Customer Capital, Talents and Stock Returns

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Abstract

Customer capital, as a form of crucial intangible assets, is embodied in customers' brand loyalty to the firm. Part of customer capital depends on key talents' specialized contribution, while the rest is retained only by customers' pure brand loyalty unrelated to key talents. The latter (pure-brand-based) component is immune to the firm's financial constraint risk, whereas the former (talent-based) component is fragile to the financial constraints risk, as key talents tend to escape from the firm, damaging talent-based customer capital when the firm is financially constrained. Using granular proprietary brand perception survey data, we construct the firm-level brand-talent ratio (BTR) to capture the relative importance of talent-based customer capital. We document new joint cross-sectional patterns: the firms with lower BTRs have higher (risk-adjusted) average returns, higher talent turnover rates, and more precautionary financial policies. We develop an asset pricing model to explain these findings. Additional empirical tests support the theoretical mechanism.

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

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1 Introduction

Customer capital – customers' brand loyalty to the firm – is one of the most crucial assets, even though it does not explicitly appear on the balance sheet. Creating and sustaining customer capital is essential for a firm's survivorship, growth, profitability, and thus its valuation. All other assets, whether tangible or intangible, yield their values mainly from the complementary interaction with customer capital.[1]

Existing studies have focused on the implications of customer capital and product market characteristics on corporate policies (see, e.g. Titman, 1984; Titman and Wessels, 1988; Gourio and Rudanko, 2014). The primary objective of our paper is to investigate the composition of customer capital and its financial implications. Customer capital is partly maintained by customers' brand loyalty related to key talents' unique contributions (i.e. talent-based customer capital), while the rest is retained only by customers' pure brand loyalty unrelated to key talents (i.e. pure-brand-based customer capital). The former component is fundamentally linked to key talents' inalienable human capital as they can leave the firm, taking away or damaging talent-based customer capital, especially when the firm is financially constrained. Thus, talent-based customer capital is fragile to financial constraints risk, whereas pure-brand-based customer capital is immune to the firm's financial constraints risk. Our paper is the first to dissect total customer capital and highlight how different components of customer capital interact with financial constraints risk, generating important financial implications. Without differentiating the two components' fragility to financial constraints risk, the existing studies may inflate or overestimate the amount of customer capital robustly owned by the firm. Moreover, the fragility of talent-based customer capital to financial constraints risk reinforces the channel of losing market shares as the substantial ex-ante indirect costs of financial distress (see, e.g. Opler and Titman, 1994); it also adds a new channel to the interaction between firms' liquidity condition and product market behavior (see, e.g. Chevalier and Scharfstein, 1996; Gilchrist et al., 2017).

As a major empirical contribution, we use granular proprietary customer survey data on consumers' perceptions of brands to decompose the firm-level customer capital and construct the brand-talent ratio (BTR) to capture the relative contributions of pure-brand-based customer capital and talent-based customer capital. We document new cross-sectional asset pricing patterns: the firms with lower BTRs have higher average excess returns and risk-adjusted

[1] One example to demonstrate the uniqueness and necessity of customer capital for firms is Iridium's bankruptcy case. The global satellite phone company backed by Motorola filed for bankruptcy in 1999 due to its failure to create and maintain customer capital. The system that cost Motorola more than $5 billion to build (the book value) was ultimately sold for $25 million, or about half a penny for every dollar it originally cost. In general, the risk of losing customers was rated as the top one business risk according to Lloyd's 2011 risk index report and the top two risk according to Llyod's 2013 risk index report (https://www.lloyds.com). As emphasized by Rudanko (2017), customer capital is crucial for other assets of firms to be profitable. An extreme exception is the pure holding company, which is not relevant for our analysis.

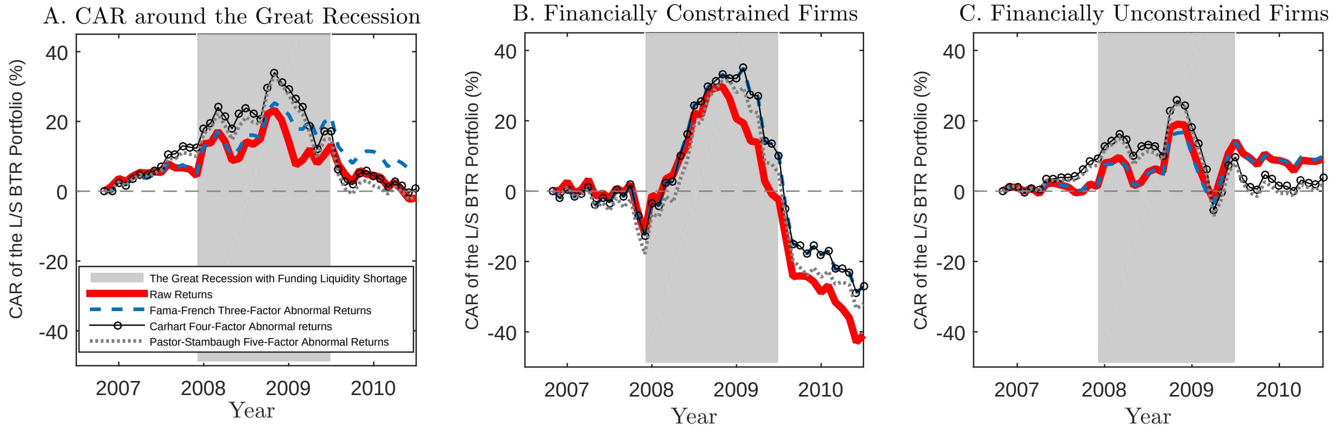
returns, even after controlling for organization capital and R&D intensity. In contrast to other brand metrics derived from firms' financial and accounting variables, our survey-based BTR measure is unlikely to be mechanically linked to the outcome financial variables we study.

Measuring the quantitative importance of the interaction between customer capital compositions and financial constraints risk in explaining the cross-sectional patterns presents a challenge. Firms' turnover decisions are endogenous, as are firms' precautionary actions for hedging and mitigating the damage caused by potential turnovers. They further generate endogenous asset pricing and corporate policy patterns. There are no obvious instruments. Therefore, evaluating the magnitude of the implications of customer capital components requires estimating or calibrating a dynamic structural model. We thus develop a new asset pricing model featuring product market search frictions and inalienable talent-based customer capital. Our calibrated model is consistent with the data and quantitatively explains the cross-sectional stock return patterns. Moreover, as the main mechanism directly implies, the firms with lower BTRs have higher talent turnover rates and more precautionary financial policies, which are also supported by the data.

Our model itself has twofold theoretical contributions: first, it incorporates the idea of inalienable human capital (see, e.g. Hart and Moore, 1994; Lustig, Syverson and Nieuwerburgh, 2011; Bolton, Wang and Yang, 2016) into a dynamic model emphasizing the interplay between product market search (see, e.g. Moen, 1997; Gourio and Rudanko, 2014) and endogenous financial constraints risk; second, it endogenizes talent turnovers driven by corporate liquidity condition, which differentiates our model from other dynamic structural models investigating the valuation effect of endogenous turnovers (see, e.g. Taylor, 2010; Eisfeldt and Papanikolaou, 2013).

As a motivating fact, Figure 1 presents the cumulative abnormal returns for the long-short portfolio based on BTR sorting. The time series are displayed around the Great Recession, which featured poor liquidity conditions for U.S. firms. As shown by Figure 1, the firms with lower BTRs have lower abnormal returns during the period of poor liquidity condition, while this pattern reverses when the liquidity condition improves due to economic recovery. This pattern is especially pronounced in financially constrained firms. These stylized facts suggest that high BTR firms are generally far more resilient than low BTR firms against adverse aggregate liquidity shocks.

Inspired by the stylized facts in Figure 1, we develop a theoretical framework to shed light on the underlying mechanism. In our model, the customer relationship is endogenously a long-term one, since the product market has search frictions. Thus, the existing customer base, as a collection of existing customer relationships, is sticky. In other words, the existing customers exhibit brand loyalty. The value of customer capital is the present value of the net profit attributed to the existing customer base during their entire relationship with the firm.



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

Figure 1: Motivating facts for the importance of customer capital composition.

It is coined *customer lifetime value* by Farris et al. (2010) in the marketing literature. The firm's external financing is costly, motivating retained earnings; thus, it faces endogenous financial constraints risk. The level of internal funds determines the firm's marginal value of liquidity.

Customer capital has two unique features that determine the firm's exposure to systematic financial constraints risk. First, key talents have limited commitment to the firm – they can leave the firm and take away a fraction of talent-based customer capital. To retain talent-based customer capital, the firm compensates key talents and thus is subject to operating leverage. Second, key talents enjoy non-pecuniary private benefits from the firm's customer capital, because high brand values with strong public recognition implicitly offer identity-based benefits, signaling values of human capital quality, and social status. As a result, pure-brand-based customer capital is robust against financial constraints risk; by contrast, talent-based customer capital is fragile particularly when the firm's liquidity condition is poor, as the effective cost of compensation increases with the firm's marginal value of liquidity. The fragility of talent-based customer capital is the main reason for which the firms with lower BTRs have higher exposure to financial constraints risk; non-pecuniary private benefits generated by customer capital (i.e. brand recognition) make it easier to retain talent-based customer capital and thus amplify the effect of BTR on firms' heterogenous exposure to financial constraints risk. Quantitatively, our calibrated model implies that human capital inalienability is the essential feature that generates the spread in risk-adjusted returns across BTR portfolios. Non-pecuniary private benefits contribute to the spread by about 20% as an amplification channel.

Our model highlights an intertemporal tradeoff between risks and returns when the firm decides whether to retain talent-based customer capital. When the firm's liquidity condition is poor, key talents may find it optimal to *escape from a sinking ship* or *jump to a safer boat* (see, e.g. Brown and Matsa, 2016; Baghai et al., 2017); 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). Although retaining talent-based customer capital on average brings positive net cash flows, the operating leverage increases the firm's exposure to financial constraints risk. Therefore, the firm tends to replace talents with less-cash-compensated ones when it is financially constrained. As key talents play an important role in bringing new customers, the firing decision also involves an intertemporal tradeoff between the short-run liquidity benefit and the long-run customer capital growth.

Our empirical analysis is based on a proprietary granular brand perception survey database, the world's most comprehensive database of consumers' perception of brands. The database is provided by the BAV Group. We use the ratio between *brand stature* and *brand strength*, the two major brand metrics developed by the BAV Group, as our measure for BTR. By BAV's design, brand stature quantifies brand loyalty as of today, which provides an approximation for the existing customer capital; brand strength quantifies brand loyalty of existing customers, as well as the attractiveness of brands to potential customers, attributed to innovative and distinctive features of the products and services. By nature, the maintenance of brand strength relies mainly on firms' key talents, as innovation and product differentiation require significant intellectual inputs. Thus, brand strength naturally provides an approximation for talent-based customer capital. BTR captures the relative importance of pure brand loyalty in building and maintaining the firm's customer capital.

To understand the difference between high BTR firms and low BTR firms, we investigate the relation between firms' customer capital compositions quantified by BTR and firms' growth and cash flow patterns. We find that the firms with higher BTRs have steadier sales growth and less volatile cash flows. Moreover, we show that the growth of these firms is less negatively affected by peers' competition through innovative activities. Therefore, the firms with high BTRs are referred to as *robust firms*, because these firms mostly consist of pure-brand-based customer capital, which is less fragile to aggregate shocks and peers' competition.

As our main results, we find that the firms with lower BTRs have higher average excess returns and greater alphas in various factor models. This negative relation between BTRs and stock returns is especially pronounced among financially constrained firms. A number of robustness checks indicate that the return difference between high BTR firms and low BTR firms is robust after controlling for various proxies of key talent compensation, organization capital, total customer capital, and various industry classifications.

In addition to testing the asset pricing implications, we conduct direct empirical tests on our model's mechanism. First, we test BTR's implications on talent turnovers and firms' financial policies. In the data, as in the model, the firms with lower BTRs are associated with higher turnover rates of both CEOs and innovators; moreover, this negative relation is more pronounced among financially constrained firms. On the other hand, the firms with lower BTRs 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 lower amounts of payout. Next, we provide evidence for non-pecuniary private benefits by showing that key talents have lower compensation when they work in the firms with greater brand stature. Finally, we show that the duration of executive compensation is longer in low BTR firms, suggesting that these firms actively manage pay duration. However, the difference in duration appears to be too small to fundamentally alleviate the liquidity constraints faced by low BTR firms.

In this paper, we emphasize the financial implications of customer capital compositions through the retaining costs of talent-based customer capital. The retaining costs impose operating leverage to the firm, and thus connect BTR to financial constraints risk and stock returns. In this sense, our empirical and theoretical findings provide a particular micro-foundation of the operating leverage channel for understanding stock returns. It is worth pointing out that other financial proxies for the relative importance of key talents' human capital (such as talent compensation) can be severely subject to endogeneity issues. They can be endogenously driven by many other factors (e.g. firms' past performance and future growth prospects) that are correlated with firms' expected returns. By contrast, we focus on the interaction between customer capital and human capital, and our BTR measure of key talents' importance through firms' customer capital alleviates this concern as it is not directly controlled by firms' endogenous financial decisions.

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

Our paper contributes to the emerging literature on the interaction between customer capital and finance. Titman (1984); Titman and Wessels (1988) provide the first piece of theoretical insight and empirical evidence about the interaction between firms' financial and product market characteristics (customers, workers, and suppliers). In this literature, a large body of research studies how financial characteristics influence performance and decisions in product market (see, e.g. Chevalier and Scharfstein, 1996; Fresard, 2010; Phillips and Sertsios, 2013; Gilchrist et al., 2017; D'Acunto et al., 2017), while only a few papers focus on the implication of product market characteristics on financial decisions and financial performance (see Banerjee, Dasgupta and Kim, 2008; Larkin, 2013; Gourio and Rudanko, 2014; Belo, Lin and Vitorino, 2014; Dou and Ji, 2017). We depart from the existing literature by investigating how the composition of customer capital (measured by BTR) affects firms' stock returns, talent turnovers, and financial policies. As a main contribution to this literature, we highlight that talent-based customer capital is fragile to financial constraints risk, while pure-brand-based customer capital is not; therefore, a deflated customer capital measure is proposed. Gourio and Rudanko (2014) introduce search frictions in the product market and develop a model that generates long-term customer relationships. They find that the product market search frictions affect the level and volatility of firms' investment and also the relation between investment and Tobin's q. Belo, Lin and Vitorino (2014) develop a model in which the firms with higher ratios of advertising expenditure stock to the number of employees are riskier because they are endogenously less productive due to the existence of adjustment costs. Using the BAV survey data, Larkin (2013) studies the role of brand stature in financial policies. She finds that firms with higher brand stature have larger net debt capacity, measured by higher leverage ratio and lower cash holdings. Our paper differs from Larkin (2013) in at least three ways: first, we investigate the role of compositions of customer capital; second, we find significant and robust asset pricing patterns and talent turnover patterns associated with the composition of customer capital; and third, building on the model of Gourio and Rudanko (2014), we embed customer capital in a tractable structural corporate model with endogenous value of liquidity to explain the new patterns.

Our paper is also related to the literature on inalienable human capital dating back to Hart and Moore (1994). Human capital is embodied in the firm's key talents who have the option to walk away. Thus, shareholders are exposed to the risk from key talents' limited commitment and firms' limited enforcement. The talent-based customer capital investigated in our paper provides one of the most concrete and convincing examples for inalienable human capital. Lustig, Syverson and Nieuwerburgh (2011) develop a model with optimal compensation to managers who cannot commit to staying with the firm. Their calibrated model can quantitatively reproduce the increase in managerial compensation and sensitivity of pay to performance in the data. Eisfeldt and Papanikolaou (2013) show that the firms with more organization capital are riskier due to greater exposure to technology frontier shocks. In the model of Eisfeldt and Papanikolaou (2013), talent turnovers are essentially technology adoptions with fixed costs. Our model focuses on a different angle, emphasizing that key talents may leave due to corporate financial constraints risk, and that this hurts the firm through a decrease in customer capital. Therefore, our theory is related to the work of Bolton, Wang and Yang (2016), who analyze the implication of inalienable human capital on corporate liquidity and risk management in a standard optimal contracting framework. By contrast, we focus on asset pricing implications.[2]

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

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

The rest of paper is organized as the follows. Section 2 describes the data sources. Section 3 explains the methodology to construct BTR measure, provides validity test to the measure, and illustrates the relation between BTR and firm characteristics. Section 4 presents our main empirical findings on the asset pricing implications of BTR. Section 5 develops an industry equilibrium asset pricing model. Section 6 calibrates the model's parameters and illustrates the model's predictions through simulation. Section 7 provides additional empirical support for the theoretical mechanism. Section 8 concludes.

2 Data

Our brand metrics data are from the BAV Group; it is regarded as the world's most comprehensive database of consumers' perception of brands. The BAV Group is one of the largest and leading consulting firms that conduct brand valuation surveys and provide brand development strategies for clients. The BAV brand perception survey consists of more than

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

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

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

The BAV brand perception survey is conducted at the brand level. We identify the firms that own the brands over time and then link the brand-level BAV survey data with Compustat and CRSP. We pay particular attention to the brands involved in M&As and make sure the brands are assigned correctly to firms. For each firm in a given year, we calculate the average scores of various brand metrics over all the brands owned by the firm.[3] We further merge the data with Execucomp and the Harvard Business School patent and innovator database (see Li et al., 2014; Brav et al., 2017). Our merged data span 1993-2016 and include firms listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from our analyses. In total, there are 1004 unique firms, and on average there are about 400 firms in the yearly cross section. The firms in the merged sample collectively own 4745 unique brands covered by the BAV survey. The entry and exit rates of the firms in the merged sample are around 7%, which are comparable to those in the Compustat data. We provide more details on the merged sample, including its distribution across industries, in Appendix E.3. Table F.1 in Appendix presents the summary statistics of main variables. Firms in the BAV sample and in the Compustat/CRSP sample have comparable book-to-market ratios and debt-to-asset ratios. The median book-to-market ratio of the BAV sample is 0.37, while it is 0.49 in the Compustat/CRSP sample. The median debt-to-asset ratio of the BAV sample is 0.55, while it is 0.44 in the Compustat/CRSP sample. The BAV sample is biased towards large firms. The median market capitalization of the BAV sample is $\$4,915$ million, while it is \$420 million in the Compustat/CRSP sample. Similarly, the median sales of the BAV sample is

[3] 58% of firm-year observations have only one brand in the BAV data. For firms that have more than one brand in the BAV data, we use several alternative methods to compute the firm-level brand metrics from the brand-level BAV data. We provide details on these methods in Appendix E.2. Our results are robust to the choice of these methods.

\$5,115 million, while it is \$424 million in the Compustat/CRSP sample. Since the BAV sample is not a random sample of the U.S. public firms, In Section E.4 in the Appendix, we replicate our analyses shown in the main text using the extended samples that cover the cross-section of all U.S. public firms.

3 The BTR Measure and Robust Firms

In this section, we first illustrate how we construct the brand-to-talent ratio (BTR) to measure the relative contribution of pure-brand-based customer capital and talent-based customer capital. We then study the firm characteristics associated with the BTR measure. In particular, we show that high BTR firms, a group of firms we refer to as robust firms, are associated with steady cash flows, and that their growth rates are less negatively affected by their peers' innovative outputs.

3.1 The BTR Measure

BTR is derived from brand stature and brand strength, the two most important brand metrics developed by the BAV Group. The BAV Group constructs brand stature to measure existing customers' loyalty. Brand stature quantifies, as an approximation, how much a brand is held in high esteem by existing customers. Brand stature is thus a proxy for current customer capital, which is the sum of pure-brand-based customer capital and talent-based customer capital. The BAV Group constructs brand strength to measure how much a brand is perceived to be innovative and distinctive. Brand strength quantifies, as an approximation, the degree of a brand's energized differentiation from similar products perceived by existing and potential customers. Since the creation of innovative products and distinctive brands requires significant contribution from key talents, we use brand strength as a proxy for talent-based customer capital. We provide more details on the construction of these two metrics in Appendix E.1.

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

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

BTR is a proxy for the relative contribution between pure-brand-based customer capital and talent-based customer capital. The implicit assumption we make here is that brand strength reflects more about talent-based customer capital compared to brand stature. We do not assume that brand strength is entirely contributed by talent-based customer capital. Since the distribution of BTR is skewed, we use the log transformation of BTR (denoted as lnBTR) in our empirical analysis. As shown in Appendix E.3, lnBTR exhibits a good amount of variations and the distribution of lnBTR is approximately normal.

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

Relation to Organization Capital. Following Eisfeldt and Papanikolaou (2013), we construct organization capital from SG&A expenditures using the perpetual inventory method. As shown by Column (5) of Table 1, the relation between BTR and organization capital is weak. This is because SG&A contains both selling expenses and administrative expenses. Selling expenses boost brand loyalty and are positively related to BTR (see Column 4 of Table 1), while administrative expenses mainly reflect key talents' compensation and are negatively related to BTR (see Column 1 of Table 1). The weak correlation between BTR and organization capital suggests that the two measures capture different firm characteristics. In fact, we include organization capital as a control variable in studying the relation between BTR and the outcome variables.

3.2 Robust Firms: High BTR Firms

We define the high BTR firms as robust firms because they mostly consist of pure-brand-based customer capital, which is less fragile to aggregate shocks and peers' competition. This is consistent with the firm characteristics shown in Table 2; that is, high BTR firms tend to have high profitability; they are less innovation intensive, and as a result, they tend to have low asset growth rates. Below, we further document that high BTR firms are associated with steady cash flows, and that their growth rates are less negatively affected by their peers' innovative outputs.

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

	(1)	(2)	(3)	(4)	(5)
			$ln\text{BTR}_t$		
$ln(\text{AdminExpenses/Sales})_{t-1}$	-0.159^{***}				
	[−4.191]				
$ln(\text{R\&D/Sales})_{t-1}$		-0.211^{***}			
		[−6.735]			
$ln(\text{ExecuComp/Sales})_{t-1}$			-0.254^{***}		
			[−8.225]		
$ln(\text{AdvExp/Asset})_{t-1}$				0.065^{**}	
				[2.296]	
$ln(\text{OC/Asset})_{t-1}$					0.012
					[0.589]
$ln\text{size}_{t-1}$	0.125^{***}	0.120^{***}	−0.021	0.152^{***}	0.146^{***}
	[6.425]	[4.986]	[−0.963]	[7.886]	[7.486]
$ln\text{BEME}_{t-1}$	0.088^{**}	0.006	0.003	0.132^{***}	0.129^{***}
	[2.477]	[0.133]	[0.084]	[3.581]	[3.538]
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5250	2656	4831	5767	5589
R-squared	0.266	0.342	0.287	0.250	0.247

Note: This table shows the relation among BTR, key talent compensation, and organization capital. *ln*BTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The dependent variable is *ln*BTR. We standardize *ln*BTR to ease the interpretation of the coefficients. The independent variables are the natural log of the administrative-expenses-to-sales ratio, the natural log of the R&D-to-sales ratio, the natural log of the executive-compensation-to-sales ratio, the natural log of the advertisement-to-asset ratio, and the natural log organization-capital-to-asset ratio. Control variables include the natural log of firm market capitalization (*ln*size) and the nature log of the book-to-market ratio (*ln*BEME). We include year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

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

$$\text{Vol}_{i,t} = \alpha_{ind} + \alpha_t + \beta ln\text{BTR}_{i,t-1} + \gamma'\text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{3.1}$$

The dependent variables are the measures of cash flow volatility including: 1) volatility of the forward-looking growth rates of sales, 2) volatility of the forward-looking net-income-to-asset ratios, 3) volatility of the forward-looking EBITDA-to-asset ratios, and 4) volatility of stock returns. The main independent variable is the lagged *ln*BTR, which is standardized to ease the interpretation of its coefficients. Control variables are lagged firm characteristics, including the natural log of the organization-capital-to-asset ratio $ln(\text{OC/Asset})$, the natural log of firm market capitalization (*ln*size), the natural log of the book-to-market ratio (*ln*BEME), and the natural log of the debt-to-equity ratio (*ln*lev). We include year fixed effects and the SIC-2 industry fixed effects in the regressions. Standard errors are clustered by firm and year. As shown in Table 3, the coefficients of *ln*BTR are negatively associated with all four cash flow

Table 2: Firm characteristics and BTR.

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

Note: This table shows the characteristics of the five portfolios sorted on BTR. We report the mean and median firm characteristics for each portfolio. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period spans 1993 and 2016. We explain the definition of the variables in Appendix Table A.1.

volatility measures. These results are both statistically and economically significant. Taken together, our analysis suggests that high BTR firms are a group of firms associated with steady sales growth and stable cash flows.

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

Table 3: BTR and cash flow volatility.

	(1) Vol(Sales Growth)$_t$ (%)	(2) Vol($\frac{NI}{Asset}$)$_t$ (%)	(3) Vol($\frac{EBITDA}{Asset}$)$_t$ (%)	(4) Vol(Daily Ret)$_t$ (%)
$ln\text{BTR}_{t-1}$	-1.801^{**}	-0.713^{*}	-0.334^{*}	-0.274^{***}
	[−2.196]	[−1.837]	[−1.916]	[−5.870]
$ln(\text{OC/Asset})_{t-1}$	−0.328	0.270^{**}	0.173^{***}	0.060^{***}
	[−0.682]	[2.382]	[3.558]	[3.839]
$ln\text{size}_{t-1}$	-1.625^{*}	-1.045^{**}	-0.587^{***}	-0.249^{***}
	[−2.037]	[−2.783]	[−3.828]	[−9.969]
$ln\text{BEME}_{t-1}$	-0.933	-0.357	-0.867***	0.125
	[−1.124]	[−0.600]	[−3.401]	[1.545]
$ln\text{lev}_{t-1}$	0.302	−0.119	-0.497^{***}	0.163^{***}
	[0.410]	[−0.426]	[−4.050]	[2.860]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5452	5452	5448	5828
R-squared	0.085	0.167	0.220	0.505

Note: This table shows the relation between BTR and firms' cash flow volatilities. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The dependent variables are the volatility of the forward-looking growth rates of sales (standard deviation of the six yearly growth rates of sales over the period t through $t+5$), the volatility of the forward-looking net-income-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$), the volatility of the forward-looking EBITDA-to-asset-ratio (standard deviation of the six yearly ratios from the period t through $t+5$), and the volatility of daily stock returns in current year (t). These dependent variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), and the natural log of the debt-to-equity ratio (lnlev). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

$$
\begin{aligned}
&ln(\text{Outcome}_{i,t+5}) - ln(\text{Outcome}_{i,t}) = \alpha_{ind} + \alpha_t + \beta_1 \text{Innovation\_Peers}_{i,t} \\
&+ \beta_2 \text{Innovation\_Peers}_{i,t} \times ln\text{BTR}_{i,t-1} + \beta_3 \text{Innovation\_Self}_{i,t} + \beta_4 \text{Innovation\_Self}_{i,t} \times ln\text{BTR}_{i,t-1} \\
&+ \beta_5 ln\text{BTR}_{i,t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \qquad (3.2)
\end{aligned}
$$

The outcome variables are the five-year growth rates of the (a) firm gross profits, (b) the value of output, (c) capital stock, and (d) the number of employees. The growth rates are computed by $ln(\text{Outcome}_{i,t+5}) - ln(\text{Outcome}_{i,t})$. We standardize the innovative outputs and lnBTR to ease the interpretation of their coefficients. Following Kogan et al. (2017), we include the one-year lagged value of firm capital, the one-year lagged value of the number of employees, and the firm's idiosyncratic volatility as controls. We also include industry and year fixed effects in the regressions. Standard errors are clustered by firm and year.

Table 4 presents the results of the regressions. Consistent with Kogan et al. (2017), we find that firm growth is negatively related to peers' innovative outputs. Importantly, we find that

BTR mitigates this negative relation. The coefficients β_2 are positive and statistically significant, suggesting that the firms with higher BTRs react less negatively to peer firms' innovative outputs. Since the firms with higher BTRs suffer less from product market competition, their growth is less volatile. The relation between BTR and the sensitivity of firm growth to innovative outputs is economically significant. For firms with the average level of lnBTR, a one standard deviation increase in the peer firms' innovative outputs is associated with a 9.2% drop of profits over five years. The sensitivity of firm growth to innovation reduces significantly when BTR increases. For the firms whose lnBTR is two standard deviations above the average, the sensitivity of their profit growth to the innovative outputs of their peers' is indistinguishable from zero.

Examples for high BTR and low BTR firms. Do these robust firms have to be value firms? Not necessary. We emphasize that high BTR firms can be either value firms or growth firms; meanwhile, value firms and growth firms may also be associated with low BTRs. Let us provide a few concrete real-life examples in 2016. Among the growth firms, Coca-Cola is a typical high BTR firm, whose customers' loyalty is unrelated to executives or innovators and mainly depends on customers' habits and tastes. By contrast, Tesla is a typical growth firm with a low BTR, whose value crucially depends on its R&D team and probably the charismatic leadership of Elon Musk. Among the value firms, Delta Air Lines (DAL) is a typical high BTR firm since customers' brand loyalty is largely from memberships and rewards programs. By contrast, Yahoo is a typical value firm with a low BTR, which exposes Yahoo to the displacement risk.

4 Main Empirical Results

In this section, we systematically examine the asset pricing implications of BTR. We show that the firms with lower BTRs have higher average excess returns and risk-adjusted returns. This pattern is particularly pronounced among financially constrained firms, suggesting that the firms with lower BTRs are more exposed to financial constraints risk. The negative relation between BTR and cross-sectional stock returns is robust after controlling for the measures of customer capital, organization capital, key talent compensation, as well as various industry classifications. Finally, we construct proxies of BTR and extend the analysis to the universe of the U.S. publicly listed firms. We show that the proxies of BTR are negatively priced in the extended sample.

Table 4: BTR and the displacement risk in creative destruction.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\frac{\text{Profits}_{t+5}}{\text{Profits}_t})$		$\ln(\frac{\text{Output}_{t+5}}{\text{Output}_t})$		$\ln(\frac{\text{Capital}_{t+5}}{\text{Capital}_t})$		$\ln(\frac{\text{Labor}_{t+5}}{\text{Labor}_t})$	
Innovation_Peers$_t$	-0.079^{***}	-0.092^{***}	-0.069^{***}	-0.084^{***}	-0.069^{***}	-0.083^{***}	-0.076^{***}	-0.099^{***}
	[−3.966]	[−3.736]	[−3.996]	[−4.322]	[−3.457]	[−3.737]	[−3.781]	[−4.272]
Innovation_Peers$_t$ * lnBTR$_{t-1}$		0.033^{*}		0.036^{**}		0.037^{*}		0.055^{***}
		[1.813]		[2.604]		[2.025]		[3.201]
Innovation_Self$_t$	0.025^{***}	0.030^{***}	0.027^{***}	0.033^{***}	0.039^{***}	0.044^{***}	0.031^{***}	0.040^{***}
	[3.033]	[3.409]	[3.795]	[4.050]	[4.935]	[4.767]	[4.239]	[4.924]
Innovation_Self$_t$ * lnBTR$_{t-1}$		-0.017^{*}		-0.016^{**}		-0.017^{*}		-0.026^{***}
		[−1.933]		[−2.105]		[−2.043]		[−3.683]
lnBTR$_{t-1}$		0.023		0.015		0.000		0.048
		[0.529]		[0.400]		[0.007]		[1.209]
lnCapital$_{t-1}$	0.004	0.004	0.014	0.014	-0.156^{***}	-0.156^{***}	0.114^{**}	0.114^{***}
	[0.104]	[0.093]	[0.341]	[0.348]	[−3.047]	[−3.010]	[2.855]	[2.894]
lnLabor$_{t-1}$	-0.102^{**}	-0.106^{**}	-0.124^{***}	-0.126^{**}	0.043	0.044	-0.268^{***}	-0.278^{***}
	[−2.298]	[−2.183]	[−2.904]	[−2.746]	[0.954]	[0.966]	[−5.713]	[−5.711]
IVOL$_{t-1}$	0.000	0.000	−0.000	0.000	−0.000	−0.000	−0.000	−0.000
	[0.347]	[0.502]	[−0.019]	[0.184]	[−0.967]	[−0.962]	[−1.490]	[−1.276]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3583	3583	3556	3556	3589	3589	3573	3573
R-squared	0.246	0.250	0.287	0.291	0.366	0.371	0.298	0.309

Note: This table shows the relation between BTR and the sensitivity of firm growth to innovative outputs. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The dependent variables are the five year growth rate of the (a) firm gross profits (Compustat item *sale* minus Compustat item *cogs*, deflated by the CPI), (b) value of output (Compustat item *sale* plus change in inventories Compustat item *invt*, deflated by CPI), (c) capital stock (Compustat item *ppegt*, deflated by the NIPA price of equipment), and (d) number of employees (Compustat item *emp*). The main independent variables include the innovative outputs of the firms (Innovation_Self), the innovative outputs of the peer firms (Innovation_Peers), the interaction between lnBTR and the two innovative output measures, and lnBTR. Following Kogan et al. (2017), we measure the innovative outputs of a given firm (Innovation_Self) using the sum of patent value normalized by the firm's book asset. The patent value is measured in dollars based on stock market reaction to the patent issuance. We measure the innovative outputs of the peer firms (Innovation_Peers) using the sum of patent value of the peer firms in the SIC-3 industry normalized by the sum of the book assets of the peer firms. We standardize the innovative outputs and lnBTR to ease the interpretation of the coefficients. Control variables include the lagged value of firm capital (lnCapital), the lagged value of number of employees (lnLabor), and the firm's idiosyncratic volatility (IVOL). We include industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We download the innovation data from Noah Stoffman's website and the data span 1926-2010. Our merged sample spans 1993-2010. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.1 Portfolio Returns Sorted on BTR

In June of year t, we sort firms into five quintiles based on their BTRs in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We compute the value-weighted portfolio returns and estimate their alphas and betas using various asset pricing models.[4]

Table 5 presents the cross-sectional asset pricing results of the sorted portfolios based on BTR. As shown in Panel A, the high BTR portfolio (Quintile 5) has 9.64% annualized average

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

excess return. By contrast, the low BTR portfolio (Quintile 1) has 15.36% annualized average excess return. The -5.72% return of the long-short BTR portfolio, referred to as the brand-minus-talent (BMT) portfolio, is statistically significant; the magnitude of the return spread is also economically significant since it is close to the level of equity premium and value premium. Because high BTR firms may have differential exposures to risk factors, we estimate the alphas using the following asset pricing models for risk adjustment: the Fama-French three-factor model (see Fama and French, 1993), the Carhart four-factor model (see Carhart, 1997), the Pástor-Stambaugh five-factor model (see Pastor and Stambaugh, 2003)[5], and the Fama-French five-factor model (see Fama and French, 2015). We find that the BMT portfolio has significantly negative alphas in all models. The annualized alphas range from -5.67% to -9.81%. All alphas are statistically significant. These results suggest that BTR largely determines firms' exposures to some factors that are probably not fully explained by traditional asset pricing factors.

We have documented the negative relation between portfolio alphas and BTR. Here, we further examine the persistence of this negative relation. We use an event study approach to estimate the alphas around the formation of BTR portfolios. Figure 2 plots the alphas of the value-weighted portfolios estimated by various asset pricing models. We find that the negative relation between portfolio alphas and BTR exists three years before and continues to exist three years after portfolio formation. This result reinforces the findings in Table 5 in the sense that BTR is a persistent firm characteristic priced in the cross section.[6]

Table 5 also tabulates the factor loadings (i.e. betas) of the Fama-French five-factor model, with the factor loadings of other models postponed to Appendix Table F.5. We find that high BTR firms load positively on the HML, RMW and CMA factors[7], suggesting that these firms tend to be value firms with high profitability and low asset growth rates. On the contrary, low BTR firms load negatively on these three factors. As a result, the BMT portfolio loads positively on the HML, RMW and CMA factors with large t-statistics $(3, 83$, 5.19 and 3.49, respectively). The alpha is -9.81% with t-statistic of -4.32.

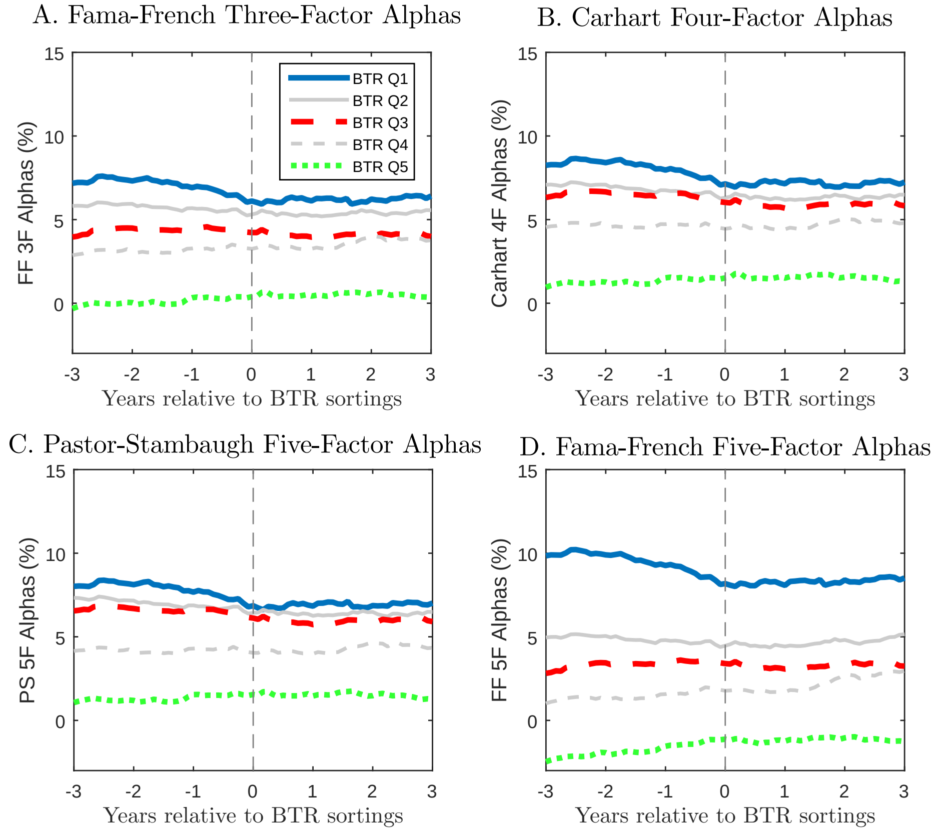
4.2 BTR Return Spreads Unexplained by Mispricing Factors

We have shown that the alpha of the long-short BTR portfolio cannot be explained by the traditional risk-based asset pricing factors. Could the alpha be explained by mispricing? Given the persistence of the alpha over time, it seems unlikely that the return spreads across

[5]The Pástor-Stambaugh five-factor model contains the Fama-French three factors (see Fama and French, 1993), the momentum factor (see Carhart, 1997), and the Pástor-Stambaugh liquidity factor (see Pastor and Stambaugh, 2003).

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

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



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

Figure 2: Before- and after-sorting alphas for BTR quintiles in event time

BTR portfolios are due to mispricing. Nonetheless, we test this possibility directly using the Stambaugh-Yuan Mispricing Factor model (see Stambaugh and Yuan, 2016).[8]

Table 6 tabulates the alphas and betas of the BTR portfolios estimated by the Stambaugh-Yuan Mispricing Factor model. The BMT portfolio loads positively on the MGMT factor, and negatively on the PERF factor. However, the alphas of the BMT portfolio remain robust after we control for the mispricing factors, suggesting that the returns spreads across BTR portfolios are likely due to risk-based factors.

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

Table 5: Portfolio excess returns and alphas sorted on BTR.

BTR Portfolios	1 (Low)	2	3	4	5 (High)	$5-1$
			Panel A: Average Excess Returns			
$\mathbb{E}[R]-r_f$ (%)	15.36***	13.43***	13.14***	11.19***	9.64***	−5.72**
	[3.54]	[3.46]	[4.00]	[3.57]	[2.77]	[−2.03]
			Panel B: Fama-French Three-Factor Model			
α (%)	6.58***	4.24**	5.26***	3.64***	0.67	−5.91**
	[3.25]	[2.49]	[3.59]	[2.86]	[0.45]	[−2.57]
			Panel C: Carhart Four-Factor Model			
α (%)	7.89***	5.81***	6.29***	4.63***	1.75	−6.14***
	[3.98]	[3.62]	[4.41]	[3.78]	[1.22]	[−2.63]
			Panel D: Pástor-Stambaugh Five-Factor Model			
α (%)	7.32***	5.52***	6.00***	4.62***	1.65	−5.67**
	[3.70]	[3.43]	[4.20]	[3.74]	[1.15]	[−2.42]
			Panel E: Fama-French Five-Factor Model			
α (%)	7.38***	2.63	2.04	1.85	−2.43*	−9.81***
	[3.51]	[1.54]	[1.49]	[1.44]	[−1.75]	[−4.32]
β_{mkt}	1.15***	1.18***	1.09***	1.00***	1.12***	−0.04
	[24.61]	[30.96]	[35.63]	[34.95]	[36.25]	[−0.73]
β_{smb}	0.10	0.17***	0.04	0.03	0.16***	0.07
	[1.63]	[3.35]	[0.91]	[0.87]	[4.11]	[1.00]
β_{hml}	−0.04	0.15**	0.10**	0.07	0.28***	0.32***
	[−0.54]	[2.45]	[1.98]	[1.55]	[5.47]	[3.83]
β_{rmw}	−0.03	0.31***	0.45***	0.20***	0.43***	0.46***
	[−0.34]	[4.65]	[8.38]	[4.06]	[8.01]	[5.19]
β_{cma}	−0.22**	−0.06	0.21***	0.20***	0.19***	0.41***
	[−1.99]	[−0.71]	[2.94]	[2.98]	[2.70]	[3.49]
R^2	0.795	0.831	0.849	0.854	0.862	0.434

Note: This table shows the asset pricing tests for portfolios sorted on BTR. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. In June of year t, we sort firms into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We compute the value-weighted portfolio returns and report the average excess returns of the individual portfolios and the long/short portfolio. We also report the portfolio alphas estimated by the Fama-French three-factor model, the Carhart four-factor model, the Pástor-Stambaugh five-factor model, and the Fama-French five-factor model. The portfolio betas of the Fama-French five-factor are also tabulated. Data on the Fama-French three factors and five factors are from Kenneth French's website. The Pástor-Stambaugh liquidity factor is from L'uboš Pástor's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.3 BTR and Financial Constraints

To further understand the cross-sectional relation between BTR and stock returns, we double sort the portfolios based on BTR and the measures of financial constraints. We find that the negative relation between BTR and stock returns are more pronounced among financially constrained firms, suggesting that the firms with lower BTRs have larger exposure to financial constraints risk. In addition, we verify that the negative relation between BTR and stock returns

Table 6: BTR return spreads cannot be explained by mispricing factors.

BTR Portfolios	1 (Low)	2	3	4	5 (High)	5 − 1
			Stambaugh-Yuan Mispricing Factor Model			
α (%)	6.475***	5.214***	4.227***	3.446**	−0.220	−6.695**
	[2.963]	[2.800]	[2.611]	[2.528]	[−0.127]	[−2.539]
β_{mkt}	1.194***	1.086***	0.994***	0.930***	1.031***	−0.164***
	[24.594]	[26.227]	[27.628]	[30.716]	[26.643]	[−2.795]
β_{smb}	0.085	0.010	−0.116***	−0.029	0.002	−0.082
	[1.552]	[0.224]	[−2.864]	[−0.864]	[0.056]	[−1.249]
β_{mgmt}	−0.096	0.127**	0.293***	0.216***	0.429***	0.525***
	[−1.444]	[2.248]	[5.972]	[5.225]	[8.134]	[6.565]
β_{perf}	0.037	−0.096***	−0.033	−0.074***	−0.083**	−0.121**
	[0.904]	[−2.740]	[−1.093]	[−2.863]	[−2.534]	[−2.422]
R^2	0.790	0.809	0.798	0.843	0.793	0.274

Note: This table shows the asset pricing tests for portfolios sorted on BTR. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. In June of year t, we sort firms into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We compute the value-weighted portfolio returns and report the portfolio alphas and betas estimated by the Stambaugh-Yuan Mispricing Factor model (see Stambaugh and Yuan, 2016). Data on the mispricing factors (mgmt and perf) are from Yu Yuan's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

is robust in a number of robustness checks using double-sort analyses.

Following the literature, we use three measures to capture financial constraints: the HP index (see Hadlock and Pierce, 2010), the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007), and firm size measured by the market capitalization of equity (see, e.g. Gilchrist and Himmelberg, 1995; Livdan, Sapriza and Zhang, 2009; Hadlock and Pierce, 2010; Li, 2011). The firms with higher HP index, higher WW index, and smaller size are more likely to be financially constrained.

In June of year t, we sort firms into three groups based on their financial constraint measures. We further sort firms in each group into five quintiles based on firms' BTR in year $t-1$. We compute the value-weighted portfolio returns and estimate their alphas using various asset pricing models. Table 7 presents the average excess returns and alphas of the BMT portfolios. Although the average excess returns and alphas of the BMT portfolios are negative in all groups, the magnitudes of the average excess returns and alphas are much larger among financially constrained firms. This pattern is robust to the choice of financial constraint measures and asset pricing models. These findings suggest that the asset pricing implications of BTR are closely related to firms' financial constraints risk. Therefore, in Section 5, we develop a model emphasizing firms' differential exposure to financial constraints risk due to operating leverage.

Table 7: Excess BMT portfolio returns across subsamples split by financial constraints.

Low HP	Medium HP	High HP	Low WW	Medium WW	High WW	Big Size	Medium Size	Small Size
				Panel A: Excess Return (%)				
−2.40	−0.06	−10.46**	−1.65	−4.64	−10.01**	−1.64	−8.64***	−9.23*
[−1.39]	[−0.02]	[−2.41]	[−0.66]	[−1.55]	[−1.98]	[−0.53]	[−2.65]	[−1.89]
				Panel B: Fama-French Three-Factor α (%)				
−3.13*	−0.13	−9.66**	−2.11	−4.99*	−9.48**	−1.05	−9.94***	−10.47**
[−1.81]	[−0.04]	[−2.46]	[−0.89]	[−1.78]	[−2.10]	[−0.41]	[−3.32]	[−2.25]
				Panel C: Carhart Four-Factor α (%)				
−2.51	−1.10	−9.28**	−2.29	−5.58**	−9.82**	−2.20	−9.07***	−11.49**
[−1.44]	[−0.39]	[−2.33]	[−0.96]	[−1.97]	[−2.15]	[−0.86]	[−3.01]	[−2.45]
				Panel D: Fama-French Five-Factor α (%)				
−2.45	−2.81	−13.06***	−4.34*	−7.39**	−14.12***	−6.94***	−11.98***	−11.81**
[−1.37]	[−0.99]	[−3.22]	[−1.79]	[−2.56]	[−3.05]	[−2.93]	[−3.85]	[−2.43]

Note: This table shows the brand-minus-talent (BMT) portfolio returns across subsamples split by financial constraints. In June of year t, we sort firms into three groups based on the finanical constrain measures: the HP index (see Hadlock and Pierce, 2010), the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007), and the firm size measured by the market capitalization of equity. We then sort firms in each group into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We compute the value-weighted portfolio returns and report the average excess returns of the long/short BTR portfolio, which is deonoted as the brand-minus-talent (BMT) portfolio. We also report the alphas of the BMT portfolios estimated by the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. Data on the Fama-French three factors and five factors are from Kenneth French's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.4 Double-Sort Analyses

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

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

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

As a robustness check, we reverse the order of the double sort and test whether BTR is priced in the cross section after controlling for the three measures of customer capital. As shown in Appendix Table F.7, BTR remains priced in the cross section after controlling for customer capital.[9] Taken together, the above results suggest that it is essential to examine the composition when we study the asset pricing implications of customer capital.

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

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

[9] We find that the negative relation between BTR and stock returns mainly concentrates in the firms with high fluidity, suggesting that the operating leverage imposed by talent-based customer capital makes firms particularly risky when they face intense competition in the product market. This result is consistent with Opler and Titman (1994), who find the performance of financially distressed firms declines more in concentrated industries as their competitors reduce price and gain market share from them.

Industry Classifications. Finally, we test whether the cross-sectional relation between BTR and stock returns holds within industries (see Appendix Table F.9). We find that the BMT portfolios within industries have negative average excess returns and alphas, which are both statistically and economically significant. The return patterns are robust across various industry classifications, suggesting that BTR's within-industry variations are priced in the cross section.[10]

4.5 Analyses in the Extended Sample

We use two approaches to overcome the limitation in the breadth and length of the BAV data. We briefly describe these two approaches here and explain the details in Appendix E.4 and in Online Appendix. In the first approach, we estimate the BMT betas for all publicly listed firms by regressing the stock returns of individual firms on the returns of the BMT portfolio using a rolling estimation window approach. We then use these BMT betas as our proxies for BTRs. This allows us to extend the sample cross sectionally to all publicly listed U.S. firms in the time period covered by the BAV sample. We verify that BMT is an asset pricing factor as the BMT beta is priced in the cross-section of U.S. public firms. In the second approach, we extend our sample both cross sectionally and in time series using a mimicking portfolio method. We construct the mimicking portfolio by projecting the returns of the BMT portfolio onto the space of excess returns of asset pricing factors and industry portfolios. We then compute the mimicking portfolio beta for all the stocks in the CRSP-Compustat universe and use it as a proxy for BTR in the extended sample. We find that the mimicking portfolio beta is priced cross sectionally in the CRSP-Compustat universe.

5 Model

In this section, we develop an industry equilibrium asset pricing model of heterogeneous firms to explain the asset pricing pattern. We incorporate product market search frictions and key talents' inalienable human capital into a structural model with liquidity constraints.

5.1 Basic Environment

Firms and Agents. In the economy, there is a continuum of firms and agents. Some agents are talents who manage firms and the others are shareholders who fund firms by holding equity. Talents and shareholders are also customers of firms, and they purchase the goods produced by

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

firms. We assume that agents can trade a complete set of contingent claims on consumption. Thus, there exists a representative agent who owns the equity and consumes the goods of all firms. The representative agent is only exposed to the economy's aggregate shocks. Without creating confusions, we omit the subscript for each firm in the rest of the paper to simplify the notations.

The Firm's 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:

$$\mathrm{d}K_t = -\delta_K K_t \mathrm{d}t + \mathrm{d}I_t, \tag{5.1}$$

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

$$Y_t = e^{a_t} K_t. \tag{5.2}$$

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

$$\mathrm{d}a_t = -\mu_a(a_t - \overline{a})\mathrm{d}t + \sigma_a \sqrt{a_t}\mathrm{d}Z_t^a, \tag{5.3}$$

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

Demand orders come from the firm's customer capital B_t, which can be thought of as a measure of the firm's existing customer base due to brand loyalty. Over $[t, t + \mathrm{d}t]$, the firm receives flow demand $B_t \mathrm{d}t$. The units of goods sold by the firm is $S_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$:

$$S_t = \min\left(Y_t, B_t\right), \tag{5.4}$$

capturing the fact that total sales cannot exceed production output or the size of customer base.

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

$$B_t = P_t + T_t. \tag{5.5}$$

The two components are distinguished by the fragility to key talent turnovers, which is elaborated in the next subsection. Denote $m_t \equiv T_t / B_t$ as the fraction of customer capital that is talent based, reflecting the inverse of our empirical BTR measure.[11]

In Appendix C, we micro found the creation and maintenance of customer capital by introducing search frictions in the product market using competitive search (see Moen, 1997; Gourio and Rudanko, 2014). The firm offers initial discounts τ_t and hires sales representatives s_t to build new customer capital at convex costs $\alpha s_t^{\eta} T_t \mathrm{d}t$ over $[t, t+\mathrm{d}t]$. The evolution of customer capital B_t is given by

$$\mathrm{d}B_t = [\mu(\tau_t, s_t) - \delta_B / m_t] T_t \mathrm{d}t, \tag{5.6}$$

where the Poisson rate δ_B reflects customer capital depreciation due to idiosyncratic exogenous reasons. In equilibrium, we have

$$\mu(\tau_t, s_t) = \psi \tau_t^{\chi - 1} s_t, \tag{5.7}$$

implying that the firm can grow customer capital faster by offering greater initial discounts and hiring more sales representatives. The parameters ψ and χ capture the degree of search frictions in the product market. New customer capital is randomly split into pure-brand-based customer capital P_t and talent-based customer capital T_t.[12] In particular, the two components evolve according to

$$\mathrm{d}P_t = [f_t \mu(\tau_t, s_t) - \delta_B (1 - m_t)/m_t]\, T_t \mathrm{d}t; \tag{5.8}$$

$$\mathrm{d}T_t = [(1 - f_t)\mu(\tau_t, s_t) - \delta_B]\, T_t \mathrm{d}t. \tag{5.9}$$

The variable f_t reflects the fraction of new customers whose brand loyalty is unrelated to the firm's key talents. We assume f_t to follow a Markov process with finite possible values $0 < f_{(1)} < \cdots < f_{(N)} < 1$. Within the next instant $\mathrm{d}t$, f_t has intensity π to jump. Conditional on that f_t jumps in the next instant $\mathrm{d}t$, it immediately reaches its new possible levels with probability $\Phi(f_{(j)})$ for $j = 1, \cdots, N$.

The Firm's Liquidity. The firm faces cash flow shocks proportional to customer capital, modelled as $\sigma_B B_t \mathrm{d}Z_t^B - \zeta B_t \mathrm{d}M_t$. Here, Z_t^B is a standard Brownian motion that is independent of Z_t^a, capturing small idiosyncratic cash flow shocks. M_t is a Poisson process with time-varying intensity ξ_t, capturing the firm's exposure to idiosyncratic negative jump shocks with proportional jump size ζ.

We assume that the firm has access to the equity market but not the corporate debt market.[13]

[11] We focus on the inverse of BTR because m_t naturally has support $[0, 1]$, which ensures the simplicity of our PDE formulas.

[12] Our model does not speak to the micro-foundation of BTR. In reality, new customers brought by key talents' personal connections are more likely to be talent-based customer capital while customers attracted by advertisements are less likely to be maintained by key talents. We leave the task of understanding the formation of BTR for future research.

[13] The assumption is innocuous for our purpose since we focus on endogenous time-varying marginal value of

The firm has the option to pay out lump-sum dividend $\mathrm{d}D_t$ or issue equity $\mathrm{d}H_t$ to finance various expenses. Equity financing is costly. The financing cost includes a fixed cost γ proportional to customer capital B_t and a variable cost φ proportional to the amount of issued equity as in Bolton, Chen and Wang (2011). All the financing costs are borne by shareholders while key talents are not required to chip in.

The financial constraints risk motivates the firm to hoard cash W_t on its balance sheet. However, holding cash is costly due to the agency costs associated with free cash in the firm or tax distortions.[14] We thus assume that the rate of return from the firm's cash inventory is the risk-free rate r minus a carry cost $\rho > 0$. The cash-carrying cost implies that the firm would pay out dividends when cash holdings W_t are high.

Aggregate Liquidity Shocks and Pricing Kernel. All firms' liquidity condition, or marginal value of liquidity, can be simultaneously affected by an economy-wide shock. Such aggregate shocks are generically referred to as *aggregate liquidity shocks*, which could be driven by different fundamental forces. For example, the poor liquidity condition can be the result of tight supply of liquidity due to financial sector dysfunction (see, e.g. Jermann and Quadrini, 2012; Gilchrist and Zakrajšek, 2012; Bolton, Chen and Wang, 2013; Iyer et al., 2014), or it could be the result of excessive demand for liquidity due to good investment opportunities (see, e.g. Gomes, Yaron and Zhang, 2006; Riddick and Whited, 2009).

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

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

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t - \kappa_a \mathrm{d}Z_t^a + \sum_{\xi' \neq \xi_t} \left[e^{-\kappa(\xi_t,\xi')} - 1 \right] (\mathrm{d}N_t^{(\xi_t,\xi')} - q^{(\xi_t,\xi')}\mathrm{d}t). \tag{5.10}$$

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

liquidity. The simplification captures the main idea of our theory while maintaining tractability.

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

5.2 Turnovers and Non-Pecuniary Private Benefits

We now introduce the two unique features of customer capital – non-pecuniary private benefits and inalienable human capital. As we show in Section 6, the two features play quantitatively important roles in explaining the cross-sectional stock return patterns.

Non-Pecuniary Private Benefits. When managing a firm with customer capital B_t, key talents enjoy non-pecuniary private benefits hB_t with a positive constant h. The assumption that non-pecuniary private benefits are proportional to customer capital B_t reflects the findings and discussions in the existing literature. For example, key talents can gain identity-based benefits (see Akerlof and Kranton, 2005) while working at the firms with strong brand values. This is because the firms with stronger brands offer key talents more opportunities of self-enhancement, higher visibility among their peers, and larger likelihood to be perceived as being successful. Moreover, future employers may rely on the brand affiliation as a credible indicator of human capital quality. Thus working for high-brand-value firms benefits key talents by bringing a positive signal on their unobserved abilities (see Weiss, 1995). The proportional non-pecuniary private benefits for key talents hB_t is commonly adopted in the literature as a parsimonious modeling technique and an approximation Eisfeldt and Rampini (2008).

Inalienable Human Capital. Shareholders have the option to fire key talents, and in the meanwhile, key talents have the option to leave the firm and start a new business.[15] When key talents leave, a fraction ω of talent-based customer capital T_t is taken away and shareholders hire new key talents to manage the rest talent-based customer capital $(1-\omega)T_t$. This implies that the firm's key talents cannot costlessly be replaced by shareholders, sharing the spirit of "inalienable human capital" coined by Hart and Moore (1994).

Optimal Long-Term Contract. To prevent key talents from leaving the firm, shareholders compensate key talents through a long-term contract, as in DeMarzo and Sannikov (2006); DeMarzo et al. (2012); Eisfeldt and Papanikolaou (2013), that endogenously determines the payoffs to both parties. We now derive the optimal long-term contract.

Upon termination of the employment relationship, key talents create a new firm with customer capital $(\omega+\ell)T_t$, where ωT_t is the customer capital taken away from the firm and ℓT_t is the new customer capital created by key talents' business idea. The new firm is sold to the representative agent. At the inception, the representative agent builds up internal liquidity by issuing equity. Let $V(B_t, T_t, W_t, f_t, a_t, \xi_t)$ denote the firm's value. The new firm's value after

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

equity issuance is $V((\omega+\ell)T_t,(1-f')(\omega+\ell)T_t,W_0,f',a_t,\xi_t)$, given initial cash cash holdings W_0 and pure-brand-based transformation rate f'. The representative agent chooses the optimal amount of equity financing W_0^* to maximize the new firm's value before equity issuance:

$$V^n(T_t,a_t,\xi_t)=\max_{W_0}-\gamma(\omega+\ell)T_t-(1+\varphi)W_0+\mathbb{E}\left[V((\omega+\ell)T_t,(1-f')(\omega+\ell)T_t,W_0,f',a_t,\xi_t)\right], \tag{5.11}$$

where the expectation is taken over f'. As key talents do not bear financing costs, the value of key talents' outside option is given by

$$V^o(T_t,a_t,\xi_t)=V^n(T_t,a_t,\xi_t)+\gamma(\omega+\ell)T_t+\varphi W_0^*. \tag{5.12}$$

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. The present value of Γ_t and hB_t is equal to the value of key talents' outside option $V^o(T_t,a_t,\xi_t)$:[16]

$$0=\Lambda_t(\Gamma_t+hB_t)\mathrm{d}t+\mathbb{E}_t\left[\mathrm{d}\left(\Lambda_t V^o(T_t,a_t,\xi_t)\right)\right], \tag{5.13}$$

where the expectation is taken with respect to $\mathrm{d}a_t$ and $\mathrm{d}\xi_t$. The cash compensation Γ_t imposes operating leverage to the firm. Holding B_t constant, Γ_t increases with T_t, implying that the firm with more talent-based customer capital has greater operating leverage. Moreover, holding T_t constant, Γ_t decreases with B_t, suggesting that the firm with a weaker brand (smaller customer capital B_t) needs to offer greater compensating wage differential to keep key talents due to smaller non-pecuniary private benefits.[17] The link between compensation and brand values has been documented in the literature. In a laboratory setting, researchers find that undergraduate students are willing to accept lower hypothetical salary for the firms with higher reputation because reputation affects the pride that individuals expect from organizational membership (see, e.g. Gatewood, Gowan and Lautenschlager, 1993; Cable and Turban, 2003). Using BAV and Execucomp data from 2000 to 2010, Tavassoli, Sorescu and Chandy (2014) show that CEOs and top executives are willing to accept lower pay when they work for the firms with stronger brand values. We provide further evidence in Section 7.

[16]Our formulation rules out the possibility of further delaying cash payment Λ_t into future periods through contract renegotiation. This is a theoretical simplification that makes the model more tractable. In reality, liquidity constrained firms may promise key talents more equity or option-based compensation in order to postpone cash expenses. Although this arrangement can temporarily alleviate the firm's liquidity problem, postponing cash payment does not reduce the firm's operating leverage as long as all the payments are honoured in the end. In Subsection 7.4, we provide some evidence showing that low BTR firms tend to use more stocks and options. However, the economic magnitude is not large enough to overturn our model's prediction.

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

Talent Turnovers During Financial Stress. The empirical corporate finance literature documents that key employees extract rents at the expense of creditors when firms are financially stressed (see Bradley and Rosenzweig, 1992; Henderson, 2007; Goyal and Wang, 2017). Firms frequently offer golden parachutes in terms of pay retention and incentive bonuses to key talents to persuade them to stay with the firm through the restructuring process. To capture the rent extraction from key talents during financial distress, we assume that key talents extract $\varpi V^o(T_t, a_t, \xi_t)$ from shareholders when the firm runs out of cash (i.e. $W_t = 0$).

Shareholders replace key talents upon the arrival of turnover shocks modeled as a Poisson process with intensity ϑ_t. Shareholders control the replacement intensity ϑ_t, which takes two values. 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 CEO 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 liquidity. Intuitively, replacing key talents reduces the firm's exposure to financial constraints risk through lower operating leverage but it also reduces the firm's future profits due to the loss of talent-based customer capital.

5.3 Firm Optimality

To make the model tractable, we assume that there is no physical capital adjustment cost. This means that the units of sales $S_t\mathrm{d}t$ given by (5.4) is optimally determined by the demand orders $B_t\mathrm{d}t$ from the firm's customer capital.[18] The firm produces the demand orders by employing physical capital $K_t = B_t/e^{a_t}$. Using Ito's lemma, we derive incremental investment $\mathrm{d}I_t$ over $[t, t+\mathrm{d}t]$ as:

$$\frac{\mathrm{d}I_t}{K_t} = \left[\mu(\tau_t, s_t)m_t - \delta_B + \delta_K + \mu_a(a_t - \overline{a}) + \frac{1}{2}\sigma_a^2 a_t\right]\mathrm{d}t - \sigma_a\sqrt{a_t}\mathrm{d}Z_t^a. \tag{5.14}$$

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

$$\mathrm{d}O_t = uB_t\mathrm{d}t - \mathrm{d}I_t + \sigma_B B_t \mathrm{d}Z_t^B - \zeta B_t \mathrm{d}M_t - \phi(s_t)T_t\mathrm{d}t - \Gamma_t\mathrm{d}t, \tag{5.15}$$

where $uB_t\mathrm{d}t$ is the sales revenue from customer capital, with u being the price of goods. $\sigma_B B_t\mathrm{d}Z_t^B - \zeta B_t\mathrm{d}M_t$ represents operating cash flow shocks. $\phi(s_t)T_t\mathrm{d}t$ is the cost of hiring sales

[18] Our calibration ensures that the firm makes positive profit by serving customers. Thus it is a optimal for the firm to produce all demand orders $B_t\mathrm{d}t$. In the presence of convex adjustment costs, Gourio and Rudanko (2014) find that the complementarity of customer capital with physical capital plays a key role in generating delayed investment responses.

representatives and $\Gamma_t \mathrm{d}t$ is the compensation to key talents.

The firm's cash inventory evolves according to the following cash accumulation equation:

$$\mathrm{d}W_t = \mathrm{d}O_t + (r-\rho)W_t\mathrm{d}t + \mathrm{d}H_t - \mathrm{d}D_t, \tag{5.16}$$

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

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

$$V(B_t, T_t, W_t, f_t, a_t, \xi_t) = \max_{s_t, \tau_t, \mathrm{d}D_t, \mathrm{d}H_t} \mathbb{E}\left[\int_0^\infty \Lambda_t(\mathrm{d}D_t - \mathrm{d}H_t - \mathrm{d}X_t)\right], \tag{5.17}$$

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

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

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

See Appendix D for model solutions.

6 Quantitative Analyses

In this section, we calibrate the model's parameters and illustrate the model's qualitative and quantitative predictions through simulation.

6.1 Parametrization

We discipline the model based on both existing estimates and micro data. A set of parameters is determined using external information. These parameters are either already estimated in existing literature or can be estimated separately without simulating the model. The remaining parameters are calibrated internally from moment matching. Appendix Table D.1 summarizes our parameter choice.

Externally Determined Parameters. The annual interest rate is set to be $r = 5\%$. The physical capital's depreciation rate is set to be $\delta_K = 10\%$ per year. We choose the variable cost of financing to be $\varphi = 6\%$ based on the estimates reported by Altinkilic and Hansen (2000). Following

Bolton, Chen and Wang (2011, 2013), we set the fixed financing cost to be $\gamma = 1\%$ of the firm's physical capital and the cash carrying cost to be $\rho = 1.5\%$, resulting from tax disadvantage or agency frictions. We normalize the matching efficiency ψ and the dis-utility of search x to be 1. We set $\chi = 2.12$, which implies that the elasticity parameter in the Cobb-Douglas matching function is $\frac{\chi-2}{\chi-1} = 0.11$, consistent with Gourio and Rudanko (2014)'s estimate based on the share of labor force in sales-related occupations and the amount of time consumers spend on shopping. We consider a quadratic specification for the hiring function of sales people by setting $\eta = 2$. Survey evidence suggests that the customer turnover rates have significant heterogeneity across different industries. The typical range of annual customer turnover rate is between 10% – 25%. We thus set the customer capital depreciation rate to be $\delta_B = 15\%$. We set $\omega = 0.1$, so that in our model, key talents leave with 10% of talent-based customer capital.[19]

The long-run average level of aggregate productivity $\bar{a}$ is a scaling variable. We set its value to be $\bar{a} = 0.5$. We set the persistence parameter to be $\mu_a = 0.275$, following Gomes, Kogan and Zhang (2003). The transition intensities between the two aggregate states are estimated based on the regime-switching dynamics of the estimated alphas of the BMT portfolio between 1975 – 2016. The transition intensity from ξ_L to ξ_H is $q^{(\xi_L,\xi_H)} = 0.16$ and the transition intensity from ξ_H to ξ_L is $q^{(\xi_H,\xi_L)} = 0.20$. We set the price of risk of productivity shocks to be $\kappa_a = 0.4$, and the price of risk of liquidity shocks to be $\kappa^{(\xi_L,\xi_H)} = -\ln(3)$ and $\kappa^{(\xi_H,\xi_L)} = \ln(3)$. The risk-neutral transition intensities are

$$\hat{q}^{(\xi,\xi')} = e^{-\kappa(\xi,\xi')} q^{(\xi,\xi')}, \quad \text{for } \xi \neq \xi'. \tag{6.1}$$

Internally Calibrated Parameters. The rest parameters are calibrated through indirect inference. Specifically, we start with a sample of 1000 firms and simulate their behavior for 100 years according to the computed policy functions. The first 20 years are dropped as burn-in. When key talents leave the firm, new firms are created and will be included in the sample for the remaining simulation period. We then compute the model-implied moments and adjust parameters until the model-implied moments are roughly in line with their values in the Compustat-CRSP sample (see Table 8). Below we briefly discuss the moments used in our calibration.

The consumers' willingness to pay determines the firm's net cash flows. We sets $u = 0.27$ to match the average cash-asset ratio in the data. We set the rent extraction parameter to be $\varpi = 0.08$ so that the retention bonuses are between 30% and 70% of key talents' compensation

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

Table 8: Moments in data and model.

Panel A: Aggregate Moments

	Data	Model		Data	Model
Cash Holdings/Lagged Asset	23.6%	22.5%	Retention Bonuses	30% – 70%	58.9%
Autocorrelation in BTR	0.96	0.97	Talent Compensation/Sales	14.9%	14.5%
Volatility of Net Income/Sales	16.8%	16.0%	Equity Issuance Frequency	25.2%	28.4%
Skewness of Net Income/Sales	−0.47	−0.54	Key Talents' Turnover Rate	4.3%	5.0%
Advertisement Expenditure/Sales	5.1%	5.9%	Compensation reduction (Q1→Q5)	22.3%	23.1%
Volatility of Market Returns	0.165	0.158			

Panel B: Compensations across BTR Portfolios

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

(see Goyal and Wang, 2017). We calibrate hiring efficiency $\alpha = 1.5$ to target the advertisement expenditure as a percent of sales. The parameter ℓ reflects the number of new customers attracted by key talents when a new firm is created. This parameter controls the value of key talents' outside option. We set $\ell = 0.45$ to match the average key talents' compensation as a percent of sales. We set the replacement intensity $\vartheta_H = 10\%$ to match the average key talents' turnover rate in the data.

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

The distribution of brand-based customer capital transformation rate determines the equilibrium distribution of cross-sectional BTR. Since our empirical BTR measure does not have the same units as in our model, we infer the transformation rate using the distribution of key talent compensation. As key talents mainly represent executives and innovators, we approximate key talent compensation using the sum of 50% of R&D expenses and executive compensation.[20] We allow the brand-based customer capital transformation rate to take two extreme values, $f_{(1)} = 0$ and $f_{(2)} = 1$, to ensure that the model is able to generate a wide range of BTRs. We then choose

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

the probability, $\Phi(f_{(1)}) = 0.15$ and $\Phi(f_{(2)}) = 0.85$, so that the model-implied distribution of average talent compensation as a percent of sales across the five quintiles sorted on BTR is roughly in line with the data. The parameter h controls the amount of non-pecuniary private benefits proportional to the firm's customer capital. We calibrate its value to match the decrease in compensation when executives move from the low BTR quintile to the high BTR quintile.

6.2 Simulation Results

Firm Value, Financial, and Hiring Decisions. We now turn to the model's implications. Panel A of Figure 3 plots the firm's normalized enterprise value (i.e. $v(m, w, f_{(2)}, \bar{a}, \xi_L) - w$, the value of all the firm's marketable claims minus cash ratio) as a function of cash ratio when aggregate liquidity condition is good (i.e. $\xi = \xi_L$). It shows that the high BTR firm ($m = 0.1$) has significantly higher enterprise value relative to the low BTR firm ($m = 0.8$). Moreover, both the optimal financing amount (w_h^*) and the payout boundary ($\overline{w}_h$) of the high BTR firm are to the left of those of the low BTR firm (w_l^* and $\overline{w}_l$), suggesting that the high BTR firm endogenously holds less cash on its balance sheet. We provide empirical evidence for these predictions in subsection 7.2.

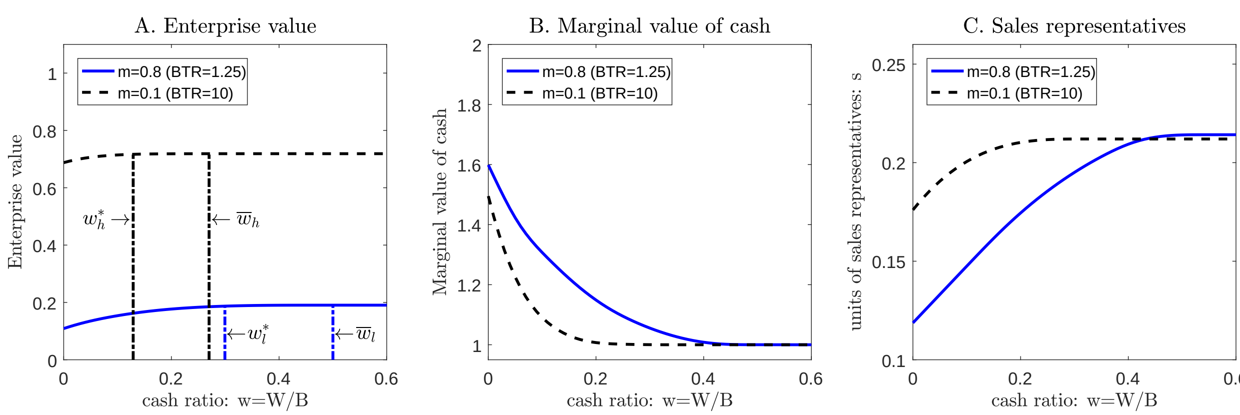
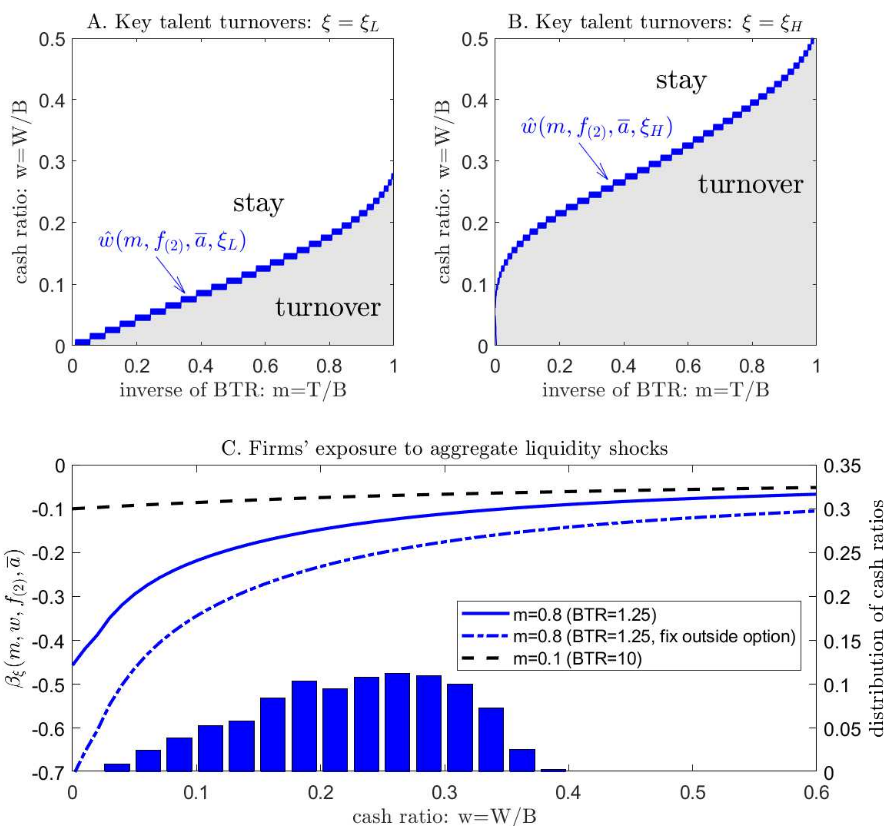


Figure 3: Firm value, financial, and hiring decisions for different levels of BTR.

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



Note: Panel A and B plot the firm's firing decisions when cash ratios and BTR vary for good (ξ_L) and bad (ξ_H) aggregate liquidity conditions. Panel C plots the change in firm value when the aggregate liquidity condition changes from ξ_L to ξ_H. The right axis corresponds to the histogram of the firm's steady-state distribution of cash ratios. The blue dash-dotted line plots the change in for value for the low BTR firm when key talents' outside option is fixed at the value under good aggregate liquidity condition (i.e. $V^o(T_t, a_t, \xi_L)$).

Figure 4: Key talent turnover decisions and the sensitivity of enterprise value to aggregate liquidity shocks.

Key Talent Turnovers. Panel A and B of Figure 4 plot the key talent turnover decisions made by the firms with different BTRs and cash ratios. Regardless of the aggregate liquidity condition, the firms with lower BTRs and lower cash ratios are more likely to replace key talents. We provide empirical evidence for these predictions in subsection 7.1. Specifically, the firm consisting entirely of talent-based customer capital would like to terminate the employment contract when cash ratio drops below 0.28 when aggregate liquidity condition is good (Panel A). The turnover boundary increases to 0.5 when aggregate liquidity condition becomes bad (Panel B). Intuitively, retaining key talents is beneficial to the firm because on average talent-based customer capital generates positive net cash inflows. However, when the firm is financially stressed, the increased exposure to financial constraints risk due to operating leverage outweighs the benefit from higher average demand, motivating the firm to replace key talents and downsize the scale of production. A worsening in aggregate liquidity condition increases financial constraints risk exposure, resulting in an expansion of the employment termination region. Although the firm has the option to replace key talents when liquidity condition is bad, the ex-ante optimal decision to terminate the contract would result in an ex-post loss of talent-based customer capital. Therefore, low BTR firms' customer capital is more fragile to financial constraints risk.

Response to Aggregate Liquidity Shocks. Panel C of Figure 4 illustrates the asset pricing implications of our model. We consider the firms' exposure to aggregate liquidity shocks by plotting their betas defined as the percent changes in normalized firm value when ξ increases from ξ_L to ξ_H, i.e. $\beta_{\xi}(m, w, f, \overline{a}) = v(m, w, f, \overline{a}, \xi_H)/v(m, w, f, \overline{a}, \xi_L) - 1$. Both the high BTR firm and the low BTR firm experience a decrease in firm value due to higher financial constraints risk. The decrease in enterprise value is larger for the low BTR firm because it is more likely to lose talent-based customer capital and bears greater operating leverage.

The exact effect of aggregate liquidity shocks depends on the firm's current liquidity condition. For the low BTR firm, the decrease in firm value is about 10% when the cash ratio is around zero, and the decrease is about 5% when the cash ratio is around 0.5. The difference in the change of firm value between the low BTR firm and the high BTR firm is as large as 35% when the cash ratio is low. Even for the firm with abundant cash (i.e. $w = 0.5$), the difference is still economically significant, around 1.5%. Figure 4 also plots the endogenous distribution of cash ratios. It is shown that during more than half of the time, the firm's cash ratios are between 0.1 and 0.3, in which the difference in the response to aggregate liquidity shocks is about 10%.

The quantitatively differential response to aggregate liquidity shocks between the high BTR firm and the low BTR firm also incorporates a countervailing force that dampens the relative response of the low BTR firm. This is because adverse aggregate liquidity shocks reduce key talents' compensation as the outside option of creating a new firm becomes worse. From shareholders' perspective, the reduction in compensation provides insurance against aggregate liquidity shocks, increasing the firm's value. This insurance effect is especially beneficial for the low BTR firm as it consists of more talent-based customer capital. To understand the quantitative importance of this countervailing force, we plot the change in firm value for the low BTR firm when key talents' outside option is exogenously fixed (blue dash-dotted line).[21] We find that in this case, the reduction in firm value would be increased by about

[21]For the high BTR firm, the countervailing force has a negligible effect because only 10% of the firm's customer capital is talent-based. For clarity, we do not show this curve in the figure.

Table 9: Simulated returns of portfolios sorted on BTR.

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

	All Firms	Low Constraints			Medium Constraints			High Constraints		
		HP	WW	Size	HP	WW	Size	HP	WW	Size
Quintile 1 (%)	6.58	2.51	2.36	3.78	1.74	5.20	8.81	16.15	16.13	14.24
Quintile 5 (%)	0.67	−0.61	0.25	2.73	1.62	0.21	−1.13	6.49	6.65	3.76
Q5 − Q1 (%)	−5.91	−3.13	−2.11	−1.05	−0.13	−4.99	−9.94	−9.66	−9.48	−10.47

Panel B: Model

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

10% on average for the low BTR firm. This suggests that although the countervailing force is economically significant, it is dominated by the even more significant force through greater operating leverage.

Quantitative Implications on Asset Prices. To evaluate the model-implied risk premium, we sort the simulated firms into five quintiles based on their BTRs. We then compute the portfolio alphas of each quintile by regressing excess portfolio returns on excess returns of the market portfolio, SMB, and HML, constructed using simulated data. Column 1 of Table 9 shows that the model-implied difference in portfolio alphas between Quintile 5 and Quintile 1 is about -5.63% (Panel B), roughly in line with the alpha of the long-short portfolio in our data based on the Fama-French three factor model (Panel A).

To investigate the implication of financial constraints, we continue to do a split sample analysis using the simulated firms. Specifically, we first sort firms into three groups based on their marginal value of liquidity. In each group, we further sort firms into five quintiles based on their BTRs. Columns 2-4 of Table 9 show that the difference in portfolio alphas between Quintile 5 and Quintile 1 is about -11.59% among the financially constrained firms and -1.09% among the financially unconstrained firms. Again, these differences are quite consistent with the ones in our data based on the Fama-French three factor model.

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

To quantify its importance, we calibrate a model without non-pecuniary private benefits to match the same moments tabulated in Table 8. Table 10 shows that the alpha of the long-short portfolio is reduced to -4.49%. Compared with the alpha of our baseline model, -5.63%, about 20% of the cross-sectional variation in portfolio alphas is attributed to the variation in private benefits. Therefore, we argue that the composition of customer capital matters for stock returns, quantitatively, both because of human capital inalienability and non-pecuniary private benefits.

Table 10: Simulated portfolio returns without non-pecuniary private benefits.

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

7 Empirical Tests for the Theoretical Mechanism

In this section, we provide four additional empirical evidence to support our model. First, we provide evidence for the model's mechanism by showing that the firms with lower BTRs have higher talent turnover rates. This pattern is mainly driven by financially constrained firms. Second, we verify that the firms with lower BTRs adopt more precautionary financial policies. Third, the model assumes that key talents receive non-pecuniary private benefits proportional to the firm's total customer capital. We provide evidence for this assumption by showing that key talents receive lower compensation when they work in the firms with greater brand stature. Finally, we show that the duration of executive compensation is longer in low BTR firms, suggesting that these firms tend to actively alleviate their liquidity constraints by increasing pay duration and reducing the compensation flow of key talents.

7.1 BTR and Key Talent Turnovers

Next, we examine the relation between BTR and talent turnover rates. We find that the firms with lower BTRs are indeed associated with higher turnover rates for both CEOs and innovators. Moreover, this negative relation is more pronounced when firms are financially constrained.

7.1.1 BTR and CEO Turnovers

In studying the relation between BTR and CEO turnovers, we focus on the non-retirement CEO turnovers. This is because: 1) CEO retirements are mostly due to age, health status, and life style choices of CEOs, which do not reflect firms' active decisions of key talent turnovers; and 2) the non-retirement turnovers are more likely to cause damage to talent-based customer capital and thus are more relevant to the cross-sectional relation between BTR and stock returns. We use two approaches to define non-retirement turnovers. The first approach is solely based on the age of CEOs. We follow the literature (see, e.g. Parrino, 1997; Jenter and Kanaan, 2015) and use age 60 as the cutoff for the retirement age.[22] We define CEO turnovers as non-retirement turnovers if CEOs leave their firms at age 59 or younger due to reasons other than death. The indicator variable for non-retirement turnovers for firm i in year t is denoted as $\text{Turnover}^{(1)}_{i,t}$. The second approach uses additional information from Execucomp, which classifies CEO turnovers into four groups: retirement, death, unknown, and resignation. We define CEO turnovers as non-retirement turnovers if CEOs leave their firms at age 59 or younger due to reasons other than death or if CEOs leave their firms due to resignations according to the Execucomp data. The indicator variable for the non-retirement turnovers for firm i in year t is denoted as $\text{Turnover}^{(2)}_{i,t}$.

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

$$\text{Turnover}_{i,t} \times 100 = \alpha_{ind} + \alpha_t + \beta ln\text{BTR}_{i,t-1} + \gamma'\text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{7.1}$$

The dependent variables are indicators for the non-retirement CEO turnovers. The main independent variable is the lagged *ln*BTR. We standardize *ln*BTR to ease the interpretation of the coefficients. Control variables are lagged firm characteristics, which include the natural log of the organization-capital-to-asset ratio *ln*(OC/Asset), the natural log of firm market capitalization (*ln*size), the natural log of the book-to-market ratio (*ln*BEME), the natural log of the debt-to-equity ratio (*ln*lev), and the 12-month lagged stock returns (*StockRet*). We also include an indicator variable for CEO gender (*Female*) in the regressions. Note that we do not include age as a control variable since age is used to classify the non-retirement turnovers. We include year fixed effects to control for the aggregate time-series pattern of CEO turnovers. We run regressions both with and without SIC-2 industry fixed effects to ensure that our findings are robust to industry controls. Standard errors are clustered by firm and year.

Table 11 shows that non-retirement CEO turnover rates are significantly lower in the firms with higher BTRs. This result is robust to the two definitions of the non-retirement turnovers, and it is also robust to the inclusion of the SIC-2 industry fixed effects. The negative relation between BTR and CEO 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 *ln*BTR leads to a decrease in the probability of the non-retirement CEO turnovers by 0.902 percentage point, which is roughly 1/5 of the average non-retirement turnover rate in the data.

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

Table 11: BTR and key talent turnovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEOs				Innovators			
	$\text{Turnover}_t^{(1)} \times 100$		$\text{Turnover}_t^{(2)} \times 100$		$ln(1+\text{leavers})_t$		$ln(1+\text{new hires})_t$	
$ln\text{BTR}_{t-1}$	-0.902^{***}	-0.870^{***}	-0.899^{***}	-0.881^{**}	-0.163^{**}	-0.170^{**}	-0.156^{*}	-0.158^{*}
	[−3.948]	[−3.240]	[−2.841]	[−2.595]	[−2.198]	[−2.299]	[−2.097]	[−2.113]
$ln(\text{OC/Asset})_{t-1}$	0.143	0.151	0.221	0.156	0.050	0.066	0.032	0.048
	[0.629]	[0.539]	[1.044]	[0.588]	[0.749]	[0.904]	[0.518]	[0.729]
$ln\text{size}_{t-1}$	−0.110	0.144	−0.034	0.235	0.538^{***}	0.574^{***}	0.538^{***}	0.580^{***}
	[−0.560]	[0.570]	[−0.167]	[0.823]	[8.321]	[9.434]	[8.253]	[9.488]
$ln\text{BEME}_{t-1}$	0.105	0.674	0.395	0.986^{*}	0.348^{***}	0.416^{***}	0.322^{***}	0.393^{***}
	[0.229]	[1.216]	[0.848]	[1.836]	[4.071]	[4.886]	[3.738]	[4.696]
$ln\text{lev}_{t-1}$	0.360	0.415	0.484	0.537	0.165^{*}	0.215^{***}	0.149^{*}	0.208^{***}
	[1.244]	[1.003]	[1.709]	[1.274]	[2.045]	[3.043]	[1.862]	[2.969]
StockRet_{t-1}	-4.258^{***}	-4.274^{***}	-4.217^{***}	-4.207^{***}	0.176^{*}	0.095^{*}	0.164^{*}	0.082^{*}
	[−3.505]	[−3.224]	[−3.654]	[−3.299]	[2.008]	[1.869]	[1.911]	[1.764]
Female	0.259	−0.534	0.521	−0.284				
	[0.245]	[−0.480]	[0.434]	[−0.229]				
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4875	4875	4875	4875	1780	1774	1780	1774
R-squared	0.012	0.028	0.012	0.031	0.381	0.596	0.385	0.601

This table shows the relation between BTR and key talent turnovers. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. CEO turnover data come from Compustat. In Column (1) and (2), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) and (4), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise. We track the innovator turnovers using the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), which provides the names of the innovators and their affiliations from 1975 to 2010. Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year. The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), and a dummy variable for the gender of the CEOs (Female). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 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.

7.1.2 BTR and Innovator Turnovers

Next, we study the relation between BTR and the turnovers of innovators, another important group of firms' key talents. We track the employment history of innovators based on the HBS patent and innovator database, which provides innovators' names and affiliations from 1975 to 2010. Following Li et al. (2014), we define a mover in a given year as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. The mover is considered as a leaver for her former employer and a new hire for her new employer. We run the following regression to study the relation between BTR and innovator turnovers:

$$ln(1+\text{movers})_{i,t} = \alpha_{ind} + \alpha_t + \beta ln\text{BTR}_{i,t-1} + \gamma'\text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{7.2}$$

The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is lagged lnBTR. The control variables include lagged firm characteristics. We include year fixed effects and run regressions both with and without industry fixed effects. Standard errors are clustered by both firm and year.

Table 11 shows that the firms with higher BTRs are associated with significantly fewer innovator turnovers. According to the specifications with both year fixed effects and industry fixed effects, a one standard deviation increase in lnBTR is associated with a 17.0% reduction in the number of innovator departures and a 15.8% reduction in the number of innovator arrivals.

7.1.3 Role of Financial Constraints

Since the operating leverage associated with BTR is exacerbated by financial constraints, we expect to see the relation between BTR and key talent turnovers to be more pronounced among financially constrained firms. To test this prediction, we classify firms into a constrained group and an unconstrained group at the yearly basis. We examine the relation between BTR and key talent turnovers separately in these two groups. Consistent with the prediction of our model, we find that the coefficients of BTR are significantly negative among the financially constrained firms but not among the financially unconstrained firms. This pattern is robust for both CEO turnovers and innovator turnovers, and it is robust across the two proxies for financial constraints (see Table 12 for the results on the HP index and Appendix Table F.10 for the results on the WW index).

7.1.4 Interaction with BMT Returns

We have shown that BTR is cross-sectionally priced. The BMT (i.e., brand-minus-talent) returns are unconditionally negative, and their time-series variation captures the changes in the aggregate funding liquidity conditions. When the economy faces funding liquidity shortage, BMT returns become positive (shown by Figure 1). Our model predicts that the key talent turnover rates of low BTR firms are higher due to their higher levels of operating leverage. The difference in the turnover rates should be stronger when firms face adverse aggregate funding liquidity conditions. To test this prediction, we interact the standardize lnBTR with BMT and include the interaction term as the main independent variable in the following regressions:

Table 12: BTR and key talent turnovers: the role of financial constraints.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEOs				Innovators			
	$\text{Turnover}_t^{(1)} \times 100$		$\text{Turnover}_t^{(2)} \times 100$		$ln(1+\text{leavers})_t$		$ln(1+\text{new hires})_t$	
Sample	High HP (Constrained)	Low HP (Unconstrained)	High HP (Constrained)	Low HP (Unconstrained)	High HP (Constrained)	Low HP (Unconstrained)	High HP (Constrained)	Low HP (Unconstrained)
$ln\text{BTR}_{t-1}$	-0.951^{***}	-0.601	-1.025^{***}	-0.542	-0.241^{**}	-0.048	-0.238^{**}	-0.045
	[−2.944]	[−0.986]	[−2.891]	[−0.742]	[−2.860]	[−0.358]	[−2.825]	[−0.338]
$ln(\text{OC/Asset})_{t-1}$	-0.074	0.290	-0.175	0.430^{**}	0.133	0.045	0.128	0.028
	[−0.198]	[1.508]	[−0.471]	[2.508]	[1.660]	[0.581]	[1.588]	[0.401]
$ln\text{size}_{t-1}$	0.269	-0.272	0.264	-0.190	0.411^{***}	0.746^{***}	0.405^{***}	0.748^{***}
	[0.943]	[−1.010]	[0.966]	[−0.582]	[5.048]	[6.281]	[4.923]	[6.361]
$ln\text{BEME}_{t-1}$	-0.666	1.203^{*}	-0.615	1.657^{**}	0.296^{***}	0.401^{**}	0.246^{**}	0.403^{**}
	[−0.736]	[1.963]	[−0.725]	[2.429]	[2.952]	[2.625]	[2.419]	[2.730]
$ln\text{lev}_{t-1}$	0.225	0.821^{*}	0.448	0.827^{*}	0.023	0.327^{**}	-0.003	0.308^{*}
	[0.464]	[1.795]	[0.858]	[1.767]	[0.254]	[2.165]	[−0.038]	[2.085]
StockRet_{t-1}	-5.521^{***}	-2.468	-5.771^{***}	-2.132	0.083	0.360^{*}	0.052	0.385^{*}
	[−3.448]	[−1.685]	[−3.754]	[−1.608]	[0.984]	[1.944]	[0.650]	[2.028]
Female	-0.716	1.502	-0.952	2.225				
	[−0.395]	[1.003]	[−0.545]	[1.297]				
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2380	2492	2380	2492	804	979	804	979
R-squared	0.024	0.013	0.025	0.016	0.331	0.376	0.329	0.385

Note: This table shows the relation between BTR and key talent turnovers in firms with and without financial constraints. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We classify firms into financially constrained firms and financially unconstrained firms based on the HP index (see Hadlock and Pierce, 2010). The classification is performed at yearly basis. The financially constrained firms are the firms with HP index larger than the median values. CEO turnover data come from Execucomp. In Column (1) and (2), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) and (4), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise. We track the innovator turnovers using the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), which provides the names of the innovators and their affiliations from 1975 to 2010. Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year. The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), and a dummy variable for the gender of the CEOs (Female). Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The CEO turnover sample spans 1993 to 2016, while the innovator turnover sample spans 1993 to 2010. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

$$\text{Turnover}_{i,t} \times 100 = \alpha_{ind} + \alpha_t + \beta_1 ln\text{BTR}_{i,t-1} + \beta_2 ln\text{BTR}_{i,t-1} \times \text{BMT}_{t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \quad (7.3)$$

$$ln(1+\text{movers})_{i,t} = \alpha_{ind} + \alpha_t + \beta_1 ln\text{BTR}_{i,t-1} + \beta_2 ln\text{BTR}_{i,t-1} \times \text{BMT}_{t-1} + \gamma' \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \quad (7.4)$$

As shown by Table 13, we find that the coefficients for the interaction terms (β_2) are negative, suggesting that the difference in key talent turnover rates between high BTR firms and low

Table 13: BTR and key talent turnovers: interaction with BMT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEOs				Innovators			
	$\text{Turnover}_t^{(1)} \times 100$		$\text{Turnover}_t^{(2)} \times 100$		$ln(1+\text{leavers})_t$		$ln(1+\text{new hires})_t$	
$ln\text{BTR}_{t-1}$	-1.033^{***}	-1.012^{***}	-1.044^{***}	-1.021^{**}	-0.181^{**}	-0.180^{**}	-0.169^{**}	-0.165^{*}
	[−4.171]	[−3.513]	[−2.989]	[−2.653]	[−2.397]	[−2.368]	[−2.214]	[−2.136]
$ln\text{BTR}_{t-1} \times \text{BMT}_{t-1}$	-5.157^{**}	-5.422^{***}	-5.786^{**}	-6.134^{**}	-0.326^{***}	-0.246^{**}	-0.281^{**}	−0.202
	[−2.652]	[−2.857]	[−2.432]	[−2.643]	[−5.543]	[−2.282]	[−2.445]	[−1.618]
$ln(\text{OC/Asset})_{t-1}$	0.261	0.128	0.338	0.135	0.043	0.059	0.029	0.047
	[1.083]	[0.437]	[1.502]	[0.488]	[0.609]	[0.759]	[0.437]	[0.651]
$ln\text{size}_{t-1}$	−0.194	0.046	−0.117	0.141	0.534^{***}	0.572^{***}	0.532^{***}	0.577^{***}
	[−1.035]	[0.185]	[−0.572]	[0.491]	[8.122]	[9.205]	[8.014]	[9.198]
$ln\text{BEME}_{t-1}$	0.496	1.007	0.744	1.272^{**}	0.329^{***}	0.404^{***}	0.301^{***}	0.380^{***}
	[0.983]	[1.698]	[1.491]	[2.237]	[3.706]	[4.667]	[3.327]	[4.378]
$ln\text{lev}_{t-1}$	0.600	0.695	0.713^{*}	0.806^{*}	0.160^{*}	0.213^{**}	0.141	0.204^{**}
	[1.680]	[1.493]	[2.066]	[1.731]	[1.955]	[2.975]	[1.732]	[2.807]
StockRet_{t-1}	-4.354^{***}	-4.312^{**}	-4.342^{***}	-4.282^{***}	0.185^{*}	0.101^{*}	0.169^{*}	0.085
	[−2.974]	[−2.812]	[−3.020]	[−2.824]	[2.040]	[1.951]	[1.861]	[1.640]
Female	−0.037	−0.919	0.212	−0.689				
	[−0.036]	[−0.820]	[0.179]	[−0.544]				
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4875	4875	4875	4875	1780	1774	1780	1774
R-squared	0.015	0.030	0.015	0.033	0.381	0.600	0.385	0.603

This table shows the relation between key talent turnovers and the interaction between BTR and BMT. *ln*BTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. CEO turnover data come from Compustat. In Column (1) and (2), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) and (4), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise. We track the innovator turnovers using the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), which provides the names of the innovators and their affiliations from 1975 to 2010. Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year. 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 variables are the lagged *ln*BTR, and the products between the lagged *ln*BTR and the lagged BMT. BMT is the yearly returns for the brand-minus-talent (Quintile 5 − Quintile 1 BTR) portfolio. The mean of BMT is 0.064 (i.e., 6.4%), while the standard deviation of BMT is 0.190 (i.e., 19.0%). We standardize *ln*BTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio $ln(\text{OC/Asset})$, the natural log of firm market capitalization (*ln*size), the natural log of the book-to-market ratio (*ln*BEME), the natural log of the debt-to-equity ratio (*ln*lev), the 12-month stock returns in the previous year (StockRet), and a dummy variable for the gender of the CEOs (Female). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

BTR firms is indeed larger conditional on worse aggregate funding liquidity condition. This interaction effect is both statistically and economically significant.

7.2 BTR and Firms' Financial Policies

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

$$y_{i,t} = \alpha_{ind} + \alpha_t + \beta ln\text{BTR}_{i,t-1} + \gamma'\text{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{7.5}$$

Here, the outcome variables $y_{i,t}$ are the amount of cash holdings normalized by lagged assets, the change of cash holdings normalized by contemporaneous net income, the amount of equity issuance normalized by lagged assets, the amount of total payout normalized by lagged assets, the amount of dividend issuance normalized by lagged assets, and the amount of share repurchases normalized by lagged assets. The outcome variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. The main independent variable is the natural log of the lagged lnBTR. We standardize lnBTR to ease the interpretation of its coefficients. Control variables include lagged firm characteristics. We include year fixed effects and SIC-2 industry fixed effects in the regressions. Standard errors are clustered by firm and year.

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

7.3 Brand Values and Private Benefits

We find that executives of the firms with stronger brand values receive lower compensation.[23] Specifically, this result remains robust when we include executive fixed effects and focus on the within-executive variations. Thus, our findings cannot be explained by unobserved heterogeneity across executives. The relation between brand value and executive pay is also economically significant. According to the regression with executive fixed effects, industry fixed effects, and year fixed effects, a one standard deviation increase in brand stature is associated with a 10.8% reduction in managerial compensation (see Column 4 of Table 15).

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

Table 14: BTR and firms' financial policies.

	(1) $\frac{\text{Cash}_t}{\text{Asset}_{t-1}}$ (%)	(2) $\frac{\Delta\text{Cash}_t}{\text{NI}_t}$ (%)	(3) $\frac{\Delta\text{Equity}_t}{\text{Asset}_{t-1}}$ (%)	(4) $\frac{\text{Payout}_t}{\text{Asset}_{t-1}}$ (%)	(5) $\frac{\text{Dividend}_t}{\text{Asset}_{t-1}}$ (%)	(6) $\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$ (%)
$ln\text{BTR}_{t-1}$	-3.475^{***}	-9.421^{**}	-0.665^{*}	0.903^{***}	0.310^{***}	0.591^{***}
	[−5.786]	[−2.219]	[−1.928]	[4.457]	[3.111]	[3.934]
$ln(\text{OC/Asset})_{t-1}$	1.336^{***}	0.339	0.163^{**}	0.283^{**}	0.112^{**}	0.161^{**}
	[4.467]	[0.190]	[2.205]	[2.525]	[2.239]	[2.293]
$ln\text{size}_{t-1}$	-1.207^{***}	0.085	-0.775^{**}	0.616^{***}	0.245^{***}	0.411^{***}
	[−3.128]	[0.050]	[−2.520]	[5.202]	[5.074]	[4.449]
$ln\text{BEME}_{t-1}$	-7.038^{***}	−1.638	-2.283^{***}	-2.375^{***}	-0.565^{***}	-1.609^{***}
	[−9.157]	[−0.378]	[−3.706]	[−8.412]	[−5.684]	[−7.619]
$ln\text{lev}_{t-1}$	-5.592^{***}	4.716	-0.744^{**}	-1.401^{***}	-0.195^{**}	-1.042^{***}
	[−10.224]	[1.104]	[−2.483]	[−7.305]	[−2.473]	[−7.281]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5842	4958	5842	5842	5842	5842
R-squared	0.439	0.032	0.106	0.296	0.349	0.248

Note: This table shows the relation between BTR and firms' financial policies. *ln*BTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The dependent variables are the amount of cash holdings (% of lagged assets), the change of cash holdings (% of contemporaneous net income), the amount of equity issuance (% of lagged assets), the amount of total payout (% of lagged assets), the amount of dividend issuance (% of lagged assets), and the amount of share repurchases (% of lagged assets). The outcome variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. In Column (2), we only include observations with positive net income. The main independent variable is the lagged *ln*BTR. We standardize *ln*BTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (*ln*size), the natural log of the book-to-market ratio (*ln*BEME), and the natural log of the debt-to-equity ratio (*ln*lev). We include SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 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.

We continue to hypothesize that younger executives are more likely to enjoy non-pecuniary private benefits at the firms with strong brand values. One interpretation is that they have longer career ahead of them and thus gain more non-pecuniary private benefits such as the identity-based benefits and the signaling benefits. To test this hypothesis, we interact age with brand value and include the interaction terms in the regressions. We do not include executive fixed effects in this set of regressions because we would like to exploit the age variations across executives. Consistent with our hypothesis, we find that the coefficients for the interaction term between age and brand stature are positive and statistically significant, suggesting that younger executives are indeed more willing to take lower compensation when they work in the firms with stronger brand values. According to the specification with both industry fixed effects and year fixed effects, a 30-year old executive is willing to take a 15.8% cut in compensation with a one standard deviation increase in the brand stature of her employee; whereas a 67-year old executive is not willing to accept any compensation discount.

Table 15: Brand values and talents' non-pecuniary private benefits: evidence from managerial compensation.

	(1)	(2)	(3)	(4)	(5)	(6)
			lnExecuComp$_t$			
lnStature$_{t-1}$	-0.096^{***}	-0.063^{**}	-0.113^{**}	-0.108^{**}	-0.173^{***}	-0.158^{***}
	[−4.002]	[−2.704]	[−2.524]	[−2.303]	[−3.542]	[−3.561]
lnStature$_{t-1} \times (\text{Age}_{t-1} - 30)$					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]
lnStrength$_{t-1} \times (\text{Age}_{t-1} - 30)$					0.001	0.001
					[0.412]	[0.350]
ln(OC/Asset)$_{t-1}$	0.023^{*}	0.019	−0.018	−0.016	0.023^{*}	0.018
	[1.843]	[1.511]	[−1.332]	[−1.179]	[1.836]	[1.463]
lnsize$_{t-1}$	0.368^{***}	0.377^{***}	0.164^{***}	0.157^{***}	0.368^{***}	0.378^{***}
	[25.755]	[22.738]	[4.344]	[3.690]	[26.386]	[23.021]
lnBEME$_{t-1}$	0.177^{***}	0.174^{***}	−0.065	−0.070	0.178^{***}	0.175^{***}
	[7.262]	[5.750]	[−1.469]	[−1.552]	[7.261]	[5.763]
lnlev$_{t-1}$	0.172^{***}	0.178^{***}	−0.011	−0.012	0.172^{***}	0.178^{***}
	[5.727]	[5.605]	[−0.320]	[−0.322]	[5.817]	[5.663]
StockRet$_{t-1}$	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	[3.369]	[3.210]	[2.886]	[2.838]	[3.387]	[3.215]
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]
Female	−0.028	−0.020			−0.029	−0.021
	[−0.543]	[−0.439]			[−0.557]	[−0.453]
Executive FE	No	No	Yes	Yes	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23496	23496	22267	22267	23496	23496
R-squared	0.283	0.299	0.748	0.749	0.283	0.299

Note: This table shows the relation between brand values and managerial compensation. lnExecuComp is the natural log of the managerial compensation (*tdc*1 in the Execucomp data). Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The main independent variables are the natural log of the brand values (lnStature and lnStrength). We standardize both lnStature and lnStrength to ease the interpretation of the coefficients. In Column (5) and (6), we include the interaction terms between the brand values and executive age in the regressions. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), age of the executives (Age), and a dummy variable for the gender of the executives (Female). We include executive fixed effects, SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 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.

7.4 BTR and Compensation Duration

As our main theoretical channel, a greater BTR renders the firms more liquidity constrained, and thus in principle, these firms should have stronger incentives to alleviate the liquidity constraints by adjusting compensation contracts. Following this logic, we further hypothesize that the firms with lower BTRs are more likely to increase the pay duration of key talents and thus delay cash payments. In particular, they can choose to substitute the cash payment (salary

Table 16: BTR and the duration of executive compensation.

	(1)	(2)	(3)	(4)
	$\frac{\text{(Stocks+Options)}_t}{\text{Total Pay}_t}$ (%)		Duration$_t$	
$ln\text{BTR}_{t-1}$	-3.513^{***}	-3.583^{***}	-0.098^{*}	-0.102^{*}
	[−3.717]	[−3.587]	[−2.181]	[−2.054]
$ln(\text{OC/Asset})_{t-1}$	−0.270	−0.257	0.053	0.028
	[−0.954]	[−0.831]	[0.947]	[0.429]
$ln\text{size}_{t-1}$	2.377^{***}	2.520^{***}	0.090	0.053
	[3.475]	[2.881]	[1.380]	[0.639]
$ln\text{BEME}_{t-1}$	−1.676	−1.527	−0.005	−0.027
	[−1.486]	[−1.228]	[−0.069]	[−0.322]
$ln\text{lev}_{t-1}$	−1.177	−1.317	−0.001	−0.031
	[−1.286]	[−1.317]	[−0.015]	[−0.398]
StockRet_{t-1}	-0.052^{***}	-0.051^{***}	−0.001	−0.001
	[−6.210]	[−2.894]	[−1.114]	[−0.967]
Age_{t-1}	-3.004^{***}	-3.918^{***}	0.123^{***}	-1.759^{***}
	[−2.947]	[−11.813]	[3.857]	[−4.713]
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 BTR and the duration of executive compensation. In Column (1) and (2), the dependent variables are the stocks/options-to-total-pay ratio. Data on the executive pay are from Execucomp and they span 1992 to 2016. In Column (3) and (4), the dependent variables are the duration of executive compensation. We follow Gopalan et al. (2014) and compute pay duration as the weighted average duration of the four components of pay (i.e., salary, bonus, restricted stock, and stock options). Data on the vesting schedules of restricted stock and stock options are from Equilar Consultants and they span 2006 to 2016. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization-capital-to-asset ratio ln(OC/Asset), the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), age of the executives (Age). We include executive fixed effects, SIC-2 industry fixed effects and year fixed effects in the regressions. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period in Column (1) and (2) is 1993 to 2016, and the sample period in Column (3) and (4) is 2006 to 2016. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

and bonus) with stocks and stock options which have longer pay duration due to the existence of vesting schedule. To test this hypothesis, we examine the relation between BTR and the pay duration of top executives.[24]

We first use the Execucomp data to examine the relation between BTR and the stocks/options-to-total-pay ratio. We include executive fixed effects in the regressions to make sure that our findings are not explained by the unobserved heterogeneity across executives. As shown by Table 16, the firms with lower BTRs are associated with higher stocks/options-to-total-pay ratio. A one standard deviation decrease in lnBTR is associated with around a 3.5 percentage points increase in the stocks/options-to-total-pay ratio (the mean and median of the stocks/options-to-total-pay ratio in our sample are 35.8% and 36.2%, respectively). Our finding is consistent with

[24] We focus on top executives because of data availability.

Yermack (1995), who shows that financially constrained firms are more likely to award CEO stock options.

Next, we further quantify the relation between BTR and compensation duration. Following Gopalan et al. (2014), we compute pay duration as the weighted average duration of the four components of pay (i.e. salary, bonus, restricted stock, and stock options). As shown by Table 16, the firms with lower BTRs are indeed associated with longer pay duration. However, we find that the magnitude of the changes in pay duration is very small. A one standard deviation decrease in lnBTR is associated with around a 0.10 year increase in pay duration (the mean and median pay duration in our sample are 1.57 and 1.70, respectively). Taken together, we find that low BTR firms actively manage the pay duration of their talents, but the capacity of delaying seems to be too limited to fundamentally alleviate the liquidity constraints faced by low BTR firms.

8 Conclusion

In this paper, we provide the first elements of a conceptual framework to theoretically analyze and empirically test an economic mechanism by which the composition of pure-brand-based and talent-based capital influences firm valuation and asset prices. We argue that the firms with different BTRs have distinctive financial constraints risk exposures. As a result, the variation in firm-level BTR is informative about the cross-sectional stock returns. Based on proprietary brand perception survey data, we find the empirical evidence strongly supporting our model's predictions. BTR is negatively associated with average excess returns and risk-adjusted returns in the cross section, and this pattern is more pronounced among financially constrained firms. High BTR firms, which we refer to as robust firms, have steady sales growth and stable cash flows. They are also less negatively affected by peer firms' innovative activities.

Our model highlights the interaction between customer capital and human capital, implying that the financial implications of customer capital compositions come from the retaining costs of talent-based customer capital. By constructing a BTR measure using customer survey data, we capture key talents' importance without relying on firms' financial or accounting information. Compared with other financial proxies of key talents' contribution, our BTR measure alleviates the concern of endogeneity as it is not directly controlled by firms' endogenous financial decisions.

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Appendix

A Definition of Variables

Table A.1: Definition of variables.

Variables	Definition	Sources
lnBTR	The natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures the loyalty of existing customers. We use brand stature to proxy for the value of customer capital. Brand strength measures how much the brand is perceived to be innovative and distinctive. Since the creation of innovative products and distinctive brands requires significant contribution of key talents, we use brand strength as a proxy for talent-based customer capital. We provide detailed information on the BAV survey and the construction of brand stature and strength in E.1	BAV
ln(AdminExpenses/Sales)	The natural log of the normalized administrative expenses. We take out advertisement costs, R&D expenses, commissions, and foreign currency adjustments from SG&A to estimate the talent compensation.	Compustat
$ln(R\&D/\text{Sales})$	The natural log of the normalized R&D expenses.	Compustat
ln(ExecuComp/Sales)	The natural log of the normalized executive compensation. The executive compensation is the summation of the total pay ($tdc1$) for the top five executives in the Execucomp data.	Execucomp
ln(OC/Asset)	The natural log of the organization capital normalized by assets. Following Eisfeldt and Papanikolaou (2013), we construct the organization capital from SG&A expenditures using the perpetual inventory method.	Compustat
$Vol(DailyRet)_t$	Volatility of daily stock returns in year t	CRSP
$Vol(\frac{NI}{Asset})_t$	Volatility of the forward-looking net-income-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$)	Compustat
$Vol(\frac{EBITDA}{Asset})_t$	Volatility of the forward-looking EBITDA-to-asset ratio (standard deviation of the six yearly ratios from the period t through $t+5$)	Compustat
Profits	Firm gross profits (Compustat item *sale* minus Compustat item *cogs*, deflated by the CPI)	Compustat
Output	Value of output (Compustat item *sale* plus change in inventories Compustat item *invt*, deflated by CPI)	Compustat
Capital	Capital stock (Compustat item *ppegt*, deflated by the NIPA price of equipment)	Compustat
Labor	Number of employees (Compustat item *emp*)	Compustat
Innovation_Peers	Following Kogan et al. (2017), we measure patent value (in dollars) based on stock market reaction to the patent issuance. The innovative outputs of the peer firms (Innovation_Peers) are the sum of peer firms' patent values in the SIC-3 industry normalized by the sum of their book values.	Kogan et al. (2017)
Operating profitability	Revenues net of COGS, SG&A, interest expense, divided by book equity.	Compustat
ΔAsset/Lagged asset	Asset growth rate. Change in total assets normalized by lagged total assets.	Compustat
lnsize	The natural log of the market cap (in million dollars).	CRSP
lnBEME	The natural log of the book-to-market ratio.	CRSP; Compustat
lnlev	The natural log of the debt-to-equity ratio.	Compustat

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

Variables	Definition	Sources
lnExecuComp	The natural log of the managerial compensation ($tdc1$ in the Execucomp data).	Execucomp
$\frac{(\text{Stocks+Options})_t}{\text{Total Pay}_t}$	The stocks/options-to-total-pay ratio.	Execucomp
Duration	Duration of executive compensation. We follow Gopalan et al. (2014) and compute pay duration as the weighted average duration of the four components of pay (i.e., salary, bonus, restricted stock, and stock options). Data on the vesting schedules of restricted stock and stock options are from Equilar Consultants and they span 2006 to 2016.	Execucomp; Equilar
StockRet	The 12-month stock returns.	CRSP
Age	The age of the executives	Execucomp
Female	A dummy variable that equals one if the executive is a female.	Execucomp
$\text{Turnover}_t^{(1)}$	A dummy variable that equals one if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise.	Execucomp
$\text{Turnover}_t^{(2)}$	A dummy variable that equals one if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise.	Execucomp
$ln(1 + \text{leavers})$	Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year.	HBS innovator
$ln(1 + \text{new hires})$	Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year.	HBS innovator
$\frac{Cash_t}{Asset_{t-1}}$	The amount of cash holding (che) normalize by lagged total assets (at).	Compustat
$\frac{\Delta Cash_t}{NI_t}$	The change of cash holding ($chech$) normalize by the contemporaneous net income (ni). We only include observations with positive net income.	Compustat
$\frac{\Delta Equity_t}{Asset_{t-1}}$	The amount of equity issuance ($sstk$) normalize by lagged total assets (at).	Compustat
$\frac{Payout_t}{Asset_{t-1}}$	The amount of total payout (dv + $prstkc$) normalize by lagged total assets (at).	Compustat
$\frac{Dividend_t}{Asset_{t-1}}$	The amount of dividend issuance (dv) normalize by lagged total assets (at).	Compustat
$\frac{Repurchases_t}{Asset_{t-1}}$	The amount of share repurchases ($prstkc$) normalize by lagged total assets (at).	Compustat
β_{mp}^Q	Quitiles of the mimicking portfolio betas (β_{mp}) for BTR. We provide detailed information on the estimation of the mimicking portfolio betas in E.4	BAV; CRSP

B Examples of Building and Maintaining Customer Capital

Now, let us elaborate on how key talents and pure brand loyalty create and maintain a firm's customer capital in different ways. Key talents are the essential employees of a firm, mainly including managers and innovators. Managers frequently bring in new businesses and customer relationships through personal connections and specialized skills; meanwhile, innovators in R&D teams often develop products with creative features that can attract new customers. These are typical examples of customer capital growth due to key talents' unique contributions. Managers can also bring in new customers through designing advertisement and marketing campaigns. These are examples of customer capital growth due to the combination of both forces. Moveover, pure brand perception alone can also bring in new customers. For example, consumers sometimes become aware of the firm's products after friends' recommendations based on their pure brand loyalty, which is referred to as *word-of-mouth marketing*. As supported by ample evidence in the marketing literature, the main force of future customer capital growth is key talents' contribution. In addition to creating future customer capital growth, both key talents and pure brand loyalty are also important in maintaining the existing customer relationships. When new customers are brought into the firm, some become part of talent-based customer capital, while others become loyal to the firm's brands. New customers brought by personal connections or innovations, for example, are more likely to become part of talent-based customer capital, compared to new customers brought by advertisements and friends' recommendations.

C Micro Foundation for Customer Capital

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

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

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

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

The specification of an increasing and convex hiring cost function follows Gourio and Rudanko (2014), which guarantees a decreasing-return-to-scale profit function for hiring sales representatives. By modeling the hiring cost proportional to T_t, we ensure that the firm does not grow out of the cost. We assume that each sales representative has search efficiency T_t to capture the idea that key talents (whose importance is reflected by the value of T_t) are important in bringing new customers. Thus, the firm's effective number of sales representatives is $s_t T_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$.

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

$$\theta_t = \frac{s_t T_t}{b(\tau_t, s_t; T_t)}. \tag{C.2}$$

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

$$\lambda(\theta_t) = (\psi\theta_t)^{1/\chi}, \tag{C.3}$$

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

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

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

Intuitively, this is because the firm offering greater discounts or hiring more sales representatives will attract more potential buyers. The free entry condition ensures that the firm-specific market tightness will adjust until the expected consumer surplus is equalized across all firms. As a result, in equilibrium, agents are indifferent about where to purchase goods. In particular, the firm's existing customers have no incentive to purchase goods from other firms, implying that the customer relationship is long-term in nature.[25]

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

$$b(\tau_t, s_t; T_t) = \psi\tau_t^{\chi} s_t T_t. \tag{C.5}$$

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

$$\mu(\tau_t, s_t) = \psi\tau_t^{\chi-1} s_t. \tag{C.6}$$

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

D Model Solution

The firm simultaneously makes five sets of decisions: production, discounts, sales representatives hiring, key talent turnovers, and financial decisions. Since both key talent turnovers and financial decisions are discrete in our model, they can be sufficiently characterized by "decision boundaries". The illustrative diagram (see Figure D.1) elaborates this idea.

Basically, the firm's financial decisions are characterized by three regions: (1) an external financing/liquidation region ($w < \underline{w}(m, f, a, \xi)$) within which the firm pursues external financing ($\mathrm{d}H > 0$); (2) an internal liquidity

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

hoarding region ($\underline{w}(m,f,a,\xi) \le w \le \overline{w}(m,f,a,\xi)$) within which the firm keeps net profits as cash holdings on its balance sheet ($\mathrm{d}H = \mathrm{d}D = 0$); and (3) a payout region ($w > \overline{w}(m,f,a,\xi)$) within which the firm chooses to pay out dividends ($\mathrm{d}D > 0$). Within the internal liquidity hoarding region, there exists a conditional external financing ($\underline{w}(m,f,a,\xi) < w < \underline{w}'(m,f,a,\xi)$), within which the firm issues equity conditional on the arrival of lumpy cash flow shocks ζ.

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

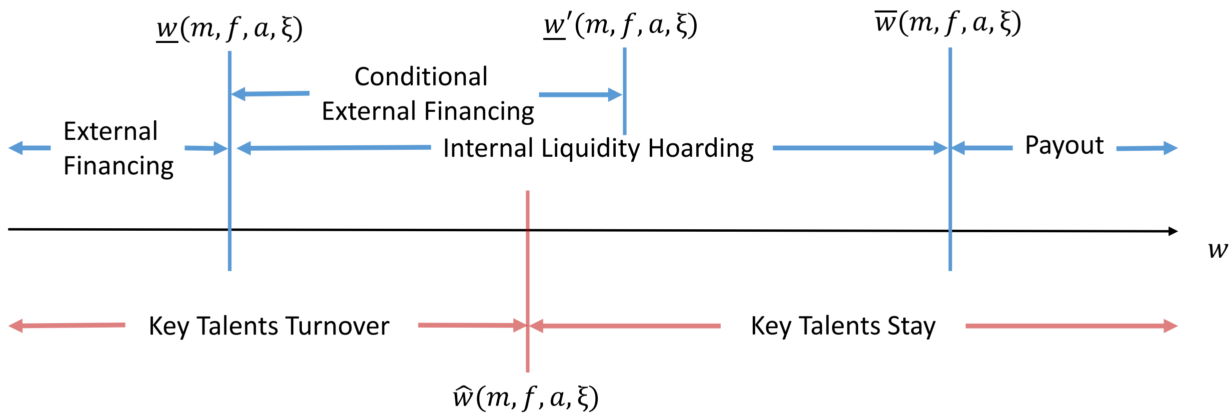


Figure D.1: Illustrative graph for the decision boundaries and regions.

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

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

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

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

$$v(m, w, f, a, \xi) = v(m, w^*(m, f, a, \xi), f, a, \xi) - \gamma - \varpi m v^o(a, \xi) - (1 + \varphi)[w^*(m, f, a, \xi) - w], \quad \text{for } w \leq 0. \tag{D.1}$$

The LHS of equation (D.1) is the firm's value right before equity issuance. The RHS of equation (D.1) is the firm's value right after equity issuance minus both the fixed and variable financing costs for issuance amount $w^*(m, f, a, \xi) - w$. The first-order optimality condition for the return cash ratio leads to the smooth pasting condition

$$v_w(m, w^*(m, f, a, \xi), f, a, \xi) = 1 + \varphi. \tag{D.2}$$

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

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

$$v\left(m, \widehat{w}(m, f, a, \xi), f, a, \xi\right) = (1 - \omega m) v \left(\frac{(1 - \omega) m}{1 - \omega m}, \frac{\widehat{w}(m, f, a, \xi)}{1 - \omega m}, f, a, \xi \right). \tag{D.3}$$

The LHS of (D.3) is the firm's value for not replacing key talents at the threshold $\widehat{w}(m, f, a, \xi)$, while the RHS is the firm's value of replacing key talents at the threshold $\widehat{w}(m, f, a, \xi)$. The optimization condition is referred to as the value matching condition (see Dumas, 1991). It is essentially the first-order condition with respect to the turnover boundary $\widehat{w}(m, f, a, \xi)$.

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

$$0 = \max_{s_t, \tau_t} \mathbb{E}_t \left[\mathrm{d}\left(\Lambda_t v(m_t, w_t, f_t, a_t, \xi_t)\right) + \xi_t \left(v(m_t, w_t - \zeta, f_t, a_t, \xi_t) - v(m_t, w_t, f_t, a_t, \xi_t) \right) | \vartheta_t = \vartheta_H \right], \tag{D.4}$$

for all $(m_t, w_t, a_t) \in \mathcal{F} \equiv \{(m, w, a) \ : \ 0 \leq m \leq 1, 0 \leq w \leq \widehat{w}(m, f, a, \xi), a \in \mathbb{R}\}$. The HJB equation (D.4) leads to $2N$ coupled partial differential equations (PDE) for $\{f_{(1)}, ..., f_{(N)}\} \times \{\xi_L, \xi_H\}$ using the Ito's lemma and the optimal conditions for s_t and τ_t. It is a standard free-boundary PDE problem since the boundaries of $\mathcal{F}$ need to be solved simultaneously with the firm's value $v(m, w, f, a, \xi)$.

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

$$0 = \max_{s_t, \tau_t} \mathbb{E}_t \left[\mathrm{d}\left(\Lambda_t v(m_t, w_t, f_t, a_t, \xi_t)\right) + \xi_t \left(v(m_t, w_t - \zeta, f_t, a_t, \xi_t) - v(m_t, w_t, f_t, a_t, \xi_t) \right) | \vartheta_t = \vartheta_L \right], \tag{D.5}$$

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

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

Table D.1: Summary of parameters

Parameters	Symbol	Value
Risk-free rate	r	5%
Fixed financing costs	γ	0.01
Variable financing costs	φ	0.06
Long run average aggregate productivity	$\bar{a}$	0.5
Mean-reversion of aggregate productivity	μ_a	0.275
Volatility of aggregate productivity	σ_a	0.07
Physical capital depreciation rate	δ_K	0.1
Cash holding costs	ρ	1.5%
Consumers' willingness to pay	u	0.27
Stealing cost	ϖ	0.08
Matching efficiency	ψ	1
Matching elasticity	χ	2.12
Agents' search costs	x	1
Sales' people hiring costs (scale)	α	1.5
Sales' people hiring costs (convex)	η	2
Fraction of customer extraction	ω	0.1
New customers created by a new brand	ℓ	0.45
Private benefits	h	0.007
Customer capital depreciation rate	δ_B	0.15
Intensity of pure-brand-based transformation	$f_{(1)}, f_{(2)}$	$0, 1$
Probability of pure-brand-based transformation	$\Phi(f_{(1)}), \Phi(f_{(2)})$	$0.15, 0.85$
BTR shock arrival intensity	π	1
Turnover successful rate	ϑ	0.1
Shocks to cash flows	σ_B	0.15
Lumpy cash flow shock size	ζ	0.1
Lumpy cash flow shock frequency	ξ_L, ξ_H	$0, 0.5$
Price of risk	$\kappa^{(\xi_L,\xi_H)}, \kappa^{(\xi_H,\xi_L)}$	$-\ln(3), \ln(3)$
Transition probability	$q^{(\xi_L,\xi_H)}, q^{(\xi_H,\xi_L)}$	$0.16, 0.2$

following boundary condition:

$$v_w(m, \overline{w}(m, f, a, \xi), f, a, \xi) = 1. \tag{D.6}$$

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

$$v(m, w, f, a, \xi) = v(m, \overline{w}(m, f, a, \xi), f, a, \xi) + w - \overline{w}(m, f, a, \xi), \quad \text{for} \quad w \geq \overline{w}(m, f, a, \xi). \tag{D.7}$$

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

$$v_{ww}(m, \overline{w}(m, f, a, \xi), f, a, \xi) = 0, \tag{D.8}$$

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

E Data and Additional Empirical Results

E.1 BAV Consumer Survey and BAV Brand Metrics

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

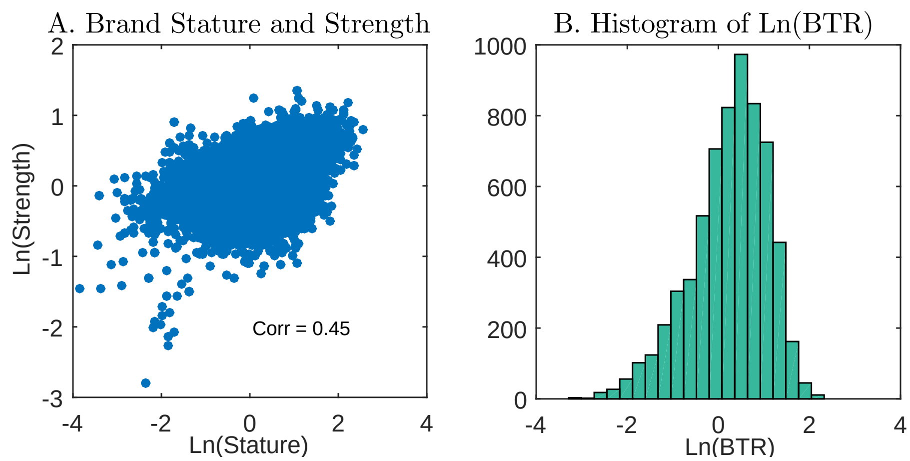
Brand Stature. The BAV Group constructs the brand stature measure to capture brand loyalty of existing customers (see Gerzema and Lebar, 2008). Brand stature reflects the current value of a brand, and it is the product between *Esteem* and *Knowledge*. *Esteem* is a measure of respect and admiration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

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

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

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

E.3 Sample Characteristics



Note: Panel A shows the relation between stature and strength. Panel B shows the distribution of lnBTR. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is from 1993 to 2016.

Figure E.2: The Brand-talent ratio.

As shown in Table F.2, our merged data cover a wide range of industries and represent all the major sectors. Compared to the Compustat-CRSP data, our sample contains more observations from the consumer non-durables and retail sectors. This pattern is not surprising since most of the firms in these sectors are business-to-consumer firms. Financial firms (SIC classification between 6000 and 6999) and utility firms (SIC classification between 4000 and 4999) are under-represented in the BAV data. Given that we exclude financial firms and utility firms from our analysis, the underrepresentation of these two industries does not affect us. The distribution of the remaining segments in the BAV data is comparable to the Compustat-CRSP universe. Table F.3 tabulates the distribution of the BAV data across GICS industries. Although the BAV data are biased towards final consumption good firms, the data also provide a significant amount of coverage for the investment good firms. Final consumption good firms are firms in the following GICS industries: Automobiles & Components, Consumer Durables & Apparel, Consumer Services, Media, Retailing, Food & Staples Retailing, Food, Beverages & Tobacco, and Household & Personal Products. In the BAV data, 55.9% of firm-year observations come from final consumption good firms, while this percentage is 21.0% in the Compustat/CRSP data. We also follow Gomes, Kogan and Yogo (2009) and classify each SIC industry into categories (durables, non-durables, services, domestic investment, government, and net exports) according to its contribution to final demand. Table F.4 tabulate the distribution of this durability industry classifications within each BTR quintiles. We do not observe any obvious clustering pattern across BTR quintiles for all durability categories.

Panel A of Figure E.2 shows that brand stature and brand strength are positively correlated with each other, with the correlation coefficient being 0.45. However, the relation between stature and strength is far from a one-to-one mapping. Panel B of Figure E.2 shows that lnBTR has a good amount of variation and its distribution is close to normal.

E.4 Extended Sample Analyses

We use two approaches to extend our sample. In the first approach, we compute the BMT beta for U.S. public firms and use it as a proxy for BTR. This approach allows us to extend the sample cross sectionally in the sample period covered by the BAV data (i.e. 1993 - 2016). We verify that the BMT beta is an asset pricing factor. In the second approach, we extend our analyses both in the cross section and in time series using a mimicking portfolio method. We show that our previous results of BTR are robust in the extend sample.

E.4.1 BMT is an Asset Pricing Factor

We compute the BMT beta for U.S. public firms by regressing their stock returns on the returns of the BMT portfolio. Since the BMT portfolio has risk exposure to the traditional asset pricing factors, we control for these factors when estimating the BMT beta.[26] We then sort firms into quintiles based on the BMT betas. Table F.11 tabulates the average excess returns and alphas of the BMT beta portfolios. We find that the firms with lower BMT betas have significantly higher average excess returns and alphas. This pattern is robust to the choice of asset pricing models used for estimating the BMT beta. It is also robust to the choice of asset pricing models used for computing the alphas of the BMT beta portfolios. The results in Table F.11 indicate that BMT is an asset pricing factor that cannot be explained by traditional asset pricing factors.

Our model predicts that the firms with lower BMT betas should have greater exposure to financial constraints risk in the cross section. To provide empirical support for this prediction, we sort firms into quintiles based on their BMT betas and document their characteristics.[27] Table F.12 tabulates the firm characteristics in the Compustat-CRSP universe. We find that the firms with lower BMT betas are more likely to be growth firms with higher cash flow volatilities. These firms pay out more to their key talents and experience higher talent turnover rates. They also adopt more precautionary financial policies and have lower leverage ratios. Table F.12 tabulates the results in the BAV-Compustat-CRSP merged sample. We confirm that higher BMT betas are indeed associated with higher BTRs. The distribution of other firm characteristics is similar to those in the Compustat-CRSP merged sample. Taken together, the findings suggest that the firms with lower BMT betas have higher exposures to liquidity shocks.

E.4.2 Mimicking Portfolio Analysis

We construct the mimicking portfolio for BTR by projecting the BMT portfolio returns onto the space of excess returns of asset pricing factors and industry portfolios. We use the mimicking portfolio betas as a proxy for BTR and repeat our empirical analyses. We find that the firms with higher mimicking portfolio betas are associated with lower alphas. The details on the construction of the mimicking portfolio and results of the analyses based on the mimicking portfolio betas can be found in online appendix.

[26] Pastor and Stambaugh (2003) use the same approach to study the asset pricing implications of their market liquidity factor. They estimate the market liquidity beta in regressions that control for the Fama-French three factors.

[27] The sorting is performed based on the univariate BMT betas. The relation between BMT betas and other asset pricing factors (e.g. whether low BMT beta firms are growth firms) is part of the focus of our test in Table F.12. This is different from the analysis in Table F.11, where we aim to seperate out the correlation between BMT beta and asset returns from the correlation between other asset pricing factors and asset returns.

F Supplementary Tables

Table F.1: Summary statistics.

Variables	Mean	Median	10%	90%	S.D.	# of obs.
BAV Variables						
ln(Stature)	0.32	0.48	−1.00	1.36	0.92	6,420
ln(Strength)	0.09	0.12	−0.45	0.59	0.42	6,420
lnBTR (unstandardized)	0.23	0.35	−0.96	1.21	0.84	6,420
Firm Characteristics						
lnsize	8.47	8.50	5.97	10.99	1.92	6,254
lnBEME	−1.01	−0.99	−2.04	0.05	0.92	6,004
lnlev	0.24	0.20	−0.97	1.41	1.01	6,004
ln(OC/Asset)	−0.36	−0.05	−1.46	0.75	1.55	6,089
Cash Flow Volatility						
Vol(Daily Ret) (%)	2.45	2.09	1.21	4.03	1.40	6,399
Vol(Sales_Gr) (%)	12.96	8.05	2.66	24.98	24.84	5,962
Vol(Net Income/Asset) (%)	5.05	2.74	0.81	11.07	8.07	5,971
Vol(EBITDA/Asset) (%)	3.40	2.41	0.84	6.80	3.88	5,967
Key Talent Compensation						
Administrative Expenses/Sales (%)	22.81	21.04	7.55	40.03	13.16	5,690
R&D/Sales (%)	7.07	2.98	0.57	17.50	11.24	2,763
Execucomp/Sales (%)	0.47	0.26	0.06	1.06	0.61	5,171
CEO Turnover						
$\text{Turnover}_t^{(1)} \times 100$	4.63	0	0	0	21.02	5,247
$\text{Turnover}_t^{(2)} \times 100$	5.05	0	0	0	21.91	5,247
Innovator Turnover						
$ln(1+\text{leavers})$	1.43	1.10	0	3.71	1.46	1,865
$ln(1+\text{new hires})$	1.44	1.10	0	3.69	1.47	1,865
Corporate Financial Policy						
Cash/Lagged Asset (%)	15.38	9.21	1.29	36.47	18.03	6,253
ΔCash/Net Income (%)	15.32	4.50	−73.45	111.70	185.79	5,380
ΔEquity/Lagged Asset (%)	1.80	0.48	0	2.84	7.79	6,253
Payout/Lagged Asset (%)	5.91	3.62	0	16.04	6.64	6,253
Dividend/Lagged Asset (%)	1.91	1.07	0	5.28	2.48	6,253
Repurchases/Lagged Asset (%)	3.77	1.28	0	12.19	5.20	6,253

Note: This table presents the summary statistics for the main variables of our sample. We merge BAV brand survey data with Compustat and CRSP data to construct a firm-year panel. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We construct the BTR using the ratio of brand stature and brand strength. CEO turnover variables are derived from Execucomp. Innovator turnover variables are derived from the Harvard Business School patent and innovator database (see Li et al., 2014). Corporate financial policy variables, firm characteristics, and key talent compensation variables are derived from Compustat and Execucomp. Cash flow volatility variables are derived from Compustat and CRSP. Our sample spans the period between 1993-2016 and includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analyses. The definition of the variables is listed in Appendix Table A.1.

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

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

Note: This table presents the distribution of BAV data and CRSP-Compustat universe by industry for the period 1993-2016. Industries are defined according to the Fama-French 12-industry classification. We report the total number of firm-year observations and the proportion (in percentage) of the number of observations in each industry in both BAV data and the Compustat-CRSP universe. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We include the observations from financial firms and utility firms in this table, but we exclude them in the analyses of our paper.

Table F.3: GICS industry distribution of the BAV sample.

GICS Inudstry Group	Industry Code	# Firm-Year Obs.	% Firm-Year Obs.
Energy	1010	162	2.22
Materials	1510	218	2.99
Capital Goods	2010	390	5.35
Commercial Services & Supplies	2020	74	1.02
Transportation	2030	268	3.68
Automobiles & Components	2510	128	1.76
Consumer Durables & Apparel	2520	753	10.34
Consumer Services	2530	556	7.63
Media	2540	369	5.07
Retailing	2550	1,105	15.17
Food & Staples Retailing	3010	203	2.79
Food, Beverage & Tobacco	3020	669	9.18
Household & Personal Products	3030	271	3.72
Health Care Equipment & Services	3510	146	2.00
Pharmaceuticals, Biotechnology & Life Sciences	3520	200	2.75
Banks	4010	189	2.59
Diversified Financials	4020	294	4.04
Insurance	4030	168	2.31
Software & Services	4510	555	7.62
Technology Hardware & Equipment	4520	281	3.86
Semiconductors & Semiconductor Equipment	4530	73	1.00
Telecommunication Services	5010	186	2.55
Utilities	5510	15	0.21
Real Estate	6010	12	0.16

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

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

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

Note: This table presents the distribution of the durability industry classifications within each BTR quintile. The durability industry classification comes from Gomes, Kogan and Yogo (2009), who classify each SIC industry into six categories (durables, non-durables, services, private domestic investment, government, and net exports) according to its contribution to final demand, with a detailed breakdown for personal consumption expenditures (PCE). The durability classification is constructed based on NIPA's Benchmark Input-Output Accounts. The durability classification does not include wholesale and retail firms (SIC 5000-5999) because a detailed breakdown of value added by PCE category is not available for them. We label wholesale and retail firms as "others" in the table. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude utility firms and financial firms in the analysis. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The BTR quntiles are formed at the yearly basis based on the lagged BTR ratio. Our sample spans 1993 to 2016.

Table F.5: Excess portfolio returns sorted on BTR: factor loadings

BTR Portfolios	1 (Low)	2	3	4	5 (High)	5 − 1
			Panel A: Fama-French Three-Factor Model			
β_{mkt}	1.19***	1.12***	0.95***	0.92***	0.99***	−0.20***
	[30.42]	[33.89]	[33.62]	[37.57]	[34.66]	[−4.54]
β_{smb}	0.08	0.03	−0.12***	−0.04	0.01	−0.07
	[1.50]	[0.77]	[−3.18]	[−1.11]	[0.19]	[−1.20]
β_{hml}	−0.13**	0.23***	0.31***	0.21***	0.50***	0.63***
	[−2.26]	[4.91]	[7.50]	[6.01]	[12.11]	[9.75]
R^2	0.792	0.815	0.810	0.842	0.828	0.360
			Panel B: Carhart Four-Factor Model			
β_{mkt}	1.13***	1.05***	0.91***	0.88***	0.94***	−0.19***
	[28.23]	[32.20]	[31.42]	[35.49]	[32.51]	[−4.06]
β_{smb}	0.10*	0.06	−0.11***	−0.02	0.02	−0.08
	[1.95]	[1.43]	[−2.84]	[−0.66]	[0.67]	[−1.25]
β_{hml}	−0.18***	0.16***	0.26***	0.17***	0.45***	0.64***
	[−3.29]	[3.63]	[6.49]	[4.90]	[11.14]	[9.63]
β_{mom}	−0.15***	−0.18***	−0.12***	−0.11***	−0.12***	0.03
	[−4.40]	[−6.50]	[−4.78]	[−5.40]	[−5.03]	[0.65]
R^2	0.806	0.840	0.824	0.857	0.842	0.361
			Panel C: Pástor-Stambaugh Five-Factor Model			
β_{mkt}	1.12***	1.04***	0.90***	0.88***	0.94***	−0.18***
	[27.64]	[31.53]	[30.77]	[34.88]	[31.88]	[−3.71]
β_{smb}	0.09*	0.06	−0.11***	−0.02	0.02	−0.07
	[1.85]	[1.36]	[−2.93]	[−0.66]	[0.64]	[−1.17]
β_{hml}	−0.18***	0.17***	0.27***	0.17***	0.45***	0.63***
	[−3.19]	[3.71]	[6.59]	[4.89]	[11.15]	[9.57]
β_{mom}	−0.16***	−0.18***	−0.12***	−0.11***	−0.13***	0.03
	[−4.62]	[−6.62]	[−4.91]	[−5.38]	[−5.06]	[0.79]
β_{ps}	11.48**	5.80	5.71*	0.22	2.00	−9.49*
	[2.52]	[1.56]	[1.73]	[0.08]	[0.60]	[−1.76]
R^2	0.810	0.842	0.826	0.857	0.843	0.368

Note: This table shows the asset pricing tests for portfolios sorted on BTR. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. In June of year t, we sort firms into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We compute the value-weighted portfolio returns and report the portfolio betas estimated by the Fama-French three-factor model, the Carhart four-factor model, and the Pástor-Stambaugh five-factor model, which includes the Fama-French three factors, the momentum factor, and the Pástor-Stambaugh liquidity factor (Pastor and Stambaugh, 2003). Data on the Fama-French three factors and the momentum factor are from Kenneth French's website. The Pástor-Stambaugh liquidity factor is from L'uboš Pástor's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.6: Long-short portfolio returns associated with various customer capital measures

Long-short Portfolios	High Brand Stature - Low Brand Stature	High Brand Strength - Low Brand Strength	High Product Fluidity - Low Product Fluidity
Panel A: Excess return of the long-short portfolios (%)			
Single Sort	-4.45^{**}	1.70	0.15
	$[-2.39]$	[0.74]	[0.05]
Double Sort	-0.65	0.73	4.61
(First Sort on BTR)	$[-0.37]$	[0.35]	[1.06]
Panel B: Fama-French three-factor α of the long-short portfolios (%)			
Single Sort	-4.32^{**}	1.64	-0.71
	$[-2.33]$	[0.82]	$[-0.29]$
Double Sort	-0.62	0.49	3.93
(First Sort on BTR)	$[-0.36]$	[0.27]	[1.42]
Panel C: Carhart four-factor α of the long-short portfolios (%)			
Single Sort	-3.82^{**}	2.48	0.06
	$[-2.05]$	[1.25]	[0.02]
Double Sort	0.35	1.39	3.87
(First Sort on BTR)	[0.20]	[0.75]	[1.38]
Panel D: Fama-French five-factor α of the long-short portfolios (%)			
Single Sort	-4.39^{**}	3.64	3.82
	$[-2.27]$	[1.41]	[1.56]
Double Sort	1.13	3.14	3.28
(First Sort on BTR)	[0.65]	[1.26]	[1.36]

Note: This table shows long-short portfolio returns associated with three customer capital measures: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). We sort stocks into quintiles based on the customer capital measures and then compute the average excess returns and alphas for the value weighted long-short portfolios. We also perform a double-sort analysis in which we first sort firms into three groups based on BTR and then sort the firms in each group into five quintiles based on the customer capital measures. The fluidity measure, as developed in Hoberg, Phillips and Prabhala (2014), measures how intensively the product market around a firm is changing in each year. It is downloaded from the Hoberg-Phillips data library. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. Data on the Fama-French three factors and five factors are from Kenneth French's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.7: Excess BMT portfolio returns controlling for customer capital measures using a double-sort approach

Panel A: Excess return (%)			
First Sort Variables	Brand Stature	Brand Strength	Product Fluidity
High BTR − Low BTR	−3.12	−6.84***	−5.74***
	[−1.34]	[−2.91]	[−2.43]

Panel B: Fama-French three-factor α (%)			
First Sort Variables	Brand Stature	Brand Strength	Product Fluidity
High BTR − Low BTR	−3.74*	−6.51***	−6.33***
	[−1.94]	[−3.19]	[−3.24]

Panel C: Carhart four-factor α (%)			
First Sort Variables	Brand Stature	Brand Strength	Product Fluidity
High BTR − Low BTR	−4.35**	−6.69***	−6.47***
	[−2.24]	[−3.24]	[−3.27]

Panel D: Fama-French five-factor α (%)			
First Sort Variables	Brand Stature	Brand Strength	Product Fluidity
High BTR − Low BTR	−7.63***	−8.61***	−9.38***
	[−4.14]	[−4.13]	[−4.83]

Note: This table shows the brand-minus-talent (BMT) portfolio returns controlling for customer capital measures using a double-sort approach. In June of year t, we sort firms into three groups based on three measures of customer capital: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). We then sort firms within each group into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. The fluidity measure, as developed in Hoberg, Phillips and Prabhala (2014), measures how intensively the product market around a firm is changing in each year. It is downloaded from the Hoberg-Phillips data library. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We compute the value-weighted portfolio returns and report the average excess returns of the long/short BTR portfolio, which is deonoted as the brand-minus-talent (BMT) portfolio. We also report the alphas of the BMT portfolios estimated by the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. Data on the Fama-French three factors and five factors are from Kenneth French's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.8: Excess BMT portfolio returns controlling for key talent compensation using a double-sort approach

Panel A: Excess return (%)				
First Sort Variables	Admin. Expenses	R&D Expenditure	Managerial Comp.	Organization Capital
High BTR − Low BTR	-5.69^{**}	-5.57^{**}	-3.84^{*}	-5.86^{**}
	[−2.49]	[−2.35]	[−1.80]	[−2.23]
Panel B: Fama-French three-factor α (%)				
First Sort Variables	Admin. Expenses	R&D Expenditure	Managerial Comp.	Organization Capital
High BTR − Low BTR	-5.29^{***}	-5.93^{***}	-4.38^{**}	-5.90^{***}
	[−2.79]	[−3.00]	[−2.44]	[−2.75]
Panel C: Carhart four-factor α (%)				
First Sort Variables	Admin. Expenses	R&D Expenditure	Managerial Comp.	Organization Capital
High BTR − Low BTR	-5.72^{***}	-6.10^{***}	-4.21^{**}	-5.91^{***}
	[−2.98]	[−3.05]	[−2.32]	[−2.72]
Panel D: Fama-French five-factor α (%)				
First Sort Variables	Admin. Expenses	R&D Expenditure	Managerial Comp.	Organization Capital
High BTR − Low BTR	-7.64^{***}	-8.96^{***}	-6.51^{**}	-9.73^{***}
	[−3.96]	[−4.58]	[−3.58]	[−4.64]

Note: This table shows the brand-minus-talent (BMT) portfolio returns controlling for key talent compensation using a double-sort approach. In June of year t, we first sort firms into three groups based on four measures of key talent compensation: administrative expenses, R&D expenditure, managerial compensation, and organizational capital. We then sort firms within each group into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. BTR is the ratio between brand stature and brand strength. Administrative expenses are computed from SG&A by taking out advertisement costs, R&D expenses, commissions, and foreign currency adjustments. R&D expenditure comes from Compustat. Managerial compensation is the summation of the total pay ($tdc1$) for the top five executives in the Execucomp data. Administrative expenses, R&D expenditure, and managerial compensation are normalized by sales. Organization capital is constructed from SG&A expenditures using the perpetual inventory method, following Eisfeldt and Papanikolaou (2013). Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We compute the value-weighted portfolio returns and report the average excess returns of the long/short BTR portfolio, which is deonoted as the brand-minus-talent (BMT) portfolio. We also report the alphas of the BMT portfolios estimated by the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. Data on the Fama-French three factors and five factors are from Kenneth French's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.9: Excess BMT portfolio returns within different industries

Panel A: Excess return (%)							
Industry Classifications	SIC2	FF5	FF10	FF12	FF17	FF48	Durability
High BTR − Low BTR	-3.39^{**}	-5.36^{***}	-5.11^{***}	-4.96^{***}	-5.24^{**}	-4.40^{***}	-5.06^{**}
	[−2.23]	[−3.04]	[−2.96]	[−2.87]	[−2.49]	[−2.71]	[−2.24]
Panel B: Fama-French three-factor α (%)							
Industry Classifications	SIC2	FF5	FF10	FF12	FF17	FF48	Durability
High BTR − Low BTR	-3.07^{**}	-5.06^{***}	-4.43^{***}	-4.29^{**}	-4.84^{***}	-3.57^{**}	-5.01^{***}
	[−2.21]	[−2.92]	[−2.60]	[−2.51]	[−2.74]	[−2.27]	[−2.66]
Panel C: Carhart four-factor α (%)							
Industry Classifications	SIC2	FF5	FF10	FF12	FF17	FF48	Durability
High BTR − Low BTR	-2.60^{*}	-4.60^{***}	-3.98^{**}	-3.93^{**}	-5.01^{***}	-3.18^{**}	-4.69^{**}
	[−1.86]	[−2.63]	[−2.32]	[−2.27]	[−2.80]	[−2.01]	[−2.46]
Panel D: Fama-French five-factor α (%)							
Industry Classifications	SIC2	FF5	FF10	FF12	FF17	FF48	Durability
High BTR − Low BTR	-4.28^{***}	-5.09^{***}	-4.81^{***}	-4.63^{***}	-7.78^{***}	-4.28^{***}	-7.71^{***}
	[−2.98]	[−2.84]	[−2.72]	[−2.62]	[−4.47]	[−2.63]	[−4.11]

Note: This table shows the brand-minus-talent (BMT) portfolio returns controlling for different industry classifications. In June of year t, we group firms into different industries based on various industry classifications. We then sort firms within each industry into five quintiles based on firms' BTR in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. SIC2 is the two-digit SIC industry. FF5, FF10, FF12, FF17, and FF48 are corresponding Fama-French industry classifications. The durability industry classification comes from Gomes, Kogan and Yogo (2009), who classify each SIC industry into six categories (durables, non-durables, services, private domestic investment, government, and net exports) based on its contribution to final demand. BTR is the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We compute the value-weighted portfolio returns and report the average excess returns of the long/short BTR portfolio, which is deonoted as the brand-minus-talent (BMT) portfolio. We also report the alphas of the BMT portfolios estimated by the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. Data on the Fama-French three factors and five factors are from Kenneth French's website. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period is 1993 to 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.10: BTR and key talent turnovers: the role of financial constraints, WW index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEOs				Innovators			
	$\text{Turnover}_t^{(1)} \times 100$		$\text{Turnover}_t^{(2)} \times 100$		$ln(1+\text{leavers})_t$		$ln(1+\text{new hires})_t$	
Sample	High WW (Constrained)	Low WW (Unconstrained)	High WW (Constrained)	Low WW (Unconstrained)	High WW (Constrained)	Low WW (Unconstrained)	High WW (Constrained)	Low WW (Unconstrained)
$ln\text{BTR}_{t-1}$	-1.213^{***}	-0.481	-1.163^{**}	-0.537	-0.203^{**}	-0.098	-0.212^{**}	-0.067
	[−2.957]	[−1.378]	[−2.731]	[−1.096]	[−2.472]	[−0.755]	[−2.676]	[−0.512]
$ln(\text{OC/Asset})_{t-1}$	0.405	0.044	0.404	0.135	0.077	0.030	0.065	0.009
	[1.484]	[0.146]	[1.524]	[0.481]	[1.641]	[0.351]	[1.260]	[0.121]
$ln\text{size}_{t-1}$	0.804^{***}	-0.849^{**}	0.909^{***}	-0.822^{*}	0.392^{***}	0.736^{***}	0.385^{***}	0.714^{***}
	[2.865]	[−2.077]	[2.856]	[−1.809]	[5.763]	[4.746]	[5.590]	[4.631]
$ln\text{BEME}_{t-1}$	0.667	-0.204	0.976	0.064	0.360^{***}	0.255	0.323^{***}	0.218
	[0.999]	[−0.389]	[1.415]	[0.106]	[3.628]	[1.477]	[3.351]	[1.284]
$ln\text{lev}_{t-1}$	0.634^{*}	-0.146	0.814^{**}	-0.136	0.163^{**}	0.221	0.145^{**}	0.191
	[2.042]	[−0.357]	[2.360]	[−0.307]	[2.424]	[1.250]	[2.147]	[1.083]
StockRet_{t-1}	-3.487^{**}	-5.822^{***}	-3.690^{**}	-5.382^{***}	0.171	0.145	0.153	0.131
	[−2.112]	[−4.371]	[−2.234]	[−3.413]	[1.729]	[1.246]	[1.577]	[0.880]
Female	-2.029	2.198	-2.115	2.820				
	[−0.887]	[1.301]	[−0.928]	[1.495]				
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2369	2499	2369	2499	896	887	896	887
R-squared	0.022	0.018	0.022	0.018	0.257	0.304	0.255	0.305

Note: This table shows the relation between BTR and key talent turnovers in firms with and without financial constraints. lnBTR is the natural log of the ratio between brand stature and brand strength. Brand stature and brand strength are two brand metrics constructed by the BAV Group based on its comprehensive brand perception survey. Brand stature measures brand loyalty of existing customers. Brand strength measures how much the brand is perceived by the consumers to be innovative and distinctive. We classify firms into financially constrained firms and financially unconstrained firms based on the WW index (see Whited and Wu, 2006; Hennessy and Whited, 2007). The classification is performed at yearly basis. The financially constrained firms are the firms with WW index larger than the median values. CEO turnover data come from Execucomp. In Column (1) and (2), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, and it is 0 otherwise. In Column (3) and (4), the dependent variable is 100 for a given CEO-year observation if the CEO leaves the firm at age 59 or younger due to reasons other than death, or if the CEO resigns according to the Execucomp data, and it is 0 otherwise. We track the innovator turnovers using the Harvard Business School (HBS) patent and innovator database (see Li et al., 2014), which provides the names of the innovators and their affiliations from 1975 to 2010. Following Li et al. (2014), a mover in a given year is defined as an innovator who generates at least one patent in one firm and generates at least one patent in another firm in the later time period of the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that given year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that given year. The dependent variables are the natural log of one plus the number of leavers, and the natural log of one plus the number of new hires. The main independent variable is the lagged lnBTR. We standardize lnBTR to ease the interpretation of the coefficients. Control variables include lagged firm characteristics such as the natural log of the organization capital-to-asset ratio $ln(\text{OC/Asset})$, the natural log of firm market capitalization (lnsize), the natural log of the book-to-market ratio (lnBEME), the natural log of the debt-to-equity ratio (lnlev), the 12-month stock returns in the previous year (StockRet), and a dummy variable for the gender of the CEOs (Female). Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The CEO turnover sample spans 1993 to 2016, while the innovator turnover sample spans 1993 to 2010. We include t-statistics in parentheses. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.11: Excess portfolio returns sorted on beta with BMT portfolio.

BMT Beta Portfolio	1 (Low)	2	3	4	5 (High)	5 − 1
Panel A: BMT Beta Estimated from the Fama-French Three-factor Model						
Excess return (%)	19.64***	13.02***	11.84***	11.91***	13.67***	−5.97*
	[3.40]	[3.08]	[3.30]	[3.32]	[3.20]	[−1.91]
Fama-French three-factor α (%)	10.32***	4.97***	4.46***	4.06***	4.68***	−5.64**
	[4.64]	[3.15]	[3.94]	[3.23]	[2.97]	[−2.31]
Carhart four-factor α (%)	11.73***	5.82***	5.05***	4.54***	5.05***	−6.69***
	[5.33]	[3.85]	[4.62]	[3.59]	[3.08]	[−2.66]
Pástor-Stambaugh five-factor α (%)	11.21***	5.20***	4.70***	4.11***	4.56***	−6.65***
	[5.31]	[3.67]	[4.59]	[3.32]	[2.74]	[−2.67]
Fama-French five-factor α (%)	13.12***	4.95***	3.21***	1.76	2.77*	−10.35***
	[5.76]	[3.02]	[2.95]	[1.50]	[1.77]	[−4.33]
Panel B: BMT Beta Estimated from the Carhart's Four-factor Model						
Excess return (%)	20.25***	13.38***	11.53***	12.01***	13.17***	−7.09**
	[3.43]	[3.21]	[3.26]	[3.31]	[3.09]	[−2.14]
Fama-French three-factor α (%)	10.80***	5.35***	4.18***	4.15***	4.22***	−6.58**
	[4.63]	[3.43]	[3.77]	[3.26]	[2.71]	[−2.51]
Carhart four-factor α (%)	12.15***	6.33***	4.89***	4.50***	4.48***	−7.67***
	[5.23]	[4.23]	[4.60]	[3.55]	[2.75]	[−2.83]
Pástor-Stambaugh five-factor α (%)	11.58***	5.86***	4.47***	3.98***	4.04**	−7.54***
	[5.21]	[4.07]	[4.53]	[3.23]	[2.45]	[−2.81]
Fama-French five-factor α (%)	14.13***	4.97***	2.61**	2.20*	2.33	−11.80***
	[5.96]	[3.16]	[2.52]	[1.75]	[1.52]	[−4.69]
Panel C: BMT Beta Estimated from the Fama-French Five-factor Model						
Excess return (%)	19.50***	13.21***	11.48***	11.98***	14.31***	−5.19*
	[3.51]	[3.25]	[3.19]	[3.24]	[3.22]	[−1.91]
Fama-French three-factor α (%)	10.44***	5.62***	4.03***	3.92***	4.91***	−5.53**
	[4.70]	[4.22]	[3.68]	[3.16]	[3.14]	[−2.40]
Carhart four-factor α (%)	11.75***	6.35***	4.67***	4.55***	5.32***	−6.43***
	[5.35]	[5.10]	[4.47]	[3.72]	[3.36]	[−2.75]
Pástor-Stambaugh five-factor α (%)	10.93***	5.95***	4.31***	4.06***	5.01***	−5.92**
	[5.17]	[4.95]	[4.49]	[3.44]	[3.14]	[−2.57]
Fama-French five-factor α (%)	12.33***	5.60***	3.02***	1.91	3.91**	−8.42***
	[5.52]	[3.93]	[2.72]	[1.60]	[2.46]	[−3.73]

Note: This table shows the asset pricing tests for portfolios sorted on the beta with the BMT portfolio. In each month, we estimate the BMT beta by regressing monthly stock returns on the returns of the BMT portfolio and the returns of asset pricing factors in the preceding 36 months. In the beginning of the sample, when there are less than 36 monthly historical BMT returns, we require at least 12 monthly BMT returns to estimate the BMT beta. We then average the monthly BMT beta into yearly BMT beta for each stock and sort the stocks into quintiles based on their lagged yearly BMT beta. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample spans 1993 and 2016. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table F.12: Firm characteristics and BMT beta: Compustat-CRSP sample.

	Median					Mean				
BTM Beta Portfolios	Low	2	3	4	High	Low	2	3	4	High
Firm Characteristics										
*ln*size	5.60	5.97	6.28	6.36	6.00	5.67	6.00	6.28	6.37	6.09
*ln*BEME	−0.84	−0.74	−0.70	−0.66	−0.65	−0.90	−0.78	−0.74	−0.69	−0.70
*ln*lev	−0.53	−0.33	−0.19	−0.14	−0.06	−0.51	−0.36	−0.21	−0.17	−0.07
Operating profitability (%)	13.90	19.23	22.35	23.74	22.44	8.25	16.68	21.46	24.10	22.68
ΔAsset/Lagged Asset (%)	5.13	5.54	5.81	5.19	4.79	14.72	12.69	11.72	10.46	11.52
Cash Flow Volatility										
Vol(Daily Ret) (%)	3.82	3.11	2.66	2.45	2.75	4.25	3.53	3.10	2.90	3.25
Vol(Sales_Gr) (%)	19.23	14.24	12.54	11.25	12.40	43.76	28.49	23.32	22.04	24.26
Vol(Net Income/Asset) (%)	7.57	4.76	3.44	3.08	3.62	14.19	9.47	7.14	6.29	7.69
Vol(EBITDA/Asset) (%)	5.30	3.66	3.05	2.84	3.16	9.33	6.51	5.19	4.70	5.60
Key Talent Compensation										
Administrative Expenses/Sales (%)	26.51	23.00	20.25	19.53	18.93	31.56	26.77	23.72	22.42	22.73
R&D/Sales (%)	16.44	9.43	4.61	3.25	3.44	46.79	32.29	20.22	22.57	17.74
Execucomp/Sales (%)	1.06	0.68	0.50	0.44	0.45	1.52	1.08	0.82	0.70	0.75
Corporate Financial Policy										
Cash/Lagged Asset (%)	26.26	14.64	9.11	7.99	8.09	34.31	24.06	17.94	15.70	16.66
ΔCash/Net Income (%)	17.72	7.99	6.07	5.30	5.83	37.90	24.38	17.41	17.33	18.61
ΔEquity/Lagged Asset (%)	1.03	0.58	0.45	0.39	0.35	10.32	5.95	3.79	3.06	4.52
Payout/Lagged Asset (%)	0	0.39	1.20	1.58	0.80	2.23	3.08	3.69	3.83	3.08
Dividend/Lagged Asset (%)	0	0	0	0.32	0	0.37	0.79	1.13	1.42	1.08
Repurchases/Lagged Asset (%)	0	0	0.04	0.07	0	1.70	2.11	2.37	2.23	1.86

Note: This table shows the characteristics of the five portfolios sorted on the univariate BMT beta. In each month, we estimate the univariate BMT beta by regressing monthly stock returns on the returns of the BMT portfolio in the preceding 36 months. In the beginning of the sample, when there are less than 36 monthly historical BMT returns, we require at least 12 monthly BMT returns to estimate the BMT beta. We then average the monthly BMT beta into yearly BMT beta for each stock and sort the stocks into quintiles based on their lagged yearly BMT beta. We report the mean and median firm characteristics for each portfolio. We sort BMT beta in the Compustat-CRSP sample. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period spans 1993 and 2016. We explain the definition of the variables in Appendix Table A.1.

Table F.13: Firm characteristics and BMT beta: BAV-Compustat-CRSP sample.

	Median					Mean				
BTM Beta Portfolios	Low	2	3	4	High	Low	2	3	4	High
lnBTR (standardized)	−0.28	0.11	0.37	0.43	0.46	−0.36	−0.03	0.27	0.34	0.39
Firm Characteristics										
lnsize	8.57	8.56	8.82	8.89	8.70	8.44	8.55	8.79	8.82	8.59
lnBEME	−1.04	−1.01	−1.00	−1.03	−0.96	−1.07	−1.04	−1.04	−1.04	−1.02
lnlev	−0.19	0.07	0.25	0.23	0.46	−0.13	0.12	0.32	0.27	0.53
Operating profitability (%)	25.11	31.78	31.76	33.54	30.95	23.93	34.40	38.58	38.94	38.44
ΔAsset/Lagged Asset (%)	5.65	5.54	4.39	3.81	3.13	12.48	8.53	9.00	6.66	6.56
Cash Flow Volatility										
Vol(Daily Ret) (%)	2.60	2.13	1.87	1.81	2.00	2.91	2.41	2.14	2.06	2.28
Vol(Sales_Gr) (%)	9.63	7.69	7.44	6.90	7.17	15.52	10.86	11.20	10.50	11.17
Vol(Net Income/Asset) (%)	3.99	2.60	2.24	2.33	2.51	7.41	4.52	3.95	3.68	4.04
Vol(EBITDA/Asset) (%)	3.22	2.39	2.11	2.19	2.10	4.10	3.20	2.86	2.80	2.92
Key Talent Compensation										
Administrative Expenses/Sales (%)	23.47	21.36	20.77	20.22	19.13	25.89	22.63	21.78	21.36	20.74
R&D/Sales (%)	10.25	2.70	3.30	2.20	2.07	14.78	8.13	6.45	4.05	3.29
Execucomp/Sales (%)	0.41	0.29	0.24	0.22	0.22	0.74	0.45	0.42	0.37	0.38
Corporate Financial Policy										
Cash/Lagged Asset (%)	20.35	9.91	7.71	6.87	7.62	25.98	16.06	12.25	11.35	11.25
ΔCash/Net Income (%)	7.73	4.74	4.09	2.75	4.40	26.87	19.07	11.64	10.36	16.77
ΔEquity/Lagged Asset (%)	0.72	0.56	0.56	0.46	0.39	2.65	1.55	1.29	0.98	1.18
Payout/Lagged Asset (%)	2.88	4.24	4.96	5.07	3.43	5.82	6.47	6.88	6.84	5.64
Dividend/Lagged Asset (%)	0	0.97	1.68	2.02	1.46	1.14	1.72	2.30	2.61	2.27
Repurchases/Lagged Asset (%)	1.25	2.14	2.20	2.06	1.03	4.29	4.48	4.35	4.07	3.22

Note: This table shows the characteristics of the five portfolios sorted on the univariate BMT beta. In each month, we estimate the univariate BMT beta by regressing monthly stock returns on the returns of the BMT portfolio in the preceding 36 months. In the beginning of the sample, when there are less than 36 monthly historical BMT returns, we require at least 12 monthly BMT returns to estimate the BMT beta. We then average the monthly BMT beta into yearly BMT beta for each stock and sort the stocks into quintiles based on their lagged yearly BMT beta. We report the mean and median firm characteristics for each portfolio. We condition our sorting in the BAV-Compustat-CRSP merged sample. Our sample includes firms that are listed on NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms from the analysis. The sample period spans 1993 and 2016. We explain the definition of the variables in Appendix Table A.1.