IMPACT OF PRODUCT MARKET COMPETITION ON EXPECTED RETURNS

by

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DISSERTATION ABSTRACT

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This paper examines how competition faced by firms affects asset risk and expected returns. Contrary to Hou and Robinson's (2006) findings, I find that cross-industry variation in competition, as measured by the concentration ratio, is not a robust determinant of unconditional expected stock returns. In contrast, within-industry competition, as measured by relative price markup, is positively related to expected stock returns. Moreover, this relation is not captured by commonly used models of expected returns. When using the Markov regime-switching model advocated by Perez-Quiros and Timmermann (2000), I test and find support for Aguerrevere's (2009) recent model of competition find risk dynamics. In particular, systematic risk is greater in more competitive industries during bad times and greater in more concentrated industries during good times. In addition, real investment by firms facing greater competition leads real investment by firms facing less competition, supporting Aguerrevere's notion that less competition results in higher growth options and hence higher risk in good times.

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CHAPTER I

INTRODUCTION

It is reasonable to believe that the uncertainty of real investment opportunities and the state of competition in the product markets faced by firms may affect firms' behaviors and thus the risks of firms. Recently scholars have examined such economically intuitive measures to explain the cross-sectional differences in stocks returns. For example, Hou and Robinson (2006) use a Herfindahl-Hirschman Index as a measure of market power and find that firms in a more competitive industry have higher expected returns. They provide two possible explanations for their results. First, according to Schumpeter (1912), competitive firms engage in more innovations and therefore are exposed to a higher level of risks. Second, firms in a more concentrated industry may have higher barriers to entry, and thus have lower distress risk and lower average returns.

Hou and Robinson's (2006) empirical result may also be interpreted by one fundamental assumption that the cost of production increases the leverage of the cash flows and the risk of the firms used in many real option models. Novy-Marx(2011) states that "variable (i.e., flow) production costs[1] play much the same role as debt servicing in levering the exposure of a firm's assets to underlying economic risks." Therefore, the firms with lower price-to-cost margin will be riskier. The intuition is that while the price of the goods sold varies with demand shifts, the costs are less sensitive to the economic changes. Given low sensitivity of cost to the economic changes which implies no systematic movement

[1] In some of the real options model, the operating cost comes from the deployed capital investment, i.e., the variable costs are affected by the fixed cost chosen to be invested during the same period. Thus, the variables costs plays basically the same role as the fixed cost. Novy-Marx(2011) also addresses the possibility that higher variables costs can be associated with more flexibility on the cost side. Which effect dominates the risk of the firms should then be an empirical issue. To make the operating leverage hypothesis from Novy-Marx(2011) to be valid, the bottom line is that the variable operating costs must be less sensitive to the demand shifts. This assumption should be true under increasing marginal costs.

on the supply side, a firm in a more competitive industry or with lower price markup ratio should be riskier because it will have higher operating leverage. This assumption has been documented as early as in Thomadakis (1976) and Subrahmanyam and Thomadakis (1980), and also in recent works such as Ortiz-Molina and Phillips (2009) who find that asset-liquidity discount is higher during the bad time, which means inflexibility on the cost side does increase the risk faced by the firm. This relation is important for most real option models because this relation can make asset-in-place riskier than growth options, causing value firms to be riskier than growth firms. Given that the fundamental industry organization theories that firms in more concentrated industries should have higher price-to-cost margin because they can extract more rents from consumers and that lower price margin firms have higher risk due to low sensitivity on the cost side, we should also expect a "competitive premium" as documented in Hou and Robinson's work.

However, there are two issues to use this "operating leverage hypothesis", as named by Carlson, Fisher, and Giammarino (2004), to explain Hou and Robinson's (2006) results. First, if what affects the operating leverage is firms' ability to extract rents, using the firm-level price-to-cost margin rather than the industry-level concentration ratio should be more straightforward in identifying this relation. Simply speaking, when only the industry level concentration ratio is used to measure the competition faced by the firm, a firm with higher price-to-cost margin in a competitive industry may be incorrectly recognized as a high operating leverage firm. Second, while the correctly measured price-to-cost margin may negatively correlate with the operating leverage as argued in real option models, high observed price-to-cost margin may also represent higher non-capital fixed cost, which suggests that price-to-cost margins should positively correlate with operating leverage, In fact, Domowitz, Hubbard, and Petersen (1988) find that much of the estimated markup of price over marginal cost is due to non-capital fixed costs. It seems that the results found in Hou and Robinson's work may not be solely explained by this intuitive explanation. In this paper, I try to use different measures in the cross- and within- industry level to identify whether the product market structures can affect firms' risk and whether this crucial assumption of operating leverage hypothesis is the main force that drives this relation.

As the theories progress, many strategic tools have been developed and the competitive environment may affect firms risk in more dynamic fashions and these strategic behaviors may also affect firms' risk. When competing with each other, a firm no longer just simply set the price and quantities under fixed production functions but instead, chooses to adjust its capacity by exercising their growth options. Aguerrevere (2009) develops a theoretical model and suggests that firms facing different demand may change their investment behaviors and conclude that those in more concentrated industries are riskier in good times, but less risky in bad times. The intuition behind the model is that while firms in more competitive industries are riskier due to higher operating leverage, but firms in more concentrated industries will delay the exercise of their growth options during high demand periods, and thus the risk driven by these excess growth options offsets or even exceeds the impact of lower operating leverage. Therefore, these firms are riskier in good times. These competitive behaviors may also affect the relative risk of firms within an industry. For example, Carlson, Dockner, Fisher, and Giammarino (2008) develop a duopoly model and find that the risk of the leaders may be affected by the strategic behaviors of the follower and identify that within-industry competition may also affect firms' risk. In both cases, because firms may choose to exercise their growth options sequentially, the static competitive models which suggest low price-to-cost margin firms are riskier may no longer be applied because these asynchronous changes of capacity can bring risk to the cost side as well. These impacts may not only affect the sign of the relation between product market measures and risk, but also change the signs of the relation under different economic states.

It is not an easy task to empirically test the relation between product market structure variables and firms' systematic risk and historically many proxies have been used to measure some facets of the product market structure. The most commonly used measures of the market structure, such as used in Hou and Robinson's (2006) work, may be the concentration ratios, especially the Herfindahl-Hirschman Index (HHI). The problem to use this measure is that this proxy can be measured only at the industry level. This problem may not be a big issue in most theories because most theoretical models assume that firms in any industry are homogeneous. In that case, firms in more concentrated industries are able to capture more economic rents for certain. However, practically we never observe an industry with identical firms and ignoring the possible impacts of firm-level market power may invalidate the conclusions from these theoretical models. Moreover, as suggested above, if the operating leverage hypothesis is truly the main force driving the relation between market competition and firms' risk, this impact should work more directly at the firm level rather than industry level. For example, as suggested by Novy-Marx (2011), this operating leverage impacts will cause that "the relationship between expected returns and industry book-to-market is weak and non-monotonic, but that the relationship between expected returns and book-to-market within industries is strong and monotonic."

Another commonly used measure which can capture the firm level market power is the price-to-cost margin, or the price markup ratio. In the microeconomic literature, the price markup ratio is usually interpreted as the degree of a firm's market power on setting its output price. A simple and well known measure of market power is the Lerner Index, which is measured with the following formula: $L = (P - MC)/P$. The Lerner Index ranges from 0 to 1, and can be simply interpreted as the mark-up rent. In a competitive market, the Lerner Index equals 0, and as the market power of the firm increases, L will increase to $1/e$, where e is the elasticity of demand, when the firm has monopoly power in the market. Ideally, this measure should capture the ability of firms to capture producer surplus and correctly measure either the industry or firm level market competition. In practice, however, high price markup ratios may also capture the degree of non-capital fixed cost other than the firms' ability to capture rents as stated before. This problem will be especially troublesome when the price markup ratio is used as the industry level market competition measure because the technologies used across industries should be widely different and thus the proportion of non-capital fixed cost should also vary significantly across industries. Moreover, higher price markup firms may represent more dominant players in a competitive industry or a less dominant players in a concentrated industries. If cross- and within- industry competition can affect firm's risk differently, this single measure of market power may not be sufficient.

Given that both proxies of market structure variables may not be measured correctly on all the competitive facets faced by firms[2], in this paper I use both the industry-level HHI and the firm-level price markup ratio to better capture the true competitiveness faced by the firms. Specifically, I will use HHIs to capture the inter-industry difference in market competition, and use price markup ratio to measure the intra-industry variation in market power. This way of defining market structure is also applied in Gasper and Massa's (2006) work when testing the relation between volatilities and market structures. The first measure represents the degree of competition in an industry, while the second measure determines the relative position of a firm in a given industry. These two measures should complement each other and jointly better describe the competition faced by firms. The separations of cross- and within- industry market competition can also help us to more directly link the empirical results to the theories. Some theoretical models, especially the recent strategic models, concern whether the competition are the industry-wide, such as Aguerrevere's

[2]Also, these two measures are not always correlated empirically, which will be addressed later.

(2009) mode, or relative between competitors among a industry, such as Carlson, Dockner, Fisher, and Giammarino (2008). Although whether industry level and firm level market power can affect firms risk differently is an empirical issue, this separation can at least help us better identify this possibility. For simplicity, I will always use "market power" when mentioning within-industry competitiveness and "market competition" when mentioning industry-wide competitiveness in later sections.

To briefly summarize the result, I find that the annualized alpha between low and high intra-industry price markup portfolios ranges from 3.2% to 4.9%, which is economically and statistically different from zero. This suggests that higher within-industry market power firms have higher expected returns. On the other hand, the common measures used for industry-level differences in market competition, such as various concentration ratios, do not have direct impacts on expected return. The different relations between expected return and inter- and intra- industry measures suggest that industry level competition and within-industry market power may capture different effects of firms' product market competition on risk. This finding is not inconsistent with some established theoretical models[3] which suggest that firms in more competitive industry are riskier and the operating leverage hypothesis suggested by Novy-Marx (2011) and Carlson, Fisher, and Giammarino (2004) cannot fully explain the relation between product market structure and the risk of the firms. The positive relation between within-industry market power and expected return can at least partially explained by Carlson, Dockner, Fisher, and Giammarino's (2008) sequential game model. If high price markup firms are the firms with more growth option, as suggested by the negative correlation between book-to-market ratio and price markup ratio found empirically, the existence of these high growth option firms provide a hedge for the low price markup competitors and cause the latter firms to be less risky as suggested

[3]Most of these models assume all firms in the industry are homogeneous.

by their model. The low risk of these low price markup firms can therefore cause the price markup premium within industries.[4]

Although I find unconditionally that firms in more competitive industries are not riskier than firms in more concentrated industries, the systematic risk faced by these two types of firms may be different in different states as suggested by Aguerrevere (2009). I use the Markov regime-switching model with unidentified states suggested by Perez-Quiros and Timmermann (2000) to test if the return spread between high and low HHI portfolios has opposite loadings on market premiums in different states. The results are consistent with Aguerrevere's prediction that firms in more competitive industries are riskier in recessions but less risky in expansions. Also, as predicted by the model, firms in more competitive industries may choose to exercise their growth options earlier during increasing demand periods, i.e., the investment from these firms lead the investment from firms in concentrated industries. These findings provide further evidence that changes in firm's decision patterns suggested by the industrial organization literature can have direct links to asset pricing. Moreover, although Aguerrevere's model does not specify which types of state variables should be used as the conditional variables because the model assumes the demand of all industries are perfectly correlated with the market portfolio, I find that this conditional relation is more significant if we use the industry-wide state variables instead of the economy-wide state variables. This finding suggests that even without the assumption that all the industries' demands are perfectly correlated with the market portfolio prices, this conditional patterns should still exist as predicted by the model.

To summarize, my empirical findings can contribute to the current literature in the following ways. First, this paper provides to the currently limited empirical evidences in

[4]This relation may also by affected by the positive relation between profitability, as suggested by Fama and French(2000, 2006) and expected return but less by the competitiveness of the industries these firms are in.

accessing the relation between product market competitive behavior and expected returns in the financial market. Second, most theoretical models developed in the asset pricing literature assume homogeneous firms in every industry, but the finding on the significant relation between within industry market power and firms' expected returns demonstrates that it is also important to evaluate the relative firm characteristics within each industry. Third, the fundamental and crucial operating leverage hypothesis used in most real-option models can at most explain only parts of the relation between market structure variables and firm's risk. Last but not least, the findings in the conditional beta section shows that firms actions under different competitions and different states may generate the conditional patterns on betas.

This paper is organized as follows. Discussions of the impact of market competition to expected return are summarized in Section II. In Section III, I describe my measurement of market competition for both inter- and intra- industry. In Section IV, I provide empirical results using the Fama MacBeth method, multifactor time-series regressions on accessing impacts of within-industry market power and cross-industry market competition on expected returns. Section V provides the framework of the conditional beta model and empirical results supporting Aguerrevere's (2009) theoretical model. Lastly, Section VI concludes and provides some further research directions for explaining the anomaly found in this paper.

CHAPTER II

RELATION BETWEEN PRODUCT MARKET STRUCTURE AND FIRM RISKS

Empirically many different proxies for market structure variables, such as size, price over cost ratio, or industry concentration ratios, have been used to test if these variables affect the cross-sectional expected returns of firms. Theoretically these variables may be perfectly correlated under certain model assumptions. For example, given a fixed demand curve and identical firms in any industry, a firm in a more competitive industry should also have lower price markup ratio and smaller size if firms are playing the Cournot game. Therefore, in theory, it is often difficult to distinguish if the impact of market competition on firms' systematic risk is due to any specific measures from the above list. This situation can be observed in early theoretical models, in which the relative sensitivities of the supply and demand curve to general economic shocks are usually used to explain the empirical findings of relations between different market structure variables, such as price markup ratios and industry concentration ratios, and firms' risks. More recent models have started to discuss the impacts of competition on current investments or future investment opportunities and provide more insights on how product market structures affect firms' risks and expected returns.

Much empirical work in finance and economics seems to suggest that there is a relation between product market structure and firm risk. Keeley (1990) tests the relation between industry competition and firms' risk in the banking industry. He finds that increases in competition decrease the value of a firm, and thus increases the probability of default. Sullivan (1978) and Sullivan (1982) find that there are negative relations between CAPM beta and either concentration ratio or size, both of which are used as proxies for market power. The study by Melicher, Rush, and Winn (1976) also indicates that firms from the most concentrated industries tend to have more stable average monthly returns, which suggests that high market power firms are less risky. Allayannis and Ihrig (2001) find that as an industry's price markup ratio, or market power, falls, its sensitivity of return to exchange-rate change increases. Recently, Hou and Robinson (2006) find that firms in highly concentrated industries have lower returns and argue the risk premium can be associated with more innovations by firms in competitive industries. It appears that most of the empirical literature agrees on that there is a "competition premium," which means more competitive industries or lower price markup ratio firms are riskier.

However, some other empirical and theoretical work shows that the relation between market structure variables and firm or industry risks is ambiguous. For example, Curley, Hexter, and Choi (1982) find that the concentration ratio has no impact on the CAPM beta. Even Sullivan (1982), who empirically finds there is a negative relation between market structure variables, such as size and concentration ratio, and CAPM beta, admits that "the available evidence is mixed and that the issue (the relation between risk and market power) is far from settled." This unsettled question seems to unsolved even in more recent literature. Although Hou and Robinson(2006) empirically find that there is an inverse relation between concentration ratio and expected return and use Schumpeter's (1912) argument to defend this result, they also provide a related but opposite view asserted by Schumpeter (1942). Schumpeter argues that monopolistic firms have strong incentives for innovation because these firms can realize the profit generated by these innovations. Because these innovations are riskier, more concentrated industries should earn higher average returns. The possible interaction between product market structure and systematic risk in the financial market seems to be still controversial. Moreover, it seems that it is hard to find dominant theoretical foundations in this area, which may explain why Hou and Robinson decide to cite arguments from early twentieth century work.

The most intuitive way of why market structure variables, especially the price markup ratio, can affect firms' or industries' risk may be the explanation that the different elasticities of supply and demand to general market movements may lead firms with different degrees of price over cost ratio to have different levels of risk. Because firms' risk depends on the risk of their cash flows, it is intuitive to believe that the relation between the product price or cost and macro factors or market premium is important to establish the relation between risk and market power. Intuitively, given insensitive cost function which implies no systematic movement on the supply side, a firm in a more competitive industry or with lower price markup ratio should be riskier because it has higher operating leverage. This approach is first applied in the industry organization literature and uses the market beta as a measure of systematic risk. Early studies report an inverse relation between market power and beta. Thomadakis (1976) argues that monopoly rents will not give rise to excess returns since they are already capitalized by expectation, but will influence the level of systematic risk of the firm. In a single period setting, when the risk of revenue and that of cost is different, the degree of monopoly power does affect the systematic risk of the firm's average rate of return. In a multi period setting, average return depends on the certainty equivalent of intraperiod fluctuation in current revenue and changes in expectation of future capital gains, where the second term will be magnified through a firm's ability to set a large price markup. Subrahmanyam and Thomadakis (1980) use a similar model to provide further insights. Unlike papers focusing on the impacts of fluctuations of output on a firm's return, this paper explicitly recognized that optimal price and quantity behavior depend not only on total demand, but also on a firm's characteristics, such as the market power. If all firms are perfectly competitive, the beta of the firm is linear in the labor/capital ratio.[1] When some firms have market power and have the ability to set the price higher than marginal cost, other things equal, the firm with higher market power tends to have a lower beta. However, this relation is not for certain given different assumptions on price and cost's sensitivity to economic states. Peyser (1994) identifies that the relation between the beta on market excess returns and market power can be ambiguous depending on the model's assumptions. To be more specific, this relation will depend on the assumption of relative fluctuations of product price and factor prices. O'Brian (2007) also argues that this relation can go either way depending on whether marginal cost is increasing or decreasing. This stream of research focuses on the relative fluctuations of price (demand) and cost (supply) corresponding to the total wealth change, i.e., CAPM beta. Most studies in this line of research suggest that there is a inverse or ambiguous relation between market power and beta. To conclude, if the cost function is less sensitive to the general economic conditions, firms in more competitive industry or firms with lower price markup ratio should be riskier because the the cash flow, as determined by total revenue minus total cost, will be more volatile. This assumption will be generally true if there is a large fraction of the costs are not reversible. In that case, the cost function should be less sensitive to the economic factors.

The insensitive cost function is commonly seen in finance literature as well. Most of the investment based theoretical models assume investments are irreversible. As noted before, Ortiz-Molina and Phillips (2009) find that asset-liquidity discount is higher during the bad time, which means it is more difficult to downsize production at least during recessions. This assumption is usually required in the models to make assets-in-place riskier. Novy-Marx (2011) also models the relation between market power and value

[1] As identified by Sudarsanam (1992), here the labor wage cost is the stochastic part of the cost but capital cost is non-stochastic. As a consequence, higher labor/capital ratio will induce higher exposure to macroeconomic factors.

premium. In his model, high growth firms have lower sensitivities to demand risk due to lower operating leverage.[2] Aguerrevere (2009) argues that operating leverage makes assets-in-place of firms in competitive industries riskier during recessions. There are two issues of this explanation worth noting. First, the relation implied by different sensitivities of supply and demand should work not only at the industry level but also at the firm level if insensitivity of cost function is common at both firm and industry levels. Second, the risk differences driven by the price markup ratio differences may be reflected not only CAPM beta but also other risk factors. For example, Novy-Marx's model links the market power to the value premium. He shows that high growth industries, which are more exposed to growth options, have lower sensitivities to demand risk through both lower operating leverage and less risky growth options. He further argues that sorting by book-to-market ratio generates a sort on elasticity, i.e. market power, and firms in industries that produce goods where demand is elastic will be more sensitive to their cost due to lower tolerance of inefficient production, thus resulting in higher risk. Because value firms are riskier during periods of economic downturns, the value premium will be higher during the same period, which causes a counter-cyclical value premium. The book-to-market ratio difference between low cost and high cost producers is then magnified by the difference between firms' sizes, which capture the production efficiency of each firm. The net impact of size and book-to-market ratio depends on the level of industry concentration relative to demand elasticity. If the final net impact on asset pricing is what we are concerned about, it is reasonable to believe that the degree of market power may help explain assets' return through affecting loadings on the value and size premium.

As the economic theories progress, new economic concepts and methodologies have been incorporated in discussing the relation between market structure and risk, and product

[2]There are other side impacts of market powers on risk in his study, such as change of risk in growth options and relative firm sizes.

market competition may affect firms' risk not only through supply and demand elasticities but also through other channels. Peress (2008) develops a noisy rational expectation model in which firms operate under monopolistic competition to explain the relation between product market competition and stock market reactions through information clarity. He argues that firms with higher market power can pass the demand shocks to their customers, and this pass-through leads the profitability of these firms more stable and transparent to the investors. Thus, higher market power firms provide clear information to the investors and should have less volatile cash flows and lower systematic risk. Also, new theoretical models start to consider the interactions between firms competing with each other especially on changing their production capacities.[3] Carlson, Dockner, Fisher, and Giammarino (2008) find that theoretically competition within an industry may affect the firms with different position in an industry have different level of risk, and market competition may reduce the risk of firms. They develop a duopoly model in which both firms have only fixed cost and growth options, where two firms move sequentially. They argue that strategic competition can lower firm risk. When two firms do not interact with each other, any demand shock will be transferred directly to the cash flow of each firm. When there are strategic competitions and the leader[4] has already exercised its investment option and cannot change its capacity, the risk faced by the leader will be hedged by the sequential behavior of the followers. As a consequence, the leader's risk is reduced. They argue that more market competition causes lower risk. These new studies suggest that not only the sensitivity to demand and supply shock but also the interactions among competitive firms can determine the risk of firms.

[3]Most of this line of research assume homogeneous firms in an industry and therefore the concentration ratio is usually used as the major proxy for market competition.

[4]Here the leader does not have to be the firms with higher market power but the ones whose growth opportunities are not affected by other firms' choices.

The second channel may be consistent with the first channel, such as Peress, or drive the relation to the opposite direction, such as Carlson et al.

Because there are many channels that decide the relation between market competition and firms' risk, the joint relation between product market structure and risk may be more dynamic and cannot be explained by a single theory. By combining the effects of insensitive cost functions and investment decisions affected by the degrees of industry competition, Aguerrevere (2009) develops a theoretical model that explains how the beta can change with the competitiveness in an industry in different states. During recessions, firms that face a more competitive environment would be riskier because their assets-in-place have higher operating leverage. This relation is similar to the traditional models evaluating the supply and demand side sensitivities as discussed in earlier paragraphs. On the other hand, when the economy is doing well, other things equal, concentrated firms have a larger fraction of their firm values in growth options due to the delay of exercising their growth options, and thus become riskier. Based on Aguerrevere's model, whether firms in competitive industries are riskier than firms in concentrated industries should be conditional on demand. The unconditional concentration, or competition, premiums can go either way based on the cost functions and the distribution of the aggregated demand.

Because more profitable firms are usually the firms with higher price markup ratios or the firms who can capture more economic rents, it is possible that the price markup ratio and expected returns of firms are positive correlated as implied by the positive relation between profitability and expected returns. Lyanders and Watanabe (2010) theoretically derive the positive relation between within-industry relative profitability and expected return from their two period stylized model. They find that expected returns of a firm should be positively correlated with the book-to-market ratio and within-industry earnings to investment ratio: (p.23 or combining equation (33) and (35) in their paper)

$$ER_k = BM_k \frac{E\pi_k}{I_k} - R_f \qquad \text{(Equation 2.1.)}$$

They interpret this equation as more profitable firms and value firms earn higher returns. In fact, if we use their model setting, the denominator, investment, is exactly equal to the cost in the one period model. Therefore, earning divided by the investment is basically the price markup ratio. ($\frac{\pi}{I} = \frac{P-C}{C}$) Although it's still controversial why more profitable firms have higher expected returns, there are some reasons that may help explain this relation. For example, Fama and French (2000) find that earnings and profitability tend to be mean reverting. In a competitive environment, profitable industries (or firms) will attract more competitors both from outside or from mimicking in the same industry, and as a consequence, drive the industry (or firm) profitability down. This argument seems to suggest that firms with higher profit will tend to have riskier future cash flows, and as a result, higher expected return. Fama and French (2006) also find empirically there is a positive relation between firms' profitabilities and their expected returns. Some behavioral explanations, such as underreactions in Cohen, Gompers, and Vuolteenaho (2002), also confirm the positive relation between profitability and expected returns. In short, if market structure variables affect firms' or industries' expected returns only through these variables' impacts on profitabilities, firms in more concentrated industries or firms earn higher returns than their peers should have higher expected returns.

To conclude, there is limited and inconsistent empirical evidence on the relation between product market structure and the expected return of a firm. Even for the theoretical models, there may be different impacts from different channels of competition. As mentioned in Lyanders and Watanabe (2010), "Aguerrevere (2009) analyzes how competition in a product market affects the relation between firms' real investment decisions and the dynamics of their asset returns. ... In contrast, while firms in our model likewise maximize profits, they do not have an option to expand their productive capacity. ... Aguerrevere (2009) studies the important link between beta and the book-to-market ratio, whereas we analyze the relation between expected returns and firm characteristics such as intra-industry profitability, size, the book-to-market ratio, and investment, for some of which we provide empirical evidence." This quote implies that different channels may affect the relation differently, and cross- and within- industry level market structure may be driven by different forces. Most current empirical evidence, such as the recent Hou and Robinson (2006), suggests that there is a negative relation between market power and expected returns, although financial economic theorists have not agreed on this relation. Theoretical models developed so far suggest that market competition can affect the risk of a firm by the demand shock, including demand elasticity and product price fluctuation, the supply function, including asset irreversibility and operating leverage, or strategy components, including the ability to pass-through a demand shock to customers and capital investment option decisions. Moreover, these channels can affect the risk of a firm through market premium, value premium, or size premium. These complexities make the relation between product market structure and financial market risk a still unsolved question.

CHAPTER III

MEASURE OF INTER- AND INTRA-INDUSTRY MARKET STRUCTURE VARIABLES

As stated in previous section, different market structure variables may capture different facets of the competition faced by a firm. For example, a firm which is a follower in a concentrated industry may have relatively low but not high price markup ratio in the product market due to its inability to capture rents, and which proxies to choose could affect our interpretations on the relations between product market structure and expected returns. Among all the measures, industry level market concentration ratios may be the most widely used one in most theoretical and empirical literatures. For example, Hou and Robinson (2006) associate the HHI with expected returns and Lang and Stulz (1992) find that the values of firms in the industry with lower HHI are lower when there are other competitors announcing bankruptcy.[1] In this paper, the HHI is defined as the squared sum of the fractions of industry sales by the firms in the same industry with the same 4-digit SIC code using the data from Compustat.[2] In general, an increase in the HHI indicates a decrease in industry competition because this measure gives higher weights to larger firms. The value of the HHI is bounded between 0 (perfect competition) and 1 (monopoly).

However, as indicated in the introduction, using HHI calculated with Compustat data as the sole measure of market structure may have at least two problems. First, because Compustat data includes only public firms, it may not be representative for the true degree of concentration of an industry and produces measuring errors. Ali, Klasa, and

[1] A more complete set of the literature using HHI can be found in Ali, Klasa, and Yeung (2009).

[2] Hou and Robinson (2006) uses 3-digit level industry groups. The results in this paper are qualitatively equivalent if 3-digit level industry definitions are used.

Yeung (2009) find that the HHIs calculated with Compustat data have very low correlation with the corresponding U.S. Census measures and they argue that the HHI calculated with Compustat data may proxy for some other industry characteristics than industry competition.[3] Second, the leaders and followers in the same industry may face different degrees of competition, and assigning the same HHI for all the firms in the same industry may be misleading. For example, MacKay and Phillips (2005) find that financial structure, technology, and risk are jointly determined within industries through system of equations models, which suggests that the relation between market competition and risk can vary within an industry. The research in this area, especially theoretical models, usually assumes homogeneous firms. As a consequence, firms in a more competitive industry all have lower price markup ratio and there is no within- industry market power difference. Under the homogeneous firms assumption, a firm in a less concentrated industry should have lower ability to set their price much over the costs, which leads to a positive correlation between these two measures. However, empirically these two measures are not always correlated. For example, Kwoka and Ravenscraft (1986) find that the relation between concentration ratio and price markup ratio is ambiguous. Domowitz, Hubbard, and Petersen (1988) find that the relations between concentration ratios and price markups are only significant within some industries. This evidence suggests that at least one of these two measures, if not both, cannot perfectly represent the market power of a firm. Therefore, a measure capturing intra-industry dispersion on market power should be also important in understanding the interaction between financial markets and product markets.

Ideally, if all the parameters of the cost function are observable, the price markup ratio, or the Lerner index, can be used as the sole measure, both within- and cross-industry, of market power. However, because of the difficulties of measuring economic

[3]This issue will be addressed in later sections.

costs, the estimation of a price markup ratio is almost an impossible task even though revenue or price data are generally available. Because of the measurement errors of the parameters in the cost function, price markup ratios can be interpreted in two ways. The interpretation of price markup ratio as a measure of market power has been widely used in the Industrial Organization literature (See Tybout's (2003) survey paper) and some in the finance literature (e.g., Peress 2007). However, if we assume perfect competition and any profits earned are caused by unobserved fixed costs, such as human capital and other intangible fixed assets, the price markup ratio can also be a proxy for the levels of operating leverage.[4] In fact, Domowitz, Hubbard, and Petersen (1988) find that much of the estimated markup of price over marginal cost is due to non-capital fixed costs. Therefore, if the price markup ratio is used as the firm level market power variable, this ratio may capture not only the market power but also the operating leverage effect.

To demonstrate the possible bias brought by relation between price markup ratios and operating leverage, suppose that every firm faces a perfectly elastic demand curve. In the long run equilibrium, these firms will earn zero profit (price equals average costs.) We can draw two implications under these assumptions. If we can precisely measure all the economic costs, the ratio of price to average cost will be close to one, as a result of nearly perfect competition in long run. If we can not precisely measure all the fixed costs, the inverse of the ratio of price to average variable cost will be equal to one minus the inverse of the ratio of price to average fixed cost. Thus, the higher the firms' dependence on its fixed assets, the higher the price markup over average variable cost. Because fixed assets have longer life and are harder to liquidate, firms depending more on these assets for production will be stuck with a sub-optimal production plan relative to the one they would choose under zero adjustment cost. Thus firms with a higher price to average variable cost ratio

[4]For example, see Gulen, Xing, and Zhang (2008)

are exposed to higher risk during downturns in the economy, and consequently, become riskier.

When the price markup ratio is used as an intra-industry measure of market power, the ambiguity caused by the measurement error of the parameters in the production function may be minimized. This can be explained in the following. If two firms have the same ratio of fixed cost to sales, both observable and unobservable, the one with the higher price markup ratio should have higher market power. It is more plausible to assume that two firms use similar technologies when both firms are in the same industry. Combined with the assumption that the technology functions are homothetic, or that both firms have similar quantities of output, both firms should demand a similar optimal ratio of fixed to variable cost, and the one with a higher observed price markup ratio should earn more economic rent, or higher market power. In other words, under the assumption that technologies are similar, and either both firms have a similar quantity of output or the production function is homothetic, then the price markup ratio can well represent market power even if part of the fixed costs are unobservable. Note that this is not to say that the observed price markup ratio is measured precisely in absolute terms, but can be used to compare the relative market power of two or more firms in the same industry because the unobservable part of fixed costs will be cancelled for each firm within the same industry. Therefore, the price markup ratio may not be generally used as a firm level market power variable, but if we can find a suitable proxy for industry level competition, the intra-industry dispersion in price markup ratio should better explain the relative market power inside each industry.

Because the mean and standard deviation of price markup ratio of each industry can vary if each industry has different technologies and different proportions of fixed assets, comparing the absolute deviation from industry price markup ratio for each firm may be misleading. Therefore, I use a similar method as applied by MacKay and Phillips (2005) to form the price markup industry position variable.

$$MP\_PC_{i,j} = \frac{pmkup_i - MC\_PC_j}{range\{pmkup_k | \forall k \in j\}} \qquad \text{(Equation 3.1.)}$$

This measure provides the intra-industry dispersion of price markup ratio for firm i in industry j and should fall between -1 and 1. The numerator measures the difference between a firm's price markup ratio and its industry's average price markup ratio. This difference is then normalized by the range of the price markup ratios of all the firms in the industry, which measures the dispersion of the firms in that industry.[5] When there is only one firm in an industry, value 0 is given for this measure because the denominator will be zero and the value of this measure would be undefined.

In sum, the HHI is widely accepted as a measure of industry concentration, but it ignores the variation of competition faced by firms within an industry. On the other hand, the price markup ratio, or the Lerner Index, can distinguish the market power faced by firms in the same industry, but may proxy instead for operating leverage if the technologies used by two firms are different, which is more likely to occur between firms in different industries. By combining these two measures, where the HHI measures inter-industry market power, and the price markup ratio measures intra-industry market power, we should be able to better measure the market power of a firm and therefore better estimate on the relation between market competition and risks.

[5]This measure can also be normalized by the standard deviation of the price markup ratio. However, there are limited numbers of industries with enough observations in any given year, and standard deviations may not do better than the range of the price markup ratio. Moreover, this new measure will not be bounded between -1 and 1 and is consequently more difficult to interpret.

CHAPTER IV

RELATION BETWEEN INTER- AND INTRA-MARKET POWER MEASURES AND ASSET PRICING

In this section I will empirically evaluate the relation between expected return and industry level market competition or firm-level market power. To see if there is a risk premium associated with these market structure variables, I use the Fama MacBeth method and time-series regressions of market-power-sorted portfolios to test if these variables can affect average stock returns. To estimate the necessary parameters for the econometric tests, I use accounting data from Compustat and financial data from CRSP. For each year t between 1963 and 2007, accounting data including sales, operating income before depreciation and amortization, gross and net PPE, total assets, sales, and book value of equity are obtained from Compustat. From CRSP, I follow the tradition and use the market capitalization in June of year t+1 to proxy for size and divide the book value of equity in year t by the market capitalization in December of year t to form the book-to-market ratio for year t. I also form the following yearly variables. Price markup ratio (pmkup) equals to operating income before depreciation and amortization divided by total sales.[1] Operating leverage (FA_TA) is defined as gross PPE divided by total assets[2] The beta of each firm year is estimated with the 30 monthly observations before June of year t+1. The estimation of betas on market premium is included only when there are at least 20 valid observations. Firm characteristics data are matched with the return data from July of year t+1 to June of year t+2.

[1]The price markup ratio is censored at -1. This lower bound is arbitrarily chosen, but seems reasonable given that a firm with a price markup ratio less than -1 would lose more than its sales

[2]The results don't change when the net PPE is used.

After individual firm characteristic variables are obtained, the next step is to form the industry characteristic variables. The corresponding 4-digit SIC code industry[3] characteristics are weighted averages of the firms' characteristics in the same industries. The weighting criteria of various variables depend on the underlying firm characteristics. For example, the industry price markup ratio is defined as a sales-weighted average of firm price markup ratios and the industry book-to-market ratio is defined as market-value-weighted average of firm book-to-market ratio. These industry-level variables can be used to represent inter-industry differences in characteristics. The detailed definitions of these variables can be found in the Appendix.

Two measures of market concentration are used to measure inter-industry differences in market competition. The first measure, the MC_HHI, is defined as the squared sums of the fractions of industry sales by the firms in the same industry with the same 4-digit SIC code using the data from Compustat. This is the same definition used in Hou and Robinson (2006). The second measure, CR4, is obtained from the U.S. Census and is defined as the aggregated percentages of the market shares of the largest four companies in an industry. This information is reported for each 4-digit SIC industries between 2000-3999 every 5 years till 1997.[4] For the years between two reports, I use linear interpolation to estimate the CR4 for missing years because the CR4 measure for each industry does not move in a short period, which minimized the errors in estimation caused by interpolations.[5]

[3]For all the tables in this section, I also perform robustness check by using 3-digit SIC code, and most figures are qualitatively similar, and some of the results are even more significant. The reason to use more detailed grouping criteria is to make sure the underlying production technologies within each group are more similar, and this is also why Fama French industry group definitions are not used here.

[4]The gap between each observation may be less than 5 years but does not affect any procedure performed in this paper. If the gaps are smaller, the interpolation can still be performed

[5]However, in the unreported result, most industries show observable differences on the HHI in long horizon. For example, we should not expect the HHIs of a specific industry at 1970 and at 2000 to be similar.

Although I have already defined the firm and industry level variables, the equally important characteristics are the variables that describe how a firm deviates from other firms in the same industry, i.e., intra-industry variables. For example, one firm can have a higher price markup ratio than another in its industry or perform better than its peers. If the competition works only on the industry level, we should expect the within industry level market power measure plays no role in explaining the expected returns of a firm. In general, these variables are defined as the difference between individual firm characteristics and industry characteristics, except the intra-industry price markup ratio, which is normalized and has already been discussed in the previous section.

Table 1 shows the summary statistics for both firm and industry characteristics in two cross sections, 1978 and 1997, which are 10 years after the beginning of sample and 10 years before the end of the sample. The reason to provide two cross sections is that some of these variables have time-trends. For example, the average size of a publicly traded firm is almost 10 times higher in the more recent cross section. If only pooled averages are calculated, the standard deviation may be overstated.

Table 1: Summary statistics of the sample

Panel A shows the summary statistics for individual firms, and panel B shows the summary statistics for the industries. For each panel, the summary statistics of two cross sections, year 1978 and year 1997, are provided. The definitions of each variable can be found in Appendix.

Panel A: Summary statistics for firm characteristics

Year	1978					Year	1997				
	N	MIN	MAX	MEAN	STD		N	MIN	MAX	MEAN	STD
Beta	2259	-0.634	3.494	1.233	0.729	Beta	3340	-1.741	3.93	0.953	0.851
BM	2340	-0.19	5.253	1.32	0.893	BM	3671	-0.561	4.258	0.578	0.532
Size	2342	0.593	4864	164	520	Size	3628	2.093	63894	1630	6450
Ln(BM)	2325	-5.953	1.659	0.046	0.76	Ln(BM)	3605	-6.286	1.449	-0.822	0.806
Ln(Size)	2342	6.384	15.397	10.254	1.792	Ln(Size)	3628	7.646	17.973	12.134	2.003
PC	2404	-0.82	0.718	0.13	0.124	PC	3692	-0.992	0.653	0.103	0.193
MP_PC	2404	-0.988	0.96	-0.049	0.342	MP_PC	3692	-0.991	0.987	-0.051	0.273
FA_TA	2400	0	3.218	0.571	0.317	FA_TA	3681	0	6.688	0.519	0.403

Panel B: Summary statistics for industry characteristics

Year	1978					Year	1997				
	N	MIN	MAX	MEAN	STD		N	MIN	MAX	MEAN	STD
ind_beta	355	-0.634	3.494	1.239	0.51	ind_beta	378	-0.488	2.825	0.86	0.468
ind_FA_TA	357	0.055	1.763	0.579	0.263	ind_FA_TA	380	0.066	1.465	0.547	0.28
ind_BM	358	-0.023	3.948	1.102	0.535	ind_BM	380	-0.029	2.139	0.445	0.277
ind_size	358	1.379	28044	1073	2643	ind_size	380	2.093	577916	15654	40993
Ln(ind_BM)	357	-2.041	1.373	-0.023	0.52	Ln(ind_BM)	379	-4.164	0.76	-0.971	0.593
Ln(ind_size)	358	7.229	17.149	12.379	1.929	Ln(ind_size)	380	7.646	20.175	14.915	2.076
MC_PC	358	-1.223	0.493	0.12	0.113	MC_PC	379	-0.589	0.577	0.137	0.099
MC_HHI	358	0.091	1	0.496	0.273	MC_HHI	380	0.064	1	0.466	0.268
Count	358	1	104	6.821	7.683	Count	380	1	187	10.332	16.004

Comparing 1978 to 1997, both firm size and average number of firms, overall and in each industry, are increasing. All other variables do not appear to have any trend. Given the low mean value of the number of firms per industry and the fact that the minimum count equals to 1, it appears that there are some industries that include only one firm. It is possible that going public decisions cluster for an industry in a given time period, and some industries may not have an incentive to go public, resulting in very few firms included in Compustat data for a given industry. Through the whole sample, about 2% of the observations have HHIs equal to 1, which means that these firms are in industries with only one firm included in the Compustat and CRSP databases. This ratio increases to about 14% when I use industry-level data. Therefore, this bias may not have a strong impact when firm-level data are used to perform the test, but may provide misleading results for all the tests at the industry level.

To briefly test if defined market structure variables have desired relations with other firm and industry characteristics, Table 2 shows the correlation between characteristics variables at the firm and industry levels. Because the correlations are calculated by using pooled data, most correlations are significant and thus the p-values are not reported. Panel A shows the correlation between each intra-industry variable. Prop_size, defined as firm size divided by industry size, sometimes also served as a proxy for the position of a firm in the industry. Higher values of this measure means a firm plays a bigger role in this industry, and thus should have higher market power than its peers. This measure has a positive correlation with intra-industry price markup ratio and a negative correlation with intra-industry book to market difference, i.e., larger firms in an industry usually have higher price markup ratio and lower book-to-market value relative to their peers. Both relations are consistent with higher market power for these sets of firms. The correlation between intra-industry price markup ratio is positive correlated with the fixed asset to total asset ratio but small in magnitude. This evidence does not support Novy-Marx's(2011) model, which links the book-to-market ratio (positively) and market power (negatively) to the operating leverage.

Table 2: Correlations between industry and firm level characteristics

Panel A reports the correlations of the variables on the individual firm level, and panel B reports the correlations of the variables on the industry level. Most of the figures are significantly different from zero because the pooled data is used to calculate these correlations. The definitions of all these variables are in the Appendix.

Panel A: correlation between intra-industry variables

	dif_beta	MP_PC	prop_size	ln(dif_BM)	ln(dif_FA_TA)
dif_beta	1				
MP_PC	-0.017	1			
prop_size	0.007	0.197	1		
ln(dif_BM)	-0.072	-0.145	-0.191	1	
ln(dif_FA_TA)	-0.077	0.064	0.082	0.034	1

Panel B: correlation between inter-industry variables

	ind_beta	MC_HHI	MC_PC	ln(ind_size)	ln(ind_BM)	ln(ind_FA_TA)	CR4	HHI50
ind_beta	1							
MC_HHI	-0.038	1						
MC_PC	0.020	-0.059	1					
ln(ind_size)	-0.073	-0.434	0.14	1				
ln(ind_BM)	-0.025	0.039	0.002	-0.417	1			
ln(ind_FA_TA)	-0.095	0.014	-0.017	-0.018	0.086	1		
CR4	-0.002	0.255	0.022	0.241	0.027	0.112	1	
HHI50	0.004	0.207	0.007	0.184	0.057	0.044	0.842	1

Panel B shows the correlation between variables across industries. Industry size and book to market ratio are highly negatively correlated, which suggests that larger industries are usually the industries with higher growth options.[6] The industry price markup ratio (MC_PC) is not strongly correlated with other variables except industry size, which implies that industry price markup ratio and intra-industry price markup ratio (MP_PC) may represent different aspects of a firm's operation. I include three measures for industry concentration in this table: HHI calculated from Compustat data (MP_HHI), HHI (HHI50) and CR4 from U.S. Census data. As suggested by Ali, Klasa, and Yeung (2009), the HHI reported by the U.S. Census Bureau should represent market concentration better because the firms used to calculate this measure include both public and private firms. The concentration ratios provided by U.S. Census include market shares for the top N firms (CR4, CR8, CR20, CR50)[7], and the Herfindahl-Hirschman Index for the largest 50 firms (HHI50). The data is available for the manufacturing sectors and are published every five years starting from 1947 for CR4, and from 1982 for HHI50. All the information is available for the manufacturing firms, which has 4-digit SIC codes between 2000-3999. These measures are provided only once every 5 years and the data after 1997 are organized on the NAICS system.

The correlation between CR4 and HHI50 is about 84%. Due to the data availability, I will use CR4 instead of HHI50 in later tables for robustness check. An important finding here is that the HHI calculated from Compustat data is negatively correlated with industry size, while HHI50 (CR4) from U.S. Census data is positively correlated with industry size. Both correlations are large in magnitude, and this evidence suggests that the HHI

[6]Also, the negative correlation can be caused simply by the fact that market capitalization is the denominator of the book-to-market ratio.

[7]CR states for concentration ratio. For example, CR4 is defined as the total percentage of market shares held by the largest 4 firms in the industry.

calculated from Compustat data may capture more than just market concentrations. In fact, although not shown here, the HHI calculated from the Compustat data have a highly positive correlation (43%) with prop_size, which can proxy for the position of a firm in the industry, while the correlation between CR4 and prop_size is less than 4%. This finding is consistent with Ali, Klasa, and Yeung (2009). This high correlation is not surprising because prop_size (size divided by the industry size) is similar to market share (sales divided by the industry sales), which appears in the numerator of the HHI. These two pieces of information suggest that the HHI calculated from Compustat may not be a good proxy for the competitions at firm level without controlling for firm level properties due to its correlation with intra-industry market position variables and mismeasurement issues. The second issue will be evaluated and discussed in later section.

4.1. Fama-MacBeth Estimations

In this section I present the Fama-MacBeth (1973) method results of the estimated risk premium associated with price markup ratios for individual firms and industries, respectively. Book to market ratio, size, and market beta are generally accepted as controls when the Fama-MacBeth method is performed. The variables of interest here are the concentration ratio and the price markup ratio, both of which are proxies for product market structure. This setup focuses on whether price markup ratio has an incremental impact on expected returns rather than through its correlation with other risk-related measures, such as book to market ratio, size, and market beta.[8] As noted in the previous section, the price markup ratio can also be used as a proxy for levels of operating leverage.[9] To further filter out this impact, I also include the fixed asset to total asset ratio to control for operating

[8]The discussion of the latter relation will be examined in time series regressions described in the next subsection.

[9]For example, see the empirical work by Gulen, Xing, and Zhang(2008).

leverage. The other reason to use the Fama-MacBeth method is that this procedure allows for changing betas, which a single unconditional cross-sectional regression or a time-series regression test cannot easily handle.[10] I will use this feature to take a first glance on Aguerrevere's conditional model.

The Fama-MacBeth method is quite common in the empirical asset pricing literature. To perform this test, in the first stage, a cross-sectional regression of excess return on market structure proxies and other control variables is performed for each month. The time series mean, standard errors, and t-statistics of the estimated coefficients are then calculated and reported in the tables. The point estimates and t-statistics of these coefficients calculated from the second step can be used to determine whether the risk premium associated with given firm characteristic, such as the CAPM beta or price markup ratio, is significant. The t-statistics on market structure related variables can then be used to test the hypothesis that product market structure has an impact on expected return and risk even after controlling for other firm or industry characteristics.

$$r_{i,t} = \lambda_t X_{i,t} + \epsilon_{i,t}$$

$$t = \frac{E(\hat{\lambda}_t) - 0}{SE(\hat{\lambda}_t)}$$

Table 3 shows the Fama-MacBeth results when the sample contains individual firms. Column (a) to (d) use different sets of variables in the first stage regressions. As seen in the table, the estimations of these coefficients are not significantly affected by which variables are included. The premium on beta is insignificant, the premium on size is marginally negatively significant, and the loading on book to market ratio is positively significant. All these results are consistent with the previous literature. The premium on the fixed

[10] See Asset Pricing by Cochrane (2001, p.249).

to total asset ratio is significantly positive, this result is also reasonable because higher operating leverage firms tend to have more irreversible fixed assets and should be more vulnerable to macroeconomic shocks. The proxies for market structures, HHI (MC_HHI) and price markup ratio (PMKUP), show conflicting results. The premium on HHI is negatively significant, which confirms the results in Hou and Robinson (2006) and also the operating leverage hypothesis, which states that firms in more competitive industries have higher operating leverage and are thus riskier. The negative average coefficient implies that firms in a more concentrated industry have lower expected returns. Under homogeneous firms hypothesis, all these firms should also have higher price markup ratio. However, the premium on price markup ratio is positively significant, which implies that firms with more market power (higher profit margin) should have higher expected return. This conflicting result seems to suggest that both market structure variables may represent different types of competitiveness or at least one of them is affected by other firm characteristics.

Table 3: Fama MacBeth method and the risk premium

This table shows the average and t-stat of the coefficients estimated by using the Fama-MacBeth procedure. Panel (a) to (d) shows the risk premiums estimated on each firm characteristic by including various variables in the first-step cross section regressions. Panel (e) and (f) use the same variable as in panel (d) and show the results under different economic conditions. Panel (e) includes only the months when the economy is in expansion as defined by NBER business cycle, while panel (f) includes the contraction months. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively.

	Premium	t-stat		Premium	t-stat		Premium	t-stat	
	(a)			(b)			(c)		
Beta	0.00002	0.02		0.00019	0.21		0.00012	0.13	
MC_HHI							-0.00338	-3.35	***
PMKUP				0.00376	2.44	**			
ln(size)	-0.00072	-1.46		-0.00086	-1.83	*	-0.00080	-1.68	*
ln(BM)	0.00298	4.57	***	0.00290	4.29	***	0.00278	4.47	***
FA_TA				0.00171	1.59		0.00213	1.93	*
	(d) All years			(e) Expansion			(f) Contraction		
Beta	0.00015	0.16		0.00055	0.58		-0.00233	-0.83	
MC_HHI	-0.00333	-3.34	***	-0.00326	-3.04	***	-0.00378	-1.38	
PMKUP	0.00382	2.47	**	0.00367	2.55	**	0.00474	0.72	
ln(size)	-0.00086	-1.84	*	-0.00108	-2.18	**	0.00043	0.30	
ln(BM)	0.00295	4.90	***	0.00273	4.24	***	0.00430	2.52	**
FA_TA	0.00163	1.52		0.00267	2.44	**	-0.00472	-1.31	
	(g) CR4								
Beta	-0.00028	-0.24							
CR4	-0.00001	-0.60							
PMKUP	0.01070	2.16	***						
ln(size)	-0.00099	-1.73	*						
ln(BM)	0.00339	3.82	***						
FA_TA	0.00246	1.42							

To test if the risk premium on these market structure variables, especially the industry-level measured HHI and price markup ratio, is conditional on the economic state as predicted by Aguerrevere (2009), column (e) and (f) use the same set of variables as in column (d) but use only the monthly coefficients in expansions and contractions, respectively. The definitions of expansion and contraction months are defined by the commonly used NBER business cycle. The signs in column (e) are similar to the those in column (f), but almost all the average coefficients in column (f) are insignificant, which suggest either the observed competition premium does not exist during contraction or the test has low power due to limited observations. The first explanation is probably not likely because the sign is totally opposite to the model prediction, which suggest higher competition premium during recessions. The more plausible reason may be that this result is caused by low statistical power in the sample of contractions. Because the majority of the sample period is when the economy is experiencing expansion, the number of observation months is only 66 in the contraction sample, which is approximately one-sixth of the observations in the expansion sample.

In column (g), I use CR4 instead of HHI to check the robustness of the relation between market concentration ratios and expected returns. Although the mean of the premium on CR4 is still negative, it is no longer significant.[11] This result raises the question whether concentration ratio is negatively correlated with the expected return and the risk as found by Hou and Robinson (2006). As noted above, the Compustat based HHI is highly correlated with the intra-industry market position. Therefore, it is possible that the competitive premium found by using the Compustat based HHI is driven by some intra-industry variations in firm characteristics.

[11] The estimations on other variables may be different because CR4 for SIC industries contains only manufacturing firms and is only available till 1997. Therefore, the sample used here contains only the data between 1963 and 1997. The same can be applied in later tests when CR4 is used.

To further distinguish between the within- and cross- industry difference in product market structures, in Table 4 Panel A, I separate each individual firm characteristic into cross-industry and intra-industry characteristics. When both sets of measures are included, the risk premium on MC_HHI loses its power and becomes insignificant. This result is consistent with the possibility that without controlling for intra-industry variation, the observed coefficients on the HHI may be misleading. The coefficients on fixed-to-total assets are only significant at the intra-industry level, which suggests that either these measures cannot explain inter-industry level difference in technologies, or the impact of industry-level operating leverage on risk is captured by other industry-level variables, such as industry price markup ratio and book to market ratio, as suggested in previous sections. This is consistent with the hypothesis that industry level price markup ratio may not just capture the economic rent or profitability earned by the whole industry, but instead, capture some unobserved fixed cost of the industry. Thus, the positive coefficient on industry-level price markup ratio may be driven either by high profitability or by high operating leverage. Both coefficients on book to market ratio and price markup ratio are significant in intra- and inter- industry level, and have the same signs as in Table 3. Book to market ratios are especially important in the intra-industry level with the highest t-statistics. This result is consistent with the theoretical model developed by Novy-Marx(2008), in which he argues the value premium is mainly driven by intra-industry variation.

Table 4: Fama MacBeth method and the risk premium on within- and cross- industry variables

This table contains the risk premiums estimated by Fama MacBeth method similar to the previous table. In panel (a) and (d), all the inter- and intra- industry measures of firm characteristics are included in the cross-section regression, while HHI is used in panel (a) and CR4 is used in panel (d) to measure the industry concentration. Section (b) and (c) use the same setup as panel (a) but separate the sample for the expansion and contraction periods, respectively. Panel (d) and (g) use only the industry characteristics and perform industry-level cross sectional regression in the first step, while HHI is used in panel (d) and CR4 is used in panel (g) to measure the industry concentration. Section (e) shows the results for the months of expansions. The results for contraction months are excluded because all the coefficients are insignificant. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively.

Panel A: Risk premiums estimated by using inter- and intra- industry characteristics

	Premium	t-stat		Premium	t-stat		Premium	t-stat	
	(a) All years			(b) Expansion			(c) Contraction		
Ind_beta	-0.00011	-0.08		0.00069	0.45		-0.00500	-1.32	
dif_beta	0.00014	0.19		0.00032	0.40		-0.00092	-0.36	
MC_HHI	-0.00105	-0.82		-0.00040	-0.29		-0.00502	-1.34	
MC_PC	0.00912	2.54	**	0.01143	3.14	***	-0.00498	-0.40	
MP_PC	0.00220	2.28	**	0.00191	1.82	*	0.00397	1.66	*
Ln(ind_size)	0.00002	0.08		0.00003	0.10		-0.00001	-0.01	
Prop(size)	-0.00204	-0.91		-0.00300	-1.26		0.00383	0.58	
Ln(Ind_BM)	0.00227	2.95	***	0.00232	2.82	***	0.00196	0.87	
Intra_BM	0.00434	8.42	***	0.00417	7.82	***	0.00537	3.19	***
Ln(Ind_FA_TA)	-0.00031	-0.46		0.00013	0.19		-0.00300	-1.11	
intra_FA_TA	0.00158	3.82	***	0.00183	4.38	***	0.00002	0.02	

Panel B: Risk premiums estimated by industry characteristics

	Premium	t-stat		Premium	t-stat	
	(d) All years			(e) Expansion		
Ind_beta	-0.00113	-1.05		-0.00086	-0.76	
MC_HHI	-0.00037	-0.32		-0.00007	-0.05	
MC_PC	0.00730	1.98	**	0.00604	1.60	
Ln(ind_BM)	0.00279	3.75	***	0.00310	3.84	***
Ln(ind_size)	-0.00005	-0.15		0.00000	-0.01	
Ln(ind_FA_TA)	0.00116	1.62		0.00158	2.20	**

Panel C: Risk premiums estimated by using inter- and intra- industry characteristics (CR4)

	Premium	t-stat		Premium	t-stat	
	(f) Within- and Cross Industries			(g) Industry Level Only		
Ind_beta	-0.00016	-0.85		-0.00119	-0.59	
dif_beta	0.00001	0.01				
CR4	-0.00248	-0.98		-0.00001	-0.07	
MC_PC	0.01557	1.28		0.01544	1.13	
MP_PC	0.00318	1.92	*			
Ln(ind_size)	0.00014	0.28		0.00024	0.48	
Prop(size)	-0.00477	-1.85	*			
Ln(Ind_BM)	0.00334	2.17	**	0.00558	3.47	***
Intra_BM	0.00490	5.18	***			
Ln(Ind_FA_TA)	-0.00011	-0.08		-0.00100	-0.66	

There are two points worth noting here. First, although insignificant in contraction, the industry price markup ratio seems to have opposite effects on expected returns depending on market conditions. This finding may be consistent with the conditional beta model suggested by Aguerrevere (2009) and the hypothesis that competitive behaviors on other aspects may affect firm's risk. Further tests on this issue will be performed later. Second, after controlling for operating leverage, the intra-industry level price markup ratio (MP_PC) is still significant (marginal significant in contraction period), which suggests that the positive coefficients on the intra-industry price markup ratio may capture some information other than operating leverage, and support the use of price markup ratios as intra-industry market power measures. Third, the HHI loses its explanatory power when intra-industry characteristics are included, which is consistent with the assertion by Ali, Klasa, and Yeung (2009) that Compustat-based HHI may not only correlate with the industry competitions but also capture some other firm and industry characteristics.

A similar result can be found in Panel B. Unlike the regressions run for the previous test, for the first stage, the cross sectional regressions are performed on the industry level and only industry characteristics are included in this test. The only significant coefficients are the (industry) book to market ratio and price markup ratio. The MC_HHI again loses its explanatory power. Note that this result is not consistent with Hou and Robinson (2006). The reason for this inconsistency may come from the different definitions of industry characteristics. Hou and Robinson simply average all the firm characteristics, but I value-weight all these measures. If we treat each industry as a single firm, the value-weighted measures should be more representative for this firm. Also, as noted in a previous section, about 14% of the industry sample used here has HHI equal to 1, which can also bias the relation especially at the industry level. As a result, we may need to interpret the results here with caution.

To further investigate if product market competition has any impact on expected returns, in Panel C, I perform a robustness check and present firm- and industry- level Fama MacBeth estimations by using CR4 from the US Census as the concentration measures. Most figures have the same signs with their corresponding figures in Panel A and B. As in the case of market concentration proxies, the loading on CR4 is insignificant.[12] The loading on prop_size becomes marginally significant, which may suggest that HHI calculated by using Compustat data is also associated with the relative firm position within the industry.

To sum up, the empirical results from Fama-MacBeth method show that the industry level market concentration is negatively correlated with expected returns, but this relation is not persistent if both industry and firm levels variables are included or when CR4 is used as a measure of industry concentration. This result rejects the positive competition premium argued by Hou and Robinson(2006). On the other hand, both intra-industry and inter-industry price markup ratio seems to be positively correlated with firms' expected returns. This finding contradicts the general assumption that low price markup firms are riskier due to higher operating leverage, along with Peress's(2008) model. The analysis so far suggests that the industry-level market competition measures may have different impacts on the expected returns of firms from the intra-industry market power measures. Lastly, due to the low power of the tests caused by lack of sufficient contraction periods, I cannot detect sufficient conditional patterns on the risk premium associated with those industry competition measures as suggested by Aguerrevere(2009).

[12]Although not shown here, the loading on CR4 is significantly negative only for the contraction periods with t-stat of -1.94, which is opposite to the result if we use MC_HHI as the measure for market concentration. This result is consistent with the conditional beta model developed by Aguerrevere (2009), where firms in more competitive industries earn higher returns when demand is low. However, because of the limit sample size due to the use of CR4, we will need more tests to confirm this relation.

4.2. Compare Industry-level Market Competition Measures

The first set of tests on the relation between industry market competition and expected return show inconclusive results. The two proxies used to capture the industry competitiveness seem to have opposite effects on the expected returns of firms. Firms in more competitive industries have higher or the same level of expected returns while firms in industries with lower price markup ratios have lower expected returns. Given that most models assume homogeneous firms in an industry, firms in more competitive industries should have lower price markup ratios as well because competitions drive out the producer surplus which can be earned if firms face less competition. This raises the question of which industry competition measures should be used in discussing the impact of industry level competitions on firms risk.[13] Furthermore, Ali, Klasa, Yeung(2009) argues that the concentration measures calculated by using Compustat data may provide misleading proxies for the true concentration measure of an industry. They find that the measure calculated by using Compustat data, which cover only the public firms, have very low correlation with the concentration ratios provided by the U.S. Census, which also includes privately-owned firms. However, using the U.S. Census concentration ratio may not be a better idea in practice. Ideally, the HHIs and CR4 from U.S. Census should be a good proxy for the true concentration ratio of an industry. However, the limited coverage, both time-series(only till 1992 for SIC based) and cross-sectional(only manufacturing firms), of these two measures may provide biased and less powerful inferences of the true relation between product market structures and risk of the firms. These two questions regarding the proxies for market structure needed to be solved before correctly interpreting the empirical results. To provide support to the use of proxies for industry competition, I will use the Fama-

[13] Again, other reasons, such as operating leverage, may also cause these two measurements to be different as discussed before.

MacBeth method with Newey-West adjustment to examine whether these measures have properties consistent with the industrial organization literature and whether these measures can be good proxies for the the more accurate concentration measures provided by the US Census.

In the first stage, a cross-sectional regression of the dependent variables, which is the measures of market competition, on other industry level variables, which may include other measures of market competition, is performed for each year. The time series mean, standard errors, and t-statistics of the estimated coefficients are then calculated and reported in the table. The point estimates and t-statistics of these coefficients calculated from the second stage can be used to find the relation between these market competition measures and other industry level variables.

To see if these market competition proxies are adequate, first I examine whether the correlations between these proxies and other industry variables have predicted signs. Panel A of Table 5 shows the relation between these two proxies and other industry level variables. I also provide the Newey-West adjustments for standard errors (with 3 year lags)[14] to avoid the possible autocorrelation on the error terms. As stated in Cocharane (2001), this adjustment approach gives the same standard errors as the GMM procedures and should minimize the upward bias on t-statistics caused by autocorrelations.

[14]Even I expand the lags to 10 the results are materially similar.

Table 5: Relation between industry-level market competition proxies

Panel A reports the relation between industry-level market competition proxies and other industry characteristics. Panel B shows the relation between US Census market competition measures and the market competition proxies used in this paper. For both panels, a cross-sectional regression of the dependent variables, which is the measures of market competitions, on other industry level variables, which may include other measures of market competitions, is performed for each year. The time series mean and t-statistics of the estimated coefficients are then calculated and reported in the table. The Newey-West adjusted t-stats are also reported to reflect the possible autocorrelation on the error terms. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively for the t-stats after Newey-West adjustment.

Panel A: Relation between market competition measures with other industry-level variables

RHS Var	MC_HHI					MC_PC				
	Mean	t	t-NW		Expected Sign	Mean	t	t-NW		Expected Sign
Intercept	0.626	28.25	15.63	***		-0.028	-2.53	-1.61		
ENTRY	-0.005	-2.81	-1.82	*	(-)	0.001	1.18	0.78		(+)
Ln(ind_bm)	-0.037	-11.90	-7.67	***	(-)	-0.001	-0.43	-0.23		(-)
Ln(ind_size)	-0.023	-15.78	-8.77	***	?	0.011	13.83	8.49	***	?
Ln(ind_fa_ta)	0.005	1.95	1.28		?	-0.007	-1.71	-1.00		(-)
PC_RANGE	0.004	2.12	1.62		(+) or 0	0.004	2.36	1.54		(+) or 0

Panel B: Explanatory power of industry-level market competition proxies on CR4 and HHI50 from US Census

Dependent Variable	CR4				CR4				HHI50				Expected Sign
	Mean	t	t-NW		Mean	t	t-NW		Mean	t	t-NW		
Intercept	-57.96	-14.50	-8.61	***	23.82	44.67	39.48	***	-1260.77	-11.13	-9.71	***	
MC_HHI	42.13	13.67	8.55	***	28.90	14.73	9.21	***	1066.79	9.52	5.02	***	(+)
MC_PC	-14.90	-1.14	-0.72		38.99	7.31	5.23	***	-654.34	-2.32	-1.78	*	(+)
ENTRY	-0.41	-0.76	-0.78						-16.55	-1.93	-1.66	*	(-)
Ln(ind_bm)	7.43	9.10	6.49	***					187.37	6.12	3.99	***	(-)
Ln(ind_size)	6.23	19.13	11.39	***					113.56	13.16	10.49	***	?
Ln(ind_fa_ta)	-3.20	-3.43	-2.11	**					-51.84	-3.38	-3.57	***	?
PC_RANGE	-2.11	-1.33	-0.96						-0.23	-0.68	-1.01		(+) or 0

These two measures have different relations with some other variables, such as total industry market capitalization (ln(ind_size)) and the number of firms that are newly included in the sample (ENTRY).[15] A larger industry has lower HHI and a higher price markup ratio. The signs on the entry proxies seems to be plausible. An industry that is closer to a perfectly competitive market should have lower barriers to entry, which can make the entry to the industry easier. On the other hand, an industry with higher profitability or producer surplus should attract more firms, which can cause the number of entries to increase. The more troublesome result is the coefficient on the book-to-market ratio on industry price markup ratio. In theory, an industry with higher price markup ratio should also be the industry with a lower book-to-market ratio but the coefficient is insignificant here. This may suggest that high current profit margin industries may not be able to enjoy the same profit margin in the future, and the latter term should be capitalized into the market price. Therefore, the correlation between price markup ratio and book-to-market ratio is negative but not significant. This is also consistent with the mean-reversion hypothesis by Fama and French(2000) that firms with higher profits today may not have higher profits tomorrow.

Although checking the properties of these two variables are important, the more important task is to ensure that these variables can capture the industry competition after controlling for other industry variables. Panel B shows the relation between CR4 provided by the US Census and the industry market competition proxies I use in this paper. If both market concentration (MC_HHI) and industry price markup ratio (MC_PC) are included, both variables are highly significantly correlated with the CR4. However, when other industry level control variables are included, the coefficient on industry price markup ratio

[15] Here ENTRY is defined as the number of firms that enter the Compustat database. Strictly speaking, the entry should be defined as the new established firms in the industry. However, the numbers of entries to the Compustat database may represent how easily firms grow in the given industry, which should be also negatively correlated with the barrier to entry.

becomes insignificant. This finding shows that although industry price markup ratio can be used to explain CR4, the explanatory power of this variables can be absorbed by other industry level control variables. Thus, choosing to use the industry level price markup ratio as the major proxies for industry market competition may provide incorrect inference because the observed relation can be indirectly caused by other industry variables but not the competitiveness of the industries. This again confirms that the price markup ratio may be a good proxy on market structure only on the intra-industry level. Therefore, if the theoretical models are derived based on the market concentration ratios, such as the recent investment based models, we should not simply assume the industry price markup ratio can be used as a substitute for the market competition proxies.[16] On the other hand, although Compustat-based HHI may not be a clear measure for the true concentration of the industries, it should still provide extra explanatory power in understanding the relation between market competition and systematic risk.[17]

4.3. Time Series Regressions of Multi-factor Models

The result from using Fama MacBeth method provides a first glance of the relation between market competition and expected returns. However, the impact of the inter- and intra- industry level market structure variables may jointly affect the risk faced by the firm. For example, Fama and French (2000) argue that high profitability firms have higher risk because the higher profits attract mimicking behaviors and new competitors. The ease of mimic behaviors and new entries should also be determined by the general competitiveness of the industries. A more competitive industry should be the industry with lower barriers

[16] This also suggests that Peress's(2008) results, which use the price markup ratio as the market power proxies, cannot be directly compare to Hou and Robinson's (2006) work.

[17] As stated before, it is possible the Compustat-based HHI is correlated with some within-industry firm characteristics.

to entry, and thus we should expect this effect to be more important between the high and low price margin firms in more competitive industries. Also, Lynder and Watanabe's (2010) model also suggests that industry level characteristics and within-industry position may both be important in explaining expected returns. We can use the two-way sorting portfolios with time series regressions to identify this relation.

The test starts with forming the different price markup ratio portfolios. After estimating the inter- and intra- market power proxies in time t, the financial statement data are matched with the monthly return data between July of year t+1 and June of year t+2. The six month gap ensures that financial statement information is publicly available before the stock market reacts. For each year t, firms are sorted by two dimensions independently. First firms are sorted into three groups based on the intra-industry price markup ratio: top 20% (1), middle 60% (0), and bottom 20% (-1). The portfolios are then independently sorted by inter-industry market power measures into two groups separated by the median of the corresponding measure. In this step, I provide two different measures of inter-industry market power: industry price markup ratio and HHI. The characteristics of these 6 portfolios are presented in Table 6.

Table 6: Characteristics of portfolios formed by double-sorting on market structure variables

The portfolios are formed in two dimensions of market structure variables independently. All panels are sorted by intra-pmkup on one dimension for intra-industry difference in market competition. Different sorting on the second dimension is used in different panels to sort on inter-industry difference in market competition. Right panel uses the industry price markup ratio to sort the firms into two portfolios. Left panel uses MC_HHI. The last column of each panel shows the differences of characteristics of the highest intra-industry price markup ratio portfolio and the one with the lowest intra-industry price markup ratio. The bottom block of each panel shows the difference of characteristics of the high industry market competition portfolio and the low industry market competition portfolio.

	Within Industry (relative) Price margin								Within Industry (relative) Price margin			
	Follower		Leader						Follower		Leader	
MP_PC	L	M	H	H-L	MC_PC		MC_HHI	MP_PC	L	M	H	H-L
						More						
Vwret	0.0088	0.0102	0.0108	0.0021		Competition		Vwret	0.0105	0.0096	0.0111	0.0007
Ewret	0.0104	0.0134	0.0119	0.0015				Ewret	0.0119	0.0137	0.0126	0.0007
BM decile	6.7897	6.2254	5.232	-1.5577	L		L	BM decile	6.3603	5.4801	4.7971	-1.5632
size decile	3.5093	5.2963	5.7901	2.2808				size decile	3.9857	5.6844	6.7829	2.7972
FA/TA	0.4655	0.4659	0.5192	0.0537				FA/TA	0.5358	0.5589	0.6233	0.0875
						Industry-level						
Vwret	0.0099	0.0090	0.0101	0.0002				Vwret	0.0087	0.0089	0.0092	0.0005
Ewret	0.0122	0.0134	0.0128	0.0006				Ewret	0.0108	0.0123	0.0119	0.0010
BM decile	5.9358	4.9700	4.4733	-1.4625	H		H	BM decile	6.1951	5.4534	4.9772	-1.2179
size decile	4.2977	6.0466	7.2856	2.9879				size decile	3.9428	5.9684	5.9625	2.0197
FA/TA	0.5688	0.6030	0.6990	0.1303		Less		FA/TA	0.5127	0.5154	0.5721	0.0594
						Competition						
Vwret	0.0011	-0.0011	-0.0008					Vwret	-0.0018	-0.0007	-0.0019	
Ewret	0.0017	0.0001	0.0009					Ewret	-0.0011	-0.0014	-0.0007	
BM decile	-0.8539	-1.2555	-0.7587		H-L		H-L	BM decile	-0.1652	-0.0266	0.1801	
size decile	0.7884	0.7503	1.4955					size decile	-0.0429	0.2840	-0.8204	
FA/TA	0.1032	0.1370	0.1798					FA/TA	-0.0231	-0.0435	-0.0512	

Table 6 shows the differences in raw returns and average firm characteristics of the six portfolios. Two questions can be answered by the results in this table: how firms in one portfolio differ from those in other portfolios and whether we can earn zero-investment profits by simply going long one portfolio and shorting another. The left panel shows the characteristics of the portfolios formed by inter- and intra- price markup ratios (MC_PC and MP_PC). The difference of raw returns between the high price markup portfolio and the low price markup portfolio is not economically significant in both dimensions, which suggests that it is not possible to earn arbitrage profits by shorting one portfolio and going long the other because these two profolios are also different in other characteristics, such as book-to-market ratio and size, which can affect firms' expected returns. No matter which dimension is used, high price markup firms seem to have lower book to market ratios and larger size, which is consistent with most theories regarding the relation between market power and other firm characteristics. Historically, various measures of size have been used as proxies for market power (Sullivan 1978). The relation between q-ratio and market power seems to be promising as well. As suggested by Perloff, Karp, and Golan (2007), it is possible to determine the degree of monopoly overcharge if Tobin's q is measured accurately. In other words, if we can estimate the replacement costs of intangible assets, such as R&D expenses, the q ratio will provide precise information on relative market power. These common arguments in the microeconomic literature seem to suggest that firm size and q-ratio measure market power, although not perfectly. More specifically, both small firms and value firms (lower q) may imperfectly signal lower market power.

The theoretical model provided by Carlson, Fisher, and Giammarino (2004) suggests that book-to-market ratio can proxy for operating leverage. The relation between book-to-market ratio and price markup ratio documented in Table 6 is not consistent with their model, if price markup ratio is treated as a proxy for operating leverage as argued by Novy-

Marx(2011). They argue that given the assumption that fixed operating cost is proportional to capital as captured by book value of equity, fluctuations of market value reflects demand shifts. They assert that higher book-to-market value firms should have higher operating leverage. However, in the figure here, higher price markup ratio firms have lower book-to-market ratios. Although the high price markup portfolio indeed has higher fixed to total assets ratio, the negative correlation between price markup ratio and book-to-market ratio suggests that the price markup ratio does not reflect just operating leverage, as used in Gulen, Xing, and Zhang (2008)'s empirical work.

The right panel shows the results for portfolios formed by intra-industry price markup ratio (MP_PC) and MC_HHI. The high concentration portfolio seems to have lower expected return, which is consistent with Hou and Robinson (2006). However, the MC_HHI sorting portfolio seems to have ambiguous relations with book to market ratio and size. This result suggests that the industry level competition may not determine the firm level market power. Allocating all the firms with the same market concentration ratio in the same portfolio does not provide a good distinction on market power because the leaders, which have more ability to set prices, and the followers, which are price takers, will be assigned in the same portfolio. This further recommends the use of double-sorting across and within industry market competitiveness.

The difference in characteristics of these portfolios suggests that these firms are different in some characteristics which can also affect firms' risk. One way to control for these risks is through time-series regressions multi-factors model. Traditionally the CAPM has been used to evaluate the risk and mispricing of a firm (or portfolio). The β on the market premium in this model measures the systematic risk faced by a firm, and the α measure the mispricing. However, the model seems not to work very well.[18] To

[18]For example, Banz (1981) documents that NYSE small cap stocks earn higher average returns than predicted by the Sharpe-Lintner CAPM. Rosenberg, Reid, and Lanstein (1985) find that average returns of

respond to the failure on the CAPM and improve its performance, Fama and French (1993) further develop a multifactor model by using the market premium (mktrf), the premium on small minus large cap stock portfolios (SMB), and the premium on value minus growth stock portfolios (HML) to capture the cross-sectional differences in returns. This model has since been perceived as a benchmark on extending the CAPM, and HML and SMB are often included in regressions when testing mispricing. Recently, momentum factors, or the premium on winners minus losers portfolios (UMD), has also been included with HML and SMB to explain the returns of financial assets.

$$r_{p,t} - r_{ft} = \alpha_p + \beta_{1,p} mktrf_t + \beta_{2,p} HML_t + \beta_{3,p} SMB_t + \beta_{4,p} UMD_t + \epsilon_{p,t} \quad \text{(Equation 4.1.)}$$

$$p \in [\{-1, 0, 1\}, \{-1, 1\}]$$

$$\Delta r_t \equiv r_{1,t} - r_{-1,t} = \Delta\alpha + \Delta\beta_1 mktrf_t + \Delta\beta_2 HML_t + \Delta\beta_3 SMB_t + \Delta\beta_4 UMD_t + \epsilon_t$$

(Equation 4.2.)

$r_{p,t}$ is the return of portfolio p in time t and r_{ft} is the risk free rate at time t so the left hand side is the excess return of portfolio p in time t. The first element of p is the index for intra-industry price markup ratio, and the second element of p is the index for inter-industry market competition. The right hand side includes the four factors as described above. The second regressions are used to evaluate the difference in alphas ($\Delta\alpha$) and difference in betas ($\Delta\beta$) between portfolios. The main purpose of this regression is to test whether the hypotheses listed in the previous section affect firms' risk through the identified factors ($\Delta\beta$) or other channels ($\Delta\alpha$) which cannot be captured by market, value, size, and momentum premium.

U.S. stocks are positively correlated with the ratio of a firm's book value of common equity to its market value. Jegadeesh and Titman (1993) find that the zero cost portfolio of buying past winners and shorting past losers have positive alphas.

Table 7 shows the results from time series regressions of the four factor model. Regardless which industry market competition measure is used, the alpha of shorting the low intra-industry price markup portfolio and going long the high inter-industry price markup portfolio yield annualized returns of 2.2% to 10.8%, which are all economically and statistically significant. The significant alphas suggest that the risk induced by price markup ratio differences may not be simply captured by the market, value, size, and momentum premium. This result suggests that the price-markup ratio may represent not only the operating leverage, which should be captured by the coefficients on the HML as suggested by Novy-Marx (2011). For example, as noted in Novy-Marx(2011), the higher variable costs of firms with low price markup ratio may also provide flexibility of production, and therefore offset the risk of these firms. The difference on SMB between high and low price markup firms is also consistent with his theoretical model in which size can indirectly affect the impacts of book-to-market differences on the operating leverage. The same cannot be said for the portfolio formed by inter-industry measures. Almost all the differences in alphas are insignificant, and both the HHI and industry price markup ratio do not have impacts on the risk-adjusted returns. This is generally consistent with the findings from the previous section in which intra-industry market power is positively correlated with the expected return and the market concentration ratio has no significant impact after controlling for intra-industry differences. Moreover, the differences on alphas and coefficients on other risk premium between high and low industry market competition portfolios do not show a definite pattern. Even if we argue that the effects of operating leverage on the industry level should be absorbed by the value premium, we should expect to see a pattern on the differences on the coefficients of HML, which is not shown in the empirical results here.

Table 7: Time series regressions of portfolios formed by cross-industry market competition and within-industry market power

The portfolios are formed as in the previous table and each panel uses the portfolios formed in the corresponding panels in table 6. The result shows the time series regression results for the excess returns of each portfolio and the spreads between different portfolios by using the 4-factor model. The last column (row block) of each panel shows the differences in alphas and betas on various factors between high intra- (inter-) industry market power portfolios and low intra- (inter-) industry market power portfolios Panel A uses the industry level price markup ratio (HHI) as the industry level competition measure in the right (left) panel. Panel B uses the U.S. Census based CR4 as the industry level competition measure for robustness check. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively

Panel A: Risk adjusted returns for portfolio formed by industry-level market competition and intra-industry price markup (MP_PC) difference

	Within Industry (relative) Price Margin											Within Industry (relative) Price Margin							
MP_PC	L		M		H		H-L		MC_PC	MC_HHI	MP_PC	L		M		H		H-L	
									More										
Alpha	-0.0022		0.0003		0.0020	*	0.0041	***	Competition		Alpha	-0.0007		0.0011	**	0.0019	***	0.0027	**
Beta	1.1276	***	1.0735	***	1.0839	***	-0.0437				Beta	1.0562	***	1.0116	***	0.9847	***	-0.0715	***
HML	0.3375	***	0.0798	**	-0.0172		-0.3547	***	L	L	HML	0.2317	***	-0.1781	***	-0.0528	**	-0.2845	***
SMB	0.5591	***	0.2311	***	0.2557	***	-0.3034	***			SMB	0.4231	***	-0.0038		0.0305		-0.3926	***
UMD	-0.1287	***	-0.0289		-0.1079	***	0.0208				UMD	0.0197		0.0166		0.0355	**	0.0158	
									Industry-level										
Alpha	-0.0021	**	0.0011	***	0.0007		0.0028	***			Alpha	-0.0036	**	0.0008		0.0003		0.0038	**
Beta	1.0673	***	0.9762	***	0.9871	***	-0.0802	***			Beta	1.1093	***	0.9846	***	1.0536	***	-0.0556	
HML	0.3113	***	-0.2165	***	0.0031		-0.3081	***	H	H	HML	0.4244	***	-0.0824	***	0.0276		-0.3968	***
SMB	0.3654	***	-0.0977	***	-0.1050	***	-0.4704	***			SMB	0.3890	***	-0.0584	**	-0.0803	**	-0.4693	***
UMD	0.0730	***	-0.0004		0.0466	***	-0.0264		Less		UMD	0.0195		-0.0514	***	-0.0535	**	-0.0730	**
									Competition										
Alpha	0.0000		0.0008		-0.0012						Alpha	-0.0028	*	-0.0003		-0.0016			
Beta	-0.0603		-0.0973	***	-0.0967	***					Beta	0.0531		-0.0270		0.0689	**		
HML	-0.0262		-0.2963	***	0.0203				H-L	H-L	HML	0.1928	***	0.0957	**	0.0805	*		
SMB	-0.1937	***	-0.3288	***	-0.3607	***					SMB	-0.0341		-0.0546		-0.1108	***		
UMD	0.2017	***	0.0286		0.1545	***					UMD	-0.0002		-0.0680	***	-0.0890	***		

Panel B: Risk adjusted returns for portfolio formed by CR4 and intra-industry price markup difference (subsample for only manufacturing firms)

Within Industry (relative) Price Margin

CR4	MP_PC	Followers L		M		Leaders H		H-L	
More Competition	Alpha	0.0005		0.0004		0.0023	***	0.0018	*
	Beta	1.0265	***	1.0275	***	0.9871	***	-0.0388	
L	HML	0.0966	***	-0.0783	***	-0.1549	***	-0.2515	***
	SMB	0.4747	***	-0.0474	***	0.0579	***	-0.4169	***
	UMD	0.0702	***	0.0047		0.0009		-0.0693	**
Industry-level									
	Alpha	-0.0079	***	-0.0003		0.0006		0.0084	***
	Beta	1.2378	***	1.0442	***	1.1059	***	-0.1309	***
H	HML	0.4417	***	-0.0439		-0.1478	**	-0.5894	***
	SMB	0.7500	***	0.0827		0.1889	***	-0.5611	***
Less Competition	UMD	-0.0236		-0.0654		-0.1498	***	-0.1235	*
	Alpha	-0.0084	***	-0.0008		-0.0017			
	Beta	0.2108	***	0.0167		0.1187	***		
H-L	HML	0.3459	***	0.0343		0.0072			
	SMB	0.2753	***	0.1301	***	0.1311	*		
	UMD	-0.0965		-0.0700	*	-0.1507	***		

When the industry price markup ratio is used as a proxy of market competition, the relation between risk and industry price markup ratio is not monotonic. The middle portfolio seems to have different characteristics than the other two. As discussed before, inter-industry price markup ratio may proxy for not only the general profitability of the industry but also some other firm characteristics, such as the operating leverage. Because this measures may measure more than one factor which can determine the riskiness of the industries, the combined impacts can be complex and non-monotonic. The sample in Panel B contains only manufacturing firms and the concentration ratio is measured with more comprehensive sample, thus less affected by the above criticisms. In this sample, the coefficients on market premium, HML, and SMB suggest that firms with higher intra-industry price markup ratio are relatively large-growth firms with lower correlation with the market and with higher alphas. This result in alpha differences is more significant for more concentrated industries. This suggests that the industry level competition and intra-industry market power may jointly determine the risk of a firm.

Because the competitive environment of the industry may affect how price markup ratios related to the risk and returns, it is worthwhile to see whether the alpha is generated from high or low price markup portfolio under different industry competitions. Across all three proxies of industry competitions, the alphas are generated from the high price markup portfolio under high market competition and from the low price markup portfolio under low market competition. The findings under high market competition is consistent with the hypothesis that more competitive product markets usually result from lower barrier of entries and more standardized productions, and therefore, we should expect the firms which earn higher profits today may be riskier because this rent can easily be captured by outside and inside competitors. On the other hand, if industries are more concentrated, the leaders in those industries may possess unique production processes or has economic of scale so they can keep enjoying the monopoly rents, which are all difficult to be replicated by other competitors. Thus, we should expect the impact from the mean-reversion hypothesis by Fama and French(2000) is low under low competition market. As we can see, the positive price markup premium is mainly driven by the low price markup firms. This finding may be consistent with the mechanic introduced in Carlson, Dockner, Fisher, and Giammarino (2008). They argue that the option to adjust capacity held by the rival firms will reduce other firms' risk. The intuition is that when the industry demand goes up (down), the rising probability of the option exercise of expansion (contraction) will cause rival firms' value to not increase (decrease) as much as if there is no option. As a consequence, the rival firms' risk will be lower than expected.[19] The high price markup firms in a more concentrated industry should be the players in the industry which has more growth options to exercise, i.e., the sequential exercises of options should be more observable in the concentrated industries because the firms in these industries will be more different in the amount of the options held.[20] This can be demonstrated by the larger difference on the loadings on HML between high and low intra-industry price markup portfolios in the concentrated industries. Thus, we should expect that the low price markup firms in concentrated industries are less risky.

To conclude, the findings in this section suggests that in the industry level, even if the concentration ratios and price markup ratios are interpreted as the proxies for operating leverage, the impact from the difference in operating leverage do not show significant explanatory power on expected returns. Within each industry, the possible mean-reversion hypothesis and the mechanics introduced in Carlson, Dockner, Fisher, and Giammarino

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[19]This mechanic also work when both groups of firms have option of adjust capacity but they exercise option sequentially as suggested by Carlson, Dockner, Fisher, and Giammarino (2008).

[20]As suggested by Novy-Marx (2011), the loadings on HML may capture the relative weights on asset-in-place and growth options, as well as the relative risk of these two components.

(2008) can both drive the price markup premium. This result does not say that industry level competition is not important in determining the systematic risk of the firms. One possible explanation which has not been considered is that the impact of industry market competition may be conditional on economic states, as suggested by Aguerrevere (2009) and therefore cannot be observed unconditionally. I will test this hypothesis in later sections. First, I will provide some partial evidence on whether the observed intra-industry price markup premium is risk-related.

4.4. Is the Premium Risk-related?

Although it is always difficult to determine if an anomaly is risk-related, in this section I attempt to provide some evidence that the observed premium may reflect current and future economic conditions. Because there is no significant relation between industry level market competition proxies and expected returns, I will focus on the intra-industry price markup premium.

Table 8 shows the predictability of the intra-industry premium. I use the 3-month, 6-month, and 12-month leads to ensure there is no overlap on the independent variables. To argue a premium is risk-related, the premium must be correlated with expected future economic conditions and counter-cyclical. For each monthly premium observation in month t, the market premium for month t+3 and the nearest quarterly GDP growth rate data ending later than month t+5 is used in 3-month lead predictability regressions. For example, a premium observation of Feb 1990 will be matched with the market premium on May 1990 and quarterly GDP growth rate data ending Sept 1990. This mapping ensures that the premium is not used to predict the GDP growth rate including current month. The same matching criteria can be applied for 6-month and 12-month.

Table 8: Predictability for Economic Conditions of Intra-Industry Price Markup Spread

The MC_PC premium is defined as the average of the spreads between high and low intra-industry portfolios with high HHI and that with low HHI. In panel A (panel B), column (a), (b), and (c) have the 3-month, 6-month, and 12-month lead market premium (GDP growth rate) as the dependent variables and Intra-Pmkup premium as the independent variable. Column (d) and (e) use Intra-Pmkup premium as the dependent variables and future market premium (GDP growth) as independent variables, while column (e) controls for HML, SMB and UMD. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively

Panel A: Relation between Intra-Industry price markup premium and future market premium

Dependent variable	Market Premium						MP_PC Premium			
Lead	+3		+6		+12					
	(a)	t-stat	(b)	t-stat	(c)	t-stat	(d)	t-stat	(e)	t-stat
MP_PC premium	0.04465	0.65	-0.0361	-0.53	0.1449	2.07**				
HML									-0.1574	-4.02***
SMB									-0.4678	-13.28***
UMD									0.0543	1.99**
Mktrf+3							0.0187	0.65	-0.0169	-0.68
Mktrf+6							-0.0142	-0.50	-0.0102	-0.41
Mktrf+12							0.0572	2.06**	0.0537	2.24**

Panel B: Relation between Intra-Industry price markup premium and future GDP growth

Dependent variable	GDP Growth Rate						MP_PC Premium			
Lead	+3		+6		+12					
Independent variables	(a)	t-stat	(b)	t-stat	(c)	t-stat	(d)	t-stat	(e)	t-stat
MP_PC premium	-0.1604	-3.09***	-0.0809	-1.55	-0.0605	-1.15				
HML									-0.1498	-3.82***
SMB									-0.4572	-12.86***
UMD									0.0543	2.00**
GDPG+3							-0.1064	-2.76***	-0.0637	-1.90*
GDPG+6							-0.0249	-0.63	-0.0071	-0.21
GDPG+12							-0.0299	-0.79	-0.0146	-0.45

The regression results suggest that current intra-industry premium can be used to forecast 1 year market premium and 3 month GDP growth rate. The results in Panel B is especially useful because the GDP growth rate measures the supply side economic condition and the negative coefficients suggest that high premium in current period implies lower GDP growth rate in the near future. The effect is stronger for 3-month forecast, and the impacts become smaller for the GDP growth rate further into the future. [21] Again, these results suggest that the intra-industry premium is high when future economic prospects are unfavorable.

4.5. Summary

The evidence in this section suggests that product market structure does affect expected returns, and this impact may not be easily explained by any single hypothesis suggested by the current literature. Moreover, the industry level market competition and firm level market power may not have the same impact on the riskiness of firms. For the firms in the same industry, ones with higher price markup ratio have higher alphas and lower betas on the market premium, HML, SMB, and in some cases, UMD. These empirical results suggest that even if market power can affect firms' risk, the effects of operating leverage will be captured by the coefficients on HML, and the operating leverage hypothesis used in most real option models cannot be used to explain the significant alphas. The alphas from the time-series regression results suggest the impact of the intra-industry price margins are not related to the risk premium included in the four-factor model. The significant coefficients from the Fama-MacBeth method and positive alphas suggest that this impact cannot be explained by current asset pricing models. At the industry level, the

[21] To ensure the results are not driven by potential autoregressive process of GDP growth, I also test if the premium is correlated with current period GDP growth rate and the relation shows no significance.

insignificant result under different settings and tests suggest that no single hypothesis can dominate the relation between industry market competition and risk. The concentration of the industry, such as CR4 and HHI, may affect the expected returns but not directly or monotonically, which contradicts all the one-direction prediction arguments, such as Hou and Robinson (2006) and Schumpeter (1912, 1942). When analyzing the impact of intra-industry price markup ratio under industries with different levels of market competition, I find that the market competition may affect the risk indirectly through not only profitability but also other possible competitive behaviors, such as ones suggested in Carlson, Fisher, Dockner, and Giammarino (2008). No single theory by assuming insensitive cost functions can solely explain both the cross- and within- industry level competitiveness impacts because these theories ignore the possible impacts of other competitive behaviors, such as the different timing of the exercise of growth options on investments in industries with different degrees of competitiveness. In the next section, I will test Aguerrevere's (2009) conditional model that concerns these types of competition. It is possible that the market competition may affect firms' risk conditionally so we cannot easily detect this effect through the unconditional models used in this section.

CHAPTER V

CONDITIONAL BETA MODEL

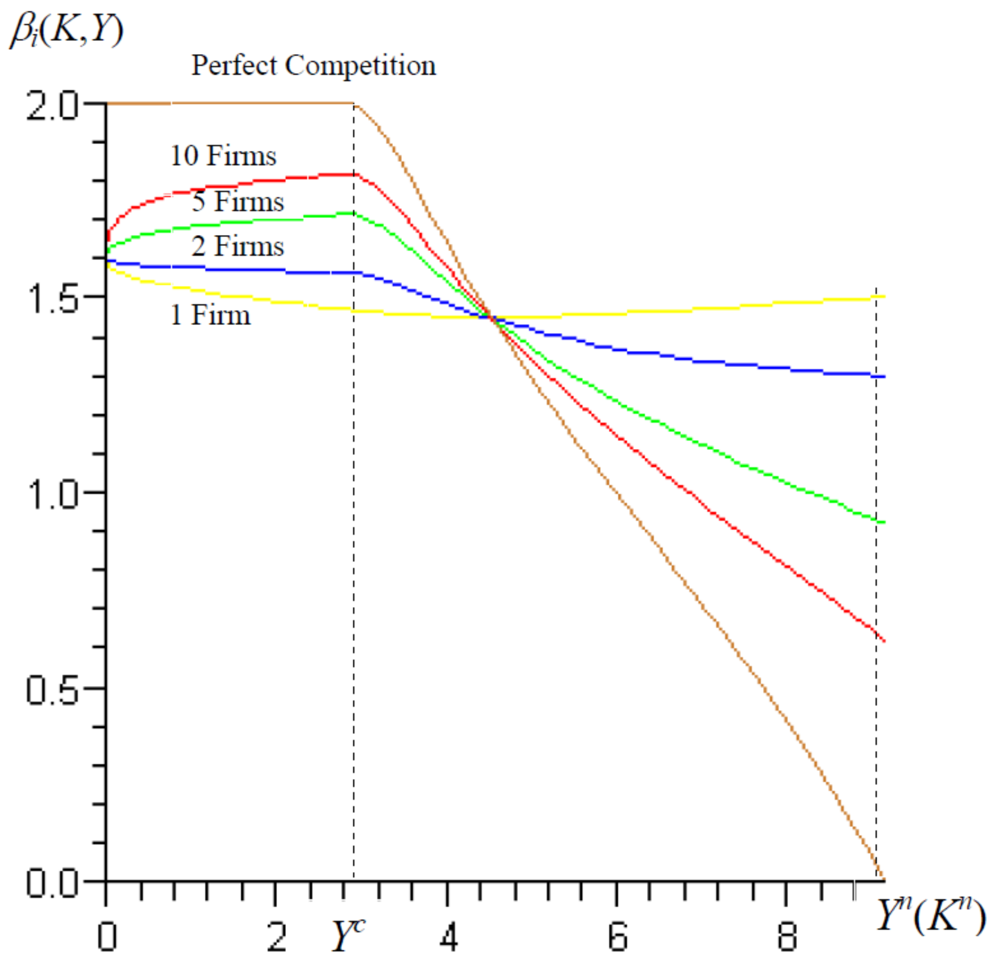
Although most of the theories suggest that higher market competition causes higher risk, previous sections show that unconditionally, the competitiveness of the industries do not have significant impacts on firms' systematic risks. While the results may suggest that competitions has no effect on firm's risk, it is also possible that market competition has different impacts on assets' betas in different periods, i.e., the beta changes differently between concentrated firms and competitive firms with general market conditions. In early sections, due to few observations and low power, I fail to find evidence that market conditions have any impact on the relation between market power and risk in Fama-MacBeth tests. In this section, I intend to use a more rigorous econometric model to test this hypothesis.

Aguerrevere (2009) theoretically predicts that the beta on the market premium can react differently to market conditions for concentrated firms and competitive firms. If the market premium and demands are both driven by the same underlying shocks, he shows that competitive firms will have higher beta during recessions, but lower beta during expansions. The intuition of this relation is as following. During recessions, firms in a competitive industry are more affected by the inflexibility of their fixed assets, and thus riskier in bad times. On the other hands, when the demand grows, the competitive firms have more incentives to exercise their growth options in fearing that the value of their growth options will drop due to option exercises by other competitors. As a consequence, firms in more concentrated industries have more risky growth options during expansion, and thus riskier in good times. The mechanics of this model suggests that during contraction periods, firms in more competitive industries are riskier because they have higher operating leverage, but during expansion periods, firms in more concentrated industries are riskier because they defer the exercise of growth options and therefore more exposed to the risk of these growth options. This argument implies that operating leverage may affect the relation between industry market competition and expected returns, but these effects are diluted by other competitive behaviors on investment decisions during the expansion periods.

Aguerrevere's (2009) predictions can be summarized in Figure 1(Figure 2 in his paper). I intend to test three predictions from his model. First, the market beta is higher for competitive firms during recession, but lower during expansion. This is the main prediction of his model. Second, because firms in more competitive industries will exercise their growth options when demand increases in fear of losing the value of these options to other competitors, firms in more concentrated industries have more growth options during expansions, and therefore should have higher loadings on HML during expansion. Third, when industry demand increases, the model shows that firms in more competitive industries should react more quickly in adjusting their capacities than firms in more concentrated industries. This sequential exercise of growth options suggest there is a lead-lag pattern between the investments in these two types of industries.

Figure 1: Theoretical predictions of Beta in different states

This figure is directly referred from Aguerrevere (2009). The Y-axis of the graph is the beta of the firm, and the X-axis of the graph is the level of demand.



To test if the coefficients on factors are conditional on economic states, the most common and intuitive way is to run OLS regression with dummy variables representing recessions periods as indicated by the NBER business cycle. I present the conditional results when OLS regressions with NBER recession dummies in Table 9.[1] Panel A shows the conditional test on the intra-industry price markup differences. As we can see, there is no definite conditional patterns on the intra-industry level. The more important test, according to Aguerrevere (2009), is whether the industry level competition can affect firms returns conditionally. The empirical result of this relation is shown in Panel B. The conditional pattern on market betas are consistent with the prediction by Aguerrevere. The lower coefficients of more concentrated industries under recessions are consistent with the operating leverage hypothesis. This result seems to suggest that although the impact of operating leverage caused by industry market competition may not show significant relation to the risk proxies unconditionally, this operating leverage effects may be important under recessions. As argued by Novy-Mark (2011), the operating leverage can affect the coefficients on HML and the magnitude of this coefficient measures not only the weights on assets-in-place but also the relative risk of asset-in-place to growth options. The operating leverage effects will make the high cost producers to be exposed to riskier assets-in-place, and the higher operating leverage, the higher the risk of assets-in-place.

[1]Note that the results in this table suffer the same problems as Table 3. The low numbers of contraction periods may cause the test to have low power.

Table 9: OLS estimation results of conditional model based on NBER business cycle

This table shows the conditional beta estimations based on NBER business cycle. Rec equals 1 when a month is included in the recession periods according to NBER, and 0 otherwise. All the independent variables, including intercept, in the 4-factor model are interacted with this Rec dummy. The estimations of intra-industry (inter-industry) spreads for both high and low inter-industry (intra-industry) firms are stated in the first and second columns in Panel A (Panel B), respectively. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively

Panel A: Conditional estimation of the spread between high and low within industry market power portfolios

	MC_HHI portfolios used in estimating within industry spread			
	High		Low	
	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.002	(1.43)	0.002*	(1.93)
Rec	0.007*	(1.93)	0.001	(0.38)
Mktrf	-0.054	(-1.41)	-0.081**	(-2.49)
Mktrf*Rec	0.239***	(3.21)	0.09	(1.42)
HML	0.038	(0.68)	-0.036	(-0.76)
HML*Rec	-0.273**	(-2.23)	-0.058	(-0.55)
SMB	-0.449***	(-9.49)	-0.539***	(-13.38)
SMB*Rec	-0.11	(-0.93)	0.137	(1.36)
UMD	0.02	(0.54)	0.081**	(2.57)
UMD*Rec	-0.069	(-0.81)	-0.059	(-0.81)

Panel B: Conditional estimation of the spread between high and low HHI portfolios

	MP_PC portfolios used in estimating cross industry spread			
	High		Low	
	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.002*	(-1.81)	-0.002	(-1.2)
Rec	0.008**	(2.49)	0.002	(0.48)
Mktrf	0.11***	(3.31)	0.083*	(1.89)
Mktrf*Rec	-0.134**	(-2.08)	-0.283***	(-3.32)
HML	0.13***	(2.68)	0.055	(0.87)
HML*Rec	-0.482***	(-4.55)	-0.267**	(-1.91)
SMB	0.089**	(2.17)	-0.001	(-0.02)
SMB*Rec	0.024	(0.24)	0.271**	(2.01)
UMD	-0.039	(-1.23)	0.022	(0.51)
UMD*Rec	0.005	(0.07)	0.015	(0.16)

As shown in the figure 1 of Aguerrevere's (2009) model, the asset-in-place of firms in competitive industries are especially risky during recessions. This may be the reason why we observe a large and significant coefficient on the interaction terms of recession dummy and HML. However, given the limited coverage of recessions in the NBER business cycle, the power of the results may be doubtful. To minimize this concern, I will also use a Markov regime switching model where the states are inferred from the data. In other words, under the regime switching model, a good state at the middle of the expansion may be different from a good state just before transitions to the bad states because the likelihood of transition for these two examples are different. This regime-switching model has been used in previous finance literature. For example, Perez-Quiros and Timmerman (2000) apply this econometric model to investigate whether size premiums change over the business cycle. Gulen, Xing, and Zhang (2008) also use this model to test if the value premium is conditional.

The specific Markov switching framework and maximum likelihood methods used in this paper follows Gray (1996) and Perez-Quiros and Timmermann (2000). To summarize the intuition of this econometric model, I allow the coefficients of the chosen asset pricing model and variance of residuals to differ between states. The probability of transition from one state to the other depends on measures of economic conditions. The likelihood for each period is then the weighted average of the likelihood calculated based on the models in each state. The sum over the log-likelihood value for each period will then provide the total likelihood function. I use the portfolios price markup and HHI sorted portfolio formed in previous section to test if these portfolios have different correlations with commonly accepted risk factors under different market conditions, but the focus will be mainly on the industry market competition because this is the dimension implied in Aguerrevere's (2009) Model.

For each zero-investment portfolio, the time series returns of the portfolios are defined as the differences of returns between two underlying portfolios. Let r_t denote the excess return of a testing portfolio and X_{t-1} be a vector of conditional variables, including intercept. The model used in these papers allows both the coefficient and variance of the model to depend on two states $S_t = 1, 2$ and the return of portfolio i can be formulated as:

$$r_t^i = \beta_{S_t}^i X_{t-1} + \epsilon_t, \epsilon_t^i \sim N(0, \sigma_{i,S_t}^2) \qquad \text{(Equation 5.1.)}$$

In this paper I choose to use the 4-factor model in testing the conditional beta model. Both Perez-Quiros and Timmermann (2000) and Gulen, Xing, and Zhang (2008) define risk factor variable vector X_t as one, lagged treasury bill rates, lagged default premium, lagged dividend yield of the market, and lagged monetary shock.[2] These variables are more commonly used in predicting aggregated market returns and the R-squares in these regressions are usually very small.[3] Thus, although these lagged macro-economic variables have been documented as determinants of market wide risk, these models are less constrained so the estimations may not be the global maximization given the low R-square. Moreover, it is not clear whether we should expect the alphas to be zero in these models or how large the coefficients should be. For example, if the coefficients on the money supply is 100, is this number plausible? Given the low constraints in these prediction regressions and the non-linearity of the regime-switching likelihood function, the obtained results are unlikely to be the global maximization and thus the relation found may not be correct. The more important reason to apply the 4-factor model is that Aguerrevere's (2009)

[2]The reasons for choosing these variables are stated in their papers.

[3]Because these variables are usually used to predict market returns, it also implies that the signs on these variables have to be consistent between states. It is not clear if these macro-variables measure the contemporary states of the economy or the future economy conditions and thus the transition of states may link the good states lagged variables to the observations in bad states.

theory suggests that firms in competitive and concentrated industries may have different combinations of asset-in-place and growth options and the risk of their asset-in-place may differ under different states. The loadings on the macroeconomic variables used in Perez-Quiros and Timmermann (2000) may not directly link to this relation.

Because the variance of returns during recessions are usually higher, I also allow the variance of the residuals to depend on one-month lagged treasury bill rate.

$$log(\sigma^2_{i,S_t}) = \lambda^i_{0,S_t} + \lambda^i_{1,S_t} TB_{t-1} \quad \text{(Equation 5.2.)}$$

The main regression has been set and now we need to define how the economy switches from one state to the other. Assume the state transition probability follows a first-order Markov chain, which means:

$$p_t = P(S_t = 1|S_t - 1 = 1, Y_{t-1}) = p(Y_{t-1}) \quad \text{(Equation 5.3.)}$$

$$1 - p_t = P(S_t = 2|S_t - 1 = 1, Y_{t-1}) = 1 - p(Y_{t-1})$$

$$q_t = P(S_t = 2|S_t - 1 = 2, Y_{t-1}) = q(Y_{t-1})$$

$$1 - q_t = P(S_t = 1|S_t - 1 = 2, Y_{t-1}) = 1 - q(Y_{t-1})$$

where Y_{t-1} is a vector of variables publicly known at time $t-1$ which affect the state transition between $t-1$ and t. Following Perez-Quiros and Timmermann (2000), I use the 2-month lagged composite leading index as the sole explanatory variable in Y. Therefore, for each portfolio i, the transition probability can be further defined as:

$$p^i_t = P(S^i_t = 1|S^i_t - 1 = 1, Y_{t-1}) = \Phi(\pi^i_0 + \pi^i_1 \Delta CLI_{t-2}) \quad \text{(Equation 5.4.)}$$

$$q_t^i = P(S_t^i = 2|S_t^i - 1 = 2, Y_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-2})$$

where ΔCLI_{t-2} is the two month lagged value of the year-on-year log-difference in the Composite leading index, S_t^i is the state variable and Φ is the cumulative density function of a standard normal distribution. This specification intends to capture investors' information on the expectation of the state changes of the future economy.

To perform the MLE method and estimate the parameters of the model, first the likelihood function needs to be defined. Let θ denote the vector of parameters entering the likelihood function for the model and assume that the density conditional on being in state j, $f(.)$ is Gaussian, the likelihood function can be defined as:

$$f(r_t|\Omega_{t-1}, S_t = j; \theta) = \frac{1}{\sqrt{2\pi\sigma_j^2}} exp\left(\frac{-(r_t - \beta_j X_{t-1})^2}{2\sigma_j^2}\right), j = \{1, 2\} \qquad \text{(Equation 5.5.)}$$

Ω_{t-1} denotes the information set that contains $X_{t-1}, r_{t-1}, Y_{t-1}$ and the lagged valued of these variables, i.e., Ω_{t-2}. The density for each time t will then be the state weighted density.

$$\phi(r_t|\Omega_{t-1}; \theta) = \sum_{j=1}^{2} f(r_t|\Omega_{t-1}, S_t = j; \theta) P(S_t = j|\Omega_{t=1}; \theta) \qquad \text{(Equation 5.6.)}$$

where $P(S_t = j|\Omega_{t=1}; \theta)$ is the conditional probability of state j at time t given information at $t - 1$. If we can get this conditional probability, we can get the log-likelihood function which takes the form:

$$\ell(r_t|\Omega_{t-1}; \theta) = \sum_{t=1}^{T} log(\phi(r_t|\Omega_{t-1}; \theta)) \qquad \text{(Equation 5.7.)}$$

The conditional probability of state j can be obtained recursively:

$$P(S_t = i|\Omega_{t=1};\theta) = \sum_{j=1}^{2} P(S_t = i|S_{t-1} = j, \Omega;\theta)P(S_{t-1} = j|\Omega_{t=1};\theta) \qquad \text{(Equation 5.8.)}$$

Note that the first term is the state transition probability, and the second term, conditional state probability, can be obtained by Bayes's rule:

$$P(S_{t-1} = j|\Omega_{t=1};\theta) = \frac{f(r_{t-1}|\Omega_{t-2}, S_{t-1} = j;\theta)P(S_{t-1} = j|\Omega_{t=2};\theta)}{\sum_{k=1}^{2} f(r_{t-1}|\Omega_{t-2}, S_{t-1} = k;\theta)P(S_{t-1} = k|\Omega_{t=2};\theta)} \qquad \text{(Equation 5.9.)}$$

Table 10 shows the estimation results from the model. I define a state as a good state if the probability of a state occurring is negatively correlated with NBER recession dummies.[4] Although there is no direct theoretical support on the conditional pattern at the intra-industry level, Panel A shows the conditional estimation of the spread formed by going short on low and long on high intra-industry price markup ratio portfolios for reference. The top row shows the spread formed between high and low intra-industry price markup ratio portfolios for the firms in high HHI industries, and the bottom row shows the spread for the firms in low HHI industries. For both rows, the spread has positive significant intercepts in good states, which is consistent with the result in the previous section. However, the intercepts are both higher but insignificant in bad states. This results provides weak evidence on the assertion that 4-factor model unconditionally misprice the return spreads between high and low intra-industry price markup portfolios. An interesting finding here is on the loading on HML. The spreads have negative loadings on HML in good states, but positive loadings in bad states. This finding suggests that firms with relative higher market power have more growth options (or less risky growth options) in good

[4]The correlation between the estimated probability of state occurred and NBER recession dummies are all significant, which suggests that the estimated states are correlated with general economic conditions.

times, but not in bad times. This result is against the operating leverage hypothesis which suggests that the assets-in-place of low price markup firms (high cost producers) are riskier especially during the low demand periods.

Table 10: Coefficients estimations from Markov regime-switching model for portfolio spreads

The MLE estimations results of the Markov regime-switching models for both intra-industry market power spread (Panel A) and inter-industry market competition spread (Panel B) are shown in this table. The estimations of intra-industry (inter-industry) spreads for both high and low inter-industry (intra-industry) firms are stated in the first and second rows in Panel A (Panel B), respectively. Panel C shows the market beta differences between good and bad states for concentrated firms and competitive firms. The left column uses only high intra-industry market power firms, and the right column uses only low intra-industry market power firms. Panel D shows the conditional results when past macroeconomic variables are used as the independent variables. TB states for the Treasury bill rate. DEF states for the default premium. M states for the money supply changes. DIV states for the market dividend yields. All these macro variables have been shown to have predictability power on expected returns and detail definition of these variables can be found in the main texts. The asymptomatically consistent standard errors are presented in parentheses.

Panel A: Conditional estimation of the spread between high and low within industry market power portfolios

State			Good					Bad		
Coefficient	Intercept	Mktrf	hml	smb	umd	Intercept	mktrf	hml	smb	umd
MC_HHI										
High	0.004***	0.009	-0.257***	-0.47***	0.006	0.006	0.155	0.918***	0.058	-0.084
	(3.14)	(0.31)	(-5.61)	(-11.79)	(0.18)	(0.72)	(1.02)	(4.47)	(0.32)	(-0.66)
Low	0.002***	-0.017	-0.263***	-0.482***	0.037	0.007	-0.22*	0.349***	-0.414***	0.000
	(2.59)	(-0.76)	(-7.24)	(-14.59)	(1.28)	(1.1)	(-1.83)	(2.38)	(-3.35)	(0.01)

Panel B: Conditional estimation of the spread between high and low HHI portfolios

State			Good					Bad		
Coefficient	Intercept	Mktrf	hml	smb	umd	Intercept	mktrf	hml	smb	umd
MP_PC										
High	0.000	0.125***	-0.166***	0.133***	0.029	-0.008**	-0.075	0.268***	0.133	-0.036
	(0.31)	(4.79)	(-3.65)	(3.65)	(1.00)	(-2.24)	(-0.93)	(2.57)	(1.47)	(-0.60)
Low	-0.002	0.081***	-0.138***	0.127***	0.118***	-0.005	0.057	0.146	0.013	-0.074
	(-1.54)	(2.61)	(-2.86)	(2.57)	(3.29)	(-1.49)	(0.77)	(1.33)	(0.13)	(-1.11)

Panel C: Conditional estimation of market beta for the spread between high and low HHI portfolios

MC_HHI	State	MP_PC	
		High	Low
High	Good	1.068	1.075
	Bad	1.086	1.059
	Difference	-0.018	0.016
Low	Good	0.962	0.995
	Bad	1.118	1.356
	Difference	-0.156	-0.362

Panel D: Conditional estimation of the spread between high and low HHI portfolios (macro variables)

State	Good					Bad				
Coefficient	Intercept	TB	DEF	M	DIV	Intercept	TB	DEF	M	DIV
MP_PC										
High	-0.088*	5.726	6.338***	-0.782***	0.772	-0.001	-0.654	0.547*	0.098	-0.090
	(-1.93)	(0.81)	(3.21)	(-2.84)	(0.96)	(-0.34)	(-0.98)	(1.88)	(0.80)	(-0.57)
Low	-0.020	-9.119**	5.633*	-0.607	0.351	-0.004	-0.176	0.291	0.173	-0.036
	(-0.60)	(-2.06)	(1.95)	(-1.41)	(0.51)	(-0.94)	(-0.23)	(0.83)	(1.06)	(-0.18)

Panel B shows the conditional estimation of the spreads formed by going short on low and long on high HHI portfolios for both high and low intra-industry price markup firms and make direct empirical evidence to Aguerrevere's (2009) model. The conditional patterns are mainly driven by the differences between high and low concentration portfolios during the good times. The high concentrated industries tend to have higher betas on the market portfolios during the good times, and are no different from competitive industries during the bad times. It appears that firms in more concentrated industries are riskier in the good times because the growth options of these firms will be exercised later, which can also be demonstrated from the negative loadings on the HML. If the operating leverage is less important during the good times because all the firms may enjoy higher profits in general, the relative risk of asset-in-place should not be too different as well. Therefore, the loadings on the HML may capture more on the relative weights on growth options and assets in place rather than the relative riskiness of these two components.[5]

During the bad state, most of the results are not significant except the positive coefficient on the HML between high intra-industry price markup firms. This finding is again against the operating leverage hypothesis in which firms in more competitive industries should have higher operating leverage during recessions. This raise the doubt whether the industry level competition does determine the operating leverage of the industries. In fact, the results in Table 2, 5, and 6 also suggest that the relation between market concentration ratios and operating leverage, as measured by fixed assets to total

[5]If firms have contraction options, competitive firms will be more reluctant to exercise these options in fearing of the benefits from production reductions may be shared by other competitors. This explanation is also consistent with the conditional pattern here. However, the interpretation may violate the general believe of irreversibility assumptions.

assets, are mostly insignificant. This suggests that operating leverage may not be the primary reasons that drives the risk of the firms at the industry level.[6]

Aguerrevere's (2009) model explicitly predicts that the competition of the industries may affect systematic risk through the market beta. Therefore, it is worthwhile to test whether this conditional pattern holds when only market premium is included as the dependent variable. The conditional result is also confirmed when the CAPM is used. Although not reported here, the difference in market betas between firms in competitive and concentrated industries is 0.183 (with t-stat=7.82) in good times and -0.257 (with t-state=-3.08) in bad times for the high intra-industry price markup firms.[7] The effects are stronger for firms with higher intra-industry market power, which suggest that the theories may be more applicable to comparing the leaders between concentrated and competitive industries. This finding is intuitive at least. The competition faced by followers in more concentrated industries and followers in more competitive industries may be more similar and less consistent with the theoretical prediction, in which all the firms in the industries are identical and therefore provide no theoretical prediction on the impacts of intra-industry market power differences. The statistical significance for the coefficients in bad states are lower, reflecting the fact that the general economy experiences recession with lower probability.

Panel C shows the difference in market beta between two states. The tables shows the market beta estimations for four portfolios, not the spreads, with difference level of inter- and intra- industry market power measures. The results shows that for both high and low intra-industry price markup firms, the beta for firms in more competitive industries are

[6]Note that even without the operating leverage during the bad times, the competitive behaviors during the good times in Aguerrevere's (2009) model can still produce a conditional beta model.

[7]The estimation conditional market beta differences for the low intra-industry price markup firms are similar to the results in Panel B.

more different between good and bad states (-0.156 and -0.362). This is consistent with the prediction that firms in more concentrated industries have more consistent betas because the lower risk caused by high demand will be offset by the higher risk caused by more growth options.

Panel D shows the estimation results when macro economic variables are used as the dependent variables. The specifications used here follows Perez-Quiros and Timmermann (2000) and Gulen, Xing, and Zhang (2008).[8] I define the risk factor variables $X_t = [1, TB_t, DEF_t, M_{t-1}, DIV_t]$. TB is the lagged value of the one-month Treasury bill rate. A negative shock to real economic growth may lead to an increase in current and expected inflation, and in turn increase the Treasury bill rate. Moreover, the Federal Reserve usually lowers short-term interest rate to counter the recessions. Therefore, interest rates and stock returns should be negatively correlated. The default spread, or DEF, and aggregated dividend yield, or DIV, are both commonly used to proxy for risk factors. DEF is defined as the difference between yields on Baa and Aaa rated corporate bonds. Empirical macroeconomics literature shows that the default spread is one of the strongest forecasters of the business cycle and is positively correlated with stock returns. DIV is defined as total dividends on the stocks in CRSP over the prior 12 months divided by the total market cap. The dividend yield captures mean reversion in expected stock returns because a higher dividend yield means that dividends are discounted at a higher rate. However, the predictive power of this variable has diminished in recent literatures. M is the growth in the money stock and is defined as the 12-month log difference in the monetary base reported by the Federal Reserve Bank in St. Louis. It measures the monetary policy shocks as well as the liquidity changes in the economy and is negatively correlated with stock returns.

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[8]The large literature which covers the predictability of macro economic variables on stock returns can be found in these two papers.

The results in Panel D show that firms in more concentrated industries are more correlated with the past macro economic variables that have previously been documented to predict expected returns. The signs on these macroeconomic variables are generally consistent with the expected signs listed in the previous paragraph. This suggests that firms in more concentrated industries are riskier in good times. The estimations for the coefficients during bad times are generally insignificant, which again implies that the operating leverage effects may not be as large as previously thought. These results confirm the finding that risk between firms in high and low concentration ratio industries may be conditional on economic states, and this conditional patterns are mainly driven by the impact in good states. In other words, the main force which drives the conditional patterns in risk may be the change in investment decisions, rather than the differences in operating leverage.

Although the results in the regime-switching models do not provide consistent evidence on the operating leverage effects, the results are generally consistent with Aguerrevere's(2009) model. The early exercise of growth options for firms in competitive industries make these firms less risky in good times, i.e., the competitive behavior on the supply side, which captured by the exercise of growth options, may be one force which drives the conditional pattern in beta. This may be the reason why the differences in risk between high and low HHI portfolios occur mainly in good states. In the next section, I will provide further evidence on this sequential exercise of options to support these mechanics. The empirical results shown in this section provide the first direct evidence on the mechanics of Aguerrevere's (2009) model. Although Hoberg and Phillips (2010) find that systematic risk decreases for the competitive firms after high industry valuations period and argue that this relation is consistent with Aguerrevere's model, their empirical evidence suggest that the industry demand "leads" the changes in systematic risk, rather than being contemporaneous. The findings in this section provide more direct empirical evidence on Aguerrevere's conditional model.

5.1. Lead-lag Pattern in Option Exercises

Although the conditional result in the previous table suggests that the growth options, as measured by the loadings on the HML, react differently to the state of the economy between firms in competitive industries and concentrated industries, it is not clear that the sensitivity to the HML factor can accurately be used as a proxy for growth options. The more direct evidence on the exercise of growth options should be reflected by increases in capital investments. In this section, I measure investment on fixed assets and check if the results are consistent with Aguerrevere's (2009) prediction.

The essence of Aguerrevere's(2009) model suggests that firms in a more competitive industry would have incentives to exercise growth options earlier when facing high demand because the increase in demand would be shared by all firms in the same industry, and the cost of early exercise (compared to firms in more concentrated industry) would also be borne by all the peers. This argument implies that when the state of the economy changes, firms in more competitive industries will choose to invest earlier than those in more concentrated industries. Therefore, I will test if the investment of the firms in more competitive industries leads the investment of the firms in more concentrated industries.

Table 11 shows the estimates of the vector autoregressive process with exogenous regressors models (VARX). The dependent variables are a vector with two elements, proxies of growth option changes for high HHI firms (concentrated industries) and for low HHI firms (competitive industries). The right hand side variables are the lagged dependent variables and other controls. The idea is to test if there is cross correlation between the investment behaviors between firms in these two types of industries. Here I use two proxies for the change in growth options. First is the percentage change in the book to market ratio, and second is the ratio of capital expenditure to fixed assets(net PPE). Although the book to market ratio may capture something other than the change in growth options, this ratio has been commonly used to represent the degree of future growth opportunities. The second proxy is also used by Cao, Simin, and Zhao (2008) and may be more suitable in the context here.[9] The change of growth option may be affected by other firm and industry characteristics, or even the state of the economy. However, what we are interested in is whether the firms in competitive industries exercise their growth option, or invest in the fixed assets, earlier than firms in concentrated industries. Although this measure may not fully capture all the growth options held by the firms, it does directly reflect the exercise of the growth options.

[9]Some of the other measures for growth options suggested by Cao, Simin, and Zhao(2008) and Anderson and Garcia-Feijoo (2006) are either not applicable in my situation because the growth options need to be fluctuate with economy state and these measures need prior several years, which may be in the different states, to obtain the measures of growth options, or have some outliers which may severely affect the empirical result.

Table 11: Relation between changes in growth option in concentrated and competitive industry

This table shows the VARX estimation results on whether firms in more competitive industries (right columns) exercise their growth options earlier than firms in more concentrated industries (left columns). Panel A and B use the vector of change in the book to market ratio for high and low HHI portfolio as the depend variables. Panel C and D use the vector of capital expenditure to net PPE ratio as the dependent variables for the same two portfolios. The estimated results include the coefficients on control variables and autoregressive terms. For the control variables, NBERexpD is a dummy variable which equals one when the year contain only expansion month according to NBER, and 0 other wise. SG states for the sales growth rate. FATA is the fixed to total asset ratio. The time marks inside the parenthesis determine if the variable is measured contemporary or lagged with 1 to 3 years. *, **, and *** represents the estimations are significant at 10%, 5%, and 1%, respectively

		Concentrated Industry (H)		Competitive Industry (L)	
RHS variables	LHS variables	Coefficient	t-stat	Coefficient	t-stat
Panel A: VARX(3,0) with the dependent variables average book-to-market ratio					
BM growth	Intercept	-0.142	-0.41	-0.091	-0.32
(BMgrowth)	NBERexpD(t)	-0.149	-1.66	-0.168	-2.44 **
	SG(t)	1.624	2.41 **	1.757	2.91 ***
	ROE(t)	-0.347	-0.64	-0.271	-0.40
	FATA(t)	0.111	0.19	0.010	0.02
	BMgrowthH(t-1)	-0.031	-0.06	0.300	0.80
	BMgrowthL(t-1)	-0.172	-0.30	-0.536	-1.23
	BMgrowthH(t-2)	0.337	0.65	0.622	1.68
	BMgrowthL(t-2)	-0.601	-1.04	-0.945	-2.23 **
	BMgrowthH(t-3)	0.134	0.28	0.410	1.13
	BMgrowthL(t-3)	-0.232	-0.40	-0.495	-1.14
Panel B: VARX(1,0) with the dependent variables average book-to-market ratio					
BM growth	Intercept	-0.077	-0.26	-0.090	-0.36
	NBERexpD(t)	-0.169	-2.08 **	-0.184	-2.72 **
	SG(t)	1.692	3.01 ***	1.584	2.77 ***
	ROE(t)	-0.394	-0.81	-0.425	-0.64
	FATA(t)	0.011	0.02	0.082	0.20
	BMgrowthH(t-1)	-0.238	-0.55	-0.021	-0.06
	BMgrowthL(t-1)	0.106	0.22	-0.135	-0.34
Panel C: VARX(1,0) with the dependent variables average capital expenditure to net PPE					
CAP/NPPE	Intercept	0.082	1.51	0.081	1.94 *
(CAPN)	NBERexpD(t)	0.002	0.22	0.001	0.09
	BM(t)	-0.006	-0.37	-0.004	-0.28
	SG(t)	0.153	2.20 **	0.223	3.84 ***
	ROE(t)	0.058	0.77	0.075	0.79
	FATA(t)	0.014	0.25	-0.060	-1.45
	CAPNH(t-1)	0.171	0.88	0.074	0.55
	CAPNL(t-1)	0.400	2.23 **	0.585	4.56 ***
Panel D: VARX(1,1) with the dependent variables average capital expenditure to net PPE					
CAP/NPPE	Intercept	0.151	2.49 **	0.071	1.55
	NBERexpD(t)	-0.011	-1.01	-0.002	-0.26
	BM(t)	0.006	0.31	0.024	1.25
	SG(t)	0.061	0.55	0.007	0.06
	ROE(t)	-0.039	-0.43	0.276	2.36 **
	FATA(t)	-0.092	-0.48	-0.182	-0.88
	NBERexpD(t-1)	0.011	1.11	0.020	2.37 **
	BM(t-1)	-0.031	-1.52	-0.029	-1.66
	SG(t-1)	-0.133	-1.47	-0.068	-0.92
	ROE(t-1)	0.294	3.46 ***	-0.051	-0.48
	FATA(t-1)	0.076	0.40	0.133	0.65
	CAPNH(t-1)	0.140	0.73	0.093	0.66
	CAPNL(t-1)	0.352	2.11 **	0.644	4.53 ***

Panel A and B shows the estimated results when the changes in the book to market ratio are used as the dependent variables with different lags. The results from both panels are not consistent with Aguerrevere's (2009) prediction. Almost all the autoregressive terms show no significance. The growth rate on the book-to-market ratio from high and low HHI portfolios are positively related to the current economic state (NBERexpD) and negatively related to the current sales growth rate (SG). It is clear that when the economy is expanding, the aggregated stock market should also perform well. As a consequence, the book to market ratio will fall even given no change on firms' behaviors. This problem exists because we estimated the model in the time-series. Therefore, although the results in this part are not consistent with the prediction, the inconsistency is likely caused by the different conditional means of the book to market growth rate.

The lead and lag pattern can be observed when capital expenditures are used as the dependent variables. I report only the one year lagged result because the coefficients on the second and third years are all insignificant when 3 years of lags are used. Panel C uses the lagged dependent variables and contemporary control variables. Both the investments of firms in high and low HHI industries are led by the investments of firms in low HHI industries(in competitive industries). This result is consistent with the model prediction, in which firms in competitive industries exercise their growth option earlier than firms in concentrated industries. Panel D provides more evidences consistent with the prediction. In panel D, I lag also the control variables. The main lead and lag pattern is almost unchanged. Furthermore, the investment of firms in concentrated industries are positively correlated with the 1 year lagged ROE, and the investment of firms in competitive industries are positively correlated with the contemporary ROE. This result implies that firms in more concentrated industries will delay their investment when the firms have higher earnings, which may be caused by the high industry demand. On the other hand, firms in more competitive industries react quickly when there is excess demand. The lead and lag pattern on the investment behaviors and different reaction time of these two types of firms provide indirect evidence supporting Aguerrevere's (2009) model.

5.2. Conditional Beta Model on Industry-wide and Economy-wide State Variables

Although Aguerrevere (2009) argues that the market beta will depend on the economic states, he does not specify which state should be used in his model. In fact, he assumes that the market return (premium) and industry demand is perfectly correlated, which seems to be nonrealistic. In this section I test if the industry level state variables provide extra explanatory power in the conditional relation between market beta and market competition as a robustness check.[10]

The problem to test the industry level conditional model is that we can no longer use the portfolio forming approach to test the conditional model, i.e., the model used in the previous section will no longer be applicable here. At any given moment, some industries with high competition may be enjoying an expansion period, but others with the same degree of market competition may suffer from low industry demand. This fact makes regime-switching model used in previous section not applicable and raises difficulties to identify this industry level conditional relation. The difference between industry- and economy- wide state variables can be simply demonstrated in Table 12.

[10]The definitions of the industry demand conditions may not be perfect and will suffer the same problem as using NBER business cycle state variables because the states are determined but not chosen by the model.

Table 12: Correlation between industry-wide and economy-wide business cycle indicators

For each year, two variables for economy-wide and industry-wide are set and the correlations between any of the two variables are presented in this table. The first two variables measure the economy-wide business conditions and the remaining two measure the industry-wide business conditions.
In the economy level, GDPgD is formed by first computing the yearly GDP growth rate from Bureau of Economic Analysis. Next, I subtract the bench market GDP growth rate from the GDP growth for each year to get the "abnormal" GDP growth rate. The variable GDPgD then takes value 1 when the abnormal GDP growth rate is greater than 0, and value 0 otherwise. ExpD for each year takes value 0 if there exists any contraction month according to the NBER business cycle during that year, and value 1 otherwise.
In the industry level, Prop SalesGrowth (Prop ROE) measures the percentage of industries in a given year is in relative high sales growth rate (ROE) period. For each year, the value weighted sales growth rates (ROE) for each 4-digit industry are calculated and the difference between the sales growth rate (ROE) and the time-series mean sales growth rate (ROE) of that industry are defined as the "abnormal" sales growth rate (ROE). Prop SalesGrowth (Prop ROE) takes value 1 if the abnormal sales growth rate is greater than 0 and 0 otherwise. *** denote the coefficient is significant (at 1%).

Level	Variables	GDPgD	ExpD	Prop SalesGrowth	Prop ROE
Economy	GDPgD	1	0.6233***	0.2055	-0.128
Economy	ExpD		1	0.0476	-0.2918
Industry	Prop SalesGrowth			1	0.481***
Industry	Prop ROE				1

Table 12 shows the correlation between economy-wide and industry-wide state variables. Two variables of each category are included in this table. GDPgD represents the dummy variable which takes value 1 if the economy is in a relatively high GDP growth period, and 0 otherwise. ExpD for each year takes value 0 if there exists any contraction month according to the NBER business cycle during that year, and value 1 otherwise. The industry level demand proxies include two variables: sales growth rate and return on equity (ROE). Prop SalesGrowth and Prop ROE measures the percentage of industries in (time-series) relatively high industry demand period in any given year. As shown in the table, two economy (or industry) wide state variables are highly correlated with each other, but the correlation between industry and economy wide state variables is low and insignificant. This result is consistent with the prediction that industries do not always have high demand at the same time, and the economy-wide expansion periods can be generated by some but not all the industries in the whole economy.

To test if the market beta is conditionally affected by the market competition, first we need to estimate the market beta of each industry. Here I use the weekly returns to estimate the yearly market beta for each industry. I calculate the weekly returns by multiplying the value weighted industry daily returns from Thursday to Wednesday to avoid the possible seasonal effect on weekdays, such as the Monday effect.[11] The estimated industry betas for any given year will be included in the final sample only if they pass the following two criteria: First, there are at least 20 weekly returns for the industry in that year, and second, there are at least five firms in the industry in that year. The first criterion is to ensure there is enough degrees of freedom when estimating the beta. The second criterion is to minimize the high HHI and volatile industry level variable driven by few firms in the industry and

[11]Defining a week as Wednesday to Tuesday does not change the result.

at the same time, to minimize the idiosyncratic risk which can affect the standard errors of the coefficients.

The difference between the estimated yearly beta of any industry and its time-series mean of the beta is then defined as the standardized industry beta (SBETA). The standardized industry betas are then regressed on market competition proxies and interaction terms on state variables. Two economy wide state variables, GDPgD and ExpD, and two industry wide variables, dummy variables on standardized sales growth rate (ID_S) and ROE (ID_E) are used to estimate the conditional relation. The industry level market competition is measured by two variables, HHI (MC_HHI) and industry price markup ratio (MC_PC).[12] The final sample of this panel data includes 6885 industry-year observations, which means approximately 150 industries are included in my sample for each year on average. In general, we test the following regression:

$$SBETA = \alpha + \beta_1 MC + \beta_2 MC * (\text{Economy or Industry wide variables}) + \text{other variables}$$

(Equation 5.10.)

If the beta is affected conditionally by the market competition as predicted by Aguerrevere (2009), we will expect a positive and significant β_2 in this equation. The results of the pooled regression are shown in Table 13.

[12]Detailed definitions of these variables can be seen in Table 12 and 13.

Table 13: Pooled (conditional) regression between industry beta and market competition

Four sets of yearly variables are used in evaluating the conditional relation between market beta and market competition.

1. Standardized industry beta (SBETA): For each year, the weekly returns of each industry are calculated and are regressed on the weekly market premium. The difference between the yearly beta of any industry and its time-series mean of the beta is the defined as the standardized industry beta.
2. Market competition (MC): two market competition measures are used: HHI (MC_HHI) and sale weighted average industry price markup ratio (MC_PC).
3. Industry-wide state(demand) variables (ID): standardized sales weighted sales growth rate (ID_S) and ROE (ID_E) are used in measuring industry demand. The dummy variable ID_SD (ID_ED) takes value if ID_S (ID_E) is greater than 0, 0 otherwise.
4. Economy-wide state variables: two yearly measures of economy states, GDPgD and ExpD, as defined in the previous table are used here.

The dependent variable industry beta is then matched with the ID, MC and economy state variables by year and 4-digit sic. The results of the pooled regression between industry beta and other variables are shown in this table. *, **, *** denote the significance level at 10%, 5%, and 1%, respectively.

RHS variables	Coefficient	Standard Error		Coefficient	Standard Error		Coefficient	Standard Error		Coefficient	Standard Error	
Panel A: Conditional on economy-wide state variables												
Intercept	0.015	0.009	*	0.015	0.009	*	0.000	0.007		0.000	0.008	
MC_HHI	-0.109	0.034	***	-0.044	0.038							
MC_PC							-0.017	0.055		0.030	0.067	
GDPgD*MC_HHI	0.083	0.031	***									
GDPgD*MC_PC							0.030	0.053				
ExpD*MC_HHI				-0.021	0.035							
ExpD*MC_PC										-0.032	0.063	
Panel B: Conditional on industry-wide state variables												
Intercept	0.015	0.009	*	0.016	0.009	*	-0.001	0.008		0.000	0.008	
MC_HHI	-0.157	0.032	***	-0.096	0.034	***						
MC_PC							-0.150	0.048	***	-0.120	0.051	***
ID_SD*MC_HHI	0.204	0.031	***									
ID_SD*MC_PC							0.320	0.051	***			
ID_ED*MC_HHI				0.058	0.031	*						
ID_ED*MC_PC										0.217	0.051	***

Panel C: Conditional on industry-wide state variables, controlling for industry sales growth rate

Intercept	0.016	0.008	*	0.016	0.009	*	0.002	0.008		0.001	0.008	
ID_S	0.220	0.039	***				0.228	0.039	***			
ID_E				0.104	0.040	***				0.078	0.039	**
MC_HHI	-0.103	0.033	***	-0.079	0.035	**						
MC_PC							-0.080	0.050		-0.113	0.051	**
ID_SD*MC_HHI	0.090	0.037	**									
ID_SD*MC_PC							0.130	0.060	**	-0.190	0.053	***
ID_ED*MC_HHI				0.028	0.033							
ID_ED*MC_PC												

Panel D: Conditional on economy- and industry-wide state variables, controlling for industry sales growth rate

Intercept	0.015	0.008	*	0.002	0.008		0.016	0.009	*	0.002	0.008	
ID_S	0.217	0.039	***	0.229	0.039	***	0.222	0.039	***	0.229	0.039	***
MC_HHI	-0.139	0.037	***				-0.078	0.042	*			
MC_PC				-0.076	0.061					-0.054	0.072	
ID_SD*MC_HHI	0.087	0.037	**				0.089	0.037	**			
ID_SD*MC_PC				0.130	0.060	**				0.129	0.060	**
GDPgD*MC_HHI	0.060	0.031	*									
GDPgD*MC_PC				-0.004	0.052							
ExpD*MC_HHI							-0.034	0.035				
ExpD*MC_PC										-0.030	0.062	

Panel A of Table 13 shows the conditional pattern on economy wide state variables, and panel B and C shows the conditional pattern on industry wide state variables. The coefficients on MC_HHI or MC_PC (β_1) are usually significantly negative. This finding is consistent with the predication that competitive industries are riskier than concentrated industries during the low demand period. In the four different settings used in panel A, only the first one has a positive and significant coefficient on the interaction term. On the other hand, both industry state variables seem to work as predicted by Aguerrevere (2009)'s model. The results generally don't change qualitatively when including the industry sales growth rate and ROE as control variables. This observation does not change when both economy- and industry- wide variables are included in the regression as shown in Panel D.[13] The results in Table 13 show that industry-level states seem to be more important than economy-wide states. This finding is reasonable. As argued in Aguerrevere (2009), the conditional pattern is driven by the competitive behavior on investment when the industry demand varies. Thus, the main force of the conditional relation should be explained more by the individual industry's demand curve rather than the economy as a whole.

Although it seems that less competitive industries (higher value in MC) have higher beta when industry demands are high and the market competition seems to affect the market beta conditionally, the result is not fully consistent with the theoretical model. The sum of β_1 and β_2, which represents the relation between market competitions and market betas during the high industry demand periods, is not always positive. Therefore, the more concentrated industries are not always riskier during the high demand period. Combining with the observation that the coefficients on MC (β_1) are usually significantly negative, there seems to be an industry level competitive premium if there exists enough low demand periods to estimate the effect.

[13] I include only four specifications in Panel D. The other four specifications have qualitatively similar results.

Note that I use pooled regressions instead of standard panel data models such as fixed effects models in this section. I choose the pooled regressions based on two reasons. First, there will be higher collinearity if time and industry fixed effects are included in the model. For example, because market competition measures, especially the HHI, don't vary much over several years, MC can be highly correlated with the industry specific dummy variables. Second, the composition and characteristic of the industries can change dramatically in more than 40 years. Thus, assigning the same fixed effect for each industry may actually lower the explanatory power of the model.

CHAPTER VI

CONCLUSION

During the development of asset pricing theory, many studies focus on determining which firm characteristics affect the systematic risks of firms. The value premium and size premium are both products of this research. However, to better understand why these characteristics affect firms' risks, we must understand how the future cash flows of firms react to demand or supply shocks, or to general economic conditions. The competition faced by firms can certainly affect demand or production functions, and therefore, may affect the relation between firm characteristics and expected returns. The previous literature on how market competition affects firms' risk or expected returns has been discussed. This paper provides some new and direct empirical evidence on the relation between market competition and expected returns, and at the same time, points out some unaddressed issues in the current theoretical and empirical work in this line of research.

In this paper, I use price markup ratios, or the Lerner Indexes, and industry concentration ratios as two proxies for the product market positions of firms. This double sorting has not been done by previous studies in evaluating the relation between product market competition and expected returns, and results in this paper show that market power across and within industries may indeed play different roles in determining firms' returns. I find that firms with higher price markup ratios have higher expected returns, and this relation is especially significant within industries. This is consistent with the profitability hypothesis and risk induced by other competitive behaviors on the supply side, such as the option to expand or contract capacities. The concentration ratios, however, have less direct impact on the expected returns of firms. The previous findings by Hou and Robinson (2006) that there is a negative relation between concentration ratios and expected returns may be misleading because either there are many forces that drive the relation between industry-level market competition and expected returns of these industries, or the impact of market competition is conditional on economy states. The results from the conditional models suggest that market competition may affect expected returns only conditionally as predicted by Aguerrevere's (2009) model. The competitiveness of industries may affect firms' behaviors in their project selections under different economic states, and as a consequence, affect the risk of the firm in a dynamic pattern.

The evidence documented in this paper suggests that the relation between competition faced by a firm and the risk faced by a firm can be complicated, and the intra- and inter- industry level market structure may jointly affect the riskiness of firms. A more sophisticated model that includes both inter- and intra- industry market competition may be needed to further explain all the findings in this paper.

APPENDIX

DEFINITIONS OF VARIABLES

BM: book to market ratio. This variable is defined as the book value of the equity, defined as stockholders' equity plus deferred tax, at year t-1 divided by the market cap in December at year t-1.

Ind_BM: the value weighted average of the book to market ratio of firms in the same industry.

Intra_BM: the difference between Ln(BM) and Ln(Ind_BM).

FA_TA: Operating leverage, defined as the gross PPE divided by the total asset.

Ind_FA_TA: asset weighted average of the operating leverage of firms in the same industry.

Intra_FA_TA: the difference between Ln(FA_TA) and Ln(Ind_FA_TA).

MC_HHI: Herfindahl-Hirschman Index, defined as the squared sum of the fractions of industry sales by the firms in the same industry with the same 4-digit SIC code using the data from Compustat.

PMKUP: the price mark up ratio, defined as the operating income before depreciation and amortization divided by the sales.

MC_PC: sales weighted average of the price markup ratio of firms in the same industry.

MP_PC: defined as the difference between firm price markup ratio and industry markup ratio divided by the difference between the highest and lowest price markup ratio in the same industry.

PC_RANGE: The range of PMKUP for a given year-industry pair.

Size: market cap, defined as the shares outstanding times trading price in June at year t.

Ind_Size: the sum of the market caps of firms in the same industry.

Prop(size): firm size divided by Ind_size.

ENTRY: Changes in numbers of firms in a given industry.

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