Competition, Investment Reversibility and Stock Returns *

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ABSTRACT

This paper investigates the role of investment reversibility in determining the relation between product market competition and stock returns. We develop a unified real-option framework involving corporate investment and disinvestment decisions in a continuous-time Cournot-Nash equilibrium. The model predicts that stock returns are more negatively correlated with the level of competition when investment is more reversible. We use asset redeployability as a measure of investment reversibility and find robust empirical evidence supporting our theoretical prediction. This paper provides a new perspective (i.e. investment reversibility) to understand the competition-return relation which has mixed evidence in the existing literature.

JEL classification: D25, G12, G31.

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I. Introduction

How does product market competition affect stock returns? This question has implications for how a firm's external rather than internal environment influences its own risk. However, the relation cannot be simply signed given that mixed empirical evidence has been found in the literature (e.g., Hou and Robinson, 2006; Bustamante and Donangelo, 2017). In this paper, we revisit this important question and highlight the crucial role of investment reversibility in determining the competition-return relation both theoretically and empirically.

Aguerrevere (2009) first theoretically links firms' investment decisions under competition to their systematic risk. He assumes investment is irreversible and considers only expansion options. In fact, most investment is not completely irreversible but partially reversible. Thus, we relax this assumption and consider a wider range of firms' decisions (i.e. both investment and disinvestment decisions). An increasing number of researchers have recognised that accounting for investment reversibility and disinvestment options is necessary when predicting firms' systematic risk and stock returns (e.g., Hackbarth and Johnson, 2015; Gu, Hackbarth, and Johnson, 2017; Aretz and Pope, 2018). However, how competition interacts with investment reversibility and what the implications on risk are have not yet been studied. We bridge this gap in the literature and find an alternative perspective to understand the mixed evidence mentioned at the beginning of this paper.

To show the effect of investment reversibility on the competition-return relation, we develop a more comprehensive Cournot competition model in which firms can scale up or down their capacity as the market demand stochastically evolves. In contrast to prior such models (e.g. Grenadier, 2002; Aguerrevere, 2009; Morellec and Zhdanov, 2018), we further incorporate contraction options in addition to assets in place and expansion options. Each firm makes investment and disinvestment decisions simultaneously under competition, which determines the dynamics of expansion and contraction option values. Thus, the presence of competitors can influence the riskiness of the firm's options. On the other hand, by introducing production costs, the assets-in-place component can also affect the firm's risk through the channel of operating leverage as first noted by Carlson, Fisher, and Giammarino (2004).

We find two opposing effects of competition on firms' risk and the relative importance of these two opposing effects is determined by investment reversibility. If investment is highly reversible, the negative effect dominates the positive effect. Therefore, the competition-return relation is more negative for higher investment reversibility.

For either expansion options or contraction options, the option-implied component of risk is lower for firms in more competitive industries. This is called the *real option effect*. More competition implies that firms exercise expansion options earlier because of the fear of pre-emption by other competitors. Expanding at a lower threshold destroys the firm's option value of waiting. On the other hand, given that the output price is inversely correlated with total output, an increase in the output price follows any firm's disinvestment *ceteris paribus*. That is, a firm benefits from other firms' disinvestment as its existing assets then generate a higher profit. Hence, competition increases the value of contraction options. Exercising an expansion option can be viewed as exchanging riskless cash for risky assets whereas exercising a contraction option implies an opposite action (i.e. exchanging risky assets for riskless cash). Option values illustrate the likelihood of exercising them. Therefore, a firm with a higher value of expansion (contraction) options is more (less) risky. The *real option effect* predicts that competition reduces risk since the value of expansion (contraction) option decreases (increases) with the level of competition.

Regardless of options to adjust capacity, competition increases the firm's operating leverage and thus its risk. Intuitively, firms in more competitive industries earn less profit. Since firms are committed to production costs, lower profitability implies higher operating leverage. Meanwhile, a firm's profit margin works as a cushion to buffer negative demand shocks. Competition reduces the firm's profit margin, thereby increasing the firm's sensitivity to the demand shock. This *operating leverage effect* is also documented by Aguerrevere (2009) and Bustamante and Donangelo (2017). However, they conclude that the operating leverage effect dominates when demand is low. By endogenizing the option to disinvest, the firm can smooth out profit flows by reselling its assets and saving associated production costs if demand goes down. Disinvestment options attenuate the operating leverage effect.

We further show that which of these two opposing effects dominates depends on investment reversibility instead of the level of demand as in Aguerrevere (2009). Intuitively, if investment is more reversible, firms are more likely to adapt their scale of capital in response to the market demand and are less committed to the production costs. That is, firms are less sensitive to the risk arising from assets in place. Therefore, the operating leverage effect which predicts the positive effect of competition is reduced as investment reversibility increases. In other words, the real option effect dominates for higher investment reversibility. Overall, our model predicts a negative interaction effect of competition and investment reversibility on the firms' risk.

The paper proceeds by taking our theoretical prediction to data. We measure product market competition by the widely used sales-based Herfindahl-Hirschman Index (*HHI*). Notably, *HHI* is an inverse measure of competition. To measure investment reversibility, we use the asset redeployability index constructed by Kim and Kung (2016). By using the Bureau of Economic Analysis (BEA) capital flow table, they first compute the asset-level redeployability as the proportion of firms that use a given asset. Then they compute the industry-level redeployability by taking the value-weighted average of asset-level redeployability. Lastly, they compute the firm-level redeployability index as the sales-weighted average of industry-level redeployability across business segments in which the firm operates. The redeployability index will be higher for firms that use assets with more alternative uses. If a given asset can be used by more industries or firms, there should be more potential buyers in the secondary market. The high demand of assets tends to increase the resale prices which coincides with the definition of investment reversibility in our model. Kim and Kung (2016) also relate the asset redeployability measure to the inverse of investment irreversibility and real options theory.

In the empirical analysis, we first examine the monthly excess returns of portfolios constructed via independent sorts on *HHI* and asset redeployability. For the low redeployability quintile, returns increase with the level of competition. However, competition decreases returns for the high redeployability quintile. This pattern shows that the competition-return relation is more negative for firms with more redeployable assets. Specifically, buying the high-minus-low competition portfolio for firms with a low redeployability index and selling the high-minus-low competition portfolio for firms with a high redeployability index yields a monthly excess return of 0.58%. After controlling for other standard risk factors in asset pricing, the abnormal returns show similar patterns cross constructed portfolios. Next, we run panel and Fama-MacBeth regressions at the firm or industry level including controls. The interaction effect of competition and investment reversibility on stock returns is significantly negative. Additional tests using alternative measures of competition (i.e. assets-based *HHI* and concentration ratio) show significant results that further confirm our main prediction. Lastly, we show that our results are also robust to a different measure of investment reversibility—inflexibility—which is motivated by real options theory and reflects the width of the inaction region (see Gu et al., 2017).

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the model and derives the main prediction. Section 4 presents the empirical measures and results. Section 5 concludes.

II. Related Literature

This paper is part of a growing literature on investment-based asset pricing. More specifically, our paper explores the implications of product market competition. Aguerrevere (2009) is among the first to theoretically study the relationship between competition and firms' risk. Based on the Cournot oligopoly framework developed by Grenadier (2002), he shows that the cross-sectional effect of competition on expected return depends on the level of demand. To investigate the time-series dynamics of betas, Carlson, Dockner, Fisher, and Giammarino (2014) consider an asymmetric duopoly game and study the impacts of own and rival expansion or contraction actions on risk. In a leader-follower equilibrium, the rival's action always reduces own-firm risk, namely the hedging effect. By focusing on different investment equilibria in a duopoly, Bustamante (2014) predicts that close competitors are more likely to invest simultaneously, which helps to explain return co-movement. Bustamante and Donangelo (2017) study how competition interacts with stock returns by allowing potential entry by new firms. They find that firms in more competitive industries are faced with greater entry threat by new firms. Bustamante and Donangelo (2017) also document the operating leverage effect and further allow entry threat by new firms. Consistent with Carlson et al. (2014), they show that potential entry lowers the systematic risk of incumbents (i.e. hedging effect). Empirically, they find an overall negative relationship between competition and stock returns. With a model similar to Grenadier (2002) and Aguerrevere (2009), Morellec and Zhdanov (2018) show that competition yields a negative relation between volatility and equity returns and the relation is more negative when the degree of competition increases. Our paper augments this line of literature by further incorporating the possibility of disinvestment and highlighting the role of investment reversibility.

Our study is also related to the literature that links firms' contraction options to stock returns. Although original real options models (e.g., Dixit and Pindyck, 1994; McDonald and Siegel, 1986) typically assume irreversible investment, in reality, investment is mostly partially reversible. Partially reversible investment implies that firms hold not only expansion options (or investment options) but also contraction options (or disinvestment options). By introducing disinvestment options, Aretz and Pope (2018) find a near-monotonically negative relation between capacity overhang and stock returns. This is because disinvestment options reduce systematic risk especially when disinvestment options are most valuable and disinvestment option values increase with the degree of capacity overhang. Hackbarth and

Johnson (2015) develop a unified model that combines firms' expansion options, assets in place and contraction options and predict that risk and expected return are sinusoidal functions of productivity. Their findings reconcile several seemingly contradictory anomalies. Specifically, value and investment effects coincide with the region where operating leverage effects dominate (i.e. downward sloping risk-profitability relation), while momentum and profitability effects are consistent with an upward sloping relation caused by real options effects. Using the same modelling method, Gu et al. (2017) further show how firms' flexibility to scale up and down their asset base determines the relation between operating leverage and systematic risk. They predict that flexibility makes risk negatively related to operating leverage. Our paper contributes to this strand of literature by extending the analysis to a competitive setting (i.e. including strategic interactions between firms). Our model predicts a negative relation between competition and stock returns for expansion and contraction option regions and a positive relation for assets-in-place region. More importantly, we find that the relative importance of these two opposing effects depends on investment reversibility.

Empirically, our paper is related to the literature on the relationship between product market competition and stock returns. Hou and Robinson (2006) find a negative relation between industry concentration and stock returns. Gu (2016) documents that firms in competitive industries have higher expected returns than firms in concentrated industries, especially among R&D-intensive firms. In contrast to Hou and Robinson (2006), Bustamante and Donangelo (2017) find a positive relation between industry concentration and stock returns using alternative measures of industry concentration. The mixed empirical evidence calls for more understanding of the complex competition-return relation. Building on our theory, we reconcile the seemingly conflicting empirical evidence by showing that the effect of competition on stock returns is more negative when investment is more reversible.

Our empirical analysis is also related to the literature on investment reversibility. Balasubramanian and Sivadasan (2009) construct an industry-level measure of capital resalability. They find that industry mean productivity increases with capital resalability and productivity dispersion decreases with capital resalability. Kim and Kung (2016) propose an asset redeployability index measuring the extent to which assets have alternative uses. Their empirical results show that corporate investment is more negatively correlated with uncertainty when firms' assets are less redeployable. Thus, it is evident that irreversibility indeed significantly influences firms' investment decisions, capital accumulation and ultimately economic growth. Motivated by real options theory, Gu et al. (2017) construct a measure for the firm's inflexibility to adjust their installed capital. Investment is less reversible for more inflexible firms. Empirically, they find a positive interaction effect between operating leverage and inflexibility in predicting returns. Our paper uses both the asset redeployability index constructed by Kim and Kung (2016) and the inflexibility measure as in Gu et al. (2017) to examine how these measures interact with the level of competition in determining stock returns.

III. Theoretical Analysis

A. Model

Our model is based on Grenadier (2002), Aguerrevere (2009) and Morellec and Zhdanov (2018), who use a real-option framework to derive equilibrium investment strategies in symmetric Cournot competition. Notably, they assume that investment is irreversible. We further relax this assumption suggesting that firms can scale down their capacity by reselling installed capital. Thus, our model incorporates disinvestment decisions in addition to investment decisions.

Consider an oligopolistic industry with n identical firms producing a single, homogeneous product. The degree of product market competition is measured by the number of firms (i.e. more firms implies a higher degree of competition). Each unit of capacity can produce one unit of output per unit of time at a variable cost of c. All the firms produce at full capacity. Let $q_{i,t}$ denote the firm i's capacity (or output produced by firm i) at time t. Then the total industry output Q_t is given by $Q_t = \sum_{i=1}^{n} q_{i,t}$. Assume that the output price P_t is a function of Q_t and a stochastic demand shock Y_t, i.e.

$$P_t = Y_t {Q_t}^{-\frac{1}{\gamma}} \tag{1}$$

where the elasticity of demand γ is a constant greater than 1. Equation (1) is also known as the inverse demand function. The output price P_t is strictly decreasing in Q_t. The demand shock Y_t under the risk-neutral measure follows the stochastic process

$$dY_t = \mu Y_t dt + \sigma Y_t dW_t \tag{2}$$

where μ and σ are positive constants corresponding to drift and volatility, and dW_t is the increment of a standard Wiener process. For convergence, the drift satisfies $\mu < r$ where r is the risk-free interest rate.

For model tractability, we follow Grenadier (2002), Aguerrevere (2009) and Morellec and Zhdanov (2018) and thus focus on open-loop equilibria [1]. For a given level of total output Q_t, firms play a static Cournot game where each firm can choose its own capacity level to maximize profits given other firms' choices.

As the market demand Y_t evolves stochastically, each firm has the flexibility to scale its capacity level upward or downward. The investment cost of one extra unit of capacity is a constant $I > 0$. We assume investment is partially reversible and the resale price for disinvesting one unit of capacity is $k * I$ where $0 < k < 1$ [2]. A higher k indicates the investment is more reversible. There is a sunk cost of $(1 - k)I$ when expanding the firm with an additional unit of capacity. Investment timing decisions are also important under uncertainty given part of the investment cost can never be recovered.

[1] In open-loop equilibria (also known as pre-commitment equilibria), firms simultaneously commit themselves to entire time paths of investment (Fudenberg and Tirole, 1991, Chap.13). See Back and Paulsen (2009) for more discussions on this assumption.

[2] k is less than 1 to preclude any arbitrage opportunity.

We assume that the capacity Q_t is infinitely divisible. Since firms are identical in the same industry, we have $q_{i,t} = \frac{Q_t}{n}$ for any firm i. For a finite number of firms, $q_{i,t}$ is also infinitely divisible. It implies that each firm can increase or decrease its capacity by an infinitesimal amount $dq_{i,t}$. The problem for the firm is to choose the optimal path of capacity that maximizes the present value of its future cash flows. The firm's value is contingent on the total industry capacity Q_t and the level of the demand shock Y_t, i.e.

$$V_n(Y, Q) = \max_{\{q_{i,t}:t>0\}} \mathbb{E}\left[\int_0^{+\infty} e^{-rt}\left((Y_t {Q_t}^{-\frac{1}{\gamma}} - c)q_{i,t}dt - Idq_{i,t}^{+} + kIdq_{i,t}^{-}\right)\right] \tag{3}$$

where $dq_{i,t}^{+}$ and $dq_{i,t}^{-}$ represent increased or decreased amount of capacity at time t. The subscript n denotes that the firm is in an industry with n identical firms hereafter. The instantaneous cash flow of the firm comes from the revenue of ongoing operations, the cost of investment in new capacity (if investment occurs), and the revenue of reselling existing capacity (if disinvestment occurs).

The optimization problem for firm i can be viewed as a sequence of investment and disinvestment options. For a given level of Q_t, firm i needs to make decisions on when to invest and disinvest in a marginal unit of capital. As in Grenadier (2002), a simplified approach is to consider a myopic strategy assuming that the supply by firm i's competitors, Q_{-i}, remains fixed [3]. In Proposition 1, we derive the optimal investment and disinvestment thresholds.

PROPOSITION 1: *In the n-firm industry, when investment is partially reversible, a firm's investment in a marginal unit of capital occurs as soon as Y rises to reach the threshold $\overline{Y_n}(Q)$ which satisfies*

$$\overline{Y_n}(Q) = \frac{\beta_1}{\beta_1 - 1}\frac{n\gamma}{n\gamma - 1}(r - \mu)\left(I + \frac{c}{r}\right)\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}Q^{\frac{1}{\gamma}} \tag{4}$$

[3] Leahy (1993) shows that a competitive firm's optimal investment strategy coincides with a myopic monopolist's. The optimal investment timing is determined by comparing the value of investing later with the value of investing immediately. Competition erodes both values simultaneously and therefore the trade-off is unaffected. Grenadier (2002) extends this to an oligopoly setting.

or the output price P_t hits the threshold $\overline{P_n}$ from below

$$\overline{P_n} = \frac{\beta_1}{\beta_1 - 1} \frac{n\gamma}{n\gamma - 1}(r - \mu) \left(I + \frac{c}{r}\right) \frac{\phi - x^{\beta_2}}{x - x^{\beta_2}} \tag{5}$$

The firm's disinvestment in a marginal unit of capital occurs as soon as Y falls below the threshold $\underline{Y_n}(Q)$ which satisfies

$$\underline{Y_n}(Q) = \frac{\beta_2}{\beta_2 - 1} \frac{n\gamma}{n\gamma - 1}(r - \mu) \left(kI + \frac{c}{r}\right) \frac{x - \phi^{-1} x^{\beta_1 + 1}}{x - x^{\beta_1}} Q^{\frac{1}{\gamma}} \tag{6}$$

or the output price P_t hits the threshold $\underline{P_n}$ from above

$$\underline{P_n} = \frac{\beta_2}{\beta_2 - 1} \frac{n\gamma}{n\gamma - 1}(r - \mu) \left(kI + \frac{c}{r}\right) \frac{x - \phi^{-1} x^{\beta_1 + 1}}{x - x^{\beta_1}} \tag{7}$$

β_1 and β_2 are the positive and negative roots of the quadratic equation $\frac{\sigma^2}{2}\xi(\xi - 1) + \mu\xi - r = 0$. ϕ is defined as $\phi = (kI + \frac{c}{r})/(I + \frac{c}{r})$ and x solves $\frac{\beta_2}{\beta_2 - 1}\frac{\phi - x^{\beta_1}}{x - x^{\beta_1}} = \frac{\beta_1}{\beta_1 - 1}\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$.

Proof. See Appendix A.

For a given level of Q, both the investment threshold $\overline{Y_n}(Q)$ and the disinvestment threshold $\underline{Y_n}(Q)$ decrease with the number of firms n. However, the implications of competition on investment and disinvestment timing appear to be different. A lower investment threshold implies accelerated exercise of investment options whereas a lower disinvestment threshold implies delayed exercise of disinvestment options.

Intuitively, competition accelerates investment as the possibility of pre-emption by competitors diminishes the value of waiting. Since the output price is a decreasing function of the total output, investing before other competitors enables the firm to sell its products at a higher price until other firms invest [4]. Compared with the investment threshold for completely irreversible investment (see Morellec and Zhdanov, 2018, Appendix), we have an extra term $\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$ in the expression for the investment threshold $\overline{Y_n}(Q)$. Corollary 1 shows

[4]This result is consistent with Grenadier (2002), Aguerrevere (2009) and Morellec and Zhdanov (2018).

that the investment threshold is even lower after incorporating disinvestment options.

COROLLARY 1: *The investment threshold for partially reversible investment is strictly lower than that for completely irreversible investment, i.e.* $0 < \dfrac{\phi - x^{\beta_2}}{x - x^{\beta_2}} < 1$.

Proof. See Appendix A.

Real option theory demonstrates that the optimal investment decisions are not determined by the traditional NPV rule if the investment is irreversible and future profit flows are uncertain. Irreversibility and uncertainty jointly create the value of waiting. A reduction in either dimension diminishes the value of waiting. The firm would be less hesitant to invest if more investment cost can be recovered. In extreme, if investment is completely reversible (i.e. no sunk cost associated with investment), the firm can stop producing and fully recover the investment cost whenever the profit drops below zero. In this case, the firm is unlikely to suffer from loss even if uncertainty exists. Thus, the firm is more willing to invest. Consequently, the investment threshold decreases as investment becomes more reversible.

Meanwhile, competition delays disinvestment. The output price would increase after disinvestment and this is beneficial to the existing capacity of the firm. Disinvesting after other competitors allows the firm to enjoy a price boost induced by other firms' disinvestment. Hence, each firm has an incentive to be the last-mover when facing disinvestment decisions. This is also known as *war of attrition* [5].

Since firms are identical within one industry, in equilibrium each firm should have the same level of capacity at every instant. This implies that symmetric firms move simultaneously. In our continuous-time model, the firms can adjust their capacity within an infinitesimal time based on the realization of Y_t. That is, the desired capacity conditional on the current demand level, $Q_n^*(Y_t)$, can be reached at every instant. The investment and disinvestment rules are given by Proposition 1, which provide mappings between the demand

[5] Disinvestment decisions resemble exit decisions. Murto (2004) studies the problem of exit and shows that, in contrast to an entry game, strategic interaction leads to a war of attrition in exit.

level and the capacity level for an n-firm industry. Comparing $Q_n^*(Y_t)$ with the optimal capacity for a monopoly industry $Q_1^*(Y_t)$ using either Equation (4) or (6) yield the same following relationship

$$Q_n^*(Y_t) = \left[\frac{n\gamma - 1}{n(\gamma - 1)}\right]^{\gamma} Q_1^*(Y_t) \tag{8}$$

Note that $Q_n^*(Y_t)$ increases with n since $\left[\frac{n\gamma-1}{n(\gamma-1)}\right]^{\gamma}$ is an increasing function of n. This relationship has a natural interpretation. Competition accelerates investment and delays disinvestment suggesting that capital accumulation is faster for more competitive industries.

Next we consider the value of the firm in the inaction region. Following standard arguments, $V_n(Y, Q)$ satisfies the following differential equation

$$rV_n(Y,Q) = \mu Y \frac{\partial V_n(Y,Q)}{\partial Y} + \frac{1}{2}\sigma^2 Y^2 \frac{\partial^2 V_n(Y,Q)}{\partial Y^2} + \frac{Q}{n}(YQ^{-\frac{1}{\gamma}} - c) \tag{9}$$

With the optimal investment and disinvest thresholds derived in Proposition 1, the value-matching conditions are given by

$$V_n(\overline{Y_n}, Q) = V_n(\overline{Y_n}, Q + dQ) - \frac{I}{n}dQ \tag{10}$$

$$V_n(\underline{Y_n}, Q) = V_n(\underline{Y_n}, Q - dQ) + \frac{kI}{n}dQ \tag{11}$$

where $\overline{Y_n}$ is the optimal investment threshold for firm i to increase its capacity from q_i to $q_i + dq$ and $\underline{Y_n}$ is the optimal disinvestment threshold for firm i to decrease its capacity from q_i to $q_i - dq$. In the symmetric equilibrium, the total industry capacity increases (decreases) by dQ if each firm invests (disinvests) dq at the cost (benefit) of Idq ($kIdq$). The following proposition solves for $V_n(Y, Q)$.

PROPOSITION 2: *In the n-firm industry where symmetric Cournot competition is consid-*

ered and investment is partially reversible, the firm has the value function given by

$$V_n(Y,Q) = \underbrace{A(Q)Y^{\beta_1}}_{\textit{expansion option}} + \underbrace{B(Q)Y^{\beta_2}}_{\textit{contraction option}} + \underbrace{\frac{Q}{n}\left(\frac{YQ^{-\frac{1}{\gamma}}}{r-\mu} - \frac{c}{r}\right)}_{\textit{assets in place}} \tag{12}$$

where

$$A(Q) = \frac{Q}{n}\frac{\gamma}{\gamma-\beta_1}a(\underline{P_n},\overline{P_n})Q^{-\frac{\beta_1}{\gamma}} \tag{13}$$

$$B(Q) = \frac{Q}{n}\frac{\gamma}{\gamma-\beta_2}b(\underline{P_n},\overline{P_n})Q^{-\frac{\beta_2}{\gamma}} \tag{14}$$

$$a(\underline{P_n},\overline{P_n}) = \frac{1}{\overline{P_n}^{\beta_1}\underline{P_n}^{\beta_2} - \underline{P_n}^{\beta_1}\overline{P_n}^{\beta_2}}\left[\left(I + \frac{c}{r} - \frac{\gamma-1}{\gamma}\frac{\overline{P_n}}{r-\mu}\right)\underline{P_n}^{\beta_2} - \left(kI + \frac{c}{r} - \frac{\gamma-1}{\gamma}\frac{\underline{P_n}}{r-\mu}\right)\overline{P_n}^{\beta_2}\right] \tag{15}$$

$$b(\underline{P_n},\overline{P_n}) = \frac{1}{\underline{P_n}^{\beta_1}\overline{P_n}^{\beta_2} - \overline{P_n}^{\beta_1}\underline{P_n}^{\beta_2}}\left[\left(I + \frac{c}{r} - \frac{\gamma-1}{\gamma}\frac{\overline{P_n}}{r-\mu}\right)\underline{P_n}^{\beta_1} - \left(kI + \frac{c}{r} - \frac{\gamma-1}{\gamma}\frac{\underline{P_n}}{r-\mu}\right)\overline{P_n}^{\beta_1}\right] \tag{16}$$

Proof. See Appendix A.

Equation (12) shows that the firm's value can be decomposed into three components, i.e. the expansion option, the contraction option, and assets in place. As Y goes to zero, the first term representing the expansion options disappears. This is because the firm would be unlikely to exercise options to expand if the market demand declines to an extremely low level. Likewise, the component of contraction option becomes absent as Y tends to infinity. The contraction option is valuable when the firm is likely to disinvest. The last term represents the value of assets in place (i.e. the present value of profit flows for a fixed level of market capacity).

B. Hypothesis Development

To explore the asset pricing implications, we can use the firm's valuation to derive the function for beta. Following Carlson et al. (2004), the systematic risk β is defined as the elasticity of the firm's value with respect to the underlying stochastic demand, i.e. $\beta =$

$\frac{\partial V_n(Y,Q)}{\partial Y}\frac{Y}{V_n}$.

PROPOSITION 3: *The firm's systematic risk is given by*

$$\beta = 1 + \underbrace{(\beta_1 - 1)\frac{A(Q)Y^{\beta_1}}{V_n}}_{\textit{expansion option}} + \underbrace{(\beta_2 - 1)\frac{B(Q)Y^{\beta_2}}{V_n}}_{\textit{contraction option}} + \underbrace{\frac{Q}{n}\frac{c/r}{V_n}}_{\textit{operating leverage}} \tag{17}$$

Proof. See Appendix A.

As seen in Equation (17), β is associated with the relative values of the firm's expansion option, contraction option, and operating leverage. As $\beta_1 > 1$, expansion option increases the firm's risk. Similarly, as $\beta_2 < 1$, the contraction option decreases the firm's risk. β also increases with operating leverage.

In contrast to Aguerrevere (2009), we extend the firm's range of options by introducing a contraction option. Thus, the effect of competition on the value of the contraction option also plays an important role in determining β. Different from the effect on expansion options, competition has a positive impact on the value of contraction options. One firm can benefit from its competitors' disinvestment as the output price increases more if more firms contract at the same time. Hence, more competition implies higher values of contraction options. As for the firm's risk, the contraction option lowers risk as it features an opportunity to exchange risky assets for riskless cash. The effect is even stronger when the contraction option is more valuable (see e.g., Aretz and Pope, 2018). Consequently, as the market demand decreases (i.e. the contraction option constitutes a significant component of the total firm value), firms in more competitive industries are less risky.

On the other hand, when the demand is high, the component of the expansion option becomes dominant. Consistent with prior research, we find a negative competition-return relation as competition erodes the value of the expansion option. For illustration purposes, we use the term *real option effect* to describe the negative effect of competition on β through either expansion or contraction option channel. For a moderate level of demand, neither expansion nor contraction is likely to occur. Then the firm's risk is mainly affected by operating leverage. Competition reduces the firm's profit margin and thus increases operating leverage. Since risk increases with operating leverage, the effect of competition on β is positive. This *operating leverage effect* is first noted by Aguerrevere (2009). However, we further show that when the *operating leverage effect* dominates depends on the level of investment reversibility instead of the market demand.

To delineate these effects, for a given value of k, we plot betas for different levels of competition (i.e. the number of firms n). Then we gradually increase k to see how the effect of competition on β changes as the reversibility of investment increases.

[**Place Figure 1 about here**]

Figure 1 plots firms' systematic risk β against market demand Y in the inaction region. The lower boundary $\underline{Y_n}$ is the disinvestment threshold. Once Y decreases to $\underline{Y_n}$, it becomes optimal for the firm to exercise the contraction option. Similarly, the expansion option is close to exercise when Y is about to hit the upper boundary $\overline{Y_n}$ from below. In Figure 1(a), 1(b), and 1(c), as Y increases, there are three distinct regions corresponding to where the contraction option, operating leverage, or the expansion option dominate respectively.

As investment reversibility k increases, the middle region where *operating leverage effect* is dominant shrinks. In Figure 1(d), this region even disappears when the investment reversibility k is high. That is, the *real option effect* is dominant for higher values of investment reversibility k. A higher level of investment reversibility implies a greater liquidation value and thus provides more incentive for firms to disinvest when the demand level goes down. Upon disinvestment, the firm is no longer committed to the production costs induced by the assets that have been sold off. The operating leverage effect emerges because of the commitment to production costs. The possibility of disinvestment helps the firm suffer less from the risk of reduced demand. Hence, increases in investment reversibility weaken the operating leverage effect which predicts a positive effect of competition on the firm's risk.

Therefore, betas are more negatively correlated with the level of competition for a higher level of investment reversibility.

To sum up, our model predicts a negative interaction effect of product market competition and investment reversibility on the firm's exposure to the systematic risk. The standard asset pricing theory suggests that expected excess return is proportional to the systematic risk loading. Our conclusion can also be applied to the prediction of firms' excess returns.

IV. Empirical Analysis

This section first introduces details on the construction of empirical measures and then presents empirical findings confirming our model's prediction. Lastly, we also show robustness checks for alternative measures.

A. Data

Our sample is constructed with data from multiple sources. We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) database. Our sample only includes NYSE-, Amex- and Nasdaq-listed securities with share codes 10 or 11. Firms in financial (SIC codes between 6000 and 6999) and regulated (SIC codes between 4900 and 4999) industries are removed from our sample.

The accounting data is taken from COMPUSTAT annual files. The asset redeployability index is obtained from Kim and Kung (2016). In order to ensure that information on firm characteristics (including COMPUSTAT-based variables and asset redeployability index) are incorporated into stock returns, we match monthly returns from January to June of year t with firm-level characteristics variables of year $t-2$ and returns from July to December of year t with these variables of year $t-1$. Our final sample covers the period from 1990 to 2016 [6].

[6] The choice of sample period is constrained by the availability of asset redeployability.

Following Hou and Robinson (2006) and Gu (2016), we use three-digit Standard Industrial Classification (SIC) code to classify industries. This is a reasonable choice as an extremely fine industry classification (e.g. four-digit SIC) has the risk of separating firms operating similar businesses and produces statistically unreliable results. On the other hand, an insufficiently fine-grained classification (e.g. two-digit SIC) may mistakenly group firms operating in unrelated business lines together [7].

B. *Empirical Measures*

B.1. Industry concentration

Herfindahl–Hirschman Index

Industry competition is inversely related to industry concentration. We adopt the most widely used measure of industry concentration in the economics and finance literature: Herfindahl–Hirschman Index (HHI) [8], defined as below

$$HHI = \sum_{i=1}^{N} {s_i}^2 \tag{18}$$

where N is the number of firms within the same three-digit SIC industry and s_i is the market share of firm i. From its definition, values of the Herfindahl–Hirschman Index range from 0 to 1 since market share s_i is non-negative. A higher Herfindahl–Hirschman Index corresponds to higher industry concentration and thus lower level of competition level. The most common proxy for s_i is firm i's net sales relative to the total net sales of the industry. Thus, we use sales-based HHI as the main measure for industry concentration throughout this paper. As a robustness check, we also use total assets to compute market share and construct assets-

[7] For example, the industry with SIC code 3740 and the industry with SIC code 3743 have the same description "Railroad Equipment". However, other industries that have SIC codes also starting with 37 are described as aircraft, ship, or motorcycle equipment, which are less relevant.

[8] Numerous empirical research, including Hou and Robinson (2006), Giroud and Mueller (2011), and Gu (2016), uses the *HHI* to measure industry competition. It is also supported by economic theory, such as Tirole (1988).

based HHI. Following Hou and Robinson (2006), we take average values of annual HHI over past three years in case there may be potential data errors or outliers. This is also consistent with our model's assumption that industry concentration is not time-varying.

B.2. Investment reversibility

In order to empirically test our prediction, we need a measure for the reversibility of investment. According to Kim and Kung (2016), asset redeployability describes how widely the asset can be used in other firms or industries. Higher asset redeployability suggests more potential buyers in the second-hand market and thus higher resale price of the asset. This is consistent with the definition of k.

Asset Redeployability Index

The key variable to measure the firm's investment reversibility is asset redeployability index constructed by Kim and Kung (2016). Here we briefly outline the construction procedure.

The procedure starts with the construction of asset-level redeployability scores. As in Kim and Kung (2016), the score is computed using 1997 Bureau of Economic Analysis (BEA) capital flow table. The BEA capital flow table contains the usage of 180 asset categories by 123 industries. The asset-level score is computed as the sum of weights of industries that use the asset among the 123 industries. There are two choices of weights: (i) equal weight (one over the total number of BEA industries); (ii) value weight (the sum of market capitalization of all public firms in an industry over the sum of market capitalization across all public firms). We adopt the second method in our main specification. The formula for computing the asset-level score is:

$$Redeployability_{a,t} = \sum_{j=1}^{123} I_{a,j} * \frac{MV_{j,t}}{\sum_{j=1}^{123} MV_{j,t}} \tag{19}$$

where $Redeployability_{a,t}$ is the redeployability score of asset a. $I_{a,t}$ is an indicator equal to 1 if asset a is used by BEA industry j and 0 otherwise. $MV_{j,t}$ is the market value of Compustat firms in BEA industry j in year t.

In the second step, an industry-level asset redeployability score is constructed by taking the weighted average of the asset-level redeployability scores across all 180 assets. The weight is the fraction of industry expenditure on a specific asset. Therefore, if an asset is not used by an industry in the production process, then the weight assigned to that asset is zero. The formula for computing industry-level redeployability is:

$$Redeployability_{j,t} = \sum_{a=1}^{180} w_{j,a} * Redeployability_{a,t} \tag{20}$$

$$w_{j,a} = \frac{E_{j,a}}{\sum_{a=1}^{180} E_{j,a}} \tag{21}$$

where $Redeployability_{j,t}$ is the asset redeployability index of industry j in year t and $Redeployability_{a,t}$ is the redeployability score of asset a in year t. $w_{j,a}$ is the weight assigned to asset a in computing the index of industry j. $E_{j,a}$ is industry j's expenditure on asset a.

The last step is to compute firm-level asset redeployability index as the weighted average of industry-level redeployability indices across business segments in which the firm operates. The weight is computed as:

$$Redeployability_{i,t} = \sum_{j=1}^{n_{i,t}} w_{i,j,t} * Redeployability_{j,t} \tag{22}$$

$$w_{i,j,t} = \frac{s_{i,j,t}}{\sum_{j=1}^{n_{i,t}} s_{i,j,t}} \tag{23}$$

where $Redeployability_{i,t}$ is the asset redeployability index of firm i in year t and $Redeployability_{j,t}$ is the asset redeployability index of industry j in year t. $n_{i,t}$ is the number of industry segments that firm i is affiliated with in year t [9]. $w_{i,j,t}$ is the weight assigned to industry segment j in computing the index of firm i. $s_{i,j,t}$ is firm i' sales revenue from industry segment j in

[9] This information can be extracted from Compustat Segment Files.

year t [10].

Generally, asset redeployability index measures how widely assets owned by the firm on average can be used in other industries. If assets can be reused in many other industries, then search costs for potential buyers would be lower and the resale prices would be correspondingly higher. Recall that investment reversibility can be described by the liquidation values of assets relative to their initial purchase prices. Higher asset redeployability indicates higher investment reversibility. Kim and Kung (2016) also link asset redeployability to investment reversibility and further test the implications of real options theory. Given a real-option framework has been applied in this paper, we regard asset redeployability index as a suitable measure for investment reversibility.

C. Empirical Results

The central prediction of our model is that the competition-return relation depends crucially on the firm's asset redeployability. If the firm's asset redeployability is high, then the real option effect would dominate the operating leverage effect and competition is more likely to decrease the firm's systematic risk. On the other hand, if the firm's asset redeployability is low, then the operating leverage effect prevails over the real option effect and competition is more likely to increase the firms' systematic risk. Therefore, we first investigate the negative interaction effect between competition and asset redeployability.

C.1. Summary Statistics

Table I lists the top five and bottom five industries sorted by sales-based HHI for least and most redeployable quintiles respectively. Within the lowest redeployablility quintile, the most competitive industries include crude petroleum and natural gas, coal mining, and air transportation. Meanwhile, the least competitive industries within the lowest redeploy-

[10] In Kim and Kung (2016), if Compustat Segment Files do not contain the date for a firm in a year, they impute the firm-level asset redeployability index from industry-level index based on the firm's industry classification in Compustat.

ablility quintile include rubber product, fibre and silk. On the opposite side, the most competitive industries within the highest redeployablility quintile include equipment rental and leasing, machinery. The least competitive industries within the highest redeployablility quintile include rubber footwear, paper product, and non-residential building contractors.

[Place Table I about here]

Table II reports summary statistics of industry concentration measures and investment reversibility measures used in our paper [11]. The mean of *HHI(sales)* in our sample is 0.189 and the standard deviation of $HHI(sales)$ is 0.155. $HHI(assets)$ has a similar magnitude to $HHI(sales)$. The mean of the concentration ratio ($CR5$) is 0.689. The firm-level *Redeployability* measure constructed by Kim and Kung (2016) is the main measure of investment reversibility in our empirical analysis. Theoretically, its value should range from 0 to 1. Here in our sample, *Redeployability* has a mean around 0.4. As an alternative measure of investment reversibility, $Inflexibility$ constructed as in Gu et al. (2017) has a mean of 1.794.

[Place Table II about here]

In Table III, we summarise the average characteristics of sorted portfolios. The first two rows present the sorting variables $HHI(sales)$ and *Redeployability*. As expected, $HHI(sales)$ increases as the intensity of competition goes down and this pattern is similar for both low and high redeployability quintiles. *Redeployability* is around 0.25 (0.54) for the low (high) redeployability quintile. log($Size$) exhibits a decreasing(an increasing) trend when asset redeployability is low (high), which is consistent with our model's prediction about stock returns. This is because market values can be better preserved if returns are higher. Average book-to-market ratios are generally higher in less competitive industries. Similar to the findings of MacKay and Phillips (2005) and predictions by Brander and Lewis

[11] Table II also shows summary statistics of alternative measures of industry concentration (i.e. $CR5$) and investment reversibility (i.e. $Inflexibility$) which have detailed definitions in Section C.3.

(1986) and Maksimovic (1988), financial leverage is higher in more concentrated industries . log($Assets$) and log($Sales$) are increasing as competition decreases since firms in less competitive industries might have a larger scale. The average return on assets is roughly flat across different levels of competition and redeployability.

[Place Table III about here]

C.2. Interaction effect between competition and redeployability

Portfolio sorts

Table IV reports equal-weighted and value-weighted average monthly excess returns and abnormal returns for portfolios sorted based on HHI and asset redeployability independently. In Panel A, we show the equal-weighted portfolio returns. In Panel B, we calculate value-weighted portfolio returns instead.

[Place Table IV about here]

Specifically, in month t, stocks are sorted into terciles based on their HHI. Then, independently, we assign these stocks into quintile portfolios based on asset redeployability. This procedure results in fifteen portfolios with different levels of competition and asset redeployability. Cross-sectional average monthly returns in month $t+1$ are calculated within each portfolio. The portfolios are rebalanced every month.

In Table IV, we display the results for firms with low redeployablity (i.e. lowest quintile of asset redeployability) and high redeployablity (i.e. highest quintile of asset redeployability), respectively. As shown in both Panel A and B, portfolio returns increase monotonically with industry competition for the low redeployability quintile, while returns decrease with industry competition for the high redeployability quintile. The results hold for both equal-weighted and value-weighted returns. To construct the interaction portfolio, we first form high-minus-low competition portfolios based on industry competition (HHI) for high and low redeployability respectively (see Column (4) and (9)). Then we long the competition high-minus-low portfolio with high redeployability and short the competition high-minus-low portfolio with low redeployability (see Column (11)). The equal-weighted (value-weighted) interaction portfolio yields a monthly return of 0.58% (0.59%). It is also statistically significant, confirming our double sorting pattern.

To account for other risk factors, we also use several well-known factor models to adjust returns. The classic Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model and the Stambaugh and Yuan (2016) four-factor model are considered [12]. We regress the monthly excess returns of portfolios on the factors and the abnormal returns are the estimated constant in the regressions. In addition, we also compute characteristics-adjusted returns according to the methodology developed by Daniel, Grinblatt, Titman, and Wermers (1997), who propose a procedure to adjust individual stock returns for size, book-to-market, and momentum. They employ a sequential sorting methodology. In each month, all stocks are first sorted into size quintiles. Within each size quintile, the stocks are further sorted into quintiles based on their book-to-market ratio [13]. Within each of the 25 portfolios constructed from previous sorting step, stocks are sorted into quintiles again based on their past 12-month return, excluding the most recent month. The characteristics-adjusted returns are computed by subtracting corresponding benchmark returns from individual stock returns.

For adjusted returns, we still see a significant interaction effect between competition and asset redeployablity on returns. Interestingly, adjusted returns are typically lower than excess returns. For instance, the excess return for the quintile of the most (least) competitive industries within low redeployability tercile is 1.02% (0.62%) whereas Fama and French (2015) five-factor model adjusted return is 0.30% (-0.35%). This is consistent with Hou and

[12] Fama and French (1993) three-factor model includes market, size, and value factors. Carhart (1997) adds momentum to Fama and French (1993)'s model. Fama and French (2015) add profitability and investment patterns to Fama and French (1993) model. Stambaugh and Yuan (2016) include two mispricing factors apart from market and size factors in their model.

[13] Following Daniel et al. (1997), we use industry-adjusted book-to-market ratio by subtracting the long-term industry average book-to-market ratio from each individual firm's ratio.

Robinson (2006)'s results. However, the spreads of the interaction portfolios are of a similar magnitude even if we adjust for risk factors, ranging from 0.51% (0.52%) to 0.68% (0.71%) for equal-weighted (value-weighted) portfolios. These patterns verify our theoretical conclusion: the effect of competition on stock returns becomes more negative as investment reversibility increases. The effect cannot be explained by traditional risk factors or mispricing. Therefore, the interaction between competition and redeployability is important in understanding the cross-section of stock returns.

Panel regressions

To control for more factors that could also affect expected returns, we run panel regressions of excess returns on the interaction between the competition measure and the asset redeployability index. Specifically, we estimate the following model.

$$Y_{i,t} = \alpha + \beta_1 HHI_{i,t-1} + \beta_2 AR_{i,t-1} + \beta_3 HHI_{i,t-1} * AR_{i,t-1} + \beta_4 X_{i,t-1} + v_t + \epsilon_{i,t} \tag{24}$$

where $Y_{i,t}$ is monthly excess return for firm i at time t, $HHI_{i,t-1}$ is firm i's lagged Herfindahl–Hirschman Index, $AR_{i,t-1}$ is firm i's lagged asset redeployability index, and $X_{i,t-1}$ represents a set of control variables. v_t represents the time fixed effect.

Here we include control variables standard in the asset pricing literature, namely, size, book-to-market ratio, reversal, momentum and leverage. $\log(size)$ is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of the book value of equity to the market value of equity. *lag(1-month return)* is the stock return over previous month. It is included to control for the reversal effect. *lag(12-month return)* is the stock return over the 11 months preceding the previous month. It is included to control for the momentum effect. *Leverage* is the total liabilities over the sum of the market value of equity and total liabilities. We include the time fixed effect to examine the cross-sectional effect. Standard errors are double clustered by firm and time to suppress both cross-sectional correlation and time-series correlation in error term (see, e.g. Petersen, 2009; Cochrane, 2009).

The hypothesis derived from our model asserts a significant and positive coefficient on the interaction term (i.e. positive β_3) since HHI, as an industry concentration measure, is inversely related to competition.

[Place Table V]

Table V reports the results for panel regressions. In Column (1), we perform a univariate analysis by regressing excess return on the HHI and find an insignificant coefficient. This implies that the competition-return relation is mixed [14], which calls for our further understanding. Asset redeployability (*Redpb*) alone also exhibits an insignificant effect as shown in Column (2). Column (3) reports the results for the baseline regression with an interaction term between HHI and *Redpb*. The coefficient on the interaction term is significantly positive supporting our results from the double sorts. After controlling for other asset pricing factors as in Column (4), the coefficient on the interaction term remains significantly positive and similar in magnitude.

In Column (4), we include control variables. The coefficient on the interaction term remains statistically positive. The magnitude is even larger after adding control variables. The return spread between a monopolist [15] and a firm in the most competitive industry is 4.718% higher for firms with highest redeployability than it is for those with lowest redeployability. All control variables, such as size, book-to-market, have the same sign as in the literature.

Columns (5) and (6) use alternative asset redeployability measures constructed in different ways but the same vein. The difference between asset redeployability index used in specification (5), (6) and baseline specification (3) lies in the construction of asset-level redeployability score. As explained in section IV.B.2, asset-level redeployability score employed by specification (3) uses industry value as weights in computing how the asset is used among the 123 BEA industry. The asset-level redeployability score employed by specification (6)

[14] Even from the existing literature, we cannot draw a clear conclusion about the effect of competition on stock returns. Hou and Robinson (2006) find a positive relation whereas Bustamante and Donangelo (2017) find it to be negative.

[15] The highest value of HHI in our sample period is 1 suggesting that there exist monopoly industries when using three-digit SIC to classify industries.

uses equal weights for each industry in determining how the asset is used among the 123 BEA industry. The asset-level redeployability score employed by specification (5) incorporates the correlation of outputs among firms within a given industry. The intuition is that, when the output comovement within an industry is high, a firm that intends to resell its assets is more likely to find that other firms in the industry also perform poorly. This would decrease the demand for the asset [16] and increase the supply of the asset. As a result, it is more difficult for firms in such industries to resell their assets, especially during economic downturns. This leads to lower asset redeployability in such industries [17].

Using panel regressions, we find that the coefficient of interest, β_3, is positive and statistically significant in all specifications. These findings are highly consistent with our model prediction that the effect of competition (concentration, in our estimation) on stock return is more negative (positive) when the firm's asset redeployability is higher.

Fama-Macbeth regressions

As a standard method in asset pricing, Fama-Macbeth regressions are conducted to further confirm the interaction effect of our interest. For all the Fama-Macbeth regressions throughout the paper, the estimates of the coefficients are the time-series average of cross-sectional regression loadings. The t-statistics based on Newey-West standard errors are reported in square brackets below.

Table VI reports the firm-level Fama-Macbeth regressions and we use the same set of control variables as in the panel regressions (Table 5). Column (1) shows that competition alone has no significant effect on stock returns although the sign of the coefficient is negative suggesting a positive competition-return relation. Column (2) investigates the effect of asset redeployability on stock returns. The effect is also ambiguous as the coefficient is insignificant.

[Place Table VI about here]

[16] Peer firms in the same industry are considered as high valuation buyers.

[17] Kim and Kung (2016) multiply each industry's weight by an adjustment term to construct asset-level scores. The adjustment term is inversely related to the within-industry output correlation.

The last four columns incorporate the interaction term. Different asset redeployability measures are used in Columns (5) and (6). Overall they show very strong and positive interaction effect between HHI and asset redeployability. This is consistent with our previous results.

Industry-level regressions

Table VII repeats the empirical analysis in Table VI but uses all the variables at industry level. As an industrial concentration measure, HHI is an industry-level variable that remains the same as in Table VI. We take average values of stock returns, asset redeployability and other control variables by SIC three-digit industries. Our main results are also robust after controlling for size, book-to-market, past stock returns and financial leverage. The interaction term between HHI and *Redpb* is still positive and significant at 5% level. Comparing with firm-level regression results, size and past 1-month return have an inverse effect on stock returns. The positive sign of size implies that industries with greater average market value earn higher returns. The insignificantly positive coefficient on past 1-month return suggests that reversal effect is not evident at industry level. Together with the significantly positive effect of past 1-year return, the trend of average industry returns is more likely to persist.

[Place Table VII about here]

Unlevered returns

One potential concern about using the asset redeployability measure is that it might be positively correlated with corporate financial leverage and the results are thus driven not by redeployability but by leverage. Intuitively, firms with more redeployable assets are more likely to have a higher liquidation value in the event of bankruptcy. Implicitly, debt holders have better protection so that they are willing to accept an even lower interest rate. This makes debt more accessible and cheap to these firms. Therefore, more redeployable firms should have higher leverage.

Although leverage has been controlled for in the previous regressions, we further address this concern by using unlevered returns as a robustness check [18]. Unlevered returns are stock returns without the impact of firms' financial leverage. Following the standard procedure, we delever stock returns by dividing excess returns by the sum of one plus the leverage ratio, i.e.

$$\text{Unlevered return} = \frac{\text{excess return}}{1 + \text{liabilities}/(\text{liabilities} + \text{market value})} \tag{25}$$

Table VIII reports the results of regressing unlevered returns on the same set of variables except for leverage [19]. In the univariate regressions (i.e. Columns (1) and (2)), HHI or asset redeployability have an insignificantly negative effect on unlevered returns. This is similar to the effects on excess returns. Columns (3) to (6) show that the coefficient on the interaction term is still positive and significant at 1% level, although the magnitude slightly decreases compared to that for excess returns. Interestingly, after controlling for the interaction effect between HHI and redeployability, we see a significantly negative effect of redeployability on unlevered returns. Overall, we find supportive evidence on the positive interaction effect even when accounting for the impact of asset redeployability on financial leverage.

[Place Table VIII about here]

C.3. Robustness checks

Alternative measures of industry concentration

Next we explore the robustness of our main results to an alternative measure of industry concentration. We perform the Fama-Macbeth regression analysis again for asset-based HHI and 5-firm concentration ratio (CR5).

Asset-based HHI uses total assets to calculate market share instead of using net sales.

[18] Doshi, Jacobs, Kumar, and Rabinovitch (2019) shows that leverage induces heteroskedasticity in returns and unlevering returns removes this pattern.

[19] Here the control variable *leverage* is excluded since we already removed the leverage effect by unlevering returns.

The concentration ratio is defined as the ratio of the sales of the top n firms in an industry to total industry sales. This ratio, by definition, ranges from 0 to 1. A low concentration ratio for an industry indicates that there are many firms with similar size, while a high concentration ratio suggests a few large firms dominate the industry. Thus, similar to HHI, a higher value of the concentration ratio implies lower industry competition. Here we use the 5-firm ratio, i.e. the ratio of the sales of the top five firms in an industry to total industry sales. Similar to the construction of sales-based HHI, we average the values of both measures over the past 3 years.

We regress the excess stock returns on asset-based HHI or CR5, asset redeployability, the interaction term and controls. In Table IX, Panel A (i.e. columns (1) to (5)) presents the results for asset-based HHI. Panel B reports the results for CR5. As shown in the table, the results mirror our findings in the previous analysis. The impact of industry concentration on stock returns is negative but insignificant (see Columns (1) and (6)). The effect of industry concentration becomes significant after adding in the interaction term. In both panels, we find the coefficients on the interaction term are both statistically and economically significant and positive. Hence, we show that the positive interaction effect between industry concentration and asset redeployability is robust to alternative concentration measures.

[**Place Table VIII about here**]

Alternative measure of investment reversibility

In this section, we use firm-level inflexibility measure as an alternative measure of investment reversibility. Inflexibility measure is an inverse proxy for investment reversibility. It is first used by Gu et al. (2017), who develop this measure based on their theory. They utilize the fact that the firm's flexibility to adjust its capacity is correlated with the width of the firm's inaction region. A firm with less flexible operations would wait longer before adjusting its scale to adapt to changes in profitability.

The firm-level inflexibility is defined as the firm's historical range of operating costs scaled by sales over the standard deviation of the log growth rate of sales scaled by total assets, i.e.

$$INFLEX_{i,t} = \frac{\max_{i,0,t}\left(\frac{OPC}{Sales}\right) - \min_{i,0,t}\left(\frac{OPC}{Sales}\right)}{\mathrm{std}_{i,0,t}\left(\Delta\log\left(\frac{Sales}{Assets}\right)\right)} \tag{26}$$

where $\max_{i,0,t}\left(\frac{OPC}{Sales}\right)$ is the maximum value of firm's operating cost (Compustat item XSGA + COGS) over sales (Compustat item SALE) from year 0 (i.e. the initial year that the firm appears in Compustat) until year t. Similarly, $\min_{i,0,t}\left(\frac{OPC}{Sales}\right)$ is the minimum value of the firm's scaled operating cost over the period from year 0 to year t. Thus, $\max_{i,0,t}\left(\frac{OPC}{Sales}\right) - \min_{i,0,t}\left(\frac{OPC}{Sales}\right)$ is the historical range of operating cost over sales, which is equivalent to the range of profit over sales. It is a proxy for the width of the inaction region of the state variable in the theoretical model of Gu et al. (2017). Intuitively, the firm's optimal strategy is to scale up capacity when productivity or profitability increases, while it is optimal to scale down capacity when profitability decreases. Holding uncertainty constant, if the firm has enough flexibility, i.e. the adjustment cost is low, we should observe a narrow inaction region as the firm would quickly respond to changes in profitability.

The denominator on the right hand side of equation (36), $\mathrm{std}_{i,0,t}\left(\Delta\log\left(\frac{Sales}{Assets}\right)\right)$, is the standard deviation of the growth rate of sales scaled by total assets (Compustat item AT) over the period from year 0 to year t. Based on real options theory, when uncertainty is higher, the value of waiting is higher. Thus, it is optimal for the firm not to make adjustments quickly. In this case, the inaction region could be wide even if the firm is fully flexible. We thus use the standard deviation of the sales growth rate to adjust for the effect of uncertainty on the width of the inaction region. The Inflexibility measure reflects firms' investment irreversibility when controlling for uncertainty. Our model predicts that the impact of industry competition on stock returns becomes more negative when investment is more reversible. In other words, the competition-return relation should be more positive for firms with high inflexibility (i.e. more irreversible investment).

We use the sales-based HHI to measure industry concentration. Since HHI is negatively correlated with industry competition, we should expect a negative interaction effect between HHI and inflexibility. Table X reports the results for Fama-Macbeth regressions using inflexibility measure instead of asset redeployability. In Column (1), we re-examine the unconditional effect of HHI on stock returns and the coefficient is insignificantly negative. Column (2) shows that inflexibility has a significantly negative impact on returns but the coefficient on inflexibility becomes insignificant once the interaction term is included. Columns (3)-(5) report the results with the interaction term. With or without control variables, the coefficient on the interaction term is consistently significant and negative. These findings again support our hypothesis. As an alternative measure of investment reversibility, inflexibility indeed has an explanatory power for the competition-return relation, which is consistent with our theoretical prediction.

[Place Table X about here]

V. Conclusion

The relationship between competition and stock returns is a subject of continued attention in the literature. Given the mixed evidence on this relationship in the existing literature, we seek an alternative perspective to analyse this important question.

Recently, investment-based asset pricing has featured the reversibility of investment by showing that a firm's options to expand and contract jointly determine the dynamics of its systematic risk. Motivated by this growing strand of literature, we relax the assumption that investment is irreversible. We develop a more comprehensive Cournot-competition framework that incorporates contraction options in addition to assets in place and expansion options. In contrast to Aguerrevere (2009), we find that the effect of competition on return does not necessarily depend on the level of market demand. Instead, the competition-return relation is more negative as investment becomes more reversible.

Specifically, we have shown that product market competition has distinct impacts on the risk associated with assets in place and options held by the firm. Regardless of the firm's options to adjust capacity, competition increases risk as operating leverage is higher for firms in more competitive industries. This is called the *operating leverage effect*. On the other hand, competition can also reduce risk through the option channel. A firm in more competitive industries is less sensitive to the changes in the market demand as the reactions of other competitors would attenuate its potential gains or losses. This negative effect of competition is called the *real option effect*, which dominates the positive *operating leverage effect* when investment is highly reversible. This is because investment reversibility enables the firm to escape from the risk arising from assets in place.

We also find empirical evidence consistent with our theoretical prediction that there is a negative interaction effect between competition and investment reversibility on stock returns. Our results are robust to different measures of competition and investment reversibility. Overall, this paper contributes to the investment-based asset pricing literature by revealing the important role of investment reversibility in affecting the competition-return relation.

REFERENCES

Aguerrevere, Felipe L, 2009, Real options, product market competition, and asset returns, *The Journal of Finance* 64, 957–983.

Aretz, Kevin, and Peter F Pope, 2018, Real options models of the firm, capacity overhang, and the cross section of stock returns, *The Journal of Finance* 73, 1363–1415.

Back, Kerry, and Dirk Paulsen, 2009, Open-loop equilibria and perfect competition in option exercise games, *The Review of Financial Studies* 22, 4531–4552.

Balasubramanian, Natarajan, and Jagadeesh Sivadasan, 2009, Capital resalability, productivity dispersion, and market structure, *The Review of Economics and Statistics* 91, 547–557.

Brander, James A, and Tracy R Lewis, 1986, Oligopoly and financial structure: The limited liability effect, *The American Economic Review* 956–970.

Bustamante, M Cecilia, 2014, Strategic investment and industry risk dynamics, *The Review of Financial Studies* 28, 297–341.

Bustamante, M Cecilia, and Andres Donangelo, 2017, Product market competition and industry returns, *The Review of Financial Studies* 30, 4216–4266.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of finance* 52, 57–82.

Carlson, Murray, Engelbert J Dockner, Adlai Fisher, and Ron Giammarino, 2014, Leaders, followers, and risk dynamics in industry equilibrium, *Journal of Financial and Quantitative Analysis* 49, 321–349.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *The Journal of Finance* 59, 2577–2603.

Cochrane, John H, 2009, *Asset pricing: Revised edition* (Princeton university press).

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *The Journal of finance* 52, 1035–1058.

Dixit, Avinash K, and Robert S Pindyck, 1994, *Investment under uncertainty* (Princeton university press).

Doshi, Hitesh, Kris Jacobs, Praveen Kumar, and Ramon Rabinovitch, 2019, Leverage and the cross-section of equity returns, *The Journal of Finance* 74, 1431–1471.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of financial economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of financial economics* 116, 1–22.

Fudenberg, Drew, and Jean Tirole, 1991, Game theory, 1991, *Cambridge, Massachusetts* 393, 80.

Giroud, Xavier, and Holger M Mueller, 2011, Corporate governance, product market competition, and equity prices, *The Journal of Finance* 66, 563–600.

Grenadier, Steven R, 2002, Option exercise games: An application to the equilibrium investment strategies of firms, *The Review of Financial Studies* 15, 691–721.

Gu, Lifeng, 2016, Product market competition, r&d investment, and stock returns, *Journal of Financial Economics* 119, 441–455.

Gu, Lifeng, Dirk Hackbarth, and Tim Johnson, 2017, Inflexibility and stock returns, *The Review of Financial Studies* 31, 278–321.

Hackbarth, Dirk, and Timothy Johnson, 2015, Real options and risk dynamics, *The Review of Economic Studies* 82, 1449–1482.

Hou, Kewei, and David T Robinson, 2006, Industry concentration and average stock returns, *The Journal of Finance* 61, 1927–1956.

Kim, Hyunseob, and Howard Kung, 2016, The asset redeployability channel: How uncertainty affects corporate investment, *The Review of Financial Studies* 30, 245–280.

Leahy, John V, 1993, Investment in competitive equilibrium: The optimality of myopic behavior, *The Quarterly Journal of Economics* 1105–1133.

MacKay, Peter, and Gordon M Phillips, 2005, How does industry affect firm financial structure?, *The Review of Financial Studies* 18, 1433–1466.

Maksimovic, Vojislav, 1988, Capital structure in repeated oligopolies, *The RAND Journal of Economics* 389–407.

McDonald, Robert, and Daniel Siegel, 1986, The value of waiting to invest, *The quarterly journal of economics* 101, 707–727.

Morellec, Erwan, and Alexei Zhdanov, 2018, Product market competition and option prices, *The Review of Financial Studies, forthcoming* .

Murto, Pauli, 2004, Exit in duopoly under uncertainty, *RAND Journal of Economics* 111–127.

Petersen, Mitchell A, 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435–480.

Stambaugh, Robert F, and Yu Yuan, 2016, Mispricing factors, *The Review of Financial Studies* 30, 1270–1315.

Tirole, Jean, 1988, *The theory of industrial organization* (MIT press).

Appendix A. Technical proofs

Proof of Proposition 1

Let $M(Y, q_i, Q_{-i})$ denote the value of the myopic firm. Using standard dynamic programming method, $M(Y, q_i, Q_{-i})$ satisfies

$$rM = \mu Y \frac{\partial M}{\partial Y} + \frac{1}{2}\sigma^2 Y^2 \frac{\partial^2 M}{\partial Y^2} + \left[Y(q_i + Q_{-i})^{-\frac{1}{\gamma}} - c\right] q_i \tag{A1}$$

subject to the following value-matching conditions

$$M(\overline{Y}(q_i, Q_{-i}), q_{-i}, Q_{-i}) = M(\overline{Y}(q_i, Q_{-i}), q_i + dq_i, Q_{-i}) - Idq_i$$

$$M(\underline{Y}(q_i, Q_{-i}), q_{-i}, Q_{-i}) = M(\underline{Y}(q_i, Q_{-i}), q_i - dq_i, Q_{-i}) + kIdq_i$$

where $\overline{Y}(q_i, Q_{-i})$ and $\underline{Y}(q_i, Q_{-i})$ are the optimal investment and disinvestment triggers respectively. Rearranging and taking the limit to give

$$\frac{\partial M}{\partial q_i}\Big|_{Y=\overline{Y}(q_i,Q_{-i})} = \lim_{dq_i \to 0} \frac{M(\overline{Y}(q_i, Q_{-i}), q_i + dq_i, Q_{-i}) - M(\overline{Y}(q_i, Q_{-i}), q_{-i}, Q_{-i})}{dq_i} = I \tag{A2}$$

$$\frac{\partial M}{\partial q_i}\Big|_{Y=\underline{Y}(q_i,Q_{-i})} = \lim_{dq_i \to 0} \frac{M(\underline{Y}(q_i, Q_{-i}), q_i, Q_{-i}) - M(\underline{Y}(q_i, Q_{-i}), q_{-i} - dq_i, Q_{-i})}{dq_i} = kI \tag{A3}$$

The smooth-pasting conditions are

$$\frac{\partial^2 M}{\partial q_i \partial Y}\Big|_{Y=\overline{Y}(q_i,Q_{-i})} = 0 \tag{A4}$$

$$\frac{\partial^2 M}{\partial q_i \partial Y}\Big|_{Y=\underline{Y}(q_i,Q_{-i})} = 0 \tag{A5}$$

Let $m(Y, q_i, Q_{-i})$ denote the marginal value of the myopic firm, i.e. $m(Y, q_i, Q_{-i}) = \frac{\partial M(Y, q_i, Q_{-i})}{\partial q_i}$. In a symmetric Cournot equilibrium, $q_i = \frac{Q}{n}$ and $Q_{-i} = \frac{(n-1)Q}{n}$. Substituting the equilibrium results into above equations, we have $m(Y, \frac{Q}{n}, \frac{(n-1)Q}{n}) = m(Y,Q)$ given by

$$rm(Y,Q) = \mu Y \frac{\partial m}{\partial Y} + \frac{1}{2}\sigma^2 Y^2 \frac{\partial^2 m}{\partial Y^2} + \frac{n\gamma - 1}{n\gamma} Y Q^{-\frac{1}{\gamma}} - c \tag{A6}$$

s.t.

$$m(\overline{Y}(Q), Q) = I \tag{A7}$$

$$m(\underline{Y}(Q), Q) = kI \tag{A8}$$

$$\left.\frac{\partial m}{\partial Y}\right|_{Y=\overline{Y}(Q)} = 0 \tag{A9}$$

$$\left.\frac{\partial m}{\partial Y}\right|_{Y=\underline{Y}(Q)} = 0 \tag{A10}$$

The solution of $m(Y,Q)$ has the form

$$m(Y,Q) = a(Q)Y^{\beta_1} + b(Q)Y^{\beta_2} + \frac{n\gamma - 1}{n\gamma}\frac{YQ^{-\frac{1}{\gamma}}}{r-\mu} - \frac{c}{r} \tag{A11}$$

where β_1 and β_2 are the positive and negative roots of the quadratic equation $\frac{\sigma^2}{2}\xi(\xi-1) + \mu\xi - r = 0$. To simplify calculation, we set $\underline{Y}(Q) = x\overline{Y}(Q)$ with $0 < x < 1$. Substituting this equation into (A.7) - (A.10) and solving those equations simultaneously yield the triggers

$$\overline{Y_n}(Q) = \frac{\beta_1}{\beta_1 - 1}\frac{n\gamma}{n\gamma - 1}(r-\mu)\left(I + \frac{c}{r}\right)\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}Q^{\frac{1}{\gamma}} \tag{A12}$$

$$\underline{Y_n}(Q) = \frac{\beta_2}{\beta_2 - 1}\frac{n\gamma}{n\gamma - 1}(r-\mu)\left(kI + \frac{c}{r}\right)\frac{x - \phi^{-1}x^{\beta_1+1}}{x - x^{\beta_1}}Q^{\frac{1}{\gamma}} \tag{A13}$$

where $\phi = (kI + \frac{c}{r})/(I + \frac{c}{r})$ and x solves $\frac{\beta_2}{\beta_2 - 1}\frac{\phi - x^{\beta_1}}{x - x^{\beta_1}} = \frac{\beta_1}{\beta_1 - 1}\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$. The subscript n indicates the triggers are for the firm in an n-firm industry. Notably x is independent of Q and n. Since $P = YQ^{-\frac{1}{\gamma}}$, the price thresholds are

$$\overline{P_n}(Q) = \frac{\beta_1}{\beta_1 - 1}\frac{n\gamma}{n\gamma - 1}(r-\mu)\left(I + \frac{c}{r}\right)\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}} \tag{A14}$$

$$\underline{P_n}(Q) = \frac{\beta_2}{\beta_2 - 1} \frac{n\gamma}{n\gamma - 1}(r - \mu) \left(kI + \frac{c}{r}\right) \frac{x - \phi^{-1} x^{\beta_1 + 1}}{x - x^{\beta_1}} \tag{A15}$$

■

Proof of Corollary 1

Consider $\frac{\beta_2}{\beta_2 - 1} \frac{\phi - x^{\beta_1}}{x - x^{\beta_1}} = \frac{\beta_1}{\beta_1 - 1} \frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$ where $\beta_2 < 0$ and $\beta_1 > 1$. We have

$$0 < \frac{\beta_2}{\beta_2 - 1} < 1 < \frac{\beta_1}{\beta_1 - 1} \tag{A16}$$

and thus

$$\frac{\phi - x^{\beta_1}}{x - x^{\beta_1}} > \frac{\phi - x^{\beta_2}}{x - x^{\beta_2}} \tag{A17}$$

Since $0 < x < 1$, we have $0 < x^{\beta_1} < x$ and $x^{\beta_2} > 1 > x$. Inequation (A.17) can be rewritten as

$$(x - x^{\beta_2})(\phi - x^{\beta_1}) < (x - x^{\beta_1})(\phi - x^{\beta_2}) \tag{A18}$$

Equivalently,

$$(x^{\beta_1} - x^{\beta_2})\phi < (x^{\beta_1} - x^{\beta_2})x \tag{A19}$$

Given that $x^{\beta_1} < x^{\beta_2}$, thus $\phi > x$. Subtract both sides by x^{β_2} and divided by $x - x^{\beta_2}$ to give

$$0 < \frac{\phi - x^{\beta_2}}{x - x^{\beta_2}} < \frac{x - x^{\beta_2}}{x - x^{\beta_2}} = 1 \tag{A20}$$

When comparing our investment threshold, Equation (4), with Equation (22) in Grenadier (2002) or Equation (A1) in Morellec and Zhdanov (2018), we notice that $\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$ is the only extra term[20]. Since it has been proved that $\frac{\phi - x^{\beta_2}}{x - x^{\beta_2}}$ is a number between 0 and 1, the investment threshold in the reversible investment case is strictly lower than the threshold of irreversible case. ■

[20] Grenadier (2002) does not consider variable cost c and thus there is no $\frac{c}{r}$ in his formula.

Proof of Proposition 2

In the inaction region, the firm's value $V_n(Y,Q)$ satisfies the differential equation given in Equation (4), which has the general solution

$$V_n(Y,Q) = A(Q)Y^{\beta_1} + B(Q)Y^{\beta_2} + \frac{Q}{n}\left(\frac{YQ^{-\frac{1}{\gamma}}}{r-\mu} - \frac{c}{r}\right) \tag{A21}$$

where $\beta_1 > 1$ and $\beta_2 < 0$ are the two roots of the quadratic equation $\frac{\sigma^2}{2}\xi(\xi-1)+\mu\xi-r=0$. The first and second terms coexist for that the firm holds both investment and disinvestment options.

Considering the value-matching conditions given by Equation (5) and (6), we can rearrange and take the limit to give

$$\frac{\partial V_n(\overline{Y_n}(Q),Q)}{\partial Q} = \lim_{dQ\to 0}\frac{V_n(\overline{Y_n}(Q),Q+dQ) - V_n(\overline{Y_n}(Q),Q)}{dQ} = \frac{I}{n} \tag{A22}$$

$$\frac{\partial V_n(\underline{Y_n}(Q),Q)}{\partial Q} = \lim_{dQ\to 0}\frac{V_n(\underline{Y_n}(Q),Q) - V_n(\underline{Y_n}(Q),Q-dQ)}{dQ} = \frac{kI}{n} \tag{A23}$$

Plugging Equation (A.21) into Equations (A.22) and (A.23) respectively yields

$$A'(Q)\overline{Y_n}(Q)^{\beta_1} + B'(Q)\overline{Y_n}(Q)^{\beta_2} + \frac{1}{n}\left(\frac{\gamma-1}{\gamma}\frac{\overline{Y_n}(Q)Q^{-\frac{1}{\gamma}}}{r-\mu} - \frac{c}{r}\right) = \frac{I}{n} \tag{A24}$$

$$A'(Q)\underline{Y_n}(Q)^{\beta_1} + B'(Q)\underline{Y_n}(Q)^{\beta_2} + \frac{1}{n}\left(\frac{\gamma-1}{\gamma}\frac{\underline{Y_n}(Q)Q^{-\frac{1}{\gamma}}}{r-\mu} - \frac{c}{r}\right) = \frac{kI}{n} \tag{A25}$$

Thus, we can solve for $A'(Q)$ and $B'(Q)$. Integrating $A'(Q)$ and $B'(Q)$ between 0 and Q, $A(Q)$ and $B(Q)$ can be expressed as

$$A(Q) = \frac{Q}{n}\frac{\gamma}{\gamma-\beta_1}a(\underline{P_n},\overline{P_n})Q^{-\frac{\beta_1}{\gamma}} \tag{A26}$$

$$B(Q) = \frac{Q}{n}\frac{\gamma}{\gamma - \beta_2} b(\underline{P_n}, \overline{P_n}) Q^{-\frac{\beta_2}{\gamma}} \tag{A27}$$

where

$$a(\underline{P_n}, \overline{P_n}) = \frac{1}{\overline{P_n}^{\beta_1} \underline{P_n}^{\beta_2} - \underline{P_n}^{\beta_1} \overline{P_n}^{\beta_2}} \left[\left(I + \frac{c}{r} - \frac{\gamma - 1}{\gamma} \frac{\overline{P_n}}{r - \mu} \right) \underline{P_n}^{\beta_2} - \left(kI + \frac{c}{r} - \frac{\gamma - 1}{\gamma} \frac{\underline{P_n}}{r - \mu} \right) \overline{P_n}^{\beta_2} \right] \tag{A28}$$

$$b(\underline{P_n}, \overline{P_n}) = \frac{1}{\underline{P_n}^{\beta_1} \overline{P_n}^{\beta_2} - \overline{P_n}^{\beta_1} \underline{P_n}^{\beta_2}} \left[\left(I + \frac{c}{r} - \frac{\gamma - 1}{\gamma} \frac{\overline{P_n}}{r - \mu} \right) \underline{P_n}^{\beta_1} - \left(kI + \frac{c}{r} - \frac{\gamma - 1}{\gamma} \frac{\underline{P_n}}{r - \mu} \right) \overline{P_n}^{\beta_1} \right] \tag{A29}$$

Notably, we assume that $\beta_1 > \gamma$ to ensure the existence of an equilibrium as in Grenadier (2002), Aguerrevere (2009), and Morellec and Zhdanov (2018). ■

Proof of Proposition 3

The firm's systematic risk β can be derived as

$$\beta = \frac{\partial V_n(Y, Q)}{\partial Y} \frac{Y}{V_n(Y, Q)} \tag{A30}$$

where $V_n(Y, Q)$ is given by Equation (12). Taking the partial derivative with respect to Y yields

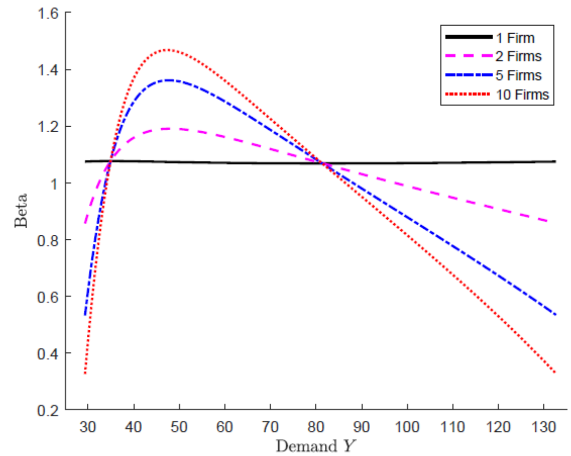
$$\frac{\partial V_n(Y, Q)}{\partial Y} = \beta_1 A(Q) Y^{\beta_1 - 1} + \beta_2 B(Q) Y^{\beta_2 - 1} + \frac{Q}{n} \frac{Q^{-\frac{1}{\gamma}}}{r - \mu} \tag{A31}$$

Thus,

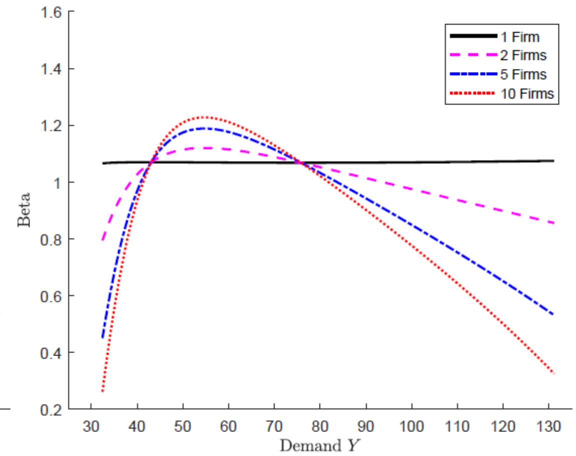
$$\beta = 1 + (\beta_1 - 1)\frac{A(Q)Y^{\beta_1}}{V_n} + (\beta_2 - 1)\frac{B(Q)Y^{\beta_2}}{V_n} + \frac{Q}{n}\frac{c/r}{V_n} \tag{A32}$$

■

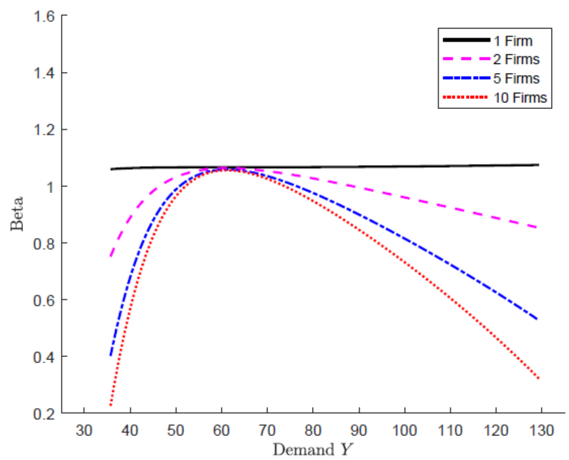
Appendix B. Figures and Tables



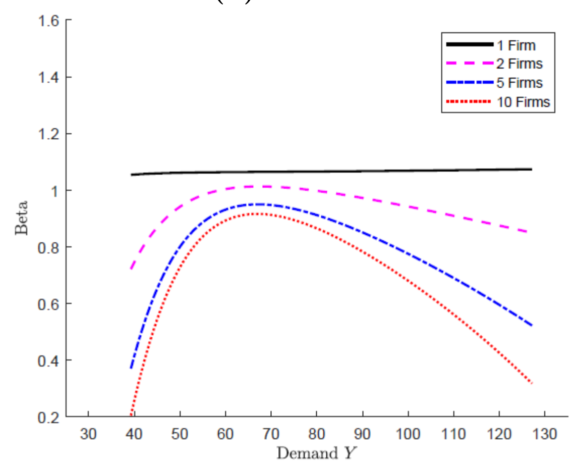
(a) k = 0.2



(b) k = 0.3



(c) k = 0.4



(d) k = 0.5

Figure 1: Betas of firms in different competitive industries for different levels of asset redeployability. Each subfigure shows the beta of the firm as a function of Y for a given level of k when the industry's total output at time t depends on the number of firms in the industry. Parameter values are $r = 0.06$, $\mu = 0.01$, $\sigma = 0.2$, $I = 1$, $c = 0.06$ and $\gamma = 1.1$.

Table I: Most and Least Competitive Industries by Redeployability

This table presents the top 5 and bottom 5 three-digit SIC industries sorted by HHI for the first (low) and fifth (high) of the average redeployability measure in 2014. We use the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight.

	Most competitive industries		Least competitive industries	
	SIC	Industry Title	SIC	Industry Title
	131	Crude Petroleum and Natural Gas	109	Miscellaneous Metal Ores
	820	Educational Services	306	Fabricated Rubber Products
Low redpb	451	Air Transportation, Scheduled, And Air Courier	222	Broadwoven Fabric Mills, Manmade Fiber And Silk
	799	Miscellaneous Amusement And Recreation	387	Watches, Clocks, Clockwork Operated Devices, and Parts
	122	Bituminous Coal And Lignite Mining	301	Tires And Inner Tubes
	738	Miscellaneous Business Services	835	Child Day Care Services
	508	Machinery, Equipment, And Supplies	784	Video Tape Rental
High redpb	735	Miscellaneous Equipment Rental And Leasing	154	General Building Contractors-Nonresidential
	504	Professional And Commercial Equipment And Supplies	302	Rubber And Plastics Footwear
	517	Petroleum And Petroleum Products	511	Paper And Paper Products

Table II: Summary of Measures

This table presents summary statistics of industry concentration measures and investment reversibility measures. The sample Industry is defined at the level of three-digit SIC codes. HHI(sales) is the 3-year average Herfindahl-Hirschman Index based on net sales. HHI(assets) is the 3-year average Herfindahl-Hirschman Index based on total assets. CR5 is the concentration ratio of the combined net sales of top 5 firms to the industry's total net sales. Redeployability is a firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. Redeployability(R2) is a firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight, and incorporates correlation of outputs among firms within industries in the measure. Redeployability(EW) is a firm-level asset redeployability measure based on asset-level redeployability score that uses the equal weight for each BEA industry-year. Inflexibility is the firm's historical range of operating costs scaled by sales over the volatility of the logarithm growth rate of sales over assets. The sample period is from January 1990 to December 2016.

	Mean	Std. Dev.	25%	Median	75%
HHI(sales)	0.189	0.155	0.085	0.144	0.238
HHI(assets)	0.194	0.159	0.081	0.143	0.252
CR5	0.689	0.184	0.530	0.679	0.839
Redeployability	0.405	0.104	0.358	0.416	0.467
Redeployability(R2)	0.208	0.055	0.183	0.214	0.240
Redeployability(EW)	0.340	0.083	0.307	0.353	0.384
Inflexibility	1.794	3.701	0.474	0.956	1.672

Table III: Characteristics of Sorted Portfolios

This table presents summary statistics of portfolio characteristics sorted on sales-based Herfindahl-Hirschman Index (HHI) and firm-level asset redeployability. In each month t, NYSE-, AMEX- and NASDAQ-listed stocks are sorted into quintiles based on firm-level asset redeployability. Independently, firms are sorted into terciles based on industry-level HHI, where $\mathrm{Comp_H}$($\mathrm{Comp_L}$) contains the stocks with lowest(highest) HHI. HHI(sales) is the 3-year average Herfindahl-Hirschman Index based on net sales. Redeployability is a firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. log(Size) is the logarithm of market equity. B/M is the book value of equity divided by market equity. Leverage is the ratio of total liabilities to the sum of market value of equity and total liabilities. log(Assets) is the logarithm of total assets. log(Sales) is the logarithm of net sales. Return on assets the operating income before depreciation (OIBDP) divided by lagged total assets. Capital expenditure is defined as capital expenditure (CAPX) divided by lagged total assets. The sample period is from January 1990 to December 2016.

	Low redeployability			High redeployability		
	$\mathrm{Comp_H}$	$\mathrm{Comp_M}$	$\mathrm{Comp_L}$	$\mathrm{Comp_H}$	$\mathrm{Comp_M}$	$\mathrm{Comp_L}$
HHI(sales)	0.07	0.15	0.37	0.08	0.15	0.38
Redeployability	0.24	0.26	0.26	0.55	0.53	0.53
log(Size)	20.05	19.99	19.86	19.87	19.92	20.05
B/M	0.50	0.52	0.66	0.51	0.57	0.54
Leverage	0.25	0.31	0.37	0.32	0.37	0.36
log(Assets)	19.61	19.75	19.90	19.60	19.87	19.95
log(Sales)	19.25	19.51	19.70	19.48	20.10	20.15
Return on assets	0.14	0.14	0.14	0.13	0.15	0.16

Table IV: Cross-section Returns of Portfolios Sorted by HHI and Asset Redeployability

This table presents the monthly excess returns (in percentage) of portfolios sorted on sales-based Herfindahl-Hirschman Index (HHI) and firm-level asset redeployability. In each month t, NYSE-, AMEX- and NASDAQ-listed stocks are sorted into quintiles based on firm-level asset redeployability. Independently, firms are sorted into terciles based on industry-level HHI, where $\mathrm{Comp_H}$($\mathrm{Comp_L}$) contains the stocks with lowest(highest) HHI. Monthly portfolio average returns are calculated over month $t+1$. Portfolio abnormal returns are computed by regressing monthly portfolio excess returns on risk factors in the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Stambaugh and Yuan (2016) four-facotr model. DGTW returns are adjusted for B/M, size, past returns as in Daniel et al. (1997). Stocks with share price less than $5 at the end of month t are excluded. Panal A reports the equal-weighted portfolio returns and Panal B reports the value-weighted portfolio returns. The sample period is from January 1990 to December 2016. t-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	Low redeployability					High redeployability					$\mathrm{Redeploy_L}$ - $\mathrm{Redeploy_H}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\mathrm{Comp_H}$	$\mathrm{Comp_M}$	$\mathrm{Comp_L}$	H-L	t-stat	$\mathrm{Comp_H}$	$\mathrm{Comp_M}$	$\mathrm{Comp_L}$	H-L	t-stat	(4) - (9)	t-stat
A. Equal-weighted returns												
Excess return	1.02	0.75	0.62	0.40*	[1.72]	0.56	0.73	0.74	-0.18	[-1.18]	0.58***	[2.70]
Fama and French 3-factor α	0.05	-0.14	-0.28	0.32*	[1.68]	-0.26	-0.14	-0.08	-0.18	[-1.44]	0.51**	[2.40]
Carhart 4-factor α	0.18	-0.08	-0.19	0.37*	[1.90]	-0.21	-0.07	0.00	-0.22*	[-1.67]	0.59***	[2.75]
Fama and French 5-factor α	0.30	-0.20	-0.35	0.64***	[3.37]	-0.17	-0.20	-0.21	0.04	[0.34]	0.60***	[2.73]
Stambaugh and Yuan 4-factor α	0.44	-0.01	-0.17	0.61***	[2.99]	-0.18	-0.14	-0.12	-0.06	[-0.43]	0.68***	[3.03]
DGTW (1997) adjusted return	0.35	0.10	-0.14	0.49**	[2.53]	-0.13	-0.04	-0.02	-0.11	[-0.89]	0.60***	[3.25]
B. Value-weighted returns												
Excess return	1.00	0.75	0.61	0.39*	[1.67]	0.55	0.68	0.74	-0.19	[-1.32]	0.59***	[2.68]
Fama and French 3-factor α	0.03	-0.14	-0.29	0.32*	[1.65]	-0.27	-0.18	-0.07	-0.20	[-1.62]	0.52**	[2.45]
Carhart 4-factor α	0.18	-0.07	-0.20	0.37*	[1.89]	-0.22	-0.09	0.01	-0.23*	[-1.83]	0.60***	[2.79]
Fama and French 5-factor α	0.27	-0.22	-0.38	0.65***	[3.37]	-0.21	-0.25	-0.21	-0.00	[-0.00]	0.65***	[2.94]
Stambaugh and Yuan 4-factor α	0.42	-0.02	-0.20	0.62***	[2.95]	-0.21	-0.15	-0.12	-0.09	[-0.64]	0.71***	[3.14]
DGTW (1997) adjusted return	0.31	0.10	-0.13	0.44**	[2.43]	-0.11	-0.05	-0.02	-0.09	[-0.80]	0.53***	[3.04]

Table V: Panel Regressions

This table presents results from panel regressions of firms' excess returns on Herfindahl-Hirschman Index (HHI), asset redeployability (*Redpb*), the interaction term ($HHI*$*Redpb*), and other control variables. log($Size$) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). $Leverage$ is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. Column (2)-(4) use the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. Column (5) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight, and incorporates correlation of outputs among firms within industries in the measure. Column (6) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses the equal weight for each BEA industry-year. The sample period is from January 1990 to December 2016. All regressions include year-month fixed effects. Standard errors are clustered by firm and year-month. t-statistics are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	-0.095		-1.956**	-2.318***	-2.828***	-2.603***
	[-0.23]		[-2.26]	[-2.87]	[-3.69]	[-2.84]
$Redpb_{t-1}$		-0.408	-1.198	-1.090	-2.477*	-1.124
		[-0.77]	[-1.52]	[-1.53]	[-1.82]	[-1.30]
HHI_{t-1} * $Redpb_{t-1}$			4.542**	4.718***	11.648***	6.337***
			[2.38]	[2.62]	[3.36]	[2.69]
$\log(Size)_{t-1}$				-0.010	-0.011	-0.010
				[-0.25]	[-0.27]	[-0.25]
$Book\text{-}to\text{-}Market_{t-1}$				0.250***	0.253***	0.252***
				[2.89]	[2.93]	[2.91]
lag(1-month return)				-1.730	-1.735	-1.730
				[-1.56]	[-1.57]	[-1.56]
lag(12-month return)				0.283	0.282	0.283
				[1.26]	[1.25]	[1.26]
$Leverage_{t-1}$				0.793*	0.797*	0.794*
				[1.73]	[1.74]	[1.73]
#Obs	767,109	767,109	767,109	700,457	698,296	700,457
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	14.3%	14.3%	14.3%	14.6%	14.6%	14.6%

Table VI: Fama-MacBeth Regressions for Excess Returns

This table presents results from Fama-MacBeth regressions of firms' excess returns on Herfindahl-Hirschman Index (HHI), asset redeployability (*Redpb*), the interaction term ($HHI *$ *Redpb*), and other control variables. log($Size$) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). *Leverage* is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. Column (2)-(4) use the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. Column (5) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight, and incorporates correlation of outputs among firms within industries in the measure. Column (6) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses the equal weight for each BEA industry-year. The sample period is from January 1990 to December 2016. t-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	-0.114		-2.467***	-2.886***	-2.905***	-3.125***
	[-0.24]		[-2.62]	[-3.54]	[-3.55]	[-3.37]
$Redpb_{t-1}$		-0.249	-1.188	-1.120	-2.120	-1.328
		[-0.44]	[-1.54]	[-1.63]	[-1.58]	[-1.58]
HHI_{t-1} * $Redpb_{t-1}$			5.595***	5.806***	11.051***	7.541***
			[2.96]	[3.23]	[3.05]	[3.16]
$\log(Size)_{t-1}$				-0.005	-0.006	-0.006
				[-0.13]	[-0.15]	[-0.15]
$Book\text{-}to\text{-}Market_{t-1}$				0.145**	0.147**	0.146**
				[2.07]	[2.10]	[2.08]
lag(1-month return)				-1.620***	-1.628***	-1.610***
				[-3.86]	[-3.89]	[-3.84]
lag(12-month return)				0.309*	0.310*	0.312*
				[1.82]	[1.82]	[1.83]
$Leverage_{t-1}$				0.469	0.476	0.470
				[1.35]	[1.37]	[1.35]
# Months	323	323	323	323	323	323
R^2	0.4%	0.4%	0.9%	4.3%	4.3%	4.3%

Table VII: Industry Level Fama-MacBeth Regressions

This table presents results from industry-level Fama-MacBeth regressions of excess returns on Herfindahl-Hirschman Index (HHI), asset redeployability (*Redpb*), the interaction term ($HHI *$ *Redpb*), and other control variables. All variables are first averaged within each (three-digit SIC) industry. log($Size$) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). *Leverage* is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. Column (2),(3),and (5) use the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. Column (6) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight, and incorporates correlation of outputs among firms within industries in the measure. Column (7) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses the equal weight for each BEA industry-year. The sample period is from January 1990 to December 2016. t-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI_{t-1}	-0.04		-2.15**		-2.20**	-2.25***	-2.58***
	[-0.24]		[-2.56]		[-2.58]	[-2.85]	[-2.62]
$Redpb_{t-1}$		0.33	-1.13		-0.99	-2.08	-1.13
		[0.66]	[-1.56]		[-1.38]	[-1.55]	[-1.29]
HHI_{t-1} * $Redpb_{t-1}$			5.10**		4.91**	9.41**	6.87**
			[2.51]		[2.41]	[2.55]	[2.48]
$\log(Size)_{t-1}$				0.09**	0.10**	0.10**	0.09*
				[1.98]	[2.05]	[2.10]	[1.94]
$Book\text{-}to\text{-}Market_{t-1}$				0.26*	0.27*	0.28*	0.28*
				[1.73]	[1.82]	[1.87]	[1.84]
lag(1-month return)				1.20	0.97	0.95	1.02
				[1.60]	[1.29]	[1.26]	[1.37]
lag(12-month return)				0.81***	0.76***	0.76***	0.77***
				[2.97]	[2.82]	[2.80]	[2.84]
$Leverage_{t-1}$				0.30	0.32	0.30	0.32
				[0.79]	[0.83]	[0.78]	[0.84]
# Months	323	323	323	323	323	323	323
R^2	0.8%	0.9%	2.5%	9.4%	11.7%	11.7%	11.6%

Table VIII: Fama-MacBeth Regressions for Unlevered Return

This table presents results from Fama-MacBeth regressions of firms' unlevered returns on Herfindahl-Hirschman Index (HHI), asset redeployability (*Redpb*), the interaction term ($HHI *$ *Redpb*), and other control variables. Unlevered stock returns are excess returns divided by the sum of one plus leverage. log($Size$) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). *Leverage* is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. Column (2)-(4) use the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. Column (5) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight, and incorporates correlation of outputs among firms within industries in the measure. Column (6) uses the firm-level asset redeployability measure based on asset-level redeployability score that uses the equal weight for each BEA industry-year. The sample period is from January 1990 to December 2016. t-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	-0.223		-2.130***	-2.250***	-2.277***	-2.412***
	[-0.58]		[-2.89]	[-3.40]	[-3.44]	[-3.17]
$Redpb_{t-1}$		-0.252	-0.999*	-0.999*	-1.911*	-1.140*
		[-0.63]	[-1.79]	[-1.86]	[-1.84]	[-1.73]
HHI_{t-1} * $Redpb_{t-1}$			4.585***	4.607***	8.872***	5.906***
			[3.40]	[3.36]	[3.25]	[3.18]
$\log(Size)_{t-1}$				-0.001	-0.001	-0.001
				[-0.02]	[-0.04]	[-0.04]
$Book\text{-}to\text{-}Market_{t-1}$				0.136	0.138	0.138
				[1.53]	[1.56]	[1.54]
lag(1-month return)				-1.214***	-1.223***	-1.206***
				[-3.50]	[-3.54]	[-3.48]
lag(12-month return)				0.261*	0.262*	0.263*
				[1.91]	[1.92]	[1.92]
# Months	323	323	323	323	323	323
R^2	0.4%	0.4%	0.9%	3.7%	3.7%	3.7%

Table IX: Alternative Measures of Industry Concentration

This table presents results from Fama-MacBeth regressions of firms' excess returns on alternative industry concentration measures (*IndCon*), asset redeployability (*Redpb*), the interaction term (*IndCon* ∗ *Redpb*), and other control variables. In Panel A, *IndCon* is the Herfindahl-Hirschman Index using total assets to compute market share. In Panel B, *IndCon* is the concentration ratio of the combined net sales of top 5 firms to the industry's total net sales. *Redpb* is the firm-level asset redeployability measure based on asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. log(*Size*) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). *Leverage* is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. The sample period is from January 1990 to December 2016. *t*-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	Panel A: HHI(total assets)					Panel B: Concentration Ratio 5			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IndCon_{t-1}$	-0.007		-1.187	-1.511**	-1.619**	-0.019	-0.797	-0.934**	-1.081**
	[-0.02]		[-1.60]	[-2.16]	[-2.34]	[-0.07]	[-1.59]	[-2.05]	[-2.58]
$Redpb_{t-1}$		-0.186	-0.410	-0.386	-0.348		-0.759	-0.725	-0.720
		[-0.50]	[-0.85]	[-0.89]	[-0.82]		[-1.26]	[-1.32]	[-1.35]
$IndCon_{t-1}$ * $Redpb_{t-1}$			2.206*	2.378**	2.311**		1.343*	1.391**	1.456**
			[1.80]	[2.03]	[1.99]		[1.96]	[2.16]	[2.27]
$\log(Size)_{t-1}$				-0.023	-0.003			-0.022	-0.001
				[-0.54]	[-0.07]			[-0.51]	[-0.03]
$Book\text{-}to\text{-}Market_{t-1}$				0.123	0.144**			0.128	0.146**
				[1.08]	[2.06]			[1.17]	[2.12]
lag(1-month return)					-1.623***				-1.648***
					[-3.88]				[-3.97]
lag(12-month return)					0.313*				0.311*
					[1.83]				[1.83]
$Leverage_{t-1}$					0.472				0.501
					[1.36]				[1.50]
# Months	323	323	323	323	323	323	323	323	323
R^2	0.4%	0.4%	1.0%	2.2%	4.3%	0.7%	1.3%	2.4%	4.5%

Table X: Alternative Measure of Investment Irreversibility

This table presents results from Fama-MacBeth regressions of firms' excess returns on Herfindahl-Hirschman Index (HHI), firm-level inflexibility ($Inflex$), the interaction term ($HHI * Inflex$), and other control variables. $Inflex$ is defined as the firm's historical range of operating costs scaled by sales over the volatility of the logarithm growth rate of sales over assets. log($Size$) is the natural logarithm of the market value of equity. *Book-to-Market* is the ratio of book value of equity to market value of equity. lag(*1-month return*) is the stock return over previous month. lag(*12-month return*) is the past 12-month stock return excluding previous month (i.e. from month -12 to month -2). *Leverage* is defined as the ratio of total liabilities to the sum of market value of equity and total liabilities. The sample period is from January 1990 to December 2016. t-statistics using Newey-West standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)
HHI_{t-1}	-0.114		-0.050	-0.179	-0.260
	[-0.26]		[-0.14]	[-0.57]	[-1.12]
$Inflex_{t-1}$		-0.024**	0.002	0.003	0.008
		[-2.13]	[0.12]	[0.21]	[0.63]
HHI_{t-1} * $Inflex_{t-1}$			-0.181***	-0.185***	-0.192***
			[-2.86]	[-2.94]	[-3.00]
$\log(Size)_{t-1}$				-0.039	-0.022
				[-1.02]	[-0.64]
$Book\text{-}to\text{-}Market_{t-1}$				0.048	0.098
				[0.46]	[1.40]
lag(1-month return)					-1.661***
					[-3.80]
lag(12-month return)					0.278*
					[1.69]
$Leverage_{t-1}$					0.289
					[1.00]
# Months	323	323	323	323	323
R^2	0.4%	0.3%	0.7%	1.9%	4.1%