetsuypens, 1993).

While our model has stressed the importance of customer capital and its composition, we would have little to say about its empirical relevance without a measure. The main empirical challenge is to find high-quality data on customers' brand perception that is measured in a consistent way across firms. One of the purposes of this paper is to introduce a measure that approximates the composition of customer capital based on a proprietary granular brand perception survey database. The database, provided by the BAV Group, is regarded as the world's most comprehensive database of consumers' perception of brands. We use the ratio between *brand stature* and *brand strength*, the two major brand metrics developed by the BAV Group, as our measure for BTR. By BAV's design, brand stature quantifies brand loyalty as of today, which provides an approximation for the existing customer capital; brand strength

[3]Babina (2017) provides several pieces of evidence consistent with our model's implications. First, employees' exit rates are relatively higher in financially distressed firms. Second, exiting employees are more likely to pursue related economic activity in the same industry. Third, employees exiting financially distressed firms earn higher wages prior to the exit compared to employees exiting non-distressed firms. Fourth, the exit rates of employees from distressed firms is greater in the states with less enforceable non-compete agreements.

quantifies how much a brand is perceived to be innovative and distinctive. By nature, the maintenance of brand strength relies mainly on firms' key talents, as innovation and product differentiation require significant intellectual inputs. Thus, brand strength naturally provides an approximation for talent-based customer capital. Note that we do not assume that brand strength is entirely contributed by talent-based customer capital. The assumption we make here is that brand strength reflects more about talent-based customer capital compared to brand stature so that BTR captures the relative importance of talent-based customer capital.

We start our empirical analyses by evaluating the quality of our BTR measure. Following Bloom and Reenen (2007), we conduct external validation by matching the BAV data with Compustat/CRSP to investigate the association between our BTR measure and various proxies of key talent compensation. We find that the firms with lower BTRs are associated with higher one-year lagged administrative expenses, R&D expenses, and executive compensation, suggesting that key talents are more essential for these firms. In contrast to other brand metrics derived from firms' financial and accounting variables, our survey-based BTR measure is unlikely to be mechanically linked to the outcome financial variables we study.

We present two sets of main empirical results to support our model. First, we find that the firms with lower BTRs have higher average excess returns and greater alphas in various factor models. The return spread is persistent over time, and it is robust after controlling for mispricing factors, key talent compensation, organization capital, total customer capital, and industry classifications. Moreover, the return spread is highly correlated with the returns of the financial constraints factor of Whited and Wu (2006), suggesting that BTR captures the exposure to financial constraints risk. We also extend our sample and show that a proxy for BTR is priced in the cross section of all U.S. public firms. Second, we find that the firms with lower BTRs are associated with higher talent turnover rates. This pattern is robust for both executives and innovators. Moreover, we show that the negative relation between BTR and talent turnovers is more pronounced in the periods with worse aggregate liquidity condition and in the states with lower enforceability of the non-competition agreements.

Several additional empirical tests also support the mechanism of our model. First, we show that the firms with higher BTRs have steadier sales growth and less volatile cash flows. Their growth is also less negatively affected by peer firms' competition through innovative activities. Therefore, we refer to high BTR firms as *robust firms*, because these firms mostly consist of pure-brand-based customer capital, which is less fragile to aggregate liquidity shocks and peers' competition. Second, we find that low BTR firms are more likely to adopt precautionary financial policies. They hold more cash and convert a larger fraction of net income into cash holdings. They also issue larger amounts of equity and have smaller amounts of payout. Third, we provide evidence for non-pecuniary private benefits by showing that key talents have lower compensation when they work in the firms with greater brand stature. Finally, we show that the duration of executive compensation is longer in low BTR firms, suggesting that these firms actively manage pay duration. The difference in duration, however, appears to be too small to fundamentally alleviate the liquidity constraints faced by low BTR firms.

Related Literature. First, our paper lies in the large literature on cross-sectional stock returns (see, e.g. Cochrane, 1991; Berk, Green and Naik, 1999; Gomes, Kogan and Zhang, 2003; Nagel, 2005; Zhang, 2005; Livdan, Sapriza and Zhang, 2009; Belo and Lin, 2012; Eisfeldt and Papanikolaou, 2013; Belo, Lin and Bazdresch, 2014; Kogan and Papanikolaou, 2014; Belo et al., 2017). In particular, our paper is related to the works investigating the cross-sectional stock return implications of firms' fundamental characteristics through their interactions with financial constraints (see, e.g. Campbell, Hilscher and Szilagyi, 2008; Garlappi, Shu and Yan, 2008; Gomes and Schmid, 2010; Garlappi and Yan, 2011). A comprehensive survey is provided by Nagel (2013). We contribute to existing work by shedding light on firms' heterogeneous systematic risk exposure to liquidity shocks through their heterogeneous customer capital compositions as firm characteristics.

Our paper contributes to the emerging literature on the interaction between customer capital and finance. Titman (1984); Titman and Wessels (1988) provide the first piece of theoretical insight and empirical evidence about the interaction between firms' financial and product market characteristics. In this literature, a large body of research studies how financial characteristics influence performance and decisions in product market (see, e.g. Chevalier and Scharfstein, 1996; Fresard, 2010; Phillips and Sertsios, 2013; Gilchrist et al., 2017; D'Acunto et al., 2017), while only a few papers focus on the implication of product market characteristics on financial decisions and financial performance (see Banerjee, Dasgupta and Kim, 2008; Larkin, 2013; Gourio and Rudanko, 2014; Belo, Lin and Vitorino, 2014; Dou and Ji, 2017). We depart from the existing literature by investigating the financial implications of customer capital composition. The closest paper is from Larkin (2013), who finds that the firms with higher brand stature have greater net debt capacity using the BAV survey data. Our paper differs in at least three ways: first, we investigate the role of composition of customer capital; second, we find significant and robust asset pricing and talent turnover patterns associated with the composition of customer capital; and third, building on the model of Gourio and Rudanko (2014), we embed customer capital in a tractable structural corporate model with endogenous value of liquidity to explain the new patterns.

Our paper is also related to the literature on inalienable human capital dating back to Hart and Moore (1994). Human capital is embodied in the firm's key talents who have the option to walk away. Thus, shareholders are exposed to the risk from key talents' limited commitment and firms' limited enforcement. The talent-based customer capital investigated in our paper provides one of the most concrete and convincing examples for inalienable human capital.

Lustig, Syverson and Nieuwerburgh (2011) develop a model with optimal compensation to managers who cannot commit to staying with the firm. Eisfeldt and Papanikolaou (2013) show that the firms with more organization capital are riskier due to greater exposure to technology frontier shocks. In their model, talent turnovers are essentially technology adoptions with fixed costs. Berk, Stanton and Zechner (2010) develop a model with entrenched employees under long-term optimal labor contracts to analyze their implications on optimal capital structure. Their model generates large human costs of bankruptcy by assuming that firms cannot fire workers so that entrenched workers are overpaid and only leave when firms go bankrupt. Compared to the above two papers, our model focuses on a different angle, emphasizing that key talents may leave due to corporate financial constraints risk, and that this hurts the firm through a decrease in customer capital. Therefore, our theory is related to the work of Bolton, Wang and Yang (2016), who analyze the implication of inalienable human capital on corporate liquidity and risk management in a standard optimal contracting framework. By contrast, we focus on asset pricing implications.[4]

Our paper also adds to the literature on the indirect costs of financial distress (see, e.g. Baxter, 1967; Titman, 1984; Opler and Titman, 1994; Brown and Matsa, 2016; Baghai et al., 2017). In their foundational work, Opler and Titman (1994) find that financially distressed firms lose market shares to their competitors. Brown and Matsa (2016) find that distressed firms have a hard time attracting high-quality job applicants. Baghai et al. (2017) show that firms lose their most skilled workers as they approach financial distress. Babina (2017) finds that employer financial distress spurs the exit of employees to found start-ups. Consistent with these studies, we show that the firms that rely relatively more on talent-based customer capital experience higher turnover rates, especially when they are financially constrained. The damage to talent-based customer capital associated with the turnovers is an indirect cost of financial distress.

Finally, the BAV survey data is one of a few reliable and standard data sources to measure the value of brand capital (see, e.g. Keller, 2008; Mizik and Jacobson, 2008; Gerzema and Lebar, 2008; Aaker, 2012; Tavassoli, Sorescu and Chandy, 2014; Lovett, Peres and Shachar, 2014). Our study adds to this strand of literature by dissecting customer capital and providing new asset pricing and corporate policy implications of customer capital composition.

The rest of paper is organized as the follows. Section 2 develops an industry equilibrium asset pricing model. Section 3 describes the data sources and explains the methodology to construct and validate the BTR measure. Section 4 presents the quantitative results on stock

[4]These papers are different from Eisfeldt and Rampini (2008) for two reasons. First, managers are compensated due to a moral hazard problem in their model. Second, Eisfeldt and Rampini (2008) focus on the aggregate turnover pattern over the business cycle, while these papers are about the cross-sectional patterns of turnovers. Extending our model into a general equilibrium framework like Eisfeldt and Rampini (2008) to analyze aggregate turnovers is an interesting extension for future research.

returns and talent turnovers in model and data. Section 5 provides additional empirical support for the theoretical mechanism. Section 6 concludes.

2 Model

We develop an industry equilibrium asset pricing model of heterogeneous firms to explain the interaction between customer capital composition and financial constraints, as well as the role of their interactions in determining the joint patterns of asset pricing and talent turnovers.

2.1 Basic Environment

Firms and Agents. In the economy, there is a continuum of firms and agents. Agents are shareholders and consumers. They fund firms by holding equity and purchase the firms' goods. Some agents in the economy are talents who can manage firms. We assume that agents can trade a complete set of contingent claims on consumption. Thus, there exists a representative agent who owns the equity and consumes the goods of all firms. The representative agent is only exposed to the economy's aggregate shocks. Without creating confusions, we omit the subscript for each firm to simplify notations.

Production. The firm employs physical capital K_t for production at time t. We normalize the price of physical capital to unity. Let I_t be the firm's cumulative investment up to time t. Physical capital stock evolves according to the law of motion:

$$\mathrm{d}K_t = -\delta_K K_t \mathrm{d}t + \mathrm{d}I_t, \tag{2.1}$$

where δ_K is the rate of physical capital depreciation. Each firm has an AK production technology and produces a flow of goods with intensity Y_t over $[t, t+\mathrm{d}t]$:

$$Y_t = e^{a_t} K_t. \tag{2.2}$$

The firm's output is affected by an aggregate productivity shock a_t, whose evolution follows a mean-reverting process:

$$\mathrm{d}a_t = -\mu_a(a_t - \overline{a})\mathrm{d}t + \sigma_a\sqrt{a_t}\mathrm{d}Z_t^a, \tag{2.3}$$

where Z_t^a is a standard Brownian motion. The parameters are chosen such that $2\mu_a\overline{a} > \sigma_a^2$ to guarantee $a_t \geq 0$.

Instantaneous demand orders come from the firm's customer capital B_t, which can be thought of as a measure of the firm's existing customer base over $[t, t+\mathrm{d}t]$. To be more precise, the firm receives flow demand $B_t \mathrm{d}t$ over the next instant. The units of goods sold by the firm is $S_t \mathrm{d}t$ over $[t, t+\mathrm{d}t]$:

$$S_t = \min\left(Y_t, B_t\right), \tag{2.4}$$

capturing the fact that total sales cannot exceed production output or the size of customer base. More precisely, in a frictional product market where B_t can only be slowly and costly expanded, an increase in production (supply) capacity leaves the firm short of customers to sell to. Following Gourio and Rudanko (2014), we emphasize such complementarity between customer capital and physical capital by adopting the Leontief aggregation.

Customer Capital Decomposition and Growth. Our central idea is to decompose the firm's customer capital B_t into pure-brand-based customer capital P_t and talent-based customer capital T_t. In particular,

$$B_t = P_t + T_t. \tag{2.5}$$

The two components are distinguished by the fragility to talent turnovers, which is elaborated in the next subsection (Section 2.2). Denote $m_t \equiv T_t / B_t$ as the fraction of customer capital that is talent based, reflecting the inverse of our empirical BTR measure.

The firm hires sales representatives s_t to build new customer capital at convex costs $\phi(s_t) T_t \mathrm{d}t$ over $[t, t+\mathrm{d}t]$, with the adjustment cost function being $\phi(s_t) = \alpha s_t^{\eta}$. The evolution of customer capital B_t is given by

$$\mathrm{d}B_t = [\mu(s_t) - \delta_B / m_t] T_t \mathrm{d}t, \tag{2.6}$$

where the Poisson rate δ_B reflects customer capital depreciation due to idiosyncratic exogenous reasons. We assume that[5]

$$\mu(s_t) = \psi s_t, \tag{2.7}$$

implying that the firm can grow customer capital faster by hiring more sales representatives. The parameters ψ captures the effective search-matching efficiency in the product market. New customer capital is randomly split into pure-brand-based customer capital P_t and talent-based customer capital T_t.[6] In particular, the two components evolve according to

$$\mathrm{d}P_t = \left[(1-f_t)\mu(s_t) - \delta_B(1-m_t)/m_t\right] T_t \mathrm{d}t \;\text{ and }\; \mathrm{d}T_t = \left[f_t \mu(s_t) - \delta_B\right] T_t \mathrm{d}t. \tag{2.8}$$

The variable f_t reflects the fraction of new customer base incorporated into existing talent-

[5]In Online Appendix, we derive this equation endogenously as the equilibrium representation in a search-matching model.

[6]Our model does not speak to the micro-foundation of BTR. What matters for our paper is that BTR is a firm-level persistent characteristic. In reality, new customers brought by key talents' personal connections are more likely to be talent-based customer capital while customers attracted by advertisements are less likely to be maintained by key talents. We leave the task of understanding the formation of BTR for future research.

based customer capital. We assume f_t to follow a Markov process of finite possible values $\mathcal{F} \equiv \left\{f_{(1)}, \cdots, f_{(N)}\right\}$ with constants $0 \leq f_{(1)} < \cdots < f_{(N)} \leq 1$. Within the next instant dt, f_t has intensity π to jump, conditional on which f_t reaches its new possible level $f_{(j)}$ with probability $\Phi(f_{(j)})$ for $j = 1, \cdots, N$.

Therefore, the dynamics of m_t is persistent and mean-reverting:

$$\mathrm{d}m_t = \mu(s_t)m_t(f_t - m_t)\mathrm{d}t.$$

External Financial Constraints. The firm faces firm-level idiosyncratic operating cash flow shocks, modeled as $\mathrm{d}C_t = \sigma_c B_t \mathrm{d}Z_t^c - \varsigma B_t \mathrm{d}M_t$. Here, Z_t^c is a standard Brownian motion that is independent of Z_t^a, and it captures small idiosyncratic cash flow shocks. M_t is a Poisson process with time-varying intensity ξ_t, capturing the firm's exposure to idiosyncratic negative jump shocks with proportional jump size ς.[7]

We assume that the firm has access to the equity market but not the corporate debt market.[8] The key idea is simple: the external funds (new equity or debt) are not perfect substitutes for the internal funds. More precisely, the firm has the option to pay out dividend $\mathrm{d}D_t$ or issue equity $\mathrm{d}H_t$ to finance various expenses over the next instant dt. Equity financing is costly. The financing cost includes a fixed cost γ proportional to customer capital B_t and a variable cost φ proportional to the amount of issued equity as in the literature (see, e.g. Gomes, 2001; Riddick and Whited, 2009; Gomes and Schmid, 2010; Bolton, Chen and Wang, 2011; Eisfeldt and Muir, 2016). All the financing costs are borne by the representative agent, while key talents are not required to chip in.

The financial constraints risk motivates the firm to hoard cash W_t on its balance sheet. However, holding cash is costly due to the agency costs associated with free cash in the firm or tax distortions.[9] We thus assume that the rate of return from the firm's cash inventory is the risk-free rate r minus a carry cost $\rho > 0$. The cash-carrying cost implies that the firm would pay out dividends when cash holdings W_t are high.

Financial Constraints Risk Shocks. All firms' financial condition, or marginal value of internal funds, can be simultaneously affected by an economy-wide shock. Such aggregate shocks are generically referred to as *financial constraints risk shocks*, which could be driven by

[7]Technically, the idiosyncratic lumpy shock $\mathrm{d}M_t$ is effectively a firm-specific *disaster shock* and the time-varying ξ_t is effectively the *disaster probability risk* (see, e.g. Gourio, 2012; Wachter, 2013). In our model with financial constraints, the shocks to ξ_t are effectively shocks to the marginal value of internal funds.

[8]The assumption is innocuous for our purpose since we focus on the endogenous time-varying shadow value of internal funds. The simplification captures the main idea of our theory while maintaining tractability.

[9]The interest earned by the firm on its cash holdings is taxed at the corporate tax rate, which generally exceeds the personal tax rate on interest income (see, e.g. Graham, 2000; Faulkender and Wang, 2006; Riddick and Whited, 2009).

different fundamental forces. On the one hand, the heightened financial constraints risk can be the result of tight supply of funding liquidity due to financial sector dysfunction (see, e.g. Jermann and Quadrini, 2012; Gilchrist and Zakrajšek, 2012; Bolton, Chen and Wang, 2013; Iyer et al., 2014). On the other hand, the heightened financial constraints risk can be the result of excessive demand for funding liquidity due to great investment opportunities. This is because the firms in the industries with great investment opportunities are likely eager to invest aggressively, and thus be financially constrained (see, e.g. Gomes, Yaron and Zhang, 2006; Riddick and Whited, 2009). Such incentives are especially greater under the displacement risk imposed by peers' innovations (see, e.g. Kogan et al., 2017).

To capture the time-varying economy-wide financial constraints risk, the intensity ξ_t follows a two-state Markov process. More precisely, we assume ξ_t takes two values, ξ_L and ξ_H, with $\xi_L < \xi_H$. The transition intensity from ξ_L to ξ_H is $q^{(\xi_L,\xi_H)}$, and that from ξ_H to ξ_L is $q^{(\xi_H,\xi_L)}$. The Poisson processes of transitions are denoted by $N_t^{(\xi_L,\xi_H)}$ and $N_t^{(\xi_H,\xi_L)}$. A greater arrival rate ξ_t increases the firm's marginal value of internal funds due to heightened risk of idiosyncratic negative jumps. Therefore, the aggregate shocks driving ξ_t are financial constraints risk shocks.

Pricing Kernel. The representative agent's state-price density is denoted by Λ_t, whose dynamics are specified as follows:

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t - \kappa_a \mathrm{d}Z_t^a + \sum_{\xi' \neq \xi_t} \left[e^{-\kappa^{(\xi_t,\xi')}} - 1 \right] (\mathrm{d}N_t^{(\xi_t,\xi')} - q^{(\xi_t,\xi')}\mathrm{d}t). \tag{2.9}$$

The market prices of risks for aggregate productivity shocks and liquidity shocks are constant and exogenously specified, captured by $\kappa_a > 0$ and $\kappa^{(\xi,\xi')}$. We assume $\kappa^{(\xi_L,\xi_H)} < 0$, meaning that heightened financial constraints risk raises the state-price density.

2.2 Liquidity-Driven Turnovers

We now introduce the two unique features of customer capital – inalienable talent-based customer capital and non-pecuniary private benefits. As we show in Section 4, the two features play quantitatively important roles in explaining the cross-sectional stock return patterns.

Inalienable Talent-Based Customer Capital. Shareholders have the option to fire key talents, and in the meanwhile, key talents have the option to leave the firm and start a new business.[10] When key talents leave, a fraction ω of talent-based customer capital T_t is taken away and

[10] The limited commitment on both sides is discussed in DeMarzo and Sannikov (2006) as an extension of their baseline framework.

shareholders hire new key talents to manage the rest talent-based customer capital $(1-\omega)T_t$. This follows the spirit of *inalienable human capital* coined by Hart and Moore (1994).

Non-Pecuniary Private Benefits. When managing a firm with customer capital B_t, key talents enjoy non-pecuniary private benefits hB_t with a positive constant h. The assumption that non-pecuniary private benefits are proportional to customer capital B_t reflects the findings and discussions in the existing literature. For example, key talents can gain identity-based benefits (see Akerlof and Kranton, 2005) while working at the firms with strong brand values. This is because the firms with stronger brands offer key talents more opportunities of self-enhancement, higher visibility among their peers, and greater likelihood to be perceived as being successful. Moreover, future employers may rely on the brand affiliation as a credible indicator of human capital quality. Thus working for high-brand-value firms benefits key talents by bringing a positive signal on their unobserved abilities (see Weiss, 1995). The proportional non-pecuniary private benefits for key talents hB_t is commonly adopted in the literature as a parsimonious modeling technique and an approximation (see, e.g. Eisfeldt and Rampini, 2008). Importantly, the existence of non-pecuniary private benefits is not necessary for our main mechanism or results; it only has a pure amplification effect that allows the model to better match the empirical asset pricing patterns (see Subsection 4.2).

Optimal Long-Term Contracts. To prevent key talents from leaving the firm, shareholders compensate key talents through a long-term contract that endogenously determines the payoffs to both parties. We now derive the optimal long-term contract.

Upon termination of the employment relationship, key talents create a new firm with customer capital $(\omega+\ell)T_t$, where ωT_t is the customer capital taken away from the firm and ℓT_t is the new customer capital created by key talents' business idea. The new firm is sold to the representative agent. At the inception, the representative agent builds up internal funds by issuing equity. Let $V(B_t, T_t, W_t, f_t, a_t, \xi_t)$ denote the firm's value. The new firm's value after equity issuance is $V((\omega+\ell)T_t, \tilde{f}(\omega+\ell)T_t, W_0, \tilde{f}, a_t, \xi_t)$, given the initial internal funds (new equity) W_0 and the talent-based transformation rate $\tilde{f}$. The representative agent chooses the optimal amount of equity financing W_0^* to maximize the new firm's value before equity issuance:

$$V^n(T_t, a_t, \xi_t) = \max_{W_0} \underbrace{-\gamma(\omega+\ell)T_t - \varphi W_0}_{\text{deadweight loss}} + \mathbb{E}^{\tilde{f}}\left[V((\omega+\ell)T_t, \tilde{f}(\omega+\ell)T_t, W_0, \tilde{f}, a_t, \xi_t) - W_0\right],$$

where the expectation $\mathbb{E}^{\tilde{f}}$ is taken over $\tilde{f}$. As key talents do not bear financing costs, the value of key talents' outside option is given by

$$V^o(T_t, a_t, \xi_t) = V^n(T_t, a_t, \xi_t) + \gamma(\omega + \ell)T_t + \varphi W_0^*. \tag{2.10}$$

Key talents are part of the representative agent who owns all the firms in the economy, including the new firm. Thus, the net deadweight cost of external equity issuance for the new firm is $\gamma(\omega + \ell)T_t + \varphi W_0^*$ without double counting.

The participation constraint is that the firm promises (with full commitment) to make the compensation flow Γ_t over interval dt, as long as the relationship continues. The value of Γ_t and hB_t is equal to the present value change of key talents' outside option $V^o(T_t, a_t, \xi_t)$:

$$0 = \Lambda_t(\Gamma_t + hB_t)\mathrm{d}t + \mathbb{E}_t\left[\mathrm{d}\left(\Lambda_t V^o(T_t, a_t, \xi_t)\right)\right], \quad \text{(promise keeping condition)} \tag{2.11}$$

where the expectation is taken with respect to da_t and dξ_t. The cash compensation Γ_t imposes operating leverage to the firm. Holding B_t constant, Γ_t increases with T_t, implying that the firm with more talent-based customer capital has greater operating leverage. Moreover, holding T_t constant, Γ_t decreases with B_t, suggesting that the firm with a weaker brand (smaller customer capital B_t) needs to offer greater compensating wage differential to keep key talents due to smaller non-pecuniary private benefits.[11] The link between compensation and brand values has been documented in the literature. In a laboratory setting, researchers find that undergraduate students are willing to accept lower hypothetical salaries from the firms with higher reputation because reputation affects the pride that individuals expect from organizational membership (see, e.g. Gatewood, Gowan and Lautenschlager, 1993; Cable and Turban, 2003). Using BAV and Execucomp data from 2000 to 2010, Tavassoli, Sorescu and Chandy (2014) show that CEOs and top executives are willing to accept lower pay when they work for the firms with stronger brand values. We provide further evidence in Appendix B.4.1.

Turnovers and Financial Constraints. Shareholders can successfully fire key talents with intensity ϑ_t in the next instant dt. Meanwhile, shareholders can control the turnover intensity ϑ_t, which takes two values $\{\vartheta_L, \vartheta_H\}$. If shareholders want to keep key talents, the intensity is set to be $\vartheta_L \equiv 0$. If shareholders want to replace key talents, the intensity is set to be $\vartheta_H > 0$. Our assumption that shareholders can replace key talents only with some probability reflects talents' entrenchment, which is estimated to be the major reason for the low turnover rate observed in the data (see Taylor, 2010). In our model, shareholders' choice of replacement

[11] This idea is related to the concept of compensating differentials initially introduced by Adam Smith (see Rosen, 1987). The modern empirical analysis of this topic begins with Thaler and Rosen (1976). A large literature in labor economics seeks to explain why workers are systematically willing to accept lower pay in a way that cannot be accounted for by layoffs or differences in recruiting intensity (see Rosen, 1987).

intensity crucially depends on the firm's current marginal value of internal funds (i.e. the firm's current funding liquidity condition). Intuitively, the firm is more likely to replace key talents when it is financially constrained. This is because the required compensation becomes extremely expensive when the firm's marginal value of internal funds is high, and meanwhile, key talents tend to escape from the sinking ship. The mechanism has been documented and tested extensively in the empirical corporate literature (see, e.g. Brown and Matsa, 2016; Baghai et al., 2017; Babina, 2017).

In the extreme scenario, key talents extract additional rents when firms are financially distressed and the external financing/restructuring is needed. It has been extensively documented in the literature (see, e.g. Bradley and Rosenzweig, 1992; Henderson, 2007; Goyal and Wang, 2017). For example, firms frequently offer golden parachutes in terms of pay retention and incentive bonuses to key talents to persuade them to stay with the firm through the restructuring process. To capture the rent extraction from key talents during financial distress and external financing, we assume that key talents extract $\varpi V^o(T_t, a_t, \xi_t)$ from shareholders when the firm runs out of internal funds (i.e. $W_t = 0$).

2.3 Firm Optimality

To make the model tractable, we assume that there is no physical capital adjustment cost. This means that the units of sales $S_t \mathrm{d}t$ given by equation (2.4) is optimally determined by the locally-predetermined demand orders $B_t \mathrm{d}t$ from the firm's customer capital.[12] The firm produces the demand orders by employing physical capital $K_t = B_t / e^{a_t}$. Using Ito's lemma, we know that the optimal incremental investment $\mathrm{d}I_t$ over $[t, t + \mathrm{d}t]$ is:

$$\frac{\mathrm{d}I_t}{K_t} = \left[\mu(s_t)m_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right] \mathrm{d}t - \sigma_a \sqrt{a_t} \mathrm{d}Z_t^a. \tag{2.12}$$

The firm's operating profit over $[t, t + \mathrm{d}t]$ is given by

$$\mathrm{d}O_t = uB_t \mathrm{d}t + \mathrm{d}C_t - \mathrm{d}I_t - \phi(s_t)T_t \mathrm{d}t - \Gamma_t \mathrm{d}t, \tag{2.13}$$

where $uB_t \mathrm{d}t$ is the sales revenue from customer capital, u is the price of goods, $\mathrm{d}C_t$ represents the firm-level idiosyncratic operating cash flow shock, the quantity $\phi(s_t)T_t \mathrm{d}t$ is the cost of hiring sales representatives, and the quantity $\Gamma_t \mathrm{d}t$ is the compensation to key talents.

The firm's internal funds inventory evolves as follows:

$$\mathrm{d}W_t = \mathrm{d}O_t + (r - \rho)W_t \mathrm{d}t + \mathrm{d}H_t - \mathrm{d}D_t, \tag{2.14}$$

[12] Our calibration ensures that the firm makes positive profit by serving customers. Thus it is a optimal for the firm to produce all demand orders $B_t \mathrm{d}t$.

where $(r-\rho)W_t\mathrm{d}t$ is the interest income (net of cash carrying cost ρ), $\mathrm{d}H_t$ is the cash inflow from external financing, and $\mathrm{d}D_t$ is the cash outflow to shareholders.

The firm chooses its sales representatives s_t, turnover intensity ϑ_t, payout policy $\mathrm{d}D_t$, and external financing policy $\mathrm{d}H_t$ to maximize shareholder value defined below:

$$V(B_t, T_t, W_t, f_t, a_t, \xi_t) = \max_{s_t, \vartheta_t, \mathrm{d}D_t, \mathrm{d}H_t} \mathbb{E}\left[\int_t^{\infty} \frac{\Lambda_{t+t'}}{\Lambda_t}(\mathrm{d}D_{t+t'} - \mathrm{d}H_{t+t'} - \mathrm{d}X_{t+t'})\right], \tag{2.15}$$

where $\mathrm{d}X_t = [\gamma B_t + \varphi \mathrm{d}H_t + \varpi V^o(T_t, a_t, \xi_t)]\mathbb{1}_{\mathrm{d}H_t>0}$ is the deadweight financing cost.

2.4 Model Solution

A key simplification in our setup is that the firm's six-state optimization problem can be reduced to a five-state problem by exploiting homogeneity. We define the function $v(m, w, f, a, \xi)$ on $\mathcal{D} = [0,1] \times [0,\infty) \times \mathcal{F} \times \mathbb{R} \times \{\xi_L, \xi_H\}$ such that

$$V(B, T, W, f, a, \xi) \equiv v(m, w, f, a, \xi)B, \quad \text{with } m = T/B \text{ and } w = W/B.$$

The normalized value function $v(m, w, f, a, \xi)$ can be solved based on a group of coupled partial differential equations with free boundaries. The firm simultaneously makes four sets of decisions: production, sales hiring, talent turnovers, and financial decisions. Since both talent turnovers and financial decisions are discrete in our model, they can be sufficiently characterized by *decision boundaries*. The illustrative diagram (see Figure 3) elaborates this idea. The free boundaries include the optimal external equity issuance boundary denoted by $\underline{w}(m, f, a, \xi)$, the optimal payout boundary denoted by $\overline{w}(m, f, a, \xi)$, and the optimal turnover boundary denoted by $\hat{w}(m, f, a, \xi)$.

Basically, the firm's financial decisions are characterized by three regions: (1) an external financing/liquidation region ($w < \underline{w}(m, f, a, \xi)$) within which the firm pursues external financing ($\mathrm{d}H > 0$); (2) an internal liquidity hoarding region ($\underline{w}(m, f, a, \xi) \le w \le \overline{w}(m, f, a, \xi)$) within which the firm keeps net profits as cash holdings on its balance sheet ($\mathrm{d}H = \mathrm{d}D = 0$); and (3) a payout region ($w > \overline{w}(m, f, a, \xi)$) within which the firm chooses to pay out dividends ($\mathrm{d}D > 0$). Within the internal liquidity hoarding region, there exists a conditional external financing region ($\underline{w}(m, f, a, \xi) < w < \underline{w}'(m, f, a, \xi)$), in which the firm issues equity conditional on the arrival of lumpy cash flow shocks ς.

The firm's decision on talent turnovers is characterized by the turnover boundary $\widehat{w}(m, f, a, \xi)$. When the firm's cash ratio is below $\widehat{w}(m, f, a, \xi)$, the firm chooses to replace existing key talents ($\vartheta = \vartheta_H > 0$); otherwise, the firm chooses to keep existing key talents ($\vartheta = \vartheta_L = 0$). In our baseline calibration, the turnover boundary satisfies $\underline{w}(m, f, a, \xi) \le \widehat{w}(m, f, a, \xi) \le \overline{w}(m, f, a, \xi)$.

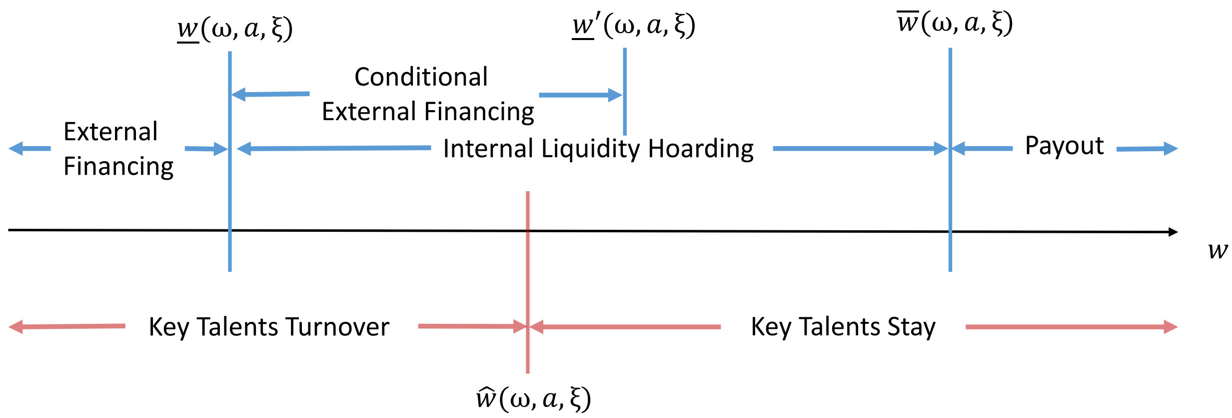


Figure 3: An illustrative graph for the decision boundaries and regions.

Intuitively, the firm finds it optimal to hoard up liquidity as a result of precautionary motives. When exogenous cash flow shocks drive cash ratio w gradually to some low level $\underline{w}(m, f, a, \xi)$ such that the current financing costs and the discounted future financing costs are equal, the firm would decide to issue equity. The key talent turnover decision essentially depends on the tradeoff between customer capital maintenance and short-run cash flows. When the cash ratio w is lower than $\widehat{w}(m, f, a, \xi)$, the marginal value of cash is large enough so that the marginal value of short-run cash flows dominates the marginal value of keeping key talents. Thus, the firm desires to decrease key talents' compensation or not to keep the compensation commitment. In this case, key talents will leave the firm, taking away a fraction of talent-based customer capital. Lastly, because holding cash is costly (captured by $\rho > 0$), the firm chooses to pay out cash when a sequence of exogenous positive cash flow shocks drive the the cash ratio w beyond some high level $\overline{w}(m, f, a, \xi)$.

External Financing Region. Although the firm can issue equity any time, it is optimal for the firm to raise equity only when it runs out of cash, which means the external financing boundary $\underline{w}(m, f, a, \xi) \equiv 0$. There are three reasons why financing costs always have smaller present values when they are paid further in the future as long as the firm has positive liquidity hoarding. First, cash within the firm earns a lower interest rate $r - \rho$ due to the holding cost. Second, the firm's expenses for customer capital growth is continuous. Third, the risk-free rate is a positive constant.

The conditional external financing boundary is determined by $\underline{w}'(m, f, a, \xi) = \underline{w}(m, f, a, \xi) + \varsigma = \varsigma$. This is because if and only if $w < \underline{w}'(m, f, a, \xi)$, lumpy cash flow shocks ς drive the firm's cash holdings below the external financing boundary $\underline{w}(m, f, a, \xi)$ and immediately triggers equity issuance.

When the firm lies in the external financing region ($w < 0$), the optimal financing amount is also endogenously determined. Let $w^*(m, f, a, \xi)$ be the optimal return cash ratio or the cash ratio after equity issuance. The value matching condition for the optimal return cash ratio $w^*(m, f, a, \xi)$ is, for any $w \leq 0$,

$$v(m, w, f, a, \xi) = v(m, w^*(m, f, a, \xi), f, a, \xi) - \gamma - \varpi m v^o(a, \xi) - (1 + \varphi)[w^*(m, f, a, \xi) - w].$$

The LHS of equation above is the firm's value right before equity issuance. The RHS of equation above is the firm's value right after equity issuance minus both the fixed and variable financing costs for issuance amount $w^*(m, f, a, \xi) - w$. The first-order optimality condition for the return cash ratio leads to the smooth pasting condition

$$v_w(m, w^*(m, f, a, \xi), f, a, \xi) = 1 + \varphi. \tag{2.16}$$

Intuitively, since $w^*(m, f, a, \xi)$ is the optimal return cash ratio, the marginal value of the last dollar raised by the firm must equal to one plus the marginal cost of external financing φ.

Internal Liquidity Hoarding Region and Turnover Boundary. The equilibrium dynamics within the internal liquidity hoarding region can be further divided into two sub-regions: (1) key talents turnover region and key talents stay region. The two sub-regions are partitioned by the turnover boundary $\widehat{w}(m, f, a, \xi)$, which is characterized by the firm's indifference condition about replacing key talents:

$$v\left(m, \widehat{w}(m, f, a, \xi), f, a, \xi\right) = (1 - \omega m) v\left(\frac{(1-\omega)m}{1-\omega m}, \frac{\widehat{w}(m, f, a, \xi)}{1 - \omega m}, f, a, \xi\right). \tag{2.17}$$

The LHS of (2.17) is the firm's value for not replacing key talents at the threshold $\widehat{w}(m, f, a, \xi)$, while the RHS is the firm's value of replacing key talents at the threshold $\widehat{w}(m, f, a, \xi)$. The optimization condition is referred to as the value matching condition (see Dumas, 1991). It is essentially the first-order condition with respect to the turnover boundary $\widehat{w}(m, f, a, \xi)$.

The dynamics of the firm's value within the sub-region of replacing key talents can be described by the following Hamilton-Jacobi-Bellman (HJB) equation:

$$0 = \max_{s_t} \mathbb{E}_t \left[\mathrm{d}\left(\Lambda_t v(m_t, w_t, f_t, a_t, \xi_t) \right) | \vartheta_t = \vartheta_H \right], \tag{2.18}$$

for all $(m_t, w_t, a_t) \in \mathcal{K}_H \equiv \{(m, w, a) \ : \ 0 \leq m \leq 1, 0 \leq w \leq \widehat{w}(m, f, a, \xi), a \in \mathbb{R}\}$. The HJB equation (2.18) leads to $2N$ coupled partial differential equations (PDE) for $\mathcal{K}_H \times \mathcal{F} \times \{\xi_L, \xi_H\}$ using the Ito's lemma and the optimal conditions for s_t. It is a standard free-boundary PDE problem since the boundaries of $\mathcal{K}_H$ need to be solved simultaneously with the firm's value $v(m, w, f, a, \xi)$.

Similarly, the dynamics of the firm's value within the sub-region of keeping key talents can be described by the following HJB equation

$$0 = \max_{s_t} \mathbb{E}_t \left[\mathrm{d} \left(\Lambda_t v(m_t, w_t, f_t, a_t, \xi_t) \right) | \vartheta_t = \vartheta_L \right], \tag{2.19}$$

for all $(m_t, w_t, a_t) \in \mathcal{K}_L \equiv \{(m, w, a) \ : \ 0 \le m \le 1, \widehat{w}(m, f, a, \xi) \le w \le \overline{w}(m, f, a, \xi), a \in \mathbb{R}\}$.

Payout Region. The firm starts to pay out cash when the marginal value of cash held by the firm is less than the marginal value of cash held by shareholders, which is one. Thus, the value matching condition gives the following boundary condition:

$$v_w(m, \overline{w}(m, f, a, \xi), f, a, \xi) = 1. \tag{2.20}$$

The payout region is characterized by $w \ge \overline{w}(m, f, a, \xi)$ for each combination of $(m, f, a, \xi) \in [0, 1] \times \mathcal{F} \times \mathbb{R} \times \{\xi_L, \xi_H\}$. Whenever the cash ratio is beyond the boundary, it is optimal for the firm to pay out all the extra cash $w - \overline{w}(m, f, a, \xi)$ in a lump-sum manner and return its cash ratio back to $\overline{w}(m, f, a, \xi)$. Thus, the firm's value in the payout region has the following form:

$$v(m, w, f, a, \xi) = v(m, \overline{w}(m, f, a, \xi), f, a, \xi) + w - \overline{w}(m, f, a, \xi), \ \text{ for } \ w \ge \overline{w}(m, f, a, \xi). \tag{2.21}$$

Lump-sum payouts can occur mainly because payout boundaries are different for different financial constraints risk shocks. It is intuitive that $\overline{w}(m, f, a, \xi_H) > \overline{w}(m, f, a, \xi_L)$. Moreover, the first-order condition for maximizing the firm's value over constant payout boundaries leads to the smooth pasting or the super contact condition

$$v_{ww}(m, \overline{w}(m, f, a, \xi), f, a, \xi) = 0, \tag{2.22}$$

where optimization is achieved at $\overline{w}(m, f, a, \xi)$.

2.5 Illustration of Basic Mechanism

We now turn to the model's implications. To highlight the importance of financial constraints risk, we compare the simulation results from the full model with those from a model without financial frictions. In the fritionless benchmark, the firm does not face financial constraints risk because equity financing costs are zero (i.e. $\gamma = \varphi = 0$). As a result, the firm does not hold cash and becomes hand-to-mouth, issuing equity for negative profit and paying out dividend for positive profit.

Panel A of Figure 4 plots the firm's normalized enterprise value (i.e. $v(m, w, f_{(2)}, \overline{a}, \xi_L) - w$,

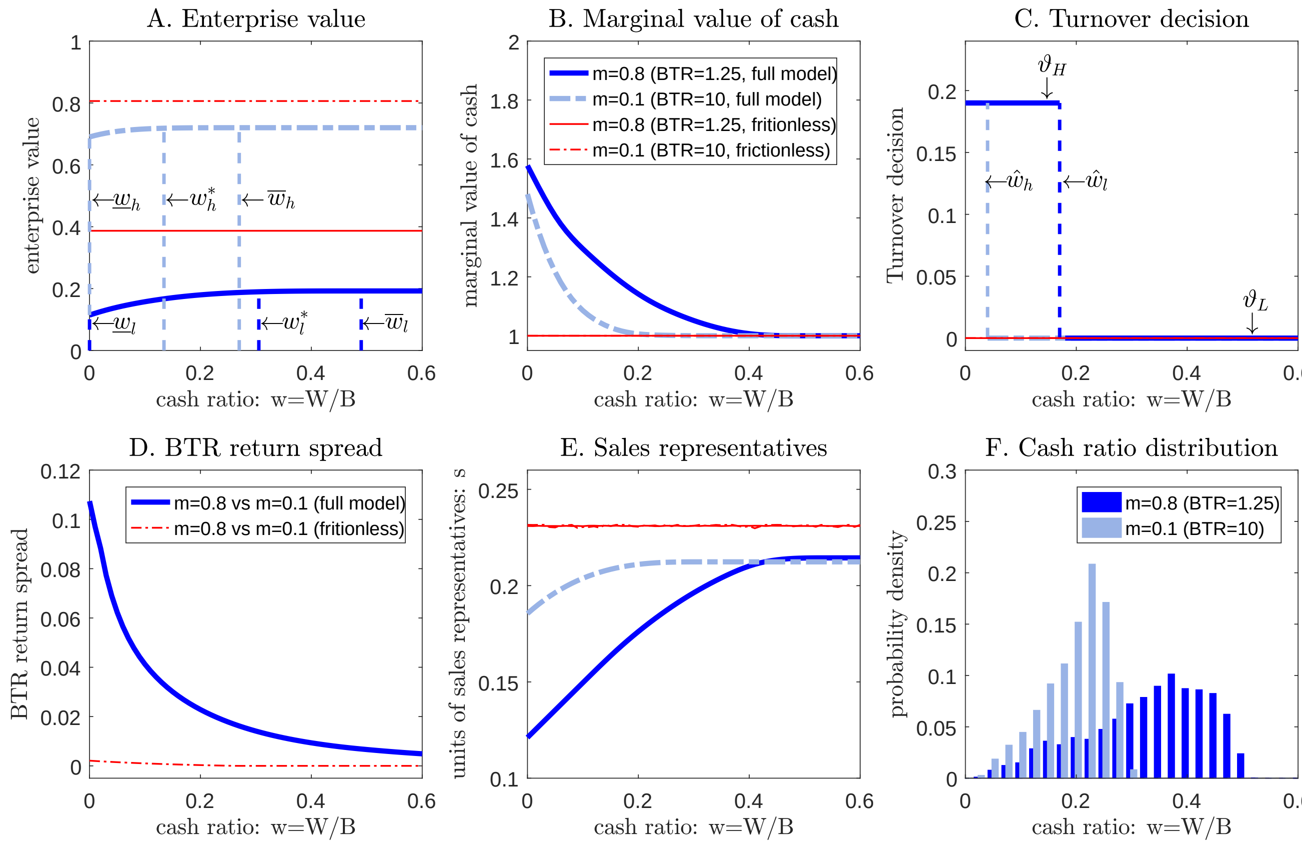


Figure 4: An illustration of the model's basic mechanism.

the value of all the firm's marketable claims minus cash ratio) as a function of cash ratio in normal regime (i.e. $\xi = \xi_L$). It shows that the high BTR firm ($m = 0.1$) has significantly higher enterprise value relative to the low BTR firm ($m = 0.8$). The firm's enterprise value increases with the firm's cash ratio, as the existence of financial constraints risk imposes a deadweight loss through costly equity financing and distorts the firm's decisions. By contrast, in the absence of financial frictions, the enterprise values of both the low and high BTR firms are higher and flat.

In principle, firms could hold an infinitely amount of cash to circumvent financial constraints risk. However, this option is not utility maximizing as hoarding cash is costly in our model. Thus the firm pays out dividend when cash ratios are high. This is why financial constraints risk plays an important role in determining firm value. In the cross section, our model predicts that the high BTR firm tends to issue less equity (i.e. optimal financing amount $w_h^* < w_l^*$) and pay out more dividend (i.e. dividend payout boundary $\overline{w}_h < \overline{w}_l$). As a result, the high BTR firm's endogenous steady-state distribution of cash ratios concentrated at lower levels (see

Panel F). We provide empirical evidence for these predictions in subsection 5.2.

The difference in financial policies can be explained by the difference in the marginal value of liquidity. As shown in Panel B, the high BTR firm has a lower marginal value of cash relative to the low BTR firm. This is because the low BTR firm is more exposed to financial constraints risk due to greater operating leverage imposed by talent-based customer capital. When the firm's cash ratios are high, the operating leverage does not increase financial constraints risk much because internal funds provide cushions against cash flow shocks. As a result, the marginal value of cash for both firms is equal to one when $w > 0.5$. However, when cash ratios are low, the greater compensation required to retain key talents significantly increases the financial constraints risk facing the low BTR firm. In the frictionless benchmark, the marginal value of cash for both the low and high BTR firms is flat and equal to one.

Panel C compares the turnover decision of the two firms. Both firms replace key talents (i.e. $\vartheta = \vartheta_H$) when cash ratios are low due to the high marginal value of cash. By contrast, there are no turnovers in the frictionless benchmark. In our model, the low BTR firm is more liquidity constrained, and thus its turnover boundary is to the right of the high BTR firm (i.e. $\hat{w}_l > \hat{w}_h$). The turnover decisions are crucially related to firms' stock returns as the firm with a higher turnover rate is riskier due to the loss of talent-based customer capital upon turnovers. In panel D, we show that the expected stock return of the low BTR firm is about 11% higher than that of the high BTR firm when the cash ratio is zero. This return spread is lower when cash ratios are high, reflecting the lower marginal value of cash and turnover probabilities. By contrast, in the frictionless benchmark, the return spread between the two firms is almost zero, merely reflecting the tiny difference in the exposure to financial constraints risk shocks.

Panel E compares the hiring decision of the two firms. The variation in the endogenous marginal value of liquidity suggests that both firms hire fewer sales representatives when cash ratios are low; On average, the high BTR firm tends to hire more sales representatives relative to the low BTR firm. This suggests that the existence of financial constraints risk also distorts the firm's performance in the product market. When the financial market has frictions, the firm cuts its own customer-base growth rate to gain short-term liquidity. In the frictionless benchmark, the first-best hiring units are higher and identical across the firms with different BTRs.

3 Measuring Brand-Talent Ratios

In our model, customer capital determines the firm's revenue through consumer demand. This suggests that we use a measure that captures customers' opinions about firms' brand and products. We thus construct a measure of customer capital and its composition using consumer survey data. In this section, we first introduce our customer survey data. Then, we illustrate how to construct BTR as a proxy for the relative contribution of pure-brand-based customer capital and talent-based customer capital. Finally, we consider several external validations of our BTR measure by relating it to the financial variables constructed from Compustat/CRSP.

3.1 Data

Our brand metrics data are from the BAV Group; it is regarded as the world's most comprehensive database of consumers' perception of brands. The BAV Group is one of the largest and leading consulting firms that conduct brand valuation surveys and provide brand development strategies for clients. The BAV brand perception survey consists of more than 680,000 respondents in total, and it is constructed to represent the U.S. population according to gender, ethnicity, age, income group, and geographic location. Survey respondents are asked to complete a 45-minute survey that yields measures of brand value. The first survey was conducted in 1993, and starting from 2001 the surveys have been conducted quarterly. The survey covers more than 3000 brands in the cross section and is not biased towards the BAV Group's clients. The BAV Group updates the list of brands to include new brands and exclude the brands that exit the market, and it does not backfill the survey data. To make the surveys manageable, each questionnaire contains less than 120 brands that are randomly selected from the list of the brands. More details regarding the BAV brand perception survey can be found in Appendix B.1.

Based on the brand perception survey data, The BAV Group has developed two major brand metrics to assess brand value: brand stature and brand strength. These two BAV brand metrics are well known and widely adopted by marketing researchers and practitioners, and they have been incorporated into major marketing textbooks (see, e.g. Keller, 2008; Aaker, 2012).

The BAV brand perception survey is conducted at the brand level. We identify the firms that own the brands over time and then link the brand-level BAV survey data with Compustat and CRSP. We pay particular attention to the brands involved in M&As and make sure the brands are assigned correctly to firms. For each firm in a given year, we calculate the average scores of various brand metrics over all the brands owned by the firm.[13] We further merge the data with Execucomp, BoardEx, and the Harvard Business School patent and innovator database (see Li et al., 2014). Our merged data span 1993-2016 and include firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from our analyses. In total, there are 1004 unique firms, and on average there

[13] 58% of firm-year observations have only one brand in the BAV data. For the firms that have more than one brand in the BAV data, we use several alternative methods to compute the firm-level brand metrics from the brand-level BAV data. We provide details on these methods in Appendix B.2. Our results are robust to the choice of these methods.

are about 400 firms in the yearly cross section. The firms in the merged sample collectively own 4745 unique brands covered by the BAV survey. The entry and exit rates of the firms in the merged sample are around 7%, which are comparable to those in the Compustat data. We provide more details on the merged sample, including its distribution across industries, in Appendix B.3. Appendix Table C.1 presents the summary statistics of main variables. Firms in the BAV sample and in the Compustat/CRSP sample have comparable book-to-market ratios and debt-to-asset ratios. The median book-to-market ratio of the BAV sample is 0.37, while it is 0.49 in the Compustat/CRSP sample. The median debt-to-asset ratio of the BAV sample is 0.55, while it is 0.44 in the Compustat/CRSP sample. The BAV sample is biased towards large firms. The median market capitalization of the BAV sample is $4,915 million, while it is $420 million in the Compustat/CRSP sample. Similarily, the median sales of the BAV sample is $5,115 million, while it is $424 million in the Compustat/CRSP sample. Since the BAV sample is not a random sample of the U.S. public firms, In Section 4.2.5, we replicate our asset pricing tests in an extended sample that covers the cross-section of all U.S. public firms.

3.2 The BTR Measure

BTR is derived from brand stature and brand strength, the two most important brand metrics developed by the BAV Group. The BAV Group constructs brand stature to measure existing customers' loyalty. Brand stature quantifies, as an approximation, how much a brand is held in high esteem by existing customers. Brand stature is thus a proxy for current customer capital, which is the sum of pure-brand-based customer capital and talent-based customer capital. The BAV Group constructs brand strength to measure how much a brand is perceived to be innovative and distinctive. Brand strength quantifies, as an approximation, the degree of a brand's energized differentiation from similar products perceived by existing and potential customers. Since the creation of innovative products and distinctive brands requires significant contribution from key talents, we use brand strength as a proxy for talent-based customer capital. Note that we do not assume that brand strength is entirely contributed by talent-based customer capital. The assumption we make here is that brand strength reflects more about talent-based customer capital compared to brand stature. We provide more details on the construction of these two metrics in Appendix B.1.

We define BTR as the ratio between brand stature and brand strength at the firm level:

$$\text{BTR}_{i,t} \equiv \frac{\text{brand stature}_{i,t}}{\text{brand strength}_{i,t}}, \quad \text{for firm } i \text{ in year } t.$$

BTR is a proxy for the relative importance of talent-based customer capital. Since the distribution of BTR is skewed, we use the log transformation of BTR (denoted as lnBTR) in our empirical analysis. As shown in Appendix B.3, lnBTR exhibits a good amount of variations and the distribution of lnBTR is approximately normal.

Let us provide a few concrete examples in 2010s. In the automobile industry, Toyota is a typical high BTR firm, which enjoys strong brand recognition all over the world. On the other hand, Tesla is a typical low BTR firm, whose value crucially depends on its R&D team and probably the charismatic leadership of Elon Musk. In the beverage industry, Coca-Cola is a typical high BTR firm, whose customers' loyalty is unrelated to executives or innovators and mainly depends on customers' habits and tastes. By contrast, Teavana, an innovative tea company which sells premium lose-leaf teas and herbal infusions, and shares "imaginative flavors from around the world", is a typical low BTR firm. Other examples of the high BTR firms include Microsoft in the IT industry and Gap in the apparel industry. Other examples of the low BTR firms include Facebook in the IT industry and Ralph Lauren in the apparel industry.

3.3 External Validation of the BTR Measure.

If BTR reflects key talents' contributions, we expect to see that the firms that pay more compensation to key talents have lower BTRs in the near future. Therefore, we examine the relation between BTR and one-year lagged key talent compensation. We use three different measures as proxies for key talent compensation. The first measure is the administrative expenses, measured by SG&A net of advertisement costs, R&D expenses, commissions, and foreign currency adjustments. The second measure is the R&D expense. According to Hall and Lerner (2010), more than 50% of R&D expenses are the wages and salaries of highly educated scientists and engineers. The third measure is the executive compensation, measured by the total compensation for the top five executives of a firm in the Execucomp data. Using panel regressions, we test the relation between BTR and the three measures of lagged key talent compensation normalized by sales. We find that the firms that pay more compensations to key talents indeed have lower BTRs in the near future (see Table 1).

Relation to Organization Capital. Following Eisfeldt and Papanikolaou (2013), we construct organization capital from SG&A expenditures using the perpetual inventory method. As shown by Column (5) of Table 1, the relation between BTR and organization capital is weak. This is because SG&A contains both advertisement expenditure and administrative expenses. Advertisement expenditure boosts brand loyalty and are positively related to BTR (see Column 4 of Table 1), while administrative expenses mainly reflect key talents' compensation and are negatively related to BTR (see Column 1 of Table 1). The weak correlation between BTR and

Table 1: BTR, key talent compensation, and organization capital.

	(1)	(2)	(3)	(4)	(5)
			$\ln\text{BTR}_t$		
$\ln(\text{AdminExpenses/Sales})_{t-1}$	-0.159^{***}				
	$[-4.191]$				
$\ln(\text{R\&D/Sales})_{t-1}$		-0.211^{***}			
		$[-6.735]$			
$\ln(\text{ExecuComp/Sales})_{t-1}$			-0.254^{***}		
			$[-8.225]$		
$\ln(\text{AdvExp/Asset})_{t-1}$				0.065^{**}	
				[2.296]	
$\ln(\text{OC/Asset})_{t-1}$					0.012
					[0.589]
Firm Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5250	2656	4831	5767	5589
R-squared	0.266	0.342	0.287	0.250	0.247

Note: This table shows the relation among BTR, key talent compensation, and organization capital. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception 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. The dependent variable is lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. The independent variables are the natural log of the administrative-expenses-to-sales ratio, the natural log of the R&D-to-sales ratio, the natural log of the executive-compensation-to-sales ratio, the natural log of the advertisement-to-asset ratio, and the natural log organization-capital-to-asset ratio. Firm-level control variables include the natural log of firm market capitalization (lnsize_{t-1}) and the nature log of the book-to-market ratio (lnBEME_{t-1}). 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.

organization capital suggests that the two measures capture different firm characteristics. In fact, we include organization capital as a control variable in studying the relation between BTR and the outcome variables.

4 Main Predictions and Empirical Tests

In this section, we calibrate the model's parameters and explore its predictions in the data. In particular, we explore whether our model can quantitatively replicate the main asset pricing findings from the data and shed light on the relative importance of underlying mechanisms.

4.1 Calibration

We discipline the model based on both existing estimates and micro data. A set of parameters is determined using external information. These parameters are either already estimated in existing literature or can be estimated separately without simulating the model. The remaining parameters are calibrated internally from moment matching. Table 2 summarizes our parameter choice.

Table 2: Calibration.

Parameters	Symbol	Value	Parameters	Symbol	Value
Risk-free rate	r	5%	Fraction of customer loss	ω	0.1
Fixed financing costs	γ	0.01	New customers created by a new brand	ℓ	0.45
Variable financing costs	φ	0.06	Private benefits	h	0.007
Long-run average aggregate productivity	$\overline{a}$	0.5	Customer capital depreciation rate	δ_B	0.15
Mean-reversion of aggregate productivity	μ_a	0.275	Intensity of talent-based transformation	$f_{(1)}, f_{(2)}$	$0, 1$
Volatility of aggregate productivity	σ_a	0.07	Prob. of talent-based transformation	$\Phi(f_{(1)}), \Phi(f_{(2)})$	$0.85, 0.15$
Physical capital depreciation rate	δ_K	0.1	Transformation shock arrival intensity	π	1
Cash-carrying costs	ρ	1.5%	Turnover success rate	ϑ	0.19
Consumers' willingness to pay	u	0.27	Shocks to cash flows	σ_c	0.15
Rent extraction	ϖ	0.08	Lumpy cash flow shock size	ς	0.1
Effective matching efficiency	ψ	7.6%	Lumpy cash flow shock frequency	ξ_L, ξ_H	$0, 0.5$
Sales' people hiring costs (scale)	α	1.5	Price of risk of productivity shocks	κ_a	0.4
Sales' people hiring costs (convex)	η	2	Price of risk of financial constraints risk shocks	$\kappa^{(\xi_L,\xi_H)}$	$-\ln(3)$
Transition probability	$q^{(\xi_L,\xi_H)}, q^{(\xi_H,\xi_L)}$	$0.16, 0.2$		$\kappa^{(\xi_H,\xi_L)}$	$\ln(3)$

Externally Determined Parameters. The annual interest rate is set to be $r = 5\%$. The physical capital's depreciation rate is set to be $\delta_K = 10\%$ per year. We choose the variable cost of financing to be $\varphi = 6\%$ based on the estimates reported by Altinkilic and Hansen (2000). Following Bolton, Chen and Wang (2011, 2013), we set the fixed financing cost to be $\gamma = 1\%$ of the firm's physical capital and the cash-carrying cost to be $\rho = 1.5\%$, resulting from tax disadvantage or agency frictions. We set the effective matching efficiency $\psi = 7.6\%$.[14] We consider a quadratic specification for the hiring function of sales people by setting $\eta = 2$. Survey evidence suggests that the customer turnover rates have significant heterogeneity across different industries. The typical range of annual customer turnover rate is between 10% – 25%. We thus set the customer capital depreciation rate to be $\delta_B = 15\%$. We set $\omega = 0.1$, so that in our model, key talents leave with 10% of talent-based customer capital.[15]

The long-run average level of aggregate productivity $\overline{a}$ is a scaling variable. We set its value to be $\overline{a} = 0.5$. We set the persistence parameter to be $\mu_a = 0.275$, following Gomes, Kogan and Zhang (2003). The transition intensities between the two regimes are estimated

[14] In Online Appendix, we show that $\psi = \overline{\psi}\overline{\tau}^{\chi-1}$ in a model with micro-founded customer capital accumulation based on competitive search. The effective matching efficiency ψ is calibrated as follows. We normalize the matching efficiency $\overline{\psi}$ and the dis-utility of search x to be 1. We set $\chi = 2.12$, which implies that the elasticity parameter in the Cobb-Douglas matching function is $\frac{\chi-2}{\chi-1} = 0.11$, consistent with Gourio and Rudanko (2014)'s estimate based on the share of labor force in sales-related occupations and the amount of time consumers spend on shopping. Finally we set $\overline{\tau}$ to be 0.10 to ensure that the firm has positive profits from new customers even highest initial discounts are offered.

[15] In existing literature, several papers have developed models with this feature. For example, Lustig, Syverson and Nieuwerburgh (2011) match the increase in intra-industry wage inequality by assuming that 50% organization capital is transferred to the next match when the manager switches to a new match. Eisfeldt and Papanikolaou (2013)'s model assumes that key talents can leave with all intangible capital. Bolton, Wang and Yang (2016)'s benchmark calibration assumes that the entrepreneur would be 20% less efficient if he walks away from the current firm.

based on the regime-switching dynamics of the estimated alphas of the BMT portfolio (see Subsection 4.2.1 for its construction) between 1975 – 2016. The transition intensity from ξ_L to ξ_H is $q^{(\xi_L,\xi_H)} = 0.16$ and the transition intensity from ξ_H to ξ_L is $q^{(\xi_H,\xi_L)} = 0.20$. We set the price of risk of productivity shocks to be $\kappa_a = 0.4$, and the price of risk of financial constraints risk shocks to be $\kappa^{(\xi_L,\xi_H)} = -\ln(3)$ and $\kappa^{(\xi_H,\xi_L)} = \ln(3)$. Our choice of the prices of risk allows the model to quantitatively match the difference in portfolio alphas between high- and low-BTR firms in the data. The risk-neutral transition intensities are

$$\hat{q}^{(\xi,\xi')} = e^{-\kappa(\xi,\xi')} q^{(\xi,\xi')}, \quad \text{for } \xi \neq \xi'. \tag{4.1}$$

Internally Calibrated Parameters. The rest parameters are calibrated through indirect inference. Specifically, we start with a sample of 1000 firms and simulate their behavior for 100 years according to the computed policy functions. The first 20 years are dropped as burn-in. When key talents leave the firm, new firms are created and will be included in the sample for the remaining simulation period. We then compute the model-implied moments and adjust parameters until these moments are roughly in line with their values in the Compustat-CRSP sample (see Table 3). Below we briefly discuss the moments used in our calibration.

The consumers' willingness to pay determines the firm's net cash flows. We set $u = 0.27$ to match the average cash-asset ratio in the data. We set the rent extraction parameter to be $\varpi = 0.08$ so that the retention bonuses are between 30% and 70% of key talents' compensation (see Goyal and Wang, 2017). We calibrate hiring efficiency $\alpha = 1.5$ to target the advertisement expenditure as a percent of sales. The parameter ℓ reflects the number of new customers attracted by key talents when a new firm is created. This parameter controls the value of key talents' outside option. We set $\ell = 0.45$ to match the average key talents' compensation as a percent of sales. We set the replacement intensity $\vartheta_H = 19\%$ to match the average key talents' turnover rate in the data.

The parameter π controls the persistence of firm-level BTR. We set $\pi = 1$ to match the autocorrelation in BTR between year t and $t-1$. The parameters related to cash flow shocks, σ_c and ς, mainly determine the volatility of cash flows. We set their values to be $\sigma_c = 0.15$ and $\varsigma = 0.1$ to target the average volatility and skewness of net income as a percent of sales across all firms. We set $\sigma_a = 0.07$ to match the volatility of the returns to the market portfolio. We normalize the arrival intensity of lumpy cash flow shocks in normal regime to be $\xi_L = 0$ and set $\xi_H = 0.5$ to match the average frequency of equity issuance with amounts larger than 1% of total assets.

The distribution of talent-based customer capital transformation rates determines the equilibrium distribution of cross-sectional BTR. Since our empirical BTR measure does not have the same units as in our model, we infer the transformation rate using the distribution of key talent

Table 3: Moments in data and model.

Panel A: Aggregate Moments

	Data	Model		Data	Model
Cash holdings/Lagged asset	23.6%	22.5%	Retention bonuses	30% – 70%	58.9%
Autocorrelation in BTR	0.96	0.97	Talent compensation/Sales	14.9%	14.5%
Volatility of net income/Sales	16.8%	16.0%	Equity issuance frequency	25.2%	28.4%
Skewness of net income/Sales	−0.47	−0.54	Key talents' turnover rate	11.8%	11.0%
Advertisement expenditure/Sales	5.1%	5.9%	Compensation reduction (Q1→Q5)	22.3%	23.1%
Volatility of market returns	0.165	0.158			

Panel B: Compensations across BTR Portfolios

BTR Portfolios		1 (Low)	2	3	4	5 (High)
Talent compensation/Sales (%)	Data	24.9	17.2	10.9	12.0	9.6
	Model	28.2	19.2	14.3	11.7	8.9

compensation. As key talents mainly represent executives and innovators, we approximate key talent compensation using the sum of 50% of R&D expenses and executive compensation.[16] We allow the talent-based customer capital transformation rate to take two extreme values, $f_{(1)} = 0$ and $f_{(2)} = 1$, to ensure that the model is able to generate a wide range of BTRs. We then choose the probability, $\Phi(f_{(1)}) = 0.85$ and $\Phi(f_{(2)}) = 0.15$, so that the model-implied distribution of average talent compensation as a percent of sales across the five quintiles sorted on BTR is roughly in line with the data. The parameter h controls the amount of non-pecuniary private benefits proportional to the firm's customer capital. We calibrate its value to match the decrease in compensation when executives move from the low BTR quintile to the high BTR quintile.

4.2 Asset Pricing Implications.

Figure 5 illustrates the asset pricing implications of our model. We consider the firms' exposure to financial constraints risk shocks by computing their betas when ξ increases from ξ_L to ξ_H:

$$\beta_\xi(m, w, f, a) = v(m, w, f, a, \xi_H)/v(m, w, f, a, \xi_L) - 1 \tag{4.2}$$

In equilibrium, the expected stock return is

$$\mathbb{E}_t\left[\mathrm{d}R_t | m, w, f, a\right] - r_t \mathrm{d}t = \beta_\xi(m, w, f, a)\left[1 - e^{-\kappa^{(\xi_L, \xi_H)}}\right] q^{(\xi_L, \xi_H)} \mathrm{d}t. \tag{4.3}$$

[16] Many papers suggest that more than 50% of R&D expenses are wage payments to highly trained scientists, engineers, and other skilled technology workers (Lach and Schankerman, 1989; Hall and Lerner, 2010; Brown and Petersen, 2011; Brown, Martinsson and Petersen, 2012). Executive compensation is measured by the total compensation for the top five executives of a firm in the Execucomp data. The moment we target is likely to be the lower bound of key talent compensation. Targeting a higher level of compensation would increase the strength of our mechanism as firms become more liquidity constrained.

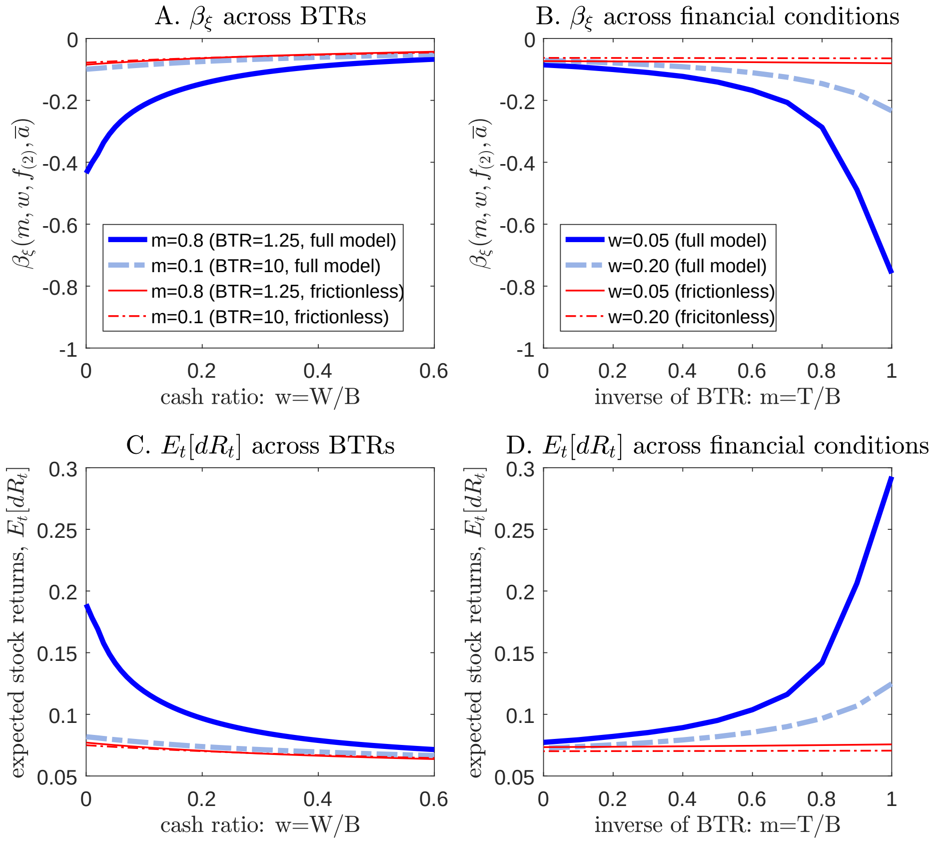


Figure 5: The sensitivity of firm values to financial constraints risk shocks.

Panel A plots the betas and stock returns for the high and low BTR firm. Both firms' exposure to financial constraints risk shocks decrease with their cash ratios. Investors require higher expected stock returns when cash ratios are lower due to greater financial constraints risk. Quantitatively, the model suggests that the difference in betas between the two firms is as large as 0.35 when the cash ratio is zero, and this translates into a 11% difference in expected stock returns.[17] By contrast, in the frictionless benchmark, the exposure to financial constraints risk shocks is low and almost identical for both firms. Similar patterns are observed in Panel B, in which we compare betas and expected stock returns of a high cash ($w = 0.25$) and a low cash ($w = 0.05$) firm.

[17] The quantitatively differential response to financial constraints risk shocks between the high and low BTR firm also incorporates a countervailing force that dampens the relative response of the low BTR firm. This is because an increase in financial constraints risk reduces key talents' compensation as the outside option of creating a new firm becomes worse. From shareholders' perspective, the reduction in compensation provides insurance against the high liquidity risk regime, increasing the firm's value. This insurance effect is especially beneficial for the low BTR firm as it consists of more talent-based customer capital. Our simulation suggests that although the countervailing force is economically significant, it is dominated by the even more significant force through greater operating leverage and customer capital loss.

Table 4: Portfolio excess returns and alphas sorted on BTR.

BTR Portfolios	1 (Low)	2	3	4	5 (High)	5 − 1
			Panel A: Average Excess Returns			
$\mathbb{E}[R] - r_f$ (%)	16.32***	13.83***	12.06***	11.30***	10.69***	−5.64**
	[3.77]	[3.53]	[3.72]	[3.47]	[2.98]	[−2.06]
			Panel B: Fama-French Three-Factor Model			
α (%)	7.08***	4.27**	3.91***	3.36**	1.23	−5.85***
	[3.47]	[2.42]	[2.87]	[2.37]	[0.80]	[−2.60]
			Panel C: Carhart Four-Factor Model			
α (%)	8.72***	5.98***	4.71***	4.59***	2.51*	−6.21***
	[4.43]	[3.60]	[3.50]	[3.39]	[1.69]	[−2.73]
			Panel D: Pástor-Stambaugh Five-Factor Model			
α (%)	8.25***	5.70***	4.54***	4.57***	2.39	−5.86**
	[4.20]	[3.42]	[3.36]	[3.35]	[1.60]	[−2.56]
			Panel E: Hou-Xue-Zhang q-factors Model			
α (%)	9.71***	4.48**	2.42*	2.70*	−0.83	−10.54***
	[4.61]	[2.42]	[1.69]	[1.76]	[−0.49]	[−4.54]
			Panel F: Fama-French Five-Factor Model			
α (%)	7.43***	2.50	0.79	1.28	−2.05	−9.48***
	[3.48]	[1.40]	[0.63]	[0.90]	[−1.41]	[−4.25]

Note: This table shows the value-weighted excessed returns and alphas for portfolios sorted on BTR. In June of year t, we sort firms into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. 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 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.

Overall, the simulation results shown in Figure 5 jointly suggest that the interaction between customer capital composition and firms' own financial conditions have crucial implications on asset prices. The firm's exposure to financial constraints risk shocks is reflected both in the cross-sectional variation in BTR and the cross-sectional variation in cash ratios.

4.2.1 Portfolio Returns Sorted on BTR.

We now turn to the data to systematically examine the asset pricing implications of BTR. In June of year t, we sort firms into five quintiles based on their BTRs 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 estimate their alphas and betas using various asset pricing models.[18]

Table 4 presents the cross-sectional asset pricing results of the sorted portfolios based on BTR. As shown in Panel A, the high BTR portfolio (Quintile 5) has 10.69% annualized average excess return. By contrast, the low BTR portfolio (Quintile 1) has 16.32% annualized average

[18]Our results also hold for equal-weighted portfolio returns.

Table 5: Factor loadings of the BMT portfolio

BMT Portfolio Returns					
Model	FF3F	FF4F	PS5F	q-factor	FF5F
MKT	-0.17^{***}	-0.16^{***}	-0.15^{***}	0.00	-0.02
	[−4.00]	[−3.43]	[−3.12]	[0.02]	[−0.42]
SMB	-0.05	-0.06	-0.05		0.07
	[−0.86]	[−0.95]	[−0.88]		[1.11]
HML	0.61^{***}	0.63^{***}	0.62^{***}		0.32^{***}
	[9.85]	[9.82]	[9.75]		[3.94]
MOM		0.04	0.04		
		[1.02]	[1.14]		
PS			-7.61		
			[−1.45]		
ME				0.06	
				[1.06]	
I/A				0.88^{***}	
				[9.46]	
ROE				0.37^{***}	
				[4.83]	
RMW					0.41^{***}
					[4.76]
CMA					0.40^{***}
					[3.48]
R^2	0.353	0.355	0.360	0.371	0.421

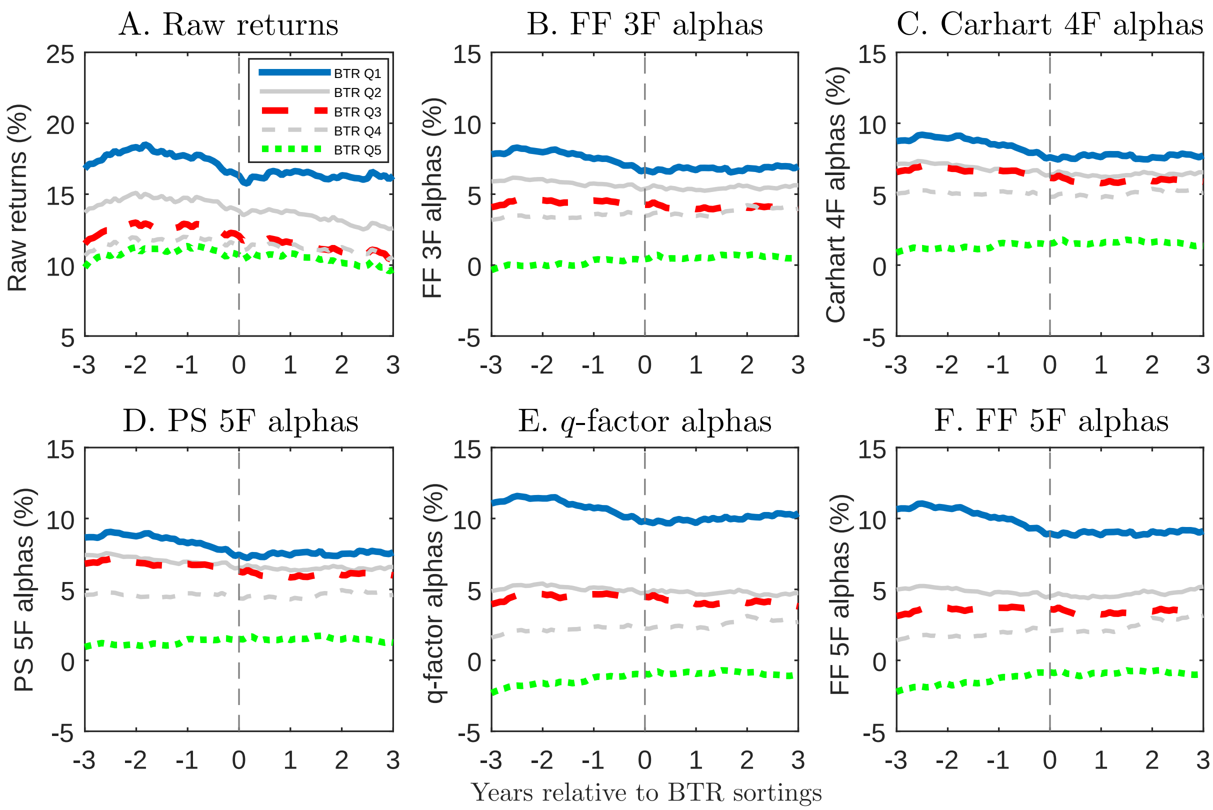
Note: This table shows the factor loadings of the value-weighted BMT portfolio. We include t-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

excess return. The −5.64% return of the long-short BTR portfolio, referred to as the brand-minus-talent (BMT) portfolio, is statistically significant; the magnitude of the return spread is also economically significant since it is close to the level of equity premium and value premium. Because high BTR firms may have differential exposures to risk factors, we estimate the alphas using the following asset pricing models for risk adjustment: the Fama-French three-factor model (see Fama and French, 1993), the Carhart four-factor model (see Carhart, 1997), the Pástor-Stambaugh five-factor model (see Pastor and Stambaugh, 2003), the Hou-Xue-Zhang q-factor model (see Hou, Xue and Zhang, 2015), and the Fama-French five-factor model (see Fama and French, 2015).[19] We find that the BMT portfolio has significantly negative alphas in all models. The annualized alphas range from −5.85% to −10.54%. All alphas are statistically significant. These results suggest that BTR largely determines firms' exposures to some factors that are probably not fully explained by traditional asset pricing factors.

We further examine the persistence of this negative relation. Figure 6 plots the alphas of the value-weighted portfolios estimated by various asset pricing models. We find that the negative

[19]The Pástor-Stambaugh five-factor model contains the Fama-French three factors (see Fama and French, 1993), the momentum factor (see Carhart, 1997), and the Pástor-Stambaugh liquidity factor (see Pastor and Stambaugh, 2003). Data on the Fama-French three factors, the momentum factor, and the Fama-French five factors are from Kenneth French's website. The Pástor-Stambaugh liquidity factor is from L'uboš Pástor's website.

relation between portfolio alphas and BTR exists three years before and continues to exist three years after portfolio formation. This result reinforces the findings in Table 4 in the sense that BTR is a persistent firm characteristic priced in the cross section.[20]



Note: This figure plots the annualized raw returns and alphas, averaged across different portfolio formation months, associated with the BTR portfolios three years before and three years after portfolio formation. Specifically, we conduct event studies for different portfolio formation months t, spanning the whole period of our BAV sample. In each portfolio formation month t, we sort stocks into quintiles based on lagged BTR to construct portfolios. Both stock allocations and weights in each portfolio are fixed at their values in portfolio formation month t. We then compute the returns of each BTR portfolio across time. Next, for each month $\tau \in [t-36, t+36]$, we estimate the parameters of the asset pricing models based on portfolio returns during $[\tau - 36, \tau)$. Using the estimated asset pricing models and portfolio returns in month τ, we estimate the portfolio alphas in month τ. Finally, we compute the average alpha for each month across all portfolio formation months t, and do time aggregation to obtain annualized alphas.

Figure 6: Before- and after-sorting raw returns and alphas for BTR quintiles in event time.

Table 5 tabulates the factor loadings (i.e. betas) of the asset pricing models. In the Fama-French five-factor model, we find that the BMT portfolio loads positively on the HML, RMW and CMA factors with large t-statistics (3.94, 4.76 and 3.48, respectively)[21], suggesting that high BTR firms tend to be value firms with high profitability and low asset growth rates. Similarly, in the Hou-Xue-Zhang q-factor model, we find that BMT portfolio loads positively on the I/A and ROE factors with large t-statistics (9.46 and 4.83, respectively), again suggesting that high

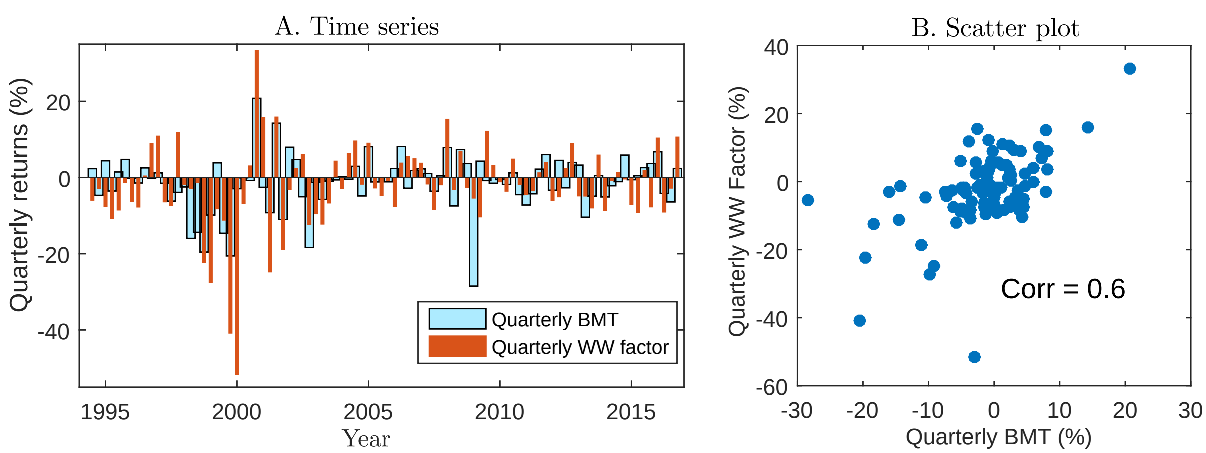
[20]The correlation in BTR is 0.96 between year t and $t-1$, and it is 0.80 between year t and $t-5$.

[21]RMW is short for robust minus weak. The sorting variable for the RMW factor is operating profitability, which is measured by revenues net of COGS, SG&A, interest expense, divided by book equity. CMA is short for conservative minus aggressive. The sorting variable is the change in total assets normalized by total assets.

BTR firms are firms with low asset growth rates and high profitability.[22] In section 5.1, we further examine the common characteristics of high BTR firms.

Could the alpha be explained by mispricing? Given the persistence of the alpha over time, it seems unlikely that the return spreads across BTR portfolios are due to mispricing. Nonetheless, we test this possibility directly using the Stambaugh-Yuan mispricing factor model (see Stambaugh and Yuan, 2016).[23] Appendix Table C.5 tabulates the alphas and betas of the BTR portfolios estimated by the Stambaugh-Yuan Mispricing Factor model. The BMT portfolio loads positively on the MGMT factor, and negatively on the PERF factor. However, the alphas of the BMT portfolio remain robust after controlling for the mispricing factors, suggesting that the returns spreads across BTR portfolios are likely due to risk-based factors.

4.2.2 BTR Captures the Exposure to Financial Constraints Risk.



Note: Panel A plots the time series of the quarterly returns of BMT and the WW factor (see Whited and Wu, 2006). We construct the WW factor following Whited and Wu (2006). First, we sort firms independently based on size and WW index into the top 40%, the middle 20%, and the bottom 40%. We then classify firms into the following nine groups: small size/low WW index (SL), small size/middle WW index (SM), small size/high WW index (SH), medium size/low WW index (ML), medium size/middle WW index (MM), medium size/high WW index (MH), large size/low WW index (BL), large size/middle WW index (BM), and large size/high WW index (BH). We calculate the value-weighted returns of each portfolio. The WW factor is constructed as the difference in the returns between the low-constrained firms and the high-constrained firms: (BL+ML+SL)/3 - (BH+MH+SH)/3. Note that the WW factor has the opposite sign to the financial constraint portfolio in Whited and Wu (2006). Panel B plots the quarterly BMT returns against the quarterly returns of the WW factor.

Figure 7: Correlation between BMT and the WW factor.

[22]The sorting variable for the I/A factor is the investment-to-asset ratio, which is the annual change in total assets divided by lagged total assets. The sorting variable for the ROE factor is the return on equity ratio, which is the income before extraordinary items divided by one-quarter-lagged book equity.

[23]Stambaugh-Yuan mispricing factor model (see Stambaugh and Yuan, 2016) includes four factors: market excess returns, SMB, MGMT, and PERF. MGMT is a factor that captures six anomalies including net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. These anomaly variables represent quantities that managers can affect rather directly. PERF is a factor that captures five anomalies including distress, O-score, momentum, gross profitability, and return on assets. These anomaly variables are related to performance and are less directly affected by firm managers. Data on the mispricing factors are from Yu Yuan's website.

Our empirical asset pricing results presented in the previous section suggests that BTR captures firms' exposure to some risk factors that are not fully explained by traditional asset pricing factors. Our model implies that the firms with lower BTRs should have greater exposure to financial constraints risk in the cross section, which could be the missing factor that explains the BMT alphas. In this subsection, we shed light on the internal linkages between BTR and financial constraints risk.

The existing literature has estimated financial constraints risk using two major approaches. The reduced-form estimates, such as the KZ index (see Kaplan and Zingales, 1997; Lamont, Polk and Saaá-Requejo, 2001), approximate the tightness of financial constraints based on directly observable firm characteristics. The structural estimate, known as the WW index (see Whited and Wu, 2006), estimates the unobservable shadow cost associated with raising equity based on the first-order investment equation derived from an economic model. Our model closely maps to the setting considered by Whited and Wu (2006) as BTR primarily affects the marginal value of internal cash in the presence of costly equity financing. And it is the variation of this unconditional marginal value of liquidity that results in the variation of talent turnover rates and BTR return spreads. Therefore, a natural starting point is to conduct an external validation by investigating the relation between our BMT portfolio returns and the financial constraints factor of Whited and Wu (2006).

Table 6: BMT alphas can be explained by PC1

	BMT Portfolio Returns					
Model	Raw	FF3F	FF4F	PS5F	q-factor	FF5F
α (%)	-5.64^{**}	-5.85^{***}	-6.21^{***}	-5.86^{**}	-10.54^{***}	-9.48^{***}
	[−2.06]	[−2.60]	[−2.73]	[−2.56]	[−4.54]	[−4.25]
α *controlling for PC1 (%)*	−2.14	−3.22	−2.76	−1.98	−4.79	−4.64
	[−1.00]	[−1.34]	[−1.22]	[−0.95]	[−1.63]	[−1.65]

Note: This table shows the alphas for the BMT portfolio with and without the control of PC1. PC1 is the first principle component between BMT and the WW factor. Since PC1 is not tradable, instead of directly controlling for PC1, we control for LS_β_{PC1}, which is the returns of the long-short portfolio sorted on the beta with PC1. In each month, we estimate the PC1 beta by regressing monthly stock returns on the returns of the PC1 portfolio and the returns of the Fama-French three factors in the preceding 36 months. In the beginning of the sample, when there are less than 36 monthly historical PC1 returns, we require at least 12 monthly BMT returns to estimate the PC1 beta. We then average the monthly PC1 beta into yearly PC1 beta for each stock and sort the stocks into quintiles based on their lagged yearly PC1 beta. LS_β_{PC1} is the difference in the returns between the Quintile 5 and Quintile 1 PC1 beta portfolios. The sample spans 1993 and 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.

We construct the WW factor following Whited and Wu (2006). Figure 7 plots the time series (Panel A) and the scatter plot (Panel B) of the WW factor and the returns of the BMT portfolio. We find that BMT is highly correlated with the WW factor, suggesting that BMT, to a large extent, also captures the same financial constraints risk as the WW factor.

Next, we construct an arguably better proxy for the financial constraints factor by computing the first principle component of BMT and the WW factor based on the correlation matrix. We denote this principle component as PC1, which is effectively the average of BMT and the WW factor. According to our theory, BMT reflects the financial constraints risk that may result in customer capital damage. Therefore, by focusing on the first principle component of BMT and the WW factor, we are able to extract the common underlying risk factor and partially eliminate measurement errors and the idiosyncratic terms unrelated the financial constraints risk.

If PC1 is an asset pricing factor that reflects financial constraints risk, it should be able to explain the alphas of the BMT portfolio according to our theory. This is indeed what we find. As shown in Table 6, we find that the magnitude of the alphas of the BMT portfolio decreases and becomes insignificant across all the asset pricing models after we control for PC1, suggesting that PC1 can indeed explain a significant portion of the alphas of the BMT portfolio.

4.2.3 Model-Implied Risk Premium.

Now we check whether the model can quantitatively replicate the above asset pricing patterns. We sort the simulated firms into five quintiles based on their BTRs. We then compute the portfolio alphas of each quintile by regressing excess portfolio returns on excess returns of the market portfolio, SMB, and HML, constructed using simulated data. Column 1 of Table 7 shows that the model-implied difference in portfolio alphas between Quintile 5 and Quintile 1 is about −5.63% (Panel B), roughly in line with the alpha of the long-short portfolio in our data based on the Fama-French three factor model (Panel A).

To investigate the implication of financial constraints, we continue to do a split sample analysis using the simulated firms. Specifically, we first sort firms into three groups based on their cash ratios. In each group, we further sort firms into five quintiles based on their BTRs. Columns 2-4 of Table 7 show that the difference in portfolio alphas between Quintile 5 and Quintile 1 is about −11.59% among the financially constrained firms and −1.09% among the financially unconstrained firms. Again, these differences are quite consistent with the ones in our data using HP or WW indexes as the sorting variable for financial constraints.[24]

In our model, customer capital plays two unique roles in generating different risk premiums across firms with different BTRs. The essential feature that generates the differential exposure to financial constraints risk shocks is that talent-based customer capital can be taken away due to human capital inalienability. In addition, key talents in low BTR firms ask for higher cash compensation because they enjoy fewer non-pecuniary private benefits. Thus the existence of non-pecuniary private benefits amplifies the effect of human capital inalienability through its influence on endogenous compensation, increasing the quantitative implication of BTR on stock returns.

[24]We split our sample into three groups based on HP or WW indexes, and then sort firms into quintiles based on BTR. Table 7 shows the Fama-French three-factor alphas of the BMT portfolios in the subgroups. The excess returns and alphas estimated from other factor models are tabulated in the Online Appendix.

Table 7: Portfolio alphas in model and data.

Panel A: Data (Fama-French Three-Factor)

	All Firms	Low Constraints		Medium Constraints		High Constraints	
		HP	WW	HP	WW	HP	WW
Quintile 1 (%)	7.08	3.26	2.99	2.10	3.98	12.86	17.17
Quintile 5 (%)	1.23	−0.05	0.52	2.21	1.32	5.35	6.85
Q5 − Q1 (%)	−5.85	−3.31	−2.46	0.11	−2.66	−7.51	−10.32

Panel B: Full Model

	All Firms	Low Constraints	Medium Constraints	High Constraints
Quintile 1 (%)	6.66	2.06	2.97	12.72
Quintile 5 (%)	1.03	0.96	0.99	1.13
Q5 − Q1 (%)	−5.63	−1.09	−1.97	−11.59

Panel C: Model without Non-Pecuniary Private Benefits

	All Firms	Low Constraints	Medium Constraints	High Constraints
Quintile 1 (%)	5.56	2.05	2.75	10.31
Quintile 5 (%)	1.07	1.00	1.02	1.16
Q5 − Q1 (%)	−4.49	−1.05	−1.73	−9.16

To quantify its importance, we calibrate a model without non-pecuniary private benefits to match the same moments tabulated in Table 3. Panel C of Table 7 shows that the alpha of the long-short portfolio is reduced to −4.49%. Compared with the alpha of our baseline model, −5.63%, about 20% of the cross-sectional variation in portfolio alphas is attributed to the variation in private benefits. Therefore, we argue that the composition of customer capital matters for stock returns, quantitatively, both because of human capital inalienability and non-pecuniary private benefits.

4.2.4 Double-Sort Analyses.

We further examine the asset pricing implications of BTR and show that the findings above are robust and not explained by other related factors.

Control for Measures of Customer Capital. Next, we compare our BTR measure with various other measures of customer capital in their ability to explain cross-sectional returns. We show that these measures of customer capital are either not priced cross sectionally or their association with stock returns can be explained away by BTR. These findings suggest that it is essential to dissect customer capital and study its composition to understand the role of customer capital in explaining the cross-sectional stock returns.

We study three measures of customer capital: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). Brand stature and and brand strength are the two brand metrics we use to construct BTR. The fluidity measure, as developed by Hoberg, Phillips and Prabhala (2014), captures "how intensively the product market around a firm is changing in each year". It is constructed based on a textual analysis of firms' product descriptions in 10-K filings. Firms with higher fluidity face a higher level of product market competition as their products are more similar to those of their peers.

We sort stocks into quintiles based on the above measures of customer capital and compute the average excess returns and alphas for the value-weighted long-short portfolios (see Appendix Table C.6). We find that out of the three measures, only brand stature is priced in the single-sort analysis, while brand strength and product fluidity are not priced. In addition, we perform a double-sort analysis in which we first sort firms into three groups based on BTR and then sort the firms in each group into five quintiles based on the three measures of customer capital. As shown in Appendix Table C.6, none of the measures (including brand stature) are priced in the cross section after we control for BTR by a double sort.

As a robustness check, we reverse the order of the double sort and test whether BTR is priced in the cross section after controlling for the three measures of customer capital. As shown in Appendix Table C.7, BTR remains priced in the cross section after controlling for customer capital.Taken together, the above results suggest that it is essential to examine the composition when we study the asset pricing implications of customer capital.

Control for Measures of Relative Importance of Human Capital. We have shown in Table 1 that BTR is correlated with various proxies for relative importance of human capital of firms, such as the administrative expenses/sales ratio, the R&D expenditure/sales ratio, the managerial compensation/sales ratio, and organization capital ratio. The relationship between stock returns and these financial proxies of human capital can be severely subject to endogeneity issues because the latter can be driven by many other factors (e.g. firms' past performance and future growth prospects) that are correlated with firms' expected returns. By contrast, we focus on the interaction between customer capital and human capital, and our BTR measure of key talents' importance through firms' customer capital alleviates this concern as it is not directly controlled by firms' endogenous financial decisions.

To empirically illustrate the difference in the asset pricing implications between the BTR measure and the financial proxies of relative importance of human capital, we use a double-sort approach and test whether BTR remains priced after controlling for the financial proxies. As shown by Appendix Table C.8, the average excess returns and alphas of the BMT portfolios remain significantly negative in the double-sort analysis, suggesting that the asset pricing implications of BTR are not entirely driven by its correlation with the financial proxies of relative importance of human capital.

Control for Industry Classifications. Finally, we test whether the cross-sectional relation between BTR and stock returns holds within industries (see Appendix Table C.9). We find that the BMT portfolios within industries have negative average excess returns and alphas, which are both statistically and economically significant. The return patterns are robust across various industry classifications, suggesting that BTR's within-industry variations are priced in the cross section.[25]

4.2.5 Extended Sample Analysis

One limitation of our analysis is that the BAV sample does not cover all the public firms. To alleviate this concern, we estimate the BMT betas for all U.S. public firms by regressing the stock returns of individual firms on the returns of the BMT portfolio using a rolling estimation window approach. We then use these BMT betas as our proxies for BTRs. This approach allows us to extend the sample cross sectionally. We show that the BMT beta is priced in the cross-section of U.S. public firms. Specifically, we sort firms into quintiles based on the BMT betas.[26] Table C.10 tabulates the average excess returns and alphas of the BMT beta portfolios. We find that the firms with lower BMT betas have significantly higher average excess returns and alphas, suggesting that BMT is an asset pricing factor that cannot be explained by traditional asset pricing factors.

4.3 Turnovers

Our model's asset pricing implications are closely connected to key talent turnovers, which result in customer capital damage. We now examine our model's prediction on turnovers and whether this is empirically supported by the data.

Panel A of Figure 8 compares the two firms' effective compensation, defined as the absolute amount of compensation to key talents multiplied by the marginal value of cash. Relative to the frictionless benchmark, the absolute amount of compensation is higher because key talents' outside options are worse in the full model. However, in the full model, both the high and low BTR firms effectively pay more to key talents when cash ratios are low due to the high marginal value of cash. Importantly, the increase in effective compensation is more significant for the low BTR firm.

The high effective costs of retaining key talents imply that the firm tends to replace key talents when cash ratios are low. As shown in Panel B, the firms with lower BTRs and lower cash ratios are more likely to replace key talents. The turnover boundary $(\hat{w}(m, f_{(2)}, \overline{a}, \xi_L))$

[25] Compared to the BMT portfolios formed based on the cross-industry sorting, the within-industry sorted BMT portfolios have slightly smaller average excess returns and alphas, suggesting that BTR's cross-industry variations are also priced cross sectionally.

[26] Since the BMT portfolio has risk exposure to the traditional asset pricing factors, we control for these factors when estimating the BMT beta. Pastor and Stambaugh (2003) use the same approach to study the asset pricing implications of their market liquidity factor. They estimate the market liquidity beta in regressions that control for the Fama-French three factors.

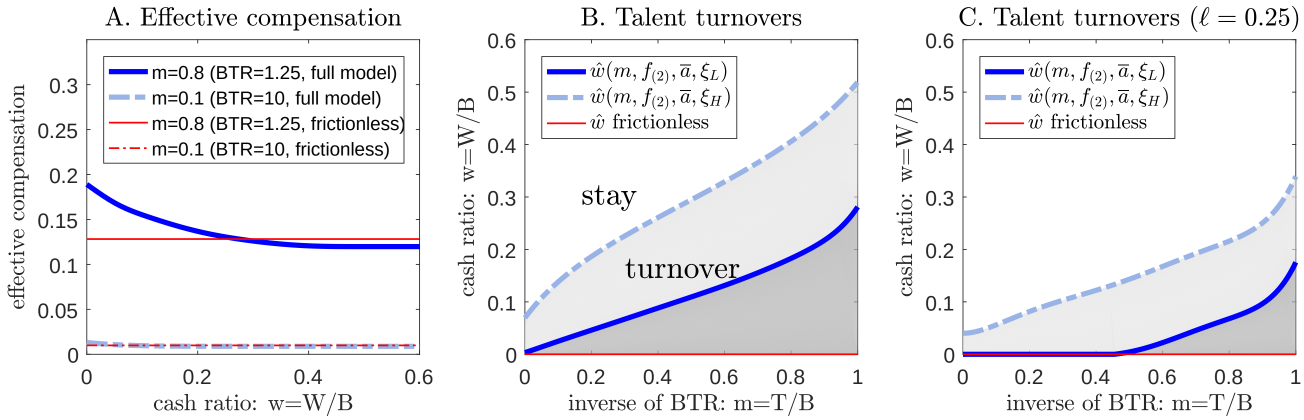


Figure 8: Model prediction on effective compensation and talent turnovers.

shifts upward when aggregate financial constraints risk is higher. The difference in turnover boundaries (i.e. $\hat{w}(m, f_{(2)}, \bar{a}, \xi_H) - \hat{w}(m, f_{(2)}, \bar{a}, \xi_L)$) increases with m. Therefore, our model suggests that the low BTR firm tends to be associated with a greater increase in turnover rates when financial constraints risk increases. Or in other words, customer capital owned by the low BTR firm is more fragile to financial constraints risk.

Intuitively, retaining key talents is beneficial to the firm because on average talent-based customer capital generates positive net cash inflows. However, when the firm is financially stressed, the increased exposure to financial constraints risk due to operating leverage outweighs the benefit from higher average demand, motivating the firm to replace key talents and downsize the scale of production. A higher financial constraints risk shock leads to an expansion of the turnover region. The low BTR firm is more liquidity constrained, and therefore responds more aggressively to the increase in financial constraints risk by expanding the turnover region more. This differentiates our mechanism from that of Eisfeldt and Papanikolaou (2013). In their model, the firm operates in a perfect financial market. Both the key talent turnover decisions and the asset pricing implications are driven by aggregate frontier technology shocks to key talents' outside option.

4.3.1 BTR and Talent Turnovers

We now empirically test the model's prediction on turnovers. First, we show BTR is negatively related to the turnover rates of two types of key talents: executives and innovators. Next, we show that this negative relation is more pronounced in time periods with worse aggregate liquidity condition, and in states with weaker enforceability of the non-competition agreements.

BTR and Executive Turnovers We first study the relation between BTR and executive turnovers. We focus on the executives in the Execucomp database, which covers the top five highest compensated executives of each S&P 1500 firm starting from 1992.[27] Since the coverage of the turnover information for executives (especially for non-CEOs) is limited in Execucomp, we further merge Execucomp with BoardEx and use the employment history data in BoardEx to identify the executive turnovers. We filter out executive turnovers due to retirements.[28] We follow the literature (see, e.g. Parrino, 1997; Jenter and Kanaan, 2015) and use age 60 as the cutoff for the retirement age.[29] We define executive turnovers as non-retirement turnovers if executives leave their firms at age 59 or younger. We also exclude executive death from the turnover sample. The indicator variable for non-retirement turnovers for firm i in year t is denoted as $\text{Turnover}_{i,t}$.

We run the following regression to study the relation between BTR and executive turnovers:

$$\text{Turnover}_{i,t} \times 100 = \alpha_{ind} + \alpha_t + \beta \ln\text{BTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{4.4}$$

The dependent variables are indicators for executive turnovers. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. We include year fixed effects to control for the aggregate time-series pattern of executive turnovers. We run regressions both with and without SIC-2 industry fixed effects to ensure that our findings are robust to industry controls. Standard errors are clustered by firm and year.

Column (1) and (2) of Table 8 show that executive turnover rates are significantly lower in the firms with higher BTRs. This result is robust to the inclusion of the SIC-2 industry fixed effects. The negative relation between BTR and executive turnovers is economically significant. According to the specification with both SIC-2 industry fixed effects and year fixed effects, a one standard deviation increase in lnBTR leads to a decrease in the probability of executive turnovers by 1.5 percentage point, roughly 1/8 of the average turnover rate in the data.

BTR and Innovator Turnovers Next, we study the relation between BTR and the turnovers of innovators, another important group of firms' key talents. We track the employment history of innovators based on the HBS patent and innovator database, which provides innovators' names and affiliations from 1975 to 2010. We define a mover in a given year 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. The mover is considered as a leaver for her former

[27] In the Online Appendix, we replicate the turnover analyses in two different samples: 1) CEOs only and 2) all managers in BoardEx. We show that the relation between BTR and turnovers is robust in these two samples.

[28] This is because: 1) retirements are mostly due to age, health status, and life style choices of executives, which do not reflect firms' active decisions of talent turnovers; and 2) the non-retirement turnovers are more likely to cause damage to talent-based customer capital and thus are more relevant to the mechanism of our paper.

[29] Our results are robust to other age cutoffs such as 65.

Table 8: BTR and talent turnovers

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	Turnover$_t$ × 100		$\ln(1+\text{leavers})_t$		$\ln(1+\text{new hires})_t$	
lnBTR_{t-1}	-1.653^{***}	-1.546^{**}	-0.163^{**}	-0.170^{**}	-0.156^{*}	-0.158^{*}
	[−3.621]	[−3.232]	[−2.198]	[−2.299]	[−2.097]	[−2.113]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Executive Controls	Yes	Yes	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24329	24329	1780	1774	1780	1774
R-squared	0.023	0.032	0.381	0.596	0.385	0.601

Note: This table shows the relation between BTR and the turnovers of managers and innovators. In Column (1) and (2), we study the turnovers of executives covered by the Execucomp data. We match Execucomp with BoardEx and use the employment history data in BoardEx to identify executive turnovers. The dependent variable is 100 for a given executive-year observation if the executive leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) to (6), we study the turnovers of innovators. We track the innovator turnovers using the Harvard Business School (HBS) patent and innovator database, which provides the names of the innovators and their affiliations from 1975 to 2010. 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. The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include $\ln(\text{OC}/\text{Asset})_{t-1}$, lnsize_{t-1}, lnBEME_{t-1}, lnlev_{t-1}, and StockRet_{t-1}. These variables are defined in Table A.1. For executives, we also control for their gender. We do not include age as a control variable since age is used to classify the non-retirement turnovers. The executive turnover sample spans 1993 to 2016, while the innovator turnover sample spans 1993 to 2010. 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.

employer and a new hire for her new employer. We run the following regression to study the relation between BTR and innovator turnovers:

$$ln(1+\text{movers})_{i,t} = \alpha_{ind} + \alpha_t + \beta \text{lnBTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{4.5}$$

The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is lagged lnBTR. Column (3) to (6) in Table 8 show that the firms with higher BTRs are associated with significantly fewer innovator turnovers. According to the specifications with both year fixed effects and industry fixed effects, a one standard deviation increase in lnBTR is associated with a 17.0% reduction in the number of innovator departures and a 15.8% reduction in the number of innovator arrivals.

4.3.2 Interaction with BMT Returns

Our model predicts that the negative relation between BTR and talent turnover rates should be stronger when firms face adverse aggregate liquidity conditions. A good internal proxy for aggregate liquidity conditions is the BMT portfolio's return. BMT returns are unconditionally negative, and become positive when the economy faces funding liquidity shortage (shown by Figure 2), providing insurance against such negative aggregate liquidity shocks. We interact

Table 9: BTR and talent turnovers: interaction with BMT

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	Turnover$_t$ × 100		ln(1 + leavers)$_t$		ln(1 + new hires)$_t$	
lnBTR$_{t-1}$	-1.909^{***}	-1.785^{***}	-0.190^{**}	-0.187^{**}	-0.178^{**}	-0.173^{**}
	[−3.881]	[−3.470]	[−2.520]	[−2.457]	[−2.337]	[−2.218]
lnBTR$_{t-1}$ × BMT$_{t-1}$	-4.495^{**}	-4.791^{**}	-0.409^{***}	-0.350^{**}	-0.376^{***}	-0.315^{*}
	[−2.573]	[−2.708]	[−5.388]	[−2.847]	[−3.287]	[−2.071]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Executive Controls	Yes	Yes	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24107	24107	1688	1682	1688	1682
R-squared	0.024	0.032	0.382	0.600	0.386	0.604

Note: This table shows the relation between talent turnovers and the interaction between BTR and BMT. BMT is the yearly returns for the brand-minus-talent (Quintile 5 − Quintile 1 BTR) portfolio. The mean of BMT is −0.055 (i.e., −5.5%), while the standard deviation of BMT is 0.160 (i.e., 16.0%). The dependent variables are defined previously in Table 8. The main independent variables are the lagged lnBTR, and the products between the lagged lnBTR and the lagged BMT. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include ln(OC/Asset)$_{t-1}$, lnsize$_{t-1}$, lnBEME$_{t-1}$, lnlev$_{t-1}$, and StockRet$_{t-1}$. These variables are defined in Table A.1. For executives, we also control for their gender. We do not include age as a control variable since age is used to classify the non-retirement turnovers. The executive turnover sample spans 1993 to 2016, while the innovator turnover sample spans 1993 to 2010. 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.

the standardized lnBTR with yearly BMT returns and include the interaction term as the main independent variable in the the regressions:[30]

As shown by Table 9, we find that the coefficients for the interaction terms are significantly negative, suggesting that the negative relation between BTR and talent turnover rates is indeed more pronounced conditional on worse aggregate funding liquidity condition. This interaction effect is also economically significant. For example, according to the specification with industry and year fixed effects, when BMT returns change from its mean value (−5.5%) to a value that is two standard deviation above the mean (26.5%), the sensitivity between lnBTR and executive turnovers nearly doubles (the coefficient changes from −1.538 to −2.975).

4.3.3 Interaction with the Non-Competition Enforceability Index

We further exploit the cross-state variation in the enforceability of non-competition agreements. We show that the negative relation between BTR and talent turnovers is weaker in the states with higher enforceability of non-competition agreements. Non-competition agreements affect the role of BTR because strictly enforced non-competition agreements reduce the outside option values of key talents. As a result, firms can reduce their payment to talents and hence decrease operating leverage (see, e.g. Garmaise, 2011), which helps low BTR firms more in retaining their talents as these firms are endogenously more constrained.

We interact BTR with the non-competition enforceability index and include this interaction

[30] Note that we omit the term BMT$_{t-1}$ in the regressions because it is absorbed by the year fixed effects.

Table 10: BTR and talent turnovers: interaction with the non-competition enforceability index

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	Turnover$_t$ × 100		$\ln(1+\text{leavers})_t$		$\ln(1+\text{new hires})_t$	
lnBTR_{t-1}	-2.049^{***}	-2.360^{**}	-0.251^{**}	-0.318^{***}	-0.206^{**}	-0.255^{**}
	[−3.658]	[−2.246]	[−2.433]	[−3.764]	[−2.103]	[−2.665]
$\text{lnBTR}_{t-1} \times \text{Enforceability}_{s,t-1}$	0.206^{*}	0.315^{**}	0.031^{**}	0.035^{**}	0.020^{**}	0.021^{**}
	[1.875]	[2.126]	[2.361]	[2.318]	[2.714]	[2.190]
$\text{Enforceability}_{s,t-1}$	-0.189^{**}	-0.161^{*}	-0.078^{**}	-0.028^{**}	-0.090^{**}	-0.029^{**}
	[−2.512]	[−1.997]	[−2.286]	[−2.064]	[−2.707]	[−2.433]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Executive Controls	Yes	Yes	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8754	8754	1248	1244	1248	1244
R-squared	0.010	0.018	0.384	0.628	0.395	0.636

Note: This table shows the relation between talent turnovers and the interaction between BTR and the non-competition enforceability index. The state-level non-compete enforceability index comes from Garmaise (2011). Higher values of the index represent higher enforceability of the non-compete covenant. The index is available from 1992 to 2004. The dependent variables are defined previously in Table 8. The main independent variables are the lagged lnBTR, and the products between the lagged lnBTR and the lagged non-competition enforceability index, and the lagged non-competition enforceability index. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include $\ln(\text{OC}/\text{Asset})_{t-1}$, lnsize_{t-1}, lnBEME_{t-1}, lnlev_{t-1}, and StockRet_{t-1}. These variables are defined in Table A.1. For executives, we also control for their gender. We do not include age as a control variable since age is used to classify the non-retirement turnovers. Both the executive turnover sample and the innovator turnover sample span 1993 to 2004. We include t-statistics in parentheses. Standard errors are clustered by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

term as the main independent variable in the regressions. The state-level non-competition enforceability index comes from Garmaise (2011). Higher values of the index represent higher enforceability of the non-compete covenant. The minimum, maximum, median, and mean of the index is 0, 9, 5 and 4.08. The standard deviation of the index is 1.83. The index is available from 1992 to 2004.

As shown by Table 10, we find that the coefficients for the interaction terms are significantly positive, suggesting that the negative relation between BTR and talent turnover rates is indeed weaker with more strictly enforced non-competition agreements. This interaction effect is economically significant. Conditional on the weakest enforceability of non-competition agreements (index equals to 0), a one standard deviation increase in lnBTR leads to a 31.8% reduction in the number of leavers for innovators. Conditional on the strongest enforceability of non-competition agreements (index equals to 9), a one standard deviation increase in lnBTR leads only to a 0.3% (insignificant) reduction in the number of leavers for innovators.

5 Empirical Tests for the Theoretical Mechanism

We provide four additional sets of empirical evidence to support our model. First, we show that high BTR firms are a group of firms with robust growth patterns. Second, we show that the firms with lower BTRs adopt more precautionary financial policies. Third, our model assumes that key talents receive non-pecuniary private benefits proportional to the firm's total customer capital. We provide evidence for this assumption by showing that key talents receive lower compensation when they work in the firms with greater brand stature. Finally, we show that the duration of executive compensation is longer in firms with lower BTRs, suggesting that these firms actively alleviate their liquidity constraints by increasing pay duration and reducing the compensation flow of key talents. We show the first two sets of evidence in this section and the rest in Appendix B.4.

5.1 Robust Firms: High BTR Firms

Table 11: Firm characteristics and BTR.

	Median					Mean				
BTR Portfolios	Low	2	3	4	High	Low	2	3	4	High
lnBTR (standardized)	−1.25	−0.28	0.27	0.68	1.14	−1.32	−0.23	0.26	0.66	1.13
Firm Characteristics										
lnsize	7.63	8.24	9.00	9.13	8.87	7.65	8.28	8.92	9.01	8.86
lnBEME	−0.97	−0.99	−1.03	−1.08	−0.92	−1.01	−1.00	−1.03	−1.14	−0.98
lnlev	−0.27	−0.06	0.14	0.45	0.59	−0.18	−0.07	0.17	0.52	0.65
Operating profitability (%)	24.60	28.55	31.84	36.07	32.57	24.59	29.05	37.52	40.57	39.31
ΔAsset/Lagged Asset (%)	7.55	5.68	3.81	3.60	3.58	14.49	11.15	6.88	7.07	7.13
Cash Flow Volatility										
Vol(Daily Ret) (%)	2.57	2.20	1.92	1.81	1.85	2.91	2.51	2.21	2.08	2.21
Vol(Sales_Gr) (%)	10.01	8.80	7.45	6.41	7.31	17.61	13.31	10.94	10.13	13.13
Vol(Net Income/Asset) (%)	3.26	3.14	2.64	2.21	2.30	7.12	5.77	4.61	3.61	3.37
Vol(EBITDA/Asset) (%)	2.79	2.66	2.42	2.05	2.02	4.33	3.83	3.02	2.79	2.50
Key Talent Compensation										
Administrative Expenses/Sales (%)	25.36	23.67	22.06	19.02	17.35	27.58	25.21	23.08	19.67	18.69
R&D/Sales (%)	10.82	3.64	2.31	1.87	1.99	14.21	5.99	4.64	3.88	3.86
Execucomp/Sales (%)	0.50	0.39	0.25	0.20	0.15	0.79	0.59	0.42	0.32	0.32
Corporate Financial Policy										
Cash/Lagged Asset (%)	19.42	12.06	8.86	6.71	6.19	25.68	18.74	14.32	9.88	9.07
ΔCash/Net Income (%)	9.08	6.33	2.68	3.60	3.86	24.25	23.35	10.63	8.03	12.08
ΔEquity/Lagged Asset (%)	0.64	0.55	0.55	0.48	0.33	3.42	2.28	1.23	1.01	0.94
Payout/Lagged Asset (%)	1.98	3.35	5.38	4.95	3.39	4.89	5.65	7.07	6.96	5.67
Dividend/Lagged Asset (%)	0.00	0.56	1.55	1.91	1.45	1.35	1.47	2.30	2.60	2.16
Repurchases/Lagged Asset (%)	0.18	1.06	2.33	2.22	1.25	3.20	3.91	4.54	4.16	3.44

Note: This table shows the characteristics of the five portfolios sorted on BTR. We report the mean and median firm characteristics for each portfolio. 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 spans 1993 and 2016. We explain the definition of the variables in Appendix Table A.1.

We investigate the firm characteristics associated with BTR to have a better understanding of the BTR measure. In particular, we show that high BTR firms, a group of firms we refer to as robust firms, are associated with steady cash flows, and that their growth rates are less negatively affected by their peers' innovative outputs. Although we do not model firms' innovation, the evidence is consistent with our model's implications. When key talents leave the firm, the firm's customer capital decreases and peers' customer capital increases, which is effectively similar to the effect of creative destruction as a result of peer firms' innovation. High BTR firms' key talents are less likely to leave due to better corporate financial conditions. The stability of these key employees ensures the stability of customer capital, implying that high BTR firms are associated with relatively more stable cash flows and growth rates. The evidence we show here is also consistent with the firm characteristics shown in Table 11; that is, high BTR firms tend to have high profitability; they are less innovation intensive, and as a result, they tend to have lower asset growth rates.

BTR and Cash Flow Volatilities. We run the following regressions to examine the relation between BTR and firms' cash flow volatility:

$$\text{Vol}_{i,t} = \alpha_{ind} + \alpha_t + \beta \text{lnBTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{5.1}$$

The dependent variables are the measures of cash flow volatility including: 1) volatility of the forward-looking growth rates of sales, 2) volatility of the forward-looking net-income-to-asset ratios, 3) volatility of the forward-looking EBITDA-to-asset ratios, and 4) volatility of stock returns. The main independent variable is the lagged lnBTR, which is standardized to ease the interpretation of its coefficients. As shown in Table 12, the coefficients of lnBTR are negatively associated with all four cash flow volatility measures. These results are both statistically and economically significant. Taken together, our analysis suggests that high BTR firms are a group of firms associated with steady sales growth and stable cash flows.

Table 12: BTR and cash flow volatility.

	(1) Vol(Sales Growth)$_t$ (%)	(2) Vol($\frac{NI}{Asset}$)$_t$ (%)	(3) Vol($\frac{EBITDA}{Asset}$)$_t$ (%)	(4) Vol(Daily Ret)$_t$ (%)
lnBTR$_{t-1}$	-1.801^{**}	-0.713^{*}	-0.334^{*}	-0.274^{***}
	[−2.196]	[−1.837]	[−1.916]	[−5.870]
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5452	5452	5448	5828
R-squared	0.085	0.167	0.220	0.505

Note: This table shows the relation between BTR and firms' cash flow volatilities. The dependent variables are the volatility of the forward-looking growth rates of sales (standard deviation of the six yearly growth rates of sales over the period t through $t+5$), the volatility of the forward-looking net-income-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$), the volatility of the forward-looking EBITDA-to-asset-ratio (standard deviation of the six yearly ratios from the period t through $t+5$), and the volatility of daily stock returns in current year (t). 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 lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include $\ln(\text{OC/Asset})_{t-1}$, lnsize_{t-1}, lnBEME_{t-1}, and lnlev_{t-1}. These variables are defined in Table A.1. The sample period is 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.

BTR and Peers' Innovation. Next, we study how BTR affects firms' reaction to the innovation of their peer firms. Following Kogan et al. (2017), we measure patent value (in dollars) based on stock market reaction to the patent issuance. The innovative outputs of the peer firms (Innovation_Peers) are the sum of peer firms' patent values in the SIC-3 industry normalized by the sum of their book values. We run the following regressions:

$$
\begin{aligned}
&ln(\text{Outcome}_{i,t+5}) - ln(\text{Outcome}_{i,t}) = \alpha_{ind} + \alpha_t + \beta_1 \text{Innovation\_Peers}_{i,t} \\
&+ \beta_2 \text{Innovation\_Peers}_{i,t} \times \text{lnBTR}_{i,t-1} + \beta_3 \text{Innovation\_Self}_{i,t} + \beta_4 \text{Innovation\_Self}_{i,t} \times \text{lnBTR}_{i,t-1} \\
&+ \beta_5 \text{lnBTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}.
\end{aligned} \tag{5.2}
$$

The outcome variables are the five-year growth rates of the (a) firm gross profits, (b) the value of output, (c) capital stock, and (d) the number of employees. The growth rates are computed by $\ln(\text{Outcome}_{i,t+5}) - ln(\text{Outcome}_{i,t})$. We standardize the innovative outputs and lnBTR to ease the interpretation of their coefficients.

Table 13 presents the results of the regressions. Consistent with Kogan et al. (2017), we find that firm growth is negatively related to peers' innovative outputs. Importantly, we find that BTR mitigates this negative relation. The coefficients β_2 are positive and statistically significant, suggesting that the firms with higher BTRs react less negatively to peer firms' innovative outputs. This relation is also economically significant. For firms with the average level of lnBTR, a one standard deviation increase in the peer firms' innovative outputs is associated with a 9.2% drop of profits over five years. The sensitivity of firm growth to innovation reduces significantly when BTR increases. For the firms whose lnBTR is two standard deviations above the average, the sensitivity of their profit growth to the innovative outputs of their peers' is indistinguishable from zero.

5.2 BTR and Firms' Financial Policies

Next we examine the relation between BTR and firms' financial policies by running the following regressions:

$$
y_{i,t} = \alpha_{ind} + \alpha_t + \beta \text{lnBTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{5.3}
$$

Here, the outcome variables $y_{i,t}$ are the amount of cash holdings normalized by lagged assets, the change of cash holdings normalized by contemporaneous net income, the amount of equity issuance normalized by lagged assets, the amount of total payout normalized by lagged assets, the amount of dividend issuance normalized by lagged assets, and the amount of share repurchases normalized by lagged assets. The outcome variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. The main

Table 13: BTR and the displacement risk in creative destruction.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\frac{\text{Profits}_{t+5}}{\text{Profits}_t})$		$\ln(\frac{\text{Output}_{t+5}}{\text{Output}_t})$		$\ln(\frac{\text{Capital}_{t+5}}{\text{Capital}_t})$		$\ln(\frac{\text{Labor}_{t+5}}{\text{Labor}_t})$	
Innovation_Peers$_t$	-0.079^{***}	-0.092^{***}	-0.069^{***}	-0.084^{***}	-0.069^{***}	-0.083^{***}	-0.076^{***}	-0.099^{***}
	[−3.966]	[−3.736]	[−3.996]	[−4.322]	[−3.457]	[−3.737]	[−3.781]	[−4.272]
Innovation_Peers$_t$ * lnBTR$_{t-1}$		0.033^{*}		0.036^{**}		0.037^{*}		0.055^{***}
		[1.813]		[2.604]		[2.025]		[3.201]
Innovation_Self$_t$	0.025^{***}	0.030^{***}	0.027^{***}	0.033^{***}	0.039^{***}	0.044^{***}	0.031^{***}	0.040^{***}
	[3.033]	[3.409]	[3.795]	[4.050]	[4.935]	[4.767]	[4.239]	[4.924]
Innovation_Self$_t$ * lnBTR$_{t-1}$		-0.017^{*}		-0.016^{**}		-0.017^{*}		-0.026^{***}
		[−1.933]		[−2.105]		[−2.043]		[−3.683]
lnBTR$_{t-1}$		0.023		0.015		0.000		0.048
		[0.529]		[0.400]		[0.007]		[1.209]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3583	3583	3556	3556	3589	3589	3573	3573
R-squared	0.246	0.250	0.287	0.291	0.366	0.371	0.298	0.309

Note: This table shows the relation between BTR and the sensitivity of firm growth to innovative outputs. The dependent variables are the five year growth rate of the (a) firm gross profits (Compustat item *sale* minus Compustat item *cogs*, deflated by the CPI), (b) value of output (Compustat item *sale* plus change in inventories Compustat item *invt*, deflated by CPI), (c) capital stock (Compustat item *ppegt*, deflated by the NIPA price of equipment), and (d) number of employees (Compustat item *emp*). The main independent variables include the innovative outputs of the peer firms (Innovation_Peers), the innovative outputs of the firms (Innovation_Self), the interaction between lnBTR and the two innovative output measures, and lnBTR. We measure the innovative outputs of a given firm (Innovation_Self) using the sum of patent value normalized by the firm's book asset. The patent value is measured in dollars based on stock market reaction to the patent issuance. We measure the innovative outputs of the peer firms (Innovation_Peers) using the sum of patent value of the peer firms in the SIC-3 industry normalized by the sum of the book assets of the peer firms. We standardize the innovative outputs and lnBTR to ease the interpretation of the coefficients. Following Kogan et al. (2017), we include the lagged value of firm capital (lnCapital), the lagged value of number of employees (lnLabor), and the firm's idiosyncratic volatility (IVOL) as the control variables. We include industry fixed effects and year fixed effects in the regressions. We download the innovation data from Noah Stoffman's website and the data span 1926-2010. Our merged sample spans 1993-2010. 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.

independent variable is the natural log of the lagged lnBTR. We standardize lnBTR to ease the interpretation of its coefficients.

Table 14 shows that the firms with higher BTRs hold less cash and convert a smaller fraction of net income to cash holdings. A one standard deviation increase in lnBTR leads to a 3.48 percentage points decrease (roughly 1/6 standard deviation) in normalized cash holdings and a 9.42 percentage points decrease (roughly 1/20 standard deviation) in the cash saving rate (ΔCash/NI). High BTR firms also issue less equity and pay out more. A one standard deviation increase in BTR leads to a 0.67 percentage points decrease (roughly 1/12 standard deviation) in equity issuance and a 0.90 percentage points increase (roughly 1/7 standard deviation) in total payout. Taken together, we find that the firms with higher BTRs are less likely to adopt precautionary financial policies.

Table 14: BTR 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) $\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$ (%)
lnBTR_{t-1}	-3.475^{***}	-9.421^{**}	-0.665^{*}	0.903^{***}	0.310^{***}	0.591^{***}
	[−5.786]	[−2.219]	[−1.928]	[4.457]	[3.111]	[3.934]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5842	4958	5842	5842	5842	5842
R-squared	0.439	0.032	0.106	0.296	0.349	0.248

Note: This table shows the relation between BTR and firms' financial policies. The dependent variables are the amount of cash holdings (% of lagged assets), the change of cash holdings (% of contemporaneous net income), the amount of equity issuance (% of lagged assets), the amount of total payout (% of lagged assets), the amount of dividend issuance (% of lagged assets), and the amount of share repurchases (% of lagged assets). 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 lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include $\ln(\text{OC/Asset})_{t-1}$, lnsize_{t-1}, lnBEME_{t-1}, and lnlev_{t-1}. These variables are defined in Table A.1. The sample period is 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.

6 Conclusion

In this paper, we provide the first elements of a conceptual framework to theoretically analyze and empirically test an economic mechanism by which the composition of pure-brand-based and talent-based customer capital influences firm valuation and asset prices. We develop a model featuring inalienable talent-based customer capital and endogenous value of liquidity to argue that the firms with different BTRs have distinctive financial constraints risk exposures.

Based on proprietary brand perception survey data, we find the empirical evidence strongly supporting our model's predictions. The firms with lower BTRs have higher average excess returns and risk-adjusted returns. This return spread is highly correlated with the returns of the financial constraints factor. Moreover, the firms with lower BTRs are associated with higher talent turnover rates, and this pattern is more pronounced in the periods with worse aggregate liquidity condition. Our model shows that the firm's exposure to financial constraints risk is reflected both in the cross-sectional variation in customer capital composition and the cross-sectional variation in financial condition. It is the endogenous interaction between the two that explains the cross-sectional patterns on stock returns and talent turnovers.

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Appendix

A Definition of Variables.

Table A.1: Definition of variables.

Variables	Definition and Data Sources
lnBTR	The natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures the loyalty of existing customers. We use brand stature to proxy for the value of customer capital. Brand strength measures how much the brand is perceived to be innovative and distinctive. Since the creation of innovative products and distinctive brands requires significant contribution of key talents, we use brand strength as a proxy for talent-based customer capital. We provide detailed information on the BAV survey and the construction of brand stature and strength in B.1. Data sources: BAV.
ln(AdminExpenses/Sales)	The natural log of the normalized administrative expenses. We take out advertisement costs, R&D expenses, commissions, and foreign currency adjustments from SG&A to estimate the talent compensation. Data sources: Compustat.
ln(R&D/Sales)	The natural log of the normalized R&D expenses. Data sources: Compustat.
ln(ExecuComp/Sales)	The natural log of the normalized executive compensation. The executive compensation is the summation of the total pay ($tdc1$) for the top five executives in the Execucomp data. Data sources: Execucomp.
ln(OC/Asset)	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. Data sources: Compustat.
lnsize	The natural log of the market cap (in million dollars). Data sources: CRSP.
lnBEME	The natural log of the book-to-market ratio. Data sources: CRSP and Compustat.
lnlev	The natural log of the debt-to-equity ratio. Data sources: Compustat.
StockRet	The 12-month stock returns. Data sources: CRSP.
Turnover	A dummy variable that equals one if an executive leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. Data sources: Execucomp and BoardEx.
$\ln(1 + \text{leavers})$	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. Data sources: HBS patent and innovator database.
$\ln(1 + \text{new hires})$	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 join new firms in a given year, they are classified as new hires of their new employers in that given year. Data sources: HBS patent and innovator database.
Age	The age of the executives. Data sources: Execucomp and BoardEx.
Enforceability	The non-competition agreement enforceability index. Data sources: Garmaise (2011).
Operating profitability	Revenues net of COGS, SG&A, interest expense, divided by book equity. Data sources: Compustat.
ΔAsset/Lagged asset	Asset growth rate. Change in total assets normalized by lagged total assets. Data sources: Compustat.
Vol(Daily Ret)_t	Volatility of daily stock returns in year t. Data sources: CRSP.
$\text{Vol}(\frac{\text{NI}}{\text{Asset}})_t$	Volatility of the forward-looking net-income-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$). Data sources: Compustat.

Table A.1: Definition of variables (continued).

Variables	Definition and Data Sources
$\text{Vol}(\frac{\text{EBITDA}}{\text{Asset}})_t$	Volatility of the forward-looking EBITDA-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$). Data sources: Compustat.
Profits	Firm gross profits (Compustat item *sale* minus Compustat item *cogs*, deflated by the CPI). Data sources: Compustat.
Output	Value of output (Compustat item *sale* plus change in inventories Compustat item *invt*, deflated by CPI). Data sources: Compustat.
Capital	Capital stock (Compustat item *ppegt*, deflated by the NIPA price of equipment). Data sources: Compustat.
Labor	Number of employees (Compustat item *emp*). Data sources: Compustat.
Innovation_Peers	Following Kogan et al. (2017), we measure patent value (in dollars) based on stock market reaction to the patent issuance. The innovative outputs of the peer firms (Innovation_Peers) are the sum of peer firms' patent values in the SIC-3 industry normalized by the sum of their book values. Data sources: Kogan et al. (2017).
$\frac{\text{Cash}_t}{\text{Asset}_{t-1}}$	The amount of cash holding (*che*) normalize by lagged total assets (*at*). Data sources: Compustat.
$\frac{\Delta\text{Cash}_t}{\text{NI}_t}$	The change of cash holding (*chech*) normalize by the contemporaneous net income (*ni*). We only include observations with positive net income. Data sources: Compustat.
$\frac{\Delta\text{Equity}_t}{\text{Asset}_{t-1}}$	The amount of equity issuance (*sstk*) normalize by lagged total assets (*at*). Data sources: Compustat.
$\frac{\text{Payout}_t}{\text{Asset}_{t-1}}$	The amount of total payout (*dv* + *prstkc*) normalize by lagged total assets (*at*). Data sources: Compustat.
$\frac{\text{Dividend}_t}{\text{Asset}_{t-1}}$	The amount of dividend issuance (*dv*) normalize by lagged total assets (*at*). Data sources: Compustat.
$\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$	The amount of share repurchases (*prstkc*) normalize by lagged total assets (*at*). Data sources: Compustat.
lnExecuComp	The natural log of the managerial compensation (*tdc*1 in the Execucomp data). Data sources: Execucomp.
$\frac{\text{(Stocks+Options)}_t}{\text{Total Pay}_t}$	The stocks/options-to-total-pay ratio. Data sources: Execucomp.
Duration	Duration of executive compensation. We follow Gopalan et al. (2014) and compute pay duration as the weighted average duration of the four components of pay (i.e., salary, bonus, restricted stock, and stock options). Data on the vesting schedules of restricted stock and stock options are from Equilar Consultants and they span 2006 to 2016. Data sources: Execucomp & Equilar.

B Additional Data Description

B.1 BAV Consumer Survey and BAV Brand Metrics

BAV Consumer Survey. The details of the survey have been described by finance and marketing academic papers (see, e.g. Larkin, 2013; Tavassoli, Sorescu and Chandy, 2014). The questionnaire asks consumers to indicate whether they consider a brand to be associated with various brand image characteristics (such as innovative and reliable). It also asks consumers to evaluate their general knowledge of a brand ("How familiar are you with this brand?"), their personal regard towards a brand ("How highly do you think of this brand?"), and the relevance of a brand ("How relevant do you feel the brand is for you?") on a seven-point scale (0-6). By averaging the scores of the above three questions across respondents, the BAV Group constructs the following variables at the brand-survey level: *Knowledge*, *Regard*, and *Relevance*. In addition, the survey collects demographic information and asks consumers how frequently they use a brand.

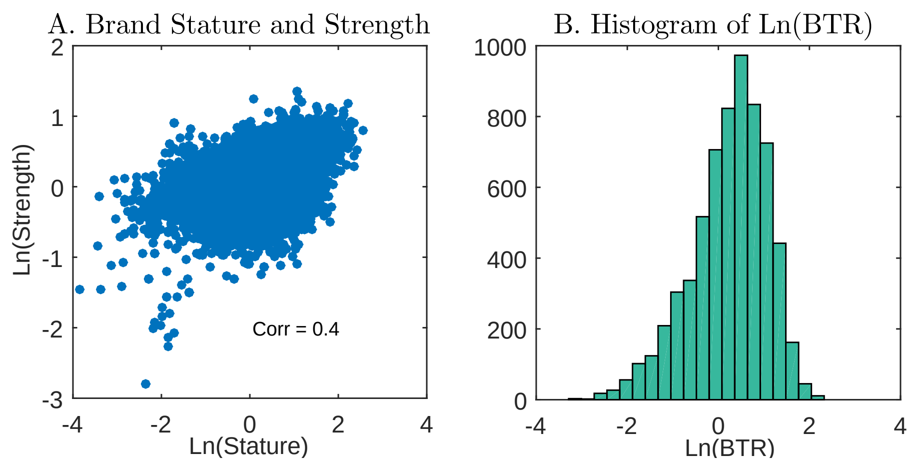
Brand Stature. The BAV Group constructs the brand stature measure to capture brand loyalty of existing customers (see Gerzema and Lebar, 2008). Brand stature reflects the current value of a brand, and it is the product between *Esteem* and *Knowledge*. *Esteem* is a measure of respect and admiration for a brand. The components of *Esteem* are (1) the brand score on *Regard* and (2) the proportions of respondents who consider the brand to be of "high quality," a "leader," and "reliable". *Esteem* reflects brand loyalty because consumers are proud to be associated with the brand that they hold in high regard. On the other hand, *Knowledge* captures the degree of personal familiarity. BAV finds that the past and current users of a brand rate themselves as being significantly more knowledgeable about the brand. Thus, *Knowledge* serves as an adjustment factor in quantifying consumers' respect and admiration for a brand, because brand users carry greater weights in determining brand stature. Since brand stature captures the brand loyalty of existing customers, we use it as a proxy for current customer capital.

Brand Strength. The BAV Group constructs brand strength to measure how much a brand is perceived to be innovative and distinctive. Brand strength predicts the growth potential of a brand (see Gerzema and Lebar, 2008), and it is the product between *Energized Differentiation* and *Relevance*. *Energized Differentiation* is the average proportion of respondents who consider a brand to be "innovative," "dynamic," "distinctive," "unique," and "different". Here, "distinctive," "unique," and "different" capture the differentiation of a brand from its peers. "Innovative" captures the innovativeness of the brand, and "dynamic" captures the vibrance of the management team. "*Energized Differentiation* excites consumers and drives future sales. On the other hand, *Relevance* captures the degree of personal appropriateness. *Relevance* serves as an adjustment factor in quantifying consumers' perception of a brand, because relevant consumers (both existing and potential customers) receive greater weights in determining brand strength. Since the creation of innovative products and distinctive brands requires significant contribution of key talents, we use brand strength as a proxy for talent-based customer capital.

B.2 Construct Firm-Level Brand Metrics Based on the Brand-Level Data

The BAV Group conducts consumer surveys at the brand-level. 58% of the firm-year observations contain one brand; 15% of the firm-year observations contain two brands; 8% of the firm-year observations contain three brands; 4% of the firm-year observations contain four brands; and 15% of the firm-year observations contain five or more brands. For the firm-year observations that contain more than one brand, we compute the average brand stature and brand strength across brands and assign the scores to the corresponding firm-year observations. As robustness checks, we use three alternative methods for the aggregation procedure. In the first and second alternative methods, we choose the maximal and median values of the brand metrics across the brands to represent a firm's brand metrics, respectively. In the third alternative method, 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. Our results are robust to these alternative methods.

B.3 Sample Characteristics



Note: Panel A shows the relation between stature and strength. Panel B shows the distribution of lnBTR. 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 from 1993 to 2016.

Figure B.1: The Brand-talent ratio.

As shown in Table C.2, our merged data cover 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 since 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 BAV data. Given that we exclude financial firms and utility firms from our analysis, the underrepresentation of these two industries does not affect us. The distribution of the remaining segments in the BAV data is comparable to the Compustat-CRSP universe. Table C.3 tabulates the distribution of the BAV data across GICS industries. Although the BAV data are biased towards final consumption good firms, the data also provide a significant amount of coverage for the investment good firms. Final consumption good firms are firms in the following GICS industries: Automobiles & Components, Consumer Durables & Apparel, Consumer Services, Media, Retailing, Food & Staples Retailing, Food, Beverages & Tobacco, and Household & Personal Products. In the BAV data, 55.9% of firm-year observations come from final consumption good firms, while this percentage is 21.0% in the Compustat/CRSP data. We also follow Gomes, Kogan and Yogo (2009) and classify each SIC industry into categories (durables, non-durables, services, domestic investment, government, and net exports) according to its contribution to final demand. Table C.4 tabulate the distribution of this durability industry classifications within each BTR quintiles. We do not observe any obvious clustering pattern across BTR quintiles for all durability categories.

Panel A of Figure B.1 shows that brand stature and brand strength are positively correlated with each other, with the correlation coefficient being 0.4. However, the relation between stature and strength is far from a one-to-one mapping. Panel B of Figure B.1 shows that lnBTR has a good amount of variation and its distribution is close to normal.

B.4 Additional Empirical Tests

B.4.1 Brand Values and Private Benefits

We find that executives of the firms with stronger brand values receive lower compensation.[31] Specifically, this result remains robust when we include executive fixed effects and focus on the within-executive variations. Thus, our findings cannot be explained by unobserved heterogeneity across executives. The relation between brand value and executive pay is also economically significant. According to the regression with executive fixed effects, industry fixed effects, and year fixed effects, a one standard deviation increase in brand stature is associated with a 10.8% reduction in managerial compensation (see Column 4 of Table C.11).

We continue to hypothesize that younger executives are more likely to enjoy non-pecuniary private benefits at the firms with strong brand values. One interpretation is that they have longer career ahead of them and thus gain more non-pecuniary private benefits such as the identity-based benefits and the signaling benefits. To test this hypothesis, we interact age with brand value and include the interaction terms in the regressions. We do not include executive fixed effects in this set of regressions because we would like to exploit the age variations across executives. Consistent with our hypothesis, we find that the coefficients for the interaction term between age and brand stature are positive and statistically significant, suggesting that younger executives are indeed more willing to take lower compensation when they work in the firms with stronger brand values. According to the specification with both industry fixed effects and

[31] This finding is constent with Tavassoli, Sorescu and Chandy (2014), who use a dataset with a shorter period and a different method to define brand value. We test the relation between these two brand metrics and managerial pay separately and find that the negative relation between brand value and managerial pay mainly comes from brand stature.

year fixed effects, a 30-year old executive is willing to take a 15.8% cut in compensation with a one standard deviation increase in the brand stature of her employee; whereas a 67-year old executive is not willing to accept any compensation discount.

B.4.2 BTR and Compensation Duration

As our main theoretical channel, a greater BTR renders the firms more liquidity constrained, and thus in principle, these firms should have stronger incentives to alleviate the liquidity constraints by adjusting compensation contracts. Following this logic, we further hypothesize that the firms with lower BTRs are more likely to increase the pay duration of key talents and thus delay cash payments. In particular, they can choose to substitute the cash payment (salary and bonus) with stocks and stock options which have longer pay duration due to the existence of vesting schedule. To test this hypothesis, we examine the relation between BTR and the pay duration of top executives.[32]

We first use the Execucomp data to examine the relation between BTR and the stocks/options-to-total-pay ratio. We include executive fixed effects in the regressions to make sure that our findings are not explained by the unobserved heterogeneity across executives. As shown by Table C.12, the firms with lower BTRs are associated with higher stocks/options-to-total-pay ratio. A one standard deviation decrease in lnBTR is associated with around a 3.5 percentage points increase in the stocks/options-to-total-pay ratio (the mean and median of the stocks/options-to-total-pay ratio in our sample are 35.8% and 36.2%, respectively). Our finding is consistent with Yermack (1995), who shows that financially constrained firms are more likely to award CEO stock options.

Next, we further quantify the relation between BTR and compensation duration. Following Gopalan et al. (2014), we compute pay duration as the weighted average duration of the four components of pay (i.e. salary, bonus, restricted stock, and stock options). As shown by Table C.12, the firms with lower BTRs are indeed associated with longer pay duration. However, we find that the magnitude of the changes in pay duration is very small. A one standard deviation decrease in lnBTR is associated with around a 0.10 year increase in pay duration (the mean and median pay duration in our sample are 1.57 and 1.70, respectively). Taken together, we find that low BTR firms actively manage the pay duration of their talents, but the capacity of delaying seems to be too limited to fundamentally alleviate the liquidity constraints faced by low BTR firms.

[32] We focus on executives because the duration data for innovators are not available.

C Supplementary Tables

Table C.1: Summary statistics.

Variables	Mean	Median	10%	90%	S.D.	# of obs.
BAV Variables						
ln(Stature)	0.32	0.48	−1.00	1.36	0.92	6,420
ln(Strength)	0.09	0.12	−0.45	0.59	0.42	6,420
lnBTR (unstandardized)	0.23	0.35	−0.96	1.21	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 Ret) (%)	2.45	2.09	1.21	4.03	1.40	6,399
Vol(Sales_Gr) (%)	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
Execucomp/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 sample. We merge BAV brand survey data with Compustat and CRSP data to construct a firm-year panel. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception 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. We construct the BTR using the ratio of brand stature and brand strength. Executive turnover variables are derived from Execucomp and BoardEx. Innovator turnover variables are derived from the Harvard Business School patent and innovator database. Corporate financial policy variables, firm characteristics, and key talent compensation variables are derived from Compustat and Execucomp. Cash flow volatility variables are derived from Compustat and CRSP. Our sample spans the period between 1993-2016 and 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 analyses. The definition of the variables is listed in Appendix Table A.1.

Table C.2: Fama-French 12 Industry distribution of the BAV sample.

FF12 Industry Name	# Firm-Year Obs.		% Firm-Year Obs.	
	BAV	Compustat-CRSP	BAV	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 BAV data 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 BAV data and the Compustat-CRSP universe. Our sample includes firms that are 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.

Table C.3: GICS industry distribution of the BAV 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 BAV data by GICS industry for the period 1993-2016. We report the total number of firm-year observations and the proportion (in percentage) of the number of observations in each industry. Our sample includes firms that are 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.

Table C.4: Durability industry classifications within each BTR quintile.

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

Note: This table presents the distribution of the durability industry classifications within each BTR quintile. 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) according to its contribution to final demand, with a detailed breakdown for personal consumption expenditures (PCE). The durability classification is constructed based on NIPA's Benchmark Input-Output Accounts. The durability classification does not include wholesale and retail firms (SIC 5000-5999) because a detailed breakdown of value added by PCE category is not available for them. We label wholesale and retail firms as "others" in the table. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude utility firms and financial firms in the analysis. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception 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. The BTR quntiles are formed at the yearly basis based on the lagged BTR ratio. Our sample spans 1993 to 2016.

Table C.5: BTR return spreads cannot be explained by mispricing factors.

BTR Portfolios	1 (Low)	2	3	4	5 (High)	$5-1$
α (%)	7.26^{***}	5.34^{***}	2.76^{*}	3.41^{**}	0.42	-6.84^{***}
	[3.29]	[2.77]	[1.83]	[2.22]	[0.23]	[−2.64]
β_{MKT}	1.16^{***}	1.07^{***}	0.98^{***}	0.94^{***}	1.04^{***}	-0.13^{**}
	[23.93]	[25.08]	[29.46]	[27.74]	[25.91]	[−2.21]
β_{SMB}	0.07	0.02	−0.05	-0.13^{***}	0.01	−0.06
	[1.27]	[0.39]	[−1.38]	[−3.51]	[0.23]	[−0.92]
β_{MGMT}	−0.08	0.15^{**}	0.28^{***}	0.23^{***}	0.45^{***}	0.52^{***}
	[−1.14]	[2.57]	[6.09]	[5.05]	[8.20]	[6.72]
β_{PERF}	0.01	-0.11^{***}	−0.02	-0.09^{***}	-0.09^{***}	-0.10^{**}
	[0.20]	[−3.06]	[−0.66]	[-3.11]	[−2.76]	[−2.11]
R^2	0.786	0.800	0.821	0.817	0.789	0.261

Note: This table shows the value-weighted portfolio alphas and betas estimated by the Stambaugh-Yuan Mispricing Factor model (see Stambaugh and Yuan, 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 C.6: 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 Fluidity
Panel A: Excess return 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 BTR)	$[-0.50]$	[0.51]	[1.03]
Panel B: Fama-French three-factor α 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 BTR)	$[-0.63]$	[0.29]	[0.84]
Panel C: Carhart four-factor α 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 BTR)	$[-0.17]$	[0.78]	[1.21]
Panel D: Pástor-Stambaugh five-factor α 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 BTR)	$[-0.09]$	[0.83]	[1.12]
Panel E: Hou-Xue-Zhang q-factor α 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 BTR)	[0.88]	[1.54]	[1.45]
Panel F: Fama-French five-factor α 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 BTR)	[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 BTR 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 is 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 C.7: BMT portfolio excess returns and alphas controlling for customer capital measures.

First Sort Variables	Brand Stature	Brand Strength	Product Fluidity
Excess return (%)	-2.90	-6.02^{**}	-5.15^{**}
	$[-1.45]$	$[-2.50]$	$[-2.19]$
Fama-French three-factor α (%)	-3.18^{*}	-5.94^{***}	-5.57^{***}
	$[-1.81]$	$[-2.85]$	$[-2.84]$
Carhart four-factor α (%)	-3.94^{**}	-6.06^{***}	-5.92^{***}
	$[-1.99]$	$[-2.87]$	$[-2.99]$
Pástor-Stambaugh five-factor α (%)	-3.94^{**}	-5.74^{***}	-5.66^{***}
	$[-1.97]$	$[-2.71]$	$[-2.84]$
Hou-Xue-Zhang q-factor α (%)	-7.62^{***}	-8.74^{***}	-9.34^{***}
	$[-3.90]$	$[-3.93]$	$[-4.66]$
Fama-French five-factor α (%)	-7.60^{***}	-7.80^{***}	-8.70^{***}
	$[-4.12]$	$[-3.63]$	$[-4.50]$

Note: This table shows the value-weighted BMT portfolio excess returns and alphas 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' BTR 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 is 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 C.8: BMT portfolio excess returns and alphas controlling for key talent compensation.

First Sort Variables	Admin. Expenses	R&D Expenditure	Managerial Comp.	Organization Capital
Excess return (%)	-5.24^{**}	-5.01^{**}	-4.26^{**}	-5.16^{*}
	$[-2.30]$	$[-2.08]$	$[-2.01]$	$[-1.95]$
Fama-French three-factor α (%)	-5.05^{***}	-5.39^{***}	-4.68^{***}	-5.28^{**}
	$[-2.72]$	$[-2.76]$	$[-2.61]$	$[-2.45]$
Carhart four-factor α (%)	-5.55^{***}	-5.99^{***}	-4.56^{**}	-5.32^{**}
	$[-2.96]$	$[-3.05]$	$[-2.51]$	$[-2.43]$
Pástor-Stambaugh five-factor α (%)	-5.22^{***}	-5.72^{***}	-4.31^{**}	-5.17^{**}
	$[-2.78]$	$[-2.90]$	$[-2.36]$	$[-2.34]$
Hou-Xue-Zhang q-factor α (%)	-8.67^{***}	-9.59^{***}	-7.20^{***}	-9.56^{***}
	$[-4.48]$	$[-4.83]$	$[-3.81]$	$[-4.29]$
Fama-French five-factor α (%)	-7.47^{***}	-8.74^{***}	-6.86^{***}	-8.83^{***}
	$[-3.97]$	$[-4.58]$	$[-3.79]$	$[-4.13]$

Note: This table shows the value-weighted BMT portfolio excess returns and alphas 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' BTR 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 is 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 C.9: BMT portfolio excess returns and alphas controlling for industry classifications.

Industry Classifications	SIC2	FF5	FF10	FF12	FF17	FF48	Durability
Excess return (%)	-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 α (%)	-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 α (%)	-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 α (%)	-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 α (%)	-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 α (%)	-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 value-weighted BMT portfolio excess returns and alphas controlling for different 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' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. SIC2 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 contribution to final demand. The sample period is 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 C.10: Excess returns and alphas for portfolios sorted on BMT betas.

BMT Beta Portfolio	1 (Low)	2	3	4	5 (High)	$5-1$
Excess return (%)	19.30^{***}	13.94^{***}	11.40^{***}	11.95^{***}	13.41^{***}	-5.89^{*}
	[3.38]	[3.36]	[3.22]	[3.26]	[3.11]	[−1.91]
Fama-French three-factor α (%)	9.93^{***}	5.79^{***}	4.15^{***}	4.18^{***}	4.12^{**}	-5.81^{**}
	[4.78]	[3.80]	[3.98]	[3.04]	[2.51]	[−2.50]
Carhart four-factor α (%)	11.38^{***}	6.21^{***}	4.92^{***}	4.76^{***}	4.54^{***}	-6.84^{***}
	[5.71]	[4.11]	[5.09]	[3.47]	[2.67]	[−2.91]
Pástor-Stambaugh five-factor α (%)	10.78^{***}	5.75^{***}	4.72^{***}	4.18^{***}	3.88^{**}	-6.90^{***}
	[5.65]	[3.98]	[5.04]	[3.13]	[2.30]	[−2.89]
Hou-Xue-Zhang q-factor α (%)	12.15^{***}	5.37^{***}	3.20^{***}	2.08	2.26	-9.89^{***}
	[5.81]	[3.38]	[3.09]	[1.57]	[1.37]	[−4.23]
Fama-French five-factor α (%)	13.71^{***}	6.61^{***}	4.48^{***}	2.97^{**}	2.85^{*}	-10.86^{***}
	[6.00]	[4.55]	[4.63]	[2.12]	[1.81]	[−4.24]

Note: This table shows the asset pricing tests for portfolios sorted on the beta with the BMT portfolio. In each month, we estimate the BMT beta by regressing monthly stock returns on the returns of the BMT portfolio and the returns of the Fama-French three factors in the preceding 36 months. In the beginning of the sample, when there are less than 36 monthly historical BMT returns, we require at least 12 monthly BMT returns to estimate the BMT beta. We then average the monthly BMT beta into yearly BMT beta for each stock and sort the stocks into quintiles based on their lagged yearly BMT beta. The sample spans 1993 and 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 C.11: Brand values and talents' non-pecuniary private benefits: evidence from managerial compensation.

	(1)	(2)	(3)	(4)	(5)	(6)
	lnExecuComp$_t$					
lnStature$_{t-1}$	-0.096^{***}	-0.063^{**}	-0.113^{**}	-0.108^{**}	-0.173^{***}	-0.158^{***}
	[−4.002]	[−2.704]	[−2.524]	[−2.303]	[−3.542]	[−3.561]
lnStature$_{t-1}$ × (Age$_{t-1}$ − 30)					0.003^{*}	0.004^{**}
					[1.747]	[2.306]
lnStrength$_{t-1}$	0.057^{*}	0.015	0.053^{*}	0.055^{*}	0.026	−0.009
	[2.035]	[0.519]	[1.863]	[1.859]	[0.307]	[−0.122]
lnStrength$_{t-1}$ × (Age$_{t-1}$ − 30)					0.001	0.001
					[0.412]	[0.350]
Age$_{t-1}$	0.019^{***}	0.019^{***}	-0.137^{***}	-0.152^{***}	0.018^{***}	0.018^{***}
	[5.365]	[6.125]	[−5.195]	[−4.655]	[5.786]	[6.690]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Executive Controls	Yes	Yes	No	No	Yes	Yes
Executive FE	No	No	Yes	Yes	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23496	23496	22267	22267	23496	23496
R-squared	0.283	0.299	0.748	0.749	0.283	0.299

Note: This table shows the relation between brand values and managerial compensation. lnExecuComp is the natural log of the managerial compensation (*tdc*1 in the Execucomp data). Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. We standardize both lnStature and lnStrength to ease the interpretation of the coefficients. In Column (5) and (6), we include the interaction terms between the brand values and executive age in the regressions. Firm-level control variables include ln(OC/Asset)$_{t-1}$, lnsize$_{t-1}$, lnBEME$_{t-1}$, lnlev$_{t-1}$, and StockRet$_{t-1}$. These variables are defined in Table A.1. We also include executive gender as an additional control variable in the specifications without the executive fixed effects. The sample period is 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 C.12: BTR and the duration of executive compensation.

	(1)	(2)	(3)	(4)
	$\frac{(\text{Stocks+Options})_t}{\text{Total Pay}_t}$ (%)		Duration$_t$	
lnBTR$_{t-1}$	-3.513^{***}	-3.583^{***}	-0.098^{*}	-0.102^{*}
	[−3.717]	[−3.587]	[−2.181]	[−2.054]
Firm Controls	Yes	Yes	Yes	Yes
Executive FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	22270	22270	8971	8970
R-squared	0.497	0.501	0.557	0.565

Note: Note: This table shows the relation between BTR and the duration of executive compensation. In Column (1) and (2), the dependent variables are the stocks/options-to-total-pay ratio. Data on the executive pay are from Execucomp and they span 1992 to 2016. In Column (3) and (4), the dependent variables are the duration of executive compensation. We follow Gopalan et al. (2014) and compute pay duration as the weighted average duration of the four components of pay (i.e., salary, bonus, restricted stock, and stock options). Data on the vesting schedules of restricted stock and stock options are from Equilar Consultants and they span 2006 to 2016. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Firm-level control variables include ln(OC/Asset)$_{t-1}$, lnsize$_{t-1}$, lnBEME$_{t-1}$, lnlev$_{t-1}$, StockRet$_{t-1}$, and Age$_{t-1}$. These variables are defined in Table A.1. The sample period in Column (1) and (2) is 1993 to 2016, and the sample period in Column (3) and (4) is 2006 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.