Customer Capital, Financial Constraints, and Stock Returns

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Abstract

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

Keywords: Brand loyalty; Financial constraints risk; Inalienable human capital; Talent turnover. (JEL: G12, G30, M31, M37, E22)

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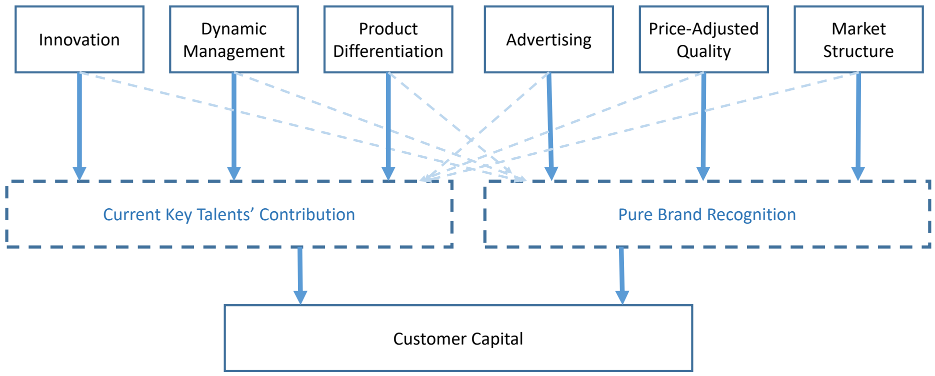
1 Introduction

Customer capital – customers' brand loyalty to the firm – is one of the firm's most crucial intangible assets, as it determines the capacity of stable demand flows by creating entry barriers and durable advantages over competitors (see, e.g., Bronnenberg, Dubé and Gentzkow, 2012). Developing and sustaining customer capital is essential for a firm's survival, growth, profitability, and ultimately its valuation, even though customer capital does not explicitly appear on the balance sheet.[1]

Conceptually, customer capital is a synthesis of various intangible assets. Figure 1 shows that the creation and maintenance of customer capital depend on innovation, dynamic management, and product differentiation, primarily through the channel of current key talents' unique contribution, as well as on advertising, price-adjusted product quality, and market structure, primarily through the channel of pure brand recognition. Firms whose customer capital depends more on current key talents' unique contribution, than on pure brand recognition, are more exposed to financial constraints risk, because when firms are financially constrained, key talents are likely to leave, taking away or damaging the associated customer capital. Retaining key talents imposes operating leverage on firms. By contrast, pure brand recognition is largely immune to key talent turnover. Thus, during periods of heightened financial constraints risk, firms whose customer capital is more talent dependent suffer more, because (1) they are more likely to experience key talent turnover due to higher operating leverage, and (2) they tend to lose a larger fraction of customer capital upon key talent departure due to the heavier dependence of customer capital on key talents. Such heterogeneous exposure to financial constraints risk is further amplified in a feedback loop, because the loss of customer capital reduces future revenue.

The extent to which a firm's customer capital depends on key talents reflects what we conceptualize as the *inalienability of customer capital (ICC)*, which gauges the fragility of customer capital to key talent turnover. We build on the notion from Hart and Moore (1994) and Bolton, Wang and Yang (2018) that human capital is inalienable; that is, the firm's capital becomes less profitable or can be (partially) taken away by key talents after their departure. In other words, key talents cannot costlessly be replaced. Unlike physical

[1] As Rudanko (2017) emphasizes, customer capital is crucial for the other assets of firms to be profitable. One example demonstrating the necessity of customer capital is the well-known case of Iridium's bankruptcy due to its failure to create and maintain customer capital.



Note: The solid arrows represent primary channels, whereas the dashed arrows represent secondary channels.

Figure 1: Different channels of creating and maintaining customer capital

or some other types of intangible capital of the firm such as patents, customer capital that relies heavily upon the unique contribution of current key talents can be taken away or seriously damaged by key talents' departure due to limited legal enforceability. Therefore, the ICC can be viewed as one concrete and important example of the inalienability of human capital.[2]

Our major contribution lies in examining how the ICC interacts with financial constraints and investigating the asset pricing implications of this interaction. Like Whited and Wu (2006) and Buehlmaier and Whited (2018), we focus on the aggregate financial-constraints-risk shock that alters the marginal value of internal funds of all firms simultaneously. The financial-constraints-risk shock can be jointly driven by multiple more primitive macroeconomic shocks such as the TFP shock, the uncertainty shock, the financing-cost shock, and so on. This shock is shown to carry a negative market price of risk (see, e.g., Whited and Wu, 2006; Buehlmaier and Whited, 2018). As the main theoretical contribution, we show that a firm's exposure to financial-constraints-risk shocks is simultaneously reflected in two cross sections: firms have higher liquidity-driven talent turnover and higher average returns, if (1) their customer capital is more talent dependent, and (2) they are more financially constrained. The cross-equation restrictions implied by the model predictions on both turnover and returns in the two cross sections over-identify

[2]The ICC is also linked to other types of inalienable capital associated with key talents, such as their social capital (see, e.g., Arrow, 1999; Glaeser et al., 1999; Durlauf, 2002; Sobel, 2002; Durlauf and Fafchamps, 2005).

the same asset pricing factor, the financial-constraints-risk factor, which makes our model more quantitatively disciplined. The empirical analyses rely upon measuring the ICC, which is challenging. As the main empirical contribution, we introduce a measure for the ICC, based on a proprietary, granular brand perception survey database. We also provide empirical evidence that strongly supports the theoretical implications.

We start by developing a baseline dynamic model to illustrate the key underlying mechanism. In the baseline model, the firm's external financing is costly, which motivates retained earnings and imposes financial constraints risk on itself. The marginal value of its internal funds is determined jointly by the endogenous level of firm-specific cash holdings and the exogenous level of financial constraints risk. The latter is time-varying and driven by an aggregate shock. Such a shock is referred to as the *financial-constraints-risk shock* and is the only systematic shock in the baseline model. Customer capital guarantees stable demand flows and is partly maintained by key talents. The contract between key talents and shareholders features two-sided limited commitment. On the one hand, key talents have outside options and limited commitment to the firm; as a result, maintaining talent-dependent customer capital requires that firms compensate key talents and thus imposes operating leverage on the firm. On the other hand, shareholders would choose to let key talents go if retaining them becomes too costly. Thus, heterogeneous levels of ICC lead to firms' differential exposure to the aggregate financial-constraints-risk shock, which simultaneously generates the spreads in (risk-adjusted) average stock returns and talent turnover rates.

More precisely, shareholders face the intertemporal trade-off between risks and returns when they decide whether or not to retain talent-dependent customer capital. Although retaining talent-dependent customer capital on average brings positive net cash flows, the associated operating leverage increases firms' exposure to financial constraints risk. When firms face heightened financial constraints risk, key talents may find it optimal to *escape from a sinking ship* or *jump to a safer boat* (see, e.g., Brown and Matsa, 2016; Babina, 2017; Baghai et al., 2017).[3] Alternatively, firms may find it optimal to conduct *operating deleveraging* by replacing incumbent talents with less-cash-compensated new talents (see, e.g., Gilson and Vetsuypens, 1993). Thus, customer capital is robust against

[3]Babina (2017) provides several pieces of evidence consistent with our model's implications. First, employees' exit rates are higher in distressed firms. Second, employees exiting distressed firms earn higher wages prior to the exit than employees exiting non-distressed firms. Third, the exit rate of employees from distressed firms is greater in the states with weaker enforcement of non-compete agreements.

financial constraints risk if it depends mainly on customers' pure brand recognition. By contrast, customer capital is fragile to financial constraints risk if it depends mainly on the contribution of current key talents, because the effective cost of compensation increases with the marginal value of internal funds of the firm. Equilibrium liquidity-driven separation and turnover due to financial constraints, which is commonly observed in the data, is the key to our model's mechanism. By contrast, in standard models of inalienable human capital, such as those of Hart and Moore (1994), Lustig, Syverson and Nieuwerburgh (2011), Eisfeldt and Papanikolaou (2013), and Bolton, Wang and Yang (2018), there is no separation in equilibrium.

After illustrating the key mechanisms using the baseline model, we formally test the model's empirical implications. The main empirical challenge lies in finding high-quality data on consumers' brand loyalty and its talent dependence measured in a consistent way across firms. We tackle this challenge by constructing a measure for the degree to which customer capital depends on talents, based on a proprietary, granular brand perception survey database. The database, provided by the BAV Group, is regarded as the world's most comprehensive database of consumer brand perception.

The talent dependence of customer capital is reflected by the extent to which brand loyalty is associated with the firm's key talents. The BAV consumer survey data directly quantify a firm's general brand loyalty and its specific components. Particularly, the BAV Group has developed two major brand metrics: *brand stature* and *brand strength*. Brand stature quantifies a firm's general brand loyalty, whereas brand strength quantifies a firm's brand loyalty specifically associated with key talents, mainly through the innovativeness and distinctiveness of the products as well as the efficiency of the management team. Thus, we use the ratio of the two as an empirical measure for the talent dependence of customer capital (i.e., the ICC). We emphasize that although the ICC can endogenously affect the extent to which a firm is financially constrained (i.e., the marginal value of internal funds), our survey-based ICC measure is not designed to be one of those empirical measures for financial constraints like the ones developed by Whited and Wu (2006) and Buehlmaier and Whited (2018). Those measures capture essentially different economic concepts.

To justify the connection between our survey-based ICC measure and its counterpart in the model, the talent dependence of customer capital, we need to show that the empirical ICC measure is able to capture the three major properties of its theoretical counterpart in our model. The three properties are that (1) firms whose talents play relatively more important roles are associated with higher ICC; (2) firms with higher ICC tend to lose a larger fraction of customer capital upon talent turnover; and (3) firms' customer capital becomes less talent dependent (i.e., the ICC declines) upon talent turnover. Following the methodology of external validation tests in the work of Bloom and Reenen (2007), we provide direct evidence that our survey-based ICC measure satisfies all of the three aforementioned properties.

We present two main sets of empirical results to support our model. The first set shows that the patterns of cross-sectional stock returns based on ICC levels are consistent with our model's implications. The second set shows that the patterns of cross-sectional talent turnover based on ICC levels support our model's main mechanism.

Regarding the first set of empirical results, we show that firms with higher ICC have higher average (risk-adjusted) excess returns. The ICC spread is persistent around the time of portfolio formation and is robust after controlling for various measures of customer capital, intangible assets, and industry classifications. Moreover, the ICC spread remains significantly positive after controlling for R&D measures using Fama-MacBeth regressions. By extending our sample to all U.S. public firms, we show that the ICC spread is an asset pricing factor, which is referred to as the *c-factor*. We further show that the c-factor is highly correlated with the financial-constraints-risk factor constructed based on the two financial constraints measures of Whited and Wu (2006) and Buehlmaier and Whited (2018), suggesting that the c-factor also captures the same financial constraints risk to a large extent. The strong comovement between the c-factor and the financial-constraints-risk factor convincingly supports the main channel of our theory — the interaction between the ICC and financial constraints.

Regarding the second set of empirical results, we show that firms with higher ICC are associated with higher talent turnover rates, a finding that is robust for both executives and innovators. Moreover, the positive relation between the ICC and the talent turnover rate is more pronounced in the periods of heightened financial constraints risk and in the states where the enforcement of non-compete agreements is weaker.

Finally, we extend the baseline model to a richer model with three additional ingredients for quantitative analysis. The first is the aggregate productivity shock to allow multiple asset pricing factors in the model; the second is the firm-specific shock to the ICC to match a more realistic cross-sectional distribution of talent compensation in the data; and the third is the non-pecuniary private benefits to the key talents who work for the firms with prestigious brands. Using the calibrated extended model, we show that the interaction between the ICC and financial constraints determines firms' exposure to the aggregate financial-constraints-risk shock, which can quantitatively explain the joint patterns in talent turnover and stock returns. The calibrated extended model also allows us to investigate the economic importance of each mechanism in the model. According to the quantitative analysis, the interaction between the ICC and financial constraints is crucial for generating the differential exposure to financial constraints risk. Missing either the ICC or financial constraints makes it impossible for the model and the data to reconcile.

Related Literature. Our paper is related to the large literature on cross-sectional stock returns (see, e.g., Cochrane, 1991; Berk, Green and Naik, 1999; Gomes, Kogan and Zhang, 2003; Nagel, 2005; Zhang, 2005; Livdan, Sapriza and Zhang, 2009; Belo and Lin, 2012; Eisfeldt and Papanikolaou, 2013; Ai and Kiku, 2013; Ai, Croce and Li, 2013; Belo, Lin and Bazdresch, 2014; Kogan and Papanikolaou, 2014; Kumar and Li, 2016; Belo et al., 2017; Hirshleifer, Hsu and Li, 2017). Nagel (2013) provides a comprehensive survey. Unlike most papers in this literature, we study the asset pricing implications in a dynamic corporate finance model with financial constraints. Indeed, research on cross-sectional asset pricing has been increasingly emphasizing the importance of financial constraints and corporate liquidity (see, e.g., Whited and Wu, 2006; Campbell, Hilscher and Szilagyi, 2008; Garlappi, Shu and Yan, 2008; Gomes and Schmid, 2010; Garlappi and Yan, 2011; Li, 2011; Ai et al., 2017; Buehlmaier and Whited, 2018). This increase is due to the empirical evidence showing that cash holdings are often large, and a more important reason is that corporate liquidity (or cash) arises naturally as an inevitable state variable in dynamic corporate finance models with financial constraints. This idea is not yet as well appreciated in the asset pricing literature as it perhaps should be. We contribute to the literature by shedding light on firms' heterogeneous exposure to financial-constraints-risk shocks through their different ICC. Moreover, our model generates asset pricing implications of financial-constraints-risk shocks in two different cross sections simultaneously.

Our paper also contributes to the emerging literature on the interaction between customer capital and finance. Titman (1984) and Titman and Wessels (1988) provide the first piece of theoretical insight into and empirical evidence on the interaction between firms' financial and product market characteristics. In this literature, a large body of research examines how financial characteristics influence firms' performance and decisions in the product market (see, e.g., Chevalier and Scharfstein, 1996; Fresard, 2010; Phillips and Sertsios, 2013; Gourio and Rudanko, 2014; Gilchrist et al., 2017; D'Acunto et al., 2018), whereas only a few papers focus on the implication of product market characteristics on valuation and various corporate policies (see, e.g., Dumas, 1989; Banerjee, Dasgupta and Kim, 2008; Larkin, 2013; Belo, Lin and Vitorino, 2014; Gourio and Rudanko, 2014; Vitorino, 2014; Dou and Ji, 2017; Belo et al., 2018). We depart from the existing literature by investigating the financial implications of the ICC.

Our paper is also related to the literature on inalienable human capital dating back to Hart and Moore (1994). Human capital is embodied in a firm's key talents, who have the option to walk away. Thus, shareholders are exposed to the risk inherent in the limited commitment of key talents. The talent-dependent customer capital we investigate provides one of the most concrete and convincing examples of inalienable human capital. Lustig, Syverson and Nieuwerburgh (2011) develop a model with optimal compensation to managers who cannot commit to staying with the firm. Eisfeldt and Papanikolaou (2013) show that the firms with more organization capital are riskier, due to their greater exposure to technology frontier shocks. Berk, Stanton and Zechner (2010) develop a model with entrenched employees under long-term optimal labor contracts to analyze their implications on the optimal capital structure. Their model focuses on entrenched workers who cannot be fired by firms and are thus overpaid. Our theory is related to the work of Bolton, Wang and Yang (2018), who analyze the implications of inalienable human capital on corporate credit limits, talents' idiosyncratic risk exposure, and liquidity and risk management, in a standard long-term optimal contracting framework. Our model does not focus on those implications. Instead, we highlight the operating leverage effect imposed by the ICC in models with financial constraints and discuss its asset pricing implications.[4]

The inalienability of human capital is essentially caused by limited commitment. Our paper is also related to the optimal contracting problem with limited commitment (see, e.g., Alvarez and Jermann, 2000, 2001; Albuquerque and Hopenhayn, 2004; Rampini and Viswanathan, 2013; Ai and Bhandari, 2018; Ai and Li, 2015; Bolton, Wang and Yang, 2018). Several papers in this literature study the asset pricing implications of limited commitment. For example, Alvarez and Jermann (2000, 2001) study its asset pricing implications in an incomplete market model with one-sided limited commitment.

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

Recently, Ai and Bhandari (2018) provide a unified view of labor market risk and asset price through a general equilibrium model with two-sided limited commitment and moral hazard. Our paper is particularly related to Ai and Bhandari (2018) because both papers emphasize that firms offering larger labor compensation effectively bear higher operating leverage, which generates cross-sectional asset pricing implications. Our model adopts a different angle, however, by emphasizing compensation to key talents due to the ICC. Moreover, we show that the presence of financial constraints risk amplifies the operating leverage channel, generating significant asset pricing implications in the cross section.

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

2 Baseline Model

We develop an asset pricing model of heterogeneous firms to explain the interaction between the ICC and financial constraints, as well as its role in determining the joint patterns of asset pricing and talent turnover. Importantly, we show that the heterogeneous exposure to aggregate financial-constraints-risk shocks is simultaneously reflected in two different cross sections — the ICC and the extent to which firms are financially constrained.

2.1 Basic Environment

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

Production. All firms have the same AK production technology with productivity e^a, and they produce a flow of goods over $[t, t + \mathrm{d}t]$ with intensity

$$Y_t = e^a K_t, \tag{2.1}$$

where physical capital K_t is rented from a capital rental market at the competitive rental rate $r + \delta_K$. Here, r is the risk-free rate and δ_K is the rate of physical capital depreciation. To keep the model manageable, we assume away physical capital adjustment costs and assume that firms can only rent physical capital. In fact, assuming that firms produce goods using rental capital is a standard modeling technique in the macroeconomics literature (see, e.g., Jorgenson, 1963; Buera and Shin, 2013; Moll, 2014) and in the corporate theory literature (see, e.g., Rampini and Viswanathan, 2013).

Instantaneous demand capacity $B_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$ depends on the firm's customer capital B_t, which can be thought of as a measure of the firm's existing customer base at time t. The amount of goods sold by the firm is $S_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$, where we require $S_t \leq Y_t$ and $S_t \leq B_t$, capturing the fact that total sales cannot exceed production output Y_t or the demand capacity B_t as in Gourio and Rudanko (2014). In the equilibrium, the sales are equal to $S_t = \min(Y_t, B_t)$. This does not mean that customer capital B_t is a production input or the production technology is Leontief. The production technology is still AK with physical capital K_t as the only input. The Leontief functional form captures only the fact that the equilibrium sales cannot exceed the smaller value between consumer demand and the firm's production.

Under our benchmark calibration in which $r + \delta_K < e^a$, it is optimal for the firm to produce and match demand capacities by employing physical capital $K_t = B_t / e^a$. Thus, all firms produce and sell all of the outputs up to the short-run demand capacity $S_t = Y_t = B_t$, and the firm size is essentially determined by the firm's customer capital B_t. As will be shown in Section 2.4, by exploiting the homogeneity of B_t, we can reduce the dimensionality of the firm's optimization problem. This modeling approach is inspired by Bolton, Chen and Wang (2011), who exploit the homogeneity of firm size, measured by physical capital K_t in their model.

Customer Capital Growth. The firm hires i_t sales representatives to build new customer capital at convex costs $\phi(i_t) B_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$, with the adjustment cost function being

$\phi(i_t) = \alpha i_t^{\eta}$. The evolution of customer capital B_t is given by

$$\mathrm{d}B_t = [\mu(i_t) - \delta_B] B_t \mathrm{d}t, \tag{2.2}$$

where δ_B is the rate of depreciation of customer capital. We assume that[5]

$$\mu(i_t) = \psi i_t, \tag{2.3}$$

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

External Financial Constraints. We assume that the firm has access to the equity market but not the corporate debt market.[6] The firm has the option to pay out dividend $\mathrm{d}D_t$ or issue equity $\mathrm{d}H_t$ to finance expenses over the next instant $\mathrm{d}t$. The financing cost includes a fixed cost γ proportional to firm size and a variable cost φ proportional to the amount of equity issued. That is, the deadweight loss of shareholders for raising funds W for a firm with customer capital B is

$$\Phi(W; B) \equiv \underbrace{\gamma B}_{\text{fixed cost}} + \underbrace{\varphi W.}_{\text{variable cost}} \tag{2.4}$$

The modelling of fixed and variable equity financing costs follows the literature (see, e.g., Gomes, 2001; Riddick and Whited, 2009; Gomes and Schmid, 2010; Bolton, Chen and Wang, 2011; Eisfeldt and Muir, 2016). The key idea is simple: external funds are not perfect substitutes for internal funds.

Financial constraints motivate the firm to hoard cash W_t on its balance sheet. Holding cash is costly due to the agency costs associated with free cash in the firm or tax distortions.[7] We assume that the return from cash is the risk-free rate r minus a carry cost $\rho > 0$. The cash-carrying cost implies that the firm would pay out dividends when

[5] In Online Appendix A1, we derive (2.3) as the equilibrium representation in a search-matching model.

[6] This assumption is innocuous for our purpose because we focus on the endogenous time-varying marginal value of internal funds. This simplification captures our theory's main idea while maintaining tractability.

[7] 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).

cash holdings W_t are high. In our model, cash holdings capture all internal liquid funds held by the firm.

Levels of Financial Constraints Risk. The firm faces firm-level idiosyncratic operating cash flow shocks over the next instant $\mathrm{d}t$:

$$\mathrm{d}C_t = \sigma_c B_t \mathrm{d}Z_{c,t} - f B_t \mathrm{d}M_t, \tag{2.5}$$

where $Z_{c,t}$ is a standard Brownian motion capturing small idiosyncratic cash flow shocks, and M_t is a firm-specific Poisson process capturing the firm's exposure to idiosyncratic negative jump shocks with proportional jump size $f > 0$. The Poisson process M_t has a time-varying intensity ξ_t.[8] We assume that idiosyncratic cash flow shocks are proportional to firm size, which is a standard way of modeling cash flow shocks in the asset pricing and macroeconomics literature (see, e.g., DeMarzo and Sannikov, 2006; Bloom, 2009; Bolton, Chen and Wang, 2011; DeMarzo et al., 2012). This specification ensures that firms cannot grow out of the exposure to idiosyncratic risks, and it is also consistent with the empirical fact that the idiosyncratic component of changes in a firm's sales is roughly proportional to firm size.

All firm-specific Poisson processes have the same time-varying intensity ξ_t, which captures the level of financial constraints risk in the economy (i.e., the marginal value of internal funds of all firms). A greater ξ_t increases the marginal value of internal funds for all firms due to heightened risk of idiosyncratic negative jumps. That is, the liquidity conditions of all firms are simultaneously affected by the economy-wide shocks driving the variations in the level of financial constraints risk ξ_t. Such aggregate shocks are referred to as *financial-constraints-risk shocks*, which could be driven by different fundamental and primitive economic forces such as financing-cost shocks, TFP shocks, investment shocks, and uncertainty shocks. For example, the heightened financial constraints risk can be the result of a tightened supply of funding liquidity due to financial sector dysfunction (see, e.g., Gilchrist and Zakrajšek, 2012; Jermann and Quadrini, 2012; Bolton, Chen and Wang, 2013; Iyer et al., 2014). Particularly, Schularick and Taylor (2012) and Baron and Xiong (2017) provide evidence showing that credit expansions can predict a subsequent banking crisis/equity value crash and financial system dysfunction. The

[8] Technically, the idiosyncratic lumpy shock $\mathrm{d}M_t$ is effectively a firm-specific disaster shock and the time-varying ξ_t is effectively the disaster probability risk (see, e.g., Gourio, 2012; Wachter, 2013).

heightened financial constraints risk could also be the result of excessive demand for funding liquidity, when firms with great investment opportunities are eager to invest aggressively (see, e.g., Gomes, Yaron and Zhang, 2006; Riddick and Whited, 2009). The incentive for making such investments is especially large under the displacement risk imposed by peer innovations (see, e.g., Kogan et al., 2017). To structurally micro-found our specification of financial-constraints-risk shocks, we develop a simple framework and formally show that primitive economic shocks can endogenously drive fluctuations in the marginal value of internal funds for firms. See Online Appendix A.2 for a more detailed discussion.

We focus on investigating the implications of the fluctuations in the marginal value of their internal funds, without specifying the underlying primitive economic aggregate forces.[9] In other words, we take a parsimonious yet generic modeling approach to capture the random fluctuations in the marginal value of firms' internal funds. We do not explicitly connect the financial-constraints-risk shock (i.e., the shock to the marginal value of internal funds) to any particular primitive shock, because we do not want to give the false impression that the financial-constraints-risk shock is purely driven by some single primitive shock.

In particular, we model financial-constraints-risk shocks by assuming that the intensity ξ_t follows a two-state Markov process, with its value being ξ_L and ξ_H, and $\xi_L < \xi_H$.[10] 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 aggregate processes of transitions are denoted by $N_t^{(\xi_L,\xi_H)}$ and $N_t^{(\xi_H,\xi_L)}$.

Pricing Kernel. Because the market is complete, only aggregate shocks are priced, and the only aggregate shock is the financial-constraints-risk shock in the baseline model. We assume that the financial-constraints-risk shock carries a negative market price of risk. As discussed above, the financial-constraints-risk shock may well be driven by the more fundamental and primitive economic shocks. The asset pricing literature has shown extensively that those primitive economic shocks are priced by investors. More precisely, the financial-constraints-risk shock should be priced with a negative market price of risk

[9]The approach we are taking is similar in spirit to that of the Lucas-tree model for studying asset pricing. In the Lucas-tree model, to study asset pricing, shocks to consumption are directly modeled even though they are driven by more fundamental and primitive economic forces.

[10]The importance of the aggregate shocks driving the variation in risks has been shown in the macroeconomics and asset pricing literature (see, e.g., Gourio, 2012; Gourio, Siemer and Verdelhan, 2013; Christiano, Motto and Rostagno, 2014).

because it is (1) positively driven by the financial-sector shock (i.e., the financing-cost shock), which carries a negative market price of risk; (2) negatively driven by the TFP shock, which carries a positive market price of risk; (3) positively driven by the cash-flow uncertainty shock, which carries a negative market price of risk; and (4) positively driven by the investment shock, which carries a negative market price of risk. Further, empirical findings support the assumption that the financial-constraints-risk shock is negatively priced by investors (see Whited and Wu, 2006; Buehlmaier and Whited, 2018).

Thus, we assume that the representative agent's state-price density Λ_t evolves as follows:

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t + \sum_{\xi' \neq \xi_t} \underbrace{[e^{-\kappa^{(\xi_t,\xi')}} - 1]}_{\text{market price of risk}} \underbrace{(\mathrm{d}N_t^{(\xi_t,\xi')} - q^{(\xi_t,\xi')}\mathrm{d}t)}_{\text{financial-constraints-risk shock}}. \tag{2.6}$$

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

2.2 Inalienability of Customer Capital (ICC)

An essential feature of customer capital is its inalienability due to its dependence on key talents' human capital, including skills, knowledge, connections, reputation, and so on. Shareholders have the option to fire key talents, and key talents have the option to leave the firm and start their own business.[11] We assume that a fraction τ_t of the firm's customer capital B_t can be affected by talent turnover. Thus, τ_t captures the degree to which customer capital depends on key talents, and we refer to $\tau_t B_t$ as talent-dependent customer capital. By definition, τ_t is the firm's ICC at time t, because it reflects the fragility of customer capital to key talent turnover.

More precisely, when key talents leave, they take away $m\tau_t B_t$, where the parameter m captures the damage ratio of talent-dependent customer capital due to turnover. Upon the occurrence of turnover over $[t, t + \mathrm{d}t]$, the remaining customer capital is $(1 - m\tau_t)B_t = B_t - m\tau B_t$, among which $(1 - m)\tau_t B_t = \tau_t B_t - m\tau_t B_t$ is maintained by key talents. Thus, τ_t jumps to $(1 - m)\tau_t/(1 - m\tau_t)$ immediately after turnover. Assume that the ICC $\tau_t \equiv e^{-\omega_t}$

[11] For simplicity, our contracting framework does not incorporate moral hazard (see, e.g., Holmstrom, 1979; Holmstrom and Milgrom, 1987) or managerial short-termism (see, e.g., Stein, 1988, 1989; Shleifer and Vishny, 1990; Bolton, Scheinkman and Xiong, 2006). Evaluating the asset pricing implications of their interactions with customer capital is an interesting topic for future research.

is mean reverting and ω_t follows

$$d\omega_t = -\mu_\omega(\omega_t - \overline{\omega})dt + \underbrace{\left[\ln\left(1 - me^{-\omega_t}\right) - \ln\left(1 - m\right)\right] dJ_t}_{\text{endogenous turnover}}, \tag{2.7}$$

where the process J_t is an idiosyncratic Poisson process of the incidences of talent turnover; that is, the Poisson process J_t jumps up by one ($dJ_t = 1$) over $[t, t + dt]$ if and only if talent turnover occurs during $[t, t + dt]$. Upon turnover, ω_t jumps upward over $[t, t + dt]$ with the amount of $\ln(1 - me^{-\omega_t}) - \ln(1 - m)$. Because the endogenous jump is always positive, ω_t is always positive, and thus $\tau_t \in (0, 1)$.

The ICC is defined following the spirit of the concept of inalienable human capital coined by Hart and Moore (1994). In the models of Hart and Moore (1994) and Bolton, Wang and Yang (2018), human capital is inalienable in the sense that, as a production input, it cannot be taken away from its possessors (i.e. key talents) due to limited legal enforcement. Also due to limited commitment of key talents, human capital cannot be fully collateralized for external financing or fully capitalized by firms for generating profits. Specifically, Hart and Moore (1994) assume that physical capital is operated most efficiently by the original key talents, and its productivity drops when it is operated by other talents. There is no separation between the firm and the key talent in the equilibrium, because their paper focuses on a deterministic contracting problem. In their deterministic model, the optimal debt contract can be achieved by restricting attention to "repudiation-proof" contracts. Their modeling specification of inalienability is essentially similar to ours, but we consider a stochastic model. In the model of Bolton, Wang and Yang (2018), human capital of key talents is a necessary input for operating a firm's physical capital. If talents leave, physical capital cannot generate any cash flows, and the firm is terminated. As a result, there is no separation in the equilibrium either. In our model, when key talents leave, a fraction of the firm's customer capital (which depends on the ICC) is taken away and thus stops generating cash flows for the firm. However, the remaining customer capital in the firm can still generate cash flows, albeit in smaller amounts, because the firm can immediately hire new talents to replace old talents without paying any upfront replacement costs. Therefore, the ICC is fundamentally linked to the inalienability of human capital. But in some sense, our notion of inalienable human capital is weaker than that of Bolton, Wang and Yang (2018), which is the key reason our model can allow for endogenous separation between key talents and firms in equilibrium.

2.3 Liquidity-Driven Turnover

Long-Term Contracts. Shareholders compensate key talents according to a long-term contract. Key talents have the option to leave the firm and start a new firm, and at the same time, shareholders can choose to replace key talents. Key talents are well diversified and do not bear idiosyncratic risks.[12] Key talents themselves are also diffused shareholders.

Upon the separation, key talents create a new firm with customer capital

$$B_t^{\text{new}} = (m + \ell)\tau_t B_t, \tag{2.8}$$

where $m\tau_t B_t$ is the customer capital taken away from the original firm and $\ell\tau_t B_t$ is the new customer capital created by key talents' business idea.

Customer capital B_t^{new} alone cannot generate profits. The new firm needs cash to operate, and thus it issues equity to diffused shareholders. All atomistic agents, including key talents, are shareholders. Key talents have no incentive to retain a non-diversified equity position in the new firm, and thus the new firm is sold to the diffused shareholders in its entirety. Thus, the new firm's valuation, which determines key talents' outside option value, is based on the state-price density Λ_t of all diffused shareholders (or the representative agent).

Let $V(W_t, B_t, \tau_t, \xi_t)$ denote a generic firm's value with firm-specific cash holdings W_t, customer capital B_t, and the ICC τ_t in the aggregate state ξ_t. Immediately after key talents create a new firm, the key talents and other diffused shareholders work together to raise funds with the optimal financing W^* for the new firm to maximize its value:

$$V_{\text{new}}(B_t, \tau_t, \xi_t) = \max_W \underbrace{\left[V(W, B_t^{\text{new}}, \overline{\tau}, \xi_t) - W\right]}_{\text{enterprise value}} - \underbrace{\Phi(W; B_t^{\text{new}})}_{\text{deadweight loss}}, \tag{2.9}$$

where $\overline{\tau} = e^{-\overline{\omega}}$ is the dependence of the new firm's customer capital on key talents (i.e., the ICC), B_t^{new} is the new firm's customer capital, defined in equation (2.8), and $V_{\text{new}}(B_t, \tau_t, \xi_t)$ is the market value of the newly created firm by key talents if they leave the existing firm whose customer capital is B_t. We assume that key talents do not bear

[12]This assumption is different from what is typically assumed in standard models with human capital inalienability. For example, Bolton, Wang and Yang (2018) emphasize that talents (entrepreneurs) are under-diversified for idiosyncratic risks, because they are unable to trade securities apart from shareholders.

financing costs and thus can gain the enterprise value of the optimally financed firm $V(W^*, B_t^{\text{new}}, \overline{\tau}, \xi_t) - W^*$, which equals $V_{\text{new}}(B_t, \tau_t, \xi_t) + \Phi(W^*; B_t^{\text{new}})$ according to (2.9).[13]

The value of key talents' outside option is

$$U(B_t, \tau_t, \xi_t) = V(W^*, B_t^{\text{new}}, \overline{\tau}, \xi_t) - W^*, \tag{2.10}$$

where B_t^{new} is the new firm's customer capital, defined in equation (2.8). In the equilibrium, the promised utility equals key talents' outside option value in all states of the world as long as key talents stay in the existing firm, because shareholders have no reason to promise more in our model, given that key talents have no bargaining power. In other words, (2.10) is the participation constraint of key talents.

Shareholders can implement the promised utility of key talents, denoted by $U(B_t, \tau_t, \xi_t)$, through promising key talents a flow payment of $\Gamma_t \mathrm{d}t$ over $[t, t + \mathrm{d}t]$ as long as the relationship continues. Hence, the promised utility of key talents equals the present value of compensation over time while key talents remain in the existing firm plus the option value of leaving the existing firm and starting a new firm:

$$U(B_t, \tau_t, \xi_t) = \underbrace{\mathbb{E}_t \left[\int_t^{\tilde{t}} \frac{\Lambda_s}{\Lambda_t} \Gamma_s \mathrm{d}s \right]}_{\text{present value of compensation}} + \underbrace{\mathbb{E}_t \left\{ \frac{\Lambda_{\tilde{t}}}{\Lambda_t} \left[V(W^*, B_{\tilde{t}}^{\text{new}}, \overline{\tau}, \xi_{\tilde{t}}) - W^* \right] \right\}}_{\text{option value of leaving and starting a new firm}}. \tag{2.11}$$

where $\tilde{t}$ is the stopping time when key talent departure occurs.

Based on equations (2.10) and (2.11), we have $U(B_t, \tau_t, \xi_t) = \mathbb{E}_t \left[\int_t^{\infty} \frac{\Lambda_s}{\Lambda_t} \Gamma_s \mathrm{d}s \right]$, and thus we can explicitly solve for the dynamics of compensation to key talents Γ_t. Intuitively, the requirement that key talents' promised utility equals their outside option in all states of the world (see equation 2.10) pins down $U(B_t, \tau_t, \xi_t)$ and $U(B_{t+dt}, \tau_{t+dt}, \xi_{t+dt})$. Shareholders will then compensate key talents according to the following way to ensure that promises are kept:

$$U(B_t, \tau_t, \xi_t) = \Gamma_t \mathrm{d}t + \mathbb{E}_t \left[\frac{\Lambda_{t+dt}}{\Lambda_t} U(B_{t+dt}, \tau_{t+dt}, \xi_{t+dt}) \right]. \tag{2.12}$$

The intuitive promise-keeping constraint (2.12) above can be formalized as

[13] This assumption is also explicitly or implicitly adopted by other models with financial constraints (see, e.g., Bolton, Chen and Wang, 2011, 2013).

$$0 = \Lambda_t \Gamma_t \mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}\left(\Lambda_t U(B_t, \tau_t, \xi_t) \right) \right], \tag{2.13}$$

where the expectation is taken with respect to the aggregate shock $\mathrm{d}\xi_t$ conditioning on the information up to t. Essentially, the limited commitment of key talents, together with inalienable customer capital, generates higher compensation and maintenance costs for retaining key talents, leading to greater operating leverage for the firm. According to equation (2.13), holding B_t constant, Γ_t increases with τ_t, implying that the firm with higher ICC has higher operating leverage.[14]

Similar optimal contracting problems with limited commitment have been studied in the literature (see, e.g., Alvarez and Jermann, 2000, 2001; Albuquerque and Hopenhayn, 2004; Rampini and Viswanathan, 2013; Ai and Bhandari, 2018; Ai and Li, 2015; Bolton, Wang and Yang, 2018). In particular, Ai and Bhandari (2018) develop a general equilibrium model with two-sided limited commitment and moral hazard to provide a unified view of labor market risk and asset prices. One of Ai and Bhandari (2018)'s key results is that firms with larger obligations to workers are associated with higher expected returns, because labor compensation delivers a form of operating leverage at the firm level. Our model focuses on a similar operating leverage channel, owing to the ICC. We emphasize that in the presence of financial constraints risk, the cross-sectional asset pricing implications from the operating leverage channel become much more significant (see Section 5.3).

Turnover and Financial Constraints. Shareholders can successfully fire key talents with intensity θ_t in the next instant $\mathrm{d}t$. They can control the turnover intensity θ_t, which takes two values $\{\theta_L, \theta_H\}$ with $\theta_L \equiv 0$ and $\theta_H > 0$. More precisely,

$$\theta_t = \begin{cases} \theta_L \equiv 0, & \text{if shareholders decide to keep key talents over } [t, t + \mathrm{d}t], \\ \theta_H > 0, & \text{if shareholders want to replace key talents over } [t, t + \mathrm{d}t]. \end{cases} \tag{2.14}$$

Even if shareholders want to replace key talents at time t (i.e., choosing $\theta_t = \theta_H$), they can only do so successfully with intensity θ_H over $[t, t + \mathrm{d}t]$. The limited power of

[14] In principle, high-ICC firms could alleviate the financial constraints by adjusting compensation contracts. For example, firms frequently adopt vesting schedules to increase pay duration for executives. Recognizing the importance of this feature of option programs, Sircar and Xiong (2007) develop a general framework for evaluating executive stock options. Our empirical results in Online Appendix D.5 indicates that firms with higher ICC are indeed more likely to increase the pay duration for key talents to delay cash payments. However, the change in duration is economically small, suggesting that high-ICC firms are unlikely to fully alleviate the financial constraints by actively managing pay duration.

shareholders to replace key talents reflects the latter' 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 $\theta_t \in \{\theta_L, \theta_H\}$ crucially depends on the firm's current marginal value of internal funds. Intuitively, the firm is more likely to replace key talents when it is financially constrained, because the required compensation becomes very costly when the marginal value of the firm's internal funds is high. The mechanism has been documented and tested extensively in the literature (see, e.g., Brown and Matsa, 2016; Babina, 2017; Baghai et al., 2017). Such endogenous separations due to heightened financial constraints risk play a crucial role in generating sizable impacts on firm value and the cross-sectional asset pricing patterns across firms with different ICC.

Key talents can extract additional rents when firms are financially distressed and external financing/restructuring is needed. This phenomenon has been extensively documented in the literature (see, e.g., Bradley and Rosenzweig, 1992; Henderson, 2007; Goyal and Wang, 2017). For example, firms frequently offer pay retention and incentive bonuses to persuade key talents to stay with the firm through the restructuring process. To capture the rent extraction from key talents, we assume that key talents extract $\lambda U(B_t, \tau_t, \xi_t)$ from shareholders when the firm runs out of cash. This is the amount of funds misappropriated by key talents rather than a deadweight loss that shareholders have to bear. Particularly, such extraction would never happen when firms are financially frictionless (i.e., $\gamma = \varphi = 0$).

2.4 Firm Optimality

Given K_t and i_t, the firm's operating profit over $[t, t + \mathrm{d}t]$ is given by

$$\mathrm{d}O_t = \underbrace{\left[p \min\left(B_t, e^a K_t\right) - (r + \delta_K) K_t\right] \mathrm{d}t}_{\text{production profits}} - \underbrace{\left[\phi(i_t) B_t + \Gamma_t\right] \mathrm{d}t}_{\text{hiring costs}} + \underbrace{\mathrm{d}C_t,}_{\text{shocks}} \tag{2.15}$$

where $\min(B_t, e^a K_t)\mathrm{d}t$ is the amount of goods sold that is capped by customer capital B_t, and p is the price of goods; the cost of renting the physical capital for production is $(r + \delta_K)K_t\mathrm{d}t$; the total cost of hiring key talents and sales representatives is $[\phi(s_t)B_t + \Gamma_t]\,\mathrm{d}t$; and the firm-specific operating cash flow shock is $\mathrm{d}C_t$, as described in (2.5).

The firm's cash holdings evolve as follows:

$$\mathrm{d}W_t = \mathrm{d}O_t + (r-\rho)W_t\mathrm{d}t + \mathrm{d}H_t - \mathrm{d}D_t, \tag{2.16}$$

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

The firm rents physical capital K_t, hires i_t sales representatives, decides the turnover intensity θ_t, and chooses payout policy $\mathrm{d}D_t$ and external financing policy $\mathrm{d}H_t$ to maximize shareholder value defined as follows:

$$V(W_t, B_t, \tau_t, \xi_t) = \max_{K_s, i_s, \theta_s, \mathrm{d}D_s, \mathrm{d}H_s} \mathbb{E}\left[\int_t^\infty \frac{\Lambda_s}{\Lambda_t}(\mathrm{d}D_s - \mathrm{d}H_s - \mathrm{d}X_s)\right], \tag{2.17}$$

where $\mathrm{d}X_t = [\gamma B_t + \varphi \mathrm{d}H_t + \lambda U(B_t, \tau_t, \xi_t)]\mathbb{1}_{\mathrm{d}H_t>0}$ is the total financing cost when external financing occurs $\mathbb{1}_{\mathrm{d}H_t>0} = 1$.

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

$$V(W,B,\tau,\xi) \equiv v(w,\tau,\xi)B, \quad \text{with } w = W/B. \tag{2.18}$$

The normalized value function $v(w,\tau,\xi)$ can be solved based on a group of two coupled partial differential equations with free boundaries. Talent turnover and financial decisions can be sufficiently characterized by decision boundaries, including the optimal external equity issuance boundary $\underline{w}(\tau,\xi)$ below which the firm pursues external financing ($\mathrm{d}H > 0$), the optimal payout boundary $\overline{w}(\tau,\xi)$ above which the firm chooses to pay out dividends ($\mathrm{d}D > 0$), and the optimal turnover boundary $\widehat{w}(\tau,\xi)$ below which the firm chooses to replace existing key talents ($\theta = \theta_H > 0$). Within the internal liquidity-hoarding region, there exists a conditional external financing region ($\underline{w}(\tau,\xi) < w < \underline{w}(\tau,\xi) + f$), in which the firm issues equity conditional on the arrival of lumpy cash flow shocks f. Figure 2 provides an intuitive illustration of the regions and boundaries.

2.5 Discussions on Modeling Ingredients

The baseline model has three state variables: the cash ratio w, the ICC τ, and the level of financial constraints risk ξ. These three state variables are the bare minimum for

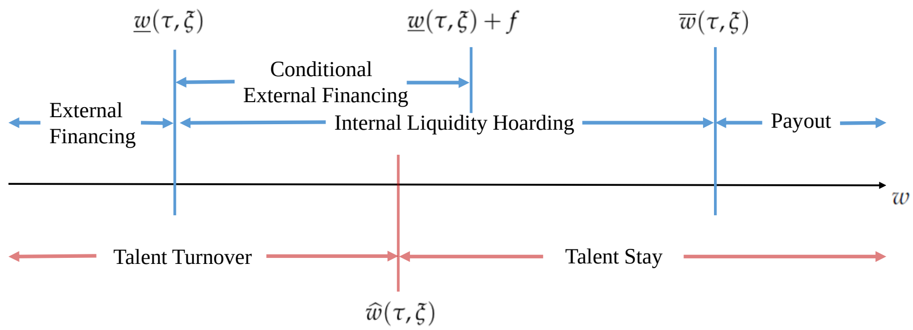


Figure 2: Decision boundaries and regions

delivering our key theoretical insights due to the following reasons: first, the cash ratio w_t, as well as the financial friction, is necessary because our key mechanism relies on liquidity-driven turnover and financial constraints risk; second, the ICC τ_t, as well as the dependence of customer capital on key talents, is necessary because it is the key cross-sectional heterogeneity, and its interaction with the financial constraints is the main focus of this paper; third, the level of financial constraints risk ξ_t is necessary because we focus on the differential levels of exposure to the aggregate shocks in the level of financial constraints risk.

We would like to emphasize that the interaction between inalienable customer capital and financial constraints is crucial for generating significant quantitative effects. Missing either the ICC or financial constraints would invalidate the model in terms of matching the data (see Section 5.3).

2.6 Main Predictions

We illustrate the basic mechanism and main predictions of the model by numerically solving the model with calibrated parameters presented in Table 9. To highlight the importance of financial constraints risk, we compare the numerical solutions from our model with those from a model without financial frictions (by setting $\gamma = \varphi = 0$).

Cash Holdings and Financial Decisions. Panel A of Figure 3 plots the firm's normalized enterprise value $v(w,\tau,\xi_L) - w$, i.e., the value of the firm's marketable claims minus the cash ratio, as a function of the cash ratio in the regime of low financial constraints risk (i.e., $\xi = \xi_L$). The figure shows that the low-ICC firm ($\tau = 0.1$) has a significantly higher enterprise value relative to the high-ICC firm ($\tau = 0.6$) primarily because talent-dependent customer capital is more costly to maintain. The firm's enterprise value increases with the cash ratio, because the financial constraints risk imposes a deadweight loss through costly equity financing and distorts the firm's decisions. By contrast, in the absence of financial frictions, both firms have higher and flat enterprise values.

Our model predicts that the low-ICC firm tends to issue less equity (i.e., optimal financing amount $w_l^* < w_h^*$) and pay out more dividends (i.e., dividend payout boundary $\overline{w}_l < \overline{w}_h$). As a result, the low-ICC firm's endogenous steady-state distribution of cash ratios is concentrated at lower levels (see panel D). We provide empirical evidence that the firms with lower ICC issue more equity, pay out less dividend, and hold more cash on average (see Appendix C.1). The difference in financial policies can be explained by the difference in the marginal value of internal funds. Panel B shows that the high-ICC firm has a higher marginal value of internal funds, because it is more exposed to financial constraints risk due to greater operating leverage. When the firm's cash ratios are high, the operating leverage does not increase financial constraints risk much, because internal funds cushion the firm from cash flow shocks. However, when cash ratios are low, the compensation required to retain key talents significantly increases the financial constraints risk that the high-ICC firm faces. In the frictionless benchmark, the marginal value of internal funds for both firms is flat and equal to 1.

Panel C compares the hiring decisions of the two firms. The variation in the endogenous marginal value of internal funds suggests that both firms hire fewer sales representatives when cash ratios are low. On average, the low-ICC firm tends to hire more sales representatives. These implications suggest that financial constraints risk also distorts the firm's decisions in the product market. When the financial market has frictions, the firm cuts its investment in customer capital to obtain short-term liquidity. In the frictionless benchmark, the first-best hiring units are higher for both firms.

Asset Pricing Implications. Panels E and F illustrate the asset pricing implications of our model by plotting the firms' exposure to financial-constraints-risk shocks, measured by the betas with respect to ξ, that is, $\beta_\xi(w, \tau) = v(w, \tau, \xi_H)/v(w, \tau, \xi_L) - 1$. Panel E shows that conditioning on the ICC, firms' exposure to financial-constraints-risk shocks increases when their cash ratios decrease. As a result, investors demand higher expected returns for the firms with lower cash ratios. Importantly, the difference in betas between

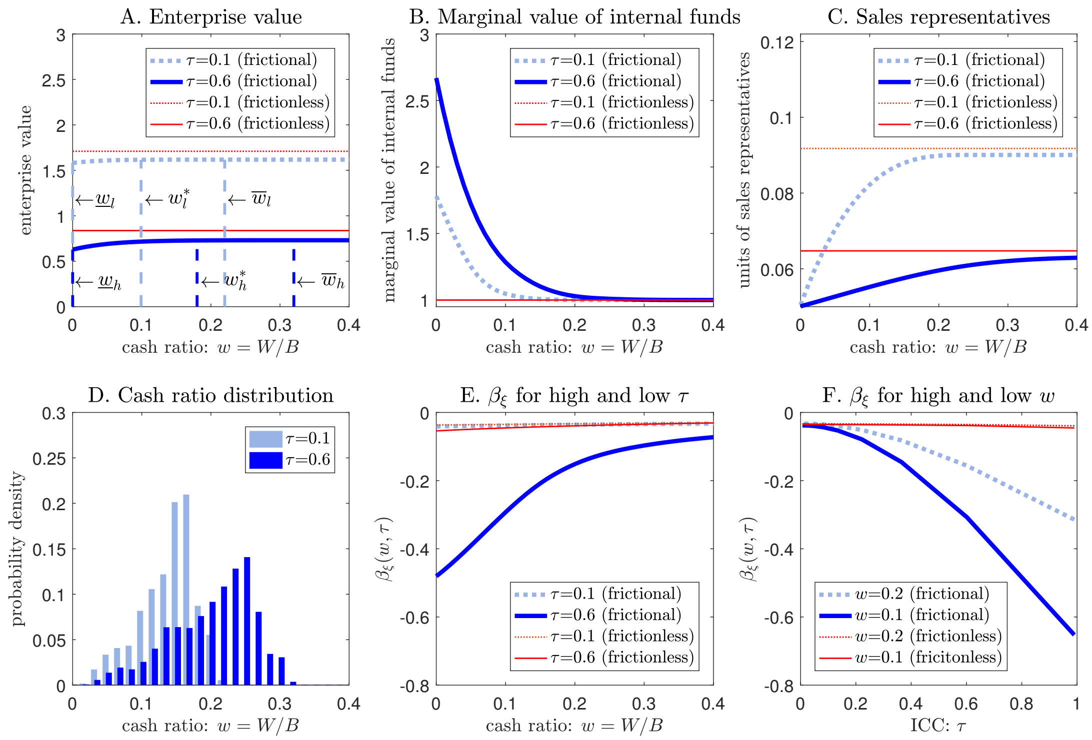


Figure 3: The model's basic mechanism and asset pricing implications

the high-ICC and the low-ICC firm decreases with cash ratios.[15] Similar patterns are observed in panel F, in which we compare betas of a high-cash firm ($w = 0.2$) and a low-cash firm ($w = 0.1$). Conditioning on the cash ratio, firms' exposure to financial-constraints-risk shocks becomes more negative as their customer capital becomes more talent dependent. Importantly, the difference in betas and expected excess returns between the high-cash and the low-cash firm increases with the ICC. By contrast, in the frictionless benchmark, betas are almost zero, regardless of the cash ratio and the ICC.

Our model highlights that the interaction between the firm's ICC and cash ratios has

[15]The quantitatively differential response to financial-constraints-risk shocks between the low and high-ICC firms also incorporates a countervailing force that dampens the relative response of the high-ICC firm, because an increase in financial constraints risk reduces key talents' compensation as the outside option of creating a new firm worsens. From shareholders' perspective, the reduction in compensation provides insurance against the regime with high financial constraints risk, increasing the firm's value. This insurance effect is especially beneficial for the high-ICC firm, in which more customer capital is maintained by key talents. Our numerical solutions suggest that this countervailing force is dominated by the main force through greater operating leverage and customer capital damage due to key talent turnover.

crucial implications for asset prices. Thus, the firm's heterogeneous exposure to financial-constraints-risk shocks is simultaneously reflected in two distinctive cross sections: the ICC and the extent to which firms are financially constrained. In other words, the model implies that the financial-constraints-risk shock can be jointly identified by two cross-sectional return spreads.

Turnover Implications. Our model's asset pricing implications are closely dependent on talent turnover and the resulting customer capital damage. Panel A of Figure 4 compares the effective compensation of high- and low-ICC firms, defined as the monetary compensation multiplied by the marginal value of internal funds. Relative to the frictionless benchmark, the effective compensation to key talents of both the low- and high-ICC firms' increases nonlinearly when cash ratios decrease. The increase in effective compensation is more dramatic and nonlinear for the high-ICC firm.

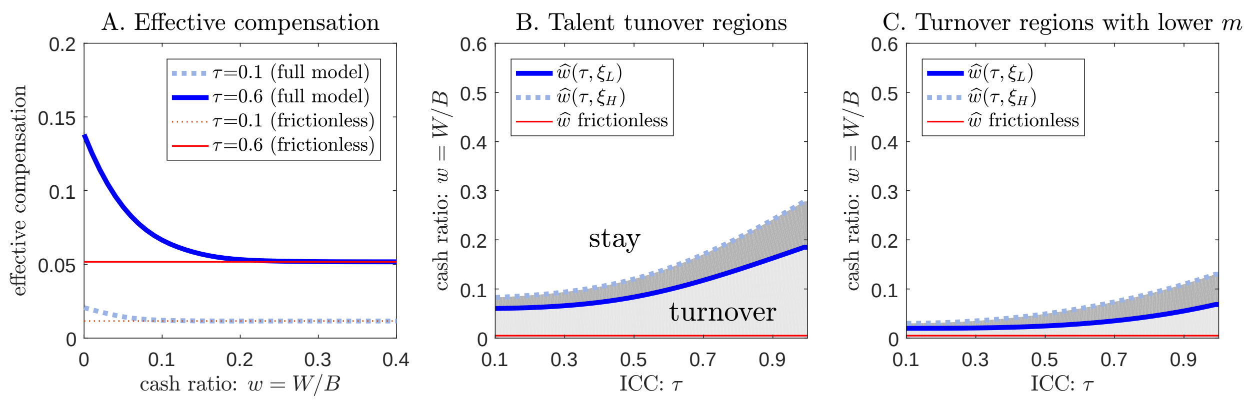


Figure 4: Model predictions on effective compensation and talent turnover

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

Intuitively, retaining key talents is beneficial to the firm because, on average, customer capital generates positive net cash inflows. However, when the firm is financially constrained, the cost of increased exposure to financial constraints risk due to operating leverage outweighs the benefit of a higher demand, motivating the firm to replace key talents and downsize the dependence of customer capital on key talents. An increase in financial constraints risk (from ξ_L to ξ_H) leads to a larger turnover region (i.e., higher likelihood of talent turnover). The high-ICC firm is more financially constrained, and therefore responds more dramatically to the increase in financial constraints risk by expanding the turnover region to a greater extent. By contrast, no turnover occurs in the frictionless benchmark regardless of the financial constraints risk. This pattern differentiates our mechanism from that of Eisfeldt and Papanikolaou (2013). In their model, the firm operates in a perfect financial market. Both talent turnover decisions and asset pricing implications are driven by aggregate frontier technology shocks to key talents' outside options.

Panel C plots the turnover boundaries with a lower value of m. Because the parameter m reflects the customer capital taken away by key talents due to turnover, a lower m reduces their outside option value of key talents. Panel C shows that when key talents' outside options worsen, turnover boundaries shift downward, indicating firms can more easily keep key talents. The reduced compensation benefits high-ICC firms more extensively because these firms are endogenously more financially constrained. Thus, the positive relationship between the ICC and talent turnover rates weaken with a lower m, as reflected by flatter turnover boundaries as the ICC increases.

3 Measuring the ICC

In this section, we exploit a comprehensive database of consumers' perception of brands to measure customer capital as well as the ICC, or the variable τ in our model. Below, we first introduce the data and construct our ICC measure. Then, similar to Bloom and Reenen (2007), we conduct external validation tests to show that our survey-based ICC measure satisfies the key theoretical properties of τ_t.

3.1 Data

Our brand metrics data come from the BAV Group. This database is regarded as the world's most comprehensive database of consumers' perception of brands. The BAV Group is one of the largest and leading consulting firms that conduct brand valuation surveys and provide brand development strategies for clients. The BAV brand perception survey consists of more than 870,000 respondents, and it is constructed to represent the U.S. population according to gender, ethnicity, age, income group, and geographic location. The details of the survey have been described by finance and marketing academic papers (see, e.g., Larkin, 2013; Tavassoli, Sorescu and Chandy, 2014). The BAV surveys are conducted at the brand level. Survey respondents are asked to complete a 45-minute survey that yields measures of brand value. The first survey was conducted in 1993, and since 2001, the surveys have been conducted quarterly. The surveys cover more than 3,000 brands and are not biased toward the BAV Group's clients. The BAV Group updates the list of brands regularly to include new brands and exclude the ones that have exited the market, and it does not backfill the survey data. To make the surveys manageable, each questionnaire contains fewer than 120 brands that are randomly selected from the list of brands.

We identify the firms that own the brands over time, and link the BAV survey data with Compustat and CRSP. We pay particular attention to the brands involved in mergers and acquisitions to ensure that 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.[16] Our merged BAV-Compustat-CRSP data span 1993 - 2016 and include firms listed on the NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11. We exclude financial firms and utility firms. We have 1,004 unique firms in total, and on average, about 400 firms in the yearly cross section. The firms in the merged sample collectively own 4,745 unique brands covered by the BAV surveys. The entry and exit rates of the firms in the merged sample are approximately 7%, which are comparable to those in the Compustat data. Firms in the merged sample and in the Compustat/CRSP sample have comparable book-to-market ratios and debt-to-asset ratios. The merged sample is biased toward large firms.[17] Because the merged sample is not a random sample of U.S. public firms, in Section 4.1.2 we replicate our asset pricing tests in an extended sample that covers the cross section of all U.S. public firms. We further

[16]In our sample, 58% of firm-year observations have only one brand. For the firms that own more than one brand, we use several alternative methods to compute the firm-level brand metrics from the brand-level data. We provide details on the construction of firm-level brand metrics in Online Appendix D1. Our results are robust to the choice of methods.

[17]In the merged sample, the median book-to-market ratio, debt-to-asset ratio, market capitalization, and sales are 0.37, 0.55, $4,915 million, and $5,115 million, respectively, whereas they are 0.49, 0.44, $420 million, and $424 million in the Compustat/CRSP sample. We provide more details on the merged sample, including its distribution across industries, in Online Appendix D2.

link the merged BAV-Compustat-CRSP data with Execucomp, BoardEx, and the Harvard Business School patent and innovator database (see Li et al., 2014). Online Appendix Table OA.5 presents the summary statistics for the main variables.

3.2 The ICC Measure

Based on the brand perception survey data, the BAV Group has developed two major brand metrics to assess the value of firms' customer capital: brand stature and brand strength.

Brand Stature. The BAV Group constructs the brand stature measure to capture customer capital (i.e., brand loyalty of existing and potential customers); see, for example, Gerzema and Lebar (2008). Brand stature is the product of esteem and knowledge. Esteem gauges consumers' respect and admiration for a brand. The components of esteem are (1) the brand score on "regard" ("How highly do you think of this brand?" on a 7-point scale) and (2) the fraction of respondents who consider the brand to be of "high quality," "reliable," and a "leader." Esteem reflects brand loyalty, because consumers are proud to be associated with the brand that they hold in high regard. To gauge the credibility and precision of the esteem measure, BAV designed the knowledge measure to capture the degree of personal familiarity ("How familiar are you with this brand?" on a 7-point scale). BAV finds that the past, current, and potential users of a brand tend to rate themselves as being significantly more knowledgeable. Thus, the knowledge measure serves as an adjustment factor for the esteem measure in quantifying brand stature (i.e., customer capital defined by brand loyalty of existing and potential customers).

Brand Strength. The BAV Group constructs the brand strength measure to capture the extent to which a brand is perceived to be innovative, distinctive, and managed by a dynamic team. Brand strength is the product of energized differentiation and relevance. Energized differentiation is the average fraction of respondents who consider a brand to be "innovative," "distinctive," "unique," "different," and "dynamic." "Innovative" captures the innovativeness of the brand. "Distinctive," "unique," and "different" capture the differentiation of a brand from its peers, whereas "dynamic" captures the vibrancy of the management team. Energized differentiation is obviously attributed to the unique contribution of key talents. The relevance measure ("How relevant do you feel the brand is for you?" on a 7-point scale) serves as an adjustment factor for the energized differentiation measure in quantifying brand strength (i.e., talent-dependent customer capital defined by brand loyalty of existing and potential customers attributed to the unique contribution of key talents). Consumers' perception of a brand's energized differentiation can better reflect the firm's talent-dependent customer capital when they are more likely to purchase the goods and become the firms' customers. The relevance measure is designed to capture the degree of personal appropriateness for consumers, which largely reflects the possibility for consumers to purchase the goods.

The ICC Measure. The ICC measure should reflect the degree to which customer capital depends on talents; thus, we measure the ICC at the firm level as follows:

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

The distribution of our ICC measure is skewed, and we use the log transformation of the ICC measure, denoted by ln(ICC). Online Appendix D2 shows that ln(ICC) exhibits a good amount of variation, with an approximately normal distribution. Moreover, brand stature and brand strength have a similar range and standard deviation. Thus the variation in ln(ICC) does not predominantly come from either brand stature or brand strength. To ease the interpretation of regression coefficients in our empirical analyses, we standardize ln(ICC) by its unconditional mean and standard deviation for all firms across the entire period. We sort the firms in our sample into five quintiles based on the ICC measure. The summary statistics are shown in Table 1.

Because our ICC measure is constructed from consumer surveys of brand loyalty, it directly captures the perception of existing and potential customers. The ICC measure is very different from brand metrics derived from firms' financial and accounting variables, which have at least two major issues: (1) the estimation error introduced by indirectly inferring the unobservable characteristics from noisy accounting information, and (2) the potential measurement bias introduced by using the stale information from accounting numbers. The BAV survey-based measures are designed to tackle these issues. In addition, because the ICC measure is not controlled by firm managers, it is unlikely to be mechanically linked to the outcome financial variables we study.

Let us provide a few concrete examples from the 2010s based on our ICC measure.

Table 1: Firm characteristics and the ICC

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

Note: This table presents characteristics of the five portfolios sorted on ICC. We report the mean and median firm characteristics for each portfolio. Our sample includes the firms listed on the NYSE, AMEX, and NASDAQ exchanges with share codes 10 or 11, over the period 1993 - 2016. We exclude financial firms and utility firms. The definition of variables is in Online Appendix Table OA.5.

In the automobile industry, Toyota is a typical low-ICC firm that enjoys strong brand recognition all over the world. Tesla is a typical high-ICC firm whose customer capital crucially depends on its R&D team. In the beverage industry, Coca-Cola is a typical low-ICC firm whose customers' loyalty relies less on the firm's current executives or innovators and more on customers' own habits and tastes. By contrast, Teavana — an innovative tea company that sources and shares high-quality teas and "imaginative flavors from around the world" with innovative brewing methods — is a typical high-ICC firm. In the IT and apparel industries, Microsoft and Gap are examples of low-ICC firms, and Facebook and Ralph Lauren are examples of high-ICC firms.

3.3 External Validation Tests on the ICC Measure

We conduct external validation tests for our ICC measure. According to our model, if the ICC measure captures the ICC (or the variable τ_t in our model), we expect the following: (1) firms whose talents play relatively more important roles are associated with higher ICC; (2) firms with higher ICC τ_t tends to lose a larger fraction of customer capital upon talent turnover; and (3) firms' customer capital becomes less talent dependent (i.e., the ICC τ_t decreases) upon talent turnover.

To test the theoretical property (1), we examine the relationship between our ICC measure and measures of various intangible assets. Conceptually, customer capital is not a new type of intangible assets. Instead, it is a synthesis of various intangible assets such as innovation and product differentiation, dynamic management, and pure brand recognition. If our ICC measure is valid to capture the ICC, we expect to see that the firms whose talents play relatively more important roles are associated with higher values of the ICC measure. Therefore, we examine the relation between our ICC measure and R&D expenditures (a measure of innovation and product differentiation), administrative expenses/executive compensation (measures of dynamic management), and advertising expenditures (a measure of pure brand recognition). Using panel regressions (see Table 2), we find that the firms with higher values of the ICC measure are indeed associated with higher R&D expenditures, higher administrative expenses, higher executive compensation, and lower advertising expenditures, suggesting that their customer capital depends more on talents than on pure brand recognition.

We would like to emphasize that customer capital cannot be fully captured by any single type of intangible assets because a firm's investment in one type of intangible assets such as R&D may not necessarily increase its customer capital. For example, when a firm increases its R&D expenditures or administrative expenses, the products and services may not necessarily improve or they may become less relevant to consumers, and thus these expenses will not always lead to higher brand loyalty. In other words, consumers may not appreciate the changes (if any) brought by increased R&D expenditures, administrative expenses, or executive compensation. By contrast, our survey-based measure from the demand side directly reflects consumers' brand perception, and thus it is able to capture customer capital in a more direct manner. Importantly, in Appendix B, we show that the asset pricing implications of our ICC measure cannot be fully explained by any single intangible-asset measure.

Table 2: The ICC measure and measures of intangible assets.

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

Note: This table shows the relation between the ICC measure and measures of intangible assets. The dependent variable ln(ICC) is the natural log of the ICC. The independent variables are the natural log of the administrative-expenses-to-sales ratio, the natural log of the R&D-to-sales ratio, the natural log of the executive-compensation-to-sales ratio, the natural log of the advertisement-to-asset ratio, and the natural log of the organization-capital-to-asset ratio, all computed using the average values from the previous three years. Our results are robust if we use the average values in other time periods (one year to six years). Administrative expenses are estimated as SG&A net of advertising costs, R&D expenses, commissions, and foreign currency adjustments. Executive compensation is measured by the total compensation for the top five executives of a firm in the Execucomp data. We construct organization capital (OC), from SG&A expenditures using the perpetual inventory method with missing values being replaced by 0. In column (2), we exclude firms with missing R&D, because these firms do not necessarily lack innovation activities (see, e.g., Koh and Reeb, 2015), unlike zero R&D firms. In column (4), we exclude firms with missing advertising expenditures following Grullon, Kanatas and Weston (2004) and Belo, Lin and Vitorino (2014). Our results remain robust if we replace missing values in R&D and advertising expenditures by zero. Firm controls include the natural log of market capitalization and the natural log of the book-to-market ratio. The sample period spans 1993 - 2016. We include t-statistics in brackets. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We also examine the relation between the ICC and organization capital (see Eisfeldt and Papanikolaou, 2013). We find a weak association between these two measures (see column 5), probably because organization capital is constructed from SG&A, which contains both advertising expenditures and administrative expenses. Advertising expenditures boost pure brand recognition and is negatively related to our ICC measure (see column 4 of Table 2), whereas administrative expenses mainly reflect the contribution of talents and thus are positively related to our ICC measure (see column 1 of Table 2). The weak correlation between our ICC measure and organization capital suggests that the two measures capture different firm characteristics.

To test the theoretical properties (2) and (3) of our ICC measure, we examine the growth rate of brand stature, a measure of customer capital, following the non-retirement turnover of CEOs. As shown in columns (1) and (2) of Table 3, the customer capital

Table 3: The ICC measure and changes in customer capital following talent turnover.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\text{Stature\_gr}_{t:t+2}$		$\text{Sales\_gr}_{t:t+2}$		$\text{Asset\_gr}_{t:t+2}$		$\Delta\text{ICC}_{t:t+2}$	
$\ln(\text{ICC})_{t-1} \times \text{Turnover}_t$	-0.041^{*}	-0.047^{**}	-0.036^{**}	-0.027^{*}	-0.065^{**}	-0.059^{**}		
	[−1.804]	[−1.982]	[−2.402]	[−1.794]	[−2.320]	[−2.302]		
Turnover_t	−0.014	−0.023	-0.073^{***}	-0.055^{***}	-0.109^{***}	-0.095^{***}	-0.181^{***}	-0.159^{**}
	[−0.634]	[−1.007]	[−3.652]	[−3.300]	[−4.508]	[−3.684]	[−2.701]	[−2.398]
$\ln(\text{ICC})_{t-1}$	0.141^{***}	0.152^{***}	0.069^{***}	0.033^{***}	0.073^{***}	0.032^{*}		
	[17.600]	[17.024]	[5.919]	[3.008]	[3.886]	[1.745]		
Firm controls	No	Yes	No	Yes	No	Yes	No	Yes
Industry FEs & Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3709	3525	4523	4285	4523	4285	4059	3855
R-squared	0.440	0.443	0.170	0.233	0.135	0.211	0.099	0.108

Note: This table shows the relation between the ICC measure and changes in customer capital following talent turnover. The dependent variables are the two-year growth rate of brand stature ($\text{Stature\_gr}_{t:t+2}$), the two-year growth rate of sales ($\text{Sales\_gr}_{t:t+2}$), the two-year growth rate of assets ($\text{Asset\_gr}_{t:t+2}$), and the two-year change in the ICC ($\Delta\text{ICC}_{t:t+2}$). CEO turnover_t is an indicator variable that equals 1 if a CEO leaves the firm at age 59 or younger. The main independent variables are lagged standardized $\ln(\text{ICC})_{t-1}$, the turnover indicator, and the interaction term between the two. Firm controls include the natural log of firm market capitalization, the natural log of the book-to-market ratio, the natural log of the debt-to-equity ratio, and the natural log of organization capital normalized by assets. We control for year fixed effects and SIC industry fixed effects. The sample spans 1993 - 2016. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

of high-ICC firms is more negatively affected by CEO turnover than that of low-ICC firms. In addition, the sales growth and asset growth of high-ICC firms also react more negatively to CEO turnover (see columns 3 – 6 of Table 3). Finally, we examine the changes in ICC after CEO turnover. As shown in columns (7) and (8), the ICC decreases following CEO turnover, suggesting that firms' customer capital depends less on talents after they leave.

4 Empirical Results

We now test the joint cross-sectional implications of the ICC on stock returns and talent turnover.

4.1 Asset Pricing Tests

We first examine the asset pricing implications of the ICC. We show that firms with higher ICC have higher average and risk-adjusted returns. Moreover, we find that the long-short portfolio sorted on ICC comoves with the financial-constraints-risk factor.

4.1.1 Portfolios Sorted on ICC

In this subsection, we document the returns of the stock portfolios sorted on ICC. In June of year t, we sort firms into five quintiles based on their ICC in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Table 4 shows that the equal-weighted (value-weighted) low-ICC portfolio (Q1) has annualized average excess returns of 10.20% (4.94%). By contrast, the equal-weighted (value-weighted) high-ICC portfolio (Q5) has annualized average excess returns of 16.18% (11.62%). The equal-weighted (value-weighted) portfolio that longs Q5 and shorts Q1 has a positive and statistically significant annualized return of 5.98% (6.68%). The magnitude of this return spread (i.e., the ICC spread) is also economically significant because it is close to the level of equity premium and value premium. The equal-weighted portfolios are preferred in our analysis, because the cross section includes about 400 firms and the overweighting of large firms and the resulting diversification failure could be a concern for the value-weighted portfolios (see, e.g., Gabaix, 2011).

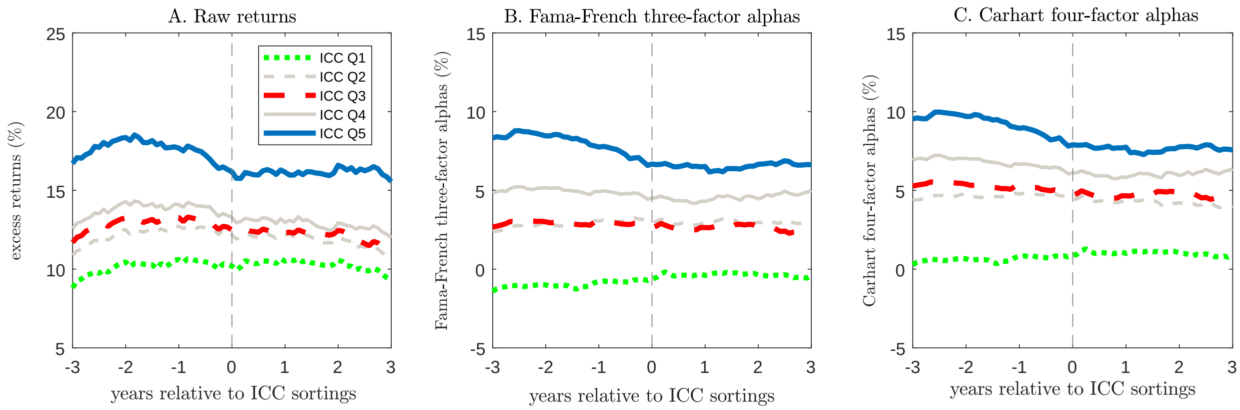
Table 4: Excess returns and alphas of portfolios sorted on ICC

	Equal weighted						Value weighted					
Portfolios sorted on ICC	1 (L)	2	3	4	5 (H)	$5-1$	1 (L)	2	3	4	5 (H)	$5-1$
Average excess returns (%)	10.20**	12.17***	12.48***	13.29***	16.18***	5.98**	4.94	9.68***	9.84***	10.04**	11.62***	6.68*
	[2.53]	[3.37]	[3.33]	[3.14]	[3.46]	[2.14]	[1.56]	[3.22]	[3.02]	[2.43]	[2.65]	[1.94]
Fama-French three-factor α (%)	-0.42	2.94*	2.72	2.67	5.50**	5.92**	-2.53*	3.47***	2.89*	1.45	4.25*	6.77**
(Fama and French, 1993)	[-0.23]	[1.70]	[1.56]	[1.32]	[2.44]	[2.44]	[-1.71]	[2.70]	[1.94]	[0.78]	[1.92]	[2.35]
Carhart four-factor α (%)	1.81	4.84***	4.40***	5.16***	8.00***	6.19**	-2.09	3.11**	3.08**	2.43	4.83**	6.92**
(Carhart, 1997)	[1.08]	[3.06]	[2.68]	[2.87]	[3.89]	[2.51]	[-1.41]	[2.40]	[2.04]	[1.32]	[2.17]	[2.37]

Note: This table shows the equal-weighted and value-weighted average excess returns and alphas for portfolios sorted on ICC. The sample period spans 1993 - 2016. We include t-statistics in brackets. 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 alphas by multiplying them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Because high- and low-ICC firms may have differential exposure to the priced risk factors, we also estimate the alphas using the Fama-French three-factor model (see Fama and French, 1993) and the Carhart four-factor model (see Carhart, 1997). We find that the long-short portfolio sorted on ICC has positive and statistically significant alphas in both models.[18]

[18]In Online Appendix Table OA.6, we show that the ICC also has positive and statistically significant alphas in the q-factor model (see Hou, Xue and Zhang, 2015), the Fama-French five-factor model (see Fama and French, 2015), and the Pástor-Stambaugh five-factor model, the latter of which contains the Fama-French three factors, the momentum factor, and the Pástor-Stambaugh liquidity factor (see Pástor



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

Figure 5: Before-/after-sorting excess returns and alphas for the ICC quintiles in event time

We further examine the persistence of the return spread around the portfolio sorting period. Figure 5 plots the excess returns and alphas of the equal-weighted portfolios. We find that the positive relation between portfolio alphas and the ICC exists three years before and continues to exist three years after portfolio formation. This result reinforces the findings in Table 4 because it indicates that the ICC is a persistent firm characteristic priced in the cross section with respect to certain asset pricing factors.[19] The finding of persistent ICC spreads supports our theory of heterogeneous persistent risk exposure due to persistent firm characteristics, rather than time-varying betas (see, e.g., Daniel and Moskowitz, 2016).

4.1.2 The c-Factor

In this subsection, we perform two tests to show that the ICC spread is an asset pricing factor that is positively priced in the cross section of all public firms, consistent with our model's implications. We refer to the ICC spread as the c-factor.

and Stambaugh, 2003).

[19] The correlation in $\ln(\text{ICC})$ is 0.96 between years t and $t-1$ and 0.80 between years t and $t-5$.

We first estimate the market price of risk for the ICC spread. As shown in Figure 5, the ICC is persistent and priced in the cross section; thus, an informative portfolio for identification purposes is the one sorted on the ICC, the corresponding firm characteristic. Estimation based on arbitrary portfolios could be noisy because they may have clustered betas (i.e., betas are not dispersed enough in the cross section). We thus sort all U.S. public firms based on their betas with respect to the ICC spread, denoted by $\beta_{\text{c-factor}}$, which is estimated with a rolling window.[20] We then sort firms into quintiles based on $\beta_{\text{c-factor}}$ and compute the average excess returns and alphas of each quintile. We find that the firms with higher $\beta_{\text{c-factor}}$ have significantly higher average excess returns and alphas (see Table A.1 in Appendix A), suggesting that the ICC spread is positively priced in the cross section of all U.S. public firms.

To show robustness, we perform further cross-sectional asset pricing tests by including a broad set of test assets (Fama-French size and value 5×5 portfolios, momentum portfolios, industry portfolios, portfolios of treasury bonds, and portfolios of corporate bonds), in addition to the portfolios sorted on ICC. Online Appendix Table OA.10 shows that the ICC spread remains positively priced. Moreover, the pricing errors are significantly reduced by including the ICC spread in the Fama-French five-factor model.

4.1.3 What Economic Force Does the c-Factor Capture?

Our model implies that firms with higher ICC have greater exposure to financial constraints risk and therefore must compensate investors with higher expected returns. In this subsection, we provide empirical evidence to support the linkage between the ICC and exposure to financial constraints risk.

Specifically, we examine the relation between our c-factor and the return spread of two financial constraints measures: (1) the WW index (see Whited and Wu, 2006), which is structurally estimated to capture the marginal value of internal funds;[21] and (2) the BW

[20] Because the ICC spread is exposed to the risk of traditional asset pricing factors, we control for these factors when estimating $\beta_{\text{c-factor}}$. Pástor and Stambaugh (2003) use the same approach to study the asset pricing implications of their market liquidity factor. They estimate the market liquidity beta in regressions that control for the Fama-French three factors. We use the equal-weighted ICC spread to estimate $\beta_{\text{c-factor}}$, because our sample contains a relatively small number of firms, and thus the value-weighted ICC spread suffers from small-sample biases.

[21] Similar financial-constraints-risk factors are structurally estimated by Eisfeldt and Muir (2016) and Belo, Lin and Yang (2018) using different approaches. We use the WW factor because it is available at monthly frequency and our model fits into Whited and Wu (2006)'s estimation setup. Several other financial constraints measures are constructed using the reduced-form approach (see, e.g., Kaplan and Zingales,

index, constructed by Buehlmaier and Whited (2018) based on Factiva textual analysis to provide a direct measure of financial constraints.[22] Figure 6 displays the time series and scatter plots of the c-factor, the WW factor, and the BW factor.[23] The c-factor is highly correlated with both the WW factor and the BW factor, with quarterly correlation being 0.59 and 0.68, respectively.

The high correlation between our theoretically motivated c-factor and the two financial constraints factors has two implications. First, these findings provide empirical support for our theory because they suggest that to a large extent, the c-factor also captures the same financial constraints risk as the WW factor and the BW factor. Second, by connecting our theoretically motivated c-factor to the financial constraints factors, we provide new economic insight on why financial constraints could be priced. Specifically, our theory suggests that one major channel through which the financial-constraints-risk factor affects stock returns is the ICC.

4.1.4 Financial-Constraints-Risk Shocks versus Primitive Economic Shocks

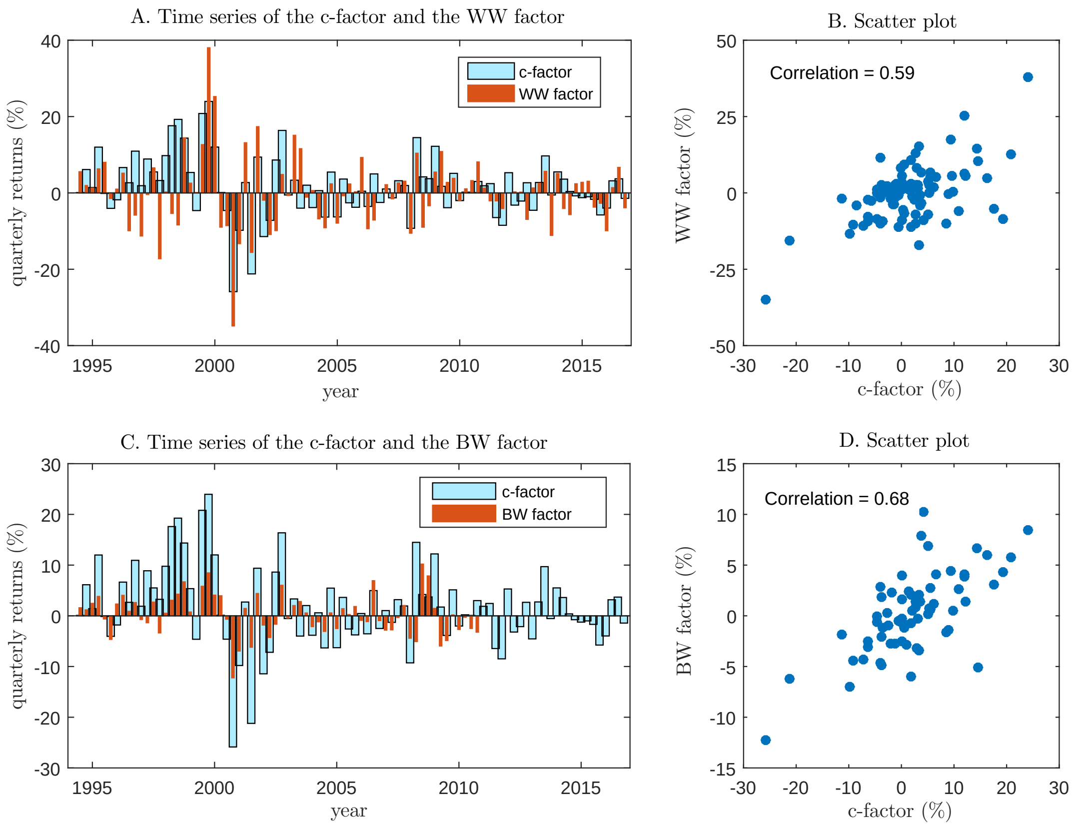
As discussed in Section 2, financial-constraints-risk shocks could be driven by many primitive economic shocks.

Separately identifying pure financial-constraints-risk shocks is challenging, primarily because the marginal value of the entire corporate sector's internal funds cannot increase or decrease without primitive economic forces. Therefore, similar to Whited and Wu (2006) and Buehlmaier and Whited (2018), we do not intend to disentangle the fundamental

1997; Hadlock and Pierce, 2010), but these estimates do not directly reflect the marginal value of internal funds.

[22] Buehlmaier and Whited (2018) develop three financial constraints measures based on textual analysis. The BW index is constructed using the Dow Jones Factiva database as the training sample and it captures general financial constraints. The other two measures capture financial constraints owing to frictions in issuing equity or issuing debt. We use the BW index because the marginal value of internal funds can be affected by both types of frictions and thus it is more accurately captured by a measure that also captures general financial constraints.

[23] We obtained the BW factor from Buehlmaier and Whited (2018) for the period 1995 - 2010. This factor is calculated as the value-weighted long-short portfolio returns sorted on BW index. We construct the WW factor following Whited and Wu (2006). First, we sort firms independently based on size and the WW index into the top 40%, the middle 20%, and the bottom 40%. We then classify firms into the following nine portfolios and calculate the value-weighted return of each portfolio: small size/low WW index (SL), small size/middle WW index (SM), small size/high WW index (SH), medium size/low WW index (ML), medium size/middle WW index (MM), medium size/high WW index (MH), large size/low WW index (BL), large size/middle WW index (BM), and large size/high WW index (BH). The WW factor is constructed as the difference in the returns between the high-constrained firms and the low-constrained firms: (BH+MH+SH)/3 - (BL+ML+SL)/3.



Note: Panels A and B illustrate the relation between the c-factor and the WW factor. Panels C and D illustrate the relation between the c-factor and the BW factor.

Figure 6: Correlation between the c-factor and the financial constraints factors

drivers of the financial-constraints-risk shock, or to claim that the financial-constraints-risk shock is a new form of primitive economic shocks. In Online Appendix Table OA.11, we show that various primitive shocks, such as uncertainty shocks, TFP shocks, and financial-sector shocks are indeed correlated with our c-factor in a coherent way, and they can explain part of the ICC spread. We find that the ICC spread remains significant after controlling for each primitive economic shock. The ICC spread may well vanish if we exhaustively control for all possible primitive economic shocks. However, identifying all shocks that explain away the ICC spread is not the main objective of our paper.

4.1.5 The c-Factor is a Common Factor for Two Cross Sections

Our model implies that the exposure to financial constraints risk is reflected in both the cross-sectional variation in the ICC and the extent to which firms are financially constrained (panels E and F of Figure 3). Thus, in principle, the c-factor should be able to simultaneously explain the return spread of the long-short portfolio sorted on ICC and the degree to which firms are financially constrained. We now provide empirical support.

First, we show that the c-factor is able to explain the ICC spread. Adopting the same methodology used in Eisfeldt and Papanikolaou (2013, Table VI), we examine the changes in the ICC spread after controlling for the returns of the long-short portfolio sorted on $\beta_{\text{c-factor}}$. As panels A and B of Table 5 show, the ICC spread decreases significantly and becomes statistically insignificant.

We continue to examine the return spreads of the BW index in panel C of Table 5. Consistent with Buehlmaier and Whited (2018), we find that the alphas for the long-short portfolio sorted on BW index are positive and statistically significant for the Pástor-Stambaugh five-factor model, the Hou-Xue-Zhang q-factor model, and the Fama-French five-factor model. However, the average excess returns and the alphas decrease significantly and become statistically insignificant after controlling for the c-factor.

These results from testing the model-implied cross-equation restrictions further corroborate our argument that both the ICC and financial constraints measures capture firms' exposure to financial-constraints-risk shocks. However, we would like to emphasize that financial constraints measures and our ICC measure capture different economic concepts. The ICC measure is not an alternative empirical measure for financial constraints. As we show in Section 2.6, the ICC and the marginal value of internal funds are endogenously linked. However, the marginal value of internal funds is not solely determined by the ICC; it is also largely determined by other factors such as cash holdings. Conditional on the same marginal value of internal funds, the exposure to financial-constraints-risk shocks still varies with a firm's ICC. Thus, even a perfect empirical measure for the marginal value of internal funds should not be considered a "sufficient statistic" for a firm's exposure to financial-constraints-risk shocks. The primary goal of our paper is to show that a firm's ICC is informative and has first-order importance as an additional complementary statistic for summarizing a firm's exposure to financial-constraints-risk shocks.

Table 5: A common factor for two cross sections

Panel A: Equal-weighted excess returns and alphas of the ICC spread						
Factor models	Excess returns	FF3F	FF4F	PS5F	q-factor	FF5F
Excess returns and α (%)	5.75*	5.91**	6.12**	5.59**	9.45***	9.24***
	[1.95]	[2.32]	[2.38]	[2.17]	[3.57]	[3.62]
Excess returns and α controlling for the c-factor (%)	3.55	4.18	3.90	3.47	5.56	5.95
	[1.00]	[1.14]	[1.05]	[0.95]	[1.36]	[1.63]
Panel B: Value-weighted excess returns and alphas of the ICC spread						
Factor models	Excess returns	FF3F	FF4F	PS5F	q-factor	FF5F
Excess returns and α (%)	6.42*	6.83**	6.95**	6.67**	11.52***	11.77***
	[1.77]	[2.29]	[2.31]	[2.19]	[3.79]	[4.04]
Excess returns and α controlling for the c-factor (%)	3.57	4.74	4.26	4.07	7.00	8.08**
	[1.13]	[1.20]	[1.28]	[1.36]	[1.53]	[2.01]
Panel C: Excess returns and alphas of the long-short portfolio sorted on BW index						
Factor models	Excess returns	FF3F	FF4F	PS5F	q-factor	FF5F
Excess returns and α (%)	1.05	2.33	2.23	3.39**	5.02**	4.60**
	[0.56]	[1.51]	[1.49]	[2.60]	[2.38]	[3.78]
Excess returns and α controlling for the c-factor (%)	−1.85	−0.37	−0.45	0.71	0.33	0.62
	[−1.52]	[−0.26]	[−0.29]	[0.47]	[0.21]	[0.39]

Note: Panel A (panel B) tabulates the equal-weighted (value-weighted) excess returns and alphas of the ICC spread, with and without controlling for the returns of the long-short portfolio sorted on $\beta_{\text{c-factor}}$ under various factor models. $\beta_{\text{c-factor}}$ is the beta with respect to the c-factor. The sample period is from 1995 to 2016, because we use data for the first two years to compute the lagged yearly $\beta_{\text{c-factor}}$. The excess returns and alphas for the ICC spread are different from those in Table 4 due to the difference in the sample period. Panel C tabulates the value-weighted excess returns and alphas of the long-short portfolio sorted on BW index, with and without controlling for the c-factor. The sample period is from 1995 to 2010, during which the BW index is available. We include t-statistics in brackets. 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 them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.1.6 Robustness

Our double-sort analyses in Appendix B indicate that the asset pricing implications of the ICC are robust and not explained by other firm characteristics. We further check the robustness of our results using the Fama-MacBeth regression method (see Fama and MacBeth, 1973). We regress individual stocks' returns on ln(ICC) and a battery of return predictors, such as size, book-to-market ratio, investment (capex-to-asset ratio), ROA, momentum, and short-term return reversal. Online Appendix Table OA.17 reports the average coefficients (in percent) from monthly Fama-MacBeth cross-sectional regressions. The coefficient of the ICC measure is positive and statistically significant. Moreover, following Li (2011), we control for various measures of firms' R&D activities (R&D-to-sales ratio, R&D-to-asset ratio, R&D-to-capex ratio, R&D-to-number-of-employees ratio, and R&D-to-market-equity ratio). Consistent with the literature (see, e.g., Li, 2011; Hirshleifer, Hsu and Li, 2013, 2017), we find that the R&D measures have positive coefficients in the Fama-MacBeth regressions. The coefficient of the ICC measure remains significantly positive after controlling for these R&D measures, suggesting that R&D is unlikely to fully explain the positive relation between the ICC and stock returns.

4.2 Turnover

We now test the model's predictions on turnover. We show that the ICC is positively related to the turnover rates of executives and innovators. Moreover, the positive relationship is more pronounced during the periods of heightened financial constraints risk and for firms located in states where the enforcement of non-compete agreements is weaker.

Table 6: The ICC and talent turnover

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

Note: This table shows the relation between the ICC and the turnover of executives and innovators. In columns (1) and (2), we study executive turnover. Turnover_t is an indicator variable that equals 1 for a given executive-year observation if the executive leaves the firm at age 59 or below, and 0 otherwise. In columns (3) to (6), we study innovator turnover. A mover in a given year is defined as an innovator who generates at least one patent in one firm and at least one patent in another firm later in the same year. If innovators leave their firms in a given year, they are classified as leavers of their former employers in that year. If innovators join new firms in a given year, they are classified as new hires of their new employers in that year. The dependent variables are the natural log of 1 plus the number of leavers and the natural log of 1 plus the number of new hires. The main independent variable is lagged standardized ln(ICC). Firm controls include the natural log of firm market capitalization, the natural log of the book-to-market ratio, the natural log of the debt-to-equity ratio, the natural log of organization capital normalized by assets, and the stock return in the previous year. Executive controls include genders. We control for year fixed effects with and without SIC-2 industry fixed effects. The executive turnover sample spans 1993 - 2016, whereas the innovator turnover sample spans 1993 - 2010. We include t-statistics in brackets. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2.1 The ICC and Talent Turnover

We first study the relation between the ICC and executive turnover. We focus on the executives in the Execucomp database, which covers the top five executives of each S&P

500 firm in terms of compensation.[24] We find that executive turnover rates are significantly higher in the firms with higher ICC (see columns 1 and 2 of Table 6). According to the specification with both year and industry fixed effects, a one standard deviation increase in ln(ICC) is associated with an increase of 1.546 percentage points in the probability of executive turnover each year, which is roughly one-eighth of the average turnover rate in the data.

Next, we study the relation between the ICC and innovator turnover. We track the employment history of innovators based on the HBS patent and innovator database, which provides innovators' names and affiliations from 1975 to 2010. We find that the firms with higher ICC are associated with significantly higher innovator turnover rates (see columns 3 – 6 of Table 6). According to the specifications with both year and industry fixed effects, a one-standard-deviation increase in ln(ICC) is approximately associated with a 17.0% increase in leavers and a 15.8% increase in new hires.

4.2.2 Interaction with Financial Constraints Risk

Our model implies that the positive relation between the ICC and turnover rates is stronger during periods with heightened financial constraints risk. Section 4.1.3 above suggests that a low level of c-factor is associated with heightened financial constraints risk. In this section, we thus include the interaction term between ln(ICC) and the yearly c-factor as the main independent variable.

Table 7 shows that the coefficients for the interaction term are significantly negative, suggesting that the positive relation between the ICC and talent turnover rates is indeed more pronounced during periods of heightened financial constraints risk. This interaction effect is economically significant. For example, according to the specification with year fixed effects (column 1), when the c-factor changes from its mean value (5.8%) to a value that is two standard deviations below the mean (-27.5%), the sensitivity between

[24] Because Execucomp provides only limited information on the turnover of executives (especially for non-CEOs), we further merge Execucomp with BoardEx and use the employment history data in BoardEx to identify executive turnover. We focus on those instances of executive turnover that are not due to retirements, because (1) retirement is mostly due to age, health status, and lifestyle choices of executives, none of which reflects firms' active decisions, and (2) non-retirement turnover is more likely to hurt customer capital and thus are more relevant to the mechanism proposed in our paper. We follow the literature (see, e.g., Parrino, 1997; Jenter and Kanaan, 2015) and use age 60 as the cutoff for the retirement age. Our results are robust to other age cutoffs, such as 65. In Online Appendix D4, we replicate the turnover analyses in two different samples: (1) CEOs only and (2) all managers in the BoardEx dataset. The relation between the ICC and turnover remains robust.

Table 7: The ICC and talent turnover: interaction with financial constraints risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Executives		Innovators			
	$\text{Turnover}_t \times 100$		$\ln(1 + \text{leavers})_t$		$\ln(1 + \text{new hires})_t$	
$\ln(\text{ICC})_{t-1}$	1.881***	1.758***	0.208***	0.209***	0.195**	0.194**
	[3.749]	[3.449]	[2.715]	[2.703]	[2.557]	[2.494]
$\ln(\text{ICC})_{t-1} \times \text{c-factor}_{t-1}$	−3.915**	−4.263**	−0.410***	−0.415**	−0.372***	−0.379*
	[−2.344]	[−2.533]	[−3.970]	[−2.672]	[−3.337]	[−2.052]
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Executive controls	Yes	Yes	–	–	–	–
Industry FEs	No	Yes	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24107	24107	1688	1682	1688	1682
R-squared	0.024	0.032	0.385	0.603	0.390	0.606

Note: This table shows the relation between talent turnover and the interaction between the ICC and the yearly c-factor. The dependent variables, firm controls, executive controls, and fixed effects are defined in Table 6. The main independent variables are lagged standardized ln(ICC) and the product of lagged standardized ln(ICC) and lagged c-factor. We omit the term c-factor_{t-1} in the regressions because it is absorbed by year fixed effects. The executive turnover sample spans 1993 - 2016, whereas the innovator turnover sample spans 1993 - 2010. We include t-statistics in brackets. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

ln(ICC) and executive turnover increases significantly (the coefficient changes from 1.654 to 2.958).[25]

4.2.3 Interaction with Non-compete Enforceability

Our model implies that the positive relation between the ICC and talent turnover is weaker for firms in which key talents have lower outside option values (see panel C of Figure 4). Thus, we expect to see a weaker relationship for firms located in states with stronger enforceability of non-compete agreements, because strictly enforced non-compete agreements decrease the outside option value of key talents. To test this hypothesis, we exploit the cross-state variation in the enforceability of non-compete agreements by including the interaction term between the ICC and the non-compete enforceability index as the main independent variable.

As Table 8 shows, the coefficients for the interaction term are significantly negative, suggesting that the positive relation between the ICC and talent turnover rates is indeed weaker when non-compete agreements are more strictly enforced. Consider column 4 as an example. Conditional on the weakest enforceability (index value = 0), a one-standard-deviation increase in ln(ICC) is associated with a 31.8% increase in the number of leavers.

[25] $1.881 + 5.8\% \times (-3.915) = 1.654$, and $1.881 + (-27.5\%) \times (-3.915) = 2.958$.

Conditional on the strongest enforceability (index value = 9), a one-standard-deviation increase in $\ln(\text{ICC})$ is associated with a 0.3% (insignificant) increase in the number of leavers.

Table 8: The ICC and talent turnover: interaction with non-compete enforceability

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

Note: This table shows the relation between talent turnover and the interaction between the ICC and the non-compete enforceability index. The state-level non-compete enforceability index comes from Garmaise (2011). Higher values of the index represent stronger enforceability of non-compete agreements. The index is available from 1992 to 2004. The minimum, maximum, median, and mean of the index are 0, 9, 5, and 4.08, respectively. The standard deviation of the index is 1.83. The dependent variables, firm controls, executive controls, and fixed effects are defined in Table 6. The main independent variables are lagged standardized ln(ICC), lagged non-compete enforceability index, and the interaction between the two. The sample spans 1993 - 2004. We include t-statistics in brackets. Standard errors are clustered by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5 Quantitative Analyses

In this section, we conduct quantitative analyses. We first extend the baseline model with three additional ingredients. Then, we calibrate the model's parameters and examine whether our model can replicate the main asset pricing and talent turnover findings from the data. Finally, we discuss the quantitative importance of different channels.

5.1 Extended Model

We extend our baseline model with the following three components.

(1) Aggregate Productivity Shocks. First, we introduce aggregate productivity shocks as an additional risk to better match the data. The firm's output in equation (2.1) is affected by an aggregate productivity shock a_t evolving as follows:

$$\mathrm{d}a_t = -\mu_a(a_t - \overline{a})\mathrm{d}t + \sigma_a\sqrt{a_t}\mathrm{d}Z_{a,t}, \tag{5.1}$$

where $Z_{a,t}$ is a standard Brownian motion independent of $Z_{c,t}$. We assume that $2\mu_a\overline{a} > \sigma_a^2$ to guarantee $a_t > 0$. The pricing kernel (2.6) thus becomes

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t - \kappa_a\mathrm{d}Z_{a,t} + \sum_{\xi'\neq\xi_t}\left[e^{-\kappa^{(\xi_t,\xi')}} - 1\right](\mathrm{d}N_t^{(\xi_t,\xi')} - q^{(\xi_t,\xi')}\mathrm{d}t), \tag{5.2}$$

where $\kappa_a > 0$ is the market price of risk for aggregate productivity shocks.

(2) Exogenous Firm-Specific Variations in the ICC. Second, to better match the cross-sectional distribution of talent compensation, we introduce an exogenous firm-specific idiosyncratic shock $\mathrm{d}Z_{\omega,t}$ to firms' ICC. Thus, equation (2.7) is modified as

$$\mathrm{d}\omega_t = \underbrace{-\mu_\omega(\omega_t - \overline{\omega})\mathrm{d}t + \left[\ln\left(1 - me^{-\omega_t}\right) - \ln\left(1 - m\right)\right]\mathrm{d}J_t}_{\text{baseline endogenous turnover}} + \underbrace{\sigma_\omega\sqrt{\omega_t}\mathrm{d}Z_{\omega,t}.}_{\text{exogenous shock}} \tag{5.3}$$

We assume that $2\mu_\omega\overline{\omega} > \sigma_\omega^2$. The process $Z_{\omega,t}$ is an idiosyncratic standard Brownian motion, independent of $Z_{a,t}$ and $Z_{c,t}$. Equation (2.9) is rewritten as

$$V_{\text{new}}(B_t, \tau_t, a_t, \xi_t) = \max_{W^*} V(W^*, B_t^{\text{new}}, \overline{\tau}, a_t, \xi_t) - W^* - \Phi(W^*; B_t^{\text{new}}).$$

(3) Non-pecuniary Private Benefits. Third, we introduce another unique feature of customer capital — the non-pecuniary private benefits, in addition to the inalienability. When managing a firm with customer capital B_t, key talents enjoy non-pecuniary private benefits hB_t with a positive constant h.[26] The promise-keeping constraint equation (2.13)

[26] The assumption that non-pecuniary private benefits are proportional to customer capital B_t reflects the findings and discussions in the existing literature. For example, key talents can gain identity-based benefits (see Akerlof and Kranton, 2005) while working at the firms with strong brand value, because the firms with stronger brands offer key talents more opportunities for self-enhancement, higher visibility among their peers, and a greater likelihood of being seen as successful (see Tavassoli, Sorescu and Chandy, 2014). Moreover, future employers may rely on the brand affiliation as a credible indicator of human capital quality. Thus, working for high brand value firms benefits key talents by signaling their unobserved abilities (see Weiss, 1995). The proportional non-pecuniary private benefits for key talents hB_t are commonly adopted in the literature as a parsimonious modeling technique (see, e.g., Eisfeldt and Rampini, 2008).

Table 9: Calibration

Parameters	Symbol	Value	Parameters	Symbol	Value
Risk-free rate	r	5%	Damage ratio of talent-dependent customer capital	m	0.35
Fixed financing costs	γ	0.01	New customer capital created by a new firm	ℓ	0.2
Variable financing costs	φ	0.06	Private benefits	h	0.011
Long-run average aggregate productivity	$\overline{a}$	1	Long-run fraction of talent-dependent customer capital	$\overline{\omega}$	0.9
Mean reversion of aggregate productivity	μ_a	0.275	Mean reversion of talent-dependent customer capital	μ_ω	0.038
Volatility of aggregate productivity	σ_a	0.07	Volatility of talent-dependent customer capital	σ_ω	0.19
Physical capital depreciation rate	δ_K	0.1	Customer capital depreciation rate	δ_B	0.15
Cash-carrying costs	ρ	1.5%	Replacement intensity	θ_H	0.19
Price of goods	p	0.46	Idiosyncratic shocks to cash flows	σ_c	0.15
Rent extraction	λ	0.06	Lumpy cash flow shock size	f	0.1
Effective matching efficiency	ψ	0.75	Lumpy cash flow shock frequency	ξ_L, ξ_H	$0, 0.5$
Sales' representative hiring costs (scale)	α	5.0	Price of risk of productivity shocks	κ_a	0.4
Sales' representative hiring costs (convex)	η	2	Price of risk of financial-constraints-risk shocks	$\kappa^{(\xi_L,\xi_H)}$	$-\ln(3)$
Transition intensities	$q^{(\xi_H,\xi_L)}$	0.2		$\kappa^{(\xi_H,\xi_L)}$	$\ln(3)$
	$q^{(\xi_L,\xi_H)}$	0.16			

is rewritten as

$$0 = \Lambda_t(\Gamma_t + hB_t)\mathrm{d}t + \mathbb{E}_t\left[\mathrm{d}\left(\Lambda_t U(B_t, \tau_t, a_t, \xi_t)\right)\right]. \tag{5.4}$$

With the introduction of private benefits, all else equal, we can see that Γ_t decreases with B_t, suggesting that the firm with a weaker brand (smaller B_t) needs to offer a greater compensating wage differential to keep key talents, due to smaller non-pecuniary private benefits. We provide supporting evidence in Appendix C.2.

5.2 Calibration and Parameter Choices

We discipline parameters based on both existing estimates and micro data (see Table 9).

Externally Determined Parameters. The annual interest rate is $r = 5\%$. The depreciation rate of physical capital is $\delta_K = 10\%$ per year. We choose the variable financing cost $\varphi = 6\%$ based on the estimates of Altinkilic and Hansen (2000). Following Bolton, Chen and Wang (2011, 2013), we set the fixed financing cost $\gamma = 1\%$ and the cash-carrying cost $\rho = 1.5\%$. We set the effective matching efficiency $\psi = 0.75$.[27] We consider a

[27] In Online Appendix A1, we show that $\psi = \overline{\psi}\overline{n}^{\chi-1}$ in a model with micro-founded customer capital accumulation based on competitive search. The effective matching efficiency ψ is calibrated as follows. We normalize the matching efficiency $\overline{\psi}$ and the disutility of search to 1. We set $\chi = 1.12$, which implies that the elasticity parameter in the Cobb-Douglas matching function is $\frac{\chi-1}{\chi} = 0.11$, consistent with Gourio and Rudanko (2014)'s estimate based on the share of the labor force in sales-related occupations and the

quadratic cost function of hiring sales representatives; that is, $\eta = 2$. We set $\delta_B = 15\%$ within the typical $10\% - 25\%$ range of the annual customer turnover rate (see Gourio and Rudanko, 2014). We set $m = 0.35$, so that in our model, key talents leave with 35% of talent-dependent customer capital.[28]

The long-run average aggregate productivity $\overline{a}$ is normalized to 1. We set $\mu_a = 0.275$, following Gomes, Kogan and Zhang (2003). The transition intensities, $q^{(\xi_L,\xi_H)} = 0.16$ and $q^{(\xi_H,\xi_L)} = 0.20$, are estimated using the regime-switching dynamics of the ICC spread. The estimates are consistent with the average length of business cycles, which is 10 years. We set the price of risk of productivity shocks to $\kappa_a = 0.4$ similar to Eisfeldt and Papanikolaou (2013), and the price of risk of financial-constraints-risk shocks to $\kappa^{(\xi_L,\xi_H)} = -\ln(3)$ and $\kappa^{(\xi_H,\xi_L)} = \ln(3)$, similar to Bolton, Chen and Wang (2013). The risk-neutral transition intensities are $\hat{q}^{(\xi,\xi')} = e^{-\kappa(\xi,\xi')} q^{(\xi,\xi')}$ between two different levels of financial constraints risk $\xi \neq \xi'$.

Internally Calibrated Parameters. The remaining parameters are calibrated by matching relevant moments. We simulate a sample of 1,000 firms for 100 years according to the computed policy functions. The first 20 years are dropped as burn-in. When key talents leave the firm, new firms are created and included in the sample for the remaining simulation period. We then compute the model-implied moments and adjust parameters until these moments are in line with their values in the data (see Table 10).

We set the price of goods $p = 0.46$ to match the average cash-asset ratio. We set rent extraction rate $\lambda = 0.06$ so that the retention bonuses are between 30% and 70% of key talents' compensation (see Goyal and Wang, 2017). We calibrate the hiring cost coefficient $\alpha = 5.0$ to target the average advertising expenditures as a percent of sales. We set $\ell = 0.2$ to match the average key talents' compensation as a percentage of sales. We set the talent replacement intensity $\theta_H = 19\%$ to match the average executive turnover rate.

Because our empirical ICC measure does not have the same units as τ_t in our model, we

amount of time consumers spend shopping. Finally, we set the maximum discount $\overline{n}$ to 0.10 to ensure that the firm makes profits from new customers even if the highest initial discounts are offered.

[28] In the existing literature, several papers have developed models with this feature. For example, Lustig, Syverson and Nieuwerburgh (2011) match the increase in intra-industry wage inequality by assuming that 50% of organization capital is transferred when the manager switches to a new firm. Eisfeldt and Papanikolaou (2013)'s model assumes that key talents can leave with all intangible capital. Bolton, Wang and Yang (2018)'s benchmark calibration assumes that the entrepreneur would be 20% less efficient if he or she walks away from the firm.

Table 10: Moments in the data and model

Panel A: Aggregate moments					
	Data	Model		Data	Model
Mean cash holdings/lagged asset	23.6%	19.7%	Mean retention bonuses	30%-70%	62.5%
Autocorrelation in ln(ICC)	0.96	0.96	Mean talent compensation/sales	14.9%	12.3%
Volatility of net income/sales	16.8%	15.9%	Mean equity issuance frequency	25.2%	25.0%
Skewness of net income/sales	−0.47	−0.62	Mean turnover rate of key talents	11.8%	10.0%
Mean advertising expenditures/sales	5.1%	5.3%	Compensation reduction (Q5→Q1)	22.3%	20.6%
Volatility of market returns	0.165	0.152			

Panel B: Average talent compensation across different firm groups sorted on ICC (i.e., the variable τ_t in the model)						
		1 (Low)	2	3	4	5 (High)
Mean talent compensation/sales (%)	Data	9.6	12.0	10.9	17.2	24.9
	Model	8.9	10.7	12.5	14.0	23.1

infer $\overline{\omega}$ and σ_ω by matching the cross-sectional distribution of key-talent compensation.[29] The parameter $\mu_\omega = 0.038$ is identified by matching the autocorrelation in ln(ICC). We calibrate the parameter h to match the decrease in compensation when executives move from the high-ICC quintile to the low-ICC quintile. We set cash flow shocks to $\sigma_c = 0.15$ and $f = 0.1$ to target the average volatility and skewness of net income as a percentage of sales across all firms. We set $\sigma_a = 0.07$ to match the volatility of the market portfolio's returns. We normalize $\xi_L = 0$ for the regime of the low financial constraints risk, and accordingly set $\xi_H = 0.5$ for the regime of the high level of financial constraints risk to match the average frequency of equity issuance whose amount exceeds 1% of the firm's total assets.

5.3 Quantitative Results

Asset Pricing. Now we check whether our model can quantitatively replicate the main asset pricing patterns. Panel A of Table 11 shows that the model-implied difference in portfolio alphas between Q1 and Q5 is about 5.88%, in line with the alpha spread in our data (5.92%) based on the Fama-French three-factor model.

In panel B, we investigate the implication of financial constraints by conducting a

[29] Because key talents mainly include executives and innovators, we approximate key-talent compensation using the sum of 50% of R&D expenses and executive compensation. Many papers suggest that more than 50% of R&D expenses are wage payments to scientists, engineers, and other skilled technology workers (see, e.g., Lach and Schankerman, 1989; Hall and Lerner, 2010; Brown and Petersen, 2011; Brown, Martinsson and Petersen, 2012).

split sample analysis. The difference in portfolio alphas between Q1 and Q5 is about 9.18% among the most financially constrained firms and 2.16% among the least financially constrained firms in our model. These spreads are quite consistent with the ones in our data using the BW index to estimate the degree to which firms are financially constrained.

In panel C, we check whether the model can generate reasonable asset pricing patterns in the two cross sections — the cross section sorted on ICC and that sorted on the extent to which firms are financially constrained. The panel shows that in the model, the alpha associated with the long-short portfolio sorted on ICC is 5.82% and it is 3.22% if the sorting variable is the cash ratio. Moreover, the alphas drop to 1.74% and 0.63% after controlling for the c-factor, which is consistent with the data.

Table 11: Asset pricing and turnover implications in model and data

	Data			Model		
Panel A: Portfolios sorted on ICC (Fama-French three-factor alphas)						
Portfolio	Q1	Q5	Q5 − Q1	Q1	Q5	Q5 − Q1
α (%)	−0.42	5.50	5.92	−1.61	4.27	5.88
Panel B. Split samples by financial constraints (Fama-French three-factor alphas)						
Portfolio	Low	Mid	High	Low	Mid	High
α spread (Q5 − Q1) (%)	4.19	3.22	8.19	2.16	2.45	9.18
Panel C. Long-short portfolio (Fama-French three-factor alphas)						
	sorted on ICC	sorted on BW index		sorted on ICC	sorted on cash	
α (%)	5.91	2.33		5.82	3.22	
α (%) controlling for the c-factor	4.18	−0.37		1.74	0.63	
Panel D. Regressing turnover on						
ln(ICC)	1.546	1.758		3.190	2.961	
ln(ICC) × c-factor	–	−4.263		–	−6.832	

Note: Panel A compares the equal-weighted alphas of portfolios sorted on ICC between model and data based on the Fama-French three-factor model (numbers are from Table 4). In the model, in each year t, we sort the simulated firms into five quintiles based on their τ_t at the beginning of the year. We then compute the portfolio alphas of each quintile by regressing excess portfolio returns on the excess returns of the market portfolio, SMB, and HML, constructed using simulated data. Panel B reports the α spread from a split sample analysis. We first sort firms into three groups based on their financial constraints (the BW index in data and cash ratios in model). In each group, we further sort firms into five quintiles based on their ICC. Panel C compares the alphas of the long-short portfolio sorted on ICC and BW index between model and data based on the Fama-French three-factor model (numbers are from Table 5). Panel D tabulates the regression coefficients of talent turnover on $\ln(\mathrm{ICC})_{t-1}$ and its interaction with the c-factor$_{t-1}$ in the model and data (numbers are from Tables 6 and 7).

Turnover. The model's prediction on turnover is qualitatively consistent with the data but has a larger magnitude. Panel D of Table 11 shows that a one-standard-deviation increase in ln(ICC) is associated with an increase of 3.190 percentage points in talent

Table 12: Inspecting the model mechanisms

	α spread on the ICC (%)	α spread on cash ratio (%)	Annual turnover rate
Full model	5.88	3.25	0.1
No ICC ($m = 0$)	0.27	0.28	0
No financing costs ($\gamma = \varphi = 0$)	0.59	0	0
No private benefits ($h = 0$)	4.73	3.09	0.12
No entrenchment ($\theta_H = \infty$)	2.72	1.33	0.25

turnover in the model, as compared with an increase of 1.546 percentage points in the data. Regarding the interaction effect with financial constraints risk, panel D shows that the coefficient is -6.832 in the model, and -4.263 in the data.[30]

Inspecting the Mechanisms in the Model. In Table 12, we conduct the quantitative comparative static analyses by turning off the key frictions one at a time.

The crucial feature of customer capital is its inalienability associated with key talents. If we instead assume that the turnover of key talents does not damage customer capital (by setting $m = 0$), the α spread drops to 0.27% and the annual turnover rate also drops to 0. This is because the value of outside options is very low for key talents, and thus firms can keep key talents at very low costs. Moreover, as firms become less financially constrained due to the absence of talent compensation, the α spread on the cash ratio also drops significantly to 0.28%. If we assume that firms have access to a perfect financial market (by setting $\gamma = \varphi = 0$), the α spread on the ICC drops significantly to 0.59%. Moreover, both the spread on the cash ratio and the annual turnover rate become zero. These results collectively suggest that the interaction between the ICC and financial constraints is what jointly determines the quantitative implications of the model in the two cross sections.

If we assume no non-pecuniary private benefits are associated with customer capital (by setting $h = 0$), the α spreads on the ICC and on the cash ratio would drop to 4.73% and 3.09%, respectively. Key talents would ask for higher compensation in the absence of non-pecuniary private benefits. The α spreads are lower because non-pecuniary private benefits mitigate the operating leverage for low-ICC firms to a larger extent. The annual turnover rate would increase by 2% as firms become more financially constrained due to

[30]We do not report the model's quantitative implication on the interaction effect with non-compete enforceability (the results in Table 8), because it is not clear how the variation in the state-level non-compete enforcement index can be quantitatively translated to the variation in the model parameter m. However, as we show in panel C of Figure 4, our model's prediction is qualitatively consistent with the data.

higher compensation.

Finally, we study the role of talents' entrenchment. If we assume that shareholders can replace key talents freely (by setting $\theta_H = \infty$), the implied annual turnover rate would increase to 25%, much larger than what we see in the data. Moreover, because replacing existing key talents with new talents receiving less compensation essentially mitigates firms' financial constraints, the α spreads on the ICC and the cash ratio would drop significantly to 2.72% and 1.33%, respectively.

6 Conclusions

This paper is the first to study the fragility of customer capital due to its inalienability caused by limited legal enforcement, and more importantly, its interaction with financial constraints such as in Bolton, Chen and Wang (2011). The model shows that the financial-constraints-risk shock (see Whited and Wu, 2006; Buehlmaier and Whited, 2018), as an aggregate economic shock, has strong asset pricing implications and is significantly priced in the cross section. Particularly, the model shows that firms' heterogeneous response to aggregate financial-constraints-risk shocks, in terms of their stock returns and talent turnover rates, is simultaneously reflected in two different cross sections — the cross section sorted on ICC and that sorted on the extent to which firms are financially constrained.

Based on a proprietary, granular brand perception survey database, we find empirical evidence strongly supporting the model's implications. The firms with higher ICC have higher average (risk-adjusted) excess returns. The ICC spread is highly correlated with the financial-constraints-risk factor constructed based on Whited and Wu (2006) and Buehlmaier and Whited (2018). Moreover, the firms with higher ICC are associated with higher talent turnover rates, and this pattern is more pronounced in the periods of heightened financial constraints risk.

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Appendix

A Return spreads of $\beta_{\text{c-factor}}$ for all U.S. public firms

Table A.1 estimates the market price of risk for the ICC spread. We sort all U.S. public firms based on their betas with respect to the ICC spread (denoted by $\beta_{\text{c-factor}}$) and estimate the betas using a rolling window. We then sort firms into quintiles based on $\beta_{\text{c-factor}}$ and compute the average excess returns and alphas of each quintile. We find that the firms with higher $\beta_{\text{c-factor}}$ have significantly higher average excess returns and alphas, suggesting that the ICC spread is positively priced in the cross section of all U.S. public firms.

Table A.1: Return spreads of $\beta_{\text{c-factor}}$ in the cross section of all U.S. public firms

	Long-short portfolios sorted on $\beta_{\text{c-factor}}$	
	Equal weighted	Value weighted
Excess returns (%)	2.04**	4.10***
	[2.02]	[2.72]
Fama-French three-factor α (%)	1.75*	4.13**
	[1.71]	[2.22]
Carhart four-factor α (%)	2.25*	5.21**
	[1.92]	[2.59]
Pástor-Stambaugh five-factor α (%)	2.08*	5.03**
	[1.87]	[2.32]
Hou-Xue-Zhang q-factor α (%)	3.45***	9.28***
	[3.30]	[3.49]
Fama-French five-factor α (%)	2.20**	8.82***
	[2.00]	[3.26]

Note: This table shows the excess returns and alphas for portfolios sorted on the beta with respect to the c-factor ($\beta_{\text{c-factor}}$). We estimate $\beta_{\text{c-factor}}$ starting from the 13th month of the sample period to ensure that the estimation is conducted based on at least 12 months of data. In each month, we estimate $\beta_{\text{c-factor}}$ for all U.S. public firms by regressing their monthly stock returns on the c-factor and the Fama-French three factors in previous months up to 36 preceding months. We then average the monthly betas into yearly betas for each stock and sort the stocks into quintiles based on their lagged yearly betas. The sample period is from 1995 to 2016, because we use data for the first two years to compute the lagged yearly betas. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for one lag of serial correlation in returns. We annualize average excess returns and alphas by multiplying them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

B Double-Sort Analyses

In this appendix, we perform various double-sort analyses, and show that the ICC spread cannot be explained by other related factors or firm characteristics.

Controlling for the Measures of Customer Capital. We show that other measures of customer capital are either not priced in the cross section or their association with stock returns can be explained away by the ICC. Specifically, we study three measures of customer capital: brand stature, brand strength, and firms' product market fluidity (see Hoberg, Phillips and Prabhala, 2014). We find that none of the three measures are priced in the cross section after controlling for the ICC (see Online Appendix Table OA.12). On the other hand, the ICC remains priced in the cross section after controlling for the three measures (see Online Appendix Table OA.13). These findings suggest that studying the degree to which customer capital depends on key talents is essential to understanding the role of customer capital in explaining cross-sectional stock returns.

Controlling for the Measures of Intangible Assets. We show that the average excess returns and alphas of the ICC spread remain significantly positive after controlling for various proxies of intangible assets (see Online Appendix Table OA.14). In addition, we find that the ICC spread is much more robust in firms that have high administrative expenses and R&D expenditures (see Online Appendix Table OA.15), suggesting an interaction effect between the ICC and intangible assets. This result is reminiscent of the findings of Li (2011), who documents that the return spread of financial constraints measures is much stronger in R&D intensive firms.

Controlling for Industry Classifications. We find that the long-short portfolios sorted on ICC within industries have positive alphas, that are both statistically and economically significant (see Online Appendix Table OA.16). The return patterns are robust across various industry classifications, suggesting that the ICC's within-industry variation is priced in the cross section.

C More Tests for the Theoretical Mechanism

In this section, we provide two sets of additional empirical evidence to support our model. First, we show that the firms with higher ICC adopt more precautionary financial policies. Second, we show that key talents receive lower compensation in firms with greater brand stature. This finding supports our extended model's assumption that key talents receive non-pecuniary private benefits from customer capital.

Table C.2: The ICC and firms' financial policies

	(1)	(1′)	(2)	(2′)	(3)	(3′)	(4)	(4′)	(5)	(6)
	$\frac{\text{Cash}_t}{\text{Asset}_{t-1}}$ (%)		$\frac{\Delta\text{Cash}_t}{\text{Net income}_t}$ (%)		$\frac{\Delta\text{Equity}_t}{\text{Asset}_{t-1}}$ (%)		$\frac{\text{Payout}_t}{\text{Asset}_{t-1}}$ (%)		$\frac{\text{Dividend}_t}{\text{Asset}_{t-1}}$ (%)	$\frac{\text{Repurchases}_t}{\text{Asset}_{t-1}}$ (%)
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Data
$\ln(\text{ICC})_{t-1}$	3.475***	2.238***	9.421**	1.904***	0.665*	0.350***	−0.903***	−0.545***	−0.310***	−0.591***
	[5.786]	[8.672]	[2.219]	[4.872]	[1.928]	[7.354]	[−4.457]	[−3.985]	[−3.111]	[−3.934]
Firm controls	Yes		Yes		Yes		Yes		Yes	Yes
Industry FEs and year FEs	Yes		Yes		Yes		Yes		Yes	Yes
Observations	5842	5000	4958	5000	5842	5000	5842	5000	5842	5842
R-squared	0.439	0.242	0.032	0.015	0.106	0.010	0.296	0.142	0.349	0.248

Note: This table shows the relation between the ICC and firms' financial policies. The dependent variables are the amount of cash holdings (% of lagged assets), the change in cash holdings (% of contemporaneous net income), the amount of equity issuance (% of lagged assets), the amount of total payout (% of lagged assets), the amount of dividend issuance (% of lagged assets), and the amount of share repurchases (% of lagged assets). The outcome variables are winsorized at the 1st and 99th percentiles of their empirical distributions to mitigate the effect of outliers. In column (2), we include only observations with positive net income. The main independent variable is lagged standardized ln(ICC). Firm controls include the natural log of market capitalization, the natural log of the book-to-market ratio, the natural log of the debt-to-equity ratio, and the natural log of organization capital normalized by assets. The sample period spans 1993 - 2016. We include t-statistics in brackets. Standard errors are clustered by firm and year. Columns (1′-4′) present the regression coefficient based on the simulated data of our calibrated extended model. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

C.1 Low-ICC Firms Adopt More Precautionary Financial Policies

Table C.2 examines the relation between the ICC and firms' financial policies. We find that high-ICC firms hold more cash and convert a larger fraction of net income to cash holdings. High-ICC firms also issue more equity and pay out less dividend. Our empirical findings are roughly quantitatively consistent with the implications of our model.

C.2 Brand Stature and Private Benefits

In this appendix, we show that the private benefits of key talents increase with total customer capital. Specifically, we show that executives are willing to accept lower pay from firms with higher brand stature, a proxy for total customer capital.[31] The relation between brand stature and executive pay is economically significant. According to the regression with executive fixed effects, industry fixed effects, and year fixed effects, a one-standard-deviation increase in brand stature is associated with a 10.8% reduction in managerial compensation (see column 4 of Table C.3). In addition, we find that younger executives are more likely to enjoy non-pecuniary private benefits at the firms with strong

[31] Our findings are consistent with the literature. In a laboratory setting, researchers find that undergraduate students are willing to accept lower hypothetical salaries from the firms with higher reputation (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 from firms with stronger brand value.

Table C.3: Brand stature and talents' non-pecuniary private benefits

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

Note: This table shows the relation between brand value and managerial compensation. lnExecuComp is the natural log of the managerial compensation (*tdc*1 in the Execucomp data). We standardize both lnStature and lnStrength to ease the interpretation of coefficients. Firm controls include the natural log of firm market capitalization, the natural log of the book-to-market ratio, the natural log of the debt-to-equity ratio, the natural log of organization capital normalized by assets, and the stock returns in the previous year. We also include executive genders as executive controls in the specifications without executive fixed effects. The sample period spans 1993 - 2016. We include t-statistics in brackets. Standard errors are clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

brand stature. According to the specification with both industry and year fixed effects (see column 6 of Table C.3), 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 the firm, whereas a 67-year-old executive is not willing to accept any compensation cut.