On the Interaction between Firm Level Variables, the CAPM Beta, and Stock Returns

Thesis by

Laura Panattoni

In Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy

California Institute of Technology

Pasadena, California

2009

(Defended August 28th, 2008)

For my family, Beth, Gina, and John Panattoni

Acknowledgements

Many people have guided and supported me on the road to my PhD. I cannot thank Bruce Lehmann, my advisor, enough for the many tireless hours he spent discussing my research with me. Bruce has an astounding knowledge of finance, and time and time again his advice cut to the core intuition of the problem at hand. Bruce patiently weeded out the worst of my ideas, and guided me through the field of empirical finance. I am also profoundly grateful to John Ledyard and Preston McAfee, two of my committee members. John provided direction, suppport, and funding when my moral was down. Preston guided my very first research paper, Chapter 1 in this thesis, and taught me much about the economic theory of "a firm".

Many others in the Department of Humanities and Social Sciences at Caltech provided much appreciated feedback and suggestions on various aspects of this thesis. I would like to thank David Grether, Michael Alvarez, Jonathan Katz, and Stuart McDonald for their help with practical econometrics; Jaksa Cvitanic for his advice on finance, and Laurent Mathevet, Matias Iaryczower, Kim Border, and Federico Echenique for their theoretical suggestions. Maggie McConnell taught me much of what I know about Stata. Also, this paper would never have been completed without the tireless and efficient help of Laurel Auchampaugh, the graduate secretary.

My undergraduate advisor at Duke University, Enrique Mendoza, inspired my original interest in economics and pushed me into graduate school. I am grateful for all his efforts and mentoring.

Finally I would like to thank my parents and sister for their loving support and encouragement throughout my time in graduate school. I could not have done this without them.

Abstract

In Chapter 1, I conduct a theoretical study of how horizontal industry concentration affects a firm's market capitalization and systematic risk. I first develop a method for incorporating an equilibrium theory of the firm, drawn from industrial organization, into a single period version of the Capital Asset Pricing Model (CAPM). This extension establishes the microeconomic determinants of systematic risk by relating firm specific variables to Beta. Unlike the previous literature, I add local product market shocks to a general, deterministic profit function and use an orthogonal decomposition of the market return to endogenize the $\mathrm{Cov}[R_i, R_M]$. I also use this method with standard Hotelling and Cournot models of firm behavior and with different sources of uncertainty to provide examples of how increasing concentration can increase, decrease, and be independent of Beta. In Chapter 2, I exploit a natural experiment afforded by the announcement of 'Paragraph IV' patent infringement decisions. These judgments have two unique features. They create an exogenous change in industry concentration, since they determine whether the corporate owner of a brand name prescription drug will maintain or lose monopoly marketing rights. They also satisfy the methodological requirements to use a short window event study. Against a backdrop of contradictory empirical evidence, this experiment provides a clean test to empirically determine the sign of how a change in horizontal industry concentration affects stock returns. For a sample of 38 District Court decisions between 1992 and 2006, I find that the announcement return is between [1.24%, 2.83%] if the brand firm 'wins' the case and between [-5.24%, -5.82%] if the brand 'loses'. Finally, I use these returns to construct the first market valuation of the monopoly rents for brand name pharmaceutical firms. I find that the value to a brand firm of maintaining marketing exclusivity for 1 'average' drug for 92 months is between [6.48%, 8.65%]. In Chapter 3, I explore the cross-sectional determinants of Beta. The two main goals of this exercise is to understand the explanatory power of popular asset pricing variables and firm level variables, such as the coefficient of variation of profit.

The estimation relies on a minimum distance approach that reduces to the familiar least squares estimators. This approach permits the estimation of a dataset where the number of cross sectional observations is larger than the number of time period and accounts for the measurement error in Beta. I use two different sets of variables where one is weighted by assets, referred to as 'Book' variables and the other is weighted by market capitalization, referred to as 'Market' variables. I include two robust checks, one of which includes adding industry fixed effects. I find some striking results with respect to both the two asset pricing variables and the coefficient of variation of profit proxy. Since my statistics are pooled over different time periods, I cite the statistics from the 2001 subperiod because it has three times as many observations as the rest of the periods combined. Turnover has the largest magnitude and t-statistics in both sets of regressions. In 2001, the means of Beta_A and Beta were .94 and 1.2 respectively. I found that a one standard deviation change in turnover increased the magnitude of Beta_A by .22 and Beta by .25. The bid ask spread percentage had a larger magnitude coefficient in the 'Market Regressions', which indicated that a one standard deviation change in this variable increased Beta by .08. On the other hand, I found that ln(assets), ln(size), and book-to-market had the smallest magnitudes and t-statistics. Finally, both regressions indicate that as the proxy for the coefficient of variation of profit variable increases (decreases) for firms with a positive (negative) expected profit, Beta increases. For the 2001 subperiod in the 'Market' regressions, a one standard deviation change in the absolute value of this proxy, increases Beta by a magnitude of .1 and .15 for firms with positive and negative 'earnings'. Finally, these results are robust to industry fixed effects.

Contents

List of Tables

Chapter 1

Industry Concentration, Systematic Risk, and a Micro-Foundation for the CAPM

1.1 Introduction

Asset pricing models have been developed, somewhat myopically, with little reference to the product market and therefore to industrial organization. The best known asset pricing models base their predictions on variations in investor preferences, behavioral biases in financial markets, or each asset's covariance with a market portfolio. Remarkably, these models disregard how economic fundamentals in the product market, such as firm specific or industry wide characteristics, may affect financial equilibria. Fama [17] acknowledged this omission when he advocated that researchers should either relate the behavior of expected returns to "the real economy in a rather detailed way" [p1610] or establish that no such relationship exists.

The Capital Asset Pricing Model (CAPM) provides an excellent example of an equilibrium financial model in which asset prices are derived independent of the 'real economy'. The CAPM's main insight is that an asset's expected excess return is determined by its covariance with a market or aggregate portfolio. The covariance is included in an assets's Beta term, which within the capital budgeting framework, may be interpreted as a risk adjusted discount rate. While the CAPM relates a firm's Beta term[1] to its expected return, the model provides no relationship between a firm's profits and its Beta term. Therefore, the model cannot predict which type of firm strategies, types of competition, or industry

[1] For the rest of this chapter, I only consider assets which derive their underlying value from a firm.

characteristics create more systematic risk. In terms of capital budgeting, there is no way to update the risk adjusted discount rate in response to product market changes.

In this chapter, I conduct a theoretical investigation of how industry concentration[2] affects a firm's market capitalization and systematic risk within the CAPM framework. I first incorporate an equilibrium theory of firm behavior into the CAPM. This extended version of the CAPM can combine models of both perfect and imperfect industry competition with a competitive model of security pricing. Therefore, I contribute to the emerging theoretical literature establishing a micro-foundation for asset pricing models.[3] I then use this extension of the CAPM with two standard models of firm behavior, the Hotelling model and the Cournot model, to test the effects of concentration.[4] These examples illustrate how product market factors, such as different types of firm competition or different sources of uncertainty, influence the way in which concentration affects financial outcomes.

Although firm level variables, such as risky cash flows and the capital structure, have been related to the CAPM since the early 1970's, (Rubinstein [55]), the literature incorporating an equilibrium theory firm behavior into the CAPM has been sparse. Subrahmanyam and Thomadakis [58] used a quantity choosing model of firm behavior and the Lerner Index to coincidentally study the effect of industry concentration. They found that for a given capital labor ratio, decreasing concentration increased systematic risk. Bhattacharyya and Leach [6] applied the CAPM valuation formula to firm profit and found conditions under which Beta is independent of the quantity chosen. Kazumori [36] used the consumption CAPM and the idea of consumption risk, the cost of switching products if the product fails, to find that increasing market share increased systematic risk. As an increasingly asymmetric distribution of market shares also represents increased concentration, Kazumori's results

[2]Because there are many different measures of horizontal industry concentration, this chapter uses the number of firms as a proxy.

[3]The current literature establishing a micro foundation for other asset pricing mostly focuses on real option models. Berk, Green, and Naik [4], who along with Gomes, Kogan, and Zhang [23], Kogan [38], Zhang [63], Carlson, Giammarino, and Fisher [11], and Cooper [12] use real options models to relate various firm characteristics, such as size, investment irreversibility, and book-to-market ratio, to systematic risk. Options models are based on an absence of arbitrage arguments, and they only look at a single asset. In contrast, the CAPM is multi-security equilibrium model. Irvine and Pontiff [33] create a simple model linking a firm's fundamental cash flow volatility to stock returns through a present discounted value argument. However, these arguments require the risk adjusted discount rate to be independent of the firm's actions since there is no mechanism to endogenize the discount rate. This is not an issue in the CAPM's equilibrium environment.

[4]These two models were chosen because the first is a standard price choosing model with the addition of product differentiation and the second is a standard quantity choosing model. I use these well established models so that outcomes from the financial model cannot be attributed to a pathological formulation of firm behavior.

contradicts the sign of the results found by Subrahmanyam and Thomadakis.

The literature in this field can be compared according to two salient features of the models. The first feature is the structure of uncertainty. In their one period model, Subrahmanyam and Thomadakis [58] use an additive shock to the demand function and to the labor supply. Bhattacharyya and Leach [6] use state probability pricing. Finally, Kazumori [36] uses a continuous time stochastic calculus framework with shocks to consumption at each period. The structure of uncertainty in these papers makes it difficult to study the effect of a different parameter on systematic risk, add uncertainty to a different parameter, or change the character of firm competition within the framework of these models.[5]

On the other hand, I add local product market shocks to a general profit function which provides a more general framework. Product market shocks are simply a shock added to any primitive of a profit function, such as costs or consumer preferences. This method characterizes the effect of a small amount of uncertainty by linearly approximating a random profit function. Many deterministic models from industrial organization can easily be used within this framework. Therefore, unlike the previous literature, my method is not dependent on the exact model of firm behavior or which parameters are shocked.

The second salient feature of the literature is the way the $\mathrm{Cov}[R_i, R_M]$, or more generally, β_i, is endogenized.[6] Let μ be the Sharpe Ratio and let π_i be firm i's random cash flow. Lustgarten and Thomadakis [44] found $\beta_i = \frac{\mathrm{Cov}[\pi_i, \sum_{j=1}^N \pi_j]}{\mathrm{Var}[\sum_{j=1}^N \pi_j]} \frac{\sum_{k=1}^N (E[\pi_k] - \mu \mathrm{Cov}[\pi_k, \sum_{j=1}^N \pi_j])}{E[\pi_i] - \mu \mathrm{Cov}[\pi_i, \sum_{j=1}^N \pi_j]}$. Bhattacharyya and Leach [6] derived $\beta_i = \frac{\mu \mathrm{Cov}[\pi_i, R_M]}{E[\pi_i] - \mu \mathrm{Cov}[\pi_i, R_M]} \frac{R_f}{E[R_M] - R_f}$. Kazumori [36] used the standard consumption $\beta_i = \frac{\sigma_{R_i(t)} \sigma_e(t)}{\sigma_e(t) \sigma_e(t)}$ which is the covariance between a security's return and aggregate consumption divided by the variance of aggregate consumption. To examine how systematic risk changes with concentration, these authors had to determine how these complicated formulations of β_i were affected.

In contrast, I orthogonally decompose the market return to rewrite the $\mathrm{Cov}[R_i, R_M]$ more tractably in terms of the standard deviation of firm i's profit. The exogenous market return is decomposed into the covariance between the product market risk and the market return multiplied by the product market risk plus another random variable that is uncorrelated with the product market risk. Then the $\mathrm{Cov}[R_i, R_M]$ can be expressed roughly as

[5] Kazumori [36] provides the most extreme example. By assuming that the dominant firm always increases its price mark-up, he finds a Markov perfect equilibria in which agents want to purchase more from the firm with the largest market share and this dominant firm always increases its market share.

[6] R_i is the return for firm i's share, R_M is the return for the market, and $\beta_i = \mathrm{Cov}[R_i, R_M]/\mathrm{Var}[R_M]$.

the covariance between the product market shock and the market return multiplied by the standard deviation of firm i's profit. Not only is this the first time that the $\text{Cov}[R_i, R_M]$ has been expressed in terms of the standard deviation of a firm's profit but this formulation adds a considerable amount of tractability. To determine how the $\text{Cov}[R_i, R_M]$ changes with some parameters, such as concentration, I only need to understand how the parameter affects the standard deviation of a firm's profit because the covariance between the market return and the product market shock is exogenous. Finally, I am also the first to write the share price in terms of the expectation and standard deviation of firm i's profit.

I chose to study industry concentration because aside from the above two conflicting theoretical results, the previous work on industry concentration has been contradictory and mostly empirical. The empirical work supports the three contradictory conclusions that increasing industry concentration decreases, increases, and does not affect a stock's expected returns. In support of the first conclusion, Hou and Robinson [31] estimate that firms in the quintile of the most competitive industries have returns nearly four percent greater than firms in the most concentrated quintile.[7] These authors argue that competitive industries are riskier because they are more likely to face change from innovation, Schumpeter's creative destruction, and that they are more sensitive to demand shocks due to lower barriers to entry. However, they do not provide a formal model that links these arguments to their econometric work, and they do not look at share prices.

In contrast, Lustgarten and Thomadakis [44] and Melicher, Rush, and Winn [48] support the other two conclusions. Lustgarten and Thomadakis found that announced changes in a firm's accounting earnings led to a greater change in the market capitalization in more concentrated industries. If future prices are treated as exogenous, this weakly implies that the stock returns increased with concentration. Finally, Melicher, Rush, and Winn look at 495 manufacturing firms and find that industry concentration has no effect on a stock return.

Using the Hotelling and the Cournot model, this chapter will provide theoretical examples of how the standard deviation of profit, the market capitalization, and the expected return approximately change with N when there are different sources of uncertainty. First, the standard deviation of profit decreases in N except in the case of a Cournot firm is facing

[7]This additional rate of return is considerable, because Mehra and Prescott [47] estimated the equity premium to be roughly six percent.

a shock to costs. The market capitalization always decreases in N for sufficiently small shocks. Finally, the expected return either increases in or is independent of N, except in the case of a Hotelling firm with a relatively large market share facing a shock to the intensity of product differentiation. The expected return increases in N when firms face shocks to costs, when a Hotelling firm with a relatively small market share is facing a shock to the intensity of product differentiation, and when a Cournot firm is facing a shock to the slope of the demand function. The expected return is independent of N when the shock simply rescales the profit function, when there is a monopoly, and when there are perfectly competitive firms.

This chapter will be divided into three main sections. The first section will incorporate an equilibrium theory of the firm from industrial organization into CAPM. The second section will use the Hotelling model of firm behavior to study how industry concentration affects a firm's market capitalization and systematic risk. Finally, the third section uses a Cournot and competitive model to study how industry concentration affects these financial outcomes.

1.2 The Model

Firm i has a C^2 profit function of the form, $\pi_i(\tau_i, N, X)$. τ_i is an exogenous collection of firm and industry characteristics, such as a firm's cost function or the amount of product differentiation in the industry. The term, N, is also an exogenous parameter. To study the effect of industry concentration, N is the number of firms in the industry. However, the theory is general enough for N to represent any firm characteristic. Finally, there is an exogenous local random shock, X, to any of the elements in τ_i. This will be known as the product market risk. Depending on which element in τ_i is affected, the shock can be understood as either a firm specific or an industry wide shock.

There are two sets of exogenous random variables, the product market shock, X, and the market rate of return, R_M. The market return is an unknown function of the product market shock, which means that X and R_M have an exogenous covariance. For example, if X is a shock to the price of oil, then the model takes the covariance of oil with the market return as given. Because I am combining a competitive model of the security market, in which firms are price takers, with an imperfect model of industry competition, I assume that a firm is non-infinitesimal relative to an industry, but it is infinitesimal relative to the market. Therefore, I assume that firm behavior in the product market does not affect the market return.

This is a one-period model with the shocks to profit occurring in the middle of the period. At the beginning of the period, one share of each firm is sold at price p_o^i. The price is derived from the financial market's belief about the expectation and standard deviation of the firm's profit at the end of the period. Before the shock is realized, the profit function is deterministic. Next, the product market shock and the market return are realised. Firms have perfect knowledge of the product market shock and its affect on the other firms. Therefore, this is a model of perfect information. Firms then play a game and re optimize their profits, unconcerned about how their actions affect the financial market. Next, profits are realized. At the end of the period, all profit is returned to the shareholders as dividends and the stock becomes worthless.

Conceptually, this models argues that at the beginning of the period, investors know what the firm's profit is, they know what elements in τ_i will be shocked, and they know the expectation and the standard deviation of the product market shock. They also know what the covariance between the product market shock and the market return is. Similar to the orignanl CAPM assumption, they all agree on this knowledge. Since investors do not know what the realization of the shock will be, they do no know what profit will be at the end of the period. Therefore, they use the expectation and standard deviation of firm profit, among the other factors, to determine the equilibrium stock prices and expected returns.

My method for adding local random shocks to profit is based on Pratt (1964)'s first order approach to characterizing the effect of a small amount of uncertainty on utility functions. However, I characterize the effect of a small amount of product market risk on firm profit. Profit is a function of k independent shocks. The shocks are represented by the variables, $X_1, ..., X_k$, where each X_k is a random variable with $E[X_k] = X_0$ and $\mathrm{Var}[X_k] = \nu_k^2$. Let X be the vector of shocks. Local shocks add uncertainty without any assumption about the exact distributions of the random variables. For example, if the future price of oil is uncertain, then investors price shares based on their expectation and standard deviation of the price of oil. However, this method only results in approximations which become more accurate with smaller shocks.

Profit at the end of the period is approximated by a Taylor series with respect to X at the point $X = X_0$. Similar to Pratt, I use a two term Taylor Series where I ignore all terms with X^s s.t. $s \geq 2$. Throughout this model, I will ignore any terms that arise with X^s st. $s \geq 2$. The Taylor Series approximation is

$$\pi_i(\tau_i, N, X) \approx \pi_i(., X_0) + \sum_{l=1}^{k} (X_l - X_0) \left[\frac{d\pi_i(.)}{dX_l} \right]_{X_l = X_0}.$$

For future ease, I will use the following notation even though it obscures the fact that all derivatives in this equation are taken with respect to X_l and then the X_1 is set to its mean of X_0 within these functions.

$$\pi_i(\tau_i, N, X) \approx \pi_i(., X_0) + \sum_{l=1}^{k} (X_l - X_0)\, \pi_i'(., X_0). \tag{1.1}$$

The profit function evaluated at $X = X_0$ is simply profit at the beginning of the period and it is deterministic. The derivatives of profit evaluated at $X = X_0$ are also deterministic and can be understood as functions of the primitives of profit at the beginning of the period. Therefore, the Taylor Series approximation estimates a firm's profit at the end of the period by profit at the beginning of the period plus product market risk multiplied by roughly how profit changes with that risk.

A Taylor Series Approximation yields simple formulations of the expectation and standard deviation of profit. They are

$$E_X[\pi_i(\tau_i, N, X)] \approx E_X \left[\pi_i(., X_0) + \sum_{l=1}^{k} (X_l - X_0)\, \pi_i'(., 0) \right] = \pi_i(., X_0) \tag{1.2}$$

$$SD_X[\pi_i(\tau_i, N, X)] \approx \sqrt{\sum_{l=1}^{k} \nu_l^2 \left[\frac{d\pi_i(.)}{dX_l} \right]^2_{X = X_0}} = \sqrt{\sum_{l=1}^{k} \nu_l^2 \pi_i'(., 0)^2}. \tag{1.3}$$

The derivation of equation (1.3) is given in full in Claim (i) of the Appendix. The standard deviation of profit is roughly the sum of the product market risks multiplied by how profit changes with each risk. The trade-off between the expectation and the standard deviation of profit, and how this changes with respect to N drives the results in this model.

So far, I have discussed characteristics of a firm's profit without any mention of a financial market. In the CAPM equilibrium, all stocks must lie on the security market line, which represents the financial market. Let $\mu \equiv {\sigma_M}^{-1}(E[R_M] - R_f)$ be the Sharpe Ratio, which is a dimensionless measure of the reward for a unit of market risk. The standard CAPM valuation formula for any cash flow $E_X[\pi(\tau_i, N, X)]$ is

$$ {p_o}^i = \frac{1}{R_f}\Big(E_X[\pi_i(\tau_i, N, X)] - \mu \mathrm{Cov}[\pi_i(\tau_i, N, X), R_M]\Big). \tag{1.4} $$

Clearly, the valuation formula can provide a direct link between the financial market and an equilibrium outcome of firm behavior. However, to understand how Beta changes with N, I need to overcome the endogeneity problem $\mathrm{Cov}[\pi_i(\tau_i, N, X)/{p_o}^i, R_M]$.

To endogenize the covariance, I first construct two orthogonal decompositions of R_M. The first decomposition is for the simpler case of one product market shock, X_1. The other more complicated decomposition is for the case of k independent shocks, $X_1, ..., X_k$. In the former case, I can use the standard orthogonal projection formula to decompose the market return into

$$ R_M = \theta_1 X_1 + Y_1, $$

where $\theta_1 = \mathrm{Cov}[R_M, X_1]/\mathrm{Var}[X_1]$, and Y_1 is the part of R_M uncorrelated with X_1. If X_1 is an oil shock, then θ_1 captures how the price of oil moves with the market return. When there are k shocks, the market return is decomposed into

$$ R_M = \theta_k \sum_{i=1}^{k} \frac{X_i}{\nu_i} + Y_k, $$

where $\theta_k = \mathrm{Cov}[\sum_{l=1}^{k} \frac{X_l}{\nu_l}, R_M]/\mathrm{Var}[\sum_{l=1}^{k} \frac{X_l}{\nu_l}]$. Weighting each shock by its standard deviation greatly assists future tractability.

I then calculate the covariance using the appropriate orthogonal decomposition of R_M and the approximation of profit given in equation (1.1). Without loss of generality, let $[d\pi(.)/dX_l]_{X_l=X_0} \geq 0 \; \forall l = 1, ..., k$. In the case of one product market shock,

$$ \mathrm{Cov}[\pi_i(\tau_i, N, X_1), R_M] \approx \frac{\mathrm{Cov}[X_1, R_M]}{SD[X_1]} SD_{X_1}[\pi_i(\tau_i, N, X_1)]. \tag{1.5} $$

See Claim (ii) in the Appendix. Conceptually, this model argues that the covariance between firm profit and the market return can be approximated by the way the product market shock moves with the market return times how the firm is affected by the product market shock. This approximation overcomes the endogeneity problem because the fraction is only a function of exogenous random variables and the standard deviation of profit depends on the exogenous parameters, τ_i, N, and X_1.

In the case of k independent product market shocks, the covariance approximation is more complicated and depends on two assumptions. The first assumption is that Cov$[X_l, Y]$ $= 0$, $\forall l = 1, ..., k$. For tractability I assume that the $[d\pi(.)/dX_l]_{X_l=X_0}$ are pairwise scalar multiples. Conceptually, this requires the shocks to affect the profit function in a fairly similar way. The resulting covariance is

$$\text{Cov}[\pi_i(.,X), R_M] \approx \left[\frac{\text{Cov}[\sum_{l=1}^{k}\frac{X_l}{\nu_l}, R_M]}{\text{Var}[\sum_{l=1}^{k}\frac{X_l}{\nu_l}]}\right]\left[\frac{\sum_{l=1}^{k}\sqrt{\nu_l^2\eta_l^2}}{\sqrt{\sum_{l=1}^{k}\nu_l^2\eta_l^2}}\right] SD_X[\pi_i(.,X)]. \tag{1.6}$$

See Claim (iii) in the Appendix. In this case, the covariance between firm profit and the market return can be approximated by the standard deviation of profit times two fractions. The first fraction captures how the market return moves with the product market shocks and the second fraction re-weighs how much the profit function is affected by each shock. Once again, these two fractions are completely exogenous to the model.

Next, I rewrite the equilibrium share price in (1.4) using the appropriate covariance. Let ρ be a constant which equals the exogenous terms in the above covariances. Therefore,

$$\rho = \begin{cases} \frac{\text{Cov}[X_l, R_M]}{SD[X_l]} & \text{if } l = 1 \\ \left[\frac{\text{Cov}[\sum_{l=1}^{k}\frac{X_l}{\nu_l}, R_M]}{\text{Var}[\sum_{l=1}^{k}\frac{X_l}{\nu_l}]}\right]\left[\frac{\sum_{l=1}^{k}\sqrt{\nu_l^2\eta_l^2}}{\sqrt{\sum_{l=1}^{k}\nu_l^2\eta_l^2}}\right] & \text{if } l \text{ finite and } l \text{ independent.} \end{cases} \tag{1.7}$$

The top ρ applies in the case of one product market shock and the bottom ρ in the case of a finite number of independent shocks. The new share price is

$${p_o}^i = \frac{1}{R_f}\Big(E_X[\pi_i(\tau_i, N, X)] - \mu\rho SD_X[\pi_i(\tau_i, N, X)]\Big). \tag{1.8}$$

This is the first time the CAPM valuation formula has been expressed in terms of the expectation and standard deviation of the risky cash flow. This formula argues that security pricing is determined by a trade off between the expectation and a weighted version of the standard deviation of firm profit, where the weights are determined by the reward for holding market risk, μ, and roughly how the product market risk co-varies with the market return, ρ.

I can now determine how the equilibrium share price and the expected return change with the number of firms in the industry. The derivative of the share price is

$$\frac{dp_o^i}{dN} = \frac{1}{R_f}\left[\frac{dE_X[\pi_i(\tau_i, N, X)]}{dN} - \mu\rho\frac{dSD_X[\pi_i(\tau_i, N, X)]}{dN}\right]. \tag{1.9}$$

Once again, because ρ is exogenously determined, it is independent of N. The behavior of this is determined by how the trade off between the expectation and the standard deviation of profit is affected by N. The derivative of the expected return is

$$\frac{dE[R^i]}{dN} = \frac{\rho\mu}{R_f\,(p_o^i)^2}\left[E_X[\pi(.)]\frac{dSD_X[\pi(.)]}{dN} - SD_X[\pi(.)]\frac{dE_X[\pi(.)]}{dN}\right]. \tag{1.10}$$

I show the derivation in Claim (iv) of the Appendix. This derivative is written in terms of two distinct groups of terms. The first group is a fraction of only financial variables and the second group, in the bracketed term, solely captures the product market effects. The only role the financial variables have in equation (1.10) is to provide an exogenously determined positive or a negative weight to the bracketed term. Therefore, understanding how N affects the expected return reduces to determining the net result of the product market effects.

An interesting way to interpret these product market effects is to multiply (1.10) by the fraction $E_X[\pi(.)]^2/E_X[\pi(.)]^2$. This allows the derivative to be rewritten as

$$\frac{dE[R^i]}{dN} \approx \frac{\rho\mu E_X[\pi(.)]^2}{R_f\,(p_o^i)^2}\frac{d}{dN}\left[\frac{SD_X[\pi_i(., N, X)]}{E_X[\pi_i(., N, X)]}\right]. \tag{1.11}$$

The sign of the first fraction is determined by ρ. The ratio of the standard deviation to the expectation of profit can be considered as a measure of firm risk where a risker firm has more uncertainty per unit of expected profit. This measure of firm risk fits works well with the mean variance framework of the CAPM. A share's expected return increases in N when the standard deviation per unit of expected profit increases in N. Therefore, equation (1.11) captures the intuition that riskier investments have higher expected returns.

To study how industry concentration affects share prices and expected returns, I need to specify how the profit function depends on X and N. I will now use the two theories of the firm from industrial organization with this extended version of the CAPM.

1.3 Hotelling Model

In this section, I test the effect of concentration when firm behavior is represented by the Hotelling circular city model.[8] In this extension of the CAPM, firms have perfect information about the realization of the product market shock. Based on this knowledge, the firms simultaneously choose prices to maximize profits.

In the basic set up, N firms are located symmetrically around a circle of circumference 1. The circle represents a unidimensional space of product differentiation and each firm's location indicates the characteristic of its product. The number of firms is determined exogenously and after an entry or exit, the firms reestablish a symmetric distance from each other. For simplicity, N will be treated as a continuous variable. In this model, profit is always weakly decreasing in N.[9]

Demand in this market is represented by a continuum of consumers around the circle with a uniform density of m. Let $t \geq 0$ be the linear disutility of consuming the wrong product. All firms will face the same t. In equilibrium, for $t > 0$, consumers located close to a firm (and therefore consuming close to their ideal one) pay higher prices and consumers located further away tend to pay lower ones.

The profit function in this model is determined by the convention that each firm only directly competes with its immediate neighbors. Each firm is still affected by the number of firms in the market, but only indirectly through the distance between each firm. Let c_i be each firm's constant marginal cost. In this study, I will only examine the cases where each firm still earns weakly positive profits after the shock and after the change in N. Therefore, firm i's profit is $\pi_i(\tau_i, N, X)$ where $\tau_i = \{c_i, c_{i+1}, c_{i-1}, t, m\}$, with $c_{N+1} = c_1$ and $c_0 = c_N$.

The distribution of profit is determined by a firm's market share (number of consumers) and the price markup (price-cost margin) charged to each consumer. The only way to change the distribution of profit among the firms is to change the distribution of costs or

[8] A good recent work using this model under uncertainty is Raith [52]'s study of product market competition and the provision of managerial incentives.

[9] The speed at which firms can reestablish themselves around the circle depends on the exact characteristic of differentiation. Departure time or product color may be examples of product differentiation that are relatively quicker for a firm to change.

t. Due to the uniform density of consumers, a change in m only affects the absolute profit of each firm but not the relative profit. Except for the case when firms have symmetric costs, the firms have both different market shares. Therefore they are not symmetric. As t decreases, the products are perceived to be more substitutable, and prices along with profits fall. Also for a given t, π_i always decreases in c_i.

I consider four different shocks to the parameters in τ_i. Without much loss of generality, all shocks are additive, even though the structure of uncertainty from section 1.2 allows for more general formulations. I first analyze a correlated shock to firm costs calculated by $\pi_i(c_i + \alpha_i X, c_{i+1} + \alpha_{i+1} X, c_{i-1} + \alpha_{i-1}, .)$ where $\alpha_i \in R\ \forall i$. In this case, each firm receives the same shock, but the α_i term allows each firm to have a different sensitivity. If the α_i are all the same, then each firm's profit is the same after the shock and the effect of the shock washes out. Secondly, I consider an independent shock to cost, which is formulated as $\pi_i(c_i + X_i, c_{i+1} + X_{i+1}, c_{i-1} + X_{i-1}, .)$ so that each firm receives a different shock to its costs. Next, the shock to t, $t+X$, simply changes how substitutable the consumers perceive the products to be. Finally, I consider a shock to demand, $m + X$, which also washes out because the uniform density of consumers makes a shock to demand increase each firm's profit by the same amount.

Before analyzing how the number of firms affects share prices and expected returns with each shock, I analyze the the sign of $dSD_X[\pi_i(X, N)]/dN$ with each shock because it plays a critical role in the sign of the above derivatives and there is very little theoretical work studying it.[10] The derivative of $SD_X[\pi_i(., X)]$ with respect to N is weakly negative for all of the shocks. The exact formulas for each of the derivatives are listed in the Appendix under Claims (vi)-(ix). Regardless of the source of uncertainty, firms in more competitive industries have a lower standard deviation of profits than firms in more concentrated industries. This result is fairly intuitive because, as N increases, q decreases in this model and it is not surprising that firm that produce less have a smaller standard deviation of profits.

[10]Raith [52], whose work is based on a similar circular city model, also looks at how the variance of profit changes when the degree of competition among firms changes. However, there are some substantial differences between our models. In his model, N is endogenous and he assumes free entry with a fixed entry cost, F. Secondly, Raith considers a normally distributed and independent additive shock to each firm's cost function. Finally, he assumes that each firm's realized cost is private information and that firms maximize profit over the expectations they have about each other's costs. Raith finds that the variance increases as the products become more substitutable (t decreases), m increases, and F increases. While the differences between our models make the results incomparable in many important ways, both models uphold the relationship $dSD_X[\pi_i(X, N)]/dq > 0$. In Raith, q increases in product substitutability, market size, and the entry cost and in my model, q decreases in N.

The following table summarizes how the standard deviation of profit, the share price, and the expected return change with N when there are different sources of uncertainty.

Table 1.1: Hotelling Model

	Correlated Costs	Indep. Costs	Shock to t	Shock to m
$dSD_X[\pi_i]/dN$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$
dp_o^i/dN	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$
$dE[R_i]/dN$	$\gtrapprox 0$	$\gtrapprox 0$	$\approxeq c_i - \frac{1}{2}(c_{i-1} + c_{i+1})$	$\approxeq 0$

The derivations are listed in the Appendix under Claims (vi)-(ix). The results for dp_o^i/dN only hold for sufficiently small shock. All the other results in Table 1.1 are global, i.e., they hold for any size shock. Market capitalization decreases in the number of firms when X is sufficiently small. This is because in equation (1.8), $dE[\pi_i]/dN \leq 0$, and, as discussed above, $-dSD_X[\pi_i]/dN \geq 0$ for all types of shocks. However, when X is sufficiently small, $-dSD_X[\pi_i]/dN$ is dominated by $dE[\pi_i]/dN$.

In contrast to the share price, the sign of the derivative of the expected return depends on the shock. In the two cases where there are correlated and independent shocks to costs, a firm's expected return increases in the number of firms. This result holds regardless of the distribution of the costs or how sensitive each firm is to the shock (through the α_i term). Equation (1.11) provides the intuition that the standard deviation of profit per unit of profit increases in N. Because both the standard deviation of profit and profit decrease in N, this means that the standard deviation of profit decreases at a slower rate than profit for these two shocks to cost.

In the case of a shock to t, the derivative of the expected return is determined by the distribution of costs. Clearly, $dE[R_i]/dN \geq 0 \iff c_i \geq \frac{1}{2}(c_{i-1} + c_{i+1})$. For a fixed t, a relatively higher cost translates into a relatively smaller market share. Therefore, the expected return of firm with a relatively smaller market share, facing a shock to t, increases in N. Equation (1.11) provides the intuition that the standard deviation of profit per unit of profit increases in N for relatively smaller firms and decreases in N for relatively larger firms.

The expected return is also approximately independent of the number of firms in many different situations. The first case applies to all the shocks and occurs when $N \to \infty$ and $\pi_i \to 0$. The second case only occurs when there are correlated shocks to cost and when each firm has the same sensitivity to the shock (when the α_i terms are equal). This shock does not even affect the absolute profit levels of the firms and so the $SD_X[\pi_i]$ is 0. The next case occurs when there are both kinds of shocks to costs, when the costs are equal, and there is no product differentiation, i.e., $t = 0$. This captures a symmetric Bertrand competition. The derivative of the expected return equals 0 because the firms earn zero profit in this model of perfect competition. In the case of a shock to t, the derivative will be approximately 0 when the firms are symmetric. Finally, in the case of a shock to m, the derivative of the expected return is always approximately 0. Due to the uniform density of consumers, this shock affects the absolute profit level of each firm but not the relative profit. Therefore, this shock simply rescales the profit function.

1.4 Cournot Model

In this section, I study the impact of industry concentration when firms behave according to a symmetric Cournot and competitive model. Firms face a linear inverse demand function, $P(Q) = a - bQ$ and have the constant industry cost function $C(q) = \frac{c}{2}Nq^2$, where all constants are strictly positive. In this case, I examine three different shocks. There are two additive demand shocks, $a + X$ and $b + X$, along with an additive shock to costs, $c + X$.

The following table summarizes the results.[11]

Table 1.2: Cournot and Competitive Models

	Shock to a		**Shock to b**		**Shock to c**	
	Comp.	Cour.	Comp.	Cour.	Comp.	Cour.
$dSD_X[\pi_i(.)]/dN$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\approxeq \xi(b,c,N)$
$dp_o^i/dN*$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$	$\lessapprox 0$
$dE[R_i]/dN$	$\approxeq 0$	$\approxeq 0$	$\approxeq 0$	$\approxeq 0, N = 1$ $\gtrapprox 0, N > 1$	$\approxeq 0$	$\approxeq 0, N = 1$ $\gtrapprox 0, N > 1$

Once again, the results for dp_o^i/dN only hold for a sufficiently small shock X, while the other results in Table 1.4 hold globally. The standard deviation of profit decreases with the number of firms, except when there is a supply shock to a Cournot firm. In this last case, the sign depends on $\xi(b, c, N) = N^2(c^2 - b^2) + b^2(8N - 3) + 4bcN$. The share price always decreases with the number of firms for sufficiently small shocks for the same reason as given

[11]The derivations for these results can be found in Panattoni (2005 - available by request).

in the previous section. The expected return is approximately independent of the number of firms in almost all of the cases. This result is not surprising in the case of a shock to a because this shock simply rescales the profit function (like the shock to m in the previous section). However, in the case of a shock to b or c for a perfectly competitive firms because although these firms price at marginal cost, they still earn a positive profit until $N \to \infty$. Finally, this result also holds in the case of a shock to b or c for a monopoly. The only time the expected share return changes with N is in a Cournot industry facing uncertainty in the slope of the demand function or the cost function. Once again, equation (1.11) provides the intuition that the ratio of the standard deviation of profit per unit of profit increases in N for these two cases.

1.5 Conclusion

The objective of this article is to theoretically investigate how industry concentration affects a firm's market capitalization and expected return. To pursue this question, I extend the CAPM by incorporating an equilibrium theory of firm behavior. Unlike previous work, I add local product market shocks to a general, deterministic profit function. Therefore, this method is compatible with many deterministic theories of the firm from industrial organization and the product market uncertainty can come from many different sources. Secondly, my method relies on an orthogonal decomposition of market returns to endogenize the $\text{Cov}[R_i, R_M]$ or β_i. This provides a new and more tractable interpretation of the $\text{Cov}[R_i, R_M]$ in terms of the standard deviation of firm profit and allows the market capitalization to be rewritten in terms of the expectation and standard deviation of firm profit.

Using the Hotelling and the Cournot model, I explore how the standard deviation of profit, the market capitalization, and the expected return change with concentration when there are different sources of uncertainty. Using the number of firms as a proxy for concentration, I find that the standard deviation of profit decreases in N except in the case of a Cournot firm facing uncertain costs. The market capitalization always decreases in N for sufficiently small shocks. Finally, the expected return either increases in or is independent of N, except in the case of a Hotelling firm with a relatively large market share facing a shock to the intensity of product differentiation. The expected return increases in N when firms face uncertain costs, when a Hotelling firm with a relatively small market share is facing a shock to the intensity of product differentiation, and when a Cournot firm is facing a shock to the slope of demand. The expected return is independent of N when the shock simply rescales the profit function, when the firm is a monopoly, and when there are perfectly competitive firms.

The relationship between this chapter's results and Hou and Robinson's work [31] raises some interesting questions. After controlling size, book-to-market, momentum, and other factors, Hou and Robinson find that a firm's expected return increases as the industry becomes more competitive. However, their empirical work is based on the argument that industry concentration does not affect expected returns through the Beta term. While this chapter provides many theoretical examples of when Beta is independent of N, it also provides many cases where Beta increases in N. Hou and Robinson create five concentration sorted portfolios and find that the average Beta is roughly constant across them. However, this is not a clean test of how industry concentration affects systematic risk. Also, Hou and Robinson run a simple regression of industry concentration on Beta in Table II and find a statistically significant result.

A better understanding of the relationship between industry concentration and stock returns may also help explain some other questions in finance. Irvine and Pontiff [33] find that the volatility of the average stock return has drastically outpaced total market volatility. They estimate idiosyncratic return volatility has increased to 6 percent per year. However, they argue this is due to industry turnover, and they do not consider a change in concentration. Also, although Banz's small stock effect has been explained by various factors such as the January effect, the relationship between a firm's absolute size, its relative size, industry concentration, and stock returns is largely unexplored. Finally, a better understanding of the relationship between concentration and asset pricing could help determine how regulating industry concentration may have important consequences for financial markets.

1.6 Appendix

Claim i: $\text{Var}_X[\pi(X_1,...,X_k)] \approx \sum_{l=1}^{k} \nu_l^2 \left[\frac{d\pi}{dX_l}\right]^2_{X_l=X_0}$

Proof of Claim i:

$\text{Var}_X[\pi_i(X_1,...,X_k)] = E_X\left[(\pi_i(X_1,...,X_k) - E_X[\pi_i(X_1,...,X_k)])^2\right]$
$\approx E_X\left[\left(\sum_{l=1}^{k}(X_l - X_0)\pi_i'(.,X_0)\right)^2\right]$
$= \sum_{l=1}^{k} E_X\left[(X_l - X_0)^2\right]\pi_i'(.,X_0)^2$
$= \sum_{l=1}^{k} \nu_l^2 \pi_i'(.,X_0)^2$ (By independence)

Claim ii: $\text{Cov}[\pi_i(\tau_i,N,X_1),R_M] \approx \frac{\text{Cov}[X_1,R_M]}{SD[X_1]} SD_{X_1}[\pi_i(\tau_i,N,X_1)]$

Proof of Claim ii:

$\text{Cov}[\pi_i(\tau_i,N,X_1),R_M] = \text{Cov}[\pi_i(\tau_i,N,X_1),\theta_1 X_1 + Y_1]$
$= \theta_1 E_{X_1}[X_1\pi_i(.,X_1)] - \theta_1 E_{X_1}[\pi_i(.,X_1)]E_{X_1}[X_1] \quad$ (decomposition of R_M)
$\approx \theta_1 E_{X_1}\left[X_1\{\pi_i(.,X_0) + (X_1 - X_0)\,\pi_i'(.,0)\}\right] - \theta_1 X_0 E_{X_1}\left[\pi_i(.,X_0)\right]$
$= \theta_1 E_{X_1}[\left(X_1^2 - X_0^2\right)\pi_i'(.,X_0)]$
$= \theta_1 \nu_1^2 \pi_i'(.,X_0)$
$= \frac{\text{Cov}[X_1,R_M]}{\text{Var}[X_1]} \nu_1 SD_{X_1}[\pi_i(\tau_i,N,X_1)]$
$= \frac{\text{Cov}[X_1,R_M]}{SD[X_1]} SD_{X_1}[\pi_i(\tau_i,N,X_1)]$

Claim iii: If (i) $\text{Cov}[X_l,Y_k] = 0\ \forall l = 1,...,k$, and (ii) $\left[\frac{d\pi}{dX_l}\right]_{X_1=X_0}$ are all scalar multiples, i.e. $\exists$ z and $\eta_l \in R$ s.t. $\left[\frac{d\pi}{dX_l}\right]_{X_1=X_0} = \eta_l z$ $\forall$ l=1,...,k, then

$$\text{Cov}[\pi_i(.,X),R_M] \approx \left[\frac{\text{Cov}[\sum_{l=1}^{k}\frac{X_l}{\nu_l},R_M]}{\text{Var}[\sum_{l=1}^{k}\frac{X_l}{\nu_l}]}\right]\left[\frac{\sum_{l=1}^{k}\sqrt{\nu_l^2\eta_l^2}}{\sqrt{\sum_{l=1}^{k}\nu_l^2\eta_l^2}}\right] SD_X[\pi(.,X)].$$

Proof of Claim iii:

$\text{Cov}[\pi_i(.,X_1,...,X_k),R_M] = \text{Cov}[\pi_i(.,X_1,...,X_k),\theta_k\left(\sum_{l=1}^{k}\frac{X_l}{\nu_l}\right) + Y_k]$
$= \text{Cov}[\pi_i(.,X_1,...,X_k),\theta_k\left(\sum_{l=1}^{k}\frac{X_l}{\nu_l}\right)] \quad$ (by assumption (i))
$\approx \text{Cov}[\pi_i(.,X_0) + \sum_{l=1}^{k}(X_l - X_0)\,\pi'(.,X_0),\theta_k\sum_{l=1}^{k}\frac{X_l}{\nu_l}]$
$= \theta_k \text{Cov}[\sum_{n=1}^{k}(X_n - X_0)\,\pi'(.,X_0),\sum_{l=1}^{k}\frac{X_l}{\nu_l}]$
$= \theta_k \sum_{n=1}^{k}\sum_{l=1}^{k}\frac{1}{\nu_l}\left[\frac{d\pi}{dX_n}\right]_{X_n=X_0}\text{Cov}[X_n,X_l]$

$= \theta_k \sum_{l=1}^{k} \nu_l \left[\frac{d\pi}{dX_l}\right]_{X_l=X_0}$ (X_l are independent and variance equals ν_l^2)

$= \theta_k \left(\sum_{l=1}^{k} \sqrt{\nu_l^2 \pi'(.,0)^2} / \sqrt{\sum_{l=1}^{k} \nu_l^2 \pi'(.,0)^2}\right) \sqrt{\sum_{l=1}^{k} \nu_l^2 \pi'(.,0)^2}$

$= \theta_k \left(\sum_{l=1}^{k} \sqrt{\nu_l^2 \eta_l^2 z^2} / \sqrt{\sum_{l=1}^{k} \nu_l^2 \eta_l^2 z^2}\right) SD_X[\pi_i(.,X)]$ (Assumption ii)

$= \theta_k \left(\sum_{l=1}^{k} \sqrt{\nu_l^2 \eta_l^2} / \sqrt{\sum_{l=1}^{k} \nu_l^2 \eta_l^2}\right) SD_X[\pi_i(.,X)]$

$= \left[\frac{\text{Cov}[\sum_{l=1}^{k} \frac{X_l}{\nu_l}, R_M]}{\text{Var}[\sum_{l=1}^{k} \frac{X_l}{\nu_l}]}\right] \left[\frac{\sum_{l=1}^{k} \sqrt{\nu_l^2 \eta_l^2}}{\sqrt{\sum_{l=1}^{k} \nu_l^2 \eta_l^2}}\right] SD_X[\pi_i(.,X)]$

Claim iv: $\frac{dE[R^i]}{dN} \approx \frac{\rho\mu}{R_f (p_o^i)^2} \left[\pi_i(X_0,N) \frac{dSD_X[\pi_i(X,N)]}{dN} - SD_X[\pi_i(X,N)] \frac{d\pi_i(X_0,N)}{dN}\right]$

Proof of Claim iv:

Accounting identity: $E[R_i] \equiv E[\pi_i]/p_o^i \Rightarrow \frac{dE[R_i]}{dN} = \frac{1}{(p_o^i)^2} \left(p_o^i \frac{dE[\pi_i]}{dN} - E[\pi_i] \frac{dp_o^i}{dN}\right)$

$= \frac{1}{R_f (p_o^i)^2} \left[\left\{\pi_i(X_0) - \rho\mu \sqrt{\sum_{l=1}^{k} \nu_l^2 \pi_i'(0)^2}\right\} \left\{\frac{d\pi_i(X_0)}{dN}\right\}\right.$

$\left. - \left\{\frac{d\pi_i(X_0)}{dN} - \rho\mu \sqrt{\sum_{l=1}^{k} \nu_l^2 \frac{d\pi_i'(X_0)^2}{dN}}\right\} \{\pi_i(X_0)\}\right]$

$= \frac{1}{R_f (p_o^i)^2} \left[-\rho\mu \sqrt{\sum_{l=1}^{k} \nu_l^2 \pi_i'(0)^2} \frac{d\pi_i(X_0)}{dN} + \rho\mu \sqrt{\sum_{l=1}^{k} \nu_l^2 \frac{d\pi_i'(X_0)^2}{dN}} \pi_i(X_0)\right]$

$= \frac{\rho\mu}{R_f (p_o^i)^2} \left[E_X[\pi_i(X,N)] \frac{dSD_X[\pi(X,N)]}{dN} - SD_X[\pi_i(X,N)] \frac{dE_X[\pi_i(X,N)]}{dN}\right]$

Claim v: $\pi_i(0) = \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2$

Proof of Claim v:

Let $h_i(x) = c_i + tx$, $h_{i-1}(x) = c_{i-1} + t(x + 1/N)$, $g_i(x) = c_i - tx$, $g_{i+1}(x) = c_{i+1} - t(x - 1/N)$, x_i be the intersection between $h_i(x)$ and $g_{i+1}(x)$, x_{i-1} be the intersection between $g_i(x)$ and $h_{i-1}(x)$, and z_{i-1} be the intersection between $g_{i+1}(x)$ and $h_{i-1}(x)$.

Then $x_i = \frac{c_{i+1} - c_i}{2t} + \frac{1}{2n}$, and $\pi_i \geq 0 \Rightarrow 0 \leq x_i \leq 1/N$; similarly $x_{i-1} = \frac{c_i - c_{i-1}}{2t} - \frac{1}{2n}$, and $\pi_i \geq 0 \Rightarrow -1/N \leq x_{i-1} \leq 0$. Finally $z_i = \frac{c_{i+1} - c_{i-1}}{2t}$, and $\pi_i \geq 0 \Rightarrow x_{i-1} \leq z_i \leq x_i$.

Thus, $\pi_i(0) = m \int_{x_{i-1}}^{z_i} g_{i+1}(x)dx + m \int_{z_i}^{x_i} h_{i-1}(x)dx - m \int_{x_{i-1}}^{0} g_i(x)dx - m \int_0^{x_i} h_i(x)dx = \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2$.

Lemma 1: $-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t \geq 0$

Proof of Lemma 1:

$$\begin{aligned}-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t &= tN\left[\frac{-2c_i + c_{i-1} + c_{i+1}}{t} + \frac{2}{N}\right] \\ &= tN\left[\left(\frac{c_{i+1} - c_i}{t} + \frac{1}{N}\right) - \left(\frac{c_i - c_{i-1}}{t} - \frac{1}{N}\right)\right] \\ &= tN[\frac{1}{2}x_i - \frac{1}{2}x_{i-1}] \geq 0 \quad \text{(Claim vi)}\end{aligned}$$

Lemma 2: $2c_i - c_{i-1} - c_{i+1} + \frac{2t}{N} \geq 0$

Proof of Lemma 2:

$$\begin{aligned}2c_i - c_{i-1} - c_{i+1} + \frac{2t}{N} &= 2t\left(\frac{c_i - c_{i-1}}{2t} - \frac{c_{i+1} - c_i}{2t} + \frac{1}{N}\right) \\ &= 2t(x_{i-1} - x_i + \frac{2}{N}) \\ &\geq 0 \quad \text{(Claim vi)}\end{aligned}$$

Claim vi: For perfectly correlated shocks to cost,

$$\frac{dE[R^i]}{dN} \approx \frac{\rho_I \mu \nu_1}{R_f\,(p_o^i)^2} \frac{|-2\alpha_i + \alpha_{i-1} + \alpha_{i+1}|(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4tN^4} \geq 0.$$

Proof of Claim vi:

Let $\alpha_i \in \mathbb{R}$, $\forall i \in 1, 2, ..., N$. Then

$$\pi_i(X_1) = \frac{m}{4t}[-2(c_i + \alpha_i X_1) + (c_{i-1} + \alpha_{i-1} X_1) + (c_{i+1} + \alpha_{i+1} X_1) + \frac{2t}{n}]^2.$$

Therefore

$$\pi_i(X_0 = 0) = \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2 \geq 0$$

$$\frac{d\pi_i(X_0 = 0)}{dN} = \frac{m}{N^3}[2Nc_i - Nc_{i-1} - Nc_{i+1} - 2t] \leq 0 \qquad \text{(by Lemma 1)}$$

$$SD[\pi_i(X_1)] = \frac{m\nu_1}{2Nt}|-2\alpha_i + \alpha_{i-1} + \alpha_{i+1}|(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t) \geq 0.$$

Since

$$|\pi_i'(X_0)| = |\frac{m\nu_1}{2Nt}(-2\alpha_i + \alpha_{i-1} + \alpha_{i+1})(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)|,$$

it follows that

$$\frac{dSD[\pi_i(X_1)]}{dN} = \frac{-m\nu_1|-2\alpha_i + \alpha_{i-1} + \alpha_{i+1}|}{N^2} \leq 0.$$

Therefore

$$\begin{aligned}
\frac{dE[R^i]}{dN} &\approx \frac{m\rho_I\mu}{R_f\,(p_o^i)^2}\left[\pi(0)\frac{dSD[\pi_i(X_1)]}{dN} - SD[\pi_i(X_1)]\frac{d\pi(0)}{dN}\right] \\
&\approx \frac{m\rho_I\mu\nu_1}{R_f\,(p_o^i)^2}\frac{|-2\alpha_i + \alpha_{i-1} + \alpha_{i+1}|(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4tN^4} \\
&\geq 0.
\end{aligned}$$

Claim vii: For independent or idiosyncratic shocks to cost,

$$\frac{dE[R^i]}{dN} \approx \frac{\rho_I\mu m\sqrt{\nu_1^2 + \nu_2^2 + \nu_3^2}}{R_f\,(p_o^i)^2}\frac{(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4tN^2} \geq 0$$

Proof of Claim vii:

$$\pi_i(X_1, X_2, X_3) = \frac{m}{4t}[-2(c_i + X_1) + (c_{i-1} + X_2) + (c_{i+1} + X_3) + \frac{2t}{n}]^2$$

This implies

$$\begin{aligned}
\pi_i(X_0) &= \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2 \geq 0 \\
\frac{d\pi_i(X_0)}{dN} &= \frac{m}{N^3}[2Nc_i - Nc_{i-1} - Nc_{i+1} - 2t] \leq 0 \qquad \text{(by Lemma 1)} \\
SD[\pi_i(X_1, X_2, X_3)] &= \frac{m}{2t}(-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N})\sqrt{\nu_1^2 + \nu_2^2 + \nu_3^2} \geq 0 \\
\frac{dSD[\pi_i(X_1, X_2, X_3)]}{dN} &= \frac{-m}{N^2}\sqrt{\nu_1^2 + \nu_2^2 + \nu_3^2} \leq 0.
\end{aligned}$$

Therefore

$$\begin{aligned}
\frac{dE[R^i]}{dN} &\approx \frac{m\rho_I\mu}{R_f\,(p_o^i)^2}\left[\pi_i(X_0)\frac{dSD_X[\pi_i(X)]}{dN} - SD_X[\pi_i(X)]\frac{d\pi_i(X_0)}{dN}\right] \\
&\approx \frac{m\rho_I\mu\sqrt{\nu_1^2 + \nu_2^2 + \nu_3^2}}{R_f\,(p_o^i)^2}\frac{(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4tN^2} \\
&\geq 0
\end{aligned}$$

Claim viii: For a shock to the parameter of product differientation, t,

$$\frac{dE[R^i]}{dN} \approx \frac{m\rho_I\mu\nu_1}{R_f\left(p_o^i\right)^2}\frac{(2c_i - c_{i-1} - c_{i+1})(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4N^4t^2} \geq 0 \Leftrightarrow c_i \geq \frac{1}{2}(c_{i-1}+c_{i+1})$$

Proof of Claim viii: First note

$$\pi_i(X_1) = \frac{m}{4(t+X_1)}[-2c_i + c_{i-1} + c_{i+1} + \frac{2(t+X_1)}{n}]^2$$

Thus

$$\pi_i(X_0 = 0) = \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2 \geq 0$$

$$\frac{d\pi_i(X_0)}{dN} = \frac{m}{N^3}[2Nc_i - Nc_{i-1} - Nc_{i+1} - 2t] \leq 0 \quad \text{(Lemma 1)}$$

$$SD[\pi_i(X_1)] = \frac{m\nu_1}{4t^2}(2c_i - c_{i-1} - c_{i+1} + \frac{2t}{n})(-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}) \geq 0.$$

Since $(-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}) \geq 0$ (by Lemma 1), and $(2c_i - c_{i-1} - c_{i+1} + \frac{2t}{N}) \geq 0$, (by Lemma 2), it follows that

$$\frac{dSD[\pi_i(X_1)]}{dN} = \frac{-2m}{N^3}.$$

Thus,

$$\begin{aligned}
\frac{dE[R^i]}{dN} &\approx \frac{m\rho_I\mu\nu_1}{R_f\left(p_o^i\right)^2}\left[\pi(0)\frac{dSD[\pi_i(X_1)]}{dN} - SD[\pi_i(X_1)]\frac{d\pi(0)}{dN}\right] \\
&\approx \frac{m\rho_I\mu\nu_1}{R_f\left(p_o^i\right)^2}\frac{(2c_i - c_{i-1} - c_{i+1})(-2Nc_i + Nc_{i-1} + Nc_{i+1} + 2t)^2}{4N^4t^2} \\
&\geq 0 \\
&\Leftrightarrow c_i \geq \frac{1}{2}(c_{i-1} + c_{i+1}).
\end{aligned}$$

Claim ix: For a shock to demand, m, $\frac{dE[R^i]}{dN} \approx 0$

Proof of Claim ix:

Given

$$\pi_i(X_1) = \frac{m+X_1}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{n}]^2,$$

we have

$$\pi_i(X_0) = \frac{m}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2 \geq 0$$

$$\frac{d\pi_i(X_0)}{dN} = \frac{m}{N^3}[2Nc_i - Nc_{i-1} - Nc_{i+1} - 2t] \leq 0 \quad \text{(by Lemma 1)}$$

$$SD[\pi_i(X_1)] = \frac{1}{4t}[-2c_i + c_{i-1} + c_{i+1} + \frac{2t}{N}]^2 \geq 0$$

$$\frac{dSD[\pi_i(X_1)]}{dN} = \frac{1}{N^3}[2Nc_i - Nc_{i-1} - Nc_{i+1} - 2t].$$

Therefore $\frac{dE[R^i]}{dN} \approx 0$.

Chapter 2

'Paragraph IV' Litigation and the Value of Marketing Exclusivity in the Pharmaceutical Industry

2.1 Introduction

Since the Hatch-Waxman Act of 1984, the pharmaceutical industry has been regulated according to a unique and complicated framework of patent protections and marketing exclusivities, granted by the US Patent and Trademark Office and the FDA respectively. The underlying goal of this regulation is to encourage firms to conduct the costly research for new or improved drugs by granting marketing exclusivity (monopoly rights) to the inventing firm. However, regulators face a delicate balance. Granting too much protection hurts society through high prices on brand name drugs while too little protection can fail to provide sufficient incentive for future drug development. Therefore, what are monopoly rights worth to brand firms?[1]

Currently, the only estimates of monopoly rents are based on *accounting valuations*, which exclude many additional sources of value only captured by *market valuations*. *Accounting valuations* are always based on discounted cash flow (DCF) models which determine discount rates and calculate present values of profitability using drug level sales data. However, while these estimates are highly sensitive to the measurement of drug sales and the discount rate calculation, the critical problem is that these estimates do not include any

[1] It is not surprising that debate about the optimal regulation persists. For example, the Pediatric Exclusivity, which grants an additional six months of marketing exclusivity to brand name drug firms that test their drugs on the pediatric population, is set to expire in December of 2007 and Congress must determine its continuance. For a list of the roughly 130 brand drugs that have been awarded the Pediatric Exclusivity since 1997, see http://www.fda.gov/cder/pediatric/labelchange.htm#New-listings.

of the benefits of monopoly rights to the brand firm outside of the individual drug's sales. One example of these potential benefits is an increased reputation that may spill over to the brand firm's other drugs allowing higher prices to be charged for them. Therefore, I create the first *market valuation* of monopoly rents because *market valuations* aggregate information from many actors, not just the researcher(s) that created the DCF model. These estimates also capture unknown yet relevant factors and they include intangible and other benefits of monopoly rights that exist in addition to sales.

However, developing a *market valuation* of monopoly rents involves first overcoming the challenges associated with estimating how horizontal industry concentration affects stock returns.[2] The previous empirical literature estimating how industry concentration affects stock returns has used a wide variety of approaches and has produced a body of contradictory of conclusions. Early work includes Melicher, Rush, and Winn [48], who found that industry concentration have no effect on returns, and Sullivan [59], who found that firms in more concentrated industries have lower returns. However, these papers from the 1970's based their conclusions on the CAPM for the return generating model. Lustgarten and Thomadakis [44] found that announced changes in a firm's accounting earnings led to a greater change in the market capitalization in more concentrated industries. Treating future prices as exogenous, this weakly implies that firms in more concentrated industries earn higher returns. These authors argue that more concentrated firms are riskier because their capital is more durable and specialized. Most recently, Hou and Robinson [31] regress returns on the Herfindahl index and estimate that firms in the quintile of the most competitive industries have returns nearly four percent greater than firms in the most concentrated quintile.[3] These authors provide a risk-based explanation for this 'concentration premium'. They argue that competitive industries are riskier because they are more likely to face change from innovation (innovation risk), or that they are more sensitive to demand shocks due to lower barriers to entry (distress risk). However, they do not create a formal model that links these arguments to their econometric work.

These papers all face three econometric difficulties, which may contribute to their conflicting results. Although regressing any function of firm profit on a measure of industry concentration raises the specter of endogeneity, in the financial context, an efficient mar-

[2]Conceptually, horizontal concentration may be thought of in terms of any of the nondecreasing convex measures of industry market shares describe in Tirole [60].

[3]This additional rate of return is considerable because the equity premium is estimated at six percent.

ket creates orthogonality between the industry concentration measure and the error term. However, endogeneity can resurface when information about industry concentration at any period is only partially incorporated into asset prices at that period. This incomplete adjustment can occur because the Herfindahl index is a slow moving measure with a large lag and therefore information about one period may not show up in the measure until many periods later. These papers all construct the concentration measure using firm level sales and not product level sales. Therefore, it is possible for some industries to appear highly competitive according to the measure, while the products in the industry actually compete with significant market power. Finally, in panel data sets, there is the potential for confounding factors.

This paper exploits a natural experiment afforded by the announcement of 'Paragraph IV' patent infringement decisions. These judgments have three unique features. They constitute an exogenous change in industry concentration, since they determine whether the corporate owner of a brand name prescription drug will maintain or lose monopoly marketing rights. They also satisfy methodological requirements to use a short window event study to capture how the financial market prices this change. Finally, they generate a binomial outcome space which can be used to value marketing exclusivity. Against a backdrop of contradictory empirical evidence, this experiment provides a clean opportunity to empirically determine the sign of how a change in horizontal industry concentration affects stock returns. Additionally, the magnitude of the effect provides the basis for developing the market valuation.

The event study methodology has many advantages over the previous work estimating how horizontal industry concentration affects stock returns. This methodology credibly establishes that the resolution of litigation causes the change in returns. The short event window also allows researchers to isolate the time frame when the financial market prices change in concentration, which minimizes the potential for confounding factors to influence the results. Finally, the intuition underlying this methodology is conceptually straightforward. Event studies usually explore hypotheses about how corporate events affect the value of claims issued against a corporation. If the rate of return earned on a security during the announcement of an event is more positive than normal, the conclusion is that the event caused the value of the corporation to increase.

The presence of market expectations about trial outcomes require additional work to isolate the sign of the concentration effect and develop the value of marketing exclusivity. The announcement of a 'Paragraph IV' decision generates a binomial outcome structure; either brand maintains monopoly rights until patent expiration or it faces generic entry. This binomial structure, combined with the one period state price (Arrow-Debreu) representation of the brand firm's stock price, is used to bound the pre-decision valuation between the two post-decision state contingent valuations. Thus the sign of the abnormal returns uniquely identifies the post decision state. Therefore, this paper finds that returns of the brand firm increases (decreases) with an announcement that it 'won' (lost) the case. This result provides a simple and clean intra-industry example of how increasing (decreasing concentration) increased (decreased) stock returns with the intuition that the value of the brand firm has increased (decreased). Finally, the value of marketing exclusivity is determined to be the abnormal return given the brand maintains monopoly rights minus the abnormal return given the brand faces generic entry.

The remainder of this paper is divided into five sections. Section 2.2 provides some industry background, including a description of the regulatory regime under the Hatch-Waxman Act and the structure of 'Paragraph IV' patent infringement cases. Section 2.3 describes the research design and methodological issues. Sections 2.4 and 2.5 describe the data and the results respectively. Finally, the conclusion discusses possible extensions to this study.

2.2 Industry Background

2.2.1 The Regulatory Environment and 'Paragraph IV' Litigation

The Drug Price Competition and Patent Term Restoration Act of 1984, commonly known as the Hatch-Waxman Act, established the current FDA regulations for approving generic copies of brand name drugs. One component of the Act created the abbreviated new drug application (ANDA), which lowered the regulatory barriers to entry for generic drugs. An ANDA enables generic manufacturers to skip most of the expensive pre-clinical and clinical testing by allowing firms to establish *bioequivalency*[4] to an approved drug. The Act also

[4]The FDA has defined bioequivalence as, "the absence of a significant difference in the rate and extent to which the active ingredient or active moiety in pharmaceutical equivalents or pharmaceutical alternatives becomes available at the site of drug action when administered at the same molar dose under similar conditions in an appropriately designed study." (http://www.fda.gov/cder/guidance/5356fnl.pdf)

permits generic firms to conduct bioequivalency testing while the referenced patents are still in force, without risking an infringement suit.[5]

The Orange Book is the FDA's official public list of all patents and exclusivities, along with their expiration dates, which protect a brand name drug.[6] In order to receive FDA approval, all ANDAs must certify that the proposed generic drug will not infringe upon any referenced patent listed in the Orange Book.[7] There are four different patent certifications an ANDA may claim.

1. 'Paragraph I Certification' – certifies that the required patent information has not been filed in connection to the referenced brand name drug.

2. 'Paragraph II Certification' – certifies that all patents listed in relation with the referenced brand name drug have expired.

3. 'Paragraph III Certification' – certifies that all patents have not expired and provides the dates the referenced patents will expire.

4. 'Paragraph IV Certification' – The listed patent is invalid or will not be infringed by the generic drug.

An ANDA with a 'Paragraph I or II Certification' may be approved by the FDA immediately, since the patents have expired or were never listed in the Orange Book. An ANDA with 'Paragraph III Certification' signals the generic manufacturer's interest in entering after the relevant patents have expired. This ANDA may only be granted 'tentative approval', as long as the bioequivalency requirements have been met, and approval is granted upon patent expiration.[8]

A generic manufacturer submits a 'Paragraph IV Patent Certification' when it is seeking approval to enter a market before the relevant patents have expired. The manufacturer is

[5] The Hatch-Waxman Act has greatly increased the volume of approved generic drugs. In 1984, only 14% of the prescriptions were written for generic copies compared to 54% in 2005. See Ted Sherwood's overview of the ANDA review process at www.fda.gov/cder/audiences/iact/forum/200609_sherwood.pdf.

[6] This publication, formally known as 'Approved Drug Products and Therapeutic Equivalents', can be found at www.fda.gov/cder/ob, and also lists all the approved brand name drugs and their respective generics, approval dates, and their approved dosages, routes of administration, and indications of usage.

[7] Patent laws are more pro-competitive for every other product than the FDA regulations are for drugs. When there is a patent dispute for other products, the potentially infringing firm may enter and sell the product until an injunction is granted. However, when the patent dispute is between pharmaceutical firms, generics are prevented from entering by every patent regardless of its merits. (Hollis [30])

[8] For excellent references on patent certifications, please see FTC [21], Bulow [8], and Higgins and Rodriguez [29].

claiming either that its formulation of the brand drug does not infringe upon the relevant patents held by the brand name company, or that the original patents should never have been granted. By filing an ANDA with 'Paragraph IV' certification, the generic manufacturer triggers two additional provisions in the Hatch-Waxman Act to resolve the conflicting patent infringement claim. The first provision is the thirty month stay. The generic manufacturer must notify the patent holder (brand name drug company) of its application and the factual and legal basis of its claim. The brand name firm then has forty-five days in which to file an infringement suit or face generic entry. As Higgins and Rodriguez [29] write,

> "...by filing the suit, the FDA can not grant approval until the earliest of: (1) the date the NDA patent being challenged expires, (2) there is a lower court ruling invalidating the patent or a decision of non-infringement, or (3) 30 months after the patent holder was originally notified of the 'Paragraph IV' ANDA certification.' [p14]

In 2002, the FTC [21] estimated that it took approximately 25 months to resolve an infringement suit, which provided the brand name company an extra two years of marketing exclusivity.

Additional features of the regulatory environment encouraged brand name firms to list patents in the Orange Book. The FDA's role in listing patents in the Orange Book is solely procedural which means that it automatically lists all patents submitted by brand name firms. The Agency states that its function is to determine the safety and efficacy of potential drugs and that it does not have the resources or expertise to resolve the complex questions of patent coverage.[9] Patents covering brand name drugs are granted by the US Patent and Trademark office anytime along the development lifeline of a drug, from pre-clinical trials to marketing. Post approval, FDA regulations allow a brand name company to list a patent in the Orange book as long as the patent was submitted to the FDA within thirty days of the patent's grant.[10] According to Hatch-Waxman regulations, even a generic with a pending ANDA when additional patents are listed must re-certify to the newly listed patents.

On the other hand, the second Hatch-Waxman provision to resolve the conflicting patent claim encourages generic manufacturers to initiate 'Paragraph IV' litigation. The FDA

[9] The Agency relies on declarations of good faith, signed by brand name firms, that submitted patents have merit. '180-Day Generic Drug Exclusivity'

[10] Voet [61]

writes 'the statute provides an incentive of 180 days of market exclusivity to the 'first' generic applicant who challenges a listed patent by filing a 'substantially complete' 'Paragraph IV Certification' and runs the risk of having to defend a patent infringement suit.' The regulatory landscape implementing the 180 day exclusivity has had a highly contentious and unstable history, which has continued to the present.[11] In the presence of pending litigation and current administrative review, the FDA had not published a final rule on the exclusivity as of July 2007.

In conclusion, the Hatch-Waxman provision establishing 'Paragraph IV' patent certifications creates uncertainty about the length of exclusive marketing for brand name firms. On one hand, exclusive marketing can be extended beyond the last date of patent expiration listed in the Orange Book shortly after approval. This could depend on factors such as whether brand name firms chooses an aggressive patent listing strategy, the timing and success of 'later' patents[12] or the outcome of 'Paragraph IV' infringement suits. On the other hand, exclusive marketing can also end earlier than anticipated if the generic manufacturer can invent around the patents, establish *bioequivalency*, and win the 'Paragraph IV' infringement suit.

2.2.2 The Structure of 'Paragraph IV' Litigation

For the majority of brand name drugs, the uncertainty generated by 'Paragraph IV' litigation is mostly resolved at the District Court level. In general, pharmaceutical patent infringement decisions are highly uncertain events for many reasons, such as patents are suppose to protect novel innovations, there may be minimal legal precedent directly applicable to the patents at issue or the exact way the generic potentially infringes on those patents may be new. These cases begin in a District Court and they nearly always proceed to the Appellate Court, where they are heard by a three judge panel. However, the Appellate Court mostly upholds the decisions of the Lower Court. Appellate cases are occa-

[11] According to the FTC [21], the FDA only granted this exclusivity to three generic manufacturers prior to 1993. However, between, 1993 and 1997, the FDA did not grant this exclusivity to any generic applicants stating that applicants must win an infringement suit against a brand name company to be eligible. These regulations were challenged by the generic firm Mova, in *Mova v. Shalala*, and in April 1998, the Court of Appeals affirmed that the FDA's interpretation of the 180 day exclusivity was inconsistent with the Hatch-Waxman statutes. From 1998 to 2001, the FDA granted the 180 day exclusivity to thirty-one generic applicants.

[12] The US Patent and Trademark office takes between one and three years to decide a patent case (Voet [61]).

sionally remanded back to the lower Court for partial reconsideration but complete reversal is rare. The Supreme Court does not hear pharmaceutical patent infringement cases where infringement is the issue at trial.

The structure of 'Paragraph IV' District Court cases generates considerable uncertainty in the outcome. Patent infringement trials are bench trials, which means they are decided by a single judge. Once the brand drug company files the suit, the judge determines whether the minimal legal requirements to proceed to trial have been met, sets the scope of the issues at trial, and hears a couple of days of oral arguments. Then the judge withdraws from the public and may announce her decision anytime within roughly the next year. After oral arguments, she typically does not communicate with the litigants or the public until she announces her decision.

'Paragraph IV' trials generate a binomial state space, either the brand wins and maintains marketing exclusivity or the brand firm loses and there is generic entry. If the judge determines the brand firm's patent is infringed by the generic's copy, then the FDA can not legally approve the generic version and the generic can not enter until the patent at issue expires.[13] With this decision, the brand firm is considered to have won the case because it continues to have exclusive marketing rights until the patent expires. On the other hand, the FDA can legally approve a generic version with a District Court decision of non-infringement. In this case, the generic may enter the market as soon as the FDA finishes its regulatory process (which typically takes roughly a month) and the company can physically bring its product to market. With this simple outcome structure, the judge is deciding whether or not the brand name firm may earn monopoly rents from roughly the current time until the patent expires or what the industry concentration is during this time period.

The binomial state space argument requires that the patents at issue in the case expire at the same time. Also, the argument claims that the number of generic defendants or the issue of validity vs. infringement does not matter for a number of reasons. Some generics decide not to enter until after the Appellate Decision to avoid the risk of potential treble damages. The '180 day exclusivity' applies to some generics but not all. There may be other cases with different generic defendants. The number of generic defendants about to receive FDA approval is unknown because the FDA does not release that information. And

[13] Assuming no other patent issues arise.

finally, cross licensing is prevalent among generics which means that the number of generics who receive FDA approval is nearly always less than those which finally enter. All of these reasons break the correlation between the number of generic defendants and the number and timing of generic entrants.

2.3 Research Design

2.3.1 An Industry with an Exogenous Change in Concentration

Ideally, to test the effects of industry concentration on any function of firm profitability, the researcher would randomly reassign a fixed production capacity to a different number of owners holding everything else, such as input prices and demand, constant. Random reassignment ensures that estimates do not suffer from the simultaneous equations and omitted variable biases that plague estimates of endogenous relationships. When random assignment is not a viable option, an alternative approach is to rely on an industry with a gate keeping mechanism that determines all facets of the concentration change independently of any action by the actual and potential industry participants.

The unique regulatory environment of the pharmaceutical industry provides the key econometric features for identifying and isolating the effects of a concentration change. The underlying source of the exogenous change in concentration stems from generic entry due to the brand drug's patent expiration. Pharmaceutical products provide the cleanest example of a change in concentration due to patent expiration because the FDA's Orange Book establishes an exact correspondence between patents and products. In using 'Paragraph IV' District Court decisions as a gate keeping mechanism, this paper takes advantage of that established correspondence. The retail market for pharmaceutical products is also cleanly defined. The FDA has the right to regulate all prescription and over-the-counter drugs in the United States. Therefore, the retail market constitutes the FDA's jurisdiction.[14]

Due to the bioequivalency requirement and other regulations, the FDA argues that brand name drugs and their generics are virtually perfect substitutes differing only in name. A brand name drug is any molecule that has had a new drug application (NDA) approved by

[14] This is an uncontroversial definition of the retail market compared to, for example, to work done on retail gasoline where a single station's market has been defined as both the set of stations within a one mile of street distance from the original station (Hastings [28]) and the set of stations along each consumer's commuting path (Houde [32]).

the FDA. A brand name drug only receives approval for specific dosages, routes of administration, and indications of usage[15] and it is only sold under a *proprietary* name agreed upon by the FDA. A generic version of a brand name drug has the same active ingredients, route of administration, dosage form, strength and indications of usage. Furthermore, the inactive ingredients must have been previously approved in a similar NDA. Formally, a generic drug must establish its bioequivalence to a brand name drug (Voet [61]). Generics may only be identified by the molecule's chemical name[16], and generics must also have the same labeling as the brand name drug.

Finally, generic entry in the pharmaceutical industry minimizes a number of potential confounding factors when trying to isolate the effects of horizontal concentration change. The pharmaceutical industry does not have the strong networking effects found in various transportation, communication, and energy industries, for example. Horizontal concentration changes in the pharmaceutical industry are not accompanied by changes in vertical integration and the complicated contractual relationships between supplier and producer typically found in the oil and gas industry. Finally, pharmaceutical industry concentration changes do not include a rebranding of the product found sometimes after mergers, although prescription drugs have a branded and an unbranded version.

2.3.2 Pricing the Concentration Change in the Financial Market

Event study methodology is rooted in the rational expectations/efficient market tradition in financial economics. There is little controversy about the underlying assumptions, statistical properties, and interpretation of short horizon event studies, as codified by Fama, Fischer, Jensen, and Roll [16]. The efficient market hypothesis argues that capital markets are efficient mechanisms which instantaneously impound all relevant information into the stock price of a firm. In such a market, share prices only change when the market receives value relevant new information. This paper examines how the announcements of 'Paragraph IV' District Court decisions impact the brand drug's stock returns. In this experiment, the methodology credibly establishes that the outcome of the litigation caused the change in returns.

Ideally, I would measure the returns on the entire residual value of the claim on brand

[15] Therefore, brand name drugs are product differentiated along four dimensions, with the active ingredient as the last dimension.

[16] For example, generic Prozac is called fluoxetine.

name drugs that can be replaced by generic competitors. However, much of the uncertainty about the value consequences of generic entry can only be resolved over long periods of time. Before the date of patent expiration, information arrives about the number of tentatively approved generics,[17] the identity of the generics, and sometimes, the date when generic entry may begin. Only after patent expiration is the uncertainty resolved concerning how quickly generics will enter (this depends partly on when the FDA awards approval), how the generics will compete with each other and with the name brand drug, the resulting prices and quantities (thus revenues), along with the total number of generic entrants. However, long horizon event study methodology has relatively lower power and is more susceptible to the joint-test problem.[18] Therefore, I use the announcement of 'Paragraph IV' decisions because they generate dramatic results above the normal background noise of returns and short window tests have higher power.[19]

Pricing the announcement of 'Paragraph IV' decisions satisfies many of the standard, short window event study assumptions. The gate keeping role of the court makes the timing and outcome of these infringement decisions exogenous to the litigants. This minimizes several biases that arise when firms are able to directly influence the event.[20] Abnormal returns are concentrated in the event window because there is no information leakage before the decision is announced. 'Paragraph IV' decisions occur randomly since their timing is the complete discretion of the judge, which means there is no event clustering in calendar time.[21] Finally, confounding effects in the event window are easily ruled out, there is no problem with inaccurate announcement dates, and the shares of the brand name companies in this sample are sold on the major American exchanges which rule out the need for thin market corrections.

The brand firm's pre-decision stock price and expectations about the trial's outcome

[17]The FDA does publicly announce tentatively approved ANDA's. Currently, this information can be found on the webpage Drugs@FDA: FDA Approved Drug Products

[18]Event study tests are joint tests of whether abnormal returns are zero, and of whether the chosen model of expected return, CAPM, market model, etc., is the true model (Khotari and Warner [37]).

[19]I also explored the announcements of tentative and full approvals of generics and the announcement of awarding the Pediatric Exclusivity which grants six months extra marketing exclusivity due to additional pediatric testing. However, these events did not generate as dramatic results.

[20]One potentially relevant bias stems from self selection which occurs because the sample of firms choosing the event is not a random subset of the relevant population. This bias has the potential to render the usual OLS/GLS estimators inconsistent. Examples of event studies with self selection biases include calling a convertible bond (Acharya [1]), takeovers (Eckbo, Maksimovic, and Williams [15]), and the choice of covenants attached to debt issues (Goyal [24]).

[21]Event clustering invalidates the assumption of independence in the cross section of abnormal returns. (Khotari and Warner [37])

can be easily interpreted within the one period state (Arrow-Debreu) price paradigm.[22] 'Paragraph IV' infringement decisions are anticipated events which means that expectations about their outcomes are already impounded into the stock price when the decision is announced.[23] The binomial state space for the trial's outcome after the completion of oral arguments is that either the brand wins or the brand loses. The state dependent valuation for the brand firm given the brand wins includes monopoly rents until the time the patent expires, V_m, compared to the valuation given the brand faces generic entry, V_g. Expectations about the likelihood of each outcome are captured in the state prices, ρ_m and ρ_g.[24] Let V_0 be the pre-decision valuation and r_f be the risk-free rate. Therefore,

$$V_0 = \frac{1}{1+r_f}\{\rho_m V_m + \rho_g V_g\}.$$

The brand firm's pre-decision stock price represents a discounted convex combination of the rents from a monopoly industry structure until the time of patent expiration and the rents from generic entry.

The analysis of the binomial state price representation results from the realization that there is no premium for the uncertainty in the announcement date. This uncertainty is not priced because there is no correlation between the time that has passed since the end of oral arguments and the likelihood of a particular decision. For example, if a judge is taking a longer time than usual to decide a case, the market does not know whether she has a difficult case, she has a full calendar, or any other of a myriad of explanations. Therefore, the market learns nothing from the passage of time. Also, the probability of a decision occurring on any date is equally likely and independent of the probability of a decision occurring on the previous date.

The binomial state price representation of the brand firm's stock price can be used to isolate the sign of the concentration effect, even in the presence of expectations. Once again, the brand firm's pre-decision stock price can be modeled by a discounted convex combination

[22] The one period state price representation argues that an asset's price today can be represented as the summation over all possible states tomorrow of the state price multiplied by the state dependent valuation all discounted by the risk free rate.

[23] Because patent expiration and the possibility of generic entry is a well known feature of a brand drug's product life cycle, prior beliefs about value relevance of patent expiration, in general, are impounded into the stock price from the brand drug's conception.

[24] State prices are often given probability interpretations since the price of a security that pays one dollar only in the realization of a certain state increases with the probability of that state occurring.

of the company's valuation given the additional months of monopoly rents of the relevant drug (i.e., the brand wins) and the valuation of the company without the additional months of monopoly rent (i.e., the brand loses). Assuming the state price probability of each trial outcome is strictly positive, then the pre-decision share price is strictly within the interval of the two post-decision state contingent valuations. Therefore, a significant positive (negative) abnormal return may be imbued with the interpretation that the market believed that the event increased (decreased) the value of the corporation.

The difference between the 'Announcement Effect' and the 'Valuation Effect' reflects how expectations impact the magnitude of the event's value consequences.[25] Conceptually, the 'Valuation Effect' reflects the entire value relevance of the event. In contrast, an 'Announcement Effect' exists when the abnormal performance captures the deviation of the realized state contingent price from a price which included the market's expectations about the likelihood of that state. In event studies, the magnitude of abnormal performance provides a measure of the unanticipated impact of the event on the wealth of firm's claim holders (Khotari and Warner [37]). When events are value relevant and complete surprises, then abnormal returns naturally capture the 'Valuation Effect'. However, in the case of anticipated uncertain events, such as infringement decisions, expectations about the outcome only allow event studies to capture an 'Announcement Effect'. The abnormal returns generated by 'Paragraph IV' decisions reflect an 'Announcement Effect' because they are a function of the pre-decision stock price, which according to the state price paradigm, includes expectations about the trial's outcome. Therefore, the abnormal return if the brand wins is $AR_t^m = V_0^{-1}(V_m - V_0)$, and if the brand loses is $AR_t^g = V_0^{-1}(V_g - V_0)$.

In contrast, the 'Valuation Effect' captures the added value a brand firm receives from competing in a monopoly compared to facing generic entry. An 'absolute' 'Valuation Effect' is the value of a brand firm given it maintains monopoly rights minus the value given in faces generic entry or $V_m - V_g$. However, it is difficult to compare this result across firms. Therefore, I use a 'relative' 'Valuation Effect', or $V_0^{-1}(V_m - V_g)$, which I will use as the value of marketing exclusivity. This value of marketing exclusivity can be related back to the abnormal returns estimated from the event study using the identity $V_0^{-1}(V_m - V_g) = AR_t^m - AR_t^g$. Since AR_t^g has a negative sign, the value of marketing exclusivity is the sum

[25] I am borrowing this terminology from the 'partial anticipation' literature in event studies which addresses events in which the firm decides whether the event occurs, its timing and its outcome.

of the two abnormal returns.

2.4 The Data

2.4.1 Description and Summary Statistics

The sample consists of all 'Paragraph IV' District Court decisions pertaining to brand name prescription drugs. The possible time period of these decisions ranges from the passage of the Hatch-Waxman Act in 1984 through to 2007. The FDA publishes a list of all brand name drugs for which a 'substantially complete' 'Paragraph IV' ANDA has been received by the Office of Generic Drugs.[26] To construct my sample, I began with the list of all brand drugs whose ANDA was filed before 12/31/2004. This cut-off date balances the trade-off of maximizing the sample while allowing enough time for the majority of drugs from this time period to reach their first District Court decision.[27] A 'drug' is defined as a molecule with a unique combination of active ingredient and brand name. Therefore, different forms, dosages, or indications within this combination do not constitute a distinct drug. There are 232 brand drugs for which an ANDA was first filed before 12/31/2004.

For each brand name drug on this list, I searched the LexisNexis® Academic Power Search of State and Federal Court Cases to find the complete set of brand drugs with a 'Paragraph IV' District Court decision.[28] The search produced 76 distinct brand drugs with at least one District Court decision.[29] Brand drugs may not have a decision for a multitude of reasons. Brand and generic companies may settle the litigation out of court. Brand companies have other legal means to prevent generic entry besides patent protection. For example, brand companies can petition the FDA challenging the safety and efficacy of a generic copy. Finally, for many ANDAs applications, the brand company never filed the infringement suit.

For the purpose of cross sectional consistency, I chose one District decision per drug.

[26] The Office of Generic Drugs is a department within the FDA. Note this list also includes the brand name drug's active ingredient, form, and dosage and it can be found on the FDA's webpage 'Paragraph IV Patent Certifications' (http://www.fda.gov/CDER/ogd/ppiv.htm).

[27] I also examined drugs through 12/31/2005, but very few had reached their first decision.

[28] I used the search terms "Brand and patent and (Paragraph IV or Hatch-Waxman or ANDA or infringe! or valid! or invalid!)"

[29] However, the 76 brand drugs corresponded to 72 series of cases because the following drugs were tried in the same case; Tenormin and Tenoretic, Wellbutrin SR and Zyban, Claritin and Claritin Reditabs, and Micro K and K Dur.

I only included those District Court decisions concerning the infringement and/or validity of a patent protecting the brand drug. While some drugs had relatively simple litigation which resulted in only one District Court decision, others can had complicated proceedings which resulted in many District Court decisions occuring both simultaneously and over time. Therefore, I developed a decision rule to select the 'main' decision in which the 'majority' of uncertainty about generic entry was resolved. For a series of District Court cases with the same litigants and different patents, I chose the last case. This situation arises when generics try to overturn patents in separate cases over time. The uncertainty about whether and when generics can enter is therefore resolved with the last case.[30] For a series of cases with different litigants and the same patent, I chose the first case because it establishes the precedent about how certain technical issues related to the patent will be interpreted.[31] Finally, for a series of cases with the same defendants and the same patents, wherethere is a District Court decision, followed by a Appellate Court decision which repeals and remands the District Court decision, followed by a second District Court decision, I chose the first of the District Court decisions.

The construction of this data set differs from two previous studies of 'Paragraph IV' filings and infringement litigation. The first study, conducted by the FTC [21], studied all brand drugs that received notification of a 'Paragraph IV' ANDA from 1/1/1992 to 1/1/2001. This selection criterion produced 104 drugs, where a drug is defined by a unique NDA. In their sample, the FTC [21] found that the brand company did NOT initiate infringement litigation for 29 drugs, that there were District Court decisions for 30 drugs[32], and that 22 drugs still had pending cases at the end of the sample. The sample in this paper expands the time period studied by the FTC and focuses solely on the outcome of District Court decisions, not the outcome of ANDA filings. Berndt, Mortimer, and Parece [5] examined whether authorized generic entry decreases 'Paragraph IV' Certification filings. They examined three data sets; the FDA data set, a proprietary survey data set by PhRMA,[33] and a proprietary dataset by Paragraphfour.com which provides data on all 'Paragraph IV' certifications that faced court challenges since 2003. The sample in this paper is the first complete single source data set of the 'main' 'Paragraph IV' patent

[30] Examples of brand drugs in this category include Augmentin, Altace, Paxil, and Taxol.
[31] An example of a brand drug in this category is Wellbutrin SR.
[32] The brand company won 8 cases and the generics won 22.
[33] The PhRMA data set includes information for about 73% of brand drugs from the FDA data set.

infringement District Court decisions. It is also free and publicly available.

I argue that the uncertainty generated by patent infringement litigation was mostly resolved at the District Court level.[34] There is a record of Appellate Court decisions for 53 of the 72 District Court decisions. The Appellate Court upheld 26 of the 53 District Court decision with no modification and the other 27 cases were either remanded back to the District Court for partial or full reconsideration, or reversed. However, not all of the 27 'modified' Appellate decisions had any effect on generic entry as determined by the District Court. Finally, the Supreme Court did not hear any of the cases in my sample where the issue at trial related to the technical merits of patent infringement or validity.

To make the study viable, I dropped three sets of District Decisions. Since I used CRSP stock pricing data, I excluded privately owned companies and companies with foreign listings. I also excluded observations without an *announcement date*. The variable 'Announcement Date' captures the date the decision became public knowledge which is operationalized as the first date any information about the decision appeared in the LexisNexis® Academic Power Search Database of US Newspapers and Wires.[35] Except for the District Case pertaining to Augmentin, the Announcement Date was always within a couple days after the District Case's official decision date. Finally, I also excluded brand drugs whose generic manufacturer entered before the District Court Decision. According to the Hatch-Waxman Act, a generic company can enter before a District Court decision if the 30-month stay runs out. However, if the generic manufacturer enters and a future District or Appellate Court decision finds for the brand, then a jury trial date is set to determine the damages.[36] Once generic manufacturers enter, trial outcomes determine damage awards and not the rents from exclusive marketing. The variable 'Generic Entry' indicates the date which the IMS Health Market Research Database Product Directory for the second quarter of 2007 recorded the first generic firm selling the molecule. If the data is missing from the IMS source, then I used the FDA's Drugs@FDA website to determine the date the first generic received FDA approval to enter.

After dropping the above observations, the sample consists of 49 District Court cases

---

[34]This is an easily testable assumption by studying the outcome of Appellate decisions and the market responses.

[35]I used the search terms "(Brand or Activeingred) and (patent or infringe! or valid! or invalid! or generic or court)".

[36]The level of damages is subject to considerable variability partly because courts have the discretion of imposing triple damages if the infringement was deemed intentional.

pertaining to 51 distinct brand name drugs. The District Court decisions included in the study are listed in Table 2.7 in the Appendix and the excluded decisions, along with the reason they were excluded are listed in Table 2.6.

The variable, 'Winner', takes on the values *Brand* or *Generic*, and indicates the realized state space or the outcome of the District case. *Brand* means the brand maintains marketing exclusivity and *Generic* means there is generic entry.[37] Winner is listed in Table 2.8. For the 49 District Case sample, the brand firm won 23 cases and the generic won 26 cases.[38] While ex-ante, the market may have believed that the likelihood of the brand winning each individual case was different than 50%, ex-post, it appeared that a brand firm had just over a 50% chance of 'winning' an average patent infringement case. As shown in Table 2.9, it does not appear there was any time trend in the number of cases won by a brand or generic.

Nearly all of the District Court decisions occur after 1997. Table 2.9 depicts the number of decisions by year for the 72 District cases, the 49 District case sample, and the number of cases won for each group. Table 2.9 also indicates that the number of decisions each year plateaued at five or six starting in 2002, which shows that besides the increasing number of 'Paragraph IV' ANDAs being filed with the FDA described in the previous section, there was an increasing number of cases reaching District Court decisions. The post-1997 rise in District Court cases coincides with a change to the FDA's interpretation of the '180-day Exclusivity Rule'.[39]

Because my study focuses on the product level, and not the entire firm, I created the variable, Sales %. Sales % is the individual drug's fraction of its total company sales during the fiscal year before the decision. I used sales data from the Compustat Industrial Annual File to find the total company sales for the respective year. The drug level sales data comes from the magazine *Drug Topics* [14], which published a list of the top 200 brand name drugs by US retail sales each year from 1999-2006. There are many limitations to using

[37] Note that these state spaces were defined to capture the legal possibility of generic entry. Typically, the Brand wins when a relevant patent is found to be both valid and infringed, however Prilosec provides an interesting counterexample. There were four generic defendants in the case and three were found to infringe, while the fourth firm, Kudco, was found not to infringe. According to my criteria, the case should have been labeled as Generic wins. However, two of the other generics, Andrex and Genpharm, had the '180 day exclusivity' which meant that no other generic could enter until they shared 180 of exclusively marketing their generic. Because, Kudco could not enter before Andrex and Genpharm, generic entry was legally prevented until the patents expires and so the case was classified as Brand wins.

[38] For the original 72 District Case sample, the brand firm won 34 cases and the generic manufacturer won 38 cases.

[39] Between 1992 and 1998, the FDA did not grant the 180-day exclusivity to any generic. However, in 1998, the FDA lost a court ruling, changed its regulations, and started awarding this exclusivity to generics.

this variable as a measure of the drug's relative value to the firm. The ideal measure would capture the market's expectations at that time about what the drug's future relative value will be. Instead, I use an ex-post measure, which summarizes the value of the drug to the firm in the past. Furthermore, this measure does not include any intangible value from the drug, such as additional firm reputation effects, and the above mentioned measurement error. However, while Sales % is thus noisy, it will provide a useful scaling variable. Sales % is listed in Table 2.8.

The distribution of 'Sales %' is highly skewed towards relatively lower value drugs.

Table 2.1: Sales Percentage Summaries

	Min	Max	Mean	SD	25%	50%	75%	Observations
Brand Wins	0.7594	63.51	10.01	15.12	1.208	2.920	13.58	23
Generic Wins	0.3864	100	12.31	23.19	0.8482	1.844	9.930	26
All Cases	0.3864	100	11.23	19.65	1.183	2.768	10.33	49

The above table indicates that the median for the various groups was between 1% and 3%, while the means were between 10% and 12%. While this sample does contain many 'blockbusters',[40] which generate significant profits in absolute terms, the U.S. sales of many of these drugs were still a relatively small fraction of the firm's total cash flow. This raises the possibility that the test statistic will not be able to capture the effect of an infringement decision for these drugs. In other words, these lower relative value drugs may not generate large enough firm level abnormal returns to be seen over the natural noise of stock prices.

Finally, I created two more variables, 'Unique Expiration Date' and 'Exclusivity at Issue' to explore the dual state space assumption and the impact of the number of months of patent protection at issue in the case. These variables were created by first looking at the patent expiration dates in the European Patent Office's online database esp@cenet. This lists the date of application, date of grant, and any known extensions. I then double checked the FDA's website to see if the brand had been granted a six month pediatric exclusivity; such information was not listed in esp@cenet. I repeated these calculations for every patent at issue for each drug, and set the unique expiration date equal to the last expiration date of all the patents at issue. Months of exclusivity at issue is then calculated as the number of months elapsing between the date of the district court decision and the unique expiration

[40] Coined in 2000 and unadjusted for inflation, 'blockbuster' is the informal industry term for any drug generating more than $1 billion of revenue for its owner each year.

date. Table 2.10 provides a list of these variables. The table below provides the summary statistics for Exclusivity at Issue.

Table 2.2: Marketing Exclusivity at Issue (Months)

	Min	Max	Mean	SD	25%	50%	75%	Observations
Brand Wins	4	180	68.57	55.63	25	60	105	23
Generic Wins	16	231	113.38	68.05	43	135	168	26
All Cases	4	231	92.35	65.88	32	70	152	49

Comparing the means of the two groups, we see the average months of patent protection for cases in which the generics won was nearly double the average number of months for generics winning.

Finally, I explore the state space assumption. According to my argument, in order for the dual state space assumption to apply, I need only one patent expiration date. This can occur when there is only one patent at issue in the case or when there are multiple patents with the same expiration date. However, there are cases in my sample with more than one patent expiration date at issue. As noted above, in this case I took the expiration date of the last patent as my unique expiration date. However, it is possible that multiple patents and expiration dates may have additional influence on the outcomes. I will test for these influences in Section 2.5.

2.5 Results and Discussion

Following standard event study methodology, I computed the abnormal returns using the market model as the benchmark. I used the value weighted CRSP index, excluding dividends, as the market index. I estimated the market model using returns from the 271 days directly preceding the announcement date. I considered the abnormal returns over three different event windows, because it is difficult to know when the market reaches its new equilibrium solely due to the District Court announcement. The different event windows provide a range of the abnormal returns, but it is still possible that the true value of the abnormal return lies outside this range. The first two event windows and their respective abnormal returns are the standard announcement day return, AR, and the announcement day plus the day after return, CAR. These event windows begin on the announcement date because there is no information leakage before the event. The last event window is the announcement day return plus the close to open return, denoted AR^+. Unfortunately, the exact time of day when the announcement is made is unknown and some announcements were definitely made after the market closed on the announcement day. In these cases, the abnormal returns do not show up in AR but do show in CAR. While the two day event window is typically used when the time of the announcement is unknown, it may allow more noise to affect the estimates. Therefore, I provide the three event windows to provide a range of estimates to account for the unknown announcement time and to allow differing amounts of time for the market to fully incorporate the information.

The results of the event study are summarized in Table 2.11. Table 2.11 divides the results into two groups according to the 'Decision' variable – whether the brand or the generic 'won' the case and reports the results for the three event windows. Not surprisingly, Table 2.11 provides a strong sign result according to whether the brand won or lost the case. The abnormal returns are positive (negative) when the brand 'wins' ('loses'), with the intuitive explanation that maintaining (losing) the right to exclusive marketing creates (destroys) firm value. Furthermore, all of the abnormal returns have the appropriate sign, given their respective trial outcomes. Because the brand firm's stock return decreases with generic entry, this experiment produces a concentration effect with the opposite sign found by Hou and Robinson [31]. On the other hand, this result supports the work done by Lustgarten and Thomadakis [44].

The table also partitions the results according to Sales %. The first three rows include all the decisions involving a brand name drug with at least the stated Sales % in the fiscal year before the decision. The last two rows include only those decisions where the brand name drug had between 0% and 1%, and between 1% and 2% of its company's sales. Comparing rows one through three, the abnormal returns in each respective group maintain their sign, but their magnitude and statistically significance decreases, although they remain significant at conventional levels. However, examination of the bottom two rows, which isolate the decisions in the lower percentages of the Sales % ranges, indicates that the magnitude of these abnormal returns is very small and has the opposite sign for the case of brand firms.

The purpose of finely partitioning the sample according to a noisy variable stems from the consequences of using an event study to value the impact of one product within a firm.[41] Short window methodology is ideal for isolating the effect of one drug in the US market when each pharmaceutical company consists of a portfolio of drugs sold in numerous countries. However, if the value of the individual drug is sufficiently small relative to some measure of the firm's value, it is possible that the effect of a 'Paragraph IV' decision would be too small to register in the abnormal return. I expect the magnitude of the abnormal returns to decrease with the Sales % until at some point, they are overwhelmed by the natural noise of stock returns. This raises the possibility of using a Sales % based weighting to recover the effect of 'Paragraph IV' decisions for drugs above this point, and requires cutting drugs below the point. I argue that because the abnormal returns for drugs with a Sales % between 0% and 1% and for which the brand firm won, have the 'wrong' sign, they are simply noise and should be cut from the sample.

Before any weighting, the magnitude of the abnormal returns and the value of marketing exclusivity for drugs with Sales % $>$ 1% is dramatic. Table 2.11 indicates that the brand firm's value increases between 1.24% and 2.83% if it 'wins', and decreases between -5.24% and -5.82% when it 'loses'. Once again, the one day returns are likely to undervalue the estimate if there are any announcements about the Court's decision that are made after the market closed. However, the two day returns can add noise to estimates if the market incorporates the information about the decision on the first day. These ranges provide the estimates of the 'Announcement Effect'. It appears that the magnitude of the abnormal returns for the generic firms are roughly twice as big the magnitude for the brand firms, in absolute value. One potential explanation is that the average number of months of marketing exclusivity at issue for cases that generics won was twice as large as those for cases that the brand won. I test the difference in magnitude shortly.

The value of marketing exclusivity (VME) for the three abnormal returns is provided in the table below, Table 2.3.

Table 2.3: The Value of Marketing Exclusivity for Drugs with Sales % $>$ 1%

Decision	Cases	AR	t-stat	AR^{+}	CAR	t-stat
Brand	20	1.24%	2.7	3.22 %	2.83 %	4.8
Generic	18	-5.24%	-6.8	-5.59 %	-5.82 %	-5.9
VME		**6.48**%		**8.81** %	**8.65** %	

[41] Most event studies focus on events that impact the entire firm, such as mergers.

Once again, the value of marketing exclusivity is $V_0^{-1}(V_m - V_g) = AR_t^m - AR_t^g$. I find that the value to a brand firm of maintaining marketing exclusivity is between 6.48% and 8.65%. However, this range provides a lower bound on the results because I use an equal weighted average. In other words, I treat drugs with a large Sales % exactly the same as one with a small Sales % and the same holds true for Exclusivity at Issue. This range applies to a sample with an average Sales % of 11.23%[42] and an average Months of Monopoly Rents at Issue of 92 months.

Before exploring a Sales % weighting, I regressed the CAR for drugs with Sales % > 1% to test some hypotheses. In order to facilitate the between group effect between brands and generics, I switched the sign of the CAR for cases in which the generic won. I ran the cross sectional regression

$$CAR_i = \lambda_o + \text{I\_generic} + \lambda_1 \text{Sales\%}_i + \lambda_2 \text{State\_Space}_i + \lambda_3 \ln(\text{Months})_i + \epsilon_i.$$

I_generic indicates whether a generic firm won, and is used to test whether the difference beween the absolute value of the magnitude of the brand and the generic is statistically significant. State_Space corresponds to the number of unique patents and is used to test whether cases without a clear binomial state space are different. ln(Months) indicates how the number of months of marketing exclusivity affects CAR. I took the natural log of this variable because the market discounts the cash flows in the distant future at a greater rate. The regression was corrected for heteroskasdicity, and the Breusch-Pagan statistics are provided below.

Table 2.4: CAR Determinants

CAR	Coefficient	Standard Error	t-test
I_generic	.0121	.0135	0.9
Sales %	.0016	.0005	3.1
State_Space	.0107	.0077	1.39
ln(Months)	.0114	.0058	2.0
Constant	-.0480	.0218	-2.2

Number of observations = 38, $F(4, 33) = 5.93$, Prob > F = 0.001, R-squared = 0.4897, Root MSE = .0474, Breusch-Pagan: Prob > χ^2 = .0004

This regression indicates Sales % and ln(Months) have significant explanatory power. On the other hand, the difference in the absolute value of the magnitude of the CAR between the

[42] Note that the median is 2.89%.

group is not significant, and State_Space is not significant indicating that the 10 potential cases with arguably more state spaces do not significantly affect my results.

Finally, I weight the abnormal returns by the inverse of Sales %. This allows me to suppose each drug constitutes 100% of its company's sales which means that the abnormal return and VME estimates apply directly to the product level. The results for the sample with Sales % greater than 1% are included in the table below.

Table 2.5: Sales Weighted Value of Marketing Exclusivity for Drugs with Sales % > 1%

Decision	Cases	AR	AR^{+}	CAR
Brand	20	4.02%	24.89%	18.37%
Generic	18	-57.75%	-69.16%	-50.45%
VME		**61.77%**	**94.05**	**68.62 %**

This table indicates that the value of maintaining marketing exclusivity for an individual drug is between 61.77% and 94.05% of the drug's monopoly value. This range applies to a sample with an average Months of Monopoly Rents at Issue of 92 months.

2.6 Conclusion

This paper takes advantage of the uncertainty and the structure embedded in 'Paragraph IV' District Court decisions. These decisions constitute a repeated exogenous change in industry concentration with many useful empirical properties. In particular, they satisfy the strict requirements for using a short window event study to estimate the decision's effect on the brand firm's stock returns. They also have a binomial outcome space, which is useful for determining the value of marketing exclusivity. However, while the short window methodology is ideal for isolating the effect of one drug within the US market, it is unable to capture the effect of drugs which constituted a small fraction of their firm's total sales.

This paper's estimates of a concentration effect produce the opposite sign to Hou and Robinson [31]'s result, but agree with sign found by Lustgarten and Thomadakis [44]. Unlike these authors, the event study methodology includes an intuitive explanation for the sign of the results. I find that the announcement return for drugs with Sales % greater than 1% is between [1.24%, 2.83%] if the brand firm maintains its monopoly rights until patent expiration, and between [-5.24%, -5.82%] if the brand faces generic entry. These results are both highly economically and statistically significant, and they indicate that 'Paragraph

IV' decisions are an important industry phenomena that may have important consequences for how the lifecycle of brand drugs are managed and for future research and development. Finally, I use these returns to construct the first market valuation of the monopoly rents. I estimate that the value to a brand firm of maintaining marketing exclusivity for an average 92 months is between [6.48%, 8.65%].

Table 2.6: 'Paragraph IV' District Court Decisions Excluded from Study

	Brand	Active Ingredient	Company	Generic Entry	Decision Date	Winner	Exclusion Reason
1.	Aciphex	Rabeprazole Sodium	Esai	N/A	5/11/2007	Brand	Foreign Stock Listing
2.	Actos	Pioglitazone Hydrochloride	Takeda	N/A	2/21/2006	Brand	Foreign Stock Listing
3.	Adalat CC	Nifedipine	Bayer	5/2000	3/16/1999	Generic	No Announcement Date
4.	Advil Cold and Sinus	Ibuprofen Potassium / Pseudoephedrine Hydrochloride	Wyeth	Unknown	8/11/2006	Generic	No Announcement Date
5.	Avelox	Moxifloxacin Hydrochloride	Bayer (Schering)	N/A	10/25/2007	Brand	No Announcement Date
6.	Axid	Nizatidine	Eli Lilly	7/2002	10/12/2001	Brand	No Announcement Date
7.	Depakote	Divalproex Sodium	Abbott	N/A	3/29/2001	Brand	No Announcement Date
8.	Diflucan	Fluconazole	Pfizer	7/2004	2/14/2002	Brand	No Announcement Date
9.	Diprivan	Propofol	AstraZeneca	9/2000*	11/2/2005	Brand	???
10.	Flexeril	Cyclobenzaprine Hydrochloride	Merck	5/1989	8/31/1998	Generic	No Announcement Date
11.	Flomax	Tamsulosin Hydrochloride	Astellas / Boehringer Ingelheim	N/A	2/21/2007	Brand	No Announcement Date
12.	Floxin	Ofloxacin	Daichii Sankyo	8/2007	8/1/2006	Brand	Foreign Stock Listing
13.	Hytrin	Terazosin Hydrochloride	Abbott	8/1999	9/1/1998	Generic	No Announcement Date
14.	Micro K; K-Dur	Potassium Chloride	A.H. Robins	6/1990	4/18/1991	Generic	No Announcement Date
15.	Neurontin	Gabapentin	Pfizer	10/2004	8/23/2005	Generic	Generic Entered Before Decision
16.	Oxycontin	Oxycodone	Purdue Pharma LP	6/2005	1/5/2004	Generic	No Announcement Date
17.	Paraplatin	Carboplatin	Bristol-Myers	7/2004	7/25/2002	Brand	No Announcement Date
18.	Plavix	Clopidogrel Bisulfate	Bristol-Myers / Sanofi Aventis	8/2006	6/19/2007	Generic	No Announcement Date
19.	Seldane	Terfenadine	Hoechst Marrion Roussel	1/1997	11/12/1996	Generic	Foreign Stock Listing
20.	Sinemet CR	Carbidopa/ Levodopa	Merck	1/1993	8/24/1998	Generic	No Announcement Date
21.	Tenormin; Tenoretic	Atenolol; Atenolol/Chlorthalidone	Imperial Chemical Industries	10/1991	11/4/1991	Brand	No Announcement Date
22.	Ultracet	Acetaminophen / Tramadol Hydrochloride	Ortho-McNeil / J&J	5/2005	10/19/2005	Generic	Generic Entered Before Decision
23.	Univasc	Moexipril Hydrochloride	Schwartz	5/2003	3/24/2003	Generic	No Announcement Date

* This date is taken from FDA data, not IMS Generic Spectra data.

Table 2.7: 'Paragraph IV' District Court Decisions Included in Study

	Brand	Active Ingredient	Company
1.	Accupril	Quinapril Hydrochloride	Pfizer
2.	Acular	Ketorolac Tromethamine	Allergan / Roche
3.	Alphagan	Brimonidine Tartrate	Allergan
4.	Altace	Ramipril	King
5.	Augmentin	Amoxicillin; Clavulanate Potassium	GlaxoSmithKleine
6.	Buspar	Buspirone Hydrochloride	Bristol Myers
7.	Celebrex	Celecoxib	Pfizer
8.	Claritin; Claritin Reditabs	Loratadine	Schering Plough
9.	DDAVP	Desmopressin Acetate	Sanofi Aventis
10.	Ditropan XL	Oxybutynin Chloride	Alza/J&J
11.	Duragesic	Fentanyl	Alza/J&J
12.	Fosamax	Alendronate Sodium	Merck
13.	Glucophage XR	Metformin Hydrochloride	Bristol Squibb
14.	Levaquin	Levofloxacin	Ortho/J&J
15.	Lexapro	Escitalopram Oxalate	Forest
16.	Lipitor	Atorvastatin Calcium	Pfizer
17.	Lovenox	Enoxaparin Sodium	Sanofi Aventis
18.	Mircette	Desogestrel; Ethinyl Estradiol	Akzo Nobel
19.	Monopril	Fosinopril Sodium	Bristol Myers
20.	Naprelan	Naproxen Sodium	Elan
21.	Norvasc	Amlodipine Besylate	Pfizer
22.	Paxil	Paroxetine Hydrochloride	GlaxoSmithKline
23.	Pepcid	Famotidine	Merck/Yamamouchi
24.	Platinol	Cisplatin	Bristol Myers Squibb
25.	Plendil ER	Felodipine	AstraZeneca
26.	Prilosec	Omeprazole	AstraZeneca
27.	Protonix	Pantoprazole Sodium	Wyeth
28.	Prozac	Fluoxetine Hydrochloride	Eli Lilly
29.	Rebetol	Ribavirin	Ribapharm
30.	Relafen	Nabumetone	GlaxoSmithKleine
31.	Remeron	Mirtazapine	Akzo Nobel
32.	Retrovir	Zidovudine	Burroughs Wellcome
33.	Risperdal	Risperidone	Johnson & Johnson
34.	Sarafem	Fluoxetine Hydrochloride	Eli Lilly
35.	Sporanox	Itraconazole	Janssen/J&J
36.	Tambocor	Flecainide Acetate	3M Pharma
37.	Taxol	Paclitaxel	Bristol Myers
38.	Tiazac	Diltiazem Hydrochloride	Biovail
39.	Topamax	Topiramate	Ortho-McNeil / J&J
40.	Toprol XL	Metoprolol Succinate	AstraZeneca
41.	Tricor	Fenofibrate	Abbott
42.	Ultane	Sevoflurane	Abbott
43.	Vicoprofen	Hydrocodone Bitartrate and Ibuprofen	Abbott
44.	Wellbutrin SR; Zyban	Bupropion Hydrochloride	GlaxoSmithKleine
45.	Wellbutrin XL	Bupropion Hydrochloride	Biovail
46.	Xalatan	Latanoprost	Pfizer
47.	Zantac	Ranitidine	Glaxo Inc
48.	Zofran	Ondansetron Hydrochloride	GlaxoSmithKleine
49.	Zyprexa	Olanzapine	Eli Lilly

Table 2.8: 'Paragraph IV' District Court Decisions Included in Study II

	Brand	Generic Entry	Decision	Announcement	Winner	Sales%
1.	Accupril	12/2004	06/28/2004	06/30/2004	Brand	1.18
2.	Acular	N/A	12/20/2003	12/31/2003	Brand	4.4**
3.	Alphagan	05/2003*	05/08/2002	05/09/2002	Generic	10.33
4.	Altace	N/A	07/17/2006	07/18/2006	Brand	39.52
5.	Augmentin	11/2002	07/19/2002	05/23/2002	Generic	6.28
6.	Buspar	04/2001	03/13/2001	03/14/2001	Generic	1.46
7.	Celebrex	N/A	03/20/2007	03/20/2007	Brand	2.75
8.	Claritin; Claritin Reditabs	01/2003	08/08/2002	08/08/2002	Generic	22.9
9.	DDAVP	02/2005	02/07/2005	02/10/2005	Generic	0.86
10.	Ditropan XL	11/2006*	09/27/2005	09/28/2005	Generic	0.71
11.	Duragesic	07/2004	03/25/2004	03/25/2004	Brand	2.51
12.	Fosamax	N/A	08/28/2003	08/28/2003	Brand	2.47
13.	Glucophage XR	04/2008	12/12/2007	12/13/2007	Brand	0.76
14.	Levaquin	N/A	12/12/2004	12/23/2004	Brand	2.76
15.	Lexapro	N/A	07/13/2006	07/14/2006	Brand	63.51
16.	Lipitor	N/A	12/16/2005	12/16/2005	Brand	11.35
17.	Lovenox	N/A	06/15/2005	06/16/2005	Generic	1.60
18.	Mircette	04/2002	12/06/2001	12/07/2001	Generic	0.76
19.	Monopril	11/2003	10/27/2003	10/27/2003	Generic	1.32
20.	Naprelan	12/2002	03/14/2002	03/15/2002	Generic	1.98**
21.	Norvasc	03/2007	02/27/2007	02/27/2007	Brand	4.46
22.	Paxil	09/2003	03/03/2003	03/04/2003	Generic	6.73
23.	Pepcid	04/2001	10/01/1998	10/14/1998	Brand	5.08
24.	Platinol	11/1999	10/21/1999	11/03/1999	Generic	0.55**
25.	Plendil ER	11/2004	08/21/2003	08/22/2003	Brand	0.96
26.	Prilosec	12/2002	10/11/2002	10/11/2002	Brand	23.74
27.	Protonix	09/2007	09/06/2007	09/07/2007	Generic	9.93
28.	Prozac	08/2001	01/12/1999	01/13/1999	Brand	22.74
29.	Rebetol	04/2004	07/14/2003	07/16/2003	Generic	48.27
30.	Relafen	08/2001	08/14/2001	08/14/2001	Generic	1.290
31.	Remeron	02/2003	12/18/2002	12/19/2002	Generic	2.70
32.	Retrovir	09/2005	07/22/1993	07/22/1993	Brand	5.56**
33.	Risperdal	N/A	10/13/2006	10/16/2006	Brand	2.92
34.	Sarafem	N/A	07/29/2004	08/16/2004	Brand	1.08
35.	Sporanox	02/2005	07/28/2004	07/29/2004	Generic	0.39
36.	Tambocor	03/2002	04/17/2001	04/17/2001	Generic	0.60
37.	Taxol	10/2000	03/01/2000	03/01/2000	Generic	-54.94**
38.	Tiazac	04/2003*	03/06/2000	03/08/2000	Generic	100**
39.	Topamax	N/A	03/20/2007	03/22/2007	Brand	2.86
40.	Toprol XL	09/2007	01/17/2006	01/18/2006	Generic	5.36
41.	Tricor	05/2002	03/19/2002	03/21/2002	Generic	1.71
42.	Ultane	03/2006	09/26/2005	09/23/2005	Generic	0.64
43.	Vicoprofen	04/2003*	09/12/2002	09/12/2002	Generic	0.85
44.	Wellbutrin SR; Zyban	01/2004	02/28/2002	03/01/2002	Generic	3.97
45.	Wellbutrin XL	01/2006*	11/22/2006	08/02/2006	Generic	33.94**
46.	Xalatan	N/A	07/06/2004	07/07/2004	Brand	0.77
47.	Zantac	07/1997	09/17/1993	09/17/1993	Brand	14.17
48.	Zofran	12/2006	08/20/2004	08/24/2004	Brand	1.21
49.	Zyprexa	N/A	04/14/2005	04/14/2005	Brand	13.58

*These dates are sourced from FDA data, not the IMS Generic Spectra Set.

** These figures are sourced from newspaper reports of company filings.

Table 2.9: Number of 'Paragraph IV' District Court Decisions by Year

Year	72 District Cases	Brand Wins	49 District Cases	Brand Wins
1991	1	1	0	0
1992	0	0	0	0
1993	2	2	2	2
1994	0	0	0	0
1995	0	0	0	0
1996	1	0	0	0
1997	0	0	0	0
1998	1	1	1	1
1999	2	1	2	1
2000	2	0	2	0
2001	4	0	4	0
2002	9	1	9	1
2003	6	3	6	3
2004	7	6	7	6
2005	8	2	6	2
2006	6	4	5	3
2007	6	4	5	4

Table 2.10: State Space and Months of Exclusivity at Issue

	Brand	Announcement	Patents	Final Patent Expiration	Unique Expiration Dates (State Space)	Exclusivity at Issue (Mnths)
1.	Accupril	06/28/2004	4,743,450	02/2007	1	32
2.	Acular	12/20/2003	5,110,493	05/2009	1	29
3.	Alphagan	05/08/2002	6,194,415	08/2020		219
			6,248,741			
4.	Altace	07/17/2006	5,061,722	10/2008	1	27
5.	Augmentin	07/19/2002	6,031,093	04/2018	1	189
			6,048,977			
			6,051,703			
			6,218,380			
6.	Buspar	03/13/2001	6,150,365	06/2020	1	231
7.	Celebrex	03/20/2007	5,466,823	09/2016	1	114
			5,563,165			
			5,760,068			
8.	Claritin; Claritin Reditabs	08/08/2002	4,659,716	04/2005	1	32
9.	DDAVP	02/10/2005	5,047,398	09/2008	1	43
10.	Ditropan XL	09/27/2005	6,124,355	05/2018	1	152
11.	Duragesic	03/25/2004	4,588,580	07/2004	1	4
12.	Fosamax	08/28/2003	5,994,329	08/2018	1	180
13.	Glucophage XR	12/12/2007	6,340,475	11/2021	2	167
			6,635,280			
14.	Levaquin	12/23/2004	5,053,407	12/2010	1	72
15.	Lexapro	07/13/2006	RE. 34,712	03/2012	1	68
16.	Lipitor	12/16/2005	4,681,893	12/2010	2	60
			5,273,995			
17.	Lovenox	06/15/2005	5,389,616	02/2012	2	80
			RE. 38,743			
18.	Mircette	12/06/2001	RE. 35,724	02/2013	1	134
19.	Monopril	10/27/2003	5,006,344	04/2008	1	56
20.	Naprelan	03/14/2002	5,637,320	06/2014	1	147
21.	Norvasc	02/27/2007	4,879,303	09/2007	1	7
22.	Paxil	03/03/2003	4,721,723	10/2006	1	43
23.	Pepcid	10/01/1998	4,283,408	10/2000	1	24
24.	Platinol	10/21/1999	5,562,925	10/2013	1	168
25.	Plendil ER	08/21/2003	4,803,081	10/2007	1	50
26.	Prilosec	10/11/2002	4,786,505	08/2006	2	70
			4,853,230			
27.	Protonix	09/06/2007	4,758,579	07/2010	1	34
28.	Prozac	01/12/1999	4,314,081	02/2001	2	25
			4,626,549			
29.	Rebetol	07/14/2003	5,767,097	09/2018	3	182
			6,063,772			
			6,150,337			
30.	Relafen	08/14/2001	4,420,639	12/2002	1	16
31.	Remeron	12/18/2002	5,977,099	06/2017	1	174
32.	Retrovir	07/22/1993	4,724,232	06/2006	6	155
			4,828,838			
			4,833,130			
			4,837,208			
			4,818,538			
			4,818,750			
33.	Risperdal	10/13/2006	4,804,663	12/2007	1	14
34.	Sarafem	07/29/2004	4,971,998	09/2018	1	170
35.	Sporanox	07/28/2004	5,633,015	05/2014	1	118
36.	Tambocor	04/17/2001	4,650,873	03/2004		35
			4,642,384			
37.	Taxol	03/01/2000	5,670,537	09/2016	2	198
			5,641,803			
38.	Tiazac	03/06/2000	5,529,791	06/2013	1	159
39.	Topamax	03/20/2007	4,513,006	09/2008	1	18
40.	Toprol XL	01/17/2006	5,001,161	01/2009	2	36
			5,081,154			
41.	Tricor	03/19/2002	4,895,726	01/2007	1	58
42.	Ultane	09/26/2005	5,990,176	01/2017	1	136
43.	Vicoprofen	09/12/2002	4,587,252	12/2004	1	27
44.	Wellbutrin SR; Zyban	02/28/2002	5,427,798	08/2013	1	138
45.	Wellbutrin XL	11/22/2006	6,096,341	10/2018	1	143
46.	Xalatan	07/06/2004	5,296,504	06/2012	2	95
			5,422,368			
47.	Zantac	09/17/1993	4,521,431	06/2002	1	105
48.	Zofran	08/20/2004	4,753,789	12/2006	1	28
			5,578,628			
49.	Zyprexa	04/14/2005	5,229,382	07/2010	1	63

Table 2.11: Sample Abnormal Returns for Brand Firms

	Brand Wins						Generic Wins					
Sales %	# Cases	AR	t-stat	AR^{+}	CAR	t-stat	# Cases	AR	t-stat	AR^{+}	CAR	t-stat
$> 2\%$	17	1.44%	2.8	3.73%	3.27%	4.5	12	-7.04%	-7.7	-7.64%	-8.26%	-6.7
$> 1\%$	20	1.24%	2.7	3.22%	2.83%	4.8	18	-5.24%	-6.8	-5.59%	-5.82%	-5.9
$> 0\%$	23	0.98%	2.2	2.67%	2.40%	4.3	26	-3.64%	-6.2	-3.86%	-4.01%	-5.4
$[1\%, 2\%]$	3	0.08%	0.1	0.32%	0.32%	0.3	6	-1.62%	-1.2	-1.47%	-0.94%	-0.5
$[0\%, 1\%]$	3	-0.70%	-0.6	-1.04%	-0.52%	-0.3	8	-0.04%	-0.1	-0.01%	-0.12%	-0.1

AR= **Announcement Day Return,** AR^{+} **= Announcement Day Return plus Close-Open Return, CAR = Announcement Day + Day After AR**

Table 2.12: Individual Abnormal Returns for Brand Firms

	Brand Drug	Decision	AR	t-stat	AR^{+}	CAR	t-stat
1.	Accupril	Brand	-0.0063	-0.4148	-0.0084	-0.0077	-0.4849
2.	Acular	Brand	0.0079	0.4103	0.0075	0.0093	0.3984
3.	Alphagan	Generic	-0.0384	-1.3322	-0.0393	-0.0955	-2.3377
4.	Altace	Brand	0.0019	0.3764	0.0149	-0.0033	-0.0820
5.	Augmentin	Generic	-0.0366	-2.0808	-0.1043	-0.1152	-6.5338
6.	Buspar	Generic	-0.0302	-0.6805	-0.0521	-0.0362	-0.6962
7.	Celebrex	Brand	0.0025	0.1652	-0.0002	0.0038	0.1832
8.	Claritin; Claritin Reditabs	Generic	-0.0779	-2.5676	0.0888	-0.0789	-2.0479
9.	DDAVP	Generic	0.0092	0.4322	0.0030	0.0071	0.2396
10.	Ditropan XL	Generic	-0.0043	-0.3912	-0.0084	-0.0014	-0.0989
11.	Duragesic	Brand	0.0016	0.1105	0.0076	0.0014	0.0789
12.	Fosamax	Brand	-0.0172	-0.9604	-0.0134	-0.0106	-0.4195
13.	Glucophage XR	Brand	-0.0019	-0.1295	-0.0092	-0.0154	-0.8174
14.	Levaquin	Brand	0.0043	0.3399	0.0072	0.0036	0.2555
15.	Lexapro	Brand	0.1601	7.5154	0.1488	0.1529	5.1137
16.	Lipitor	Brand	-0.0071	-0.3347	0.1067	0.0781	2.7383
17.	Lovenox	Generic	-0.0513	-3.2039	-0.0340	-0.0249	-1.1043
18.	Mircette	Generic	-0.0064	-0.2337	0.0048	-0.0004	-0.0106
19.	Monopril	Generic	0.0015	0.0668	0.0071	0.0016	0.0533
20.	Naprelan	Generic	-0.0266	-0.4607	-0.0122	-0.0253	-0.3452
21.	Norvasc	Brand	-0.0036	-0.2207	0.0040	-0.0134	-0.7015
22.	Paxil	Generic	-0.0200	-0.8472	-0.0200	-0.0256	-1.0356
23.	Pepcid	Brand	-0.0245	.1.1572	-0.0332	-0.0393	-1.3893
24.	Platinol	Generic	0.0104	0.4164	0.0202	0.0080	0.2277
25.	Plendil ER	Brand	-0.0147	-.4317	-0.0160	-0.0093	-0.2175
26.	Prilosec	Brand	0.0156	0.5117	0.1293	0.1374	3.4713
27.	Protonix	Generic	-0.0248	-1.5534	-0.0176	-0.0086	-0.4139
28.	Prozac	Brand	0.0603	2.1649	0.0766	0.0854	2.2655
29.	Rebetol	Generic	-0.1961	-2.9738	-0.1888	-0.1718	-1.9078
30.	Relafen	Generic	-0.0006	-0.0265	-0.0086	-0.0077	-0.2335
31.	Remeron	Generic	-0.0223	-0.9032	-0.0365	0.0198	0.7784
32.	Retrovir	Brand	0.0462	1.7067	0.0594	0.0466	1.7206
33.	Risperdal	Brand	0.0041	0.3734	0.0149	0.0235	2.1321
34.	Sarafem	Brand	0.0150	0.7836	0.0148	0.0097	0.3902
35.	Sporanox	Generic	-0.0065	-0.4737	-0.0114	-0.0109	-0.6067
36.	Tambocor	Generic	-0.0178	-0.6331	-0.0022	0.0308	0.8281
37.	Taxol	Generic	-0.1213	-4.1899	-0.1067	-0.0915	-2.6136
38.	Tiazac	Generic	-0.0283	-0.7701	-0.0294	-0.1168	-2.4303
39.	Topamax	Brand	-0.0058	-0.6737	0.0006	-0.0121	-1.1778
40.	Toprol XL	Generic	-0.0432	-2.7367	-0.0428	-0.0511	-3.1317
41.	Tricor	Generic	0.0099	0.4646	0.0116	0.0356	1.6586
42.	Ultane	Generic	0.0060	0.4479	-0.0110	-0.0308	-1.6452
43.	Vicoprofen	Generic	0.0057	0.1915	0.0057	-0.0116	-0.3331
44.	Wellbutrin SR; Zyban	Generic	0.0180	0.8853	-0.0135	-0.0090	-0.3133
45.	Wellbutrin XL	Generic	-0.2543	-6.6931	-0.2296	-0.2470	-4.8479
46.	Xalatan	Brand	-0.0059	-0.3890	-0.0059	0.0090	0.5181
47.	Zantac	Brand	0.0139	0.4869	0.0587	0.0492	1.3523
48.	Zofran	Brand	-0.0063	-0.3980	0.0030	0.0075	0.3766
49.	Zyprexa	Brand	-0.0243	-1.3336	0.0453	0.0447	1.7496

AR= Announcement Day Abnormal Return.

AR^{+}= Day After Announcement Day Abnormal Return.

CAR = Announcement Day + Day After Abnormal Returns.

Chapter 3

The Coefficient of Variation of Profit and other Cross-Sectional Determinants of Beta

3.1 Introduction

Researchers in finance often make assumptions about some proposed factors, the CAPM 'Beta', and expected returns. Examples of these factors have ranged from firm level and market variables to macroeconomic indicators. In the financial literature, there has been an enduring focus on the relationship between these variables or factors and expected returns, mostly asking what factors explain the cross section of returns and by how much. The literature has also wrestled with the relationship between Beta and expected returns, again mostly focusing on the ability of Beta to explain the cross section of expected returns. Some influential works include Fama and French [17], who argued that the static Beta had no power to explain the cross section of expected returns, Lettau and Ludvigson [42] and Jagannathan and Wang [35], who accounted for time varying risk premia, and Campbell and Vuolteenaho [9], who decomposed both a static and a time varying Beta into a discount rate and cash flow Betas.

However, the literature has largely neglected the relationship between proposed factors and Beta, either static or time varying, especially with respect to questions concerning the cross sectional determinants of Beta. In the late 1970's, Rosenberg [54] argued that the variance of earnings, the variance of cash flows, growth in earnings per share, market capitalization, dividend yield, and debt-to-assets were explanatory variables of Beta.[1] Through

[1] He went on to found Barra Inc., which developed proprietary models calculating the cost of capital.

the 1980's, Hamada [27], Myers [49], Lev [43], Manderlker and Rhee [46] among others studied financial and operating leverage and largely found that Beta increased in both types of leverages. More recently, Gebhardt, Lee, and Swaminathan [22] considered the association of firm level variables with an implied cost of capital.[2] However, there has been no recent work updating our knowledge of the cross sectional determinants of static Betas.

How could this understanding further academic research? In empirical asset pricing, Beta is one of the three (see Fama and French [17]) or four (see Carhart [10]) factors used as a benchmark model to determine whether new factors have additional power to explain the cross section of expected returns. However, there are two weaknesses of the Fama and French methodology which may hinder uncovering the true additional explanatory power of proposed factors. First, this literature relies on grouping procedures, or sorting stocks into portfolios. This practice does mitigate the attenuation bias associated with measurement error and to make the number of cross sectional observations less the the number of time periods, which increases the available econometric methodology. However, portfolio grouping also reduces the cross sectional variation in Beta which may lead to imprecise estimates. Secondly, there is no interaction term to explore how the proposed factor influence expected returns through Beta. Models without this interaction term may be overstating the importance of factor. Studying the cross sectional determinants of Beta may provide motivation and evidence for which variables should be estimated in a model with an interaction term and which should not.

Besides the relationship between asset pricing factors and Beta, understanding the firm level determinants of Beta has additional implications. Despite Beta's inability to determine the cross section of expected returns, it is still plays a primary role in capital budgeting (see Jagannathan and Meir [34]). More fundamental issues include exploring possible relationships between firm level variables and Beta with the goal of creating theoretical links between fundamental models in both industrial organization and finance. For example, there is some empirical evidence that the coefficient of variation of profit is a candidate to provide this link. Empirically, one definition of profitability is earnings scaled by assets, (see Vuolteenaho [62]). As described earlier, Rosenberg [54] has long established that explanatory power of the variance of both earnings and cash flows. Gebhardt, Lee, and

[2] Based on a discounted residual income model, an implied cost of capital is the internal rate of return that equates the current stock price to the present value of all future cash flows.

Swaminathan [22] considered the coefficient of variation of earnings with regards to the implied cost of capital. However, earnings or cash flows scaled by assets or market capitalization has not been considered and may provide empirical evidence that the coefficient of variation of profitability has cross sectional explanatory power for Beta.

The objective of this paper is to explore the cross-sectional determinants of Beta using recent data and newer econometric techniques. The two main goals of this exercise is to understand the explanatory power of popular asset pricing variables and firm level variables, such as the coefficient of variation of profit. The estimation is largely based on a procedure developed by Lehmann [41] and uses a minimum distance approach that reduces to the familiar least squares estimators. This approach permits the estimation of dataset where the number of cross sectional observations is larger than the number of time period, so that imprecise portfolio sorting procedures do not have to be used. This approach also accounts for the measurement error in Beta in the asymptotic covariance matrix of the estimates, which places more weight on observations whose Beta was estimated more accurately. To explore the potential of scaling earnings, I use two different sets of variables where one is weighted by assets and the other is weighted by market capitalization, when appropriate. Finally, I include two robust checks, one of which includes adding industry fixed effects.

The results are always presented in sets of two regressions. The first set regresses Beta Asset, Beta_A, on a set of variables that are scaled by assets, whenever applicable. These variables are financial leverage, the dividend yield, the log of assets, turnover, the bid ask spread percentage and the coefficient of variation of earnings divided by assets, henceforth known as the 'earnings' variable, to proxy for the coefficient of variation of profit. I also include an interaction term to separate out those firms with a positive earnings variable from those with a negative earnings variable. I also regress Beta on a set of variables scaled by market capitalization, whenever applications. These variables are book-to-market, the dividend yield, the log of size, turnover, the bid ask spread percentage, and the coefficient of variation of earnings divided by market capitalization, along with its interaction term.

I find some striking results with respect to both the two asset pricing variables and the 'earnings' variable (the coefficient of variation of profit proxy). Since my statistics are pooled over different time period, I cite the the statistics from the 2001 subperiod because it has three times as many observations as the rest of the periods combined. Turnover has the largest magnitude and t-statistics in both sets of regressions. In 2001, the means of Beta_A and Beta were .94 and 1.2 respectively. I found that a one standard deviation change in turnover increased the magnitude of Beta_A by .22 and Beta by .25. The bid ask spread percentage had a larger magnitude coefficient in the 'Market' regressions, which indicated that a one standard deviation change in this variable increased Beta by .08. On the other hand, I found that ln(assets), ln(size), and book-to-market had the smallest magnitudes and t-statistics, which indicates that the first two variables have little explanatory power beyond their scaling effect. Finally, both regressions indicate that as the 'earnings' variable increases (decreases) for firms with a positive (negative) 'earnings' variable, Beta increases. For the 2001 subperiod in the 'Market' regressions, a one standard deviation change in the absolute value of earnings, increases Beta by a magnitude of .1 and .15 for firms with positive and negative 'earnings'. Furthermore, none of the above results is sensitive to the inclusion of Turnover.

The remainder of this paper is divided into five sections. Section 3.2 discusses the estimation procedure. Section 3.3 describes the data construction, motivates the variables used in the study and their relationship to Beta, and includes the preliminary statistics. Sections 3.4 includes the main empirical results and describes the outcome of two different robustness checks. Finally, the conclusion discusses possible extensions to this study.

3.2 Empirical Methodology

The purpose of this exercise is to consider the cross sectional determinants of Beta disregarding the possibility of time varying parameters. The estimation is largely based on a procedure developed by Lehmann [41] but modified slightly to fit the application at hand. Conceptually, it proceeds as follows. I first divide the data into 5 year non-overlapping intervals. A 60 month period is the conventional observation interval for estimating cross sectional Betas, so I assume this length is applicable for constructing the explanatory variables. Next, I reduce the data from each 5 year interval into a single cross sectional unit for that period. Therefore, an observation is a firm with 5 years of data reduced into a single statistic for each variable. Next, I use a minimum distance approach, which reduces to the familiar least squares estimators, to determine the cross sectional parameters for each 5 year interval. Finally, I use two different methods to pool the estimates or aggregate the statistics from the five year periods.

First I reduce the data from the five year intervals into single cross sectional observations. This is a straight forward exercise with the explanatory variables because they are directly observable and they are mapped to 5 year means and standard deviations. In contrast, Beta is not directly observable and therefore I must utilize imperfect market model estimates. In each different 5 year period, t, and for each different firm, i, I estimate Beta using the standard single index market model

$$R^i_{t,t_m} = \alpha^i_t + \beta^i_t R^M_{t,t_m} + \epsilon^i_{t,t_m},$$

where t_m indicates the monthly periods within t. As $\hat{\beta}^i_t$ is a function of the residuals, ϵ^i_{t,t_m}, from its respective regression, it includes measurement error.

For the cross sectional regressions, I use a traditional method of moments or minimum distance approach as in Lehmann [41]. Conceptually, this approach is based on asymptotic theory, which means that the measurement error in the Betas is accounted for in the asymptotic covariance matrix of the parameter estimates. While the reliance on conventional asymptotic theory facilitates straightforward inference, there is no small sample measurement error correction applied directly to Beta. Therefore, the estimates are consistent and asymptotically normal, but in small samples, they suffer from the usual attenuation bias arising from measurement error. This bias diminishes as the sample moments converge to their population analogs and the measurement error in the sample moments becomes more accurately accounted for in the asymptotic covariance matrix of the parameter estimates. Since the number of observations in my intervals range from 103 in the earliest, to 930 in the latest, the estimates in the different intervals will reflect differing amounts of attenuation bias.

The measurement error in the Betas is incorporated into the cross sectional weighted least squares estimators through the construction of two weighting matrices S_t and W_t. Let X_t be the data matrix and λ_t be the vector of parameters to estimate. The cross sectional regression is

$$\beta_t = X_t \lambda_t + \nu_t. \tag{3.1}$$

However, I only observe $\hat{\beta}_t$, whose relationship to β_t is given by $\hat{\beta}_t = \beta_t + \eta_t$, where η_t is a column vector whose ith entry is given by η^i_t such that

$$\eta_t^i = \begin{pmatrix} 0 & 1 \end{pmatrix} \begin{pmatrix} \iota_{60}'\iota_{60} & \iota_{60}'R_M \\ R_M'\iota_{60} & R_M'R_M \end{pmatrix}^{-1} \begin{pmatrix} \iota_{60}' \\ R_M' \end{pmatrix} \epsilon_t^i.$$

Note that η_t^i selects only the portion of the error attributable to β_t^i, disregarding the portion due to the coefficient α_t^i. To estimate a cross sectional regression on the true β_t, equation 3.1 becomes

$$\beta_t = X_t\lambda_t + \nu_t - \eta_t. \tag{3.2}$$

This equation specifies how the errors from the market model regression interact with the errors from the cross sectional econometric model. The weighted least squares estimator and its covariance matrix are given by

$$\hat{\lambda}_t = \left(X_t'W_t^{-1}X_t\right)^{-1} X_t'W_t\hat{\beta}_t \tag{3.3}$$

$$\mathrm{Var}\left(\hat{\lambda}_t\right) = \left(X_t'W_t^{-1}X_t\right)^{-1} X_t'W_tE\left[(\nu_t - \eta_t)(\nu_t - \eta_t)'\right] W_t^{-1}X_t\left(X_t'W_t^{-1}X_t\right)^{-1}.$$

Next, I develop a sample analog for the covariance matrix. By assuming that ν_t and η_t are uncorrelated, and that ν_t is uncorrelated across assets, the covariance matrix may be reasonably approximated by

$$\mathrm{Var}\left(\hat{\lambda}\right) \approx \left(X_t'W_t^{-1}X_t\right)^{-1} X_t'W_tE\left[\eta_t\eta_t'\right] W_t^{-1}X_t\left(X_t'W_t^{-1}X_t\right)^{-1}. \tag{3.4}$$

I will use S_t as an estimate of $E\left[\hat{\eta_t}\hat{\eta_t}'\right]$ and construct it from the market model residuals such that

$$S_t : S_{t,(i,j)} = \left(\hat{\epsilon_{t,i}}'\hat{\epsilon_{t,i}}\right)/58.$$

Therefore, the weighting matrix, W_t, is

$$W_t = \left(\mathrm{diag}\left(S_t\right)\right)^{-1}$$

which is simply the standard errors of the market model regressions. Therefore, this estimation technique places more weight on observations whose β_t was estimated more accurately.

Finally, I use the two different approaches suggested by Lehmann [41] to pool the estimates. The first approach uses the asymptotic covariance matrix for each interval as weights. The pooled estimates along with the covariance matrix for the whole sample are

$$\hat{\lambda} = \left[\sum_{t=1}^{T} \hat{V}_t^{-1}\right]^{-1} \sum_{t=1}^{T} \hat{V}_t^{-1}\hat{\lambda}_t, \quad V(\hat{\lambda}) = \left[\sum_{t=1}^{T} \hat{V}_t^{-1}\right]^{-1}$$

where T is the number of 5 year subperiods. While this method incorporate information about the relative accuracy of the different cross sectional regression, it is also more susceptible to the inaccuracy of the asymptotic covariance matrices in small samples. The second approach aggregates the minimum distance estimates by a weighting based on the number of observations, n_t, in each subsample. The pooled estimates and its corresponding covariance matrix are

$$\hat{\lambda} = \sum_{t=1}^{T} \tau_t \hat{\lambda}_t, \quad V(\hat{\lambda}) = \sum_{t=1}^{T} \tau_t^2 \hat{\lambda}_t$$

where $\tau_t = n_t / \sum_{t=1}^{T} n_t$. This method is more conservative because it produces estimates with higher asymptotic variances. These two aggregation methods can produce substantially different results and considerable attention should be paid to interpreting aggregated minimum distance estimators. For the rest of this paper, I will presume that the estimates aggregated by subperiod sample size are more reasonable because they place more weight on estimates with more observations.

3.3 Variable and Data Description

3.3.1 Data Construction

The sample of firms includes all U.S. companies in the intersection of the monthly CRSP return files and Compustat industrial annual. I follow Da [13] for the exact Compustat/CRSP merging procedure. I exclude utility companies (SICCD in [4900,4999]) because regulated firms may face lower cost of capital due to lower operating risk, potentially from limited entry and exit, or because their capital structure is legally restrained. Finally, I employ the corrections suggested in Shumway [56] for the de-listing bias. This entails assigning a return of -.3 to a firm delisted for performance related reasons.[3]

[3] Performance related reasons are given a delisting code of 500 or in the range of [520, 584].

To ensure that accounting information is already impounded into stock returns, Fama and French [19] codified the practice of matching monthly return data from June of year t to May of year $t+1$ with Compustat industrial data for the fiscal year ending in December of $t-1$. All Compustat data is calculated on an annual basis, except the coefficient of variance for the earnings variables, which are calculated quarterly for more precise sample analogs. For the purposes of consistency, I use the same Compustat/CRSP matching rule for quarterly data as I do for annual data. Therefore, I substitute four quarterly observations into the same time frame I placed one annual observation.

3.3.2 Variable Description

In the following subsections, I describe the variables used in the cross sectional analysis. Throughout this paper, I consider two set of variables, referred to as 'Book' variables and 'Market' variables, for separate regressions. The 'Book' variables are characterized by the construction of all the relevant firm level variables in terms of assets, while the 'Market' variables are defined in terms of market capitalization, whenever applicable. This constant scaling makes the coefficients on these variable easier to compare and helps to determine whether the significance of these variables arises simply due to scaling or whether they should be included in their own right. Note that both the 'Book' and the 'Market' regressions include variables that obviously should not scaled by the above respective scaling variable.

Finally, throughout the history of modern finance, many variables have been considered in relation to the CAPM and the cross section of stock returns. Therefore, my operational practice is to include the variables that not only fit my original criteria, but that are also in some sense well known and well used. Variables that were considered and discarded include market financial leverage, both book and market operating leverage, earnings per share, and growth in earnings per share. There are, however, two set of variables which have been shown to be associated with Beta and which I knowingly exclude from this study. The first set of variables are based on I/B/E/S data and were also used in Gebhardt, Lee, and Swaminathan's [22] study. They are the long run earnings growth rate forecast, made famous by La Porta [39][4], the average mean absolute error of the last five annual I/B/E/S consensus forecasts, and the dispersion of analyst earnings forecasts for the current fiscal year. I exclude these variables partly because I/B/E/S data is only available starting in

[4]La Porta showed that high LTG firms earn lower subsequent returns.

1980 but mainly because according to La Porta, it is only available for a limited subset of the merged Compustat/CRSP dataset. He noted that this subset is highly biased towards large firms which may limit the cross sectional variation recorded in this study due to potentially important variables such as Size. La Porta also only uses data from 1982 – 1991 which effectively provides me with only two sample periods. La Porta shows that high LTG firms earn lower subsequent returns.

Secondly, I exclude two very interesting sets of variables from studies considering the effect of corporate governance on the cost of equity. Skaife, Collins, and Lafond [57] construct large set of governance proxies which are only available from 1996-2002. They regress Beta on their proxies and find an adjusted R-square of .17. Interestingly, they include the corporate governance index by Gompers, Ishi, and Metrick [25] and find that although it is statistically significant at the .01 level, it has a small magnitude. I also exclude the Gompers/Ishi/Metrick index partly because it only includes data from the 1990's.

The following variables were considered in this study and their construction is detailed in Appendix 1.

1. Book Financial Leverage – FL

In theory, Modigliani and Miller argued that a firm's cost of equity should be an increasing function of the amount of debt in its capital structure. This result generated an enormous empirical literature which mostly found that a firm's Beta increased in both its financial and operating leverage. In more recent work on financial leverage, Fama and French [18] found a positive relationship between market leverage and average returns and a negative relationship between book leverage and average returns, which they explained by noting the difference between book to market leverage is simply book to market equity. Unfortunately, they did not directly examine the relationship between these two types of financial leverage and Beta, nor did they provide correlations. In general, a firm level financial and operating leverage have been known to increase sensitivity to the business cycle (see Bodie, Kane, and Marcus [7]). However, I expect an unlevered Beta to decrease in financial leverage because firms with a substantial portion of debt have a larger portion of their revenues paying off creditors at a constant rate instead of investing in projects that may be more sensitive to the business cycle.

2. Dividend Yield – DY

I expect both types of Betas to decrease in dividend yield because only the managers of firms with stable earnings in the forseeable future commit to paying dividends. Therefore, dividend payments signal stable earnings to the market.

3. Assets and Size – Assets / Size

In their widely cited study, Fama and French [18] present evidence that the static CAPM's inability to explain average returns is economically important and they demonstrate that the alternative Book-to-Market and Size model captures the cross sectional variation in returns originally associated with Beta. Specifically, they find evidence that Beta is highly correlated with size and that after controlling for size, there is no relation between Beta and average returns. I expect both types of Beta to increase with Assets or Size because larger firms have more business projects and more opportunity to be exposed to sensitivities in the business cycle.

4. Coefficient of Variation of 'Profit' – EBIDA / EBIDA_A

The variance of a firm's earnings and cash flows have been included as a predictor of Beta as early as Guy and Rosenberg [54] and they have maintained their importance as a source of risk for firm valuation (see Madden [45]). They are also considered by Gebhardt, Lee, and Swaminathan [22] who believe they most likely capture fundamental cash flow risk and note there is "no large sample academic study relating earnings variability to cost-of-capital." Note that these authors only consider the effect earnings variability, as measured by the coefficient of variation of annual earnings over the past five years, on the implied cost of capital. I expect both types of Beta to increase in the coefficient of variation of profit because larger variation in profit provides more opportunity for the firm to be exposed to general market movements or economy wide trends.

5. Trading Turnover – TURN

Lee and Swaminathan [40] found firms with high trading volume earned lower future returns and that trading volume provides information about the market's relative under or over evaluation of a stock. They also found that low (high) volume stocks display many characteristics commonly associated with value (glamor) investing. Specifically, lower (higher) trading volume is associated with worse (better) current operating performance, larger (smaller) declines in past operating performance, higher (lower) book-to-market ratios, lower (higher) analyst followings, lower (higher) long-term earnings growth estimates, higher (lower) factor loadings on the Fama-French. I expect both types of Beta to increase in Turnover because Turnover is related to operating leverage.

6. Bid-Ask Spread – BAS

There is a considerable body of theoretical literature which argues that investors require a higher return for more illiquid stocks (See Habib [26] for a nice overview). Empirically, liquidity has been difficult to define and the conventional measures can be assigned roughly into two groups, trade based measures, such as volume, and order based measures, such as the bid-ask spread. The literature seems to be coalescing around order based measures (See Roll [53]) and I use the percentage bid ask spread (BAS) proposed by Amihud and Mendelson [2] as a proxy for firm level liquidity. Amihud and Mendelson determined that poor liquidity was associated with increased stock returns they provided evidence of a strong negative correlation between their liquidity proxy and Beta. However, I expect both types of Beta to increase in bid ask spread because less liquid stocks increase their exposure to market movements.[5]

7. Book-to-Market – BM

Fama and French [18] also found that the Betas of BE/ME sorted portfolios have relatively little variation and Beta is unlikely to affect the strong relationship between book-to-market and equity. I expect both types of Beta to have a weakly positive relation to book-to-market.

8. Industry Affiliation

A firm's industry membership has been acknowledged to play a role in the cross-sectional variation of Beta since Guy and Rosenberg's [54] seminal paper examining the predictive

[5] The liquidity measure of Pastor and Stambaugh [51] has recieved tremendous attention for its ability to predict the cross section of stock returns. I did not include this measure because it appeared to have little correlation with Beta.

power of a firm level financial variables. They found that after controlling for six firm level variables[6], industry membership helped to predict Beta. These authors divided firms into thirty-nine industries and generated Betas using 101 months of data from April 1966 to August 1974. They determined that a firm's Beta had a tendency to revert to a historical average industry Beta and that the magnitude of the industry Betas were different and stable throughout the sample period. Therefore, Guy and Rosenberg advocated including an industry 'adjustment factor' to proxy for what analysts loosely thought of as industry risk when exploring the cross sectional variation of Beta. These authors found that their industry factor was significant at the 95% confidence level for 22 of the 39 industries.

The measurement of industry Betas was indirectly revisited by Fama and French [20]. To explore the accuracy of discount rates used in capital budgeting, the authors noted that the precision of the risk loadings for industries are an upper bound for the accuracy of firm or project level rates. The authors estimated the precision of industry costs of capital and found they had alarmingly high standard errors. For example, if a typical industry had a five year rolling Beta of 1.0, then two standard errors indicated that the true Beta was between .76 and 1.24. Fama and French used the sample period from 1963 to 1994 and they assigned firms to forty eight value weighted industries with the intention of creating a manageable number of industries that were distinct yet covered the entire spectrum of stocks.

Besides the concerns about the precision of industry Betas, there is also no current consensus about the definition of an industry. Gompers, Ishi, and Metrick [25] use an updated version of Fama and French [20]'s classifications provided on their website. Hou and Robinson [31] follow Barclay and Smith's [3] example of using 3-digit SIC industry classifications, but reporting results for 2-digit and 4-digit classifications. Finally, Lee and Swaminathan [40] create their own classification system which results in twenty-five industries. The case for dividing firms into industries becomes even worse when one considers that many firms are conglomerates with different projects in potentially different lines of business or 'industries'.

However, despite the numerous limitations of dividing firms into industries and estimating industry level Betas, I include them in the study to determine the relative importance of

[6]The variables were the variance of earnings, variance of cash flows, growth in earnings per share, market capitalization, dividend yield, and debt-to-assets.

industry-specific versus firm-specific effects. First of all, industry groups do exhibit considerable dispersion in average returns for a given year. This is partly attributed to different sensitivity to the business cycle, which can be affected by an industry's sensitivity to sales. Industry Affiliation is included as a check because it is difficult for a firm in a troubled industry to perform well, even if all the firm level variables have been statistically associated with higher returns or Betas in the past.

3.3.3 Preliminary Statistics

This paper aggregates four non-overlapping five year periods to construct its test statistics. The periods start in 1986, 1991, 1996, and 2001 and have 103, 271, 329, and 940 number of observations in each respective period for a total of 1,643 observations. To be explicit, an observation is a firm with 5 years of complete data for each of the Crsp and Compustat variables defined in the previous section.[7] See Appendix 1 for details. The starting points of each period were also chosen to maximize the number of observations in each period. These stringent data requirements may bias the sample towards larger firms, and potentially diminish the cross sectional variation in Beta due to variables such as size.

The correlation matrices for 'Book' regressions and the 'Market' regressions for each period are provided in Appendices 2 and 3, respectively. For the 'Book' regressions, ln(Assets) and BAS have the largest correlations in absolute value ranging from -.51 to -.66. EBIDA_A has the strongest correlation with BAS at a minimum of .24 and the next strongest correlation in absolute value with ln(Assets) at a minimum in absolute value of -.13. The negative correlation, in the last case is slightly surprising since I expected larger firms in terms of the number of assets to have a large coefficient of variation due to the larger standard deviation. In general, the correlations are larger in absolute value for the 'Market' regressions. Once again ln(Size) and BAS have the largest correlations in absolute value ranging from -.65 to -.71. EBIDA's strongest correlation is with BAS for two periods, at a minimum of .2, and with ln[Size] in absolute value at a minimum of -.23.

Appendices 3 and 4 list the summary statistics for the 'Book' and 'Market' regressions for each of the four periods. The mean of Beta_A ranges between .78 and 1, while the mean for Beta ranges between .96 and 1.2. Both Beta and Beta_A have observations with negative

[7] I also checked requiring a firm to have 4 years of all the variables for any time period, but this only increased the observations by a couple in each time period.

values and while this is rare, it does occur in gold related stocks, for example. The question becomes do I view these negative observations as a good estimate of the true Beta or Beta_A , i.e., the true value is actually negative, or do I believe that the true value is actually positive and that the negative observations may be a result of the measurement error from the first stage regression? In this study, I view them as the result of measurement error and I will exclude observations with negative Betas. Financial Leverage, Book-to-Market, Dividends, Turnover, and Bid-Ask Spread all have observations with negative values even though this is economically nonsensical. I understand these negative observations as incorrect values and therefore I drop these observations.

The distributions of EBIDA and EBIDA_A raise challenging questions for including them in estimation. Both EBIDA and EBIDA_A are highly skewed and the direction of the skew is not constant across the time periods. Also, the interquartile range is roughly between 0 and 1.5 for both of the variables in all the time periods. However, in the 'Book' regressions, EBIDA_A ranges from -512.9 (1996) to 245 (2001), and in the 'Market' regressions, EBIDA ranges from -394 (1991) to 1023 (1996). While I believe these extreme values are most likely the result of incorrectly entered data, my data organization is agnostic towards them and I explore their impact through tests of robustness. The negative earnings observations, in general, raise some further issues. First, should they be understood as good estimates of the true value of earnings? Or should they be interpreted as the result of measurement error? This study will only consider the possibility that they are good estimates of the true underlying earnings.[8] On one hand, the existence of firms with negative 5 year average earnings is difficult to reconcile with the rational expectations tradition in financial economics. Assuming that ex-post estimates can proxy for ex-ante beliefs, no rational investor would ever invest in a firm with negative expected earnings. Firms with negative earnings have no place in this theoretical construct. On the other hand, there are obviously firms that lose money in the real world and it is interesting to see what their association is with Beta.

My method of cleaning the dataset is motivated by the challenges and issues discussed above. First, I trim the top and bottom 5% of EBIDA or EBIDA_A. This 5% cutoff balances the tradeoff between including extreme values that are mostly likely mistakes and have

[8] I also considered the possibility that they were the product of measurement error and used a shrinking technique to reduce the range until all the earnings were positive. The results of this exercise are available upon request.

an undue influence on the regression, with maintaining the original integrity of the data. However, the next section provides some robust checks where this cutoff level is changed. Next, I remove the negative values on the rest of the variables in a way that attempts to maintain the original distribution. Specifically, the data is subjected to an algorithm that variable by variable, including the dependent variable, determines the number of negative observations and the corresponding number of largest observations. Once the algorithm has checked all the observations, it drops any marked observations. Once again, this paper drops negative Betas because they are most likely the product of measurement error, and the other independent variables excluding earnings because negative values are nonsensical. The summary statistics for the variables after this trimming are listed in Appendices 6 and 7.

3.4 Empirical Results

3.4.1 'Book' and 'Market' Regression Comparisons

This section reports the estimates for two regressions. The first regression is formed from the 'Book' variables and it is given by

$$\beta_A = \lambda_o^t + \lambda_1^t FL^t + \lambda_2^t DY^t + \lambda_3^t Assets^t + \lambda_4^t TURN^t + \lambda_5^t BAS^t + \lambda_6^t EBIDA_A^t + \lambda_7^t Neg * EBIDA_A^t + \nu^t,$$

where each variable is a vector of cross sectional observations and t is a five year period. The second regression is formed from the 'Market' variables and it is given by

$$\beta = \lambda_o^t + \lambda_1^t BM^t + \lambda_2^t DY^t + \lambda_3^t Size^t + \lambda_4^t TURN^t + \lambda_5^t BAS^t + \lambda_6^t EBIDA^t + \lambda_7^t Neg * EBIDA^t + \nu^t.$$

Both regressions have an interaction term on the earnings variable to allow firms with positive and negative 5 year average earnings to have a different relationship with their perspective Beta. Appendix 8 provides the results for the 'Book' variable regressions and Appendix 9 for the 'Market' variable regression. The top table in each Appendix provides the estimates for the 2001 subperiod because it has three time as many observations as the next period, while the bottom two tables provide the pooled estimates aggregated by the two different methods. Finally, the variables were scaled by their standard deviation to facilitate coefficient comparison. They were not centered about their mean to preserve the original signs of EBIDA_A and EBIDA.

There are two difficulties in interpreting the results with this estimation procedure. Developing a sense of the magnitude of the coefficients is slightly more difficult because the estimates are pooled. However, it makes sense to use the summary statistics from the 2001 subperiod as rough benchmark because this time period has three times as many observations as the next. In this time period, the means of Beta_A and Beta were .9391 and 1.198 respectively and the standard deviations were .6377 and .7331 respectively. Secondly, because there is no analog of R^2 for general least squares models, it is very difficult to compare different models. I include the Buse R^2 to used for descriptive and not comparative purposes.

The 'Book' and 'Market' regression results share many commonalities. In both regressions, the magnitude of the coefficients is reasonably stable between the two aggregation methods, in the sense that none of the coefficients switch sign and the relative ranking of their importance is similar but not exact. The constant in both regressions has the largest coefficient, which is highly significant. The constant is most likely proxying for some industry level effects, which I examine in the next section. Turnover has the largest of the largest magnitude of the variable coefficients and t-statistics in all the subperiod and pooled results. In the pooled regressions, its magnitude hovers around .4, but in the 2001 subperiod it drops to around .35. Based on the 2001 results, this indicates that a 1 standard deviation change in Turnover, increases the magnitude of Beta_A by .22 and Beta by .25. On the other hand, in the 'Book' regressions, ln(Assets) consistently has the smallest coefficient and t-statistic, which indicates this variable has no additional explanatory power beyond its use for scaling. However, in the 'Market' regressions, both Book-to-Market and ln(Size) compete for the smallest coefficient and t-statistic. This result supports Fama and French [18] finding that Book-to-Market are not strongly associated, but it contradicts their finding that Beta is highly correlated with Size.

The 'Book' and 'Market' regression results reflect some important differences concerning Financial Leverage, Dividends, and Bid Ask Spread. In the 'Book' regressions, Financial Leverage has the second largest coefficient in absolute value of -.23. This indicates that a one standard deviation increase in the financial leverage of a firm decreases the magnitude of Beta_A by roughly .15. In comparison, Book-to-Market has much smaller magnitude coefficient than Financial Leverage and it has the opposite sign. This leads me to conclude these two variables are playing different roles in their respective regressions. The coefficient on Dividends varies the most between ‘Book’ and ‘Market’ regressions and the two different subperiod aggregation methods. In the ‘Book’ regressions, the magnitude is about -.08, while in the ‘Market’ regressions, it ranges from -.06 to -.15 in the 2001 subperiod.

The ‘Book’ and ‘Market’ regressions portray a striking difference in the relationship between the ‘earnings’ variable and Beta for firms with positive 5 year average earnings and firms with negative 5 year average earnings. In particular, both regressions indicate that as the ‘earnings’ variable increases for positive firms (decreases for negative firms), Beta_A increases. However, the effect is stronger for firms with negative average 5 year earnings and this difference has a large t-statistic. In the 2001 ‘Book’ regressions, which have the smallest coefficients, the coefficient for firms with positive 5 year average earnings is .08, while it is roughly -.23 for firms with negative 5 year average earnings. This indicates that for a one standard deviation change in the absolute value of earnings, Beta increases in magnitude by .05 for firms with positive earnings and .15 for firms with negative earnings. The result is very similar in the ‘Market’ regressions. Focusing on the 2001 subperiod, which is slightly larger magnitude coefficients than the pooled result, the magnitudes are .14 and -.2 for firms with positive and negative average earnings respectively. This indicates that that a one standard deviation change in the absolute value of earnings, increases Beta by a magnitude of .1 and .15 for firms with positive and negative 5 year average earnings. While the effect for firms with negative earnings is three times larger than for firms with positive earnings in the ‘Book’ regressions, it is only roughly one and half times as large in the ‘Market’ regression. However, this provides evidence that the Betas of firms with negative average earnings are more sensitive to changes in the earnings variable, than the Betas of firms with positive average earnings.

3.4.2 Robust Checks

This section reports the results for two different tests on the robustness of some of the previous results. The purpose of the first test is to see how sensitive the results for EBIDA_A or EBIDA are to perturbations in the top and bottom percentage of observations that are trimmed from this variable. Only, the top and bottom percentage of observations trimmed are altered. Otherwise, the rest of the data preparation and the regressions were exactly the same as in the previous section. The results for the pooled statistics for both the ‘Book’ and the ‘Market’ variable regressions are listed in Appendix 10. One striking feature of the results is that the magnitude of the coefficients for both the positive and negative earnings variables increases monotonically as a larger percentage of the earnings variable is trimmed. This result holds true for every observation except for the positive earnings variable trimmed at 15% in Table 3.32. Furthermore, the difference in the magnitude of the coefficient for the positive and negative earnings variable increases with the percentage of the earnings variable trimmed. For example, in the 'Market' regression results listed in Table 3.34, the magnitude for the coefficient on the positive and negative earnings variable is .11 and -.15 when only 1% is trimmed, but the coefficients jump to .17 and -.78 when 15% is trimmed. Unfortunately, I am forced to conclude that the results for earnings variable are highly sensitive to the percentage of observations that are trimmed from the top and bottom. However, I argue that chosing a 5% cutoff balances the effect of extreme observations while including as many observations as possible.

The purpose of the second test is to take the same regressions listed above, but add industry effects. Specifically, I replace the constant in the previous regression with 48 industry fixed effects based on a classification system developed by Fama and French [20] with updates from Ken French's webpage. The results for the 'Book' regression with industry effects are listed in Appendix 11, while the analogous results for the 'Market' regression are listed in Appendix 12. However, the results for the industry dummies are not included in the Appendices. By comparing the 'Book' regression with and without industry effects (i.e., Appendix 8 vs. Appendix 11) and the 'Market' regression in the same manner (i.e., Appendix 9 vs. Appendix 12), the industry dummies have virtually no effect on the results. While it is possible that the industry dummies have no explanatory power, i.e., they are simply added noise, and they have an average t-statistic of roughly 20 for the pooled statistics for both the 'Book' and the 'Market' regressions. Therefore, I believe it is more likely that the original variables are capturing within industry effects and not proxying for industry characteristics.[9]

3.4.3 Conclusion

The objective of this paper was to explore the cross-sectional determinants of Beta using recent data and newer econometric techniques. The two main goals of this exercise was to

[9] I also ran 'Book' and 'Market' regression without Turnover and the Bid Ask Spread to make sure that multicolinearity were not driving the results. This dramatically increased the result on the earnings variables.

understand the explanatory power of popular asset pricing variables and firm level variables, such as the coefficient of variation of profit. The estimation was largely based on a procedure developed by Lehmann [41] and permited the estimation of dataset where the number of cross sectional observations is larger than the number of time period, so that imprecise portfolio sorting procedures do not have to be used. It also accounted for the measurement error in Beta in the asymptotic covariance matrix of the estimates, which placed more weight on observations whose Beta was estimated more accurately. To explore the potential of scaling earnings, I used two different sets of variables where one is weighted by assets, referred to as 'Book variables' and the other is weighted by market capitalization, referred to as 'Market' variables. Finally, I included two robust checks, one of which included adding industry fixed effects.

I found some striking results with respect to both the two asset pricing variables and the coefficient of variation of profit proxy. Since my statistics were pooled over different time period, I cite the statistics from the 2001 subperiod because it has three times as many observations as the rest of the periods combined. Turnover had the largest magnitude and t-statistics in both sets of regressions. In 2001, the means of Beta_A and Beta were .94 and 1.2 respectively. I found that a one standard deviation change in turnover increased the magnitude of Beta_A by .22 and Beta by .25. The bid ask spread percentage had a larger magnitude coefficient in the 'Market' regressions, which indicated that a one standard deviation change in this variable increased Beta by .08. On the other hand, I found that ln(assets), ln(size), and book-to-market had the smallest magnitudes and t-statistics, which indicates that the first two variables have little explanatory power beyond their scaling effect. Finally, both regressions indicate that as the 'earnings' variable increases (decreases) for firms with a positive (negative) 'earnings' variable, Beta increases. For the 2001 subperiod in the 'Market' regressions, a one standard deviation change in the absolute value of earnings, increases Beta by a magnitude of .1 and .15 for firms with positive and negative 'earnings'. Furthermore, none of the above results were sensitive to the inclusion of industry fixed effects.

3.5 Appendices

Appendix 1

This appendix contains the definitions and the construction of the variables used in this study. To ensure that accounting information is already impounded into stock returns, monthly return data from July of year t to June of year $t+1$ is matched with Compustat quarterly and annual industrial data for the fiscal year ending in Dec of t-1. All Compustat data is calculated on an annual basis, except for the earnings variables, EBIDA_A and EBIDA, which are calculated quarterly for more precise sample analogs. The variables used in the 'Book' regressions are scaled by assets whenever applicable while the variables used in the 'Market' regressions are scaled by market capitalization whenever applicable.

I. 'Book' Variables

0) Asset Beta (Beta_A) – Asset (Unleveraged) Beta is Beta equity multiplied by a 'deflating' factor. The 'deflating' factor is quarterly market capitalization taken at the end of the quarter divided by quarterly market capitalization plus quarterly long term debt item 30 *Long Term Debt*. The 'deflating' factor is averaged over the five year period before it is multiplied by Beta equity.

1) Book Financial Leverage (FL) – Annual total long term debt divided by assets. Total long term debt is Compustat annual item 9 *(Total long-term debt)* and assets is annual item 6 *(Assets)*. FL is averaged over a 5 year period.

2) Dividend Yield (DY) – Annual dividends divided by market capitalization multiplied by 100. Dividends are defined as annual item 19 *(Preferred dividends)* plus annual item 21 *(Common dividends)*. CRSP market capitalization is *Price* multiplied by the *Number of Shares Outstanding* in December of each year. DY is averaged over a 5 year period.

3) Assets (Assets) – Annual assets (annual item 6 *(Total long-term debt)*) are averaged over a 5 year period and the natural log is taken of the result.

4) Coefficient of Variation of Profit (EBIDA_A) – Coefficient of variation of profit is formed from quarterly cash flows divided by assets. Cash flows are quarterly earnings item 8 *(Income before extraordinary items)* plus quarterly item 22 *(Interest expense)* plus quarterly item 5 *(Depreciation and amortization)*. Quarterly assets is quarterly item 44 *Assets*. Then the five year standard deviation and expectation are taken of the quarterly cash flows divided by market capitalization.

5) Trading Turnover (TURN) – Trading turnover is the monthly share volume divided by the monthly number of shares outstanding in CRSP. Turn is averaged over a 5 year period. [See Lee and Swaminathan [40] *Note that the authors defined the variable as average daily turnover in their study.*]

6) Percentage Bid-Ask Spread (BAS) – Bid-Ask Spread is the absolute value of the monthly bid ask spreads divided by the monthly market capitalization multiplied by 100. Monthly bid ask spread is defined Monthly CRSP *Closing bid* minus *Closing Ask*. BAS is the 5 year average.[See Amihud and Mendelson [2]. *Note that these authors used annual data from Fitch's Stock Quotations of the NYSE.*]

II. 'Market' Variables

0) Equity Beta (Beta) – Beta is calculated from a stand single index market model over a five year period.

1) Book-to-Market (BM) – Book equity divided by market equity. Book equity is shareholder equity, plus deferred taxes and minus preferred stock. Shareholder equity is annual item 216 *(Stockholders equity)* if available, or else item 60 + item 130 *(Common equity) + (Carrying value of preferred stock)* if available, or item 6 minus item 181 *(Total assets) – (Total liabilities)*. Deferred taxes is item 35 *(Deferred taxes and investment tax credits)* if available, or item 74 and/or item 208 *(Deferred taxes) and/or (Investment tax credit)*. Book value of preferred stock is item 56 *(Redemption value of preferred stock)*, if available, or item 10 *(Liquidating value of preferred stock)*, or item 130 *(Carrying value of preferred stock)*. Shareholder equity is also reduced by item 330 *(Post retirement benefit assets)* if available. Market equity is constructed in variable 2 above. BM is averaged over a 5 year period. [See Novy-Marx [50], whose definition is constructed on that of Fama and French [19]].

2) Dividend Yield (DY) – Annual dividends divided by market capitalization multiplied by 100. Dividends are defined as annual item 19 *(Preferred dividends)* plus annual item 21 *(Common dividends)*. CRSP market capitalization is *Price* multiplied by the *Number of Shares Outstanding* in December of each year. DY is averaged over a 5 year period.

3) Size (Size) – Size is the market capitalization. Size is averaged over a 5 year period and the natural log is taken of the average.

4) Coefficient of Variation of Profit (EBIDA) – Coefficient of variation of profit is formed from quarterly cash flows divided by the enterprise value. Cash flows are quarterly earnings item 8 *(Income before extraordinary items)* plus quarterly item 22 *(Interest expense)* plus quarterly item 5 *(Depreciation and amortization)*. Enterprise value is proxied by quarterly market capitalization taken at the end of the quarter plus quarterly long term debt item 30 *Long Term Debt*. Then the five year standard deviation and expectation are taken of the quarterly cash flows divided by market capitalization.

5) Trading Turnover (TURN) – Trading turnover is the monthly share volume divided by monthly number of shares outstanding in CRSP. Turn is averaged over a 5 year period. [See Lee and Swaminathan [40] *Note that the authors defined the variable as average daily turnover in their study.*]

6) Percentage Bid-Ask Spread (BAS) – Bid-Ask Spread is the absolute value of the monthly bid ask spreads divided by the monthly market capitalization multiplied by 100. Monthly bid ask spread is defined Monthly CRSP *Closing bid* minus *Closing Ask*. BAS is the 5 year average. (See Amihud and Mendelson [2]). *Note that these authors used annual data from Fitch's Stock Quotations of the NYSE*]

III. Industry Variables

1) Industry Classification – 48 industries based on the classification system used in Fama and French [20] with updates from Ken French's website.

Appendix 2: Correlation Matrices for 'Book' Variables

Table 3.1: 1986 Subperiod 'Book' Correlation Matrix

1986	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
FL	1	-.182	.279	-.031	-.090	-.157
DY		1	.107	-.301	-.118	.023
ln(Assets)			1	.181	-.662	-.237
TURN				1	-.256	-.059
BAS					1	.369
EBIDA_A						1

Table 3.2: 1991 Subperiod 'Book' Correlation Matrix

1991	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
FL	1	.049	.219	-.109	.008	-.115
DY		1	.392	-.251	-.230	-.181
ln(Assets)			1	.201	-.661	-.276
TURN				1	-.293	.148
BAS					1	.385
EBIDA_A						1

Table 3.3: 1996 Subperiod 'Book' Correlation Matrix

1996	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
FL	1	-.091	.084	-.001	.166	.104
DY		1	.407	-.079	-.163	-.055
ln(Assets)			1	.203	-.512	-.129
TURN				1	-.234	.031
BAS					1	.240
EBIDA_A						1

Table 3.4: 2001 Subperiod 'Book' Correlation Matrix

2001	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
FL	1	.001	.215	-.014	-.052	-.028
DY		1	.051	-.045	.042	.072
ln(Assets)			1	.044	-.615	-.142
TURN				1	-.184	.105
BAS					1	.246
EBIDA_A						1

Appendix 3: Correlation Matrices for 'Market' Variables

Table 3.5: 1986 Subperiod 'Market' Correlation Matrix

1986	BM	DY	ln(Size)	TURN	BAS	EBIDA
BM	1	-.031	-.457	-.062	.163	.075
DY		1	.405	.215	-.273	-.282
ln(Size)			1	.118	-.652	-.361
TURN				1	-.121	-.041
BAS					1	.393
EBIDA						1

Table 3.6: 1991 Subperiod 'Market' Correlation Matrix

1991	BM	DY	ln(Size)	TURN	BAS	EBIDA
BM	1	.214	-.250	-.091	.056	.080
DY		1	.419	-.215	-.301	-.274
ln(Size)			1	.345	-.660	-.469
TURN				1	-.306	-.009
BAS					1	.400
EBIDA						1

Table 3.7: 1996 Subperiod 'Market' Correlation Matrix

1996	BM	DY	ln(Size)	TURN	BAS	EBIDA
BM	1	-.000	-.491	-.254	.386	.076
DY		1	.358	-.110	-.151	-.020
ln(Size)			1	.336	-.685	-.236
TURN				1	-.237	.072
BAS					1	.200
EBIDA						1

Table 3.8: 2001 Subperiod 'Market' Correlation Matrix

2001	BM	DY	ln(Size)	TURN	BAS	EBIDA
BM	1	.062	-.316	-.075	.304	.161
DY		1	.006	-.148	.010	.099
ln(Size)			1	.078	-.710	-.283
TURN				1	-.156	.103
BAS					1	.316
EBIDA						1

Appendix 4: Summary Statistics for 'Book' Variables

Table 3.9: 1986 Subperiod 'Book' Summary Statistics

1986	Beta_A	FL	DY	ln(Asset)	TURN	BAS	EBIDA_A
Min	-1.875	0	-3.593	3.902	.7132	-6.456	-47.42
Max	2.119	1.894	34.13	6214	31.30	15.05	244.6
Mean	.8375	.2282	1.768	335.1	6.466	3.717	2.347
SD	.5196	.2453	4.035	772.7	5.229	2.690	25.64
LowerQ	.5240	.0670	0	38.99	2.904	2.245	.1986
Median	.8129	.1697	0	104.1	4.672	3.306	.3343
UpperQ	1.143	.3086	2.443	274.7	9.448	4.867	.7376
Obser.	103	103	103	103	103	103	103
Neg. Obser.	1	0	2	0	0	3	12

Table 3.10: 1991 Subperiod 'Book' Summary Statistics

1991	Beta_A	FL	DY	ln(Asset)	TURN	BAS	EBIDA_A
Min	-3.584	0	17.6	2.374	.1739	-16.48	-114.6
Max	5.148	1.099	269.6	14930	52.05	25.60	48.96
Mean	.8398	.1726	2.113	391.2	8.693	3.567	.5659
SD	.9087	.1687	17.20	1469	7.850	3.849	10.27
LowerQ	.3319	.0377	0	23.09	2.958	2.054	.1901
Median	.7349	.1302	0	59.78	6.599	3.390	.4045
UpperQ	1.300	.2585	.8778	217.7	11.73	5.597	1.052
Obser.	271	271	271	271	271	271	271
Neg. Obser.	25	0	17	0	0	18	31

Table 3.11: 1996 Subperiod 'Book' Summary Statistics

1996	Beta_A	FL	DY	ln(Asset)	TURN	BAS	EBIDA_A
Min	-2.779	0	-2.487	3.009	6.557	-4.445	-521.9
Max	3.531	.8731	9.718	37760	63.62	13.85	196.0
Mean	.7863	.1890	.4071	1260	11.67	2.314	-.6239
SD	.7917	.1860	1.117	4706	10.29	1.889	31.50
LowerQ	.2721	.0312	0	42.95	4.248	1.100	.1231
Median	.5575	.1413	0	114.0	9.384	1.983	.3043
UpperQ	1.218	.2800	0	307.4	15.28	3.182	.6843
Obser.	329	329	329	329	329	329	329
Neg. Obser.	18	0	5	0	0	11	67

Table 3.12: 2001 Subperiod 'Book' Summary Statistics

2001	Beta_A	FL	DY	ln(Asset)	TURN	BAS	EBIDA_A
Min	-.9974	0	0	2.065	.2910	-1.339	-341.7
Max	5.075	1.654	465.3	1163000	118.6	6.381	245.0
Mean	1.027	.2125	3.169	6228	16.10	.6362	-1.277
SD	.8214	.2000	23.49	43950	12.97	.7443	17.33
LowerQ	.5045	.0537	0	131.6	7.953	.1981	.1403
Median	.8116	.1816	0	615.8	13.20	.3626	.2921
UpperQ	1.337	.3048	1.440	2700	20.89	.7805	.6490
Obser.	940	940	940	940	940	940	940
Neg. Obser.	20	0	0	0	0	9	168

Appendix 5: Summary Statistics for 'Market' Variables

Table 3.13: 1986 Subperiod 'Market' Summary Statistics

1986	Beta	BM	DY	ln(Size)	TURN	BAS	EBIDA
Min	.1725	-.6882	-3.593	11900000	.7132	-6.456	-28.12
Max	2.522	5.081	34.13	7070000000	31.30	15.05	12.74
Mean	1.124	.9456	1.768	336000000	6.466	3.717	.1528
SD	.4561	.8419	4.035	1040000000	5.229	2.690	4.503
LowerQ	.8188	.4535	0	21600000	2.904	2.245	.2339
Median	1.127	.7935	0	64300000	4.672	3.306	.4087
UpperQ	1.404	1.156	2.443	1.80000000	9.448	4.867	1.0901
Obser.	103	103	103	103	103	103	103
Neg. Obser.	0	2	2	3	0	3	13

Table 3.14: 1991 Subperiod 'Market' Summary Statistics

1991	Beta	BM	DY	ln(Size)	TURN	BAS	EBIDA
Min	-1.294	-1.167	-17.6	-10500000	.1739	-16.47	-394.4
Max	4.329	9.305	269.6	44800000000	52.05	25.60	128.6
Mean	.9695	.6698	2.113	496000000	8.693	3.567	-9.108
SD	.7849	.8146	17.20	2940000000	7.849	3.849	28.17
LowerQ	.5059	.2588	0	14700000	2.958	2.054	.1460
Median	.8693	.5522	0	217000000	6.599	3.390	.4192
UpperQ	1.410	.9172	.8777	217000000	11.73	5.597	1.577
Obser.	271	271	271	271	271	271	271
Neg. Obser.	22	16	17	17	0	18	63

Table 3.15: 1996 Subperiod 'Market' Summary Statistics

1996	Beta	BM	DY	ln(Size)	TURN	BAS	EBIDA
Min	-.7775	-1.554	-2.487	-12400000	.6557	-4.445	-76.46
Max	3.696	10.01	9.718	220000000000	63.62	13.85	1024
Mean	.9631	.7406	.4071	2480000000	11.67	2.314	4.417
SD	.7822	.8313	1.117	14500000000	10.29	1.889	57.53
LowerQ	.3898	.2983	0	33000000	4.248	1.100	.1670
Median	.7737	.5802	0	108000000	9.384	1.983	.4353
UpperQ	1.457	.9639	0	393000000	15.28	3.182	1.131
Obser.	329	329	329	329	329	329	329
Neg. Obser.	15	9	5	7	0	11	79

Table 3.16: 2001 Subperiod 'Market' Summary Statistics

2001	Beta	BM	DY	ln(Size)	TURN	BAS	EBIDA
Min	-1.090	-11.14	0	-7820000	.2910	-1.339	-255.0
Max	5.269	84.73	465.3	325000000000	118.6	6.381	190.7
Mean	1.287	.9574	3.169	4800000000	16.10	.6362	.1489
SD	.9184	4.085	23.49	17400000000	12.97	.7443	13.67
LowerQ	.6944	.3251	0	167000000	7.953	.1981	.1577
Median	1.103	.5377	0	7020000000	13.20	.3626	.3287
UpperQ	1.665	.8445	1.440	2790000000	20.89	.7805	.7030
Obser.	940	940	940	940	940	940	940
Neg. Obser.	18	30	0	3	0	9	188

Appendix 6: Summary Statistics for 'Book' Variables after Trimming Algorithm

The top and bottom 5% of EBIDA_A are trimmed. Next, the remaining variables are subjected to an algorithm that variable by variable, including Beta_A, determines the number of negative observations and the corresponding number of largest observations. Once the algorithm has checked all the observations, it drops any marked observations.

Table 3.17: Trimmed 1986 Subperiod 'Book' Summary Statistics

1986	Beta_A	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
Min	.0973	0	0	3.902	.7132	.5257	-2.092
Max	1.942	1.894	10.98	6214	21.82	8.268	2.181
Mean	.8610	.2299	1.600	400.4	6.387	3.463	.4809
SD	.4025	.2542	2.272	858.8	4.678	1.859	.6378
LowerQ	.5595	.0810	0	37.05	3.007	2.151	.2112
Median	.8270	.1852	.0072	151.7	4.785	3.027	.3343
UpperQ	1.137	.2957	2.504	368.3	9.413	4.531	.6839
Obser.	81	81	81	81	81	81	81
Neg. Obser.	0	0	0	0	0	0	4

Table 3.18: Trimmed 1991 Subperiod 'Book' Summary Statistics

1991	Beta_A	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
Min	.0184	0	0	3.217	.1739	.2813	-2.213
Max	1.968	.8551	4.973	14930	52.05	7.175	5.318
Mean	.8162	.1776	.7293	605.8	9.985	3.412	.6787
SD	.4903	.1683	1.273	1909	8.553	1.778	1.092
LowerQ	.4191	.0363	0	37.00	3.586	2.004	.1930
Median	.7544	.1325	0	108.8	7.924	3.200	.3712
UpperQ	1.126	.2874	1.030	337.6	13.17	4.873	.9135
Obser.	154	154	154	154	154	154	154
Neg. Obser.	0	0	0	0	0	0	9

Table 3.19: Trimmed 1996 Subperiod 'Book' Summary Statistics

1996	Beta_A	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
Min	.0036	0	0	4.704	.8757	.0693	-3.217
Max	2.110	.8199	3.904	37760	63.62	6.087	2.666
Mean	.7222	.1957	.3666	1595	11.15	2.171	.2762
SD	.5508	.1833	.8018	5392	9.127	1.345	.8857
LowerQ	.3029	.0516	0	52.55	5.016	1.068	.1494
Median	.5518	.1523	0	146.3	9.315	1.958	.2968
UpperQ	1.045	.2845	.0773	393.9	14.52	2.948	.5972
Obser.	240	240	240	240	240	240	240
Neg. Obser.	0	0	0	0	0	0	36

Table 3.20: Trimmed 2001 Subperiod 'Book' Summary Statistics

2001	Beta_A	FL	DY	ln(Assets)	TURN	BAS	EBIDA_A
Min	.0004	0	0	2.065	.2910	.0496	-4.546
Max	3.321	1.654	465.3	1163000	118.6	3.607	4.358
Mean	.9391	.2192	2.872	7004.9	15.81	.5577	.3370
SD	.6377	.1967	20.21	47682	12.47	.5988	1.002
LowerQ	.5013	.0643	0	177.2	8.268	.1919	.1619
Median	.7863	.1942	0	812.3	13.10	.3261	.2975
UpperQ	1.200	.3096	1.670	3185	20.23	.6690	.5906
Obser.	794	794	v	794	794	794	794
Neg. Obser.	0	0	0	0	0	0	100

Appendix 7: Summary Statistics for 'Market' Variables after Trimming Algorithm

The top and bottom 5% of EBIDA are trimmed. Next, the remaining variables are subjected to an algorithm that variable by variable, including Beta, determines the number of negative observations and the corresponding number of largest observations. Once the algorithm has checked all the observations, it drops any marked observations.

Table 3.21: Trimmed 1986 Subperiod 'Market' Summary Statistics

1986	Beta	BM	DY	Size	TURN	BAS	EBIDA
Min	.1952	.0360	0	2252000	.7132	.5257	-2.605
Max	2.117	3.645	10.98	3660000000	18.60	8.350	3.145
Mean	1.160	.8819	1.488	235000000	6.114	3.718	.5721
SD	.4231	.5962	2.182	506000000	4.310	1.950	.9076
LowerQ	.8327	.4485	0	26800000	3.007	2.421	.2633
Median	1.180	.7761	0	69700000	4.651	3.306	.3874
UpperQ	1.409	1.132	2.403	203000000	8.965	4.837	.7506
Obser.	81	81	81	81	81	81	81
Neg. Obser.	0	0	0	0	0	0	6

Table 3.22: Trimmed 1991 Subperiod 'Market' Summary Statistics

1991	Beta	BM	DY	Size	TURN	BAS	EBIDA
Min	.0279	.0574	0	153300	.8427	.6648	-9.169
Max	2.067	1.650	5.242	1040000000	52.05	8.553	9.345
Mean	.9486	.6388	.7078	202000000	8.940	3.720	.6711
SD	.5057	.3921	1.311	247000000	7.403	1.790	2.819
LowerQ	.5829	.3402	0	31200000	3.586	2.303	.2121
Median	.8928	.5833	0	97400000	7.294	3.362	.3739
UpperQ	1.309	.8988	.7532	253000000	11.75	5.118	1.242
Obser.	143	143	143	143	143	143	143
Neg. Obser.	0	0	0	0	0	0	20

Table 3.23: Trimmed 1996 Subperiod 'Market' Summary Statistics

1996	Beta	BM	DY	Size	TURN	BAS	EBIDA
Min	.0093	.0020	0	933000	.8757	.2528	-3.894
Max	2.367	2.583	3.517	29800000000	63.62	6.452	8.505
Mean	.9549	.7152	.3140	1090000000	11.70	2.179	.5810
SD	.6189	.5112	.7335	3720000000	9.563	1.309	1.634
LowerQ	.4631	.3366	0	41100000	5.199	1.190	.2272
Median	.8143	.5897	0	142000000	9.925	1.960	.4281
UpperQ	1.433	.9614	0	441000000	14.96	2.848	.8259
Obser.	235	235	235	235	235	235	235
Neg. Obser.	0	0	0	0	0	0	42

Table 3.24: Trimmed 2001 Subperiod 'Market' Summary Statistics

2001	Beta	BM	DY	Size	TURN	BAS	EBIDA
Min	.0008	.0054	0	4899000	.2910	.0496	-4.792
Max	3.842	2.163	106.2	141000000000	118.6	3.607	3.516
Mean	1.198	.6122	1.455	4940000000	15.74	.5591	.2407
SD	.7331	.4024	5.273	14000000000	11.89	.5982	1.138
LowerQ	.7035	.3336	0	222000000	8.321	.1911	.1876
Median	1.075	.5284	0	908000000	13.35	.3181	.3262
UpperQ	1.532	.7856	1.481	3160000000	20.34	.6734	.6313
Obser.	760	760	760	760	760	760	760
Neg. Obser.	0	0	0	0	0	0	117

Appendix 8: Results for 'Book' Variable Regression

This table includes results for the following regression:

$$\beta_A = \lambda_o^t + \lambda_1^t FL^t + \lambda_2^t DY^t + \lambda_3^t Assets^t + \lambda_4^t TURN^t + \lambda_5^t BAS^t + \lambda_6^t EBIDA\_A^t + \lambda_7^t Neg * EBIDA\_A^t + \nu^t.$$

The data for this regression had the top and bottom 5% of EBIDA_A trimmed. Next, the remaining variables were subjected to an algorithm that variable by variable, including Beta_A, determined the number of negative observations and the corresponding number of largest observations. Once the algorithm has checked all the observations, it droped any marked observations. Finally, the variables were scaled by their standard deviation.

Table 3.25: 'Book' 2001 Subperiod Estimates

2001	Coefficient	Standard Error	t-test
FL	-.2394	.0046	-51.8
DY	-.0807	.0027	-30.0
ln(Assets)	.0093	.0016	5.7
TURN	.3419	.0088	38.9
BAS	.1075	.0124	8.7
EBIDA_A	.0759	.0063	12.0
NEG*EBIDA_A	-.3090	.0178	-17.4
Constant	.9773	.0126	77.8

R-squared = 0.2213, Adjusted R-squared = 0.2144, F-statistic = 31.9

Table 3.26: 'Book' Pooled Estimates Aggregated by Covariance Matrices

Pooled Cov	Coefficient	Standard Error	t-test
FL	-.2276	.0032	-70.1
DY	-.0823	.0022	-38.2
ln(Assets)	.0129	.0014	8.9
TURN	.4185	.0055	75.5
BAS	.0674	.0064	10.6
EBIDA_A	.0969	.0049	19.8
NEG*EBIDA_A	-.4049	.0151	-26.9
Constant	1.022	.0102	99.8

Table 3.27: 'Book' Pooled Estimates Aggregated by # Subperiod Observations

Pooled Obs	Coefficient	Standard Error	t-test
FL	-.2261	.0036	-62.1
DY	-.0732	.0025	-29.9
ln(Assets)	.0054	.0022	2.5
TURN	.3950	.0069	57.1
BAS	.0455	.0089	5.1
EBIDA_A	.0719	.0059	12.3
NEG*EBIDA_A	-.4647	.0188	-24.8
Constant	1.024	.0123	83.0

R-squared = 0.2896, Adjusted R-squared = 0.2750, F-statistic = 73.4

Appendix 9: Results for 'Market' Variable Regression

This table includes results for the following regression:

$$\beta = \lambda_o^t + \lambda_1^t BM^t + \lambda_2^t DY^t + \lambda_3^t Size^t + \lambda_4^t TURN^t + \lambda_5^t BAS^t + \lambda_6^t EBIDA^t + \lambda_7^t Neg * EBIDA^t + \nu^t.$$

The data for this regression had the top and bottom 5% of EBIDA trimmed. Next, the remaining variables were subjected to an algorithm that variable by variable, including Beta, determined the number of negative observations and the corresponding number of largest observations. Once the algorithm has checked all the observations, it droped any marked observations. Finally, the variables were scaled by their standard deviation.

Table 3.28: 'Market' 2001 Subperiod Estimates

2001	Coefficient	Standard Error	t-test
BM	.0474	.0053	8.9
DY	-.1596	.0069	-23.2
Size	.0475	.0036	13.4
TURN	.3680	.0092	40.0
BAS	.1440	.0124	11.6
EBIDA	.1383	.0093	14.9
NEG*EBIDA	-.3385	.0179	-18.9
Constant	.6932	.0145	48.0

R-squared = 0.1929, Adjusted R-squared = 0.1854, F-statistic = 25.7

Table 3.29: 'Market' Pooled Estimates Aggregated by Covariance Matrices

Pooled cov	Coefficient	Standard Error	t-test
BM	.0734	.0038	19.5
DY	-.0611	.0034	-17.9
Size	.0377	.0028	13.5
TURN	.4451	.0059	76.0
BAS	.1181	.0060	19.5
EBIDA	.0891	.0056	15.9
NEG*EBIDA	-.2213	.0120	-18.5
Constant	.7022	.0116	60.8

Table 3.30: 'Market' Pooled Estimates Aggregated by # Subperiod Observations

Pooled obs	Coefficient	Standard Error	t-test
BM	.0206	.0048	4.3
DY	-.1239	.0046	-26.7
Size	.0403	.0038	11.9
TURN	.4462	.0075	59.8
BAS	.1141	.0090	12.6
EBIDA	.1184	.0066	17.9
NEG*EBIDA	-.2828	.0151	-18.7
Constant	.7717	.0147	52.7

R-squared = 0.2564, Adjusted R-squared = 0.2404, F-statistic = 59.7

Appendix 10: Robust Results for EBIDA_A and EBIDA

The following results provide the effects on EBIDA_A or EBIDA after the top and bottom 5% percentage of observations trimmed from these variables was perturbed. The percentage of observations trimmed from the top and bottom is listed in the left hand column of each table. Otherwise, the rest of the data preparation and the regressions were exactly the same as in Appendices 8 and 9.

Table 3.31: 'Book' Regression - Pooled Covariance

	EBIDA_A	SE	t-stat	NEG*EBIDA_A	SE	t-stat
1%	.0597	.0068	16.3	-.1553	.0089	-17.5
5%	.0970	.0049	19.8	-.4049	.0151	-26.9
10%	.1524	.0040	38.3	-.8335	.0242	-34.5
15%	.1248	.0040	31.2	-1.0239	.0329	-31.1

Table 3.32: 'Book' Regression - Pooled Observations

	EBIDA_A	SE	t-stat	NEG*EBIDA_A	SE	t-stat
1%	.0671	.0059	11.3	-.1927	.0102	-18.9
5%	.0719	.0059	12.3	-.4647	.0187	-24.8
10%	.1570	.0050	31.1	-1.028	.0324	-31.7
15%	.1250	.0045	27.6	-1.061	.0332	-32.0

Table 3.33: 'Market' Regression - Pooled Covariance

	EBIDA	SE	t-stat	NEG*EBIDA	SE	t-stat
1%	.0449	.0057	7.9	-.1459	.0085	-17.1
5%	.0891	.0056	16.0	-.2213	.0120	-18.5
10%	.1518	.0048	31.7	-.3746	.0136	-27.6
15%	.2184	.0043	50.1	-.9048	.0208	-43.4

Table 3.34: 'Market' Regression - Pooled Observations

	EBIDA	SE	t-stat	NEG*EBIDA	SE	t-stat
1%	.1053	.0066	16.0	-.2571	.0139	-18.5
5%	.1185	.0066	17.9	-.2827	.0151	-18.7
10%	.1466	.0056	26.0	-.6476	.0245	-26.4
15%	.1682	.0050	33.2	-.9522	.0259	-36.8

Appendix 11: 'Book' Regressions with Industry Effects

For the results in this table, the data preparation and the regression was exactly the same as in Appendix 8, except 48 industry fixed effects replaced the constant. The 48 industry variables were developed by a classification system used in Fama and French [20] with updates from Ken French's webpage. Note that the results for the industry dummy are excluded from the tables.

Table 3.35: 'Book' 2001 Subperiod Estimates with Industry Effects

2001	Coefficient	Standard Error	t-test
FL	-.2217	.0050	-44.7
DY	-.0827	.0028	-29.7
ln(Assets)	.0102	.0017	6.0
TURN	.2959	.0075	39.6
BAS	.0946	.0118	8.0
EBIDA	.0961	.0065	14.7
NEG*EBIDA_A	-.2940	.0155	-19.0

R-squared = 0.3768, Adjusted R-squared = 0.3313, F-statistic = 8.3

Table 3.36: 'Book' Pooled Estimates Aggregated by Covariance Matrices with Industry Effects

Pooled Cov	Coefficient	Standard Error	t-test
FL	-.2177	.0024	-91.7
DY	-.0694	.0016	-42.7
ln(Assets)	.0045	.0011	4.1
TURN	.3772	.0034	111.0
BAS	.0631	.0041	15.4
EBIDA	.1257	.0038	33.2
NEG*EBIDA_A	.4508	.0104	-43.4

Table 3.37: 'Book' Pooled Estimates Aggregated by # Subperiod Observations with Industry Effects

Pooled Obs	Coefficient	Standard Error	t-test
FL	-.2114	.0041	-51.9
DY	-.0760	.0027	-27.7
ln(Assets)	-.0073	.0025	-3.0
TURN	.3524	.0064	54.8
BAS	.0346	.0089	3.9
EBIDA	.0872	.0063	13.7
NEG*EBIDA_A	-.4710	.0167	-28.2

R-squared = 0.4443, Adjusted R-squared = 0.3117, F-statistic = 18.0

Appendix 12: 'Market' Regressions with Industry Effects

For the results in this table, the data preparation and the regression was exactly the same as in Appendix 8, except 48 industry fixed effects replaced the constant. The 48 industry variables were developed by a classification system used in Fama and French [20] with updates from Ken French's webpage. Note that the results for the industry dummy are excluded from the tables.

Table 3.38: 'Market' 2001 Subperiod Estimates with Industry Effects

2001	Coefficient	Standard Error	t-test
BM	.1168	.0049	24.0
DY	-.1679	.0054	-31.1
Size	.0642	.0038	16.9
TURN	.3366	.0071	47.2
BAS	.1187	.0114	10.4
EBIDA	.1417	.0096	14.8
NEG*EBIDA	-.2964	.0157	-18.8

R-squared = 0.3715, Adjusted R-squared = 0.3234, F-statistic = 7.7

Table 3.39: 'Market' Pooled Estimates Aggregated by Covariance Matrices with Industry Effects

Pooled Cov	Coefficient	Standard Error	t-test
BM	.0706	.0030	23.8
DY	-.0180	.0024	-7.5
Size	.0582	.0021	28.1
TURN	.3440	.0035	97.1
BAS	.0674	.0038	17.6
EBIDA	.1358	.0039	35.1
NEG*EBIDA	-.2929	.0089	-33.0

Table 3.40: 'Market' Pooled Estimates Aggregated by # Subperiod Observations with Industry Effects

Pooled Obs	Coefficient	Standard Error	t-test
BM	.0218	.0049	4.5
DY	-.1265	.0040	-31.5
Size	.0375	.0039	9.7
TURN	.4020	.0060	66.8
BAS	.0998	.0087	11.5
EBIDA	.1378	.0072	19.2
NEG*EBIDA	-.2991	.0153	-19.5

R-squared = 0.4344, Adjusted R-squared = 0.2965, F-statistic = 16.6

Bibliography

[1] S. Acharya. A Generalized Econometric Model and Tests of a Signaling Hypothesis with Two Discrete Signals. *Journal of Finance*, 43(2):413–429, 1988.

[2] Y. Amihud and H. Mendelson. The Effects of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns. *Journal of Finance*, 44(2):479–486, 1989.

[3] M. Barclay and C. Smith. The Maturity Structure of Corporate Debt. *Journal of Finance*, 50(2):609–631, 1995.

[4] J. Berk, R. Green, and V. Naik. Optimal Investment, Growth Options, and Security Returns. *Journal of Finance*, 54(5):1553–1607, 1999.

[5] E. Berndt, R. Mortimer, and A. Parece. Do Authorized Generic Drugs Deter Paragraph IV Certifications? Working Paper, 2007.

[6] S. Bhattacharyya and C. Leach. Risk Spillovers and Required Returns in Capital Budgeting. *Review of Financial Studies*, 12(3):461–479, 1999.

[7] Z. Bodie, A. Kane, and A. Marcus. *Investments*. McGraw-Hill, sixth edition, 2005.

[8] J. Bulow. The Gaming of Pharmaceutical Patents. Stanford Business School Research Paper No. 1804, 2003.

[9] John Y. Campbell and Tuomo Vuolteenaho. Bad Beta, Good Beta. *American Economic Review*, 94(5):1249–1275, 2004.

[10] M. Carhart. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57–82, 1997.

[11] M. Carlson, A. Fisher, and R. Giammarino. Corporate Investment and Asset Price Dynamics: Implications for the Cross-Section of Returns. Working Paper, 2003.

[12] I. Cooper. Asset Pricing Implications of Irreversibility and Non-Convex Adjustment Costs of Investment. Working Paper, Norwegian School of Management, 2004.

[13] Z. Da. Cash Flow, Consumption Risk and Cross Section of Stock Returns. Forthcoming in the, 2006.

[14] Drug Topics. Top Brand-Name Drugs by Retail Sales. *Drug Topics Magazine*, 1991-2007. Presented annually in the first April issue of each year.

[15] B. Eckbo, V. Maksimovic, and J. Williams. Consistent Estimation of Cross-Sectional Models in Event Studies. *Review of Financial Studies*, 3(3):343–365, 1990.

[16] E. Fama. The Adjustment of Stock Prices to New Information. *International Economic Review*, 10(1):1–21, 1969.

[17] E. Fama. Efficient Capital Markets: II. *Journal of Finance*, 46(5):1575–1617, 1991.

[18] E. Fama and K. French. The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2):427–465, 1992.

[19] E. Fama and K. French. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

[20] E. Fama and K. French. Industry Costs of Equity. *Journal of Financial Economics*, 43(2):153–193, 1997.

[21] Federal Trade Commission. Generic Drug Entry Prior to Patent Expiration: An FTC Study. An FTC Study, July 2002.

[22] W. Gebhardt, C. Lee, and B. Swaminathan. Toward an Implied Cost of Capital. *Journal of Accounting Research*, 39(1):135–176, 2001.

[23] J. Gomes, L. Kogan, and L. Zhang. Equilibrium Cross Section of Returns. *Journal of Political Economy*, 111(4):693–732, 2003.

[24] V. Goyal. Market Discipline of Bank Risk: Evidence from Subordinate Debt Contracts. *Journal of Financial Intermediation*, 14(3):318–350, 2005.

[25] P. Grompers, J. Ishi, and A. Metrick. Corporate Governance and Equity Prices. *Quarterly Journal of Economics*, 118(1):107–155, 2003.

[26] A. Habib. Information risk and the Cost of Capital: Review of the Empirical Literature. Working Paper, 2005.

[27] R. Hamada. Portfolio analysis, Market Equilibrium and Corporation Finance. *Journal of Finance*, 24(1):13–31, 1969.

[28] J. Hastings. Vertical Relationships and Competition in Retail Gasoline Marekts: Empirical Evidence from Contract Changes in Southern California. *American Economic Review*, 94(1):317–328, 2004.

[29] M. Higgins and D. Rodriguez. The Outsourcing of R&D Through Acquisition in the Pharmaceutical Industry. *Journal of Financial Economics*, 80(2):351–383, 2006.

[30] A. Hollis. Closing the FDA's Orange Book. *Regulation*, pages 14–17, Winter 2001.

[31] K. Hou and D. Robinson. Industry Concentration and Average Stock Returns. *Journal of Finance*, 61(4):1927–1956, 2006.

[32] J. Houde. Spatial Differentiation in Retail Markets for Gasoline. Working Paper, 2007.

[33] P. Irvine and J. Pontiff. Indiosyncractic Return Volatility, Cash Flows, and Product Market Competition. Working Paper, 2005.

[34] R. Jagannathan and I. Meier. Do We Need CAPM for Capital Budgeting? Working Paper, 2001.

[35] R. Jagannathan and Z. Wang. The Conditional CAPM and the Cross-Section of Expected Returns. *Journal of Finance*, 51(1):3–53, 1996.

[36] E. Kazumori. The Industry Cross Section of Expected Stock Returns. Working Paper, 2004.

[37] S. Khotari and J. Warner. Econometrics of Event Studies. In B. Eckbo, editor, *Handbook of Corporate Finance: Empirical Corporate Finance*. North-Holland, 2006.

[38] L. Kogan. Asset Prices and Real Investment. *Journal of Financial Economics*, 73(3):411–432, 2004.

[39] R. La Porta. Expectations and the Cross Section and Stock Returns. *Journal of Finance*, 51(5):1715–1742, 1996.

[40] C. Lee and B. Swaminathan. Price Momentum and Trading Volume. *Journal of Finance*, 55(5):2017–2069, 2000.

[41] B. Lehmann. Residual Risk Revisited. *Journal of Econometrics*, 45(1-2):71–97, 1990.

[42] M. Lettau and S. Ludvigson. Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying. *Journal of Political Economy*, 109(6):1238–1287, 2001.

[43] B. Lev. On the Association Between Operating Leverage and Risk. *Journal of Financial and Quantitative Analysis*, 9(4):627–641, 1974.

[44] S. Lustgarten and S. Thomadakis. Valuation Response to New Information. *Journal of Political Economy*, 88(5):977–993, 1980.

[45] B. Madden. CFROI Valuation: A Total System Approach to Valuing the Firm. Holt Value Associates, Chicago Il., 1999.

[46] G. Manderlker and S. Rhee. he Impact of the Degrees of Operating and Financial Leverage on Systematic Risk of Common Stock. *The Journal of Financial and Quantitative Analysis*, 19(1):45–57, 1984.

[47] R. Mehra and E. Prescott. The Equity Premium: A Puzzle. *Journal of Monetary Economics*, 15(2):145–161, 1985.

[48] R. Melicher, D. Rush, and D. Winn. Degree of Industry Concentration and Market Risk-Return Performance. *The Journal of Financial and Quantitative Analysis*, 11(4):627–635, 1976.

[49] S. Myers. The Relation Between Real and Financial Measure of Risk and Return. In I. Friend and J. Bicksler, editors, *Studies in Risk and Return*. Ballinger Publishing Company, 1977.

[50] R. Novy-Marx. Operating Leverage. Working Paper at the University of Chicago Graduate School of Business, 2007.

[51] L. Pastor and R. Stambaugh. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111(3):642–685, 2003.

[52] M. Raith. Competition, Risk, and Managerial Incentives. *American Economic Review*, 28(4):1425–1436, 2003.

[53] R. Roll. Recent Research about Liquidity. Opening Lecture at the 10th Symposium on Finance, Banking, and Insurance, December 2005.

[54] B. Rosenberg and J. Guy. Prediction of Beta from Investment Fundamentals, Part Two. *Financial Analysts Journal*, 32:62–70, July-August 1976.

[55] M. Rubinstein. A Mean-Variance Synthesis of Corporate Financial Theory. *Journal of Finance*, 28(1):167–181, 1973.

[56] T. Shumway. The Delisting Bias in CRSP Data. *Journal of Finance*, 52(1):327–40, 1997.

[57] H. Skaife, D. Collins, and R. Lafond. Corporate Governance and the Cost of Equity Capital. Working Paper, 2004.

[58] M. Subrahmanyam and S. Thomadakis. Systematic Risk and the Theory of the Firm. *Quarterly Journal of Economics*, 94(3):437–451, 1980.

[59] T. Sullivan. The Cost of Capital and the Market Power of Firms. *The Review of Economics and Statistics*, 60(2):209–217, 1978.

[60] J. Tirole. *The Theory of Industrial Organization*.

[61] M. Voet. *The Generic Challenge: Understanding Patents, FDA and Pharmaceutical Life-Cycle Management*. BrownWalker Press, 2005.

[62] T. Vuolteenaho. What Drives Firm-Level Stock Returns? *Journal of Finance*, 57(1):233–264, 2002.

[63] L. Zhang. The Value Premium. Working Paper, 2003.