Customer Capital, Financial Constraints, and Stock Returns

Winston Wei Dou Yan Ji David Reibstein Wei Wu*

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Abstract

We develop a model in which customer capital depends on key talents' contributions and pure brand recognition. Customer capital guarantees stable demand, but is fragile to financial constraints risk if retained mainly by talents, who tend to escape financially constrained firms, damaging customer capital. Using proprietary granular brand-perception survey, we construct a measure of firm-level talent-to-brand ratios (TBR), which reflects the degree to which customer capital depends on talents. We document new cross-sectional patterns: firms with higher TBRs have higher average returns, more talent turnovers, and more precautionary financial policies. The TBR-sorted long-short portfolio's return comoves with the financial-constraints-risk factor.

Keywords: Intangible capital; Cross-sectional stock returns; Brand loyalty; Robust value firms; Financial constraints risk; Industrial organization, marketing and finance. (JEL: G12, G30, M31, M37, E22)

*Dou: University of Pennsylvania (wdou@wharton.upenn.edu). Ji: HKUST (jiy@ust.hk). Reibstein: University of Pennsylvania (reibstein@wharton.upenn.edu). Wu: Texas A&M (wwu@mays.tamu.edu). We thank Hengjie Ai, Markus Baldauf, Frederico Belo, Alex Belyakov, Christa Bouwman, Adrian Buss, Jeffrey Cai, Zhanhui Chen, Will Diamond, Lukasz Drozd, Bernard Dumas, Paolo Fulghieri, Lorenzo Garlappi, Ron Giammarino, Stefano Giglio, Itay Goldstein, Naveen Gondhi, Francois Gourio, Jillian Grennan, Po-Hsuan Hsu, Shiyang Huang (discussant), Chuan-Yang Hwang, Don Keim, Leonid Kogan, Adam Kolasinski, Doron Levit, Kai Li, Xiaoji Lin, Asaf Manela, Neil Morgan, Christian Opp, Pascal Maenhout, Hernan Ortiz-Molina, Carolin Pflueger, Yue Qiu (CFEA discussant), Adriano Rampini, Nick Roussanov, Leena Rudanko (AFA discussant), Alp Simsek, Bruno Solnik, Rob Stambaugh, Sheridan Titman, Kumar Venkataraman, Jessica Wachter, James Weston, Toni Whited, Yu Xu, Jialin Yu, Lu Zhang, Bart Zhou, John Zhu, as well as seminar participants at HKU, HKUST, INSEAD, NTU, Philadelphia Fed, SMU, Texas A&M, UBC, Wharton, AFA, CFEA, Rising Five-Star Workshop at Columbia Business School, the Marketing Strategy Meets Wall Street Conference (AMA) for their comments. We also thank John Gerzema, Anna Blender, and Dami Rosanvo of the BAV Group for sharing the BAV data, and Ed Lebar for his support and guidance. Particularly, we thank Alina Sorescu for her guidance on data processing. We thank Dian Yuan, Haowen Dong, and Hezel Gadzikwa for their excellent research assistance. Winston Dou is especially grateful for the generous financial support of the Rodney L. White Center for Financial Research.

1 Introduction

Customer capital – customers' brand loyalty to the firm – is one of a firm's most crucial intangible assets, because it determines the capacity of stable demand flows by creating large entry barriers and durable advantages for the firm (see, e.g. Bronnenberg, Dubé and Gentzkow, 2012). Developing 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]

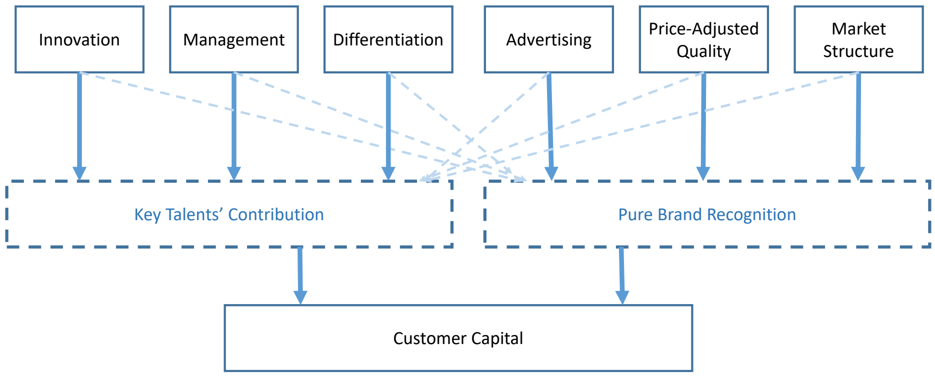
As Figure 1 illustrates, the creation and maintenance of customer capital depend on innovation, dynamic management, and product differentiation primarily through the unique contributions of key talents, as well as advertising, price-adjusted product quality, and market structure primarily through pure brand recognition.

Firms whose customer capital depends more on the unique contributions of key talents are more exposed to financial constraints risk. This is because key talents are likely to leave, taking away or damaging the associated customer capital, when firms are financially constrained. Thus, during the periods of heightened financial constraints risk, firms with more talent-based customer capital are more likely to suffer from key talents' turnovers. Such heterogeneous exposure to financial constraints risk is further amplified in a feedback loop, as the loss of customer capital reduces future revenue. Unlike physical or other types of intangible capital, talent-based customer capital is fragile due to limited legal enforceability, and thus it perfectly illustrates the idea of inalienable human capital (see Hart and Moore, 1994) and its interaction with financial frictions (see Bolton, Wang and Yang, 2018). The ratio between talent-based customer capital and total customer capital (i.e. brand loyalty) is referred to as *talent-to-brand ratio (TBR)*, which captures the degree to which a firm's total customer capital depends on its talents.

Existing studies on customer capital focus on its corporate policy implications without considering its dependence on key talents (see, e.g. Chevalier and Scharfstein, 1996; Gourio and Rudanko, 2014; Belo, Lin and Vitorino, 2014; Gilchrist et al., 2017).[2] Our paper is the first to dissect the different channels through which customer capital is maintained,

[1] As Rudanko (2017) emphasizes, customer capital is crucial for the other assets of firms to be profitable. One example to demonstrate the necessity of customer capital is the well-known case of Iridium's bankruptcy due to its failure to create and maintain customer capital. According to the structural estimation of Belo et al. (2018), brand capital on average accounts for 37.1% of the market value of U.S. publicly traded firms from 1975 to 2013, with its importance increasing over time.

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



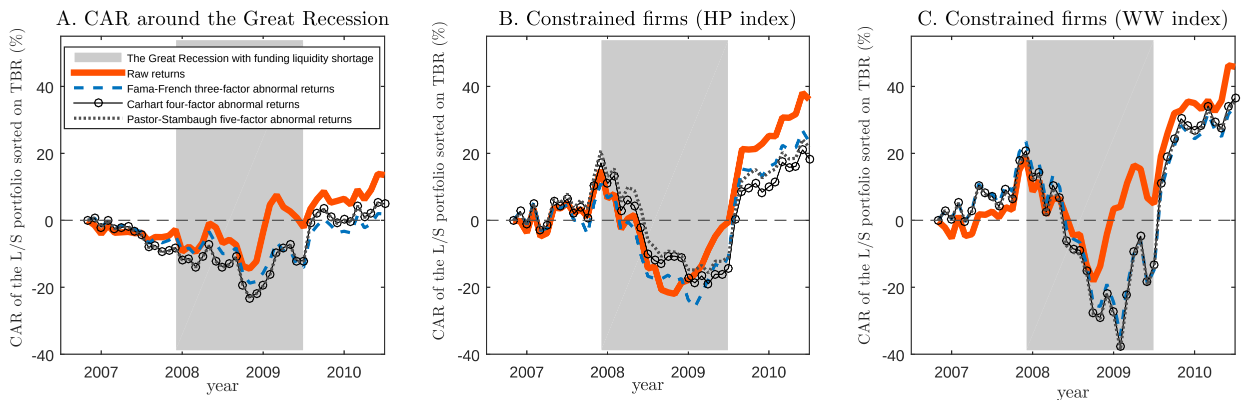
Note: The solid arrow lines stand for major channels, while the dashed arrow lines stand for secondary channels.

Figure 1: Different channels of creating and maintaining customer capital.

and to highlight how these channels interact with financial constraints risk, generating important financial implications. Without taking into account the fragility of talent-based customer capital to financial constraints risk, the existing studies may overestimate the amount of customer capital robustly owned by the firm.

In this paper, we examine how customer capital interacts with financial constraints, and investigate the associated asset pricing implications. Particularly, we show that in the model, as in the data, a firm's exposure to financial-constraints-risk factor is simultaneously reflected in two cross sections: firms have higher average returns (i) if their customer capital is more talent dependent and (ii) if they are more financially constrained. In our model, the two cross-equation restrictions based on two different cross sections jointly identify the same underlying asset pricing factor. Measuring the dependence of customer capital on talents is challenging; as a contribution, we introduce a measure for the degree to which customer capital depends on talents, based on a proprietary, granular brand-perception survey database.

Figure 2 presents the cumulative abnormal returns for the long-short portfolio constructed based on the degree to which customer capital depends on key talents. The time series are displayed around the Great Recession, featuring a funding liquidity shortage. As Figure 2 shows, the firms whose customer capital is more talent dependent have lower abnormal returns during the period of funding liquidity shortage, whereas this pattern reverses with an improvement in aggregate funding liquidity conditions. This phenomenon is especially pronounced among financially constrained firms. The stylized facts above suggest that the firms whose customer capital is more brand dependent are far more resilient against adverse aggregate financial-constraints-risk shocks relative to those firms whose customer capital is more talent dependent.



Note: We construct a measure of a firm's TBR to capture the relative importance of key talents in retaining the firm's customer capital. This figure plots the cumulative abnormal returns (CAR) for the portfolio that longs Q5 (high TBR) firms and shorts Q1 (low TBR) firms around the Great Recession. We follow NBER and define the time period of the Great Recession as 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 CAR for Dec. 2006 through July 2010. Our sample includes the firms 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's talent dependence.

Inspired by the stylized facts, we develop a dynamic asset pricing model to shed light on the underlying mechanism and to quantify the effect of customer capital on asset prices and talent turnovers. Our model features inalienable human capital and endogenous marginal value of liquidity, similar to Bolton, Wang and Yang (2018). In our model, the firm's external financing is costly, motivating retained earnings. Thus, the firm faces endogenous financial constraints risk. The level of cash holdings determines the firm's marginal value of internal funds. Our model 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. Berk, Stanton and Zechner, 2010; Taylor, 2010; Lustig, Syverson and Nieuwerburgh, 2011; Eisfeldt and Papanikolaou, 2013). Customer capital has two unique features that determine the firm's exposure to systematic financial constraints risk. First, key talents have outside options and limited commitment to the firm; as a result, maintaining talent-based customer capital requires compensation and imposes operating leverage on the firm. Second, key talents enjoy non-pecuniary private benefits from the firm's customer capital, because brands with strong public recognition offer identity-based benefits, signaling values, and social status. Thus, the firms with stronger customer capital can more easily retain key talents. The fragility of talent-based customer capital is the essential feature that generates the spread in risk-adjusted returns, whereas the non-pecuniary private benefits are an amplification channel which contributes about 20% to the spread according to our calibration.

Our model highlights an intertemporal tradeoff between risks and returns as the key mechanism 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 faces heightened financial constraints risk, 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; Babina, 2017; Baghai et al., 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). Thus, customer capital is robust against financial constraints risk if it depends mainly on customers' pure brand recognition; by contrast, customer capital is fragile to the financial constraints risk if it depends mainly on the contributions of key talents, because the effective cost of compensation increases with the firm's marginal value of liquidity.

Although our model has stressed the importance of customer capital and its talent dependence, we would have little to say about its empirical relevance without a measure. The main empirical challenge is to find high-quality data on consumers' brand perception measured in a consistent way across firms. We tackle this challenge by constructing a measure for the degree to which customer capital depends on talents, 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' brand perception.

We use the ratio between *brand strength* and *brand stature*, the two major brand metrics developed by the BAV Group, as our measure for TBR. By the design of the BAV Group,

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

brand stature quantifies a firm's brand loyalty, which provides an approximation for the existing customer capital; brand strength quantifies the extent to which a brand is perceived to be innovative/distinctive and the management team is considered to be dynamic. The maintenance of brand strength intrinsically relies on a firm's key talents, because innovation and product differentiation require significant intellectual inputs, and dynamic management requires executives' specialized skills. Thus, Our TBR measure naturally serves as a proxy for the degree to which customer capital depends on talents. Note that we do not assume that key talents are the only contributor to brand strength. For the ratio between brand stature and brand strength to be a valid measure of TBR, we only need to assume that brand strength reflects more about the input of key talents compared to brand stature. This assumption is supported by our external validation tests (similar to Bloom and Reenen (2007)), in which we merge the BAV data with Compustat/CRSP and investigate the association between our TBR measure and various proxies for the relative importance of key talents. We find that the firms with higher TBRs are indeed associated with higher administrative expenses, R&D expenses, and executive compensation, as well as lower advertisement expenditures.

We present two main sets of empirical results to support our model. First, we find that the firms with higher TBRs have higher average excess returns and greater alphas in various factor models. The return spreads are persistent around the portfolio formation, and are robust after controlling for mispricing factors, key-talent compensation, organization capital, total customer capital, and industry classifications. Moreover, the TBR-sorted long-short portfolio's return is highly correlated with the financial-constraints-risk factor of Whited and Wu (2006), suggesting that the long-short portfolio's return captures the financial-constraints-risk factor. In fact, we extend our sample to all U.S. public firms and show that the TBR-sorted long-short portfolio's return is an asset pricing factor. Second, we find that the firms with higher TBRs are associated with higher talent turnover rates. This pattern is robust for both executives and innovators. Moreover, we show that the positive relation between TBR and talent turnovers is more pronounced in the periods of heightened financial constraints risk and in the states with lower enforceability of non-competition agreements.

Several additional empirical tests also support the mechanism of our model. First, we show that the firms with lower TBRs have more stable sales growth and less volatile cash flows. Their growth is also less negatively affected by peer firms' competition through innovative activities. At the same time, low TBR firms tend to be mature value firms.

Therefore, we refer to low TBR firms, whose customer capital is more dependent on pure brand recognition, as *robust value firms*. Second, we find that high TBR 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 fewer payouts. Third, we provide evidence for non-pecuniary private benefits by showing that key talents receive lower compensation in the firms with greater brand stature. Finally, we show that the duration of executive compensation is longer in high TBR firms. However, the change in duration is economically small, suggesting that high TBR firms are unlikely to fully alleviate the financial constraints by actively managing pay duration.

Related Literature. 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; Ai and Kiku, 2013; Ai, Croce and Li, 2013; Belo, Lin and Bazdresch, 2014; Kogan and Papanikolaou, 2014; Belo et al., 2017; Hirshleifer, Hsu and Li, 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. Whited and Wu, 2006; Campbell, Hilscher and Szilagyi, 2008; Garlappi, Shu and Yan, 2008; Gomes and Schmid, 2010; Garlappi and Yan, 2011; Li, 2011; Ai et al., 2017). A comprehensive survey is provided by Nagel (2013). We contribute to existing work by shedding light on firms' heterogeneous exposure to financial-constraints-risk shocks through their heterogeneous talent dependence of customer capital as firm characteristics; moreover, our model produces asset pricing implications of financial-constraints-risk shocks jointly in two different cross sections.

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 into and empirical evidence on the interaction between firms' financial and product market characteristics. In this literature, a large body of research examines how financial characteristics influence firms' performance and decisions in the product market (see, e.g. Chevalier and Scharfstein, 1996; Fresard, 2010; Phillips and Sertsios, 2013; Gilchrist et al., 2017; D'Acunto et al., 2018), whereas only a few papers focus on the implication of product market characteristics on various corporate policies (see Dumas, 1989; Banerjee, Dasgupta and Kim, 2008; Larkin, 2013; Belo, Lin and Vitorino, 2014;

Gourio and Rudanko, 2014; Dou and Ji, 2017). We depart from the existing literature by investigating the financial implications of the dependence of customer capital on talents.

Our paper is also related to the literature on inalienable human capital dating back to Hart and Moore (1994). Human capital is embodied in a firm's key talents, and these individuals have the option to walk away. Thus, shareholders are exposed to the risk inherent in the limited commitment of key talents. The talent-based customer capital we investigate provides one of the most concrete and convincing examples of 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 entrenched workers are overpaid and only leave when firms go bankrupt. Instead, our model focuses on a different angle, emphasizing that key talents may leave due to corporate financial constraints risk, thereby hurting the firm through a decrease in customer capital. Our theory is related to the work of Bolton, Wang and Yang (2018), who analyze the implications of inalienable human capital on corporate liquidity and risk management, in a standard optimal contracting framework. Unlike their paper, our paper focuses on asset pricing implications.[4]

Finally, our paper is related to the growing literature on the intersection of marketing and finance. The BAV survey database is the standard data source for measuring brand value (see, e.g. Gerzema and Lebar, 2008; Keller, 2008; Mizik and Jacobson, 2008; Aaker, 2012; Lovett, Peres and Shachar, 2014; Tavassoli, Sorescu and Chandy, 2014). Our study adds to this strand of literature by dissecting the channels of maintaining customer capital and providing new implications of customer capital on asset prices and talent turnovers.

The rest of the paper is organized as the follows. Section 2 develops a dynamic asset pricing model. Section 3 describes the data sources and explains the methodology to

[4] Eisfeldt and Rampini (2008) also propose a model of talent turnovers. Their model is different for two reasons. First, managers are compensated due to a moral hazard problem. Second, they focus on the aggregate turnover patterns over the business cycle, instead of the cross-sectional turnover patterns. Extending our model into a general equilibrium framework to analyze aggregate turnovers is an interesting direction for future research.

construct and validate the TBR measure. Section 4 presents the quantitative results on stock returns and talent turnovers in the model and data. Section 5 provides additional empirical support for the theoretical mechanism. Section 6 concludes.

2 Model

We develop an asset pricing model of heterogeneous firms to explain the interaction between customer capital and financial constraints, as well as its role in determining the joint patterns of asset pricing and talent turnovers. Importantly, we show that the asset pricing factor that explains the return spread sorted on talent dependence of customer capital essentially captures financial constraints risk in the economy and can explain stock return patterns in two different cross sections.

2.1 Basic Environment

Firms and Agents. The economy contains a continuum of atomic firms and agents. Agents fund firms by holding equity as shareholders and purchase the firms' goods as consumers. Some agents act as talents who manage firms. We assume that agents can trade a complete set of contingent claims on consumption. There exists a representative agent who owns the equity and consumes the goods of all firms. The representative agent is only exposed to aggregate shocks. The firm subscript is omitted for simplicity.

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 $Y_t = e^{a_t} K_t$ over $[t, t + \mathrm{d}t]$.

The firm's output is affected by an aggregate productivity shock a_t evolving as:

$$\mathrm{d}a_t = -\mu_a(a_t - \overline{a})\mathrm{d}t + \sigma_a \sqrt{a_t}\mathrm{d}Z_t^a, \tag{2.2}$$

where Z_t^a is a standard Brownian motion. We assume that $2\mu_a\overline{a} > \sigma_a^2$ to guarantee $a_t > 0$.

Instantaneous demand orders $B_t\mathrm{d}t$ 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 $[t, t+\mathrm{d}t]$. The amount of goods sold by the firm is $S_t\mathrm{d}t$ over $[t, t+\mathrm{d}t]$ with

$$S_t = \min\left(Y_t, B_t\right), \tag{2.3}$$

capturing the fact that total sales cannot exceed production output or the size of customer base. In a frictional product market where B_t can only be slowly and costly built, 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 Growth. The firm hires sales representatives s_t to build new customer capital at convex costs $\phi(s_t)B_t\mathrm{d}t$ 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

$$\mathrm{d}B_t = [\mu(s_t) - \delta_B]B_t\mathrm{d}t, \tag{2.4}$$

where the Poisson rate δ_B reflects customer capital's depreciation. We assume that[5]

$$\mu(s_t) = \psi s_t, \tag{2.5}$$

implying that the firm can grow customer capital faster by hiring more sales representatives. ψ captures the effective search-matching efficiency in the product market.

External Financial Constraints. The firm faces firm-level idiosyncratic operating cash flow shocks, modeled as $\mathrm{d}C_t = \sigma_c B_t \mathrm{d}Z_t^c - \varsigma B_t \mathrm{d}M_t$ during the next instant $\mathrm{d}t$. Examples of the lumpy idiosyncratic cash flow shocks include the unexpected settlement fee paid by United Airlines for its passenger-dragging incidence. Here, Z_t^c is a standard Brownian motion independent of Z_t^a, capturing small idiosyncratic cash flow shocks. M_t is a firm-specific Poisson process with time-varying intensity ξ_t, capturing the firm's exposure to

[5]In Online Appendix A, we derive (2.5) as the equilibrium representation in a search-matching model.

idiosyncratic negative jump shocks with proportional jump size ς.[6]

We assume that the firm has access to the equity market but not the corporate debt market.[7] The firm has the option to pay out dividend $\mathrm{d}D_t$ or issue equity $\mathrm{d}H_t$ to finance expenses over the next instant $\mathrm{d}t$. The financing cost includes a fixed cost γ proportional to the firm size and a variable cost φ proportional to the amount of issued equity. The modelling of fixed and variable equity financing costs follows the literature (see, e.g. Gomes, 2001; Riddick and Whited, 2009; Gomes and Schmid, 2010; Bolton, Chen and Wang, 2011; Eisfeldt and Muir, 2016). The key idea is simple: external funds are not perfect substitutes for internal funds.

The financial constraints risk motivates the firm to hoard cash W_t on its balance sheet. Holding cash is costly due to the agency costs associated with free cash in the firm or tax distortions.[8] We assume that the return from cash 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. In our model, *cash holdings* capture all internal liquid funds held by the firm.

Financial Constraints Risk ξ_t. All firms' financial conditions, or the marginal value of cash, can be simultaneously affected by economy-wide shocks. Such aggregate shocks are generically referred to as *financial-constraints-risk shocks*, which could be driven by different fundamental forces. The heightened financial constraints risk can be the result of tightened supply of funding liquidity due to financial sector dysfunction (see, e.g. Gilchrist and Zakrajšek, 2012; Jermann and Quadrini, 2012; Bolton, Chen and Wang, 2013; Iyer et al., 2014). For example, Schularick and Taylor (2012) and Baron and Xiong (2017) provide evidence showing that credit expansions can predict subsequent banking crisis/equity value crash and financial system dysfunction; that is, the credit expansion can predict heightened financial constraints risk ξ_t. It could also be the result of excessive demand for funding liquidity, when the firms with great investment opportunities are

[6]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 essentially shocks to the marginal value of cash.

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

[8]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 (Graham, 2000; Faulkender and Wang, 2006; Riddick and Whited, 2009).

eager to invest aggressively (see, e.g. Gomes, Yaron and Zhang, 2006; Riddick and Whited, 2009). The incentive for making such investments is especially large 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, we assume that the intensity ξ_t of Poisson shock M_t follows a two-state Markov process. 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 ξ_t increases the firm's marginal value of cash due to heightened risk of idiosyncratic negative jumps. Therefore, the aggregate shocks driving ξ_t are financial-constraints-risk shocks.[9]

Pricing Kernel. The representative agent's state-price density Λ_t evolves as:

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t - \kappa_a \mathrm{d}Z_t^a + \sum_{\xi' \neq \xi_t} \left[e^{-\kappa^{(\xi_t,\xi')}} - 1 \right] (\mathrm{d}N_t^{(\xi_t,\xi')} - q^{(\xi_t,\xi')}\mathrm{d}t). \tag{2.6}$$

The market prices of risk 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 Unique Features of Customer Capital

We now introduce the two unique features of customer capital – inalienable human capital and non-pecuniary private benefits.

Inalienable Human Capital. Shareholders have the option to fire key talents, and key talents have the option to leave the firm and start a new business.[10] We assume that a fraction τ_t of the firm's customer capital B_t can be affected by talents' turnovers, and thus we refer to $\tau_t B_t$ as talent-based customer capital. When key talents leave, they take

[9] The aggregate shocks driving the variation in risks have been shown important in macroeconomics and asset pricing (Gourio, 2012; Gourio, Siemer and Verdelhan, 2013; Christiano, Motto and Rostagno, 2014).

[10] The limited commitment on both sides is also discussed in DeMarzo and Sannikov (2006) as an extension of their baseline framework. Our contracting framework does not incorporate moral hazard (see, e.g. Holmstrom, 1979; Holmstrom and Milgrom, 1987) or managerial short-termism (see, e.g. Stein, 1988, 1989; Shleifer and Vishny, 1990; Bolton, Scheinkman and Xiong, 2006) for simplicity. Evaluating the asset pricing implications of their interactions with customer capital is an interesting topic for future research.

away each unit of $\tau_t B_t$ with intensity m. Thus, τ_t captures the degree to which customer capital depends on key talents, while the coefficient m captures the average fragility of talent-based customer capital to talents' turnovers. This assumption follows the spirit of *inalienable human capital* coined by Hart and Moore (1994). By definition, τ_t is the firm's TBR at time t. We model $\tau_t \in (0, 1)$ as

$$\tau_t = e^{-\omega_t}. \tag{2.7}$$

If turnovers do not occur in the next instant $\mathrm{d}t$, ω_t evolves according to

$$\mathrm{d}\omega_t = -\mu_\omega(\omega_t - \overline{\omega})\mathrm{d}t + \sigma_\omega\sqrt{\omega_t}\mathrm{d}Z_t^\omega, \tag{2.8}$$

where Z_t^ω is an idiosyncratic standard Brownian motion independent of Z_t^a and Z_t^c.

Upon the occurrence of turnovers over $[t, t + \mathrm{d}t]$, the remaining customer capital is $(1 - m\tau_t)B_t$, among which $(1 - m)\tau_t B_t$ is maintained by key talents. Thus, ω_t jumps over $[t, t + \mathrm{d}t]$:

$$\mathrm{d}\omega_t = \underbrace{-\mu_\omega(\omega_t - \overline{\omega})\mathrm{d}t + \sigma_\omega\sqrt{\omega_t}\mathrm{d}Z_t^\omega}_{\text{exogenous smooth fluctuation}} + \underbrace{\ln\left(1 - me^{-\omega_t}\right) - \ln\left(1 - m\right)}_{\text{endogenous jump}}. \tag{2.9}$$

We assume that $2\mu_\omega\overline{\omega} > \sigma_\omega^2$. Because the endogenous jump is always positive, ω_t is always positive, and thus $\tau_t \in (0, 1)$.

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 value. This is because the firms with stronger brands offer key talents more opportunities for self-enhancement, higher visibility among their peers, and a greater likelihood of being perceived as being successful (see Tavassoli, Sorescu and Chandy, 2014). 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 (see, e.g. Eisfeldt and Rampini, 2008). Notice that the existence of non-pecuniary private benefits is not essential 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 Section 4.2.5).

2.3 Liquidity-Driven Turnovers

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 $(m+\ell)\tau_t B_t$, where $m\tau_t B_t$ is the customer capital taken away from the firm and $\ell\tau_t B_t$ is the new customer capital created by key talents' business idea. The new firm is sold to the representative agent (i.e. the representative shareholder). At the inception, the representative agent builds up cash by issuing equity.

Let $V(W_t, B_t, \tau_t, a_t, \xi_t)$ denote the firm's value. The new firm's value after equity issuance is $V(W_0, (m+\ell)\tau_t B_t, \tilde{\tau}, a_t, \xi_t)$, given the initial cash (new equity) W_0. The representative agent chooses the optimal amount of equity financing W_0^* to maximize the new firm's value before equity issuance:

$$V^{\text{new}}(B_t, \tau_t, a_t, \xi_t) = \max_{W_0} -\gamma(m+\ell)\tau_t B_t - \varphi W_0 + \mathbb{E}_t^{\tilde{\tau}}\left[V(W_0, (m+\ell)\tau_t B_t, \tilde{\tau}, a_t, \xi_t) - W_0\right],$$

where the expectation $\mathbb{E}^{\tilde{\tau}}$ is taken over $\tilde{\tau}$ based on the steady-state distribution of τ_t. Because key talents do not bear financing costs, the value of key talents' outside option is given by

$$V^o(B_t, \tau_t, a_t, \xi_t) = V^{\text{new}}(B_t, \tau_t, a_t, \xi_t) + \gamma(m+\ell)\tau_t B_t + \varphi W_0^*. \tag{2.10}$$

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 $\gamma(m+\ell)\tau_t B_t + \varphi W_0^*$ without double counting.

The participation constraint is that the firm promises (with full commitment) to make the compensation flow Γ_t over interval $\mathrm{d}t$, as long as the relationship continues.[11] The

[11] Our formulation rules out the possibility of delaying cash payment Γ_t into future periods through contract renegotiation. This theoretical simplification makes the model more tractable. In reality, financially constrained firms may compensate key talents with restricted stocks and stock options in order to postpone

sum of Γ_t and hB_t is equal to the present value of the change in key talents' outside option $V^o(B_t, \tau_t, a_t, \xi_t)$:

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

where the expectation is taken with respect to $\mathrm{d}\tau_t$, $\mathrm{d}a_t$, and $\mathrm{d}\xi_t$ conditioning on the information up to t. The cash compensation Γ_t imposes operating leverage on the firm. Holding B_t constant, Γ_t increases with τ_t, implying that the firm with more customer capital maintained by key talents has higher operating leverage. In addition, holding τ_t constant, Γ_t decreases with B_t, suggesting that the firm with a weaker brand (smaller B_t) needs to offer a greater compensating wage differential to keep key talents, due to smaller non-pecuniary private benefits. The literature has documented the link between compensation and brand value.[12] We also provide evidence in Appendix A.

Turnovers and Financial Constraints. Shareholders can successfully fire key talents with intensity ϑ_t in the next instant $\mathrm{d}t$. They 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 intensity crucially depends on the firm's current marginal value of cash. Intuitively, the firm is more likely to replace key talents when it is financially constrained, because the required compensation becomes very expensive when the firm's marginal

cash expenses. Although this arrangement can temporarily alleviate the firm's financial constraints, postponing cash payment does not reduce the firm's operating leverage as long as all the payments are honored in the end. In Appendix B, we provide some evidence showing that high TBR firms tend to use more stocks and options. However, the magnitudes of the change in pay duration seem too small to fully alleviate the financial constraints.

[12] This idea is related to the concept of compensating differentials initially introduced by Adam Smith. 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). 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 firms with stronger brand value.

value of cash is high. The mechanism has been documented and tested extensively in the literature (see, e.g. Brown and Matsa, 2016; Babina, 2017; Baghai et al., 2017).

Key talents can extract additional rents when firms are financially distressed and external financing/restructuring is needed. This phenomenon 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 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, we assume that key talents extract $\varpi V^o(B_t, \tau_t, a_t, \xi_t)$ from shareholders when the firm runs out of cash (i.e. $W_t = 0$).

2.4 Firm Optimality

To make the model tractable, we assume the absence of physical capital adjustment costs, which means that the amount of sales $S_t\mathrm{d}t$ given by equation (2.3) is optimally determined by the locally predetermined demand orders $B_t\mathrm{d}t$ from the firm's customer capital. Under our benchmark calibration, it is optimal for the firm to produce and match 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:

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

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

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

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

The firm's cash holdings evolve as follows:

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

where $(r-\rho)W_t\mathrm{d}t$ is the interest income (net of cash carrying cost ρ), H_t and D_t are cumulative issuance and cumulative payout up to t.

The firm chooses its physical investment $\mathrm{d}I_t$, 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:

$$V(W_t, B_t, \tau_t, a_t, \xi_t) = \max_{s_{t'}, \vartheta_{t'}, \mathrm{d}I_{t'}, \mathrm{d}D_{t'}, \mathrm{d}H_{t'}} \mathbb{E}\left[\int_t^\infty \frac{\Lambda_{t'}}{\Lambda_t}(\mathrm{d}D_{t'} - \mathrm{d}H_{t'} - \mathrm{d}X_{t'})\right], \tag{2.15}$$

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

2.5 Model Solution

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

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

The normalized value function $v(w, \tau, a, \xi)$ can be solved based on a group of coupled partial differential equations with free boundaries. The firm simultaneously makes four sets of decisions: physical investment, sales hiring, talent turnovers, and financial decisions. Talent turnovers and financial decisions can be sufficiently characterized by *decision boundaries*. Figure 3 elaborates on this idea. The free boundaries include the optimal external equity issuance boundary denoted by $\underline{w}(\tau, a, \xi)$, the optimal payout boundary denoted by $\overline{w}(\tau, a, \xi)$, and the optimal turnover boundary denoted by $\widehat{w}(\tau, a, \xi)$.

The firm's financial decisions are characterized by three regions: (1) an external financing region ($w < \underline{w}(\tau, a, \xi)$), within which the firm pursues external financing ($\mathrm{d}H > 0$); (2) an internal liquidity-hoarding region ($\underline{w}(\tau, a, \xi) \le w \le \overline{w}(\tau, a, \xi)$), within which the firm keeps net profits as cash holdings ($\mathrm{d}H = \mathrm{d}D = 0$); and (3) a payout region ($w > \overline{w}(\tau, a, \xi)$), 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 ($\underline{w}(\tau, a, \xi) < w < \underline{w}'(\tau, a, \xi)$), 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 $\widehat{w}(\tau, a, \xi)$. When the firm's cash ratio is below $\widehat{w}(\tau, a, \xi)$, 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

$\underline{w}(\tau, a, \xi) \leq \widehat{w}(\tau, a, \xi) \leq \overline{w}(\tau, a, \xi)$.

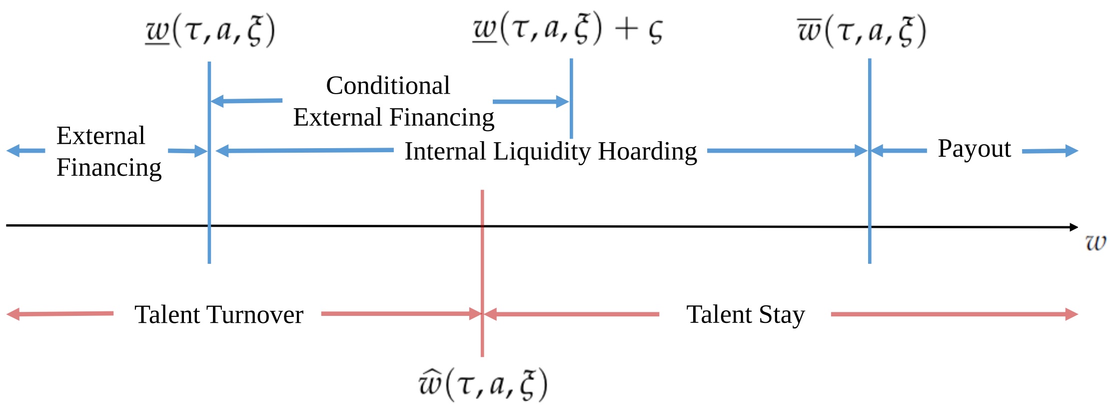


Figure 3: An illustrative graph for the decision boundaries and regions.

Intuitively, when exogenous cash flow shocks drive the cash ratio w gradually to some low level $\underline{w}(\tau, a, \xi)$ such that the current financing costs and the discounted future financing costs are equal, the firm would issue equity. Because holding cash is costly, the firm chooses to pay out cash when exogenous positive cash flow shocks drive the cash ratio w beyond some high level $\overline{w}(\tau, a, \xi)$. The talent turnover decision depends on the tradeoff between customer capital maintenance and short-run cash flows. When the cash ratio w is lower than $\widehat{w}(\tau, a, \xi)$, the marginal value of cash is large enough such 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 through turnovers, resulting in a loss of customer capital.

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 $\underline{w}(\tau, a, \xi) \equiv 0$.[13] The conditional external financing boundary is determined by $\underline{w}'(\tau, a, \xi) = \underline{w}(\tau, a, \xi) + \varsigma = \varsigma$. This is because if and only if $w < \underline{w}'(\tau, a, \xi)$, lumpy cash flow shocks ς drive the firm's cash holdings below the external financing boundary $\underline{w}(\tau, a, \xi)$ and immediately trigger equity issuance.

[13]Financing costs always have smaller present values for three reasons 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 are continuous. Third, the risk-free rate is a positive constant.

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

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

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

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

Intuitively, equation (2.16) says that the marginal value of the last dollar raised by the firm must equal 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: talent turnover region and talent stay region. The two sub-regions are partitioned by the turnover boundary $\widehat{w}(\tau, a, \xi)$, characterized by the firm's indifference condition about turnovers:

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

The LHS of (2.17) is the firm's value of not replacing key talents at the threshold $\widehat{w}(\tau, a, \xi)$, whereas the RHS is the firm's value of replacing key talents at the threshold $\widehat{w}(\tau, a, \xi)$.[14]

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

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

for all $(w_t, \tau_t, a_t) \in \mathcal{K}_H \equiv \{(w, \tau, a) \; : \; 0 \leq w \leq \widehat{w}(\tau, a, \xi), 0 < \tau < 1, a \in \mathbb{R}^+\}$. By using the Ito's lemma and the optimal conditions for s_t, we can derive two coupled partial

[14]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 $\widehat{w}(\tau, a, \xi)$.

differential equations (PDE) for $\mathcal{K}_H \times \{\xi_L, \xi_H\}$ from the HJB equation (2.18).

Similarly, the firm value dynamics within the sub-region of keeping key talents are:

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

for all $(w_t, \tau_t, a_t) \in \mathcal{K}_L \equiv \{(w, \tau, a) \; : \; \widehat{w}(\tau, a, \xi) \leq w \leq \overline{w}(\tau, a, \xi), 0 < \tau < 1, a \in \mathbb{R}^+\}$.

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:

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

The payout region is characterized by $w \geq \overline{w}(\tau, a, \xi)$ for each combination of $(\tau, a, \xi) \in (0, 1) \times \mathbb{R}^+ \times \{\xi_L, \xi_H\}$. Whenever the cash ratio is beyond the boundary, paying out the extra cash $w - \overline{w}(\tau, a, \xi)$ in a lump-sum manner and reducing its cash ratio back to $\overline{w}(\tau, a, \xi)$ is optimal. Thus, the firm's value in the payout region has the following form:

$$v(w, \tau, a, \xi) = v(\overline{w}(\tau, a, \xi), \tau, a, \xi) + w - \overline{w}(\tau, a, \xi), \;\; \text{for} \;\; w \geq \overline{w}(\tau, a, \xi). \tag{2.21}$$

Lump-sum payouts can occur mainly because payout boundaries are different for different financial-constraints-risk shocks. It is intuitive that $\overline{w}(\tau, a, \xi_H) > \overline{w}(\tau, a, \xi_L)$. 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:

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

2.6 Illustration of The Basic Mechanism

To highlight the importance of financial constraints risk, we compare the numerical solutions from the full model with those from a model without financial frictions. In the frictionless benchmark, the firm does not face financial constraints risk or hold cash, because equity financing costs are zero (i.e. $\gamma = \varphi = 0$).

Panel A of Figure 4 plots the firm's normalized enterprise value (i.e. $v(w, \tau, \overline{a}, \xi_L) - w$, the value of the firm's marketable claims minus the cash ratio) as a function of the cash

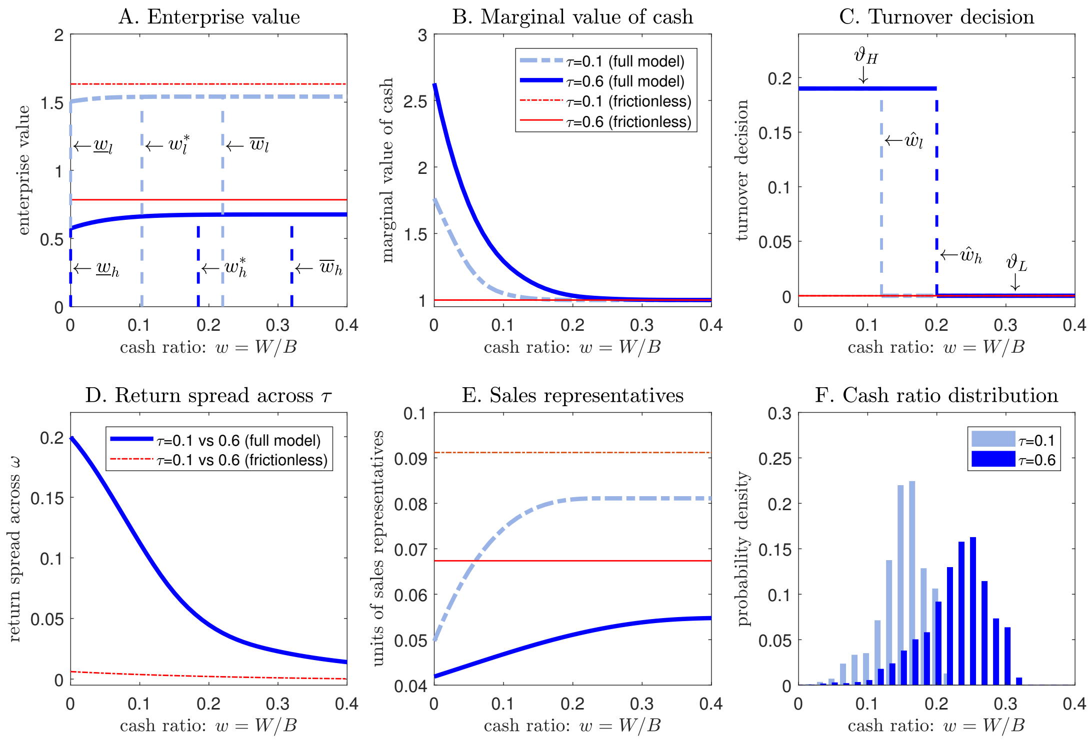


Figure 4: An illustration of the model's basic mechanism.

ratio in the normal regime (i.e. $\xi = \xi_L$). It shows that the low TBR firm ($\tau = 0.1$) has a significantly higher enterprise value relative to the high TBR firm ($\tau = 0.6$) primarily because it is more costly to maintain talent-based customer capital. The firm's enterprise value increases with the cash ratio, as the 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 firms are higher and flat.

In principle, firms could hold a sufficient amount of cash to circumvent financial constraints risk. However, this option is not utility maximizing, because hoarding cash is costly in our model. Thus, the firm pays out dividends when cash ratios are high. In the cross section, our model predicts that the low TBR firm tends to issue less equity (i.e. optimal financing amount $w_l^* < w_h^*$) and pay out more dividends (i.e. dividend payout boundary $\overline{w}_l < \overline{w}_h$). As a result, the low TBR firm's endogenous steady-state distribution of cash ratios is concentrated at lower levels (see Panel F). We provide empirical evidence for these predictions in Section 5.2.

The difference in financial policies can be explained by the difference in the marginal value of cash. As shown in Panel B, the low TBR firm has a lower marginal value of cash relative to the high TBR firm, because the high TBR firm is more exposed to financial constraints risk due to greater operating leverage. When the firm's cash ratios are high, the operating leverage does not increase financial constraints risk much, because internal cash provides cushions against cash flow shocks. As a result, the marginal value of cash for both firms is equal to one when $w > 0.3$. However, when cash ratios are low, the compensation required to retain key talents significantly increases the financial constraints risk the high TBR firm faces. In the frictionless benchmark, the marginal value of cash for both 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, no turnovers occur in the frictionless benchmark. In our model, the high TBR firm is more financially constrained, and thus its turnover boundary is to the right of the low TBR firm (i.e. $\hat{w}_h > \hat{w}_l$). The turnover decisions are crucially related to firms' stock returns, because the firm with a higher turnover rate is riskier due to the loss of customer capital upon turnovers. In Panel D, we show that the return spread is about 20 percentage points when the cash ratio is zero, and the spread decreases with cash ratios. By contrast, in the frictionless benchmark, the return spread between the two firms is almost zero.

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 low TBR firm tends to hire more sales representatives. This finding suggests that the existence of financial constraints risk also distorts the firm's decisions in the product market. When the financial market has frictions, the firm cuts its customer-base investment to gain short-term liquidity. In the frictionless benchmark, the first-best hiring units are higher for both firms.

3 Measuring Customer Capital's Talent Dependence

Our model's key variable τ_t captures the firm's TBR, reflecting the degree to which a firm's customer capital depends on talents. In this section, we use consumer survey data to construct a measure of TBR. We also perform external validation tests of our TBR measure by relating it to the financial variables constructed from Compustat/CRSP.

3.1 Data

Our brand metrics data are from the BAV Group. This database 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 870,000 respondents in total, and it is constructed to represent the U.S. population according to gender, ethnicity, age, income group, and geographic location. The details of the survey have been described by finance and marketing academic papers (see, e.g. Larkin, 2013; Tavassoli, Sorescu and Chandy, 2014). Survey respondents are asked to complete a 45-minute survey that yields measures of brand value. The first survey was conducted in 1993, and since 2001, the surveys have been conducted quarterly. The surveys cover more than 3,000 brands in the cross section and are 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 fewer than 120 brands that are randomly selected from the list of brands.

The BAV surveys are conducted at the brand level. We identify the firms that own the brands over time, and link the BAV survey data with Compustat and CRSP. We pay particular attention to the brands involved in M&As and ensure 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.[15] Our merged BAV-Compustat-CRSP 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. We have 1,004 unique firms in total, and on average, about 400 firms in the yearly cross section. The firms in the merged sample collectively own 4,745 unique brands covered by the BAV surveys. The entry and exit rates of the firms in the merged sample are around 7%, which are comparable to those in the Compustat data. Firms in the merged sample and in the Compustat/CRSP sample have comparable book-to-market ratios and debt-to-asset ratios. The merged sample is biased towards large firms.[16] Since the merged

[15]In our sample, 58% percent of firm-year observations have only one brand. For the firms that own more than one brand, we use several alternative methods to compute the firm-level brand metrics from the brand-level data. We provide details on these methods in Online Appendix D. Our results are robust to the choice of these methods.

[16]In the merged sample, the median book-to-market ratio, debt-to-asset ratio, market capitalization, and

sample is not a random sample of U.S. public firms, in Section 4.2.2, we replicate our asset pricing tests in an extended sample that covers the cross-section of all U.S. public firms. We further link the merged BAV-Compustat-CRSP data with Execucomp, BoardEx, and the Harvard Business School patent and innovator database (see Li et al., 2014). Table OA.4 in Online Appendix E presents the summary statistics for the main variables.

3.2 TBR Measure

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 widely adopted by marketing researchers and practitioners and have been incorporated into major marketing textbooks (see, e.g. Keller, 2008; Aaker, 2012).

Brand Stature. The BAV Group constructs brand stature measure to capture the brand loyalty of existing customers (see Gerzema and Lebar, 2008). Brand stature is the product between *Esteem* and *Knowledge*, reflecting the value of a brand. Esteem is a measure of respect and admiration for a brand. The components of Esteem are (1) the brand score on *Regard* ("How highly do you think of this brand?" on a seven-point scale) and (2) the fraction of respondents who consider the brand to be of "high quality," "reliable," and a "leader." 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 ("How familiar are you with this brand?" on a seven-point scale). BAV finds that the past and current users of a brand rate themselves as being significantly more knowledgeable. Thus, Knowledge serves as an adjustment factor in quantifying consumers' respect and admiration for a brand, because existing customers carry greater weights in determining brand stature.

Brand Strength. The BAV Group constructs brand strength to measure to what extent a brand is perceived to be innovative, distinctive, and managed by a dynamic team. Brand strength is the product between *Energized Differentiation* and *Relevance*. Energized Differentiation is the average fraction of respondents who consider a brand to be "innovative," "dynamic," "distinctive," "unique," and "different." "Distinctive," "unique," and

sales are 0.37, 0.55, \$4,915 million, and \$5,115 million, whereas they are 0.49, 0.44, \$420 million, and \$424 million in the Compustat/CRSP sample. We provide more details on the merged sample, including its distribution across industries, in Online Appendix E.

“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. Relevance captures the degree of personal appropriateness (“How relevant do you feel the brand is for you?” on a seven-point scale). 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.

TBR Measure. We measure TBR at the firm level as follows:

$$\text{The measure of TBR}_{i,t} \equiv \frac{\text{brand strength}_{i,t}}{\text{brand stature}_{i,t}}, \quad \text{for firm } i \text{ in year } t. \tag{3.1}$$

Since the creation of innovative products and distinctive brands requires significant contributions from key talents, brand strength reflects more about talents’ contributions than brand stature. Thus our measure defined in (3.1) captures the firm’s TBR, or the degree to which customer capital depends on talents. Because the distribution of our TBR measure is skewed, we use the log transformation of TBR measure (denoted as lnTBR). Online Appendix E shows that lnTBR exhibits a good amount of variation, with an approximately normal distribution. Moreover, brand stature and brand strength have a similar range and standard deviation; thus, the variation in lnTBR does not predominantly come from either brand stature or brand strength. In our empirical analyses, we standardize lnTBR to ease the interpretation of regression coefficients. Compared to other brand metrics derived from firms’ financial and accounting variables, the advantage of our survey-based TBR measure is that it is unlikely to be mechanically linked to the outcome financial variables we study. We sort the firms in our sample into five quintiles based on the TBR measure. The summary statistics are shown in Table 1.

Let us provide a few concrete examples from the 2010s based on our TBR measure. In the automobile industry, Toyota is a typical low TBR firm, which enjoys strong brand recognition all over the world. Tesla is a typical high TBR 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 low TBR firm, whose customers’ loyalty relies less on its current executives or innovators, and mainly depends on customers’ habits and tastes. By contrast, Teavana, an innovative tea company that sources and shares high-quality teas and “imaginative flavors from around the world”, is a typical high TBR firm. In IT and apparel industries, we have Microsoft and Gap as low TBR firms and

Facebook and Ralph Lauren as high TBR firms.

Table 1: Firm characteristics and TBR.

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

Note: This table shows the characteristics of the five portfolios sorted on TBR. We report the mean and median firm characteristics for each portfolio. Our sample includes the firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms. The sample period spans 1993 to 2016. Operating profitability is revenues net of COGS, SG&A, and interest expense, divided by book equity. ΔAsset/lagged asset is asset growth rate. We explain the definition of the other variables in Table OA.4 in Online Appendix E.

3.3 External Validation of The TBR Measure

If our TBR measure is valid to capture TBR, we expect to see that the firms whose talents play relative more important roles are associated with higher values of the TBR measure. Therefore, we examine the relation between our TBR measure and average key-talent compensation over last three years as a proxy for key talents' relative importance. We use three different compensation measures. The first measure is administrative expenses, estimated by SG&A net of advertisement costs, R&D expenses, commissions, and foreign currency adjustments. The second measure is R&D expenses. 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 executive compensation, measured by the total compensation for the top five executives of a firm in the Execucomp data. Using panel regressions, we find that the firms that pay more compensation to key talents are indeed associated with higher values of the TBR measure (see Table 2).

Relation to Organization Capital. Following Eisfeldt and Papanikolaou (2013), we construct organization capital (OC), from SG&A expenditures using the perpetual inventory method with missing values being replaced by zero. Column (5) of Table 2 shows that the relation between our TBR measure and organization capital is weak, probably because SG&A contains both advertisement expenditure and administrative expenses. Advertisement expenditure boosts brand loyalty and is negatively related to our TBR measure (see column 4 of Table 2), whereas administrative expenses mainly reflect key talents' compensation and are positively related to our TBR measure (see column 1 of Table 2). The weak correlation between our TBR measure and 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 our TBR measure and the outcome variables in our empirical analyses.

4 Main Predictions and Empirical Tests

In this section, we calibrate the model's parameters and explore its predictions in the data. We examine whether our model can replicate the main asset pricing findings from the data, and shed light on the quantitative importance of different channels. Importantly, we find an asset pricing factor capturing financial constraints risk in the economy, which can simultaneously explain the stock return patterns in two cross sections: TBR and the degree to which firms are financially constrained.

4.1 Calibration

We discipline the parameters based on both existing estimates and micro data (see Table 3) without referring to asset pricing information, and we examine whether the calibrated model can quantitatively explain the observed asset pricing patterns. Some parameters

Table 2: The TBR measure, key-talent compensation, and organization capital.

	(1)	(2)	(3)	(4)	(5)
			$\ln\text{TBR}_t$		
$\ln(\text{administrative expenses/sales})_{t-3:t-1}$	0.133***				
	[2.970]				
$\ln(\text{R\&D/sales})_{t-3:t-1}$		0.256***			
		[5.755]			
$\ln(\text{executive compensation/sales})_{t-3:t-1}$			0.252***		
			[6.469]		
$\ln(\text{advertisement expenditure/asset})_{t-3:t-1}$				−0.088**	
				[−2.478]	
$\ln(\text{OC/asset})_{t-3:t-1}$					−0.039
					[−1.307]
Firm controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5300	2695	5086	4329	5594
R-squared	0.386	0.468	0.411	0.413	0.382

Note: This table shows the relation between the TBR measure, key-talent compensation, and organization capital. The dependent variable lnTBR is the natural log of the ratio between brand strength and brand stature. 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 of the organization-capital-to-asset ratio, computed using the average values from the previous three years. Our results are robust if we use the average values in other time periods (one year to six years). In column (2), we exclude firms with missing R&D, because these firms do not necessarily lack innovation activities (see, e.g. Koh and Reeb, 2015), different from zero R&D firms. In column (4), we exclude firms with missing advertisement expenditure following Grullon, Kanatas and Weston (2004) and Belo, Lin and Vitorino (2014). Our results remain robust if we replace missing values in the R&D and advertisement expenditure by zero. Firm controls include the natural log of firm market capitalization (lnsize_{t-1}) and the natural log of the book-to-market ratio (lnBEME_{t-1}). We control for the SIC-2 industry fixed effects and year fixed effects. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

are determined using external information. The remaining parameters are calibrated internally from moment matching.

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 $\varphi = 6\%$ based on the estimates reported by Altinkilic and Hansen (2000). Following Bolton, Chen and Wang (2011, 2013), we set the fixed financing cost $\gamma = 1\%$ of the firm size and the cash-carrying cost $\rho = 1.5\%$. We set the effective matching efficiency $\psi = 0.75$.[17] We consider a quadratic specification for the hiring function of sales

[17] In Online Appendix A, we show that $\psi = \overline{\psi}\overline{f}^{\chi-1}$ 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 disutility of search to be 1. We set $\chi = 1.12$, which implies that the elasticity parameter in the Cobb-Douglas matching function is $\frac{\chi-1}{\chi} = 0.11$, consistent with Gourio

Table 3: Calibration.

Parameters	Symbol	Value	Parameters	Symbol	Value
Risk-free rate	r	5%	Fraction of customer loss	m	0.1
Fixed financing costs	γ	0.01	New customer capital created by a new firm	ℓ	0.45
Variable financing costs	φ	0.06	Private benefits	h	0.011
Long-run average aggregate productivity	$\overline{a}$	1	Long-run fraction of talent-related customer capital	$\overline{\varpi}$	0.9
Mean-reversion of aggregate productivity	μ_a	0.275	Mean-reversion of talent-related customer capital	μ_ω	0.038
Volatility of aggregate productivity	σ_a	0.07	Volatility of talent-related customer capital	σ_ω	0.19
Physical capital depreciation rate	δ_K	0.1	Customer capital depreciation rate	δ_B	0.15
Cash-carrying costs	ρ	1.5%	Turnover success rate	ϑ_H	0.19
Price of goods	u	0.34	Idiosyncratic shocks to cash flows	σ_c	0.15
Rent extraction	ϖ	0.06	Lumpy cash flow shock size	ς	0.1
Effective matching efficiency	ψ	0.75	Lumpy cash flow shock frequency	ξ_L, ξ_H	$0, 0.5$
Sales' representative hiring costs (scale)	α	5.0	Price of risk of productivity shocks	κ_a	0.4
Sales' representative hiring costs (convex)	η	2	Price of risk of financial-constraints-risk shocks	$\kappa^{(\xi_L,\xi_H)}$	$-\ln(3)$
Transition intensities	$q^{(\xi_L,\xi_H)}$	0.16		$\kappa^{(\xi_H,\xi_L)}$	$\ln(3)$
	$q^{(\xi_H,\xi_L)}$	0.2			

representatives by setting $\eta = 2$. Survey evidence suggests that the customer turnover rates have significant heterogeneity across different industries. The typical range of the annual customer turnover rate is between 10% and 25% (see Gourio and Rudanko, 2014). We thus set the customer capital depreciation rate to be $\delta_B = 15\%$. We set $m = 0.1$, so that in our model, key talents leave with 10% of talent-based customer capital.[18]

The long-run average level of aggregate productivity $\overline{a}$ is a scaling variable, which is normalized to one. We set the persistence parameter to be $\mu_a = 0.275$, following Gomes, Kogan and Zhang (2003). We estimate the transition intensities between the two regimes, $q^{(\xi_L,\xi_H)} = 0.16$ and $q^{(\xi_H,\xi_L)} = 0.20$, using the regime-switching dynamics of the estimated alphas of the long-short portfolio sorted on TBR. These transition intensities are consistent with the average length of business cycles, which is roughly 10 years. 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 $\kappa^{(\xi_H,\xi_L)} = \ln(3)$, similar to Bolton, Chen and Wang

and Rudanko (2014)'s estimate based on the share of the labor force in sales-related occupations and the amount of time consumers spend on shopping. Finally, we set the maximum discount $\overline{f}$ to be 0.10 to ensure that the firm has positive profits from new customers even if the highest initial discounts are offered.

[18] In the 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% of organization capital is transferred when the manager switches to a new firm. Eisfeldt and Papanikolaou (2013)'s model assumes that key talents can leave with all intangible capital. Bolton, Wang and Yang (2018)'s benchmark calibration assumes that the entrepreneur would be 20% less efficient if she walks away from the current firm.

(2013) and Eisfeldt and Papanikolaou (2013). The risk-neutral transition intensities are $\hat{q}^{(\xi,\xi')} = e^{-\kappa(\xi,\xi')} q^{(\xi,\xi')}$, for $\xi \neq \xi'$.

Internally Calibrated Parameters. The remaining parameters are calibrated by matching relevant moments. We simulate a sample of 1,000 firms 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 in line with their values in data (see Table 4).

The price of goods determines the firm's net cash flows. We set $u = 0.34$ to match the average cash-asset ratio in the data. We set the rent extraction parameter to be $\varpi = 0.06$ so that the retention bonuses are between 30% and 70% of key talents' compensation (see Goyal and Wang, 2017). We calibrate hiring efficiency $\alpha = 5.0$ to target the average advertisement expenditure as a percent of sales. The parameter ℓ reflects the amount of new customer capital 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 executive turnover rate in the Execucomp data.

Since our empirical TBR measure does not have the same units as ω_t in our model, we infer the three parameters governing the stochastic process of τ_t by using the cross-sectional distribution of key-talent compensation. Because key talents mainly include executives and innovators, we approximate key-talent compensation using the sum of 50% of R&D expenses and executive compensation.[19] The asymptotic distribution of ω_t follows Gamma$(2\mu_\omega\overline{\omega}/\sigma_\omega^2, 2\mu_\omega/\sigma_\omega^2)$. Thus, the steady-state distribution of average talent compensation across the five quintiles sorted on TBR is informative about $\overline{\omega}$ and $\mu_\omega/\sigma_\omega^2$. The parameter $\mu_\omega = 0.038$ is identified by matching the autocorrelation in $\ln\text{TBR}_t$. 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 high TBR quintile to the low TBR quintile. 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

[19] 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).

Table 4: Moments in data and model.

Panel A: Aggregate moments

	Data	Model		Data	Model
Mean cash holdings/lagged asset	23.6%	25.8%	Mean retention bonuses	30%-70%	38.9%
Autocorrelation in $\ln \text{TBR}_t$	0.96	0.96	Mean talent compensation/sales	14.9%	15.5%
Volatility of net income/sales	16.8%	16.3%	Mean equity issuance frequency	25.2%	27.4%
Skewness of net income/sales	-0.47	-0.41	Mean key talents' turnover rate	11.8%	12.7%
Mean advertisement expenditure/sales	5.1%	5.7%	Compensation reduction (Q5→Q1)	22.3%	20.1%
Volatility of market returns	0.165	0.152			

Panel B: Average talent compensation across different firm groups

Groups sorted on TBR (τ_t)		1 (Low)	2	3	4	5 (High)
Mean talent compensation/sales (%)	Data	9.6	12.0	10.9	17.2	24.9
	Model	9.3	13.8	16.5	19.6	26.2

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 the 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.

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 with respect to ξ:

$$\beta_\xi(w,\tau,a) = v(w,\tau,a,\xi_H)/v(w,\tau,a,\xi_L) - 1. \tag{4.1}$$

In equilibrium, the expected excess return is

$$\mathbb{E}_t\left[\mathrm{d}R_t|w,\tau,a\right] - r_t\mathrm{d}t = \beta_\xi(w,\tau,a)\left[1 - e^{-\kappa^{(\xi_L,\xi_H)}}\right]q^{(\xi_L,\xi_H)}\mathrm{d}t. \tag{4.2}$$

Panels A and C plot betas and expected excess returns for a low TBR ($\tau = 0.1$) and a high TBR firm ($\tau = 0.6$). Conditioning on TBR, firms' exposure to financial-constraints-risk shocks increases when their cash ratios decreases; as a result, investors require higher expected returns when firms' cash ratios are lower (solid blue and dashed blue lines). Importantly, the difference in betas and expected excess returns between the high TBR and the low TBR firm decreases with cash ratios. Quantitatively, the model suggests that the beta difference is as large as 0.6 when the cash ratio is zero, which translates into a

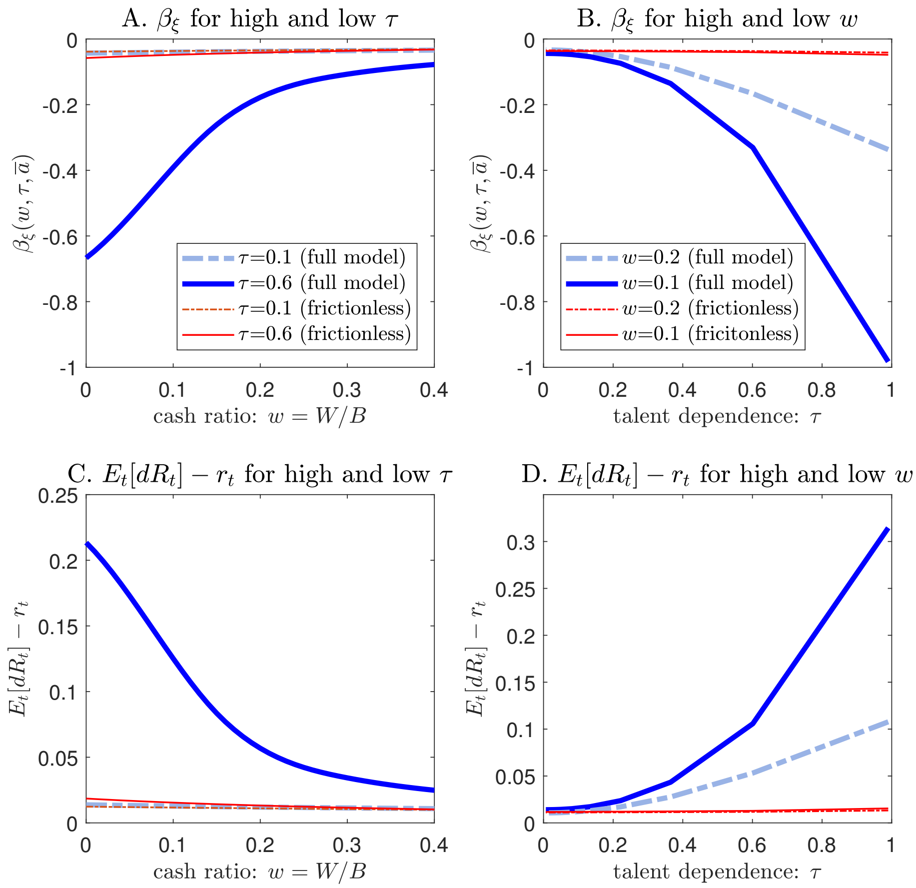


Figure 5: The asset pricing implications of ξ shocks in two cross sections.

20-percentage-point difference in expected stock returns.[20] Conditioning on the mean cash ratio (25.8%) of our simulated firms, we also observe large difference in magnitude. The difference in betas and expected excess returns are about 0.11 and 4 percentage points between the two firms. By contrast, in the frictionless benchmark, betas and expected excess returns are almost zero, regardless the degree to which customer capital depends

[20]The quantitatively differential response to financial-constraints-risk shocks between the low and high TBR firm also incorporates a countervailing force that dampens the relative response of the high TBR firm, because an increase in financial constraints risk reduces key talents' compensation as the outside option of creating a new firm becomes worse. From the 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 high TBR firm, in which more customer capital is maintained by key talents. Our numerical solutions suggest that this countervailing force is dominated by the main force through greater operating leverage and customer capital loss.

on talents (solid red and dashed red lines).

Similar patterns are observed in Panels B and D, in which we compare betas and expected excess returns of a high cash ($w = 0.2$) and a low cash ($w = 0.1$) firm. Conditioning on the financial conditions, firms' exposure to financial-constraints-risk shocks becomes more negative as their customer capital becomes more talent dependent; as a result, investors require higher expected excess returns (solid blue and dashed blue lines). By contrast, in the frictionless benchmark, betas and expected excess returns are almost zero (solid red and dashed red lines). Importantly, the difference in betas and expected excess returns between the high cash and the low cash firm increases with TBR. The difference in betas and expected stock returns between the two firms is almost zero when τ is low. However, when $\tau = 1$, beta is about -1 for the low cash firm, whereas it is -0.35 for the high cash firm. Such a difference results in about a 21-percentage-point difference in expected excess returns. Conditioning on the mean TBR (0.81) of our simulated firms, we also observe large difference in magnitude. The differences in betas and expected excess returns are about 0.33 and 12 percentage points between the two firms.

Overall, the model solutions shown in Figure 5 suggest that the interaction between the firm's customer capital and cash ratios has crucial implications for asset prices. Conditional on TBR, the marginal value of cash is entirely determined by the cash ratio. Thus our model suggests that the firm's heterogeneous exposure to financial-constraints-risk shocks is reflected both in the cross-sectional variation in TBR and the cross-sectional variation in the extent to which firms are financially constrained.

4.2.1 Portfolios Sorted on TBR

We now turn to the data to systematically examine the asset pricing implications of TBR. In June of year t, we sort firms into five quintiles based on their TBRs in year $t - 1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t + 1$. We compute the value-weighted portfolio returns and estimate their alphas and betas using various factor models.[21]

Table 5 presents the cross-sectional asset pricing results of the portfolios sorted on TBR. As shown in Panel A, the low TBR portfolio (Q1) has 10.69% annualized average excess return; by contrast, the high TBR portfolio (Q5) has 16.32% annualized average excess return. The portfolio that longs Q5 and shorts Q1, has a positive and statistically

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

Table 5: The excess returns and alphas of portfolios sorted on TBR.

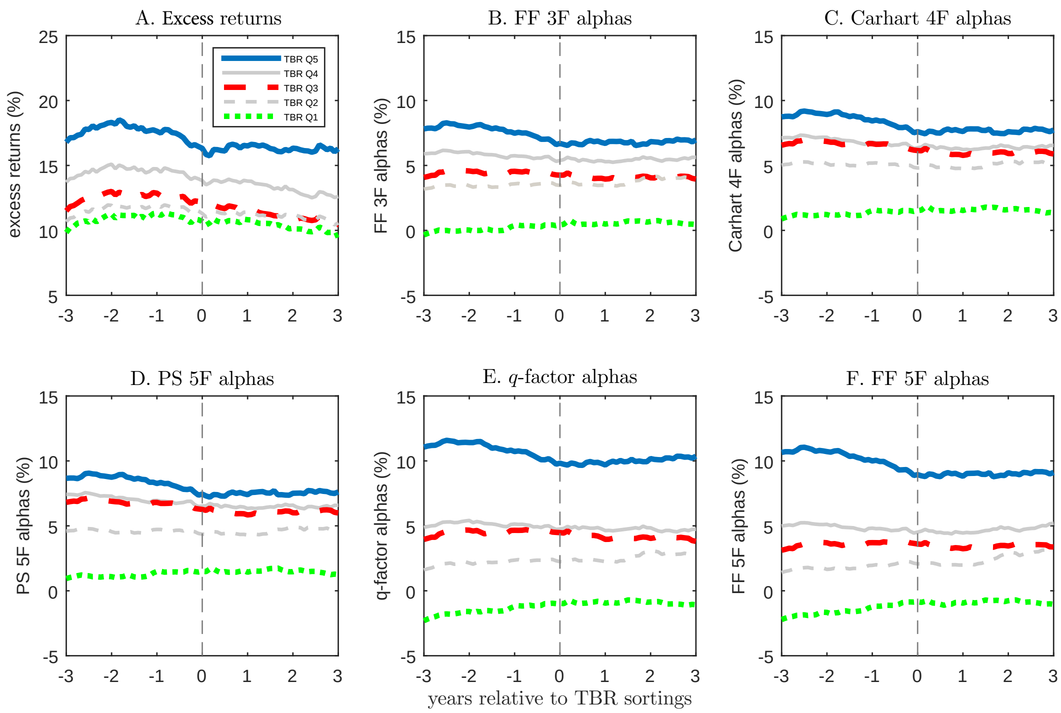
Portfolios sorted on TBR	1 (Low)	2	3	4	5 (High)	5 − 1
			Panel A: Average excess returns			
$\mathbb{E}[R] - r_f$ (%)	10.69***	11.30***	12.06***	13.83***	16.32***	5.64**
	[2.98]	[3.47]	[3.72]	[3.53]	[3.77]	[2.06]
			Panel B: Fama-French three-factor model (Fama and French, 1993)			
α (%)	1.23	3.36**	3.91***	4.27**	7.08***	5.85***
	[0.80]	[2.37]	[2.87]	[2.42]	[3.47]	[2.60]
			Panel C: Carhart four-factor model (Carhart, 1997)			
α (%)	2.51*	4.59***	4.71***	5.98***	8.72***	6.21***
	[1.69]	[3.39]	[3.50]	[3.60]	[4.43]	[2.73]
			Panel D: Pástor-Stambaugh five-factor model (Pástor and Stambaugh, 2003)			
α (%)	2.39	4.57***	4.54***	5.70***	8.25***	5.86**
	[1.60]	[3.35]	[3.36]	[3.42]	[4.20]	[2.56]
			Panel E: Hou-Xue-Zhang q-factor model (Hou, Xue and Zhang, 2015)			
α (%)	−0.83	2.70*	2.42*	4.48**	9.71***	10.54***
	[−0.49]	[1.76]	[1.69]	[2.42]	[4.61]	[4.54]
			Panel F: Fama-French five-factor model (Fama and French, 2015)			
α (%)	−2.05	1.28	0.79	2.50	7.43***	9.48***
	[−1.41]	[0.90]	[0.63]	[1.40]	[3.48]	[4.25]

Note: This table shows the value-weighted excess returns and alphas for portfolios sorted on TBR. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

significant annualized return of 5.64%. The magnitude of this return spread is also economically significant since it is close to the level of equity premium and value premium. Because high and low TBR firms may have differential exposure to the priced risk factors, we also estimate the alphas using various factor models for risk adjustment.[22] We find that the long-short portfolio sorted on TBR has positive and statistically significant alphas in all models. The annualized alphas range from 5.85% to 10.54%. All alphas are statistically significant. These positive alphas suggest that TBR largely captures firms' exposure to some factors that are probably not fully explained by traditional asset pricing factors. According to our model, thereturn spread can be explained by high and low TBR firms'

[22]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 Pástor 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 Ľuboš Pástor's website. The q factor time series are shared by Lu Zhang.

differential exposure to financial constraints risk. We provide evidence to support this prediction in Section 4.2.3 and in Section 4.2.4.



Note: This figure plots the annualized excess returns and alphas, averaged across different portfolio formation months, associated with the portfolios sorted on TBR three years before and three years after portfolio formation. Specifically, we conduct event studies for different portfolio formation months t, spanning 1993 to 2016. In each portfolio formation month t, we sort stocks into quintiles based on lagged TBR 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 of the portfolios sorted on TBR across time. Next, for each month $t' \in [t-36, t+36]$, we estimate the parameters of the factor models based on portfolio returns during $[t'-36, t')$. Using the estimated factor models and portfolio returns in month t', we estimate the portfolio alphas in month t'. Finally, we compute the average alpha for each month across all portfolio formation months t, and obtain annualized alphas by multiplying by 12.

Figure 6: Before-/after-sorting excess returns and alphas for TBR quintiles in event time.

We further examine the persistence of the return spread around the portfolio sorting period. Figure 6 plots the alphas of the value-weighted portfolios. We find that the positive relation between portfolio alphas and TBR exists three years before and continues to exist three years after portfolio formation. This result reinforces the findings in Table 5 because it indicates that TBR is a persistent firm characteristic priced in the cross section with respect to certain asset pricing factors.[23]

Table 6 tabulates the factor loadings (i.e. betas) of the factor models. In the Fama-French five-factor model, we find that the long-short portfolio sorted on TBR loads

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

Table 6: Factor loadings (betas) of the long-short portfolio sorted on TBR.

Factor models	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 (betas) of the long-short portfolio sorted on TBR. The sample period spans 1993 to 2016. We include t-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

negatively on the HML, RMW, and CMA factors,[24] suggesting that low TBR 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 the long-short portfolio sorted on TBR loads negatively on the I/A and ROE factors, again suggesting that low TBR firms are the firms with low asset growth rates and high profitability.[25] In Section 5.1, we further examine the common characteristics of low TBR firms.

Could mispricing explain the alphas? The persistence patterns in Figure 6 suggest that mispricing is unlikely to explain the return spread across portfolios sorted on TBR. Nonetheless, we test this possibility directly using the Stambaugh-Yuan mispricing factor

[24]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, and interest expense, divided by book equity. CMA is short for conservative minus aggressive. The sorting variable is the growth of total assets for the fiscal year ending in year $t-1$ divided by total assets at the end of year $t-1$.

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

Table 7: Mispricing factors cannot explain TBR return spreads.

Portfolios sorted on TBR	1 (Low)	2	3	4	5 (High)	5 − 1
α (%)	0.42	3.41**	2.76*	5.34***	7.26***	6.84***
	[0.23]	[2.22]	[1.83]	[2.77]	[3.29]	[2.64]
β_{MKT}	1.04***	0.94***	0.98***	1.07***	1.16***	0.13**
	[25.91]	[27.74]	[29.46]	[25.08]	[23.93]	[2.21]
β_{SMB}	0.01	−0.13***	−0.05	0.02	0.07	0.06
	[0.23]	[−3.51]	[−1.38]	[0.39]	[1.27]	[0.92]
β_{MGMT}	0.45***	0.23***	0.28***	0.15**	−0.08	−0.52***
	[8.20]	[5.05]	[6.09]	[2.57]	[−1.14]	[−6.72]
β_{PERF}	−0.09***	−0.09***	−0.02	−0.11***	0.01	0.10**
	[−2.76]	[−3.11]	[−0.66]	[−3.06]	[0.20]	[2.11]
R^2	0.789	0.817	0.821	0.800	0.786	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). 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 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. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

model (see Stambaugh and Yuan, 2016). Table 7 tabulates the results. The alpha of the long-short portfolio sorted on TBR (6.84%) remains positive and statistically significant after controlling for the mispricing factors, suggesting that the return spreads across portfolios sorted on TBR are likely due to risk-based factors.

4.2.2 TMB Factor

In this subsection, we provide evidence that the return of the long-short portfolio sorted on TBR is an asset pricing factor that is priced in the cross section of all public firms. We refer to it as the TMB (Talent-Minus-Brand) factor. More precisely, we estimate the betas with respect to the long-short portfolio sorted on TBR (denoted as β_{TMB}) for all U.S. public firms using a rolling-estimation-window approach.[26] We sort firms into quintiles based on β_{TMB} and find that the firms with higher β_{TMB} have significantly higher average excess returns and alphas (see Table 8), suggesting that the return of the long-short portfolio sorted on TBR is an asset pricing factor different from traditional ones.

[26]Since the long-short portfolio sorted on TBR has risk exposure to the traditional asset pricing factors, we control for these factors when estimating β_{TMB}. Pástor 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.

Table 8: The return of the long-short portfolio sorted on TBR is an asset pricing factor.

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

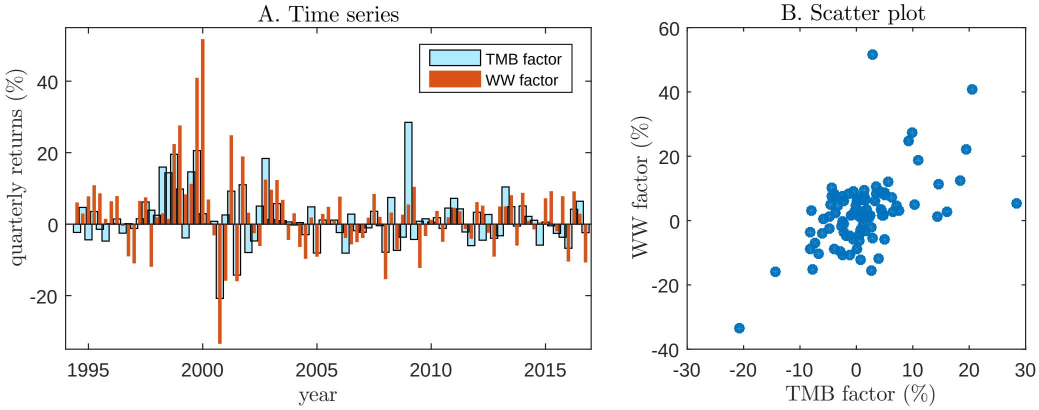
Note: This table shows the value-weighted excess returns and alphas for portfolios sorted on the beta with respect to the long-short portfolio sorted on TBR (β_{TMB}). In each month, we estimate β_{TMB} for all U.S. public firms by regressing their monthly stock returns on the returns of the long-short portfolio sorted on TBR and the returns of the Fama-French three factors in the preceding 36 months. In the beginning of the sample, when less than 36 monthly historical returns of the long-short portfolio sorted on TBR are present, we require at least 12 monthly returns to estimate β_{TMB}. We then average the monthly β_{TMB} into yearly β_{TMB} for each stock and sort the stocks into quintiles based on their lagged yearly β_{TMB}. The sample period is 1995–2016, because we use the first two years' data to compute the lagged yearly β_{TMB}. 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.

4.2.3 What Economic Force Is Captured by The TMB Factor?

We now shed light on the linkage between TBR and the exposure to financial constraints risk. Our model implies that the TMB factor captures the economy-wide financial-constraints-risk shocks after controlling for traditional factors. In particular, firms with higher TBRs have greater exposure to financial constraints risk and thus are required to compensate investors with higher expected returns. Following the literature, we construct the financial-constraints-risk factor based on the return of the long-short portfolio sorted on WW index (Whited and Wu, 2006).[27]

Figure 7 displays the time series (Panel A) and the scatter plot (Panel B) of the WW factor and the TMB factor. We find that these two factors are highly correlated, suggesting

[27] The WW index measures the marginal value of internal funds and thus the marginal cost of issuing equity. Similar financial-constraints-risk factors are also structurally estimated by Eisfeldt and Muir (2016) and Belo, Lin and Yang (2017) using different approaches; we use the WW factor because it is available in monthly frequency and our model exactly fits into the WW's estimation setup. The correlation at the annual frequency is also significant, which is around 0.33. The extent to which the firm is financially constrained is also estimated in the literature using the reduced-form approach (see, e.g. Kaplan and Zingales, 1997; Hadlock and Pierce, 2010); but these estimates do not directly reflect the marginal value of internal funds.



Note: Panel A plots the quarterly time series of the TMB factor and the WW factor. 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 high-constrained firms and the low-constrained firms: (BH+MH+SH)/3 - (BL+ML+SL)/3. Panel B plots the TMB factor against the WW factor in quarterly frequency.

Figure 7: Correlation between the TMB factor and the WW factor.

that TMB, to a large extent, also captures the same financial constraints risk as the WW factor. In our asset pricing analyses, we use the TMB factor as a proxy for the theoretical financial constraints risk, since it is directly implied by our model. As a robustness check, we use the average of the TMB factor and the WW factor to measure the financial constraints risk (denoted as TMBWW). We show that TMBWW is also an asset pricing factor (see Online Appendix F) and the main asset pricing results still hold (see Table 9).

4.2.4 The TMB Factor Is A Common Factor for Two Cross Sections

Our model implies that the exposure to financial constraints risk is reflected in both the cross-sectional variation in TBR and the cross-sectional variation in the extent to which firms are financially constrained. Thus, in principle, the TMB factor should be able to simultaneously explain the return spread of the long-short portfolio sorted on TBR and on WW index (see Figure 5). In this subsection, we provide empirical support.

Adopting the same methodology used in Table 6 of Eisfeldt and Papanikolaou (2013), we find that the average excess returns and the alphas associated with different factor models decrease significantly and become statistically insignificant after controlling for TMB or TMBWW (see Panel A of Table 9). Our finding indicates that the TMB factor is

Table 9: A common factor for two cross sections.

Panel A: Excess returns and alphas of the long-short portfolio sorted on TBR						
Factor models	Excess returns	FF3F	FF4F	PS5F	q-factor	FF5F
Excess returns and α (%)	6.26**	6.76**	7.04***	6.63**	10.96***	10.29***
	[2.03]	[2.59]	[2.63]	[2.58]	[3.63]	[3.79]
Excess returns and α	2.07	3.23	2.78	2.32	4.46*	4.73*
controlling for TMB (%)	[1.28]	[1.63]	[1.57]	[1.37]	[1.74]	[1.83]
Excess returns and α	2.14	3.22	2.76	1.98	4.79	4.64
controlling for TMBWW (%)	[1.00]	[1.34]	[1.22]	[0.95]	[1.63]	[1.65]
Panel B: Excess returns and alphas of the long-short portfolio sorted on WW index						
Tertile 1 (low TBR) firms						
Excess returns and α (%)	1.83	5.56	5.29	5.33	5.64	5.10
	[0.45]	[1.31]	[1.14]	[1.18]	[1.08]	[1.08]
Excess returns and α	0.85	4.75	4.41	4.49	3.25	3.47
controlling for TMB (%)	[0.20]	[1.15]	[1.01]	[1.04]	[0.64]	[0.74]
Excess returns and α	−1.98	−0.13	0.03	0.35	−2.22	−2.67
controlling for TMBWW (%)	[−0.49]	[−0.03]	[0.01]	[0.09]	[−0.46]	[−0.58]
Tertile 2 (medium TBR) firms						
Excess returns and α (%)	3.25	5.49*	3.11	3.21	0.63	3.98
	[0.92]	[1.67]	[0.96]	[0.99]	[0.15]	[1.15]
Excess returns and α	2.60	5.16	2.60	2.71	−2.73	2.91
controlling for TMB (%)	[0.72]	[1.46]	[0.79]	[0.83]	[−0.69]	[0.88]
Excess returns and α	0.33	1.82	0.06	0.35	−5.80	−1.83
controlling for TMBWW (%)	[0.10]	[0.59]	[0.02]	[0.12]	[−1.54]	[−0.60]
Tertile 3 (high TBR) firms						
Excess returns and α (%)	8.65**	8.69**	7.92**	6.78*	12.89***	11.64***
	[2.13]	[2.34]	[2.07]	[1.73]	[3.08]	[2.88]
Excess returns and α	4.42	4.97	3.90	3.11	6.31	5.79
controlling for TMB (%)	[1.21]	[1.32]	[1.03]	[0.78]	[1.49]	[1.47]
Excess returns and α	2.36	0.15	0.08	−0.40	1.95	0.59
controlling for TMBWW (%)	[0.68]	[0.05]	[0.02]	[−0.11]	[0.51]	[0.16]

Note: Panel A tabulates the excess returns and alphas of the long-short porfolio sorted on TBR, with and without controlling for the returns of the long-short portfolio sorted on β_{TMB} (or β_{TMBWW}) under various factor models. β_{TMBWW} is the beta with respect to the average of the TMB factor and the WW factor. The sample period of Panel A is from 1995 to 2016, because we use the first two years' data to compute the lagged yearly β_{TMB} and β_{TMBWW}. The excess returns and alphas for the long-short portfolio sorted on TBR are different from those in Table 5 due to the difference in sample period. Table B tabulates the excess returns and alphas of the long-short porfolio sorted on WW index in three groups of firms sorted on TBR. Within each group, we construct the returns of the long-short portfolio sorted on WW index following Whited and Wu (2006), with and without controlling for TMB or TMBWW. The sample period of Panel B spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

able to explain the return spread of the long-short portfolio sorted on TBR.

We continue to examine the return spreads of the long-short portfolio sorted on WW index within each of the three groups of firms classified according to TBR. Consistent with our model, Panel B of Table 9 shows that the average excess returns and the alphas associated with different factor models are positive. Their magnitudes are larger and statistically significant for high TBR firms (see Panel B of Table 9). Moreover, we find that the average excess returns and the alphas decline by a considerable amount after controlling for TMB or TMBWW; in particular, the average excess returns and the alphas of high TBR firms become statistically insignificant. These findings suggest that firms' differential exposure to financial constraints risk can be captured by the TMB factor.

The split-sample analysis in Panel B of Table 9 is designed for two reasons. First, the return spread sorted on WW index in the full sample is found to be statistically insignificant (see Whited and Wu, 2006); however, as our model predicts (see Panel C of Figure 5), the return spread sorted on WW index can be significant among high TBR firms, even though the return spread is insignificantly different from zero among low TBR firms. The results shown in Panel B of Table 9 indeed verify this theoretical prediction. Second, the positive and statistically significant alphas within the group of high TBR firms strongly suggest that TBR and the degree to which firms are financially constrained are two correlated yet distinct firm characteristics in terms of asset pricing. Our findings suggest that the TMB factor, as a proxy for financial constraints risk, is able to simultaneously explain the stock return patterns in these two distinct cross sections.

4.2.5 Model's Quantitative Asset Pricing Implications

Now we check whether our model can quantitatively replicate the main asset pricing patterns. In each year t, we sort the simulated firms into five quintiles based on their τ_t at the beginning of the year. We then compute the portfolio alphas of each quintile by regressing excess portfolio returns on the excess returns of the market portfolio, SMB, and HML, constructed using simulated data. Column 1 of Table 10 shows that the model-implied difference in portfolio alphas between Q1 and Q5 is about 5.91% (Panel B), roughly in line with the alpha of the long-short portfolio in our data (5.85%) 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 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 τ_t. Panel B of Table 10 shows that the difference in portfolio alphas between Q1 and Q5 is about 11.83% among the financially constrained firms and 0.83% among the financially unconstrained firms. Again, these differences are quite consistent with the ones in our data using WW index as the sorting variable for financial constraints (see Panel A of Table 10).

Table 10: Alphas of portfolios sorted on TBR in model and data.

	All firms	Low constraints	Medium constraints	High constraints
Panel A: Data (Fama-French three-factor)				
Quintile 1 (%)	1.23	0.52	1.32	6.85
Quintile 5 (%)	7.08	2.99	3.98	17.17
Q5 − Q1 (%)	5.85	2.46	2.66	10.32
Panel B: Full model				
Quintile 1 (%)	0.76	0.65	0.72	0.87
Quintile 5 (%)	6.67	1.48	3.25	12.70
Q5 − Q1 (%)	5.91	0.83	2.53	11.83
Panel C: Model without non-pecuniary private benefits				
Quintile 1 (%)	1.14	1.05	1.11	1.26
Quintile 5 (%)	5.82	2.02	3.02	11.31
Q5 − Q1 (%)	4.68	0.97	1.91	10.05

In our model, customer capital plays two unique roles in generating different risk premiums across the firms with different TBRs. The essential feature that generates the differential exposure to financial-constraints-risk shocks is the cross-sectional difference in the fraction of customer capital that can be taken away due to human capital inalienability. In addition, key talents in high TBR firms ask for higher cash compensation because they enjoy fewer non-pecuniary private benefits. Thus, non-pecuniary private benefits amplify the effect of customer capital's talent dependence through its influence on endogenous compensation, increasing the quantitative implication of TBR on expected stock returns.

To quantify the importance of non-pecuniary private benefits, we calibrate a model with $h = 0$ to match the moments in Table 4. Panel C of Table 10 shows that the difference in alphas between Q1 and Q5 is reduced to 4.68%. Compared with the alpha of our full model, 5.91%, about 20% of the cross-sectional variation in alphas is attributed to the cross-sectional variation in non-pecuniary private benefits. Therefore, we argue that customer capital matters for stock returns, quantitatively, because of both human capital inalienability and non-pecuniary private benefits.

4.2.6 Double-Sort Analyses

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

Control for the Measures of Customer Capital. We compare our TBR measure with various other measures of customer capital in their ability to explain stock returns. We show that other measures are either not priced in the cross section or their association with stock returns can be explained away by TBR. These findings suggest that dissecting customer capital and studying the degree of its dependence on key talents are essential to understand the role of customer capital in explaining 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 brand strength are the two brand metrics we use to construct TBR. The fluidity measure is constructed based on a textual analysis of firms' product descriptions in 10-K filings. Firms with higher fluidity face more product market competition because their products are more similar to their peers'. We find that brand stature is priced in the single-sort analysis, whereas brand strength and product fluidity are not (see Table OA.7 in Online Appendix H). We further perform a double-sort analysis in which we first sort firms into three groups based on TBR and then sort the firms in each group into five quintiles based on the three measures of customer capital. None of the three measures are priced in the cross section after we control for TBR. As a robustness check, we reverse the order of the double sort and find that TBR remains priced in the cross section after controlling for the three measures (see Table OA.8 in Online Appendix H).

Control for the Measures of Human Capital Importance. Given that Table 2 has shown that TBR is correlated with various proxies for human capital importance, it is natural to ask whether the asset pricing results based on TBR remain robust after controlling for these proxies. Using a double-sort approach, we verify that the average excess returns and alphas of the long-short portfolio sorted on TBR remain significantly positive (see Table OA.9 in Online Appendix H).[28]

Control for Industry Classifications. We test whether the cross-sectional relation between TBR and stock returns holds within industries (see Table OA.10 in Online Appendix

[28]Note that these financial proxies may not be appropriate to study the asset pricing implications of the relative importance of human capital, because the relationship between stock returns and these financial proxies can be severely subject to endogeneity issues as 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. Our TBR measure alleviates this concern because it measures key talents' importance through the perception of consumers, which is less directly controlled by firms' endogenous financial decisions.

H). We find that the long-short portfolios sorted on TBR within industries have positive alphas, which are both statistically and economically significant. The return patterns are robust across various industry classifications, suggesting that TBR's within-industry variation is priced in the cross section.[29]

4.3 Turnovers

Our model's asset pricing implications are closely dependent on key talent turnovers, which result in customer capital damage. We now examine turnovers in model and data.

Panel A of Figure 8 compares the effective compensation of high and low TBR firms, defined as the monetary compensation multiplied by the marginal value of cash. Relative to the frictionless benchmark (solid and dashed red lines), both the low and high TBR firms effectively pay more to key talents when cash ratios are low due to the high marginal value of cash. The increase in effective compensation is more dramatic and nonlinear for the high TBR firm.

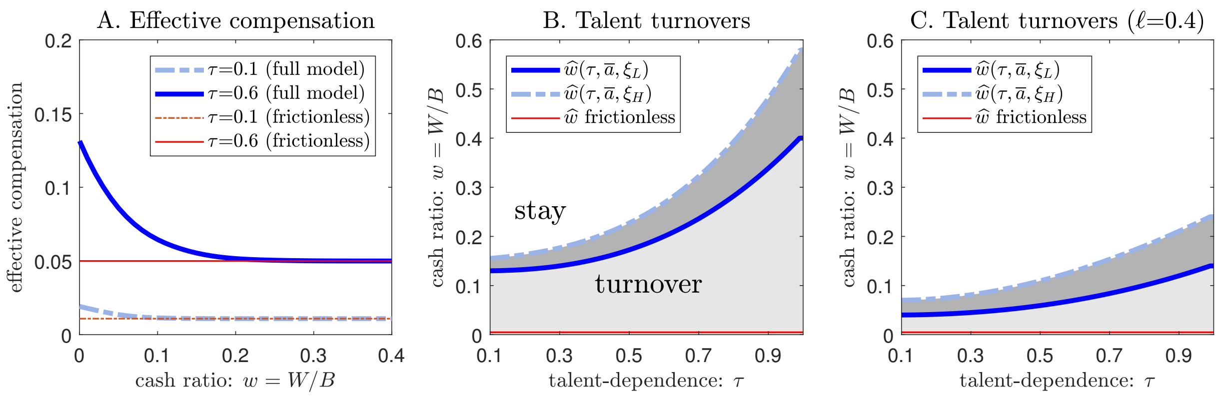


Figure 8: Model prediction on effective compensation and talent turnovers.

The high effective costs of retaining key talents imply that the firm tends to replace key talents when cash ratios are low. As Panel B shows, the firms with higher TBRs and lower cash ratios are more likely to replace key talents. The turnover boundary $\widehat{w}(\tau, \overline{a}, \xi_L)$ shifts upward when aggregate financial constraints risk increases. The difference in turnover boundaries $\widehat{w}(\tau, \overline{a}, \xi_H) - \widehat{w}(\tau, \overline{a}, \xi_L)$ increases with τ. Therefore, our model suggests that the high TBR firm tends to be associated with a greater increase in turnover rates when

[29]Compared to the results in Table 5, the long-short portfolios sorted on TBR within industries have slightly smaller alphas, suggesting that TBR's cross-industry variation is also priced in the cross section.

financial constraints risk increases. In other words, customer capital owned by the high TBR firm is more fragile to financial constraints risk.

Intuitively, retaining key talents is beneficial to the firm because, on average, customer capital generates positive net cash inflows. However, when the firm is financially constrained, the increased exposure to financial constraints risk due to operating leverage outweighs the benefit from higher demand, motivating the firm to replace key talents and downsize the scale of customer base and production. An increase in financial constraints risk (from ξ_L to ξ_H) leads to a larger turnover region (i.e. higher likelihood of talent turnovers). The high TBR firm is more financially constrained, and therefore responds more dramatically to the increase in financial constraints risk by expanding the turnover region to a larger extent. This pattern differentiates our mechanism from that of Eisfeldt and Papanikolaou (2013). In their model, the firm operates in a perfect financial market. Both talent turnover decisions and asset pricing implications are driven by aggregate frontier technology shocks to key talents' outside options.

Panel C plots the turnover boundaries when ℓ reduces from its calibrated value 0.45 to 0.4. Because ℓ reflects the new customer capital created by key talents' business idea, a lower ℓ reduces the outside option values of key talents. Panel C shows that when key talents' outside options become worse, turnover boundaries shift downward, indicating that it is easier for firms to keep key talents. The reduced compensation benefits high TBR firms more because these firms are endogenously more constrained. Thus, the positive relationship between TBR and talent turnover rates becomes weaker with a lower ℓ, as reflected by flatter turnover boundaries.

4.3.1 TBR and Talent Turnovers

We now test the model's predictions on turnovers. First, we show that TBR is positively related to the turnover rates of executives and innovators. Next, we show that this positive relation is more pronounced in the time periods of heightened financial constraints risk and in the states with weaker enforceability of non-competition agreements.

TBR and Executive Turnovers. We first study the relation between TBR and executive turnovers. We focus on the executives in the Execucomp database, which covers the top

Table 11: TBR and talent turnovers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	Turnover$_t$ × 100		ln(1 + leavers)$_t$		ln(1 + new hires)$_t$	
lnTBR$_{t-1}$	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 TBR and the turnovers of managers and innovators. In columns (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. Turnover$_t$ is a dummy variable that equals one for a given executive-year observation if the executive leaves the firm at age 59 or younger for reasons other than death, and 0 otherwise. In columns (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 lagged standardized lnTBR. Firm controls include the natural log of firm market capitalization (lnsize$_{t-1}$), the natural log of the book-to-market ratio (lnBEME$_{t-1}$), the natural log of the debt-to-equity ratio (lnlev$_{t-1}$), the natural log of the organization capital normalized by assets (ln(OC/Asset)$_{t-1}$), and the 12-month stock returns in the previous year (StockRet$_{t-1}$). Executive controls include executive genders. We control for year fixed effects with and without SIC-2 industry fixed effects. The executive turnover sample spans 1993 to 2016, whereas 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.

five highest compensated executives of each S&P 1500 firm starting from 1992.[30] 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 executive turnovers.[31] We find that executive turnover rates are significantly higher in the firms with higher TBRs (see columns 1 and 2 of Table 11). The positive relation between TBR 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 lnTBR is associated with an increase in the probability of executive turnovers each year by 1.546 percentage points, roughly 1/8

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

[31]We focus on executive turnovers that are not due to retirements, because: (1) retirements are mostly due to age, health status, and lifestyle choices of executives, which do not reflect firms' active decisions of talent turnovers, and (2) non-retirement turnovers are more likely to cause damage to customer capital and thus are more relevant to the mechanism of our paper. We follow the literature (see, e.g. Parrino, 1997; Jenter and Kanaan, 2015) and use age 60 as the cutoff for the retirement age. Our results are robust to other age cutoffs, such as 65.

of the average turnover rate in the data.

TBR and Innovator Turnovers. Next, we study the relation between TBR and innovator turnovers. 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 find that the firms with higher TBRs are associated with significantly more innovator turnovers (see columns 3 to 6 in Table 11). According to the specifications with both year and industry fixed effects, a one standard deviation increase in lnTBR is approximately associated with a 17.0% increase in innovator departures and a 15.8% increase in arrivals.

Table 12: TBR and talent turnovers: interaction with financial constraints risk.

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	$\text{Turnover}_t \times 100$		$\ln(1+\text{leavers})_t$		$\ln(1+\text{new hires})_t$	
lnTBR_{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]
$\text{lnTBR}_{t-1} \times \text{TMB}_{t-1}$	-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 TBR and the yearly TMB factor. The mean of the TMB factor is 0.055, whereas the standard deviation of the TMB factor is 0.160. The dependent variables, firm controls, executive controls, and fixed effects are defined in Table 11. The main independent variables are lagged standardized lnTBR and the products between lagged standardized lnTBR and lagged TMB factor. Note that we omit the term TMB_{t-1} in the regressions because it is absorbed by year fixed effects. The executive turnover sample spans 1993 to 2016, whereas 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.

4.3.2 Interaction with Financial Constraints Risk

Our model predicts that the positive relation between TBR and turnover rates is stronger when firms face heightened financial constraints risk. As shown previously, a low TMB is associated with heightened financial constraints risk. We include the interaction term between lnTBR and yearly TMB as the main independent variable in the regressions.

As Table 12 shows, we find that the coefficients for the interaction term are significantly negative, suggesting that the positive relation between TBR and talent turnover rates is indeed more pronounced, conditional on heightened financial constraints risk.

This interaction effect is also economically significant. For example, according to the specification with industry and year fixed effects, when TMB factor changes from its mean value (5.5%) to a value that is two standard deviations below the mean (-26.5%), the sensitivity between lnTBR and executive turnovers nearly doubles (the coefficient changes from 1.5 to 3.0).

4.3.3 Interaction with Non-competition Enforceability

Our model predicts that the positive relation between TBR and talent turnovers is weaker in the states with higher enforceability of non-competition agreements, because strictly enforced non-competition agreements decrease the outside option values of key talents and thus decrease firms' operating leverage. To test this hypothesis, we exploit the cross-state variation in the enforceability of non-competition agreements. Specifically, we include the interaction between TBR and the non-competition enforceability index as the main independent variable.

As Table 13 shows, the coefficients for the interaction term are significantly negative, suggesting that the positive relation between TBR and talent turnover rates is indeed weaker with more strictly enforced non-competition agreements. This interaction effect is economically significant. Consider column 4 as an example, conditional on the weakest enforceability (index equals to 0), a one standard deviation increase in lnTBR is approximately associated with a 31.8% increase in the number of leavers for innovators. Conditional on the strongest enforceability (index equals to 9), a one standard deviation increase in lnTBR is approximately associated with 0.3% (insignificant) increase in the number of leavers for innovators.

5 More Tests for The Theoretical Mechanism

In this section, we provide additional empirical evidence to support our model. First, we show that low TBR firms are a group of robust value firms with stable cash flows. Second, we show that the firms with higher TBRs adopt more precautionary financial policies. Third, we show that key talents receive lower compensation in firms with greater brand stature (see Appendix A). This finding supports our model's assumption that key talents receive non-pecuniary private benefits from customer capital. Fourth, we show that the duration of executive compensation is longer in high TBR firms. However, the change

Table 13: TBR and talent turnovers: interaction with non-competition enforceability.

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	Turnover$_t$ × 100		ln(1 + leavers)$_t$		ln(1 + new hires)$_t$	
$\ln\text{TBR}_{t-1}$	2.049***	2.360**	0.251**	0.318***	0.206**	0.255**
	[3.658]	[2.246]	[2.433]	[3.764]	[2.103]	[2.665]
$\ln\text{TBR}_{t-1} \times \text{Enforceability}_{s,t-1}$	−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 TBR and the non-competition enforceability index. The state-level non-competition enforceability index comes from Garmaise (2011). Higher values of the index represent higher enforceability of non-competition agreements. The index is available from 1992 to 2004. The minimum, maximum, median, and mean of the index are 0, 9, 5 and 4.08. The standard deviation of the index is 1.83. The dependent variables, firm controls, executive controls, and fixed effects are defined previously in Table 11. The main independent variables are lagged standardized lnTBR, lagged non-competition enforceability index, and the interaction between these two variables. 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.

in duration is economically small, suggesting that high TBR firms are unlikely to fully alleviate the financial constraints by actively managing pay duration.

5.1 Robust Value Firms

The HML loadings in Table 6 are all significantly negative, implying that low (high) TBR firms tend to be value (growth) firms. Intuitively, low TBR firms are those whose pure brand recognition is strong and customer capital is not talent dependent; thus, they are likely to be mature value firms. However, low TBR firms, on average, have lower expected excess returns relative to high TBR firms (see Panel A of Table 5), opposite to the prediction of value premium. This is because low TBR firms constitute the subgroup of value firms that are robust in the sense that their customer capital is more resilient to peers' innovation and competition, like Coca-Cola, Gap, and Toyota since early 2000. As a result, low TBR firms' growth rates are less negatively affected by their peers' innovative outputs, and are associated with steadier cash flows. Although we do not explicitly model firms' innovation process, the evidence is consistent with our model's implications. Peers' innovation competes for talent-based customer capital; thus, low TBR firms are naturally more resilient to their peers' competition, through innovation-related activities, for talent-based customer capital.

Table 14: TBR and the competition for customer capital through innovations.

	(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$_t$ × lnTBR$_{t-1}$		-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$_t$ × lnTBR$_{t-1}$		0.017^{*}		0.016^{**}		0.017^{*}		0.026^{***}
		[1.933]		[2.105]		[2.043]		[3.683]
lnTBR$_{t-1}$		−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 TBR and the sensitivity of firm growth to innovative outputs. The dependent variables are the five-year growth rates of the (a) firm gross profits (*Profits*, i.e. Compustat item *sale* minus Compustat item *cogs*, deflated by the CPI) (b) value of output (*Output*, i.e. Compustat item *sale* plus change in inventories Compustat item *invt*, deflated by CPI), (c) capital stock (*Capital*, i.e. Compustat item *ppegt*, deflated by the NIPA price of equipment), and (d) the number of employees (*Labor*, i.e. Compustat item *emp*). The main independent variables include the standardized innovative outputs of peer firms (Innovation_Peers), the standardized firms' own innovative outputs (Innovation_Self), lagged standardized lnTBR, and the interaction between lnTBR and the two innovative output measures. 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 lnTBR to ease the interpretation of the coefficients. Following Kogan et al. (2017), we include the lagged value of firm capital, the lagged value of the number of employees, and the firm's idiosyncratic volatility as firm controls. We include both SIC-2 industry fixed effects and year fixed effects in the regressions. We download the innovation data from Noah Stoffman's website. The sample period of this table 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.

TBR and Peers' Innovation. We first study how TBR affects firms' reaction to the innovation of their peer firms (see Table 14). Consistent with Kogan et al. (2017), we find that firm growth (measured by the five-year growth rates of gross profits, output, capital stock, and the number of employees) is negatively related to peers' innovative outputs. Importantly, we find that this negative relation is less pronounced in the firms with lower TBRs, suggesting that the firms with lower TBRs react less negatively to peer firms' innovative outputs. The above findings are economically significant. For a firm with average lnTBR, a one standard deviation increase in peer firms' innovative outputs is associated with a 9.2% drop in profits over five years. The sensitivity of firm growth to innovation decreases significantly when TBR decreases. For a firm whose lnTBR is two standard deviations below the average, the sensitivity is indistinguishable from zero.

TBR and Cash Flow Volatilities. As Table 15 shows, lnTBR is positively related to four measures of cash flow volatility with statistically and economically significant coefficients, suggesting that low TBR firms are a group of firms associated with steady sales growth and stable cash flows.[32]

Table 15: TBR and cash flow volatility.

	(1) Vol(sales growth)$_t$ (%)	(2) Vol($\frac{\text{Net income}}{\text{Asset}}$)$_t$ (%)	(3) Vol($\frac{\text{EBITDA}}{\text{Asset}}$)$_t$ (%)	(4) Vol(daily returns)$_t$ (%)
lnTBR$_{t-1}$	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 TBR and firms' cash flow volatilities. The dependent variables are the volatility of forward-looking growth rates of sales (standard deviation of yearly growth rates of sales from year t to year $t+5$), the volatility of forward-looking net-income-to-asset ratios (standard deviation of yearly ratios from year t to year $t+5$), the volatility of forward-looking EBITDA-to-asset ratios (standard deviation of yearly ratios from year t to year $t+5$), and the volatility of daily stock returns in current year (t). These variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. The main independent variable is lagged standardized lnTBR. Firm controls include the natural log of firm market capitalization (lnsize$_{t-1}$), the natural log of the book-to-market ratio (lnBEME$_{t-1}$), the natural log of the debt-to-equity ratio (lnlev$_{t-1}$), and the natural log of the organization capital normalized by assets (ln(OC/Asset)$_{t-1}$). We control for SIC-2 industry and year fixed effects. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

5.2 Low TBR Firms Adopt More Precautionary Financial Policies

We now examine the relation between TBR and firms' financial policies (see Table 16). We find that high TBR firms hold more cash and convert a larger fraction of net income to cash holdings. A one standard deviation increase in lnTBR is approximately associated with a 3.475-percentage-point increase (roughly 1/6 standard deviation) in normalized cash holdings and a 9.421-percentage-point increase (roughly 1/20 standard deviation) in the cash saving rate (Δcash/net income). High TBR firms also issue more equity and pay out less. A one standard deviation increase in TBR is approximately associated with a

[32] The four measures are: the volatility of (1) forward-looking growth rates of sales, (2) forward-looking net-income-to-asset ratios, (3) forward-looking EBITDA-to-asset ratios, and (4) stock returns.

0.665-percentage-point increase (roughly 1/12 standard deviation) in equity issuance and a 0.903-percentage-point decrease (roughly 1/7 standard deviation) in total payout.

Table 16: TBR and firms' financial policies.

	(1) $\frac{\text{Cash}_t}{\text{Asset}_{t-1}}$ (%)	(2) $\frac{\Delta\text{Cash}_t}{\text{Net income}_t}$ (%)	(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) $\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$ (%)
lnTBR_{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 TBR and firms' financial policies. The dependent variables are the amount of cash holdings (% of lagged assets), the change in 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 lagged standardized lnTBR. Firm controls are defined in Table 15. We control for both SIC-2 industry fixed effects and year fixed effects. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

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 fragility of customer capital influences firm valuation and asset prices. We develop a model featuring inalienable human capital and endogenous value of internal funds to argue that the firms with different TBRs have distinctive exposure to financial constraints risk.

Based on a proprietary, granular brand-perception survey database, we find empirical evidence strongly supporting our model. The firms with higher TBRs have higher average returns. The returns of the long-short portfolio sorted on TBR are highly correlated with the financial-constraints-risk factor. Moreover, the firms with higher TBRs are associated with higher talent turnover rates, and this pattern is more pronounced in the periods of heightened financial constraints risk. Our model shows that the firm's exposure to financial constraints risk is reflected both in the cross-sectional variation in customer capital's dependence on talents and the cross-sectional variation in the extent to which firms are financially constrained. The endogenous interaction between the two is what explains the cross-sectional patterns on stock returns and talent turnovers.

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Appendix

A Brand Stature and Private Benefits

Our model assumes that the private benefits of key talents increase with total customer capital. We provide empirical support for this assumption. In particular, we test whether executivies are willing to accept lower pay when they work in firms with higher brand stature, a proxy for total customer capital. We regress the amount of executive compensation on firms' brand stature and include brand strength as a control variable. We find that executives indeed receive lower compensation when they work in the firms with stronger brand stature. This result remains robust when we include executive fixed effects and focus on within-executive variation. Thus, our findings cannot be explained by unobserved heterogeneity across executives. The relation between brand stature 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 B.1).[33]

We continue to hypothesize that younger executives are more likely to enjoy non-pecuniary private benefits at the firms with strong brand stature. One reason is that they have longer careers ahead of them and thus gain more non-pecuniary private benefits, such as identity-based benefits and signaling benefits. To test this hypothesis, we interact age with both brand stature and brand strength, 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 variation 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. According to the specification with both industry fixed effects and 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 cut.

[33]This finding is consistent with Tavassoli, Sorescu and Chandy (2014), who examine the relation between brand value and executive compensation from 2000 to 2010.

B TBR and Compensation Duration

High TBR firms are more financially constrained. In principle, these firms should have stronger incentives to alleviate the financial constraints by adjusting compensation contracts. Following this logic, we further hypothesize that the firms with higher TBRs are more likely to increase the pay duration of key talents to delay cash payments. In particular, they can choose to substitute cash payments (salary and bonus) with stocks and stock options, which have longer pay duration due to the existence of vesting schedule.[34] To test this hypothesis, we examine the relation between TBR and the pay duration of top executives.

We first use the Execucomp data to examine the relation between TBR 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 Table B.2 shows, the firms with higher TBRs are associated with higher stocks/options-to-total-pay ratios. According to the specification with industry and year fixed effects, a one standard deviation increase in lnTBR is associated with a 3.583-percentage-point 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 study the relation between TBR and pay 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 Table B.2 shows, the firms with higher TBRs are indeed associated with longer pay duration. However, the magnitude of the changes in pay duration is very small. According to the specification with industry and year fixed effects, a one standard deviation increase in lnTBR is associated with a 0.102-year increase in pay duration. Taken together, the change in duration is economically small, suggesting that high TBR firms are unlikely to fully alleviate the financial constraints by actively managing pay duration.

[34]Firms frequently adopt vesting schedule to increase pay duration for executives. Kole (1997) shows that the average vesting period across firms for executive stock options is 23.6 months. Recognizing the importance of this feature of option programs, Sircar and Xiong (2007) develop a general framework for evaluating executive stock options.

Table B.1: Brand stature and talents' non-pecuniary private benefits.

	(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]
$\text{lnStature}_{t-1} \times (\text{Age}_{t-1} - 30)$					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]
$\text{lnStrength}_{t-1} \times (\text{Age}_{t-1} - 30)$					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
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 value and managerial compensation. lnExecuComp is the natural log of the managerial compensation (*tdc*1 in the Execucomp data). We standardize both lnStature and lnStrength to ease the interpretation of coefficients. In columns (5) and (6), we include the interaction terms between the brand value and executive age in the regressions. Firm controls include the natural log of firm market capitalization (lnsize_{t-1}), the natural log of the book-to-market ratio (lnBEME_{t-1}), the natural log of the debt-to-equity ratio (lnlev_{t-1}), the natural log of the organization capital normalized by assets ($\ln(\text{OC}/\text{Asset})_{t-1}$), and the 12-month stock returns in the previous year (StockRet_{t-1}). We also include executive genders as executive controls in the specifications without the executive fixed effects. We include year fixed effects with and without SIC-2 industry fixed effects in the regressions. The sample period spans 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table B.2: TBR and the duration of executive compensation.

	(1)	(2)	(3)	(4)
	$\frac{(\text{Stocks+Options})_t}{\text{Total Pay}_t}$ (%)		Duration_t	
lnTBR_{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: This table shows the relation between TBR and the duration of executive compensation. In columns (1) and (2), the dependent variables are the stocks/options-to-total-pay ratio. Data on the executive pay are from Execucomp. In columns (3) and (4), the dependent variables are the duration of executive compensation. Data on the vesting schedules of restricted stock and stock options are from Equilar Consultants. The main independent variable is lagged standardized lnTBR. Firm controls and fixed effects are defined in Table B.1. The sample period for columns (1) and (2) is 1993-2016, and the sample period for columns (3) and (4) is 2006-2016. 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.