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Essays in Empirical Finance: Evaluating Risk in Financial Markets.

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An abstract of
A dissertation submitted to the Faculty of the Graduate School of Emory University
in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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Abstract

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This dissertation is comprised of two parts, each addressing an important type of financial risk. The first part is composed of an essay discussing Market Risk. This essay examines a causal relationship between the series of securities returns and traded volumes in high-frequency data. Linear and nonlinear Granger causality tests are used to evaluate a causal relationship between the series of volumes and returns of various investment vehicles within the parametric and the non-parametric frameworks, and for trading and calendar time specifications.

The second part contains two essays, each addressing a specific aspect of Firm Risk. The first essay focuses on estimating obligor credit rating migration probabilities. Short- and long-run relationships between asset quality and obligor ratings are modeled and quantified. The use of a continuous-record model addresses the problems of data sparsity and control for resulting estimation errors; while the implementation of a methodology allowing us to to precisely identify the stages of the business cycle enables us to determine the incremental impact of idiosyncratic and systematic risk factors on rating transitions probabilities, resulting in more precise estimates of credit rating migration trends.

The second essay tests theoretical predictions about the relationship between leverage and firm performance set forth by the corporate finance literature. The dynamic relationship between firm performance and leverage is examined empirically using the Difference GMM method of econometric estimation. Multiple measures of performance and leverage are utilized, controlling for idiosyncrasies associated with each particular definition and allowing us to generate inferences about the practical relationship between firm performance and debt.

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Посвящение

Моим родителям,

За их безграничное понимание, неоценимую помощь, и неиссякаемую поддержку на всех стадиях этого процесса.

С Любовью,

Алиса

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Alysa V. Shcherbakova, November 2008

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Part I: Market Risk

Chapter 1

Tests of Informational Efficiency in Financial Markets: A Granger Causality Approach

In this study we examine a causal relationship between the series of securities returns and traded volumes in high-frequency data. Our analysis is based on the methodology of Ghysels, Gouriroux and Jasiak (2000), who develop a qualitative framework in which the dynamics of financial series are restricted to transitions between a finite number of states, represented by Markov chains with specific transition probabilities. Linear and nonlinear Granger causality tests are used to evaluate a causal relationship between the series of volumes and returns of various investment vehicles within the parametric and the non-parametric frameworks, and for trading and calendar time specifications. Results demonstrate evidence of three causality types, unidirectional from volumes to returns and vice versa, and instantaneous causality. The frequency with which causal relationships are observed increases rapidly as the transaction grid becomes finer, allowing us to infer that while informational efficiency of financial markets can not be rejected, opportunities for economic gains may exist at high-frequencies.

1.1 Introduction

Early empirical research examining the relationship between stock prices and traded volumes focused on the contemporaneous nature of the two series (see, for example, Clark 1973, Karpoff 1987, Gallant, Rossi, and Tauchen 1992). The introduction and subsequent implementation of electronic trading systems increased availability of high-frequency data, and new avenues of investigation for applied research emerged. The focus of current empirical literature has shifted from examining a purely contemporaneous relationship between the two series, to testing linear and nonlinear causality between volumes and returns of various investment vehicles (see Tauchen and Pitts 1983, Hiemstra and Jones 1994, Ghysels, Gouriéroux, and Jasiak 2000).

The body of theoretical literature asserting a relationship between securities returns and traded volumes is rooted in the work of Osborne (1959), who introduced the idea that price changes can be modeled according to a diffusion process, the variance of which depends on the quantity of transactions associated with a particular securities issue (see Sun 2003). Following the seminal work of Osborne, financial literature has grown to include models of market microstructure as potential sources of the relationship between volumes and securities returns. The general idea of market microstructre models is that trades are driven by key factors, more notable of which are liquidity and information.

Initially, market liquidity was considered to be the factor generating the price-volume relationship. Liquidity theory suggests that a transaction involving significant volume, even when that transaction is not motivated by specific information release, may affect the price of a stock. This adjustment in price can be attributed to opportunity cost (see Black 1976).

More recently, preferences shifted toward microstructure models that analyze dynamics of securities trading within the framework of asymmetric information. Prominent among these are the mixture of distributions models of Clark (1973) and Epps and Epps (1976). In Clark's model, traded volume serves as a proxy for the speed of information flow. The author asserts that information is a latent factor, common to volumes and securities returns; thus, there exists a contemporaneous relationship between the two series. The mixture model introduced by Epps and Epps (1976) suggests that traders constantly adjust their reservation price based on the arrival of new information into the market. In this model, traded volume is used as a measure of disagreement among traders. Greater disagreement concerning prices of securities implies higher volumes traded in the market, where increased trading drives securities prices to some equilibrium.

Other theories consider the relationship between traded volumes and returns within the framework of sequential information arrival, based on the models of Copeland (1976) and Jennings et al. (1981). These models of asymmetric information are based on the assumption that new information flows into the market, where it is disseminated to investors one at a time. This pattern of information arrival produces a sequence of momentary equilibria, consisting of various security price-volume combinations before the final, complete information equilibrium is achieved (see Hiemstra and Jones 1994).

Asymmetric information models assume the existence of investors who are better informed than the rest of the market participants, given a specific time period and environment. Well-informed traders attempt to take advantage of private information available to them by selecting appropriate trading strategies; however, in the order driven market, their actions are observed by market makers and other investors. Thus, the uninformed investors infer from the trading behavior of the informed investors about the content of their private information and implement trading strategies consistent with this new information. Asymmetric information models suggest that due to this sequential flow of information in the market, it is feasible that lagged traded volume could have predictive power for current absolute stock returns, and lagged absolute stock returns could have predictive power for current traded volume (see Ghysels et al. 2000).

This study extends the current empirical literature by utilizing linear and nonlinear Granger causality tests to examine the dynamic relationship between the series of returns and traded volumes in high-frequency data available through the NYSE TAQ database. We analyze a sample of 30 individual securities included in the Dow Jones Industrial Index, as well as an equally weighted aggregate portfolio comprised of the aforementioned stocks. We rely on individual securities analysis, in addition to the aggregated approach, as investigation of individual securities, compared to that of a portfolio, may reveal characteristics which tend to be hidden when aggregate indexes are analyzed. Informational efficiency of financial markets is tested in an effort to assess the quality of contribution that knowledge of past volume movements has in terms of improving short-run forecasts of current and future movements in securities prices, and vice versa. Weak-form informational market efficiency is evaluated in high-frequency data context, and unidirectional and instantaneous non-causality hypothesis for individual securities and the aggregated portfolio are tested for trading and calendar time specifications.

The empirical strategy used in this study is based on the methodology of Ghysels et al. (2000), who introduce an innovative approach, controlling for limitations of earlier empirical research. We begin by assuming that the dynamics of the series of traded volumes and returns are restricted to transitions between a finite number of states, represented by Markov chains with specific transition probabilities. First, dynamics of the return series for individual securities and the portfolio are examined within the univariate framework, impact of state specification on temporal dependence is determined, and weak-form market efficiency is evaluated at varying time-frequencies. Second, our analysis is extended beyond the weak-form market efficiency. A bivariate framework is introduced, allowing us to investigate co-movements between traded volumes and transaction prices, and test for Granger (statistical) causality between the two series.

Our analysis produces stylized facts about the intertemporal relationship between securities returns and traded volumes, allowing us to generate inferences regarding informational efficiency of financial markets. Empirical evidence suggests that causality directions vary in time and depend on the sampling scheme, such as the trading or calendar time specifications. Results demonstrate that instances of observed causality increase as the calendar grid becomes finer, suggesting that while informational efficiency of financial markets can not be rejected, opportunities for economic gains may exist at high-frequencies. In trading time, observed instances of causality are greatest for instantaneous causality. This result changes for calendar-time specifications where we observe unidirectional causality from volumes to returns more frequently than other causality types.

The remainder of the paper is organized as follows. In Section 2, we define the concept of Granger causality, describe traditional linear tests for its presence, and motivate the non-parametric approach introduced by Ghysels et al. (2000). In Section 3, we consider a univariate series of stock returns; a state selection yielding uncorrelated qualitative price process is discussed; and weak-form informational market efficiency is tested within the empirical framework presented. In Section 4, we develop the econometric methodology allowing us to extend the univariate approach presented in Section 3 to a bivariate framework; relationship between multivariate state transition probabilities and coefficients of a multivariate SUR model is determined; and, Granger causality tests appropriate within the bivariate framework are proposed. In Section 5, we discuss the results of the empirical estimation. Section 6 concludes.

1.2 Granger Causality

In 1969, Granger introduced the concept of statistical non-causality, which allows one to evaluate whether a particular time series is useful in predicting values of another time series. A formal definition of Granger causality follows.

Consider two arbitrary dynamic series, $\{X_t\}$ and $\{Y_t\}$. Let $F(X_t|I_{t-1})$ denote the conditional probability distribution of X_t given a bivariate information set I_{t-1} consisting of an L_X-length lagged vector of X_t and L_Y-length lagged vector of Y_t, such that

$$X_{t-L_X} \equiv (X_{t-1}, X_{t-2}, \dots, X_{t-L_X}), \tag{1.1}$$

and

$$Y_{t-L_Y} \equiv (Y_{t-1}, Y_{t-2}, \dots, Y_{t-L_Y}). \tag{1.2}$$

Given lags L_X and L_Y, the time series $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ if

$$F(X_t|I_{t-1}) = F(X_t|(I_{t-1} - Y_{t-L_Y})), \quad t = 1, 2, \dots, T. \tag{1.3}$$

That is, if the conditional probability distribution of X_t given the bivariate information set I_{t-1} equals the conditional probability distribution of X_t given the univariate information set $I_{t-1} - Y_{t-L_Y}$, where I_{t-1} consists only of an L_X-length lagged vector of X_t and does not contain any information about Y_t. If the equality in Eq.(1.3) does not hold, knowledge of past Y values helps predict current and future values of X, and Y is said to strictly Granger cause X.

Similarly, a lack of instantaneous Granger causality from Y to X implies that

$$F(X_t|I_{t-1}) = F(X_t|(I_{t-1} + Y_t)), \tag{1.4}$$

where the bivariate information set is modified to include the current value of Y. If the equality in Eq.(1.4) does not hold, then Y is said to instantaneously Granger cause X.

To summarize, strict Granger causality refers to the ability of past values of one time series to influence the present and future values of another time series. Similarly, instantaneous Granger causality relates to the ability of present values of one time series to influence the present values of another time series.

1.2.1 Parametric Approach

Typically, empirical tests of bivariate Granger causality rely exclusively on estimating a liner vector autoregressive (VAR) model of the following form (e.g. Hiemstra and Jones 1994)

$$\begin{aligned} X_t &= A(L)X_t + B(L)Y_t + U_{X,t}, \\ Y_t &= C(L)X_t + D(L)Y_t + U_{Y,t}, \end{aligned} \tag{1.5}$$

where $t = 1, 2, \ldots, T$; $A(L)$, $B(L)$, $C(L)$, and $D(L)$ denote polynomials of some order in the lag operator L such that given $P \in \{A, B, C, D\}$, $P(L) = L^0 - L^1 - L^2 - \cdots - L^P$ and $L^P V_t = V_{t-P}$, with roots outside the unit circle and no roots in common. [1] The regression errors, $\{U_{X,t}\}$ and $\{U_{Y,t}\}$, are assumed to be mutually independent and identically distributed (*i.i.d.*), with zero mean and constant variance.

To test for strict Granger causality from Y to X in this linear framework, a standard joint F-test is used to determine whether lagged Y has significant linear predictive power for current values of X. The null hypothesis that Y does not strictly Granger cause X is

[1] In this particular framework P is restricted such that $P > 0$ and $P(L) = L^1 - L^2 - \cdots - L^P$.

rejected if the coefficients on the elements in $B(L)$ are jointly significantly different from zero. Bidirectional causality exists if Granger causality runs in both directions, in which case, the coefficients on the elements in both $B(L)$ and $C(L)$ are jointly different from zero.

A significant limitation of the parametric approach is the unrealistic assumption about the distribution of the error terms, particularly in applications to financial time-series data. The empirical literature demonstrates that financial time-series frequently exhibit time-varying volatility (see, for example, Himestra and Jones 1994, Campbell, Lo, and MacKinlay 1997, Luger 2001). In the presence of exogenous shocks, financial markets react "nervously," causing the prices of financial assets to fluctuate (Straumann 2005) In statistical terms, this implies that the conditional variance given the past, $Var[X_t|X_{t-1}, X_{t-2}, \dots]$ is not constant over time, and the underlying stochastic process $\{X_t\}$ is conditionally heteroskedastic. That is, the error terms of financial series are neither independent, no identically distributed. Summary statistics for series of securities returns and traded volumes are available in Tables 1.1 and 1.2, respectively.

The presence of heteroskedastic error terms leads to poor estimates under the standard parametric approach. Although in presence of heteroskedasticity the ordinary lease squares (OLS) estimators remain unbiased, the estimated standard errors are not exact, resulting in imprecise confidence intervals and unreliable hypotheses tests. In the following section, we test the financial data for autoregressive conditional heteroskedasticity (ARCH) effects, motivating the importance of the non-parametric approach to follow.

1.2.2 Testing for ARCH Effects

In a pioneering paper, Engle (1982), introduced the autoregressive conditional heteroskedasticity model that assumes a non-constant variance of the error terms

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \sigma_{t-i}^2 \eta_{t-i}^2. \tag{1.6}$$

Specifically, the proposed model suggests that the variance of the error terms at time t is a function of the variances of the error terms of the previous time period $t-i$ $(i = 1, \dots, q)$.

To test for the presence of ARCH effects, Engle proposed a Lagrange Multiplier (LM) test where, considering the model in Eq.(1.6), the hypothesis of homoskedasticity is defined as $H_0 : \alpha_1 = \cdots = \alpha_q = 0$.

Engle's LM test assumes conditionally normally distributed data and is computed using an auxiliary regression (Raunig 2008). Empirically, in testing for ARCH(q) effects, one regresses the squared residuals of the fitted model, $\hat{u}_t^2$, on their first q lags, $\hat{u}_{t-i}^2$ ($i = 1, \ldots, q$), and a constant. The Engle test statistic is given by TR^2, where T is the sample size and R^2 is the coefficient of determination in the auxiliary OLS regression, and is asymptotically $\chi^2(q)$ under the null hypothesis of no ARCH. If TR^2 is greater than a critical χ^2 value we reject the null hypothesis of conditional homoskedasticity in favor of the alternative hypothesis.

Table 1.3 presents $\chi^2(q)(q = 1)$, statistics for the returns series of individual securities and the aggregated portfolio used in this study. We observe clear evidence of ARCH effects in these financial time-series for both the individual securities and the aggregated portfolio. It is also evident that these effects become stronger as sample frequency increases. We conclude that the error terms in the financial time-series do not meet the homogeneity assumption characteristic to the parametric approach (e.g. Dickey and Fuller 1979, Lo and MacKinlay 1988, Breitung and Gouriroux 1997, Dufour and Kiviet 1998, Dufour and Torrès 2000), potentially resulting in unreliable hypothesis tests, over-rejecting the null.

Taylor (1984) argues that the accuracy of the hypotheses tests relies on the specification of financial series with error terms that have reasonably homogeneous conditional variances. While we clearly demonstrated that the financial time-series used in this study exhibits clear heteroskedastic tendencies, it may be argued that due to the large sample size, the error terms may be asymptotically homogeneous. The empirical literature demonstrates that in the presence of heteroskedastic error terms, hypothesis tests are not exact even then the sample size is large (see Luger 2003 and Kim, Nelson, and Startz 1998). Specifically, under the parametric approach, the null is rejected too often, depending on the degree of heterogeneity in the conditional variances.

Luger (2005) suggests that sign statistics are the only statistics which can produce valid tests for hypotheses under sufficiently general distributional assumptions, allowing for possibly heteroskedastic observations. In what follows, we introduce the non-parametric framework of Ghysels, Gouriéroux, and Jasiak (2000) as a superior approach to tests for Granger causality. This non-parametric approach has an advantage over the parametric approach in that transforms a quantitative financial series into a qualitative one of sign changes, allowing us to relax the assumption about the distribution of the error terms and thereby resulting in more robust estimates.

Consider the observed process $\{y_t\}$, generated according to

$$y_t = \phi y_{t-1} + \varepsilon_t, \quad \text{for} \quad t = 1, \ldots, T. \tag{1.7}$$

Under the null hypothesis of informational market efficiency $\phi = 0$, simplifying Eq.(1.7) to yield $y_t = \varepsilon_t$, for $t = 1, \ldots, T$. Consider the first-difference $\Delta y_t = y_t - y_{t-1}$ for $t = 1, 2, \ldots, T$. We define a sign function as $s[y] = 1$ if $\Delta y > 0$, and $s[y] = 0$ if $\Delta y \leq 0$. Note that the differences Δy_t are not necessarily independent. It is mathematically correct to generalize that while the error terms of a qualitative process of sign changes are *i.i.d.* even when the error terms of a quantitative process used to generate it are not (see Luger 2003, Lemma 0.1 and Theorem 0.1; Randal and Wolfe 1979, Theorem 1.3.7, Lemma 2.4.2)

1.3 Non-Parametric Approach: Univariate

In this section we introduce a univariate framework that allows us to examine the dynamics of a quantitative series of traded volumes and returns for individual securities, as well as a market portfolio. For simplicity, consider a Markov chain, Z_t, of order one that transitions between two states, labeled *zero* and *one*, and where the transition probabilities depend only on the preceding state. Following Ghysels et al. (2000), let us assume that these states are defined according to some dichotomous qualitative features of our quantitative series of prices and volumes such that

A. *Comparison of Price Modification*:

$$Z_t(c) = \begin{cases} 1, & \text{if } log(p_t) - log(p_{t-1}) = \Delta p_t > c_p \\ 0, & \text{otherwise} \end{cases}, \tag{1.8}$$

where p_t is the price at time t; c_p is a threshold value. Note that when c is equal to zero, we are effectively evaluating the *direction* of price evolution. When c is non-zero, the model above allows us to compare price evolution relative to some specific benchmark, for example the behavior of the risk-free asset when $c = log(1 + r)$ where r is the risk-free rate.

B. *Comparison of Volume Modification*:

$$Z_t(c) = \begin{cases} 1, & \text{if } v_t > c_v \\ 0, & \text{otherwise} \end{cases}, \tag{1.9}$$

where v_t is volume at time t; and c_v is a threshold value.

Having established the mapping sequence that allows us to transform a quantitative series into a qualitative one, we define the implied transition probabilities of a first-order Markov chain Z_t by

$$P(Z_t = i|Z_{t-1} = j) = \Pi_{ij}, \quad \text{where } \ i = 0, 1 \ \text{ and } \ j = 0, 1. \tag{1.10}$$

Equivalently, the dynamics of a univariate series can be estimated using linear regressions. That is, the expected value of Z_t given the information available at time $t - 1$ can be expressed as

$$E[Z_t|Z_{t-1}] = P[Z_t = 1|Z_{t-1}] = \Pi_{11}Z_{t-1} + \Pi_{10}(1 - Z_{t-1}). \tag{1.11}$$

Rewriting Eq.(1.11) as a linear regression yields

$$
\begin{aligned}
Z_t = aZ_{t-1} + b(1 - Z_{t-1}) + u_t &= aZ_{t-1} + b - bZ_{t-1} + u_t \\
&= b + (a - b)Z_{t-1} + u_t \\
&= b + \lambda Z_{t-1} + u_t,
\end{aligned}
\tag{1.12}
$$

where the error terms, $\hat{u}_t$, are $i.i.d.$; $\lambda = a - b$ and denotes the speed of adjustment, and current state is a function of the state directly preceding it.

1.3.1 Uncorrelated States Specification

In the univariate framework specification, we took the threshold value c as given. However, it is important to consider that in general, a Markov chain $Z_t(c_0)$ does not remain Markov for state selection threshold $c \neq c_0$ (Ghysels et al. 2000). That is, specific characteristics of a Markov chain, such as serial correlation, are threshold dependent. In this sub-section we investigate the dependence of a dynamic chain on the selected threshold value.

There exists empirical evidence suggesting that even if returns exhibit some temporal dependence when analyzed as a quantitative process, the serial correlation may disappear in a qualitative series of sign change indicators (Ghysels et al. 2000). Thus, to effectively capture the characteristics of a quantitative series within the qualitative transformation we want to select a threshold value c such that the autocorrelation properties of our qualitative series are identical to those of the original quantitative series of returns.

By specifying a relationship between c and the first order autocorrelation as a function of c, we can determine the extent to which serial correlation of the underlying series is altered by imposing a qualitative representation. Following Ghysels et al. (2000), we define the new threshold estimator as

$$\hat{c}_{T,k} = min_c \rho^2_{T,k}(c), \tag{1.13}$$

where $\rho^2_{T,k}(c)$ is the first-order autocorrelation coefficient. Empirically, the estimate $\hat{c}$ is found by performing a grid search over the domain of c. Specifically, $\hat{c}$ approximates the value of c that produces the lowest absolute value of the first-order autocorrelation in the returns series.

1.3.2 Testing Weak-Form Market Efficiency

The increased availability of high-frequency data motivates current empirical research aimed at understanding return characteristics of securities and other financial vehicles. In particular, researchers seek to detect any evidence of informational inefficiency in the financial markets that could be profitably exploited for economic gain (Poshakwale 2002). In this sub-section, we apply the univariate approach described above to test the weak-form informational efficiency of financial markets as it relates to individual securities and an equally weighted portfolio of socks comprising the Dow Jones Industrial index.

It is of importance to reiterate that serial correlation is sensitive to transformations of a quantitative series. While results are too numerous to report here, we compare autocorrelograms of quantitative series of returns, for each of the individual securities and the aggregated portfolio, to their transformed, qualitative series autocorrelograms corresponding to three threshold specifications: mean, approximately zero; 10^{th}; and 95^{th} percentiles. For all securities, we observe a significant negative first order autocorrelation, consistent with the bid-ask effect. In the quantitative autocorrelogram, beyond the bid-ask bounce, higher order autocorrelations are not significant, a pattern matched closely by the zero threshold qualitative process. Computing ρ^2 we conclude that *zero* is a particular threshold where correlation is minimized. Further examination reveals that when *zero* is the threshold, value Z_t resembles white noise. Hence, we use *zero* as a threshold for our return series both here and in the joint causality analysis to follow.

The issue of intraday dependence in stocks is important because it has implication over the efficient market hypothesis; see Fama (1970), Campbell, Lo and MacKinley (1997). If the market is efficient in processing incoming information, current prices should not be predictable by their previous values. In addition to testing the efficiency of financial markets, empirical evaluation of intraday price dependence has important practical applications.

Specifically, if the dependence pattern of a financial series is economically significant, it might be used to construct profitable trading strategies in the stock market.

Traditionally analysts and investors assumed stock market efficiency because in a competitive market, prices reflect all available information. In a seminal paper, Fama (1970) classified market efficiency according to thee types: weak form, semi-strong form, and strong form. A market is considered to be efficient in the weak form if stock price changes cannot be predicted based on past returns alone. In statistical terms, this means that changes in stock returns are both independent and random. Here we evaluate the weak-form informational efficiency of financial markets within the parametric and the non-parametric frameworks presented.

We test the following martingale specification

$$\Delta P_t = \gamma_0 + \sum_{i=1}^{n} \gamma_i \Delta P_{t-i} + \varepsilon_t, \tag{1.14}$$

where ΔP_t is the continuously compounded return. Consistent with the model specification developed in the beginning of this section, we impose a restriction of $n = 1$ thereby estimating the following model

$$\Delta P_t = \gamma_0 + \gamma_1 \Delta P_{t-1} + \varepsilon_t. \tag{1.15}$$

Under the null hypothesis, if changes in daily stock prices are independent of the previously available information, parameter γ_i is expected to be equal to zero.

Tables 1.4 and 1.5 present the estimation results. We conclude that at high-frequencies data does not exhibit market efficiency. That is, for both parametric and non-parametric specifications the efficiency hypothesis is rejected for trading and calendar times, when a one minute grid is applied. This result extends to both individual securities and the aggregated, equally weighted portfolio.

First, consider the case of individual securities, Table 1.4. The entry in each cell of the table denotes the number of firms in the sample for which efficient market hypothesis was rejected. For simplicity purposes, we can establish a threshold, say 50%, where, in a sample of 30 firms, observed causality for at least 15 firms implies a rejection of the efficient-market hypothesis. Under the parametric approach, efficient-market hypothesis is rejected in trading time, as well as at one- and five-minute calendar time specifications. Under the non-parametric approach, the efficient-market hypothesis is rejected only in trading time and at a one-minute sampling frequency in calendar time. Generally speaking, results indicate that while market efficiency exhists, it is not complete. While this finding is implicit of opportunities where informational inefficiency can be sxploited for economic gains, these opporunities exist only at high-frequencies.

Results of the aggregated portfolio analysis are presented in Table 1.5, where *zero* signifies an inability to reject weak-form market efficiency hypothesis for a particular sub-sample and *one* signifies hypothesis rejection. We observe that under the parametric approach, we reject market efficiency in trading time and at the one-minute sampling frequency. Within the non-parametric framework, market-efficiency hypothesis is rejected only in trading time. We conclude that while it is feasible to develop profitable short-term trading strategies, gains are much more difficult to achieve when aggregating across securities.

Figure 1.1, Panels A-E, show changes in observed instances of weak-form market efficiency hypothesis rejection across time for the parametric and the non-parametric approaches. It is clear that as time-frequency decreases, we note a decline in the observed instances of the null hypothesis rejection for individual securities and the aggregated portfolio. Overall, the differences between the results of the two frameworks are quite clear. Specifically, within the linear parametric framework, efficient market hypothesis is over-rejected for all calendar-time specifications, further emphasizing the superiority of the non-parametric approach over the standard parametric one.

Figure 1.2, Panels A and B, show changes in observed instances of hypothesis rejection for different time specifications. Again, we observe that frequency with which weak-form market efficiency hypothesis is rejected decreases rapidly as trading intervals grow farther apart.

1.4 Non-Parametric Approach: Bivariate

In this section we extend the univariate approach introduced in Section 2 to a bivariate framework, where we examine a causal relationship between two financial series, returns and traded volumes. Consider again the qualitative state transformations for Markov chains Z_t and Y_t,

$$Z_t(c_p) = \begin{cases} 1 & \text{if } log(p_t) - log(p_{t-1}) > c_p \\ 0 & \text{otherwise} \end{cases}, \tag{1.16}$$

$$Y_t(c_v) = \begin{cases} 1 & \text{if } v_t \geq c_v \\ 0 & \text{otherwise} \end{cases}.$$

Here Z_t denotes the state of the return series at time t; Y_t denotes the state of the volume series at time t; c_p is the threshold value associated with the return series, set to equal *zero*; and c_v is the threshold value associated with the volume series, here set to equal the sample *mean*.

Let $[Z_t(a), Y_t(c)]'$ be the qualitative bivariate process of securities returns and traded volumes. Extending the univariate framework, we define bivariate transition probabilities as

$$P(Z_t = i, Y_t = j | Z_{t-1} = k, Y_{t-1} = l) = \Pi_{ij|kl}, \text{ for } i, j, k, l = 0, 1. \tag{1.17}$$

1.4.1 SUR Representation of the Markov Chain

The bivariate state specifications in Eq.(1.17), can be equivalently represented by the system of regressions

$$Z_tY_t = \beta_{11} + \alpha_{11|11}Z_{t-1}Y_{t-1} + \alpha_{11|10}Z_{t-1}(1 - Y_{t-1}) + \alpha_{11|01}(1 - Z_{t-1})Y_{t-1} + u_{11t}, \tag{1.18}$$

$$Z_t(1 - Y_t) = \beta_{10} + \alpha_{10|11}Z_{t-1}Y_{t-1} + \alpha_{10|10}Z_{t-1}(1 - Y_{t-1}) + \alpha_{10|01}(1 - Z_{t-1})Y_{t-1} + u_{10t},$$

$$(1 - Z_t)Y_t = \beta_{01} + \alpha_{01|11}Z_{t-1}Y_{t-1} + \alpha_{01|10}Z_{t-1}(1 - Y_{t-1}) + \alpha_{01|01}(1 - Z_{t-1})Y_{t-1} + u_{01t}.$$

These equations represent the Seemingly Unrelated Regression (SUR) system of equations introduced by Zellner (1962), where the elements of the transition matrix in Eq.(1.18) are directly related to the coefficients in the SUR model.

1.4.2 Non-Causality Hypothesis

Recall the definition of Granger causality introduced in Section 2. We say that Y does not Granger cause Z if the density of Z_t conditional on both Y_{t-1} and Z_{t-1} is equal to the density of Z_t when we condition on Z_{t-1} alone.

In this study, we focus on three types of causal relationships: (i) unidirectional causality from returns (Z) to volumes (Y), (ii) unidirectional causality from volumes (Y) to returns (Z), and (iii) instantaneous causality between returns (Z) and volumes (Y), which we test by deriving a set of constraints involving the parameters of the SUR model in Eq.(1.18).

Suppose we are interested in testing whether traded volumes Granger cause securities returns. That is, we are interested in all specifications for which $Z_t = 1$, that is, the first two regressions in Eq.(1.18). We transform the equations as follows

$$\begin{aligned} Z_t = \beta_{11} + \beta_{10} &+ (\alpha_{11|11} + \alpha_{10|11}) Z_{t-1} Y_{t-1} \\ &+ (\alpha_{11|10} + \alpha_{10|10}) Z_{t-1}(1 - Y_{t-1}) \\ &+ (\alpha_{11|01} + \alpha_{10|01})(1 - Z_{t-1}) Y_{t-1} \\ &+ u_{11t} + u_{10t}. \end{aligned} \tag{1.19}$$

By definition, Y does not Granger cause Z when information contained in Y_{t-1} does not affect the quality of our prediction of Z_t. Then in this particular framework, we define the null hypothesis of non-causality as

$$H^0_{Z \nrightarrow Y} : \{\alpha_{11|01} + \alpha_{10|01} = 0,\ \alpha_{11|11} + \alpha_{10|11} - \alpha_{11|10} - \alpha_{10|10} = 0\}. \tag{1.20}$$

Similarly, the null hypothesis of non-causality from Z to Y is expressed as follows

$$H^0_{Z\nrightarrow Y}:\{\alpha_{11|10}+\alpha_{01|10}=0,\ \alpha_{11|11}+\alpha_{01|11}-\alpha_{11|01}-\alpha_{01|01}=0\}. \tag{1.21}$$

The null hypothesis of instantaneous non-causality between Z and Y is satisfied when the deterministic part of Z_tY_t is the product of the deterministic parts of Z_t and Y_t. This can be represented as a system of four constraints which define the null hypothesis $H^0_{Y\nleftrightarrow Z}$:

$$\begin{aligned}\beta_{11}-&\alpha_{11|11}-\alpha_{11|10}-\alpha_{11|01}=\\&\{\beta_{11}+\beta_{10}-(\alpha_{11|11}+\alpha_{10|11})-(\alpha_{11|10}+\alpha_{10|10})-(\alpha_{11|01}+\alpha_{10|01})\}\\&\{\beta_{11}+\beta_{01}-(\alpha_{11|11}+\alpha_{01|11})-(\alpha_{11|10}+\alpha_{01|10})-(\alpha_{11|01}+\alpha_{01|10})\},\end{aligned} \tag{1.22}$$

$$\begin{aligned}\alpha_{11|11}&=(\alpha_{11|11}+\alpha_{10|11})(\alpha_{11|11}+\alpha_{01|11}),\\ \alpha_{11|10}&=(\alpha_{11|10}+\alpha_{10|10})(\alpha_{11|10}+\alpha_{01|10}),\\ \alpha_{11|01}&=(\alpha_{11|01}+\alpha_{10|01})(\alpha_{11|01}+\alpha_{01|01}).\end{aligned}$$

1.4.3 Re-parameterization of Non-Causality Hypothesis

The application of the empirical approach presented above is rather complicated. Here we provide a simplified econometric framework for the evaluation of the three non-causality hypotheses specified in the previous sub-section.

1.4.3.1 Unidirectional Causality from Returns to Volumes

In order to simplify the regression in Eq.(1.19), we specify the regression equation that relates traded volumes at time t with observed traded volumes and returns at time $t-1$:

$$Y_t=\beta_{1.}+\alpha_{1.|1.}Y_{t-1}+\alpha_{1.|.1}Z_{t-1}+\alpha_{1.|11}Y_{t-1}Z_{t-1}+u_{1.,t}. \tag{1.23}$$

The hypothesis of non-causality from Z to Y can now be states as

$$H^0_{Z \nrightarrow Y} : \{\alpha_{1.|.1} = \alpha_{1.|11} = 0\}. \tag{1.24}$$

If the null hypothesis is rejected, we can further determine whether the rejection is due to the presence of uniquely linear dependencies. That is, we can test if $\alpha_{1.|11} = 0$ and $\alpha_{1.|.1} \neq 0$.

1.4.3.2 Unidirectional Causality from Volumes to Returns

Similarly, we specify a regression equation that relates returns at time t with observed returns and traded volumes at time $t-1$

$$Z_t = \beta_{.1} + \alpha_{.1|1.} Y_{t-1} + \alpha_{.1|.1} Z_{t-1} + \alpha_{.1|11} Y_{t-1} Z_{t-1} + u_{.1,t}. \tag{1.25}$$

The hypothesis of non-causality from Y to Z corresponds to the following constraints

$$H^0_{Y \nrightarrow Z} : \{\alpha_{.1|.1} = \alpha_{.1|11} = 0\}. \tag{1.26}$$

Similar to unidirectional causality form Z to Y, in case of hypothesis rejection, we can further determine whether the rejection is due to the presence of uniquely linear dependencies. That is, we can test if $\alpha_{.1|11} = 0$ and $\alpha_{.1|.1} \neq 0$.

1.4.3.3 Instantaneous Causality between Volumes and Returns

Unlike unidirectional non-causality, instantaneous non-causality has to do with the absence of influence of current value of Z_t in the conditional distribution of Y_t, given Z_t, Y_{t-1}, Z_{t-1}. The regression corresponding to the conditional distribution is thus specified as

$$\begin{aligned} Y_t = \gamma_1 + \delta_{1..} Z_t + \delta_{.1.} Y_{t-1} + \delta_{..1} Z_{t-1} + \delta_{11.} Z_t Y_{t-1} + \delta_{1.1} Z_t Z_{t-1} \\ + \delta_{.11} Y_{t-1} Z_{t-1} + \delta_{111} Z_t Y_{t-1} Z_{t-1} + v_{1,t}. \end{aligned} \tag{1.27}$$

The null hypothesis of non-causality becomes

$$H^0_{Y \nleftrightarrow Z} : \{\delta_{1..} = \delta_{11.} = \delta_{1.1} = \delta_{111} = 0\}. \tag{1.28}$$

A rejection of the null hypothesis in this case may be either due to lack of a linear relationship between Y_t and Z_t or higher order interactions between the model variables.

1.5 Empirical Results

We examine returns and volumes of stocks included in the Dow Jones Industrial index and traded on NYSE (NASDAQ for Intel and Microsoft) during December 2005 - June 2007 time period. Consistent with empirical literature, opening trades were deleted prior to estimation.

We investigate high-frequency data using parametric and non-parametric frameworks and test linear and nonlinear causality in transaction and calendar times for individual securities and an aggregated portfolio. A unitary increment in transaction time is set by a trade arrival, disregarding the length of the waiting time between transactions. A unitary increment in calendar time corresponds to an integer multiple of one minute and is arbitrarily selected to correspond to 1-minute, 5-minute, 15-minute and 1-hour grids.

Results demonstrate that both unidirectional and instantaneous causality is time and sample dependent. The rest of the section discusses observed stylized facts about the causal relationship between traded volumes and securities returns.

1.5.1 Preliminary Results

Tables 1.6a-1.6c, Panels A and B, report observed instances of unidirectional and instantaneous causality for individual securities and across time. Each cell entry represents the aggregate of securities for which a causal relationship was recorded. Tables 1.7a-1.7c, Panels A and B, report observed instances of causality for the equally-weighted, aggregate portfolio of the aforementioned securities. As in the efficient market hypothesis, *one* denotes observed causality while *zero* signifies the lack of a statistically causal relationship between the two series.

Results suggest that on average, greater frequencies of causality are observed under the non-parametric approach as compared to the parametric one. Furthermore, instances of observed causality decline as the calendar grid becomes coarser. Finally, in trading time, causality is observed most frequently for the instantaneous causality-type. This result changes for calendar-time causality, where unidirectional causality from traded volumes to returns is observed more frequently than other causality types.

To summarize, results of the parametric approach demonstrate that on average, observed instances of causality decline with decreased frequency of trades. That is, the non-causality hypothesis holds more frequently at coarser time intervals. When it comes to unidirectional causality from volumes to returns, causality is relatively strong in both transaction and calendar times, specifically at the one-minute frequency. Averaged across the sample time period, causality is established for approximately 15 out of 30 stocks in trading time and 16 securities in calendar time, Table 1.6a. Unidirectional causality from returns to volumes, and instantaneous causality, are more frequently observed in trading time than for any calendar time specification. On average, unidirectional causality is observed for 10 firms and instantaneous causality is observed for 25 firms in trading time, while observed instances of causality drop to 3 and 8 firms when a one-minute grid is utilized, Tables 1.6b and 1.6c.

Under the non-parametric approach, observed instances of causality are relatively similar in transaction time and a one-minute grid in calendar time for instantaneous (on average 30 and 23 firms show causality, Table 1.6c) and unidirectional causality from volume to returns (27 and 28 firms, Table 1.6a). When it comes to unidirectional causality from returns to volumes, on average, we reject the non-causality hypothesis is rejected for 23 firms in trading time and 10 firms in calendar time, Table 1.6b.

Figures 1.3, 1.4 and 1.5, Panels A - E, further emphasize the differences between the parametric and the non-parametric approaches employed. Figure 1.3 shows instances of observed causality from traded volumes to returns; Figure 1.4 shows instances of observed causality from returns to traded volumes; and Figure 1.5 demonstrates instances of observed instantaneous causality between the two series. Two conclusions emerge. First, it is clear that at high-frequency, causality is observed more frequency under the non-parametric approach than under the parametric one. The differences disappear as the time grid becomes coarser. Second, under both approaches, instances of observed causality decline rapidly in low-frequency data. This result is consistent with informational efficiency of financial markets, as it effectively precludes arbitrage. Specifically, we conclude that information enters into, and is absorbed by the market almost instantaneously, signaling efficiency.

Figures 1.6 and 1.7, Panels A - E, illustrate the differences in frequencies of observed causality across the types of causal relationships: univariate from volumes to returns, $Y \rightarrow Z$; univariate from returns to volumes, $Z \rightarrow Y$; and instantaneous, $Z \leftrightarrow Y$. Figure 1.6 illustrates the results of he parametric approach, while Figure 1.7 illustrated the results of the non-parametric one. We note that instantaneous causality occurs most frequently in trading time. Within the calendar time specification, causality from volumes to returns is the most common. This is evidence supporting the theories of sequential information. The market consists of informed and uninformed investors. The informed investors act on information available to them by choosing specific trading strategies, while the uninformed investors judge the quality of information available to them, and select their trading strategies based on their evaluation of observed behavior. Thus, volume is said to Granger cause returns since a movement in trading volume leads to increased/decreased demand which results in higher/lower prices and hence, higher/lower returns.

Results suggest that financial market are efficient in the sense that unidirectional and instantaneous causality rapidly declines in time aggregation under both, the parametric and the non-parametric frameworks approaches, since causality is observed consistently only at very fine time intervals, frequency of 10^{th} of a second and higher, it is difficult to successfully exploit it for economic gain.

1.5.2 Extending Model Specifications

Recall the consistent over-rejection of the weak-form market efficiency hypothesis in Section 3. Results demonstrated the inferiority of the linear parametric approach with respect to the non-parametric approach. Results presented in the previous sub-section indicate that within the bivariate framework, it is the non-parametric approach that rejects non-causality more frequently. One reason for this may be the ability of the non-parametric framework to account for nonlinear relationships between the financial series.

In their 1994 paper, Hiemstra and Jones assert an important problem in causality testing is the limited power which the linear parametric approach has in detecting certain kinds of nonlinear causal relationships. Empirical financial literature documents extensive evidence of significant nonlinear dependence in stock returns (see Hinich and Patterson 1985, Scheinkman and LeBaron 1989, Hsieh 1991). Furthermore, Hiemstra and Jones (1992) document significant nonlinearities in aggregate trading volume. Extending previous empirical findings, we conclude that the univariate nonlinear dependence in the series of volumes and returns is likely to result in a nonlinear causal relationship between stock returns and traded volume.

To test this theory, we augment the simple bivariate parametric model introduced in Section 2 to include nonlinear interaction terms of the two variables of interest. Granger causality between the two financial series is tested under the nonlinear parametric approach, and results are compared to the previous findings. Figures 1.8a-1.8c, Panels A and B, illustrate the differences across the types of model specifications. We find that the results generated under the nonlinear parametric framework are similar to those of the non-parametric approach, providing further evidence supporting the importance of nonlinear relationships in financial analysis.

1.6 Conclusions and Extensions

This paper examines the dynamics of the quantitative and the qualitative series of returns and volumes of securities included in the Dow Jones Industrial index and traded on NYSE (NASDAQ for Intel and Microsoft) during December 2005 - June 2007 time period. We test informational efficiency of financial markets in an effort to assess the quality of contribution that knowledge of past volume movements has, in terms of improving short-run forecasts of current and future movements in securities prices, and vice versa. We analyze a sample of 30 individual securities as well as an equally weighted portfolio comprised of the aforementioned stocks. Aggregated and disaggregated approaches in testing Granger causality between series of returns and volumes are utilized as investigation of individual securities, compared to that of a portfolio, may reveal characteristics which tend to be hidden when aggregate indexes are analyzed. Weak-form market efficiency is tested in the high-frequency data context, and the unidirectional and instantaneous non-causality hypothesis for individual securities and a market portfolio are tested for trading and calendar time specifications.

Empirical results indicate that causality directions vary in time and depend on the sampling scheme, such as the real or calendar time scales. Results show that observed causality increases as calendar grid becomes finer, suggesting that while informational efficiency of financial markets holds, opportunities for economic gains may exist at high-frequencies. In trading time, observed instances of causality are greatest for instantaneous causality. This result changes in calendar causality, where we observe unidirectional causality from volumes to returns more frequently than other causality types.

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Table 1.1: Returns Series Sample Statistics

Panel A: Individual Securities

		Mean	*Std. Dev.*	*Interval*	$Z_t = 1$	$Z_t = 0$
3M Co.	MMM	-2.61E-08	0.000155	-0.0065374, 0.0064640	1,608,171	437,748
Alcoa Inc.	AA	-2.30E-08	0.000241	-0.0076764, 0.0087540	2,204,246	479,245
Altria Group	MO	-4.73E-08	0.000133	-0.0107203, 0.0183372	2,415,629	591,050
American Express Co.	AXP	5.01E-08	0.000156	-0.0086107, 0.0083356	1,840,779	407,677
American International Group Inc.	AIG	-9.20E-08	0.000138	-0.0072832, 0.0076871	2,417,530	558,300
AT&T Inc.	T	7.09E-08	0.000182	-0.0147500, 0.0147500	2,942,219	495,175
Boeing Co.	BA	-5.63E-08	0.000166	-0.0065885, 0.0085940	1,880,382	570,548
Caterpillar Inc.	CAT	-3.13E-08	0.000171	-0.0124054, 0.0063291	2,033,451	544,875
Citigroup Inc.	C	-3.97E-08	0.000139	-0.0067542, 0.0106230	3,064,248	609,122
Coca-Cola Co.	KO	6.00E-08	0.000160	-0.0060704, 0.0080760	1,972,350	431,080
E.I. DuPont de Nemours & Co.	DD	9.48E-08	0.000184	-0.0089793, 0.0126688	1,698,410	386,043
Exxon Mobil Corp.	XOM	3.32E-08	0.000118	-0.0075145, 0.0089316	5,014,672	1,131,411
General Electric Co.	GE	2.01E-08	0.000164	-0.0075023, 0.0077622	3,031,561	529,956
General Motors Corp.	GM	-6.65E-08	0.000285	-0.0225348, 0.0198462	2,100,670	453,715
Hewlett-Packard Co.	HPQ	3.18E-07	0.000183	-0.0162604, 0.0085325	2,533,995	481,025
Home Depot Inc.	HD	5.49E-08	0.000186	-0.0059636, 0.0070138	2,420,558	512,004
Honeywell International Inc.	HON	7.78E-08	0.000199	-0.0087104, 0.0087104	1,699,998	374,424
Intel Corp.	INTC	-1.45E-08	0.000167	0.0272143, 0.0272143	18,441,805	1,059,540
International Business Machines	IBM	2.14E-07	0.000134	-0.0063930, 0.0063930	2,437,753	666,873
Johnson & Johnson	JNJ	-4.49E-08	0.000131	-0.0071063, 0.0061450	2,389,470	567,534
JPMorgan Chase & Co.	JPM	1.12E-07	0.000150	-0.0077519, 0.0087252	2,647,061	515,605
McDonald's Corp.	MCD	1.71E-07	0.000175	-0.0076046, 0.0062947	1,841,167	365,850
Merck & Co. Inc.	MRK	1.55E-07	0.000181	-0.0156779, 0.0137932	2,334,773	497,727
Microsoft Corp.	MSFT	1.68E-08	0.000127	-0.0350122, 0.0353820	17,637,422	988,758
Pfizer Inc.	PFE	4.55E-08	0.000223	-0.0125887, 0.0083859	2,876,443	499,489
Procter & Gamble Co.	PG	1.42E-07	0.000139	-0.0125527, 0.0084281	2,543,087	541,291
The Walt Disney Company	DIS	2.08E-07	0.000212	-0.0093312, 0.0083683	1,830,986	352,296
United Technologies Corp.	UTX	-3.41E-08	0.000183	-0.0090017, 0.0091324	1,702,396	446,324
Verizon Communications Inc.	VZ	-1.30E-08	0.000188	-0.0103660, 0.0106819	2,188,691	424,178
Wal-Mart Stores Inc.	WMT	-1.89E-09	0.000153	-0.0048406, 0.0058365	2,691,090	587,689

Panel B: Portfolio

	Mean	*Std. Dev.*	*Interval*	$Z_t = 1$	$Z_t = 0$
Equally Weighted Portfolio	3.68E-11	0.000009	-0.0006704, 0.0009966	39,106,256	5,860,781

Table 1.2: Traded Volumes Series Sample Statistics

Panel A: Individual Securities

		Mean	*Std. Dev.*	*Interval*	$Y_t = 1$	$Y_t = 0$
3M Co.	MMM	5.448	0.904	4.605, 13.122	948,043	1,098,272
Alcoa Inc.	AA	5.698	1.068	4.605, 13.528	1,205,509	1,478,378
Altria Group	MO	5.682	1.054	4.605, 14.208	1,320,692	1,686,383
American Express Co.	AXP	5.568	1.007	4.605, 13.415	915,672	1,333,180
American International Group Inc.	AIG	5.670	1.038	4.605, 14.509	1,325,226	1,651,000
AT&T Inc.	T	6.014	1.237	4.605, 14.403	1,586,731	1,851,059
Boeing Co.	BA	5.396	0.889	4.605, 12.264	1,113,540	1,337,786
Caterpillar Inc.	CAT	5.547	0.973	4.605, 13.484	1,114,202	1,464,520
Citigroup Inc.	C	5.926	1.183	4.605, 14.761	1,778,502	1,895,264
Coca-Cola Co.	KO	5.743	1.091	4.605, 14.663	1,070,149	1,333,677
E.I. DuPont de Nemours & Co.	DD	5.608	0.988	4.605, 13.305	892,826	1,192,023
Exxon Mobil Corp.	XOM	5.993	1.079	4.605, 14.914	2,918,562	3,227,917
General Electric Co.	GE	6.182	1.334	4.605, 15.262	1,718,644	1,843,269
General Motors Corp.	GM	5.951	1.211	4.605, 17.148	1,189,136	1,365,645
Hewlett-Packard Co.	HPQ	5.937	1.173	4.605, 15.320	1,440,669	1,574,747
Home Depot Inc.	HD	5.871	1.168	4.605, 16.118	1,335,058	1,597,900
Honeywell International Inc.	HON	5.558	0.971	4.605, 14.144	912,803	1,162,015
Intel Corp.	INTC	5.974	1.000	4.605, 16.151	9,817,431	9,684,310
International Business Machines	IBM	5.536	0.969	4.605, 13.816	1,331,934	1,773,088
Johnson & Johnson	JNJ	5.714	1.094	4.605, 14.077	1,308,435	1,648,965
JPMorgan Chase & Co.	JPM	5.863	1.128	4.605, 14.400	1,517,175	1,645,887
McDonald's Corp.	MCD	5.707	1.080	4.605, 14.649	952,984	1,254,429
Merck & Co. Inc.	MRK	5.811	1.117	4.605, 14.093	1,270,388	1,562,508
Microsoft Corp.	MSFT	5.922	0.996	4.605, 16.628	17,637,422	988,758
Pfizer Inc.	PFE	6.288	1.378	4.605, 14.797	1,584,886	1,791,442
Procter & Gamble Co.	PG	5.680	1.074	4.605, 14.422	1,332,266	1,752,508
The Walt Disney Company	DIS	5.879	1.211	4.605, 14.039	987,459	1,196,219
United Technologies Corp.	UTX	5.498	0.931	4.605, 14.250	957,154	1,191,962
Verizon Communications Inc.	VZ	5.943	1.177	4.605, 13.945	1,248,628	1,364,637
Wal-Mart Stores Inc.	WMT	5.898	1.185	4.605, 14.343	1,496,812	1,782,363

Panel B: Portfolio

	Mean	*Std. Dev.*	*Interval*	$Y_t = 1$	$Y_t = 0$
Equally Weighted Portfolio	6.603	1.346	4.605, 17.148	21,498,645	23,468,788

Table 1.3: ARCH effects in Returns Series

Panel A: Individual Securities

		χ^2 Statistic				
		Trading Time	*1m Grid*	*5m Grid*	*15m Grid*	*1h Grid*
3M Co.	MMM	56,289***	6,934***	1,432***	443***	31.183***
Alcoa Inc.	AA	84,070***	8,128***	1,735***	255***	54.705***
Altria Group	MO	223,138***	14,496***	133***	77***	43.192***
American Express Co.	AXP	60,957***	8,270***	1,310***	529***	6.806***
American International Group Inc.	AIG	135,124***	6,516***	3,229***	309***	15.698***
AT&T Inc.	T	374,193***	9,195***	1,940***	156***	81.575***
Boeing Co.	BA	47,174***	7,840***	1,790***	322***	36.898***
Caterpillar Inc.	CAT	31,158***	6,126***	1,589***	334***	60.774***
Citigroup Inc.	C	170,937***	6,738***	2,049***	264***	26.230***
Coca-Cola Co.	KO	161,048***	19,683***	1,155***	165***	9.668***
E.I. DuPont de Nemours & Co.	DD	63,325***	10,222***	1,056***	534***	20.370***
Exxon Mobil Corp.	XOM	40,205***	5,387***	629***	122***	16.375***
General Electric Co.	GE	199,288***	5,512***	1,015***	127***	25.090***
General Motors Corp.	GM	28,249***	9,363***	410***	152***	4.881**
Hewlett-Packard Co.	HPQ	38,335***	11,187***	1,137***	362***	23.645***
Home Depot Inc.	HD	81,280***	7,483***	1,367***	211***	32.515***
Honeywell International Inc.	HON	106,075***	8,101***	1,096***	763***	43.778***
Intel Corp.	INTC	184,370***	10,586***	804***	334***	9.671***
International Business Machines	IBM	103,275***	8,488***	953***	161***	8.018***
Johnson & Johnson	JNJ	112,057***	9,674***	1,297***	325***	64.112***
JPMorgan Chase & Co.	JPM	222,455***	2,534***	1,185***	328***	11.262***
McDonald's Corp.	MCD	47,950***	13,903***	943***	122***	9.799***
Merck & Co. Inc.	MRK	64,829***	12,324***	1,145***	482***	8.610***
Microsoft Corp.	MSFT	225,420***	10,434***	606***	245***	37.285***
Pfizer Inc.	PFE	153,019***	5,795***	2,799***	492***	16.118***
Procter & Gamble Co.	PG	79,086***	9,669***	1,640***	813***	5.621**
The Walt Disney Company	DIS	103,908***	7,784***	3,219***	150***	3.226*
United Technologies Corp.	UTX	34,035***	7,101***	959***	279***	6.455**
Verizon Communications Inc.	VZ	86,606***	12,459***	3,059***	722***	57.610***
Wal-Mart Stores Inc.	WMT	94,936***	8,842***	724***	103***	23.565***

Panel B: Portfolio

	χ^2 Statistic				
	Trading Time	*1m Grid*	*5m Grid*	*15m Grid*	*1h Grid*
Equally Weighted Portfolio	42,485***	6,610***	1,063***	179***	17.278***

* significant at 10%
** significant at 5%
*** significant at 1%

Table 1.4: Observed Returns Series Dynamics, Individual Securities

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \rightarrow Ret_t$	*Trading Time*	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30
	1m Grid	22/30	17/30	21/30	25/30	22/30	23/30	19/30	22/30	20/30	18/30	17/30	13/30	19/30
	5m Grid	18/30	13/30	16/30	13/30	17/30	18/30	15/30	11/30	13/30	8/30	13/30	19/30	15/30
	15m Grid	6/30	1/30	8/30	6/30	4/30	9/30	0/30	11/30	7/30	3/30	13/30	5/30	12/30
	1h Grid	6/30	6/30	7/30	2/30	4/30	2/30	3/30	7/30	2/30	5/30	9/30	1/30	6/30

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	30/30	30/30	30/30	30/30	30/30	30/30	30/30
1m Grid	23/30	21/30	23/30	21/30	19/30	23/30	20/30
5m Grid	21/30	17/30	23/30	12/30	14/30	8/30	15/30
15m Grid	9/30	10/30	11/30	8/30	8/30	3/30	7/30
1h Grid	3/30	6/30	2/30	3/30	7/30	6/30	5/30

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \rightarrow Ret_t$	*Trading Time*	29/30	29/30	30/30	30/30	30/30	28/30	29/30	29/30	30/30	30/30	30/30	29/30	29/30
	1m Grid	18/30	15/30	17/30	18/30	16/30	19/30	15/30	14/30	16/30	16/30	17/30	13/30	14/30
	5m Grid	10/30	10/30	7/30	14/30	16/30	9/30	13/30	7/30	8/30	8/30	9/30	9/30	9/30
	15m Grid	1/30	1/30	5/30	4/30	2/30	3/30	1/30	2/30	3/30	4/30	2/30	4/30	6/30
	1h Grid	1/30	2/30	1/30	3/30	1/30	2/30	1/30	2/30	2/30	3/30	3/30	0/30	0/30

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	29/30	30/30	30/30	30/30	30/30	30/30	30/30
1m Grid	14/30	14/30	16/30	19/30	19/30	17/30	16/30
5m Grid	9/30	9/30	9/30	12/30	9/30	4/30	9/30
15m Grid	6/30	3/30	1/30	9/30	4/30	3/30	3/30
1h Grid	0/30	1/30	3/30	2/30	1/30	2/30	2/30

Each cell entry represents the aggregate of securities for which a causal relationship was recorded.

Table 1.5: Observed Returns Series Dynamics, Equally Weighted Portfolio

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \to Ret_t$	*Trading Time*	1	1	1	1	1	1	0	1	1	1	1	1	1
	1m Grid	1	0	0	0	1	1	1	1	1	1	1	1	1
	5m Grid	0	0	0	0	0	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	1	0	0	1	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	1	1

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	1	1	1	1	1	1	1
1m Grid	0	1	0	0	1	1	1
5m Grid	0	0	1	0	0	0	0
15m Grid	0	1	0	0	0	0	0
1h Grid	0	0	0	0	0	1	0

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \to Ret_t$	*Trading Time*	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	1	0	0	0	1	0	1	1	1	1	1	1	0
	5m Grid	1	0	0	0	1	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0	1	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	1	1	1	1	1	1	1
1m Grid	0	0	0	0	0	0	0
5m Grid	0	1	1	0	1	0	0
15m Grid	0	1	0	0	0	0	0
1h Grid	0	0	0	0	1	1	0

One denotes observed causality while *zero* signifies the lack of a statistically causal relationship between the two series.

Table 1.6a: **Observed Instances of Causality**, Individual Securities, Volumes to Returns

Panel A: Parametric Approach

		12'05	01'06	02'06	03'06	04'06	05'06	06'06	07'06	08'06	09'06	10'06	11'06	12'06
$Vol_{t-1} \rightarrow Ret_t$	*Trading Time*	18/30	16/30	16/30	15/30	13/30	14/30	11/30	11/30	15/30	16/30	15/30	14/30	15/30
	1m Grid	20/30	13/30	17/30	15/30	13/30	13/30	17/30	17/30	18/30	19/30	18/30	16/30	19/30
	5m Grid	10/30	12/30	7/30	6/30	10/30	5/30	5/30	11/30	13/30	8/30	14/30	12/30	5/30
	15m Grid	8/30	9/30	3/30	3/30	7/30	5/30	3/30	5/30	7/30	5/30	7/30	5/30	4/30
	1h Grid	3/30	5/30	3/30	0/30	4/30	3/30	2/30	2/30	7/30	3/30	4/30	8/30	3/30

	01'07	02'07	03'07	04'07	05'07	06'07	Average
Trading Time	12/30	8/30	15/30	19/30	22/30	14/30	15/30
1m Grid	15/30	9/30	15/30	21/30	19/30	15/30	16/30
5m Grid	5/30	9/30	6/30	7/30	11/30	3/30	8/30
15m Grid	2/30	6/30	2/30	5/30	6/30	3/30	5/30
1h Grid	3/30	10/30	4/30	3/30	7/30	5/30	4/30

Panel B: Non-Parametric Approach

		12'05	01'06	02'06	03'06	04'06	05'06	06'06	07'06	08'06	09'06	10'06	11'06	12'06
$Vol_{t-1} \rightarrow Ret_t$	*Trading Time*	24/30	27/30	24/30	27/30	22/30	25/30	25/30	24/30	25/30	26/30	26/30	28/30	29/30
	1m Grid	27/30	26/30	26/30	28/30	28/30	28/30	27/30	24/30	26/30	29/30	26/30	28/30	30/30
	5m Grid	14/30	4/30	3/30	15/30	13/30	11/30	15/30	13/30	15/30	8/30	14/30	16/30	16/30
	15m Grid	7/30	3/30	4/30	6/30	7/30	5/30	4/30	7/30	7/30	6/30	2/30	6/30	3/30
	1h Grid	2/30	3/30	4/30	4/30	1/30	4/30	2/30	1/30	4/30	4/30	2/30	0/30	2/30

	01'07	02'07	03'07	04'07	05'07	06'07	Average
Trading Time	30/30	29/30	28/30	29/30	30/30	30/30	27/30
1m Grid	29/30	30/30	27/30	30/30	28/30	28/30	28/30
5m Grid	15/30	18/30	13/30	13/30	17/30	19/30	13/30
15m Grid	5/30	9/30	7/30	11/30	7/30	11/30	6/30
1h Grid	0/30	0/30	5/30	2/30	1/30	0/30	2/30

Each cell entry represents the aggregate of securities for which a causal relationship was recorded.

Table 1.6b: Observed Instances of Causality, Individual Securities, Returns to Volumes

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	17/30	16/30	13/30	15/30	12/30	11/30	12/30	12/30	12/30	11/30	8/30	8/30	2/30
	1m Grid	2/30	4/30	2/30	3/30	5/30	0/30	2/30	3/30	4/30	3/30	3/30	2/30	2/30
$Ret_{t-1} \rightarrow Vol_t$	*5m Grid*	2/30	1/30	1/30	2/30	2/30	2/30	4/30	2/30	3/30	4/30	3/30	3/30	3/30
	15m Grid	2/30	4/30	2/30	0/30	0/30	1/30	0/30	5/30	2/30	4/30	0/30	2/30	1/30
	1h Grid	0/30	3/30	2/30	3/30	1/30	1/30	1/30	2/30	1/30	2/30	5/30	0/30	1/30

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	1/30	6/30	8/30	8/30	7/30	13/30	10/30
	1m Grid	2/30	3/30	0/30	2/30	5/30	3/30	3/30
	5m Grid	1/30	3/30	3/30	1/30	2/30	0/30	2/30
	15m Grid	0/30	1/30	2/30	2/30	3/30	1/30	2/30
	1h Grid	2/30	1/30	1/30	2/30	3/30	2/30	2/30

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	18/30	21/30	15/30	25/30	22/30	25/30	25/30	21/30	22/30	23/30	24/30	18/30	22/30
	1m Grid	8/30	5/30	5/30	7/30	4/30	11/30	6/30	9/30	10/30	13/30	12/30	9/30	18/30
$Ret_{t-1} \rightarrow Vol_t$	*5m Grid*	3/30	1/30	4/30	3/30	0/30	3/30	1/30	0/30	1/30	0/30	0/30	2/30	3/30
	15m Grid	3/30	1/30	2/30	2/30	1/30	2/30	4/30	1/30	2/30	4/30	3/30	5/30	3/30
	1h Grid	2/30	6/30	1/30	3/30	3/30	5/30	2/30	5/30	3/30	1/30	2/30	1/30	2/30

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	26/30	22/30	29/30	28/30	27/30	23/30	23/30
	1m Grid	10/30	17/30	10/30	15/30	13/30	12/30	10/30
	5m Grid	1/30	5/30	3/30	3/30	1/30	4/30	2/30
	15m Grid	2/30	2/30	2/30	4/30	1/30	0/30	2/30
	1h Grid	3/30	4/30	0/30	2/30	1/30	1/30	2/30

Each cell entry represents the aggregate of securities for which a causal relationship was recorded.

Table 1.6c: Observed Instances of Causality, Individual Securities, Instantaneous

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \leftrightarrow Vol_t$	*Trading Time*	24/30	23/30	26/30	25/30	25/30	24/30	23/30	27/30	23/30	26/30	22/30	23/30	27/30
	1m Grid	8/30	8/30	7/30	3/30	4/30	8/30	6/30	10/30	11/30	7/30	7/30	5/30	6/30
	5m Grid	3/30	3/30	6/30	6/30	2/30	4/30	5/30	4/30	4/30	5/30	5/30	3/30	6/30
	15m Grid	4/30	3/30	3/30	1/30	1/30	1/30	5/30	6/30	1/30	1/30	1/30	3/30	4/30
	1h Grid	1/30	4/30	1/30	2/30	1/30	1/30	3/30	2/30	2/30	2/30	5/30	1/30	2/30

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	23/30	24/30	27/30	24/30	25/30	27/30	25/30
	1m Grid	9/30	13/30	6/30	4/30	14/30	10/30	8/30
	5m Grid	3/30	0/30	6/30	4/30	5/30	3/30	4/30
	15m Grid	3/30	2/30	2/30	4/30	4/30	3/30	3/30
	1h Grid	3/30	5/30	2/30	4/30	4/30	1/30	2/30

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
$Ret_{t-1} \leftrightarrow Vol_t$	*Trading Time*	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30	30/30
	1m Grid	26/30	21/30	19/30	21/30	21/30	26/30	23/30	22/30	25/30	23/30	21/30	25/30	24/30
	5m Grid	5/30	4/30	6/30	6/30	4/30	5/30	6/30	7/30	8/30	2/30	5/30	10/30	7/30
	15m Grid	7/30	3/30	0/30	2/30	3/30	3/30	0/30	1/30	4/30	2/30	3/30	1/30	3/30
	1h Grid	5/30	2/30	2/30	6/30	3/30	2/30	1/30	1/30	0/30	3/30	1/30	1/30	4/30

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	30/30	30/30	30/30	30/30	30/30	30/30	30/30
	1m Grid	23/30	22/30	21/30	27/30	29/30	26/30	23/30
	5m Grid	5/30	4/30	3/30	7/30	8/30	8/30	6/30
	15m Grid	4/30	4/30	4/30	2/30	3/30	0/30	3/30
	1h Grid	2/30	4/30	4/30	1/30	1/30	2/30	2/30

Each cell entry represents the aggregate of securities for which a causal relationship was recorded.

Table 1.7a: Observed Instances of Causality, Equally Weighted Portfolio, Volumes to Returns

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	0	0	0	1	0	0	0	0	1	1	1	0	0
$Vol_{t-1} \rightarrow Ret_t$	*5m Grid*	0	0	0	0	0	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0	0	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	1	1	1	1	1	1	1
1m Grid	1	1	1	0	0	1	0
5m Grid	0	1	0	1	0	1	0
15m Grid	0	1	0	1	0	0	0
1h Grid	0	1	0	0	0	0	0

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	1	0	1	1	1	1	1	1	1	0	1	1	1
$Vol_{t-1} \rightarrow Ret_t$	*5m Grid*	1	0	1	1	0	0	1	0	1	0	0	0	0
	15m Grid	0	0	0	0	0	0	1	1	0	0	0	1	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

	01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
Trading Time	1	1	1	1	1	1	1
1m Grid	1	1	1	1	1	1	1
5m Grid	0	1	0	1	1	1	0
15m Grid	1	1	0	0	0	0	0
1h Grid	0	0	0	0	0	1	0

One denotes observed causality while *zero* signifies the lack of a statistically causal relationship between the two series.

Table 1.7b: Observed Instances of Causality, Equally Weighted Portfolio, Returns to Volumes

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	0	1	0	0	1	1	1	0	1	1	0
	1m Grid	0	0	0	0	0	0	0	0	0	0	0	1	0
$Ret_{t-1} \rightarrow Vol_t$	*5m Grid*	0	0	0	0	0	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0	1	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	1	1	0	1	0	0	1
	1m Grid	0	0	0	0	0	0	0
	5m Grid	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0

Panel B: Non-Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	0	0	0	0	0	0	0	0	0	0	0	1	0
$Ret_{t-1} \rightarrow Vol_t$	*5m Grid*	0	0	0	0	1	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0	0	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	1	1	1	1	1	1	1
	1m Grid	1	0	0	1	0	0	0
	5m Grid	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0

One denotes observed causality while *zero* signifies the lack of a statistically causal relationship between the two series.

Table 1.7c: Observed Instances of Causality, Equally Weighted Portfolio, Instantaneous

Panel A: Parametric Approach

		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	1	0	0	0	0	1	0	1	0	0	1	0	0
$Ret_{t-1} \leftrightarrow Vol_t$	*5m Grid*	0	0	0	0	0	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	1	1	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	1	1	1	1	1	1	1
	1m Grid	0	0	0	1	0	0	0
	5m Grid	0	0	0	0	1	0	0
	15m Grid	0	0	0	0	0	1	0
	1h Grid	1	1	0	0	0	0	0

Panel B: Non-Parametric Approach

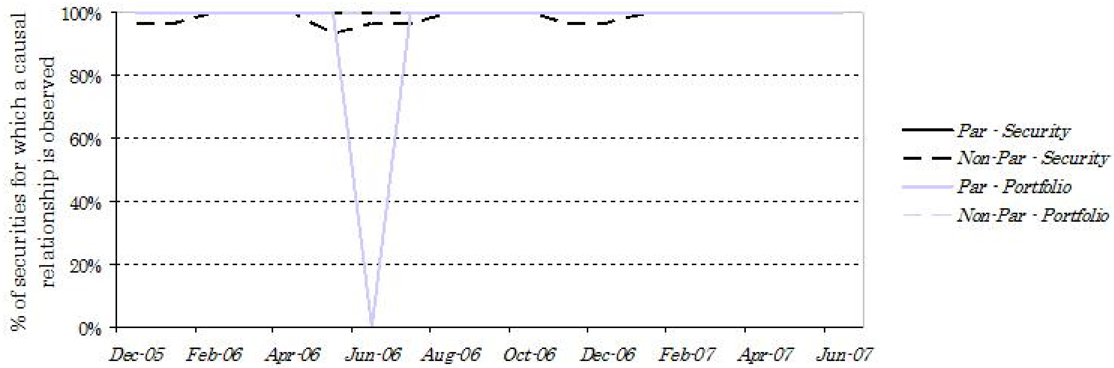
		12'05	*01'06*	*02'06*	*03'06*	*04'06*	*05'06*	*06'06*	*07'06*	*08'06*	*09'06*	*10'06*	*11'06*	*12'06*
	Trading Time	1	1	1	1	1	1	1	1	1	1	1	1	1
	1m Grid	1	0	0	1	0	0	1	1	0	0	0	0	0
$Ret_{t-1} \leftrightarrow Vol_t$	*5m Grid*	0	0	0	0	0	0	0	0	0	0	0	0	0
	15m Grid	0	0	0	0	0	0	0	1	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0	0	0	0	0	0	0

		01'07	*02'07*	*03'07*	*04'07*	*05'07*	*06'07*	*Average*
	Trading Time	1	1	1	1	1	1	1
	1m Grid	0	0	1	0	1	1	0
	5m Grid	0	0	0	0	1	0	0
	15m Grid	0	0	0	0	0	0	0
	1h Grid	0	0	0	0	0	0	0

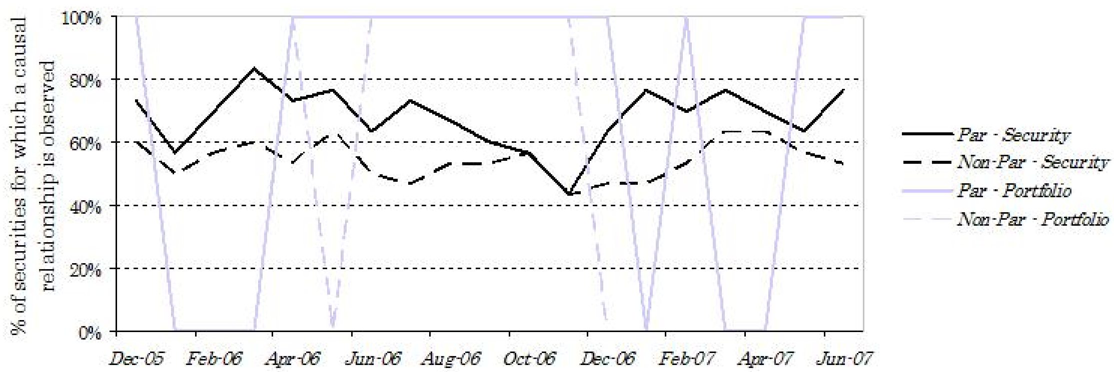
One denotes observed causality while *zero* signifies the lack of a statistically causal relationship between the two series.

Figure 1.1: Observed Returns Series Dynamics

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

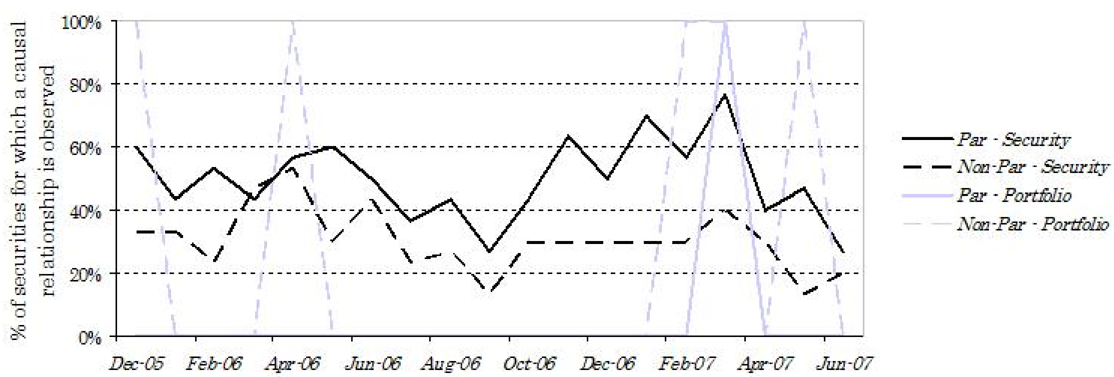
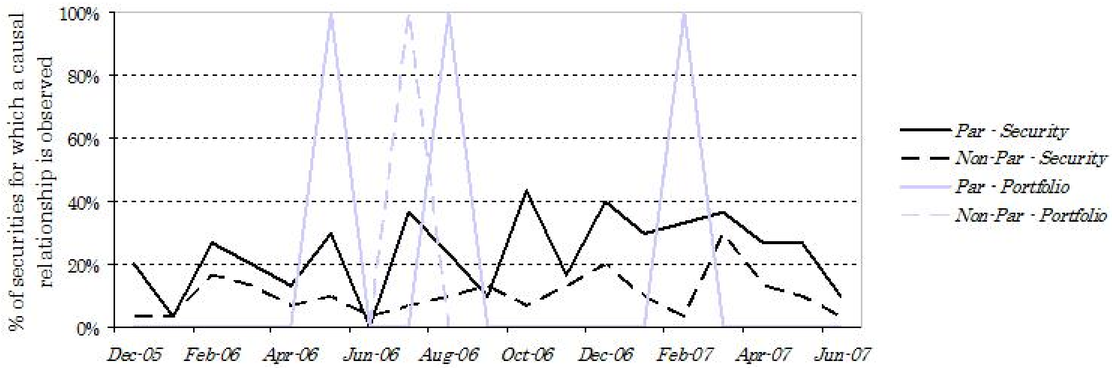


Figure 1.1: Observed Returns Series Dynamics - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

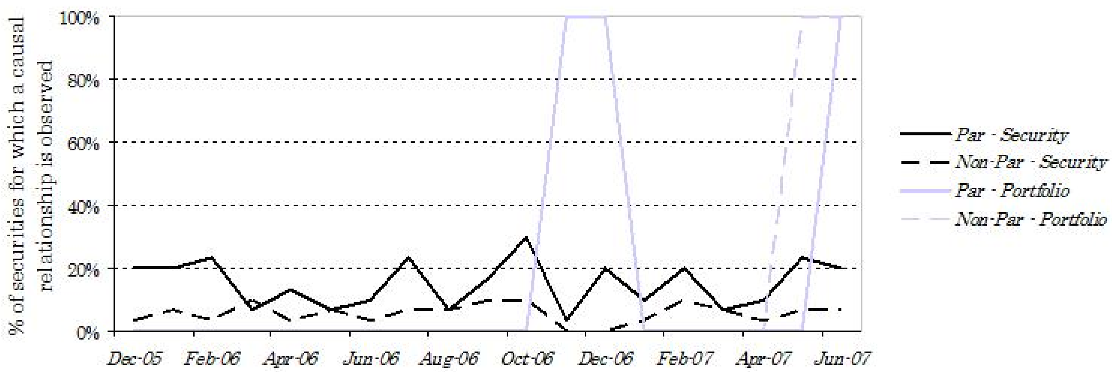
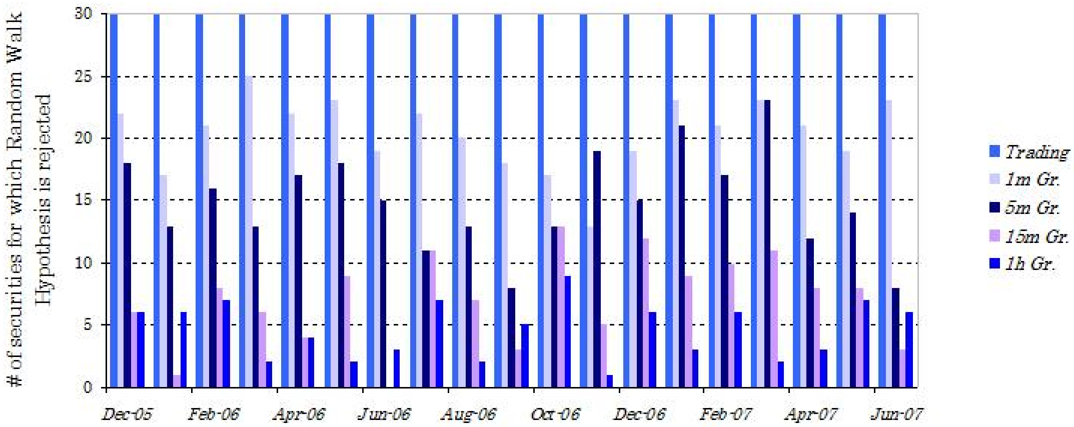


Figure 1.2: Observed Returns Series Dynamics

Panel A: Parametric Approach



Panel B: Non-Parametric Approach

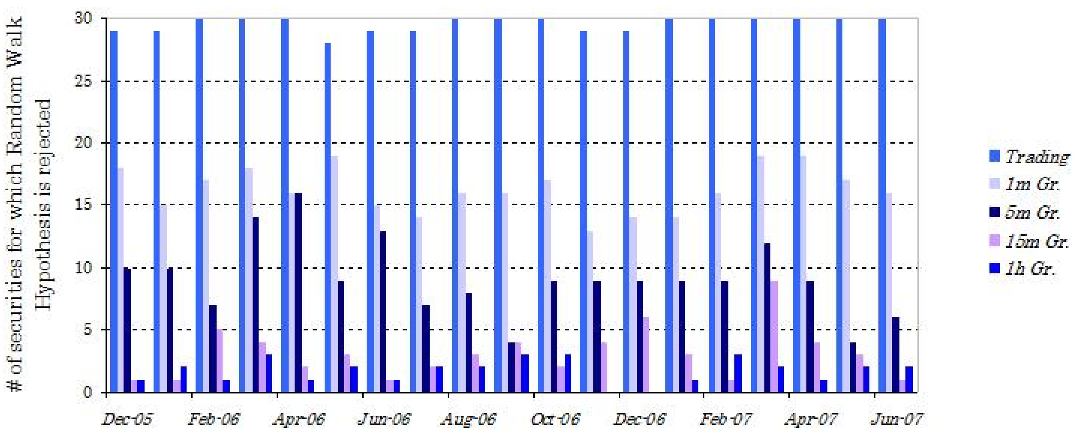
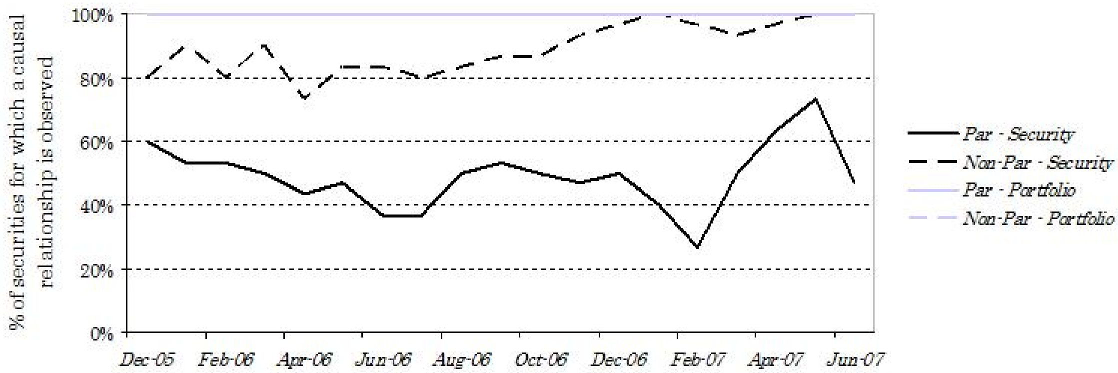
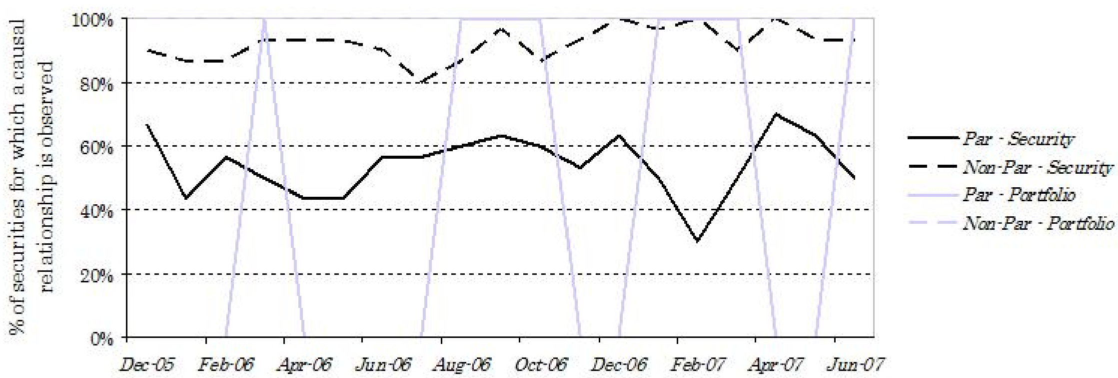


Figure 1.3: Observed Instances of Causality, Volumes to Returns

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

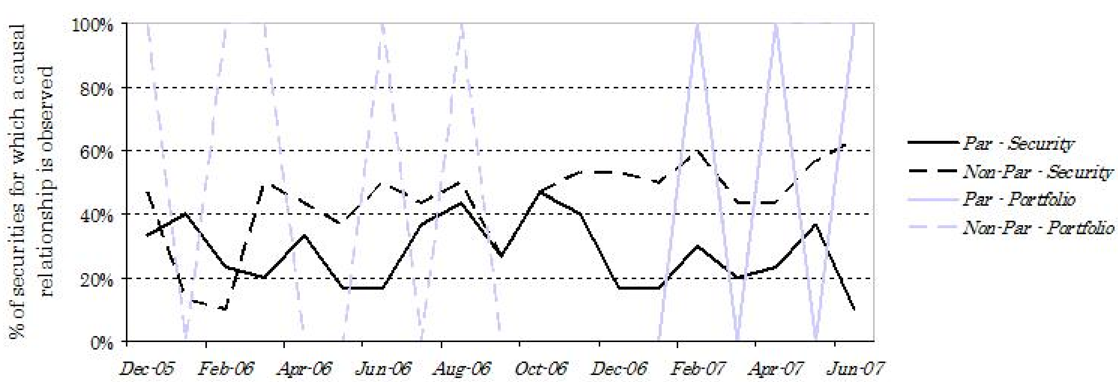
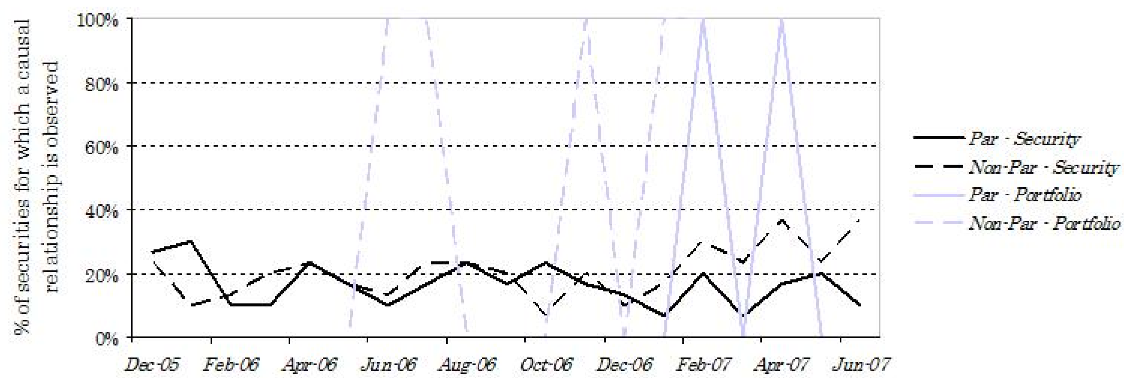


Figure 1.3: Observed Instances of Causality, Volumes to Returns - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

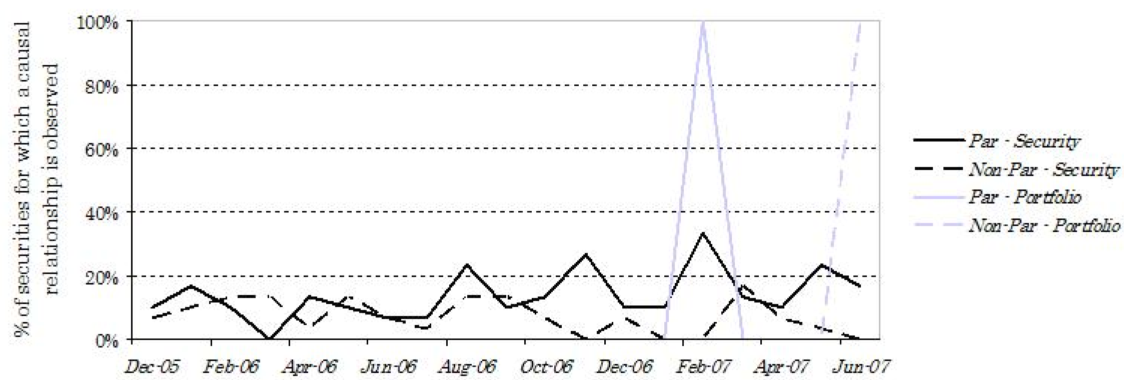
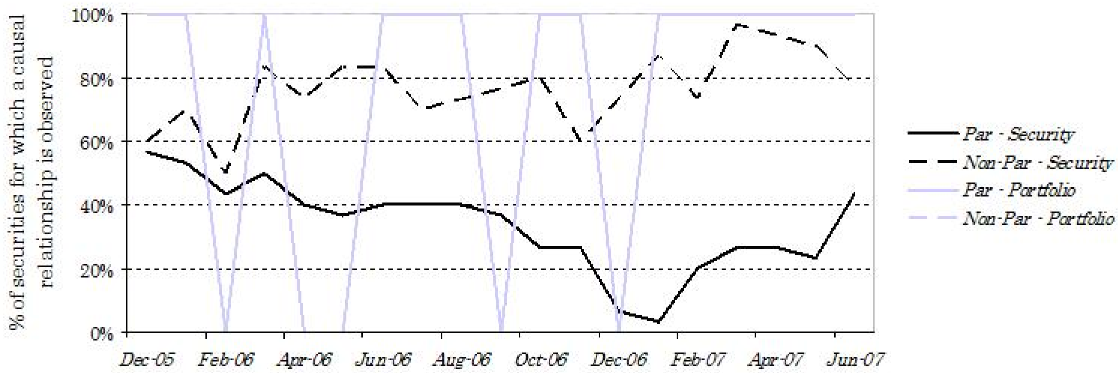
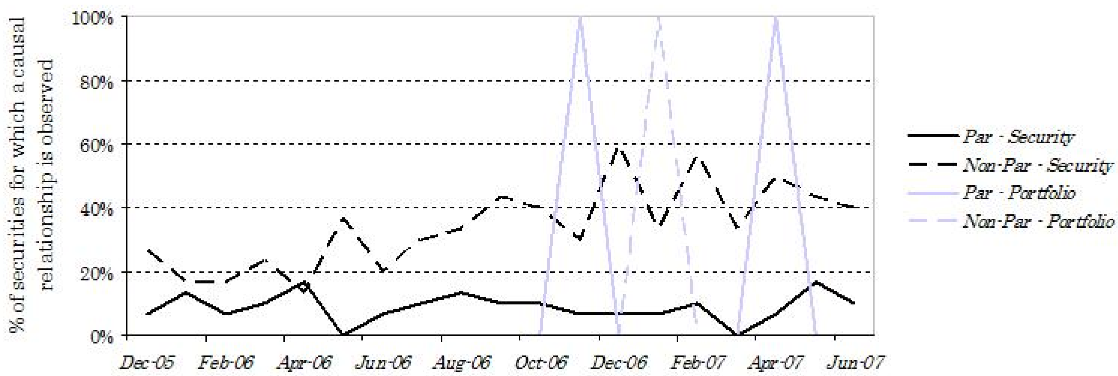


Figure 1.4: Observed Instances of Causality, Returns to Volumes

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

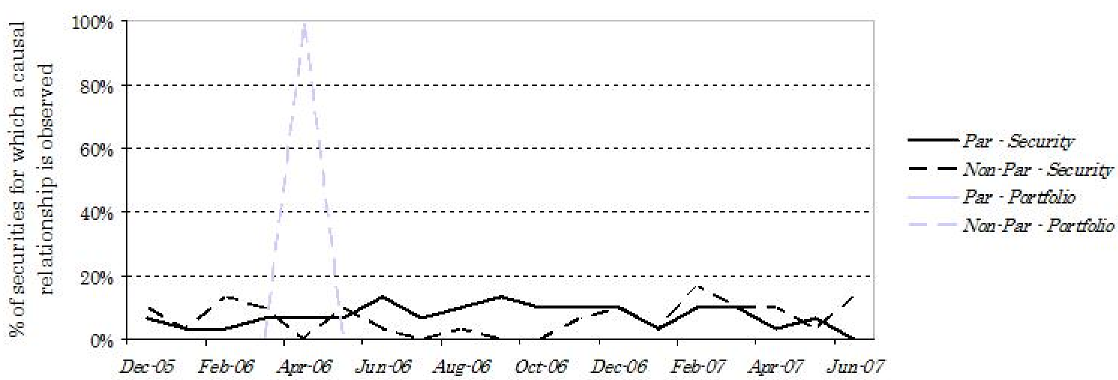
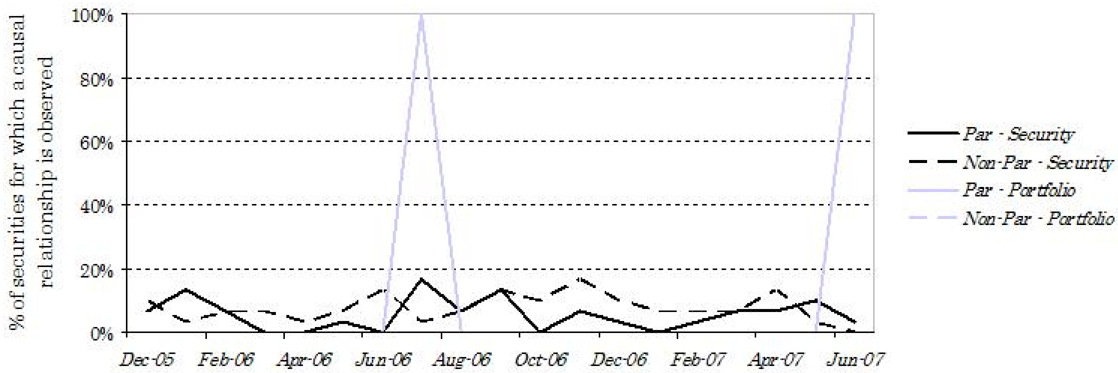


Figure 1.4: Observed Instances of Causality, Returns to Volumes - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

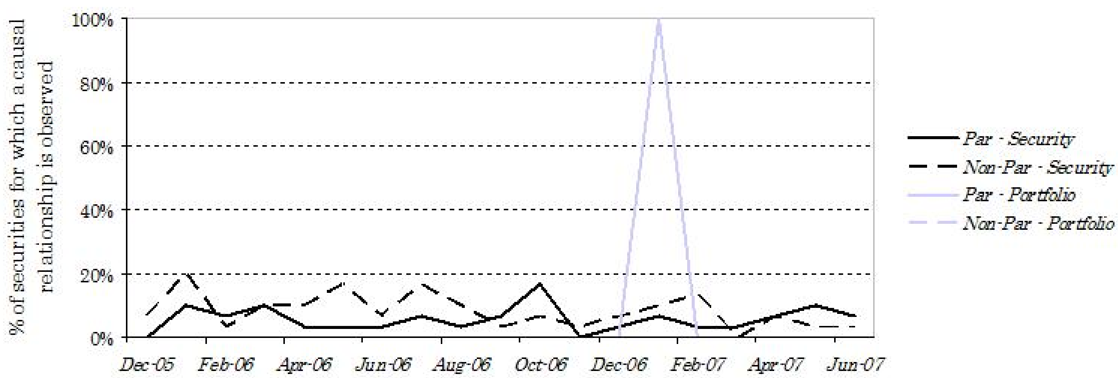
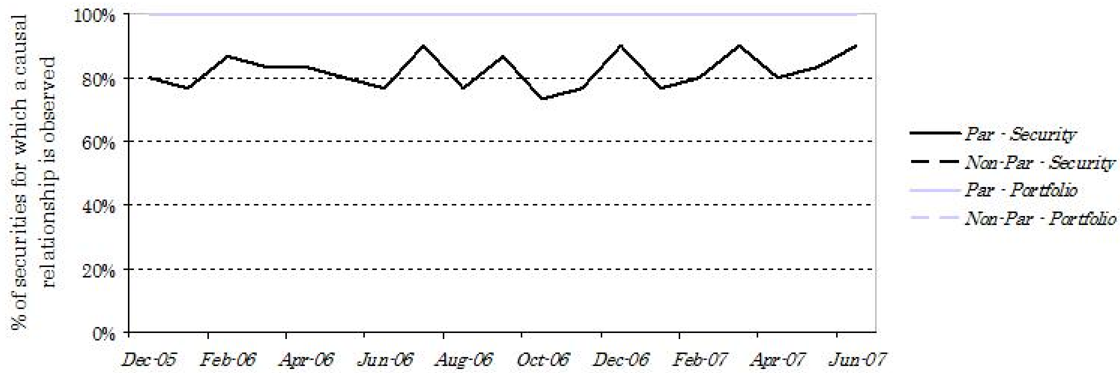
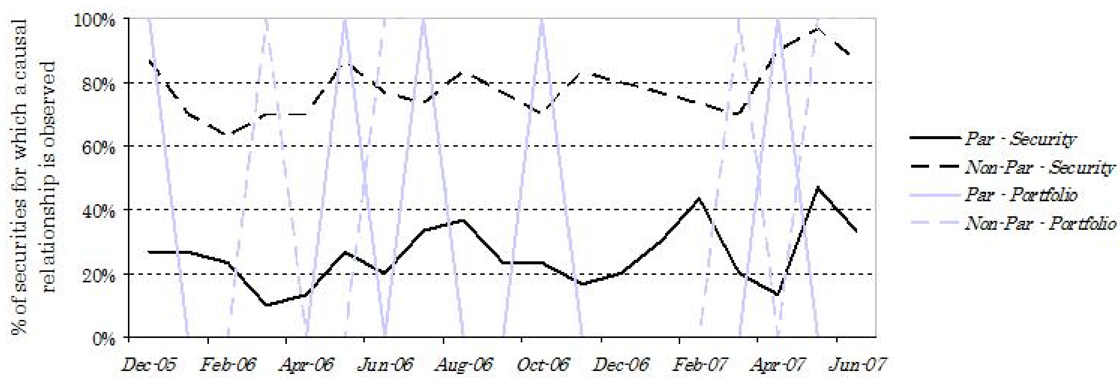


Figure 1.5: Observed Instances of Causality, Instantaneous

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

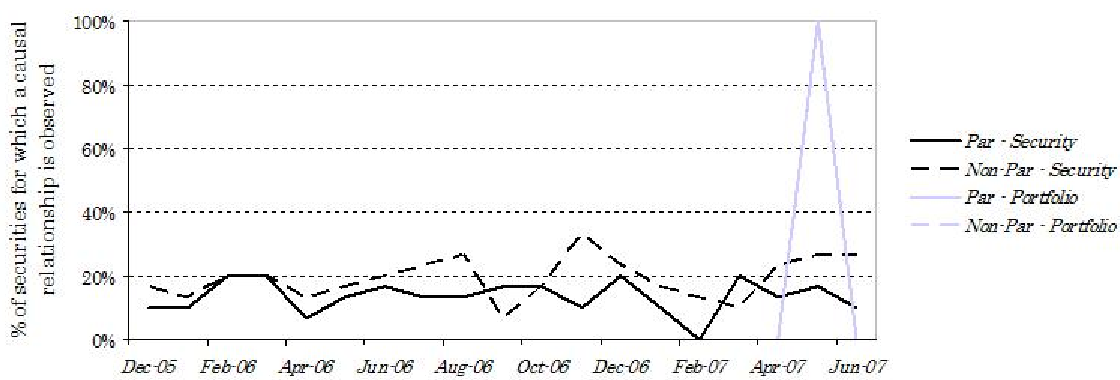
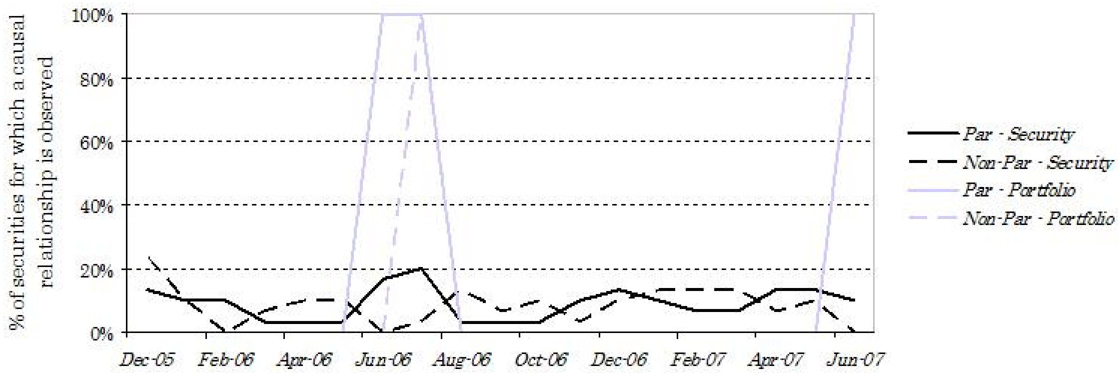


Figure 1.5: Observed Instances of Causality, Instantaneous - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

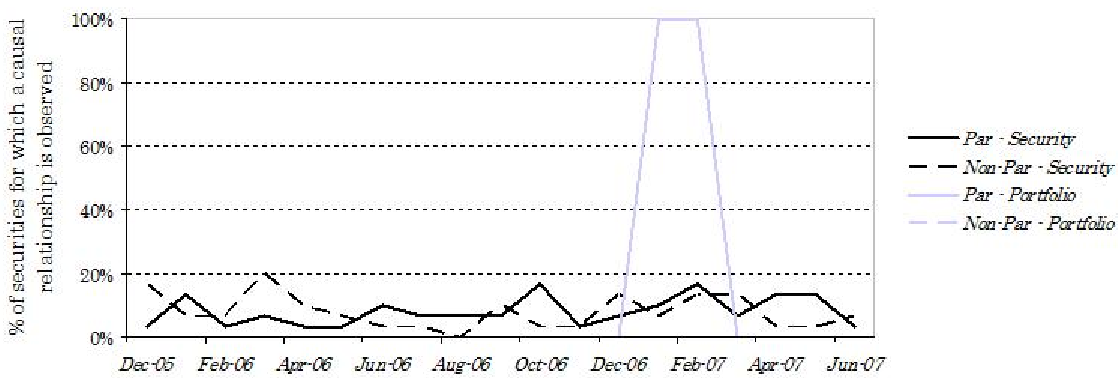
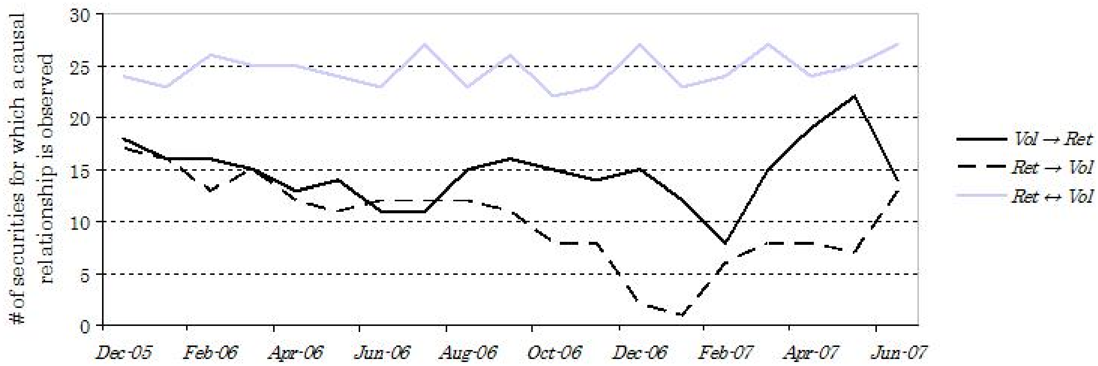
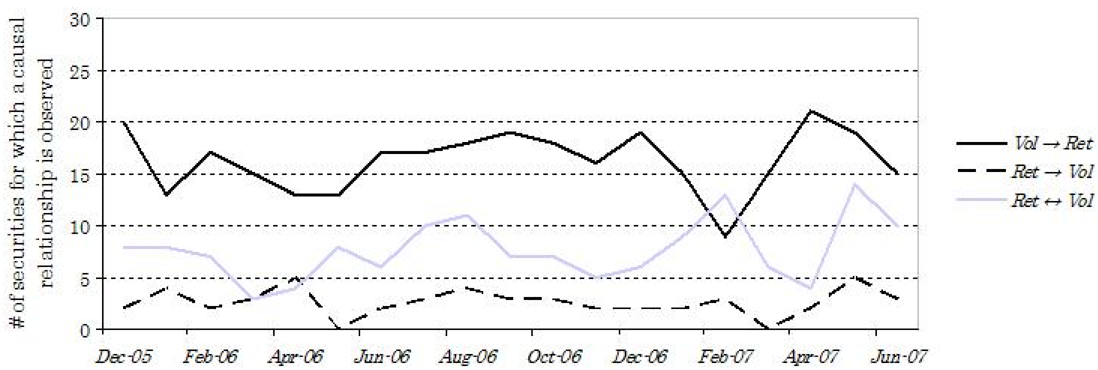


Figure 1.6: Observed Instances of Causality, Parametric Approach

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

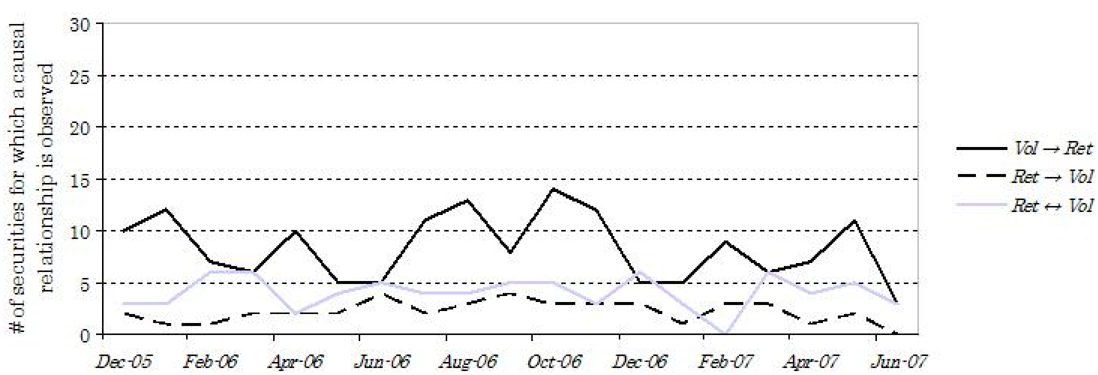
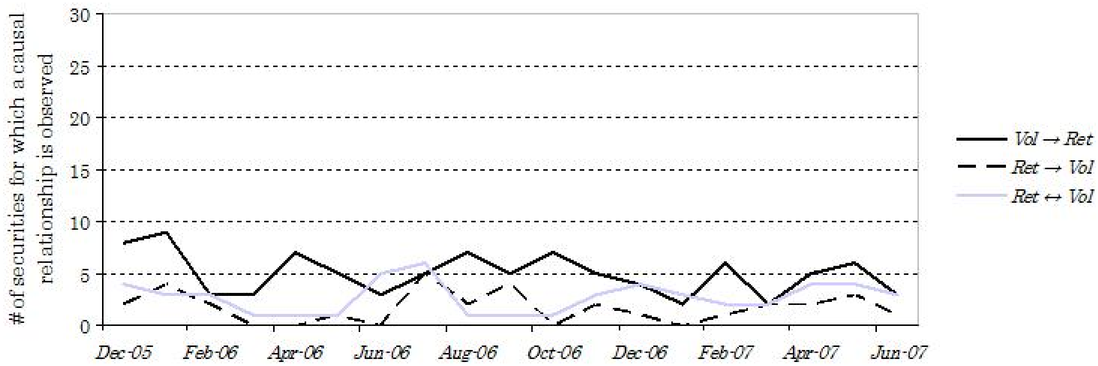


Figure 1.6: Observed Instances of Causality, Parametric Approach - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

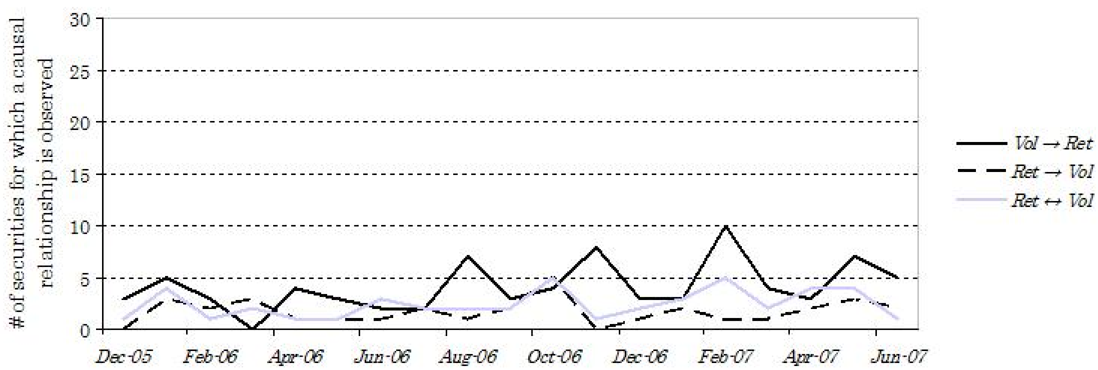
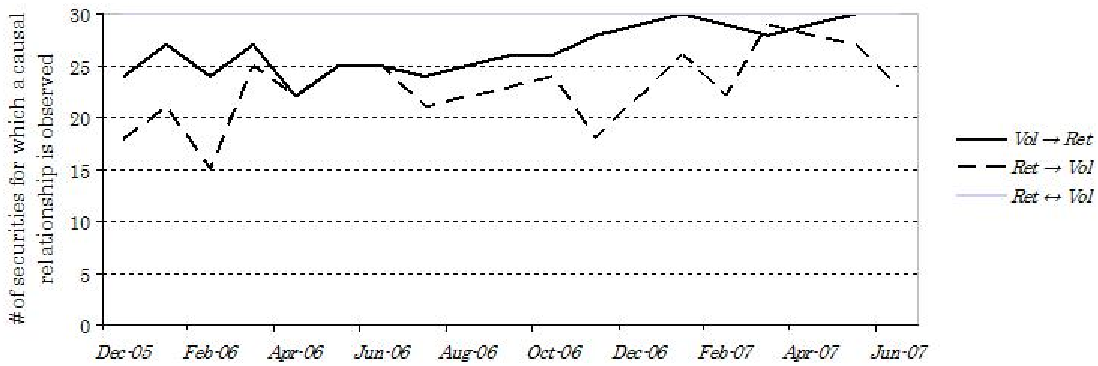
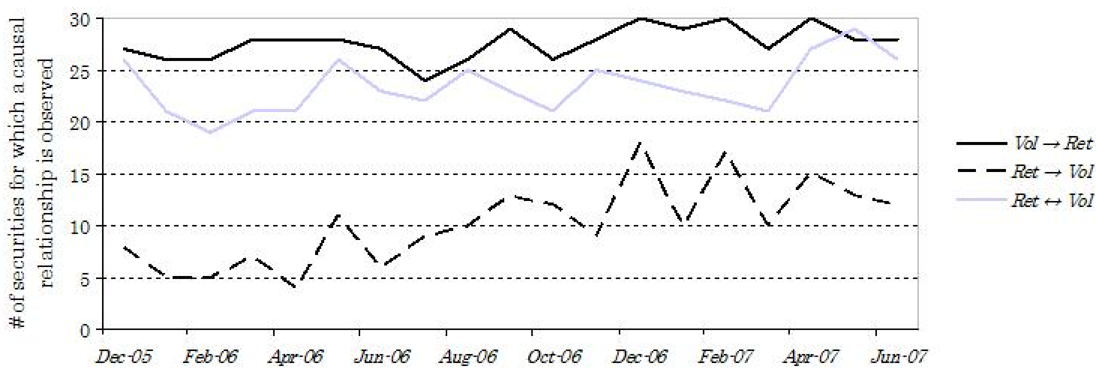


Figure 1.7: Observed Instances of Causality, Non-Parametric Approach

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Panel C: Calendar Time, 5m Grid

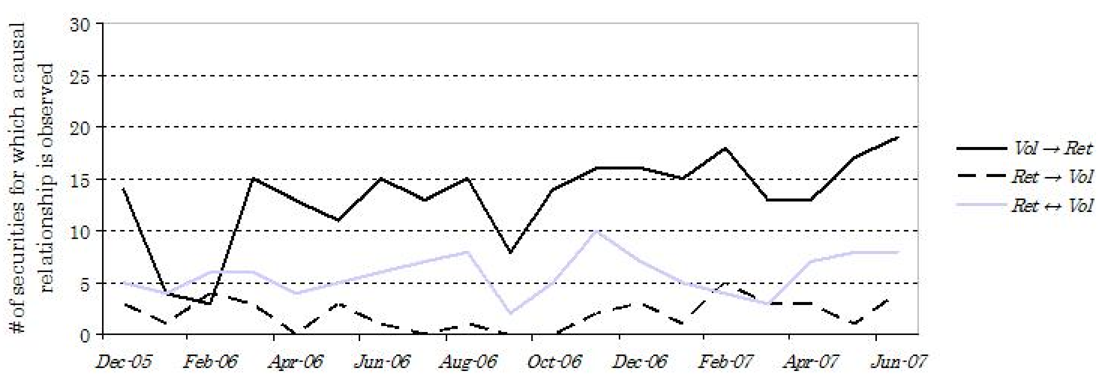
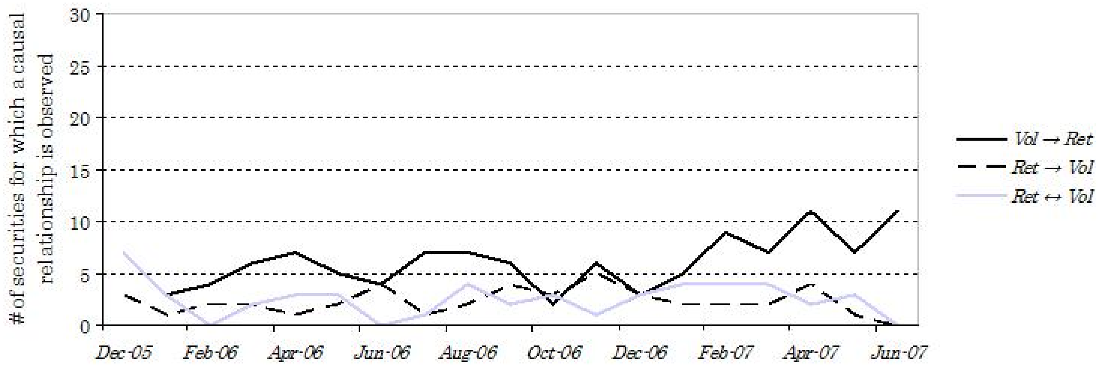


Figure 1.7: Observed Instances of Causality, Non-Parametric Approach - Continued

Panel D: Calendar Time, 15m Grid



Panel E: Calendar Time, 1h Grid

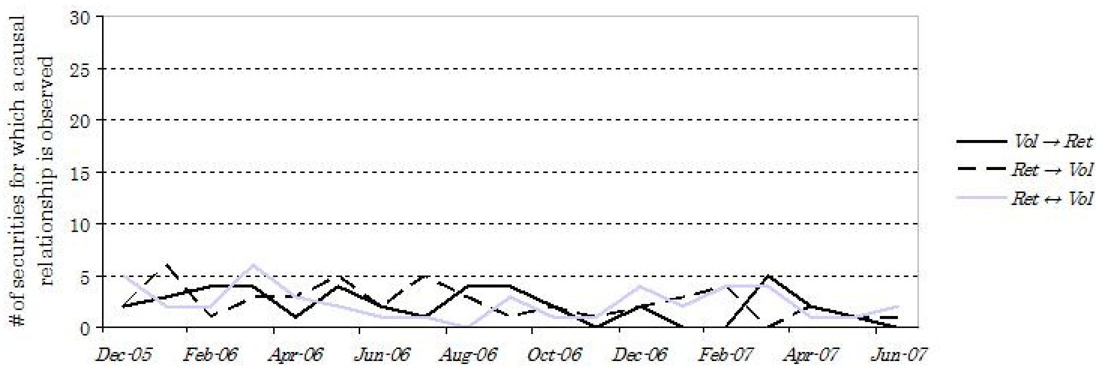
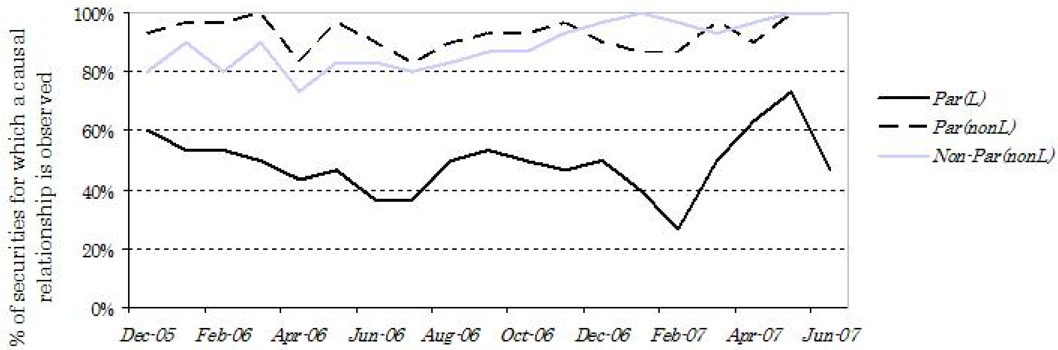


Figure 1.8a: Observed Instances of Causality, Volumes to Returns

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid

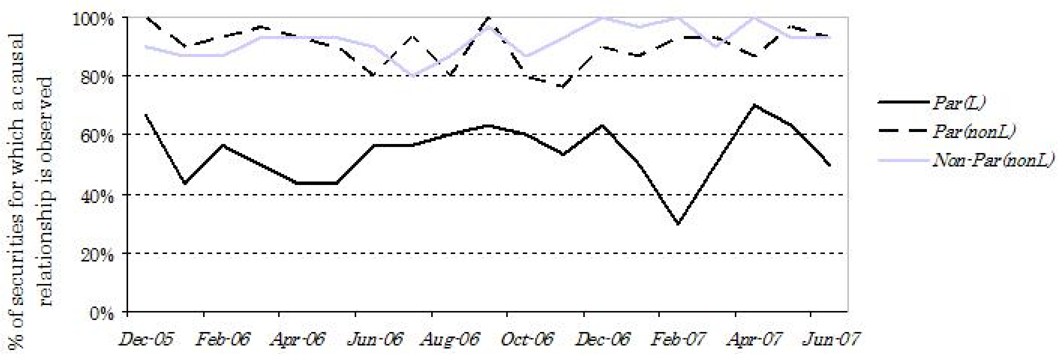
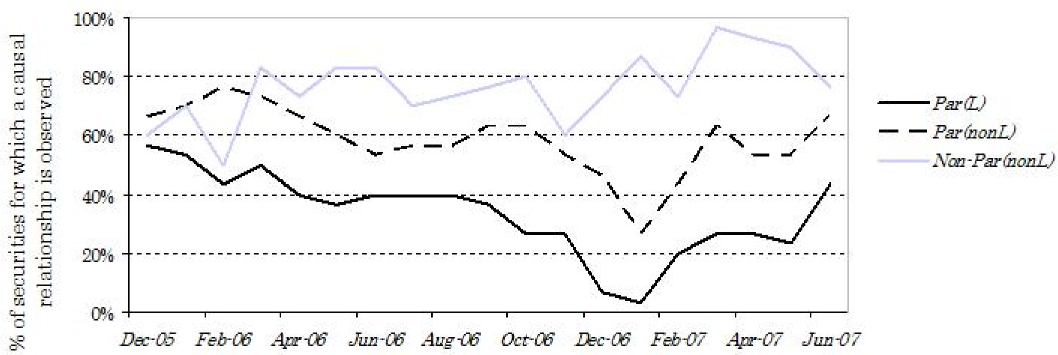


Figure 1.8b: Observed Instances of Causality, Returns to Volumes

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid

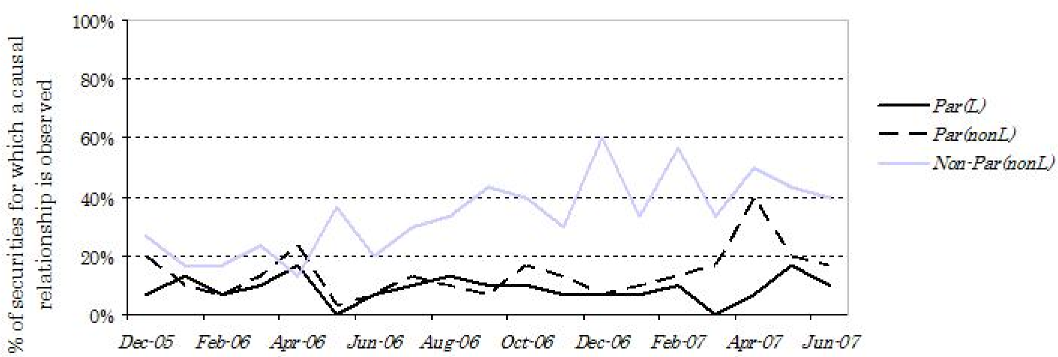
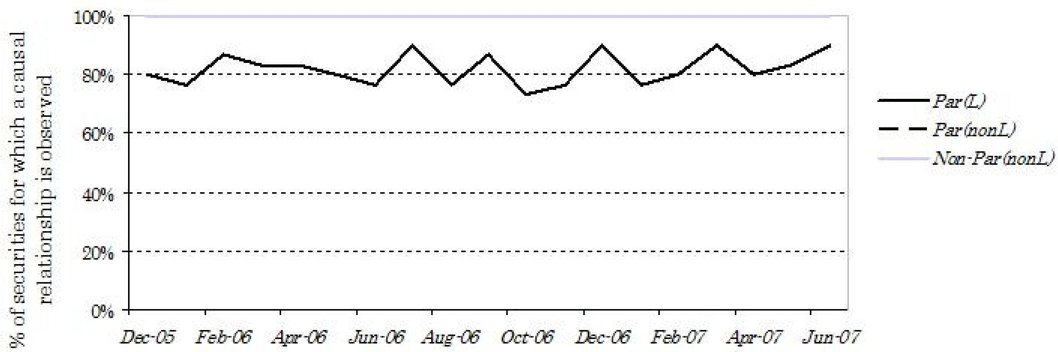
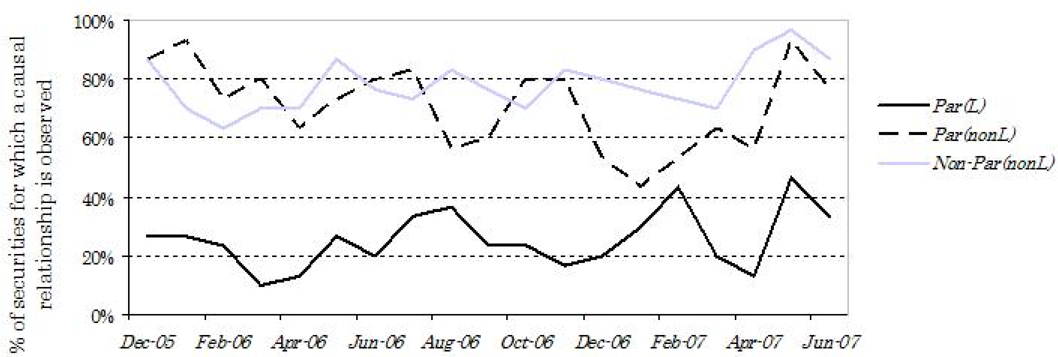


Figure 1.8c: Observed Instances of Causality, Instantaneous

Panel A: Trading Time



Panel B: Calendar Time, 1m Grid



Part II: Firm Risk

Chapter 2

Credit Ratings Migration: Quantifying Obligor Risk

This study focuses on estimating obligor credit rating migration probabilities using a continuous-record approach while controlling for the effects of idiosyncratic and systematic risk factors. Short- and long-run relationships between asset quality and obligor ratings are modeled and quantified using Moody's Default Risk Service (DRS) data on long-term bonds, rated during the 1970-2007 time period. The contribution to existing risk management literature is two-fold: first, the use of a continuous-record model addresses the problems of data sparsity and control for resulting estimation errors; second, the implementation of a methodology allowing us to precisely identify the stages of the business cycle enables us to determine the incremental impact of idiosyncratic and systematic risk factors on rating transitions probabilities, resulting in more precise estimates of credit rating migration trends. Results confirm the previous empirical finding in that obligor characteristics and business cycle stages have a strong effect on the dynamics of credit ratings, with a stronger effect observed in longer-horizon models. The importance of the business cycle effect on credit ratings is further illustrated by computing a forecast content for the business cycle variable in our model.

2.1 Introduction

Conventionally, credit risk is captured in obligor credit ratings, which are used as subjective measures of solvency and prospects of a debt issuer (see Koopman 2006). Credit ratings are computed by credit rating agencies (CRAs) and represent an overall assessment of the creditworthiness of a firm. Ratings are non-quantitative in nature, which makes their application in risk management complicated as it is difficult to precisely enumerate the risk associated with a particular issuer. To mitigate this inefficiency, a trend emerged in recent financial literature establishing a framework in which rating migration trends, and default risks, of long-term bond issuers are quantified in transition probabilities matrices.

It is widely accepted in risk management literature that credit rating distributions vary across time and issuer types (Nickell et al. 2000). It follows that, credit ratings transition probabilities are dependent on various sources of obligor risk. Ignoring these dependencies may lead to inaccurate assessments of firm creditworthiness, resulting in inefficient portfolio allocation and other financially suboptimal outcomes. In this paper, we examine rating migration dynamics of long-term bond issuers by quantifying the dependence of rating transition probabilities on idiosyncratic and systematic risk factors.

The first empirical credit rating migration model was developed by Jarrow et al. (1997) who use firm data to construct a matrix of credit rating transitions probabilities (see McBride 2006). The Jarrow et al. matrix is based on a discrete-time homogeneous Markov chain, where each element represents the frequency of a particular rating migration. Simply put, each entry of the matrix represents the probability of a specific rating transition, and is calculated by dividing the number of companies that moved from one state to another by the total number of companies in the initial rating category.

Current models describing rating migration trends have shifted away from implied firm homogeneity to focus on sources of observed heterogeneity of obligors, expanding model specification to include a number of idiosyncratic and systematic risk factors. Empirical literature provides extensive evidence to support the assumption of obligor heterogeneity. Kadam and Lenk (2008), Frydman and Schuermann (2007), Figlewski, Frydman, and Liang (2006), Bangia et al. (2002), and Nickell, Perraudin, and Varotto (2000) demonstrate that rating migration probabilities are highly correlated with issuer characteristics such as the industry of activity and domicile. Furthermore, recent studies by Figlewski et al., Bangia et al. and Nickell et al. indicate the presence of a link between rating migration trends and certain macroeconomic indicators, such as the stages of the business cycle. The notion that default probability is sensitive to macroeconomic factors is further supported by studies conducted by Duffie (2005), Couderac and Renault (2004), and Kavvathas (2001).

We complement and extend existing empirical literature by incorporating a continuous-record model, which allows us to mitigate problems of data sparsity and control for resulting estimation errors. We account for heterogeneity of obligors, and introduce a methodology to precisely identify and control for stages of the business cycle, enabling us to quantify the incremental impact of idiosyncratic and systematic risk factors on rating transition probabilities, resulting in more precise estimation of credit rating migration trends.

Our empirical strategy is based on a methodology proposed by Nickell et al. (2000), who use an ordered probit estimation technique to compute the incremental impact of obligor characteristics on migration patterns of credit ratings. Our results confirm the previous empirical findings suggesting that obligor characteristics and business cycle stages have a strong impact on credit rating migration and, further, observe a stronger business cycle effect in longer-horizon models. We illustrate the importance of the business cycle effects on the dynamics of credit ratings by computing a forecast content for the business cycle variable in our model, emphasizing the importance of idiosyncratic risk factors in precise assessment of obligor risk.

Results identify a clear ordering of issuer default probabilities across domiciles, with Japanese firms being least likely to default on their long-term obligations during economic expansions and contractions, and firms domiciled in the Lower-Middle Income countries (such as Georgia and the Philippines) demonstrating the greatest risk of default across all rating categories and business cycle stages. We observe that, on average, issuers in the Banking industry are most likely to experience an upgrade; obligors active in the Transportation sector are the riskiest in terms of default for sub-investment-grade rating categories; and, Industrial sector issuers have the highest probability of recovery following a default.

Our analysis of default instances demonstrates a clear trend, common to all countries, where the length of time for which an issuer received a rating is directly related to the probability of default for non-*Caa* ratings categories. That is, the probability of default increases with each additional year during which a firm receives its rating from a CRA.

When it comes to the Caa credit rating category, the probability of default increases during the first three years of the issuer's rating period and declines thereafter, indicating that older, insolvent firms have greater associated likelihoods of meeting their financial obligations compared to younger, less experienced firms.

The remainder of the paper is organized as follows. In Section 2 we provide a brief review of theoretical and empirical literature on credit rating migration and risk modeling. In Section 3 we describe the dataset and variable construction methodology. Sections 4 and 5 give detailed descriptions of our empirical methodology; Section 4 develops a rigorous methodology for identifying country-specific stages of the business cycle, while Section 5 details the methodology for quantifying effects of idiosyncratic and systematic risk factors on transition probabilities of obligor credit ratings. In Section 6 we discuss the paper's central findings. We conclude and offer suggestions for further research in Section 7.

2.2 Conceptual Background

Firm creditworthiness is generally modeled using the structural or the reduced form approach (see Figlewski et al. 2006). Structural models, first introduced by Merton (1974), consider the evolution of a firm's value over time and assume that a transition between rating categories occurs when a firm's value shifts between some known thresholds. In this framework, $Default$ is defined as the inability or unwillingness by the issuer to meet its financial obligations, an event which occurs when the value of the firm's assets falls below a specific threshold level.

In the lender-borrower framework, in order to secure external financing, a firm must offer some asset, V, the value of which evolves over time. As the market's valuation of the firm's asset changes, so does the issuer's ability to pay off the financial obligations backed by this particular asset. Within this framework, structural models assume that default is endogenously determined, and that the market has complete knowledge of the firm's financial situation, consequently asserting that default is predictable (Jarrow and Potter 2004).

In contrast to structural models, reduced form models treat a credit ratings change as a random event that has a positive probability of occurrence for any firm, at any time. In the reduced form framework, a transition from one credit rating to another corresponds to a jump in a Poisson process with some predetermined hazard rate. Here, $Default$ is assumed to be exogenously determined and thus, is not predictable (see Gndz and Uhrig-Homburg 2005).

This study assumes that changes in a firm's asset value are related to two types of risk factors: idiosyncratic, factors related to individual obligor characteristics; and systematic, factors affecting the creditworthiness of all obligors. That is, firm creditworthiness is both endogenously and exogenously determined. We model the relationship between a firm's value and factors affecting it as follows

$$\Delta V_{j,t} = \alpha_j X_{j,t} + \eta_j Z_t + \sigma_j \varepsilon_{j,t}, \tag{2.1}$$

where ΔV denotes a change in asset value of firm j at time t; X is a vector of idiosyncratic risk factors; Z is a vector of systematic risk factors; α_j and η_j are correlations of changes in a firm's asset value with changes in risk factors X and Z; σ_j denotes the magnitude of residual volatility in asset value that is not explained by either internal or external risk factors; and ε_j is an independent, normally distributed random shock.

Assuming a normal distribution of changes in a firm's asset value, the creditworthiness of an obligor can be expressed as a continuum of states. In this framework, a firm's default probability is the probability of a standard normal variable falling below some critical value, and transitions to other states can be characterized by some predetermined corresponding threshold values.

Asset-value thresholds can be equivalently modeled as asset-return thresholds (Bangia et al. 2002). Consider a scenario where the asset-value corresponds to a specific state on the continuum of credit ratings, C to Aaa; where C is the lowest possible rating, denoting obligor's inability to meet financial obligations, and Aaa indicates complete financial solvency. If ΔV_j is below some threshold, k_{N-1}, the obligor is assigned a rating of C. If ΔV_j is below some threshold k_1, but above another threshold, k_2, the firm is assigned a rating of

Aa, etc. The decision rule is as follows

$$\begin{array}{lll} \text{Rating} = C & \text{if} & \Delta V_j \leq k_{N-1}, \\ \vdots & \vdots & \vdots \\ \text{Rating} = Aa & \text{if} & k_2 < \Delta V_j \leq k_1, \\ \text{Rating} = Aaa & \text{if} & k_1 < \Delta V_j, \end{array} \tag{2.2}$$

where N is the number of categories in which the dependent variable may fall.

Figure 2.1 illustrates the decision rule in Eq.(1.2). Standard implementation of the approach introduced by Merton (1974) suggests that changes in asset-value are normally distributed with mean μ and standard deviation σ. Following the existing finance literature, assume that the firm's asset-returns are distributed according to a standard normal, with mean zero and standard deviation of one. In this framework, the firm's asset-returns are represented as a continuum of states, and can take on both positive and negative values. If a firm's actual asset-return, ΔV_j, falls below two asset return thresholds k_i and k_{i+1}, such that $k_{i+1} < k_i$ and where $i+1$ is the credit class below i, the company's rating in period $t+1$ will be i. specifically, if a firm's asset-return is positive, indicating a strengthening financial position, then for an asset-return large enough, a firm is likely to receive a rating upgrade. If the asset return is negative a rating downgrade is likely to follow.

Given the assumption of normality and the frequency of occurrence of each migration combination, it is possible to compute every asset return threshold corresponding to a specific credit rating

$$\begin{array}{ll} Pr\{\text{Rating} = C\} & = \Phi(k_{N-1}), \\ \vdots & \vdots \\ Pr\{\text{Rating} = Aa\} & = \Phi(k_2) - \Phi(k_1), \\ Pr\{\text{Rating} = Aaa\} & = 1 - \Phi(k_1), \end{array} \tag{2.3}$$

where $\Phi[\cdot]$ is the cumulative distribution function of the standard normal distribution.

2.2.1 Preliminary Results

Before proceeding with conditional estimates of the continuous-record credit ratings migration matrices, we consider their unconditional parameters, presented in Table 2.1, Panel A.

We observe a clear, high probability load on the diagonal, characteristic of transition probabilities matrices described in the empirical literature to date. Diagonal dominance implies that obligors are most likely to maintain their current credit rating rather than move up or down in the ratings categories. We further conclude that, given an initial rating, the second largest probabilities are generally found in a direct neighborhood to the diagonal (Bangia et al. 2002). To summarize, ratings categories farther away from the diagonal are associated with decreasing probabilities of occurrence, which is consistent with monotonicity of migration described in Bangia et al.. That is, given some initial credit rating in time period t, it is most likely that an obligor's financial situation in $t+1$ will not have changed drastically, resulting in the monotonicity of credit ratings.

It is important to note that strict monotonicity need not necessarily hold. Some empirical studies, including Nickell et al. (2000), found that Caa rating category violates monotonicity as a Caa-rated obligor is much more likely to $Default$ than be downgraded to a Ca or a C rating, thus jumping categories. One explanation for this inconsistency is noise in the observed data. In their paper, Bangia et al. (2002) explain that recent studies have challenged the assumption of strict monotonicity as unreasonable specifically when it comes to the Caa rating category. That is, rating agencies consider Caa rated obligors to be exceptionally volatile, and the risky nature of these issuers manifests itself in high probability occurrence of two specific states: $Default$ and significant rating upgrade (Lando 1998).

Results presented in Table 2.1, Panel A, demonstrate increased probabilities of default and higher migration volatility for lower-quality grades of investment. We generalize that the likelihood of default increases rapidly with a decreasing creditworthiness. Also, we note a reversion to the mean for investment-grade bonds, bonds with a rating of Baa and above. Specifically, higher-rated bonds have an increased probability of experiencing a downgrade then an upgrade; while lower-rated bonds tend to experience upgrades more frequently then downgrades. Our preliminary results are consistent with findings of previous, discrete- and continuous-time studies, summarized in Panel B of Table 2.1.

2.3 Data Description

This study uses Moody's Default Risk Service (DRS) database of ratings and defaults for issuers of long-term bonds during the 1970-2007 time period. Schuermann and Jafry (2003) argue that Moody's rating approach incorporates some judgment of recovery in the event of default. Thus, we assume the credit ratings published in the DRS to represent an overall assessment of an issuer's creditworthiness.

In order to account for each legal entity separately, we track an issuer's senior, unsecured, long-term debt rating over the sample time period. This rating serves as a measure of a firm's credit quality for as long as that rating is outstanding. As is common practice in the empirical literature, we exclude municipal debt issuers from the sample. Following Nickell et al. (2000), we restrict our sample to obligor ratings as of December 31^{st} of each observed year, removing multiple ratings for a given issuer during a particular year in an effort to reduce noise in the data.

We further refine our sample by excluding withdrawn ratings. The treatment of rating withdrawals is an important issue in the literature on credit rating migration. There are a variety of reasons for which a credit rating may be withdrawn, ranging from bond maturity to discontinuing payments of Moody's required rating fee by the obligor. It is this lack of information associated with a rating withdrawal that leads some researchers to infer that a withdrawal implies negative information about a firm. However, according to Carty (1997), deterioration in the firm's credit quality can be correlated with a mere one percent of the withdrawal cases. Since few rating withdrawals are actually correlated with changes in issuer creditworthiness we simply exclude them from the sample.

The final dataset contains credit ratings histories for 13,335 obligors, with a total of 121,776 observations. The following sections discuss the changes in the composition of our dataset over the sample time period.

2.3.1 Changes in Domicile Composition

Consistent with increased international financial activity, Moody's coverage of long-term bond issuers has expanded to include international obligors. Specifically, the portion of rated issuers domiciled in the United States has declined from 96% in the 1970s, to 58% in 2007, signaling increasing role played by international firms in the global market. Figure 2.2 details the composition of firms in our database according to domicile at the start of each decade since 1970, and in 2007.

The corporate bonds covered by Moody's span a broad range of income groups, from High Income countries such as the United States and Japan, to Lower-Middle Income countries such as Georgia and the Philippines. According to Kadam and Lenk (2008), economic, legal and political differences are a source of potentially significant variation in the domicile effect on the dynamics of obligor credit ratings. In this study we account for the national wealth effects on credit ratings of obligors located on both ends of the wealth spectrum. We use the World Bank's Income classification to distinguish between two country types: High Income countries, countries with 2006 Gross National Income (GNI) per capita of $11,116 and above; and Lower-Middle Income countries, countries with recorded $906 - $3,595 GNI per capita in 2006. Specifically, we focus on modeling differences in credit rating transition probabilities between United States, United Kingdom, Japan, and a group of Lower-Middle Income countries. Detailed income statistics for our sub-sample are available in Table 2.2.

To further motivate the importance of domicile effects to the dynamics of credit ratings we use the DRS database to model implicit country premia for our sub-sample. The most straight-forward way of computing country premium is to consider credit rating movements of sovereign bonds. Due to data limitations, we approximate country risk premium by considering ratings associated with long-term corporate bonds of issuers domiciled in a particular region. The corporate bond market is much deeper, in terms of the number of market participants, than the sovereign bond market, and thus, is less volatile on a period by period basis (see Damodaran 1999). At the same time, while ratings assigned by Moody's are intended to measure default risk, corporate bonds, to a certain extent, internalize the risk factors associated with specific domiciles, such as stability of a country's currency and its legal and economic environments. By using long-term corporate bond ratings we overcome the data limitations associated with sovereign bonds, while implicitly identifying comparative financial positions and riskiness of a particular domicile.

In calculating the implicit country premium, we focus on investment-grade bonds, ratings of Baa and higher, excluding speculative-grade bonds from our analysis. We exclude junk-bonds as speculative investments serve as indicators of investor risk tolerance, rather than the financial stability of overall economy. That is, speculative-grade investments tend to fluctuate with states of the economy; increasing during an economic expansion and declining in availability during an economic recession.

We define an implicit country rating for a given year to be the rating category where most observations occur; that is, the mode of the sample for a specific year. The implicit country premium is determined by comparing the implicit country ratings across domiciles, and is presented in Figure 2.3.

Results demonstrate that, on average, United Kingdom is the most creditworthy of domiciles included in our sample. In contrast, Lower-Middle Income countries appear to be the least creditworthy, with $Default$ category being the mode in 2001. Our results illustrate a trend among High Income countries where ratings have effectively converged to a single implicit country rating category, A. At the same time, Lower-Middle Income countries remain relatively risky, with an implicit rating of Baa, the lowest rating category for investment-grade bonds.

2.3.2 Changes in Sector Composition

Industrial composition of firms with Moody's rated debt has also shifted throughout the sample time period. While the importance of the Transportation and the Industrial sectors has visibly declined over the decades, the Banking sector has experienced rapid growth. In

1970, Transportation, Industrial, and Banking sectors made up 13%, 57%, and 0% of the rated issuers respectively. By the end of 2007, the three sectors accounted for 2%, 47%, and 16% of all issuers rated by Moody's. Figure 2.4 details industrial composition of Moody's rated corporate issuers according to industry.

Consistent with existing empirical literature this study focuses on the Banking, Industrial, and Transportation sectors of the economy.

2.3.3 Changes in Moody's Rating Methodology

In 1982 Moody's rating methodology was revised and its rating definitions expanded, resulting in a more precise firm classification system. In this study we condense more recent rating categories. That is, we focus on Aaa, Aa, A, Baa, Ba, B, Caa, and Ca/C rating categories to monitor firm credit rating migration over time. In using the original rating methodology we are able to extend our sample to include observations recorded prior to 1982, allowing for maximum sample size. Following Moody's Universal Rating system, we assign ratings of one through eight to ratings categories Aaa through Ca/C respectively.

Consistent with Moody's assessment of Ca/C-rated obligors as being on the brink of, or in, default we check our Ca/C category against the master default database available through DRS. Moody's defines $Default$ as any missed or delayed payment of interest and/or principal, bankruptcy, or distressed exchange, Hamilton and Berthault (2000). Thus, we allow the $Default$ rating category to be rather broad, including a variety of financial distress scenarios. In our database, $Default$ signifies obligors that are considered by Moody's to be in default as of December 31^{st} of a particular year for which the rating is given, and are assigned a rating of eight, thereby absorbing the Ca/C rating category.

2.4 Estimating Business Cycle Chronology

Recent studies by Duffie (2005), Couderac and Renault (2004), Bangia et al. (2002), Kavvathas (2001), and Nickell et al. (2000) provide evidence suggesting that issuer creditworthiness is correlated with real economic activity of the country in which the firm is domiciled.

As such, transition probabilities of credit ratings are assumed to fluctuate with changes in the state of the national economy. In this section we introduce a methodology widely relied upon in the macroeconomic literature (see Beaudry and Koop 1993, Hess and Iwata 1997, Garcia and Luger 2005, Milas and Rothman 2008), which we use to generate a business cycle chronology for each country represented in the sample using a methodology widely relied upon in

The empirical literature is rich with complex mathematical models used to forecast economic activity. More recently, however, simple economic and financial indicators have proven effective in predicting economic recessions. Here we test the usefulness of these two types of indicator variables in forecasting the probability of U.S. recessions.

A number of macroeconomic and financial variables have been tested in the business cycle forecasting literature. When it comes to financial variables, there is a consensus among researchers on the usefulness of interest-rate term spreads as reliable predictors of future economic activity. The spread is related to a forward interest rate, and can be broken down into a real and an inflationary component. While the expected real rate accounts for current outlook on monetary policy, the expected inflationary rate provides insight into the future real growth. Estrella and Mishkin (1998), who analyze U.S. economic activity form 1959 to 1995, find that the term spread is a good predictor of future recessions. Along with the spread, we also test the short-term interest rate, which is believed to have some predictive ability in characterizing business cycles (see Garcia and Luger 2005).

While financial variables appear to be reliable indicators of future economic activity, they are often difficult to obtain. To this extent, we must also evaluate the effectiveness of attainable macroeconomic indicators in forecasting probabilities of recession. Beaudry and Koop (1993) explain that the use of macroeconomic data in economic recession forecasting is rooted in the assumption that future output is related to the current level of output. Hess and Iwata (1997) apply the Beaudry-Koop model to U.S. economic data, generating a business cycle chronology which closely resembles that of the NBER, thereby confirming the effectiveness of macroeconomic variables as predictors of future real activity. Therefore, along with the interest rate and the term spread, we utilize the framework developed by Beaudry and Koop, and analyze the predictive power of two economic variables constructed from country-level GDP data, current depth of recession (CDR_t), and current length of recession (CLR_t).

We construct the CDR_t and CLR_t following methodology described in Garcia and Luger (2005), where the current depth of recession, CDR_t, is defined as the gap between the current level of output and the economy's historical maximum level of output:

$$CDR_t = max\{Y_{t-j}\}_{j\leq 0} - Y_t. \tag{2.4}$$

In this context, we consider the economy to be in recession when $CDR_t > 0$, and in expansion when $CDR_t = 0$. We define the current length of recession, CLR_t, by setting the variable equal to h when $CDR_{t-j} > 0$ for $j = 0, 1, \ldots, h$. The level of output and the CDR_t variable for the U.S. are plotted in Figure 2.5.

The effectiveness of our indicator variables in predicting future economic recessions is evaluated using a probit model, where the dependent variable, U_t, is a recession indicator. Specifically, we assume an unobserved variable U_t^*, for which there exists a realization of an indicator variable U_t, denoting the occurrence of a recession. Suppose

$$\begin{aligned} U_t = 1 \quad \text{if} \quad CDR_t > 0, \\ U_t = 0 \quad \text{if} \quad CDR_t = 0. \end{aligned} \tag{2.5}$$

We express U_t^*, which represents the state of the economy at time t, as being related to lagged values of the current depth and length of recession, where U_t^*, takes on the following form

$$U_t^* = \beta X_{t-1} + \gamma_1 CDR_{t-1} + \gamma_2 CLR_{t-1} + \varepsilon_t, \tag{2.6}$$

where X_{t-1} is a vector containing lagged values of all macroeconomic and financial variables (other than CDR and CLR) believed to have predictive ability for future recessions; CDR_{t-1} and CLR_{t-1} capture recession intensity and duration dependence; and error terms, ε_t, are assumed to be independent and follow a standard normal distribution.

The model in Eq.(2.6) implies that

$$Pr[U_t = 1|X_{t-1}, U_{t-1}] = \Phi[\beta X_{t-1} + \gamma_1 CDR_{t-1} + \gamma_2 CLR_{t-1}], \tag{2.7}$$

where $\Phi[\cdot]$ is the cumulative distribution function of the standard normal distribution.

2.4.1 Data

We estimate our model using the U.S. macroeconomic and financial data for the 1953-2007 time period. The reason we focus on U.S. data is that business cycle chronology is readily available through the NBER, providing us with a benchmark against which to evaluate the quality of our model. The data used to estimate our model include the three-month Treasury bill rate (Short), the yield spread (Spread), the difference between the interest rates on the ten-year Treasury note and the three-month Treasury bill, and U.S. GDP data. The model is estimated on a quarterly basis, where quarterly rates are calculated by averaging the corresponding monthly rates.

2.4.2 Estimation Results

Estimation results for our model are reported in Table 2.3. In our estimation, we address three specifications of the model in Eq.(2.6). All three specifications include CDR_{t-1} and CLR_{t-1} economic variables. When it comes to financial indicators, Specification 1 includes only lags of the short rate, Specification 2 includes only lags of the yield spread, and Specification 3 includes both the Short and the Spread. It is clear from Table 2.3 that, in predicting economic recessions, CDR_{t-1} dominates other variables, for all three specifications. This result allows us to rely on CDR_{t-1} and CLR_{t-1} variables to obtain an accurate business cycle chronology for each country in our sample.

In addition to reporting results of the probit estimation we include a matrix of model hits and misses for each of the three specifications (see Table 2.4). The matrix reports how close the model comes to being able to predict actual recessions and expansions. The matrices are generated using a 50% threshold criterion. If the predicted probability is less than 50%, the model signals an expansion since an expansion is a more likely outcome than a recession. If the probability is above 50%, a recession is more likely.

Finally, Figure 2.6 serves as a graphical representation of the effectiveness of our model in capturing business cycle chronology reported by NBER.

2.5 Empirical Methodology

The goal of this study is to quantify the dependence of credit ratings transition probabilities on a specific set of obligor characteristics, focusing on idiosyncratic and systematic sources of risk. To do so, we define a model relating obligor credit ratings at time $t+1$, to issuer characteristics and the state of the economy during the previous time period, t. The model is specified as follows

$$\text{Rating}_{t+1} = f(\text{Domicile}_{i,t}, \text{Industry}_{j,t}, CDR_t, CLR_t) + \varepsilon_{t+1}, \tag{2.8}$$

where *Rating* takes on one of eight possible credit rating values at time $t+1$; *Domicile* is a dummy variable indicating obligor's home country i, where $i \in$ {U.S., U.K., Japan, MLow Income; all other countries are included in the reference category}; *Industry* is a dummy variable indicating an obligor's main sector of activity j, $j \in$ {Banking, Industrial, Public Utilities, Transportation, Sovereign; all other industries are included in the reference category}; CDR and CLR indicate the state of the economy at time t; and ε is the error term.

A common approach to estimating the dynamic properties of credit ratings migrations is based on the assumption that, for a given sample, the probability of a transition from credit rating p to credit rating q is a constant parameter λ_{pq}. Specifically, for a given initial rating, transitions to different possible future ratings can be estimated by taking the fraction of occasions in the sample (or sub-sample) for which an obligor starts the year in state p and ends it in q (see Nickell et al. 2000). While this approach is useful in providing a general idea of credit migration trends, it has limited predictive ability when the sample is small, making it difficult to generate inferences about rating transitions for very specific sub-samples.

To correct for the disadvantages associated with this simple approach we estimate Eq.(2.8) using a discrete choice model. Specifically, we implement an ordered probit estimation technique described in Long (1997), which allows us to partially pool information from different sub-samples and calculate fitted transition probability matrices for specific obligor categories, without sacrificing predictive ability. The econometric approach used here closely follows the methodology of Nickell et al. (2000) and is executed as follows.

Consider the sub-sample of obligor ratings which are observed at times t and $t+1$. Assume that the initial ratings at t are identical but that at $t+1$ a given issuer may be in any one of N different terminal states (eight in our model specification), with one $Default$ rating category and $N-1$ non-default ratings categories. An obligor's credit rating at time $t+1$ is determined by observed and unobserved events, where we define the unobserved events as Y^*_{t+1}. We model the realization of Y^*_{t+1} as

$$Y^*_{t+1} = \beta' X_t + \varepsilon_{t+1}, \tag{2.9}$$

where t is the time subscript, X is a vector of firm characteristics and states of the economy; β is a vector of parameters to be estimated; and ε denotes the error term, where errors are assumed to be independent and, consistent with financial empirical literature, follow a standard normal distribution.

While can not be directly observed, given $k_1, \ldots, k_{N-1}$ cutoff points for possible rating categories, it is related to the observed firm rating, Y_{t+1}, as follows

$$\begin{array}{lcr}
Y_{t+1} = N & \text{if} & k_{N-1} < Y^*_{t+1}, \\
Y_{t+1} = N-1 & \text{if} & k_{N-2} < Y^*_{t+1} \leq k_{N-2}, \\
\vdots & \vdots & \vdots \\
Y_{t+1} = 1 & \text{if} & Y^*_{t+1} \leq k_1.
\end{array} \tag{2.10}$$

Estimating the parameters of the ordered probit model in Eq.(2.10) by maximum likelihood, we obtain the probability of a firm falling into each rating category

$$\begin{aligned}
Pr\{Y_{t+1} = 1\} &= \Phi(k_1 - \beta' X_t), \\
Pr\{Y_{t+1} = 2\} &= \Phi(k_2 - \beta' X_t) - \Phi(k_1 - \beta' X_t), \\
\vdots \quad & \quad \vdots \\
Pr\{Y_{t+1} = N\} &= 1 - \Phi(k_{N-1} - \beta' X_t),
\end{aligned} \tag{2.11}$$

where $\Phi[\cdot]$ is the cumulative distribution function of the standard normal distribution. Figure 2.7 provides a visual representation between the latent and coded credit rating variables characterized above.

2.6 Empirical Results

Results of our empirical estimation are presented in Table 2.5a. Due to the increasing nature of the ordered classes, the interpretation of this model's parameters is as follows. If the coefficient β_m, $m = 1, \ldots, M$, is significantly positive, we infer that an increase in x_m increases the probability of a firm's migration from a particular rating category to another. In other words, the parameter estimate β_m indicates the *sign* and *significance* of the effect of variable x_m on the probability of an issuer receiving a particular rating. For some subsamples of a particular initial rating, the sample did not contain any observations (i.e., there were no issuers from Lower-Middle Income countries, MLow Income, that Moody's rated *Aaa*), these are indicated by a dash.

As is characteristic of a point-in-time model, the variance of the unobserved variable Y^* is not constant. As we add more observations, our estimation of the probability that Y^* will take on a specific value will continuously improve, resulting in greater variability of the estimates, Williams (2005). Therefore, in order to be able to accurately compare coefficients across model specifications, for each parameter β_m we compute Y-standardized coefficients.

Following Yasar et al. (2007), let σ_Y be the unconditional standard deviation of our realized variable Y. We define the Y-standardized coefficient for x_m as

$$\beta_m^{SY} = \frac{\beta_m}{\sigma_Y}. \tag{2.12}$$

The new coefficient β_m^{SY} indicates that for a unit increase in x_m, holding other variables constant, Y is expected to increase by β_m^{SY} standard deviations.

The parameter estimates presented in Tables 2.5a and 2.5b provide some insight into the impact of obligor characteristics on the dynamics of credit ratings migrations by allowing us to compare a large number of obligor categories. As discussed previously, estimated coefficients illustrate the significance and direction of the relationship between the dependent and independent variables. The magnitude of this relationship is quantified in the Y-standardized coefficients.

In Table 2.5a, β is the parameter estimate, with corresponding standard errors presented in brackets underneath and asterisks indicating statistical significance at 10%, 5%, and 1% significance levels. Table 2.5b reports β^{SY}, the Y-standardized coefficients for each independent variable in the model.

Lower part of Table 2.5a lists monotonically increasing cutoff points $k_1, \ldots, k_{N-1}$, that determine our rating transitions. For some sub-samples of a particular initial rating the sample did not contain enough observations to identify the cutoff point parameters, these are indicated by a dash.

2.6.1 Transition Matrices

Using the model estimation results, we compute rating transitions probabilities matrices for different business cycle stages. Specifically, we compute three distinct types of matrices, based on economic expansion, a mild, and severe economic recessions. Here, a mild recession is computed according to average values of CDR and CLR variables for each domicile in our sub-sample, while a matrix consistent with a severe economic recession is calculated based on maximal CDR and CLR values.

2.6.1.1 Comparison Across Domiciles

Fitted one-year transition matrices implied by out model for obligors domiciled in the U.S., U.K., Japan ad Lower-Middle Income countries are presented in Tables 2.6a - 2.6c. Table 2.6a produces results consistent with an economic expansion, Table 2.6b shows effects of a mild recession, and Table 2.6c gives transitions probabilities matrices consistent with a severe economic recession.

From Table 2.6a we can see that during an economic expansion, Japan has the least, and Lower-Middle Income countries greatest, instances of default. Furthermore, the probability that an issuer in any rating category will experience an upgrade is highest for Japanese firms. The probability of an issuer retaining its current credit rating in the following period is highest for U.S. domiciled obligors. There are no *Aaa* rated obligors in Lower-Middle Income countries group but, compared to other domiciles, they have the greatest probability of experiencing a downgrade for all other rating categories, for example, 9.22% for *Aa* firms as compared to 5.87% for U.S. obligors and 6.79% and 7.62% for firms domiciled in the U.K. and Japan respectively.

Compared to an expansion, dynamics of obligor credit ratings change only slightly during a mild recession, Table 2.6b. On average, downgrade probabilities increase for all domiciles and across all rating categories; although frequency of default does not changed significantly. Japan still has the least, and Lower-Middle Income countries the greatest, frequency of default. The probability that an issuer in any rating category will experience an upgrade is still the highest for Japanese firms. The probability of an issuer retaining its current credit rating in the following period is highest for U.S. domiciled obligors. Compared to other domiciles, Lower-Middle Income countries have the greatest probability of experiencing a downgrade for all observed rating categories.

In contrast to a mild economic recession, a severe recession leads to significant changes in the dynamics of credit ratings migrations, Table 2.6c. The dramatic differences between matrices presented in Table 2.6c and those shown in Tables 2.5 and 2.6 vividly illustrate the effect of macroeconomic conditions on firm creditworthiness. Specifically, firms are less likely to retain their current rating during a severe recession than they are during a mild one, or an economic expansion. At the same time, firms are much more likely to remain in default at $t+1$, given they were in a $Default$ rating during the previous time period t. Here, changes in transitions probabilities are most noticeable for investment-grade bonds and are much more subtle for speculative-grade bonds. The dynamics of credit ratings of Lower-Middle Income group of countries during a severe recession is of particular interest. While performance of firms with investment-grade credit ratings declines considerably, we observe little change in performance of speculative-grade bonds, which actually demonstrate greater potential for an upgrade than during either expansion or a mild recession. A possible explanation for this phenomenon could be an increased flow of international aid and loan forgiveness, which is common for developing nations to receive in times of economic distress.

The differences in credit rating migrations across domiciles and stages of the business cycle are dramatic. Results presented here serve as a vivid example of the importance of both idiosyncratic and systematic risk factors in accurate estimation of risk and its application in modern finance.

2.6.1.2 Comparison Across U.S. Industries

Tables 2.7a, 2.7b, 2.7c show model-implied, one-year transition probabilities matrices for issuers domiciled in the U.S. Table 2.7a produces results of an economic expansion; Table 2.7b shows implications of a mild economic recession; and Table 2.7c illustrates ratings dynamics during with a severe economic recession.

We observe that during an economic expansion, Table 2.7a, issuers active in the Transportation sector are much more likely to default than issuers in other sectors, and have the highest probability of retaining their current credit rating in the following time period. Examining direction of movements for the three sectors, we see that, compared to other sectors, Banks are more likely to experience an upgrade in their credit rating, while issuers in the Industrial and Transportation sectors are more likely to have their rating revised down.

Results presented in Table 2.7b, illustrating a mild economic recession, are similar to transitions probabilities matrices estimated during an economic expansion. We observe marginally increased instances of default and downgrade probabilities. These results are consistent with previous empirical literature establishing counter-cyclicality of corporate bond defaults and pro-cyclicality of recovery rates on those bonds (Cheng and Kitsul 2008).

Comparing credit migration probabilities across industries we note that issuers in the Transportation sector have the highest probability of retaining their credit rating in the following time period. They are also most likely to default for sub-investment grade categories. Issuers in the Industrial sector are least likely to remain in Default, 60.39% as compared to 90.16% and 89.82% for Banks and Transportation firms. Banks are least likely to default for all ratings categories, although they are also unlikely to exit default once in dire financial situation. Comparing up- and down-ward rating migration movements for the three sectors we observe that Banks are much more likely to experience an upgrade in credit rating for all categories, with the exception of Aaa, while Industrial and Transportation are more likely to experience a downgrade. Also, it is noteworthy to observe that Banks rated Aaa are more likely to experience a downgrade than Banks currently holding a Caa rating are to default on their financial obligations.

Table 2.7c presents transition probabilities for U.S. Banking, Industrial and Transportation sectors when economy is experiencing a severe recession. We observe that Aaa rated firms are most susceptible to credit rating downgrades during severe economic downturns. On average, probability of default and downgrade increases across all economic sectors. Comparing credit migration probabilities across industries we note that issuers in the Industrial sector are most affected by economic recessions. Specifically, we observe that the probability that an Industrial firm will retain its $Default$ rating during a recession increases by 8% compared to an economic expansion, while Banks and Transportation firms will experience approximately a 3% increase in probability of retaining a default rating.

Results presented here further demonstrate the importance of precise estimation of economic fluctuations by illustrating that business cycles affect ratings dynamics not only across domiciles, but also across industries within a particular country.

2.6.2 Extending Model Horizon

When modeling credit risk, it is of use to be aware of default probabilities for specific obligor characteristics over different time horizons. Figures 2.8a - 2.8c show default probabilities for obligors of different initial ratings grouped by Domicile and Industry over one-, three-, and five-year horizons. Following Galbraith and Tkacz (2007), we expect predictive power of macroeconomic variables to decline with increased length of time-horizon, thus default probabilities presented here are not conditioned on business cycle effects.

We observe significant differences in obligor default probabilities across industries and domiciles. Specifically, compared to High Income countries, Lower-Middle Income countries tend to default with greater probability for all industries and across time horizons. When it comes to specific industries, obligors active in the Transportation sector are prone to experience greater instances of default than Banks or Industrials.

In general, over longer horizons, issuers in the Lower-Middle Income category behave similarly to obligors domiciled in High Income countries. Results suggest a common trend across countries where the length of time during which an issuer received a rating is directly related to the probability of default for non-*Caa* credit ratings. That is, the probability of default increases with each additional year during which a firm receives a rating from a CRA. When it comes to *Caa* credit rating category, the probability of default increases during the first three years of the issuer's rating period, it declines thereafter indicating that currently insolvent firms that have been in business longer, have greater associated likelihoods of meeting their financial obligations. Essentially there appears to be some sort of a reversion to the mean, where probability of default increases with time for investment-grade obligors and declines with time for speculative-grade obligors.

We aggregate rating migration probabilities across countries in the sub-sample to generate average defaults over one-, three-, and five year horizons, presented in Figure 2.9. Generally, total default for non-*Caa* rated obligors increases as the time-horizon increases, which is consistent with Altman (1998), who found that newly rated firms are less likely to default as compared with older, more seasoned firms of the same rating class. Our results also support the research of Figlewski et al. (2006), who demonstrate that the length of time since a firm's first rating is positively correlated with the likelihood of obligor default, referred to as the "aging effect."

2.6.2.1 Two-Year Horizon

Having established the sensitivity of issuer default to the length of time-horizon, we consider time-dependence of the dynamics of credit ratings transitions probabilities. Assuming that it takes longer than one period for the economy to adjust to business cycle fluctuations, we specify the following model

$$\text{Rating}_{t+2} = f(\text{Domicile}_{i,t}, \text{Industry}_{j,t}, CDR_t, CLR_t) + \varepsilon_{t+2}, \tag{2.13}$$

where *Rating* takes on one of nine possible credit rating values at time $t+2$; *Domicile* is a dummy variable indicating an obligor's home country i, where $i = 1, \ldots, I$; *Industry* is a dummy variable indicating an obligor's main industry of activity j, $j = 1, \ldots, J$; CDR and CLR indicate state of the economy at time t; and ε is the error term.

Model in Eq.(2.13) is estimated using the ordered probit methodology described in Section 5, with estimation results presented in Tables 2.8a and 2.8b. As discussed previously, estimated coefficients of explanatory variables illustrate the significance and direction of the relationship between the dependent and independent variables. Lower part of Table 2.8a lists monotonically increasing cutoff points $k_1, \ldots, k_{N-1}$, that determine our rating transitions. For some sub-samples of a particular initial rating the sample did not contain enough observations to identify the cutoff point parameters, these are indicated by a dash. The magnitude of this relationship is quantified in the Y-standardized coefficients, Table 2.8b.

Results confirm that statistical significance of economic variables, CDR and CLR, increases as the time horizon increases, suggesting that adjustment of credit ratings to states of economy is slow. To quantify the effect of macroeconomic variables on credit rating migrations we compute a forecast content for the business cycle effect.

2.6.2.2 Business Cycle Effect - Content Horizon

Galbraith and Tkacz (2007), demonstrate that the information content associated with conditioning models on macroeconomic variables tends to decline as the forecast horizon increases. We define a content horizon as the maximum horizon beyond which forecasts conditional on the macroeconomic variable are not significantly different from the unconditional forecasts. In this section, we estimate the content horizon for our CDR indicator variable, characterizing the pattern of decay of the influence of our macroeconomic variable of interest on credit ratings as we project farther into the future. That is, we model the rate at which the effect of current economic activity on credit migration diminishes over time.

To model the CDR content horizon we consider two matrices, **A** and **B**, where **A** is a matrix conditional on current economic activity, as measured by CDR, and **B** is an unconditional matrix of rating transition probabilities. We generate our matrices using the ordered probit model described in Section 4. That is, matrices **A** and **B** are defined by estimating the following two equations

$$\text{Rating}_{t+1} = f(\text{Domicile}_{i,t}, \text{Industry}_{j,t}, CDR_t) + \varepsilon_{t+1}, \tag{2.14}$$

and

$$\text{Rating}_{t+1} = f(\text{Domicile}_{i,t}, \text{Industry}_{j,t}) + \varepsilon_{t+1}, \tag{2.15}$$

where $Rating$ takes on one of nine possible credit rating values at time $t+1,\ldots,t+N$; $Domicile$ is a dummy variable indicating an obligor's home country i, where $i = 1,\ldots,I$; $Industry$ is a dummy variable indicating an obligor's main industry of activity j, $j = 1,\ldots,J$; CDR indicates the state of the economy at time t; and ε is the error term.

As mentioned previously, we define a content horizon as the additional predictive ability resulting from conditioning the model on macroeconomic variables representing business cycle effects. Mathematically, the concept of forecast content is formulated using probability theory. Suppose we have some variable y such that $Pr[y \geq c] = E[I\{y \geq c\}]$, where I is an indicator variable and c is some threshold value. If x and y are independent, then

$E[y|x] = E[y]$.

Applying above to our model we have

$$E[I\{Rating_{t+n} \geq c\}|CDR_t] = E[I\{Rating_{t+n} \geq c\}]. \tag{2.16}$$

Empirically, the forecast content is calculated by defining transition probability matrices for each equation for the two model specifications presented in Eq.(2.16). We then normalize the difference between each element of the resulting matrices using the Euclidean norm such that

$$\|\mathbf{C}\| = \|\mathbf{A} - \mathbf{B}\|_p = (\sum_{i=1}^{m}\sum_{j=1}^{n}|a_{ij} - b_{ij}|^p)^{\frac{1}{p}}, \tag{2.17}$$

where a_{ij} is ij^{th} element of the conditional matrix $\mathbf{A}$; b_{ij} is ij^{th} element of the unconditional matrix $\mathbf{B}$; and $p = 2$.

Estimated forecast content of economic fluctuations for U.S. obligors is presented in Figure 2.10 and is limited to seven consecutive years. We observe that the difference between the two model specifications is approaching zero as time horizon increases, signaling a decline in the effect of current economic activity on future credit rating of an obligor. Our analysis shows that business cycle effect peaks during the second period, that is, at $t + 2$, which implies that fluctuations in real economic activity have a lasting impact on long-term bond issuers.

2.7 Conclusions and Extensions

Credit ratings play an important role in the field of risk management by serving as an overall assessment of the solvency and prospects of a debt issuer. This paper focuses on understanding dynamic behavior of credit ratings, accurate modeling of which has become increasingly important in the field of modern risk management, especially so in light of the revised framework for capital measurement and capital standards, BCBS (2004), known as Basel II.

Using a continuous-record model and a sample of 121,776 rating transitions available through Moody's Default Risk Service database over the 1970-2007 time period, we verify the importance, and quantify the incremental impact of idiosyncratic and systematic factors on credit rating migrations of long-term bond issuers. Our results confirm that obligor characteristics and business cycle stages have a strong effect on credit rating migration, with a stronger effect observed in longer-horizon models. We further show the importance of business cycle effect on credit ratings by computing the forecast content for the business cycle variable in our model. Finally, we derive implicit country premium for domiciles represented in Moody's DRS database, further emphasizing the importance of idiosyncratic risk factors to precise risk estimation.

While this work represents a comprehensive study of the behavior of credit ratings, improvements can still be made to better understand the dynamics of ratings migration across different obligor types. Recent empirical studies emphasize the superiority of continuous-time Markov chain approach over the discreet-time models. Consistent with this trend, it would be of use to quantify issuer heterogeneity and business cycle effects within a Bayesian framework. Furthermore, improvements can be made in regards to increasing the accuracy of modeling business cycle chronologies for domiciles of rated obligors.

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Table 2.1: Unconditional Transition Matrices

Panel A: Moody's ratings 1970-2007

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**93.10%**	6.35%	0.55%	0.00%	0.00%	0.00%	0.00%	0.00%
Aa	1.38%	**91.91%**	6.45%	0.18%	0.04%	0.01%	0.00%	0.01%
A	0.07%	2.88%	**91.76%**	4.80%	0.36%	0.09%	0.02%	0.02%
Baa	0.05%	0.23%	5.21%	**89.20%**	4.34%	0.68%	0.16%	0.14%
Ba	0.01%	0.05%	0.39%	6.15%	**83.78%**	8.20%	0.74%	0.68%
B	0.01%	0.05%	0.20%	0.43%	6.16%	**82.94%**	6.40%	3.82%
Caa	0.00%	0.00%	0.08%	0.23%	0.80%	11.58%	**74.86%**	12.46%
Default	0.00%	0.08%	0.00%	0.25%	1.16%	9.43%	17.70%	**71.38%**

Panel B: Previous Studies

Kadam and Lenk (2008)	*Aaa*	*Aa*	*A*	*Baa*	*Ba*	*B*	*C*	*Default*
Aaa	**90.15%**	6.76%	0.88%	0.02%	0.00%	0.00%	0.00%	0.00%
Aa	0.52%	**89.55%**	6.54%	0.26%	0.04%	0.04%	0.00%	0.00%
A	0.04%	2.65%	**90.19%**	3.92%	0.26%	0.05%	0.00%	0.00%
Baa	0.05%	0.60%	6.88%	**83.65%**	4.31%	0.44%	0.06%	0.03%
Ba	0.01%	0.28%	1.98%	8.95%	**74.98%**	7.45%	0.95%	0.15%
B	0.03%	0.06%	0.35%	2.38%	10.78%	**67.62%**	10.29%	1.56%
C	0.01%	0.00%	0.05%	0.81%	1.42%	5.32%	**72.44%**	13.71%
Default	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**100.00%**

Carty (2003)	*Aaa*	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa-C*	*Default*
Aaa	**92.18%**	6.51%	1.04%	0.25%	0.02%	0.00%	0.00%	0.00%
Aa	1.29%	**91.62%**	6.11%	0.70%	0.18%	0.03%	0.00%	0.07%
A	0.08%	2.50%	**91.36%**	5.11%	0.69%	0.11%	0.02%	0.14%
Baa	0.04%	0.27%	4.22%	**89.16%**	5.25%	0.68%	0.07%	0.31%
Ba	0.02%	0.09%	0.44%	5.11%	**87.08%**	5.57%	0.46%	1.25%
B	0.00%	0.04%	0.14%	0.69%	6.52%	**85.20%**	3.54%	3.87%
Caa-C	0.00%	0.02%	0.04%	0.37%	1.45%	6.00%	**78.30%**	13.81%

Bangia et al. (2002)	*Aaa*	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**91.93%**	7.46%	0.48%	0.08%	0.04%	...	...	...
Aa	0.64%	**91.81%**	6.75%	0.10%	0.06%	0.12%	0.03%	...
A	0.07%	2.27%	**91.69%**	5.11%	0.56%	0.25%	0.01%	0.04%
Baa	0.04%	0.27%	5.56%	**87.88%**	4.83%	1.02%	0.17%	0.24%
Ba	0.04%	0.10%	0.61%	7.75%	**81.48%**	7.89%	1.11%	1.01%
B	...	0.10%	0.28%	0.46%	6.95%	**82.80%**	3.96%	5.45%
Caa	0.19%	...	0.37%	0.75%	2.43%	12.13%	**60.45%**	23.69%

Sources: Carty (2003), discrete-time model, Moody's ratings for 1920-1996 time period; Bangia et al. (2002), discrete-time model, S&P's ratings for 1981-1998 time period; Kadam and Lenk (2008), continuous-time model, Moody's ratings for 1970-2005 time period.

Data for results in Panel A are long-term unsecured bond ratings between 1970 and 2007, measured on December 31^{st} of each year.

Table 2.2: Model Implied Domicile Statistics

Panel A: High Income Countries included in Model Specification

	Number of Observations	1970 GNI per capita ($)	2006 GNI per capita ($)
United States	84,517	5,000	44,970
United Kingdom	7,152	...	40,180
Japan	4,254	1,920	38,410

Panel B: Lower-Middle Income Countries included in Model Specification

	Number of Observations	1970 GNI per capita ($)	2006 GNI per capita ($)
Azerbaijan	1	...	1,850
Bolivia	13	300	1,100
Bosnia and Herzegovina	1	...	2,980
China	262	120	2,010
Colombia	93	...	2,740
Dominican Republic	11	...	2,850
Ecuador	13	310	2,840
Egypt	10	210	1,350
El Salvador	10	320	2,540
Fiji	9	400	3,300
Georgia	1	...	1,560
Guatemala	19	...	2,640
Honduras	15	270	1,200
Indonesia	209	80	1,420
Iran	3	370	3,000
Jordan	10	...	2,660
Marshall Islands	2	...	3,000
Micronesia	14	...	2,380
Moldova	7	...	1,100
Morocco	10	270	1,900
Nicaragua	10	330	1,000
Peru	19	520	2,920
Philippines	122	230	1,420
Thailand	146	210	2,990
Tunisia	13	270	2,970
Ukraine	59	...	1,950
	Total: 1,082	Average: 281	Average: 2,218

Classification consistent with World Bank. Economies are divided according to 2006 GNI per capita, calculated using the World Bank Atlas method. The groups are: low income, $905 or less; lower middle income, $906-$3,595; upper middle income, $3,596-$11,115; and high income, $11,116 or more.

Table 2.3: Estimation Results for the probit Model

	Specification 1	*Specification 2*	*Specification 3*
Constant	-0.918	-0.553	-0.378
	(0.328)***	(0.200)***	(0.396)
$Short_{t-1}$	0.085	...	-0.342
	(0.318)		(0.386)
$Short_{t-2}$	0.702	...	1.182
	(0.525)		(0.656)*
$Short_{t-3}$	-0.589	...	-0.881
	(0.523)		(0.675)
$Short_{t-4}$	-0.270	...	-0.016
	(0.333)		(0.419)
$Spread_{t-1}$	...	0.144	0.285
		(0.276)	(0.322)
$Spread_{t-2}$	...	-0.604	-0.785
		(0.402)	(0.473)*
$Spread_{t-3}$	...	0.067	0.155
		(0.347)	(0.396)
$Spread_{t-4}$	...	-0.241	-0.221
		(0.250)	(0.270)
CDR_{t-1}	0.055	0.040	0.045
	(0.014)***	(0.012)***	(0.014)***
CLR_{t-1}	-0.200	-0.145	-0.106
	(0.168)	(0.187)	(0.182)
Observations	215	215	215

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 2.4: Forecasting Hits and Misses

Panel A: Specification 1

		Predicted		
		Ut=0	Ut=1	*Total*
Actual	Ut=0	168	3	171
	Ut=1	23	21	44
	Total	191	24	215

Panel B: Specification 2

		Predicted		
		Ut=0	Ut=1	*Total*
Actual	Ut=0	167	4	171
	Ut=1	21	23	44
	Total	188	27	215

Panel C: Specification 3

		Predicted		
		Ut=0	Ut=1	*Total*
Actual	Ut=0	168	2	171
	Ut=1	18	26	44
	Total	186	29	215

Table 2.5a: One-year Horizon Model, Raw Coefficients, $\hat{\beta}$

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
United States	-0.053	0.043	0.042	0.093	0.054	0.000	0.047	-0.300
	(-0.077)	(-0.038)	(-0.029)	(0.033)***	-0.039)	(-0.038)	(-0.078)	(0.145)**
United Kingdom	0.081	0.119	-0.004	0.02	0.061	0.025	0.221	0.149
	(-0.116)	(0.054)**	(-0.044)	(-0.055)	(-0.078)	(-0.078)	(-0.169)	(-0.306)
Japan	0.287	0.182	-0.035	-0.041	-0.243	-0.469	0.039	7.174
	(0.144)**	(0.078)**	(-0.056)	(-0.056)	(0.077)***	(0.137)***	(-0.731)	(-1800091)
MLow Income	...	0.290	1.099	0.566	0.429	0.237	0.448	0.450
		(-0.352)	(0.166)***	(0.120)***	(0.093)***	(0.112)**	(0.189)**	(-0.340)
Banking	0.252	-0.029	-0.245	-0.445	-0.257	-0.555	-0.388	0.548
	(0.107)**	(-0.047)	(0.038)***	(0.052)***	(0.073)***	(0.096)***	(-0.263)	(0.289)*
Industrial	0.077	0.161	0.198	0.187	0.194	0.079	0.082	-0.480
	(-0.104)	(0.046)***	(0.032)***	(0.036)***	(0.045)***	(-0.061)	(-0.130)	(0.169)***
Public Utilities	0.032	0.216	0.055	0.031	-0.236	-0.544	-0.482	-0.239
	(-0.124)	(0.054)***	(-0.037)	(-0.040)	(0.056)***	(0.093)***	(0.201)**	(-0.268)
Transportation	-0.199	0.078	0.068	-0.007	0.090	0.13	0.173	0.528
	(-0.252)	(-0.092)	(-0.058)	(-0.054)	(-0.071)	(-0.086)	(-0.159)	(0.189)***
Sovereign	-0.532	-0.554	-0.422	-0.116	0.060	0.135	-0.383	-0.841
	(0.125)***	(0.071)***	(0.074)***	(-0.103)	(-0.108)	(-0.128)	(-0.270)	(0.310)***
CDR	0.012	-0.002	0.000	0.000	0.000	-0.001	0.001	0.002
	(0.002)***	(0.001)*	(-0.001)	(-0.001)	(-0.001)	(-0.001)	(-0.002)	(-0.003)
CLR	0.001	0.109	0.021	-0.042	-0.006	-0.024	0.002	-0.006
	(-0.067)	(0.036)***	(-0.021)	(0.015)***	(-0.011)	(0.010)**	(-0.022)	(-0.049)
k_1	1.522	-2.201	-3.203	-3.257	-3.655	-3.767	...	...
k_2	2.683	1.591	-1.855	-2.707	-3.117	-3.259	...	...
k_3	...	2.909	1.716	-1.489	-2.502	-2.807	-3.091	-3.638
k_4	...	3.293	2.692	1.775	-1.38	-2.468	-2.658	-3.44
k_5	...	3.541	3.114	2.495	1.472	-1.469	-2.192	-2.885
k_6	...	3.709	3.472	2.913	2.365	1.322	-1.033	-1.82
k_7	...	...	3.662	3.15	2.64	1.828	1.274	-1.043
Observations	4550	13499	25271	19768	13134	12701	2606	1176

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 2.5b: One-year Horizon Model, Standardized Coefficients, $\hat{\beta}^{SZ}$

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
United States	-0.050	0.042	0.041	0.092	0.054	0.000	0.047	-0.268
United Kingdom	0.076	0.116	-0.004	0.020	0.060	0.024	0.220	0.133
Japan	0.270	0.178	-0.035	-0.041	-0.240	-0.464	0.039	6.399
MLow Income	...	0.283	1.080	0.558	0.423	0.234	0.445	0.402
Banking	0.237	-0.028	-0.241	-0.439	-0.254	-0.549	-0.385	0.489
Industrial	0.072	0.157	0.195	0.184	0.192	0.078	0.081	-0.428
Public Utilities	0.030	0.212	0.054	0.031	-0.233	-0.538	-0.479	-0.213
Transportation	-0.187	0.076	0.067	-0.007	0.089	0.128	0.172	0.471
Sovereign	-0.501	-0.541	-0.415	-0.115	0.059	0.134	-0.381	-0.750
CDR	0.011	-0.002	0.000	0.000	0.000	-0.001	0.001	0.002
CLR	0.001	0.107	0.021	-0.042	-0.006	-0.024	0.002	-0.006

Table 2.6a: Model-Based Transition Matrices, by Domicile, Expansion

Panel A: United States

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**94.24%**	5.45%	0.31%	...	...	...	...	...
Aa	1.24%	**92.68%**	5.87%	0.15%	0.03%	0.01%	0.01%	...
A	0.06%	2.83%	**92.40%**	4.31%	0.30%	0.08%	0.02%	0.01%
Baa	0.04%	0.21%	5.43%	**89.68%**	3.82%	0.58%	0.13%	0.11%
Ba	0.01%	0.07%	0.45%	7.05%	**84.61%**	6.77%	0.56%	0.49%
B	0.01%	0.05%	0.19%	0.43%	6.41%	**83.60%**	5.93%	3.38%
Caa	...	...	0.09%	0.26%	0.92%	12.73%	**75.01%**	10.99%
Default	...	...	0.04%	0.04%	0.40%	5.95%	16.44%	**77.13%**

Panel B: United Kingdom

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**92.52%**	7.01%	0.46%	...	...	...	...	...
Aa	1.02%	**91.93%**	6.79%	0.19%	0.04%	0.01%	0.02%	...
A	0.07%	3.14%	**92.52%**	3.92%	0.26%	0.07%	0.01%	0.01%
Baa	0.05%	0.27%	6.25%	**89.46%**	3.30%	0.48%	0.10%	0.09%
Ba	0.01%	0.06%	0.44%	6.96%	**84.61%**	6.85%	0.56%	0.50%
B	0.01%	0.04%	0.18%	0.40%	6.13%	**83.51%**	6.15%	3.57%
Caa	...	...	0.05%	0.15%	0.59%	9.69%	**74.90%**	14.62%
Default	...	...	0.01%	0.01%	0.10%	2.33%	9.21%	**88.34%**

Panel C: Japan

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**89.17%**	10.00%	0.83%	...	...	...	...	...
Aa	0.86%	**91.20%**	7.62%	0.23%	0.05%	0.02%	0.02%	...
A	0.08%	3.36%	**92.56%**	3.68%	0.24%	0.06%	0.01%	0.01%
Baa	0.07%	0.32%	7.01%	**89.14%**	2.91%	0.40%	0.09%	0.07%
Ba	0.03%	0.17%	0.99%	11.58%	**82.90%**	3.86%	0.26%	0.20%
B	0.05%	0.21%	0.71%	1.31%	13.57%	**80.48%**	2.58%	1.08%
Caa	...	...	0.09%	0.26%	0.94%	12.89%	**74.98%**	10.84%
Default	...	...	0.00%	0.00%	0.00%	0.00%	0.00%	**100.00%**

Panel D: MLow Income

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	...	...	...	...	...	...	...	...
Aa	0.64%	**89.70%**	9.22%	0.31%	0.08%	0.03%	0.03%	...
A	0.00%	0.16%	**72.98%**	21.30%	3.36%	1.31%	0.36%	0.52%
Baa	0.01%	0.05%	1.94%	**86.66%**	8.66%	1.74%	0.46%	0.49%
Ba	0.00%	0.02%	0.15%	3.36%	**81.64%**	12.20%	1.29%	1.35%
B	0.00%	0.02%	0.09%	0.23%	4.06%	**81.71%**	8.31%	5.58%
Caa	...	...	0.02%	0.07%	0.32%	6.51%	**72.64%**	20.43%
Default	...	...	0.00%	0.00%	0.04%	1.12%	5.61%	**93.23%**

Table 2.6b: Model-Based Transition Matrices, by Domicile, Mild Recession

Panel A: United States

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**93.53%**	6.10%	0.37%	...	...	...	...	...
Aa	1.21%	**92.61%**	5.97%	0.15%	0.04%	0.01%	0.01%	...
A	0.06%	2.81%	**92.39%**	4.33%	0.30%	0.08%	0.02%	0.01%
Baa	0.04%	0.22%	5.50%	**89.67%**	3.77%	0.57%	0.13%	0.11%
Ba	0.01%	0.07%	0.45%	7.04%	**84.61%**	6.77%	0.56%	0.49%
B	0.01%	0.05%	0.20%	0.44%	6.53%	**83.63%**	5.84%	3.31%
Caa	...	...	0.08%	0.25%	0.90%	12.62%	**75.03%**	11.11%
Default	...	...	0.04%	0.04%	0.39%	5.83%	16.26%	**77.44%**

Panel B: United Kingdom

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**91.96%**	7.52%	0.52%	...	...	...	...	...
Aa	0.94%	**91.61%**	7.16%	0.21%	0.05%	0.02%	0.02%	...
A	0.07%	3.09%	**92.50%**	3.97%	0.27%	0.07%	0.01%	0.01%
Baa	0.06%	0.28%	6.41%	**89.40%**	3.21%	0.46%	0.10%	0.08%
Ba	0.01%	0.06%	0.45%	6.97%	**84.61%**	6.84%	0.56%	0.49%
B	0.01%	0.05%	0.19%	0.42%	6.26%	**83.56%**	6.04%	3.48%
Caa	...	...	0.05%	0.15%	0.59%	9.61%	**74.88%**	14.73%
Default	...	...	0.01%	0.01%	0.10%	2.30%	9.13%	**88.45%**

Panel C: Japan

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**87.90%**	11.11%	0.99%	...	...	...	...	...
Aa	0.86%	**91.19%**	7.63%	0.23%	0.05%	0.02%	0.02%	...
A	0.08%	3.35%	**92.56%**	3.69%	0.24%	0.06%	0.01%	0.01%
Baa	0.07%	0.32%	7.07%	**89.11%**	2.88%	0.40%	0.08%	0.07%
Ba	0.03%	0.17%	0.99%	11.57%	**82.91%**	3.87%	0.26%	0.20%
B	0.05%	0.22%	0.72%	1.34%	13.75%	**80.32%**	2.54%	1.06%
Caa	...	...	0.09%	0.26%	0.92%	12.77%	**75.01%**	10.96%
Default	...	...	0.00%	0.00%	0.00%	0.00%	0.00%	**100.00%**

Panel D: MLow Income

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	...	...	...	...	...	...	...	...
Aa	0.32%	**85.41%**	13.42%	0.57%	0.15%	0.06%	0.07%	...
A	0.00%	0.13%	**71.48%**	22.30%	3.65%	1.45%	0.41%	0.59%
Baa	0.01%	0.06%	2.41%	**87.83%**	7.52%	1.43%	0.37%	0.37%
Ba	0.00%	0.02%	0.16%	3.44%	**81.81%**	12.00%	1.26%	1.31%
B	0.00%	0.02%	0.11%	0.26%	4.53%	**82.34%**	7.73%	5.00%
Caa	...	...	0.02%	0.07%	0.31%	6.43%	**72.54%**	20.62%
Default	...	...	0.00%	0.00%	0.04%	1.15%	5.70%	**93.11%**

Table 2.6c: Model-Based Transition Matrices, by Domicile, Severe Recession

Panel A: United States

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**62.24%**	30.71%	7.05%	...	...	...	...	...
Aa	1.20%	**92.55%**	6.04%	0.16%	0.04%	0.01%	0.01%	...
A	0.05%	2.61%	**92.26%**	4.63%	0.33%	0.09%	0.02%	0.02%
Baa	0.05%	0.27%	6.35%	**89.43%**	3.25%	0.47%	0.10%	0.09%
Ba	0.01%	0.06%	0.44%	6.90%	**84.60%**	6.91%	0.57%	0.50%
B	0.02%	0.09%	0.33%	0.68%	8.78%	**83.47%**	4.41%	2.23%
Caa	...	...	0.05%	0.18%	0.66%	10.42%	**75.07%**	13.62%
Default	...	...	0.02%	0.02%	0.21%	3.76%	12.49%	**83.51%**

Panel B: United Kingdom

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**85.56%**	13.12%	1.32%	...	...	...	...	...
Aa	0.48%	**88.10%**	10.83%	0.40%	0.10%	0.04%	0.04%	...
A	0.06%	2.73%	**92.35%**	4.44%	0.31%	0.08%	0.02%	0.02%
Baa	0.08%	0.38%	7.87%	**88.66%**	2.54%	0.34%	0.07%	0.06%
Ba	0.01%	0.07%	0.46%	7.08%	**84.61%**	6.74%	0.55%	0.48%
B	0.01%	0.06%	0.25%	0.54%	7.48%	**83.71%**	5.17%	2.78%
Caa	...	...	0.04%	0.13%	0.53%	9.01%	**74.65%**	15.64%
Default	...	...	0.01%	0.01%	0.09%	2.06%	8.48%	**89.37%**

Panel C: Japan

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**55.13%**	35.00%	9.87%	...	...	...	...	...
Aa	0.77%	**90.69%**	8.18%	0.25%	0.06%	0.02%	0.02%	...
A	0.07%	3.10%	**92.51%**	3.97%	0.26%	0.07%	0.01%	0.01%
Baa	0.09%	0.40%	8.12%	**88.51%**	2.44%	0.32%	0.07%	0.05%
Ba	0.03%	0.17%	0.97%	11.43%	**83.01%**	3.93%	0.26%	0.20%
B	0.09%	0.35%	1.06%	1.84%	16.84%	**77.30%**	1.83%	0.69%
Caa	...	...	0.06%	0.19%	0.71%	10.83%	**75.12%**	13.10%
Default	...	...	0.00%	0.00%	0.00%	0.00%	0.00%	**100.00%**

Panel D: MLow Income

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	...	...	...	...	...	...	...	...
Aa	0.00%	**5.92%**	34.45%	15.19%	9.55%	5.99%	28.91%	...
A	0.00%	0.02%	**51.91%**	32.79%	7.88%	3.84%	1.25%	2.31%
Baa	0.37%	1.28%	16.37%	**81.04%**	0.83%	0.08%	0.01%	0.01%
Ba	0.00%	0.03%	0.23%	4.50%	**83.41%**	9.94%	0.96%	0.93%
B	0.05%	0.21%	0.70%	1.31%	13.54%	**80.51%**	2.59%	1.09%
Caa	...	...	0.01%	0.05%	0.23%	5.29%	**70.76%**	23.65%
Default	...	...	0.00%	0.00%	0.05%	1.30%	6.23%	**92.42%**

Table 2.7a: Model-Based Transition Matrices, United States, Expansion

Panel A: Banking

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**90.71%**	8.64%	0.65%	...	...	...	...	...
Aa	1.34%	**92.92%**	5.55%	0.14%	0.03%	0.01%	0.01%	...
A	0.14%	4.79%	**92.32%**	2.56%	0.14%	0.03%	0.01%	0.01%
Baa	0.18%	0.74%	11.86%	**85.54%**	1.45%	0.17%	0.03%	0.02%
Ba	0.03%	0.15%	0.90%	10.89%	**83.34%**	4.19%	0.29%	0.22%
B	0.07%	0.28%	0.88%	1.57%	15.24%	**78.94%**	2.17%	0.86%
Caa	...	...	0.30%	0.73%	2.18%	21.21%	**70.26%**	5.32%
Default	...	...	0.01%	0.01%	0.08%	1.85%	7.90%	**90.16%**

Panel B: Industrial

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**93.30%**	6.31%	0.39%	...	...	...	...	...
Aa	0.81%	**90.92%**	7.93%	0.24%	0.06%	0.02%	0.02%	...
A	0.03%	1.78%	**91.19%**	6.29%	0.51%	0.14%	0.03%	0.03%
Baa	0.02%	0.12%	3.71%	**89.40%**	5.41%	0.92%	0.22%	0.21%
Ba	0.00%	0.03%	0.26%	4.87%	**83.77%**	9.34%	0.87%	0.84%
B	0.01%	0.04%	0.15%	0.35%	5.54%	**83.23%**	6.67%	4.02%
Caa	...	...	0.06%	0.20%	0.75%	11.24%	**75.14%**	12.60%
Default	...	...	0.21%	0.18%	1.37%	13.16%	24.68%	**60.39%**

Panel C: Transportation

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**96.20%**	3.63%	0.17%	...	...	...	...	...
Aa	1.01%	**91.92%**	6.81%	0.19%	0.04%	0.01%	0.02%	...
A	0.05%	2.42%	**92.11%**	4.93%	0.36%	0.09%	0.02%	0.02%
Baa	0.04%	0.22%	5.50%	**89.67%**	3.77%	0.57%	0.13%	0.11%
Ba	0.01%	0.05%	0.35%	5.97%	**84.42%**	7.89%	0.69%	0.63%
B	0.00%	0.03%	0.13%	0.30%	5.02%	**82.85%**	7.18%	4.48%
Caa	...	...	0.05%	0.15%	0.59%	9.70%	**74.90%**	14.60%
Default	...	...	0.01%	0.01%	0.08%	1.94%	8.15%	**89.82%**

Table 2.7b: Model-Based Transition Matrices, United States, Mild Recession

Panel A: Banking

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**89.69%**	9.54%	0.77%	...	...	...	...	...
Aa	1.31%	**92.85%**	5.64%	0.14%	0.03%	0.01%	0.01%	...
A	0.13%	4.76%	**92.33%**	2.58%	0.15%	0.03%	0.01%	0.01%
Baa	0.19%	0.75%	11.98%	**85.43%**	1.43%	0.16%	0.03%	0.02%
Ba	0.03%	0.15%	0.90%	10.88%	**83.34%**	4.19%	0.29%	0.22%
B	0.07%	0.28%	0.90%	1.61%	15.44%	**78.75%**	2.12%	0.84%
Caa	...	...	0.29%	0.72%	2.16%	21.06%	**70.39%**	5.39%
Default	...	...	0.00%	0.01%	0.07%	1.80%	7.77%	**90.34%**

Panel B: Industrial

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**92.51%**	7.03%	0.47%	...	...	...	...	...
Aa	0.79%	**90.81%**	8.05%	0.25%	0.06%	0.02%	0.02%	...
A	0.03%	1.77%	**91.16%**	6.32%	0.51%	0.14%	0.03%	0.03%
Baa	0.02%	0.12%	3.76%	**89.43%**	5.35%	0.90%	0.21%	0.20%
Ba	0.00%	0.03%	0.26%	4.87%	**83.77%**	9.35%	0.88%	0.84%
B	0.01%	0.04%	0.16%	0.36%	5.64%	**83.29%**	6.57%	3.93%
Caa	...	...	0.06%	0.20%	0.74%	11.13%	**75.14%**	12.73%
Default	...	...	0.21%	0.17%	1.34%	12.96%	24.53%	**60.79%**

Panel C: Transportation

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**95.69%**	4.11%	0.20%	...	...	...	...	...
Aa	0.99%	**91.82%**	6.91%	0.19%	0.05%	0.02%	0.02%	...
A	0.05%	2.40%	**92.09%**	4.96%	0.36%	0.10%	0.02%	0.02%
Baa	0.04%	0.22%	5.58%	**89.65%**	3.72%	0.56%	0.12%	0.11%
Ba	0.01%	0.05%	0.35%	5.97%	**84.41%**	7.89%	0.69%	0.63%
B	0.01%	0.03%	0.14%	0.31%	5.12%	**82.93%**	7.08%	4.38%
Caa	...	...	0.05%	0.15%	0.58%	9.60%	**74.87%**	14.74%
Default	...	...	0.01%	0.01%	0.08%	1.89%	8.02%	**90.00%**

Table 2.7c: Model-Based Transition Matrices, United States, Severe Recession

Panel A: Banking

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**52.37%**	36.50%	11.13%	...	...	...	...	...
Aa	1.29%	**92.80%**	5.71%	0.14%	0.03%	0.01%	0.01%	...
A	0.12%	4.45%	**92.44%**	2.78%	0.16%	0.04%	0.01%	0.01%
Baa	0.24%	0.91%	13.41%	**84.08%**	1.19%	0.13%	0.02%	0.02%
Ba	0.03%	0.15%	0.87%	10.69%	**83.46%**	4.28%	0.30%	0.23%
B	0.12%	0.46%	1.34%	2.25%	19.02%	**74.83%**	1.46%	0.52%
Caa	...	...	0.20%	0.52%	1.66%	18.17%	**72.58%**	6.87%
Default	...	...	0.00%	0.00%	0.03%	1.04%	5.32%	**93.60%**

Panel B: Industrial

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**59.29%**	32.56%	8.15%	...	...	...	...	...
Aa	0.78%	**90.73%**	8.13%	0.25%	0.06%	0.02%	0.02%	...
A	0.03%	1.63%	**90.84%**	6.72%	0.56%	0.16%	0.03%	0.04%
Baa	0.03%	0.16%	4.39%	**89.67%**	4.67%	0.75%	0.17%	0.16%
Ba	0.00%	0.03%	0.25%	4.76%	**83.67%**	9.52%	0.90%	0.87%
B	0.01%	0.07%	0.26%	0.56%	7.69%	**83.70%**	5.03%	2.68%
Caa	...	...	0.04%	0.14%	0.54%	9.11%	**74.69%**	15.48%
Default	...	...	0.10%	0.09%	0.78%	9.21%	20.85%	**68.97%**

Panel C: Transportation

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	**69.53%**	25.74%	4.74%	...	...	...	...	...
Aa	0.97%	**91.76%**	6.99%	0.20%	0.05%	0.02%	0.02%	...
A	0.04%	2.22%	**91.90%**	5.29%	0.40%	0.11%	0.02%	0.02%
Baa	0.06%	0.28%	6.43%	**89.40%**	3.20%	0.46%	0.10%	0.08%
Ba	0.01%	0.05%	0.34%	5.84%	**84.37%**	8.05%	0.71%	0.65%
B	0.01%	0.06%	0.23%	0.49%	7.04%	**83.71%**	5.46%	3.01%
Caa	...	...	0.03%	0.10%	0.42%	7.78%	**73.91%**	17.76%
Default	...	...	0.00%	0.00%	0.04%	1.09%	5.51%	**93.36%**

Table 2.8a: Two-year Horizon Model, Raw Coefficients, $\hat{\beta}$

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
United States	0.023	0.078	0.039	0.115	0.041	0.000	-0.029	-0.142
	(-0.065)	(0.034)**	(-0.026)	(0.030)***	(-0.038)	(-0.039)	(-0.092)	(-0.179)
United Kingdom	0.136	0.151	-0.014	0.065	-0.017	0.017	-0.025	0.405
	(-0.100)	(0.048)***	(-0.039)	(-0.051)	(-0.076)	(-0.081)	(-0.207)	(-0.367)
Japan	0.419	0.245	0.059	-0.028	-0.281	-0.605	0.095	...
	(0.125)***	(0.068)***	(-0.049)	(-0.050)	(0.072)***	(0.134)***	(-1.145)	
MLow Income	...	0.378	1.258	0.649	0.493	0.334	0.777	0.679
		(-0.321)	(0.158)***	(0.111)***	(0.090)***	(0.114)***	(0.216)***	(-0.433)
Banking	0.386	-0.036	-0.194	-0.502	-0.484	-0.452	-0.443	0.755
	(0.095)***	(-0.042)	(0.034)***	(0.048)***	(0.069)***	(0.096)***	(-0.279)	(0.300)**
Industrial	0.204	0.097	0.246	0.261	0.152	0.253	0.183	-0.319
	(0.091)**	(0.041)**	(0.029)***	(0.032)***	(0.042)***	(0.063)***	(-0.141)	(0.188)*
Public Utilities	0.178	0.153	0.097	0.054	-0.385	-0.570	-0.591	-0.362
	(0.105)*	(0.048)***	(0.033)***	(-0.036)	(0.052)***	(0.093)***	(0.210)***	(-0.283)
Transportation	-0.511	-0.701	-0.495	-0.112	-0.044	0.274	-0.587	-0.587
	(0.108)***	(0.062)***	(0.064)***	(-0.093)	(-0.101)	(0.126)**	(0.285)**	(0.334)*
Sovereign	-0.079	0.045	0.088	0.027	0.038	0.298	0.263	0.844
	(-0.210)	(-0.080)	(0.050)*	(-0.048)	(-0.065)	(0.085)***	(-0.168)	(0.206)***
CDR	0.009	-0.002	-0.002	-0.001	0.001	-0.002	0.000	0.004
	(0.002)***	(0.001)*	(0.001)**	(-0.001)	(0.001)*	(-0.001)	(-0.002)	(-0.003)
CLR	0.039	0.090	-0.020	-0.043	-0.021	-0.020	0.009	-0.056
	(-0.054)	(0.033)***	(-0.020)	(0.015)***	(0.011)*	(0.011)*	(-0.023)	(-0.057)
k_1	1.261058	-1.99355	-2.95091	-2.96005	-3.43121	-3.3946	...	...
k_2	2.422296	1.188602	-1.53421	-2.39611	-3.0062	-2.95375	...	...
k_3	3.325148	2.430081	1.392537	-1.0841	-2.30089	-2.49462	-2.78879	-3.27645
k_4	3.389494	2.940009	2.325851	1.52386	-1.10055	-2.00706	-2.23007	-2.83608
k_5	...	3.273004	2.785911	2.199927	1.035368	-0.96537	-1.7482	-2.17189
k_6	...	3.670116	3.176118	2.626812	1.906392	1.1901	-0.60221	-1.20371
k_7	...	3.827298	3.348677	2.92934	2.207645	1.747192	1.159438	-0.48555
Observations	4211	11885	22569	17654	11428	10010	1783	868

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 2.8b: Two-year Horizon Model, Standardized Coefficients, $\hat{\beta}^{SZ}$

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
United States	0.021	0.076	0.038	0.113	0.040	-0.001	-0.029	-0.124
United Kingdom	0.126	0.146	-0.014	0.064	-0.016	0.017	-0.025	0.355
Japan	0.388	0.238	0.058	-0.027	-0.275	-0.595	0.094	...
MLow Income	...	0.366	1.234	0.636	0.482	0.329	0.765	0.595
Banking	0.357	-0.035	-0.190	-0.491	-0.473	-0.444	-0.436	0.662
Industrial	0.189	0.094	0.241	0.256	0.148	0.249	0.181	-0.280
Public Utilities	0.165	0.148	0.095	0.053	-0.377	-0.561	-0.582	-0.318
Transportation	-0.474	-0.680	-0.486	-0.110	-0.043	0.269	-0.578	-0.514
Sovereign	-0.073	0.043	0.086	0.026	0.037	0.293	0.259	0.740
CDR	0.009	-0.002	-0.002	-0.001	0.001	-0.002	0.000	0.003
CLR	0.036	0.088	-0.019	-0.042	-0.020	-0.020	0.009	-0.049

Figure 2.1: Probability Distribution

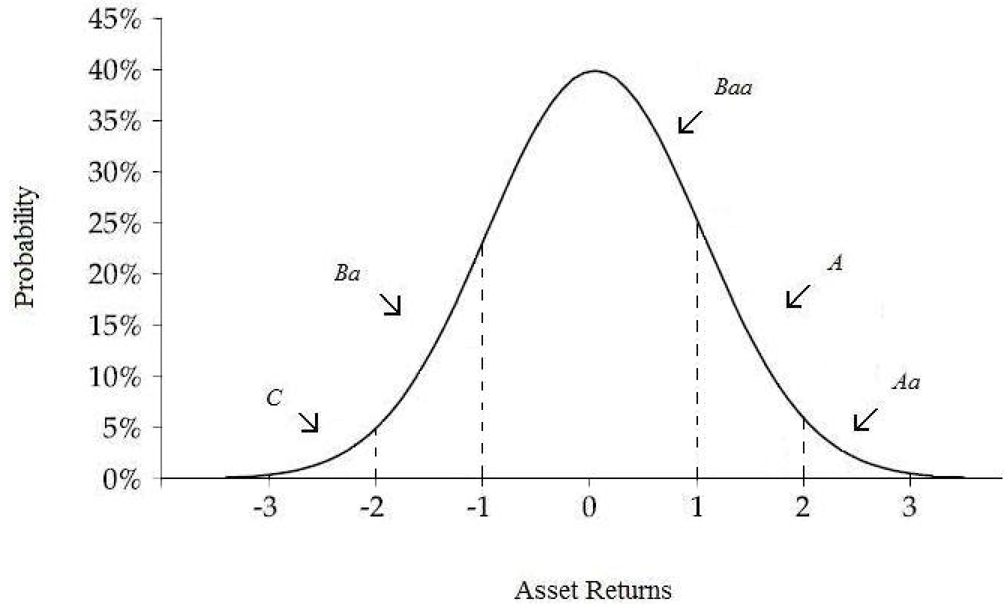


Figure 2.2: Moody's Issuer Domicile Composition, 1970-2007

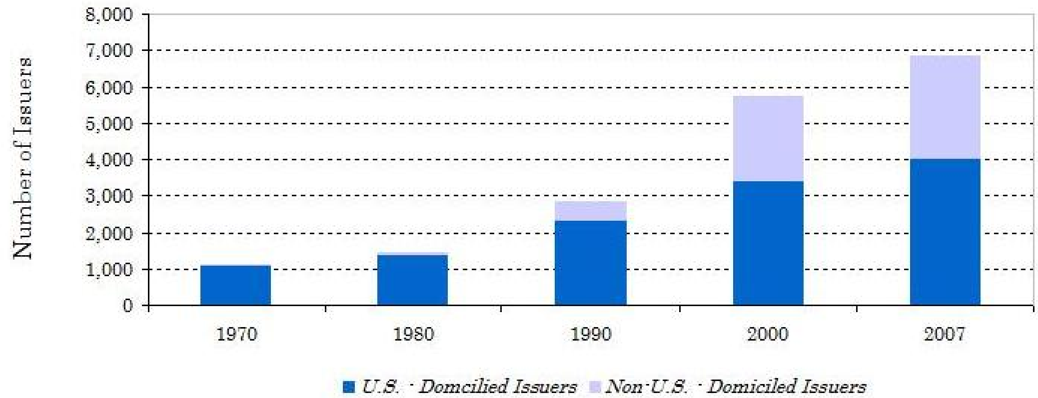


Figure 2.3: Implicit Country Premium

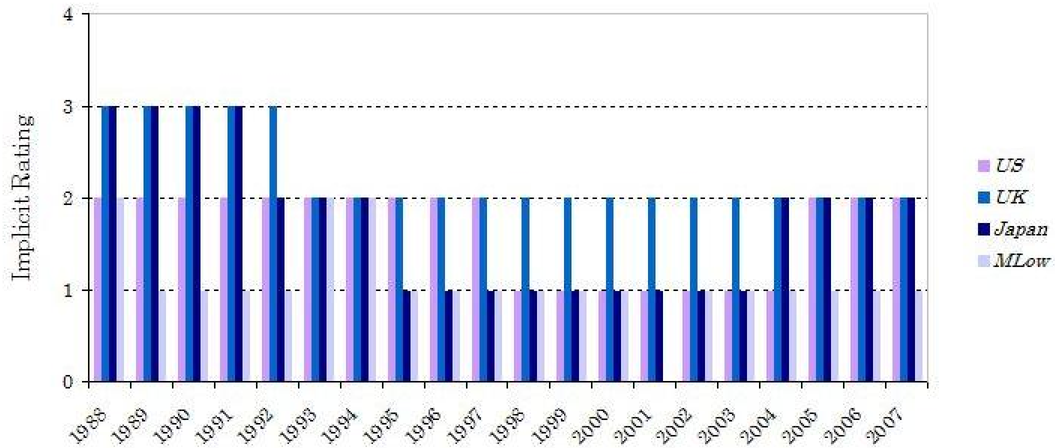


Figure 2.4: Moody's Issuer Industry Composition, 1970-2007

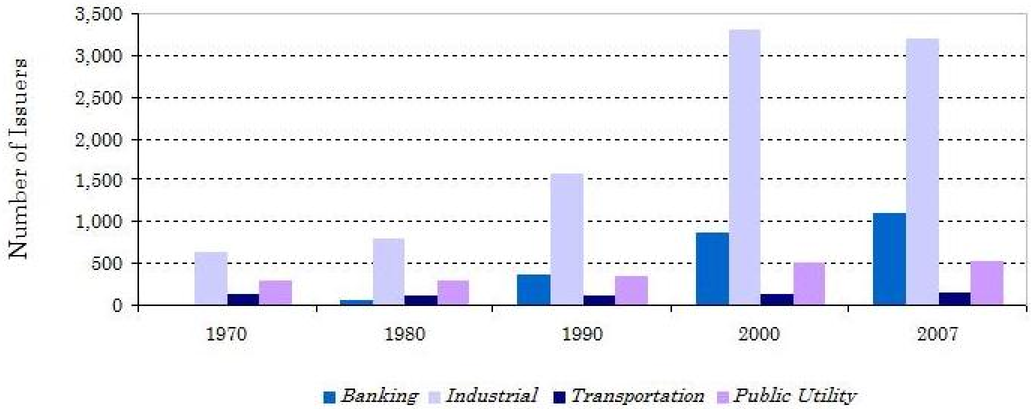


Figure 2.5: U.S. GDP (top panel) **and Current Depth of Recession** (bottom panel)

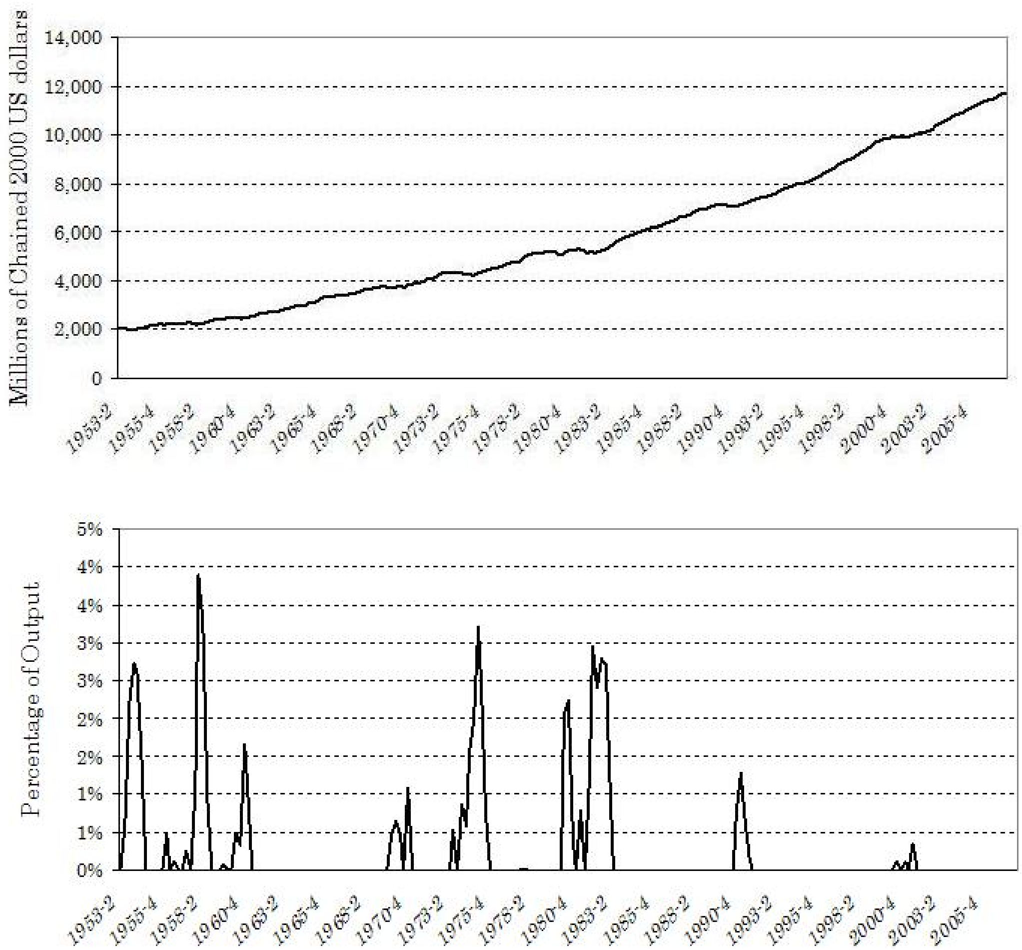


Figure 2.6: Business Cycle Chronology, NBER vs. probit Forecasting Model

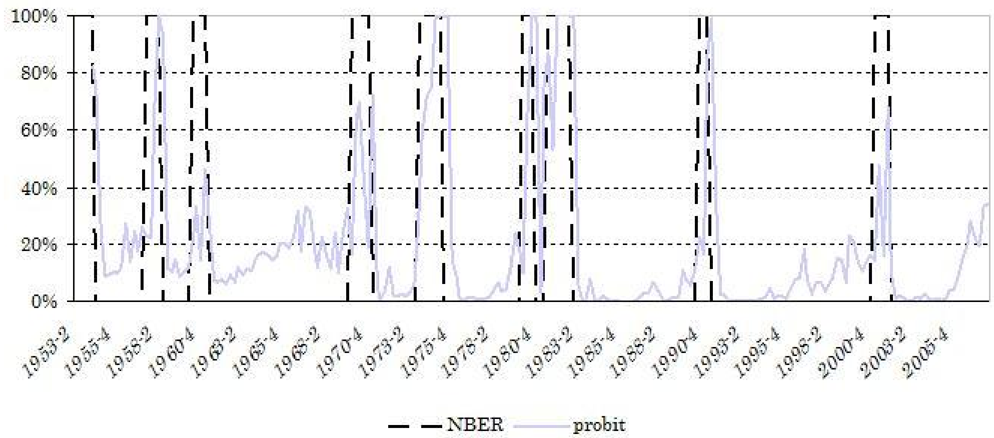


Figure 2.7: Relationship Between Latent and Coded Credit Ratings Variables

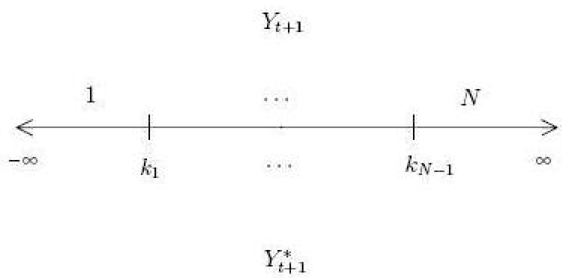
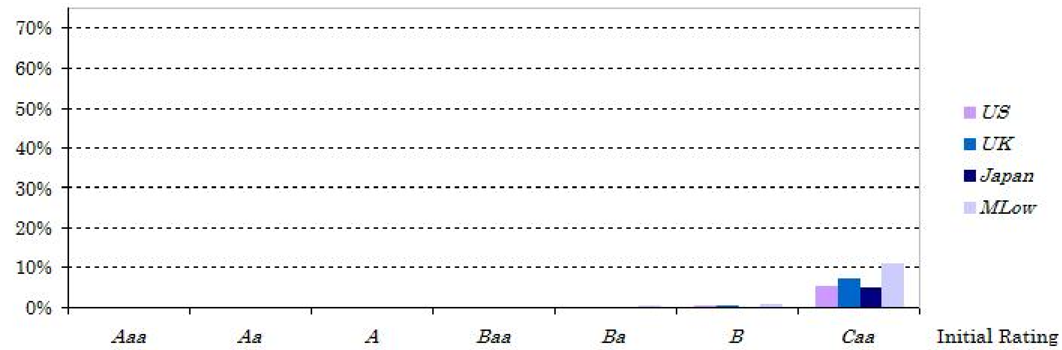
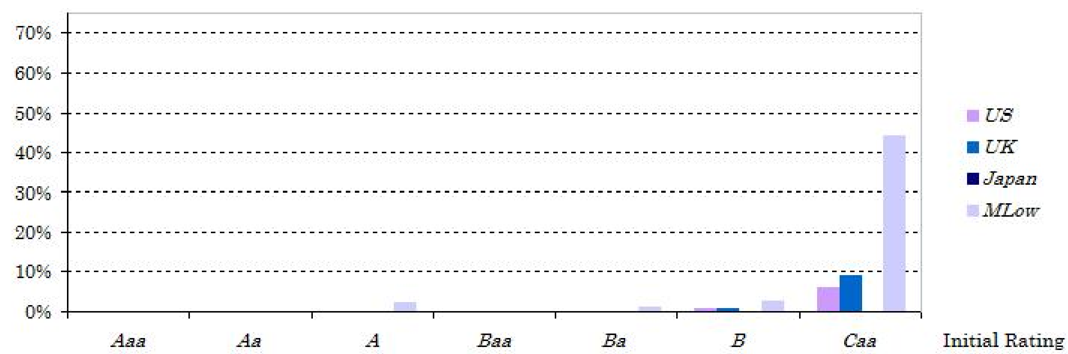


Figure 2.8a: Probabilities of Default over Different Horizons, Banking Sector

Panel A: One-Year Horizon



Panel B: Three-Year Horizon



Panel C: Five-Year Horizon

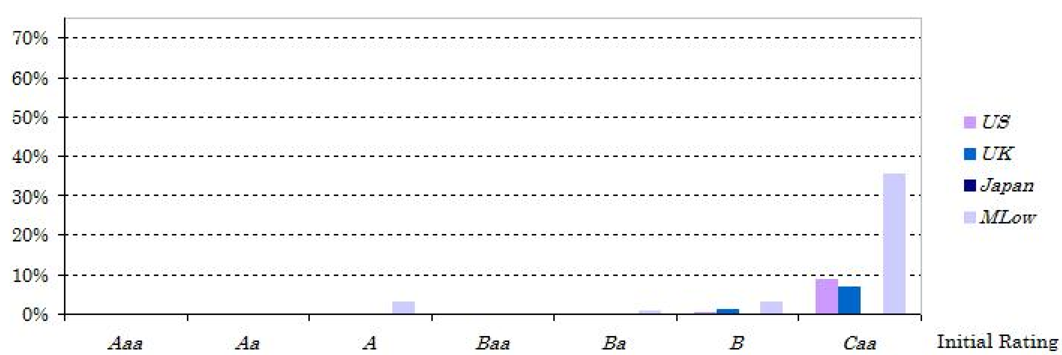
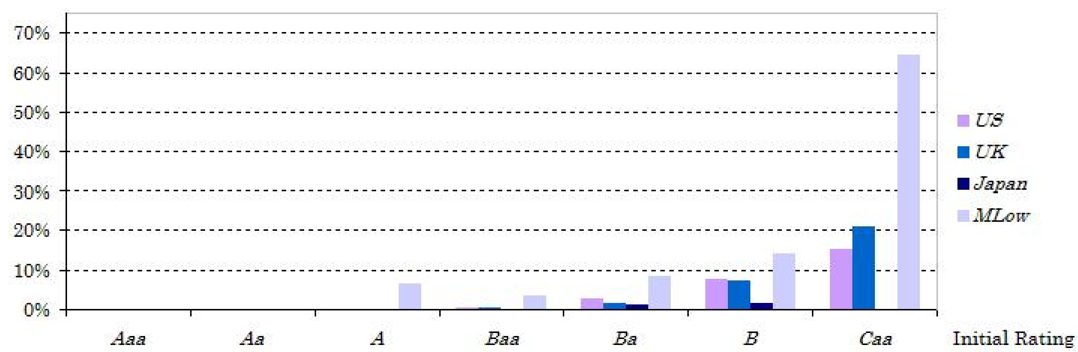


Figure 2.8b: Probabilities of Default over Different Horizons, Industrial Sector

Panel A: One-Year Horizon

Panel B: Three-Year Horizon



Panel C: Five-Year Horizon

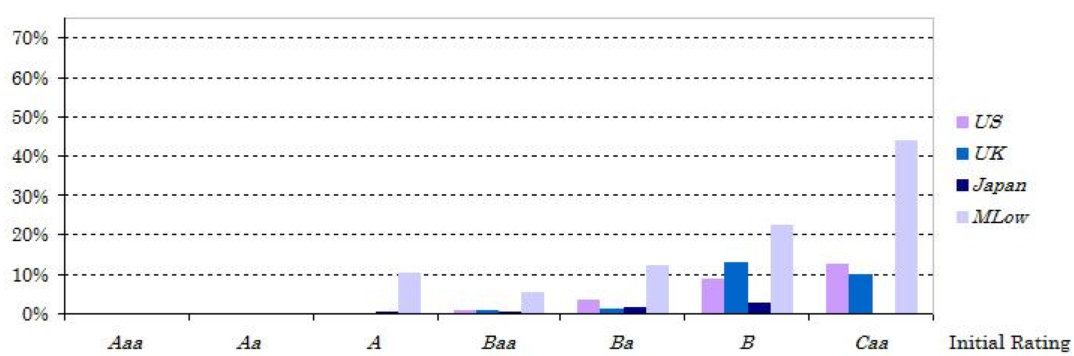
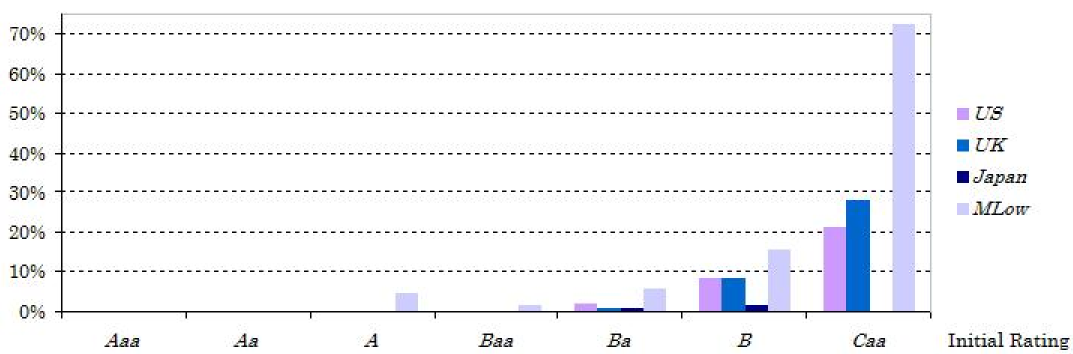


Figure 2.8c: Probabilities of Default over Different Horizons, Transportation Sector

Panel A: One-Year Horizon

Panel B: Three-Year Horizon



Panel C: Five-Year Horizon

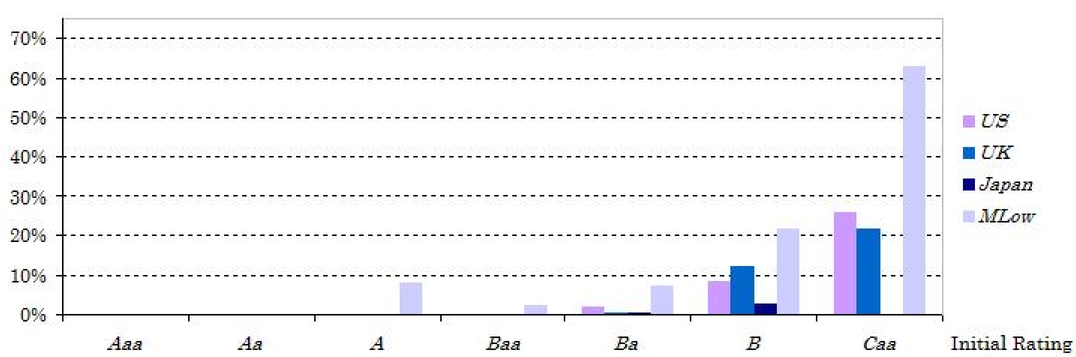


Figure 2.9: Average Probabilities of Default over Different Horizons

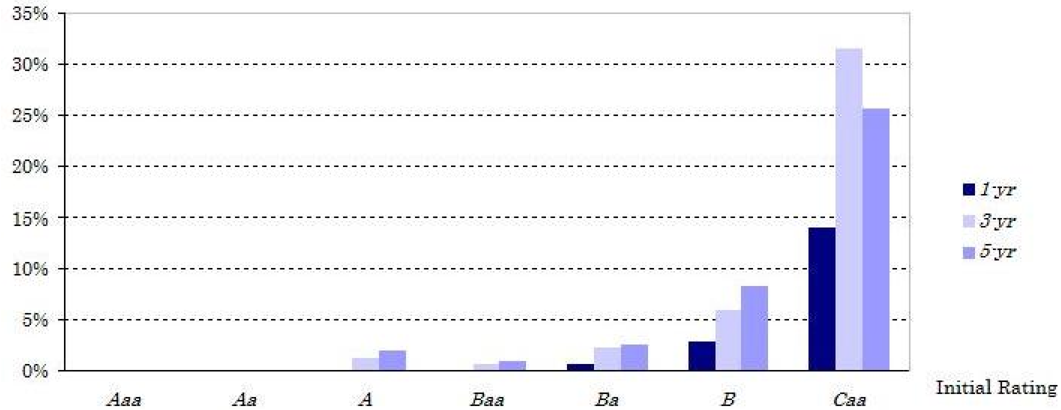
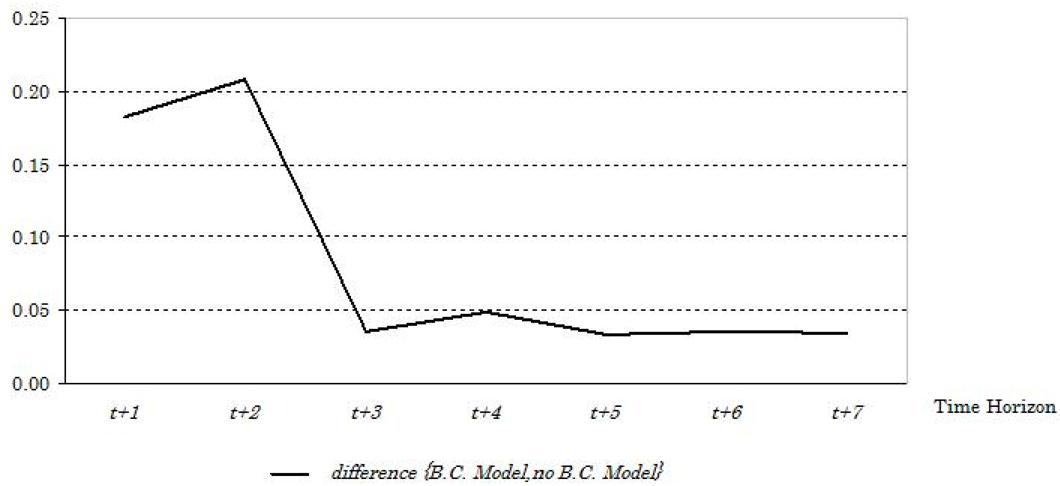


Figure 2.10: Forecast Content for the Business Cycle Effect



Chapter 3

Performance and Capital Structure: A Study of Firm Dynamics

This study tests theoretical predictions about the relationship between leverage and firm performance set forth by the corporate finance literature. We empirically examine a dynamic relationship between firm performance and leverage using Difference GMM method of econometric estimation, based on a sample of 5,357 firms, for the 1988-2002 time period. We utilize multiple measures of performance and leverage, thereby controlling for idiosyncrasies associated with a particular definition, which allows us to generate inferences about the practical relationship between firm performance and debt. Results suggest that forward looking measures of performance such as Tobin's q and firm Market Value are positively related to the debt-equity ratio. We argue that this provides evidence to support the signaling nature of debt, as higher levels of debt are interpreted as a credible signal of future performance. We also find that Return on Equity, Profitability, and Total Factor Productivity are negatively related to the debt-equity ratio, supporting agency costs theories, where additional debt is associated with inefficient allocation of existing resources. Decomposition of short- and long-run effects of leverage on performance demonstrates the persistent nature of the effect over time.

3.1 Introduction

Theoretical literature in the field of corporate finance suggests that there exists a relationship between a firm's financial structure and its performance. While much attention has been devoted to the characterization of capital structure-performance interaction, improvements can still be made to better understand the real-world features of this relationship. In this study we use a flexible approach to model the impact of debt on performance, allowing us to accommodate a broader spectrum of theoretical predictions. While the standard empirical approach permits debt to manifest only its immediate effect on performance, the empirical strategy presented here allows us to distinguish between long- and short-run implications of this relationship.

In this paper we introduce three innovations. First, we do not restrict the performance measure to a single definition. Instead, we employ different standards of quantifying performance, each consistent with accounting, financial and economic literature. Specifically, we concentrate on Return on Equity, Profitability, Tobin's q, Market Value, and Total Factor Productivity measures of firm performance. Second, we define three variations of leverage, thus controlling for idiosyncrasies associated with each particular definition. Finally, we incorporate dynamics into the model, allowing us to distinguish between short- and long-run effects of leverage on firm performance. These innovations allow us to characterize the real-world relationship between performance and debt, and reconcile empirical results with existing corporate finance theory.

Results suggest that debt is positively associated with current and future performance when firm performance is measured in a forward-looking fashion; that is, when investor sentiment is present. To be precise, after controlling for idiosyncratic time and industry effects, as well as relative corporate size, R&D expenditures, and growth opportunities, we find that higher levels of debt in a firm's capital structure serve as a strong signal of firm potential. At the same time, the "leverage effect" becomes negative when performance measure is based strictly on firm fundamentals and past performance, such as Return on Equity, Profitability and Total Factor Productivity. That is, the immediate effect of taking on additional debt is a decrease in both current profitability and efficiency of the firm.

Results show that capital structure-performance interactions are highly persistent, and increase in magnitude over time. This finding is intriguing as it implies that while the market has a positive perception of corporate borrowing, the actual effect of increase in debt is reduced firm efficiency, resulting in hindered financial performance.

We study the relationship between firms' financial structure and their productivity based on a large, detailed panel of U.S. Manufacturing firms, for the 1988-2002 time period. The model is estimated using a number of econometric approaches, focusing on Difference-GMM method of econometric estimation, which addresses our concerns that unobservable, time-varying industry effects could bias the estimation coefficients.

The remainder of the paper is organized as follows. In Section 2 we discuss the body of corporate finance literature relevant to our research question, and implied predictions for the relationship between firm financing and performance. Section 3 describes our data and variable construction methodology. Section 4 discusses our model and the empirical testing design. Section 5 contains the paper's central empirical findings regarding the interaction between capital structure and performance outcomes. Section 6 concludes.

3.2 Literature Review

The relationship between leverage and corporate performance was first addressed by Modigliani and Miller (1958) who suggested that financial structure of a corporation has no influence on its value. A number of theoretical works have since contested the accuracy of the Modigliani-Miller "irrelevance proposition," arguing in favor of non-neutrality of financial structure, and concluding that a distinct relationship between the performance of a firm and its capital structure can be characterized. In analyzing the leverage-performance interaction, this paper focuses on two of the competing groups of theories, agency costs and information asymmetry.

3.2.1 Agency Costs

Agency costs are costs that arise due to conflicts of interest. In 1976, Jensen and Meckling described two categories of agency conflicts: conflicts of interest between managers and shareholders, and conflicts of interest between equity- and debt-holders.

3.2.1.1 Manager-Shareholder Conflicts

Manager-shareholder conflicts arise as a result of an incentive problem. That is, while managers bear the full cost of operating activities of a firm, they do not capture the entire gain resulting from their activities. Rather, shareholders are entitled to some portion of positive cash-flow from operations and investment activities. This means that managers have a lesser incentive to invest fully into managing firm resources, and a greater incentive to use some resources for their personal benefit, i.e., as corporate perks. This incentive divergence creates inefficiency, as managerial behavior is suboptimal from the shareholder point of view, but is, in fact, optimal from the managerial perspective.

Under the manager-shareholder conflict theory, increasing ratio of debt in a firm's capital structure has an ambiguous effect on firm performance. Although debt can aid in aligning managerial and shareholder goals, significant increases in debt can lead to a reduction in overall efficiency of the firm, hindering performance.

One way in which debt can help mitigate manager-shareholder conflict is by reducing resource constraints, rooted in the fact that managers respond to incentives, Jensen and Meckling (1976). As previously discussed, using equity to finance operations will reduce the amount of resources available for incentives that are necessary to entice management to closely monitor firm performance. Issuing debt frees up resources that would not have been available otherwise, avoiding sacrificing incentive intensity associated with equity financing. Since managers can internalize the benefits of superior performance to a greater degree, debt financing provides managers with appropriate incentives (i.e. bonuses) to work hard. However, an increase in debt means managers commit the firm to payments which, in the long run, can intensify the resource constraint problem, leading to a reduction in efficiency and decline in firm performance.

Debt can also reduce manager-shareholder conflict by serving as a monitoring tool. First, since debt commits the firm to pay out cash, the amount of cash available to managers for discretionary spending and personal misuse is reduced, ensuring that managers behave in a value-maximizing manner. That is, managers have less temptation and, therefore, concentrate their resources on improving firm performance. Second, debt increases outside monitoring of firm activities. Corporate debt is generally issued by large banks, the superior monitoring abilities of which should keep managers in check, reducing moral hazard problems associated with agency. Thus an increase in debt will increase the value of the firm by reducing the incentive for managers to behave sub-optimally and through increased external monitoring of firm activities.

3.2.1.2 Debt-holder and Equity-holder Conflicts

The relationship between a firm's performance and its capital structure can also be explained in terms of conflicts between debt- and equity-holders. These conflicts arise because a debt contract gives equity-holders an incentive to invest sub-optimally. That is, if an investment generates returns greater than the face-value of debt, equity-holders will capture most of the gain. However, if an investment fails it will be debt- and not equity-holders who bear the consequences of the loss. Thus, equity-holders have an incentive to invest in high-risk projects, as they will benefit if the project succeeds, and will not loose if the project fails. This creates a problem of overinvestment described by Stulz (1990).

The overinvestment problem has ambiguous implications for the relationship between leverage and firm performance. While more investment projects are likely to be undertaken by the firm, it is difficult to predict whether, on average, the effect on performance will be positive or negative.

Conflicts between debt- and equity-holders can also result in an underinvestment problem. Myers (1977) observes that for highly levered, poorly performing firms, equity-holders have little incentive to contribute new capital to investment projects even if these projects are value-increasing. The reasoning is as follows, while equity-holders bear the entire cost of the investment, debt-holders will capture most of the returns, providing little incentive for equity-holders to invest. Underinvestment not only prevents firms from investing in profitable projects, but also hinders current firm productivity and efficiency by interfering with firm's operating activities. We can, therefore, infer that this type of conflict is likely to lead to a negative relationship between leverage and performance, since high amounts of debt actually prevent managers from investing in value-increasing projects.

3.2.2 Information Asymmetry

Information theories discussed in this section are theories which are based on the premise that firm insiders possess some private information about the firm's characteristics that are unavailable to outsiders. These capital structure theories can be divided into two sub-groups: pecking order and signaling theories.

3.2.2.1 Pecking Order Theory

In 1984, Myers and Majluf suggested that capital structure helps mitigate inefficiencies caused by information asymmetries. That is, if investors are less informed than insiders about characteristics and opportunities of the firm, then it is very likely that securities issued by the firm in the market will be mispriced. This mispricing may lead to rejection of an investment project with positive net present value (NPV) because only new investors will be able to profit from it, leaving nothing to the existing shareholders and thus creating an underinvestment problem. The underinvestment, however, can be avoided if managers can fund investment projects using less risky securities such as debt, which involve no undervaluation. An increase in leverage, therefore, implies that the firm is unable to finance its activities with equity, suggesting a negative relationship between debt and firm performance.

Myers (1984) formalized the notion of information costs associated with valuation of debt and equity issue in the pecking order theory. The pecking order of corporate financing is such that firms prefer internal funds over all other financing options, followed by debt, and finally, equity as a last resort. That is, due to information costs, internal funding is the most inexpensive way to finance investment activities. However, if internal funds are insufficient to adequately finance some project, then debt is preferred over equity as a source of financing. Only if the market is able to price equity fairly accurately, does it become optimal as means of financing.

The pecking order theory would suggest a negative relationship between leverage and firm performance as higher levels of debt provide much needed funds, allowing currently cash-strapped firms to pursue profitable investment opportunities. Thus, according to the theory, most profitable firms tend to borrow less simply because they do not need the external financing. Less profitable firms issue debt because they do not have sufficient internal funds to pursue investment opportunities and debt costs lower than equity issues.

3.2.2.2 Signaling with Debt

While pecking order theory deals with firms' inability to finance investment opportunities, another category of models considers debt as a signal of private information. Ross (1977) proposed that if two firms have prospects that are known to management but not to investors, debt can be used to signal the fact that prospects differ, and create expectations about the quality of those prospects.

Information asymmetries between lenders and borrowers lead to adverse selection problems, and the inability of lenders to accurately price a loan according to borrower quality results in imperfect pricing and credit rationing, as suggested by Weill (2003) and Stiglitz and Weiss (1981).

High quality borrowers have an incentive to reveal their quality; however, they need a credible signal to provide this private information, a signal that cannot be imitated by low quality borrowers. Signaling literature suggests that debt can be used as such a signal. Ross (1977) argues that investors interpret larger levels of debt as a signal of higher quality. The reasoning behind his argument is as follows. Debt is a contractual obligation to repay principal and interest. Failure to make payments can lead to bankruptcy, a sub-optimal outcome for both the firm and its managers. In contrast, equity is much easier to manage as managers have some flexibility in adjusting dividend payouts and can decrease them in times of financial distress. Therefore, higher levels of debt in the capital structure of a firm can be interpreted as a credible signal of future performance. Lower quality firms will not be able to imitate high quality firms by taking on debt because of high bankruptcy costs associated with any level of debt. Accordingly, Ross concludes that investors take higher levels of debt as a signal of firm's higher quality, generating a positive relationship between leverage and performance.

3.2.3 Summary

Theoretical literature is specific in asserting a relationship between a firm's capital structure and its performance. However, after much research, the exact nature of this relationship remains unclear. Theoretical models suggest conflicting outcomes. A set of theories argues that agency and bankruptcy costs drive better performers toward higher leverage ratios, implying a positive relationship between leverage and performance. That is, bankruptcy costs decline as profitability increases, allowing firms to borrow larger amounts cheaper, thereby creating an incentive to finance projects with debt. Also, higher leverage ratios help mitigate inefficiency associated with the agency problem by increasing outside monitoring [see Jensen and Meckling (1976), Jensen (1986)]. Signaling hypothesis, introduced by Ross (1977), corroborates the positive direction of the relationship between leverage and performance, considering higher levels of debt as a managerial tool intended to signal an optimistic future for the firm.

On the other hand, pecking order theory predicts that higher earnings should result in lower leverage ratios. Myers (1984) argues that costs associated with information asymmetries can prevent firms from issuing equity. That is, under information asymmetries, it may be cheaper, and therefore optimal, for firms to take on debt rather than finance activities by issuing equity. As investor sentiment toward a particular firm improves, it becomes unnecessary for the firm to take on debt and cheaper to issue equity. Thus, leverage ratio is expected to decline as corporate performance improves.

3.3 Data Description

This study is based on a sample of firm-level data collected for U.S. manufacturing firms listed in Full COMPUSTAT Annual (Industrial) database over the 1988-2002 time period. The reason we focus on this particular time period is that deflators necessary for accurate estimation of our model are readily available from NBER-CES Manufacturing Industry Database. Also, by allowing for a sufficiently long time period, we are able to incorporate dynamics into the model while retaining maximum number of observations.

The sample is composed of 5,357 U.S. manufacturing firms, SIC code 2000-3999. To keep the sample as large as possible we retain all firms, including those with some missing observations for some years, resulting in an unbalanced panel data set. Omitting years for which a firm has zero observations leaves us with a panel of 78,560 observations.

3.3.1 Proxies for Performance

Performance can be, and is, measured in different ways. This, perhaps, is the greatest contributor to the lack of consensus among empirical works addressing the nature of the relationship between performance and capital structure. While some studies rely on basic accounting principles to measure performance, such as Majumdar and Chhibber (1999) who use return on net worth (RONW), others employ more sophisticated methods, such as the economic concept of total factor productivity, first introduced into the corporate structure-performance analysis by Pushner (1995), or the efficiency frontier analysis implemented by Weill (2003).

In this study we expand our definition of performance by focusing on three categories of performance indicators: (i) accounting, (ii) financial, and (iii) economic. Accounting measures of performance used here are Return on Equity (ROE) and Profitability; financial measures of performance are Tobin's q and Market Value; and economic measure of performance employed is the Total Factor Productivity (TFP) analysis. The following sub-sections provide a complete discussion of the five performance indicators.

3.3.1.1 Accounting Performance

The selection of accounting measures of performance is based on the notion that performance can be adequately captured by return on equity (ROE) and profitability. Accounting profitability is the most straight-forward measure of performance, and is calculated as the ratio of operating income to total assets. When profitability goes up, performance improves and vise versa. On the other hand, ROE is a more sophisticated measure of performance.

Simply put, ROE reveals the portion of profits that were generated using funding obtained from shareholders, signaling to investors the efficiency with which their investment was being utilized by the firm.

While both profitability and ROE are indicative of firm performance, it is important to note that there is a difference in what the two variables actually measure. That is, since profitability and ROE are measured using different financial line items, it is possible that the nature of the relationship between leverage and each of the performance measures is different. Specifically, ROE measures how efficient a company is at utilizing investor resources. In this study ROE is defined following Barth, Beaver and Landsman (1998), and is calculated as the ratio of net income (or loss) to the book value of equity. We note that given this particular definition, return on equity can be inflated by reducing common shareholder equity, which generally involves issuing debt. Although debt can increase for a variety of reasons, it can be argued that generally, managers increase debt in an effort to pursue projects that would improve corporate performance in the future. Thus, in the long-run, debt can lead to improved performance even if it is damaging to ROE ratio in the short-term.

Table 3.1 and Figure 3.1 report sample summary statistics for the ROE accounting measure of performance. While Table 3.1 presents average sample statistics, Figure 3.1 illustrates the evolution of ROE over time for small, medium and large firms, as well as for the average company.

Profitability captures the current financial state of a company. Thus, it is reasonable to conclude that as profitability increases, the firm has more resources at its disposal, allowing it to be less reliant on leverage and so, the relationship between the two is expected to be negative.

Table 3.2 and Figure 3.2 report sample summary statistics for the profitability accounting measure of performance. Table 3.2 presents average sample statistics, while Figure 3.2 illustrates the evolution of profitability over time for small, medium and large firms, as well as for the average company.

3.3.1.2 Financial Performance

Traditionally, financial economists relied on Tobin's q to provide a valid measure of corporate performance. The reason we include Tobin's q as one of our performance measures is that it takes into account the future profit stream of a corporate entity, capturing not only present moment scenario, but also allowing us some insight into the future growth opportunities available to the firm. In this sense, Tobin's q delivers the total value of a corporation at a particular moment, where a higher q ratio is taken to imply greater potential, and thus, better performance.

We generate a simple approximation of Tobin's q following the methodology of Chung and Pruitt (1994), where q is measured as the sum of book value of debt and market value of equity divided by the book value of total assets. Although simple in its calculation, authors show that a q constructed using their approximation successfully explains 96.6% of variability of Tobin's q constructed using the more complete and theoretically correct model of Lindenberg and Ross (1981). Because Tobin's q takes into account future performance of a firm, we can conclude that it will be positively related to leverage as, consistent with the signaling theory, greater amount of debt should imply that a firm is anticipating future growth opportunities.

Table 3.3 and Figure 3.3 report summary statistics for Tobin's q financial measure of performance. Table 3.3 presents average sample statistics and Figure 3.3 illustrates the evolution of Tobin's q over time for small, medium and large firms, as well as for the average company.

Another measure of financial performance used in this study is firm market value. Market value is an important reference point as it characterizes the market's valuation of the firm, providing an accurate impression of investor sentiment as it pertains to a particular corporation. In our model, market value is measured as the sum of market equity, value of preferred stock, long-term debt, and debt in current liabilities.

As the name suggests, market value as a performance measure includes more than just the current financial position of the company but also investor sentiment; that is, how the company and its future opportunities are perceived by investors. A greater market value should imply better opportunities in the future, which may require financing in the current time period. And, similar to Tobin's q, we expect market value of a firm to be positively related to its leverage ratio.

Table 3.4 and Figure 3.4 report sample statistics for the market value financial measure of performance. Table 3.4 presents average sample statistics, while Figure 3.4 illustrates time dependence of market value for small, medium and large firms, as well as for the average company.

3.3.1.3 Economic Performance

A study by Nucci et al. (2005) suggests that there exists an equilibrium relationship between a firm's share of intangible assets and its financial structure. Firms involved in innovative activities typically invest in specialized equipment and intangible assets such as patents and human capital. Ultimately, as described by Griliches and Lichtenberg (1984), differences in propensity to innovate are likely to translate into different total factor productivity (TFP) levels for firms, where more innovative firms should experience higher productivity and, therefore, better performance.

The economic measure of total factor productivity is a comprehensive measure of firm performance, allowing us to assess the degree of technological advancement of a particular company, Sampat (2005). TFP is formally described as a portion of the increase in output that can not be attributed to an increase in inputs. Intuitively, total factor productivity measures how efficient a company is at producing output; which is an indicator of competitiveness and thus is a comprehensive measure of performance.

Output growth can be attributed to one of two events: increased magnitude of factor inputs, or improvement of production technology. We thus infer that an increase in TFP is associated with increased amount of output that can be produced from a given level of inputs; or, that a smaller quantity of input is required to produce a given level of output. We conclude that growth of total factor productivity is desirable as it implies that more output can be produced utilizing limited resources. The law of diminishing returns suggests that in the long-run, increased use of inputs does not lead to increased output; so it will be precisely the advancements in TFP that will allow firms to lower costs and improve quality of their products, facilitating competitiveness and thus, allowing them to improve their performance.

Plant-level estimates of total factor productivity are computed econometrically using Olley and Pakes (1996) approach. A detailed description of our methodology is available in the Technical Appendix. Table 3.5 and Figure 3.5 report sample summary statistics for the TFP economic measure of performance. Table 3.5 presents average sample statistics, while Figure 3.5 illustrates the evolution of TFP over time for small, medium and large firms, as well as for the average company.

3.3.2 Capital Structure Proxies

Before we begin our discussion, it is important to define exactly what is meant by the term "capital structure." Generally, capital structure refers to the way in which a corporation finances its activities. For the purposes of this study, we take the term to mean a combination of different types of securities (i.e., long vs. short-term debt, common vs. preferred stock) issued by a company in order to finance its operations. In this context, a company is said to be "levered" if it carries debt in its capital structure, and a firm is said to be "unlevered" if it has accrued zero debt. Thus, leverage is synonymous with capital structure.

It may be of some use to note that there exist two types of leverage, operational and financial, Song (2005). Operational leverage refers to a firm's operating costs and is associated with business risk. Financial leverage refers to a firm's cost of taking on debt, and is associated with financial risk of a corporation. In this study, we are concerned with financial leverage and its effect on a firm's performance.

Since Modigliani and Miller (1958) published their seminal paper detailing the irrelevance proposition, a large body of literature focused on analyzing capital structure and its determinants. As a result, there now exist many different measures of leverage, where each measure itself can be measured in different ways. Generally speaking, we broadly classify leverage measures into two categories: those based on the market value of equity, and those based on its book value, Lf (2004). The question then becomes: should leverage be calculated as the ratio of book or market value of equity? Titman and Wessels (1988) refer to a study by Bowman (1980), who demonstrates that the cross-sectional correlation between the book value and market value of debt is very large. Furthermore, Fama and French (2000) argue that most of the theoretical predictions apply to book leverage, as book ratios better reflect management's target debt ratios and market value of equity is dependent on a number of factors which are out of direct control of a corporation. Therefore, using market values may not reflect the underlying alterations within the firm. In fact, according to Drobetz (2003), corporate treasurers often explicitly claim to use book ratios to avoid "distortions" in their financial planning caused by the volatility of market prices. In this study we focus only on book value leverage ratios.

In choosing an appropriate measure of leverage as the dependent variable of interest we follow Rajan and Zingales (1995), concentrating on three alternative definitions of leverage. First, we define leverage as the ratio of total (non-equity) liabilities to total assets, denoted Lev1. This leverage ratio serves as a proxy for what is left for shareholders if firm assets are suddenly liquidated. It must be noted that this particular measure is not a good indicator of whether the firm is at risk of default in the near future. Also, since the accounting definition of total liabilities includes items indicating transactions, along with financing activities, this particular definition may overestimate the actual amount of leverage attributable to a firm.

Second, we define financial leverage as the ratio of total debt (both short term and long term) to total assets, denoted Lev2. This measure of leverage covers only interest-bearing debt and excludes provisions that were a potential source of bias in the first definition of leverage. However, as with the first definition of leverage, this measure has some drawbacks. Specifically, it fails to account for assets which are offset by specific, non-interest bearing debt liabilities, such as trade credit.

Finally, we define leverage as the ratio of total debt to capital, where capital is defined as total debt plus equity, denoted Lev3. This measure of leverage considers the actual capital employed by the firm, and thus provides the best representation of the effects of past financing decisions.

Table 3.6 reports summary statistics for the three definitions of leverage for each year in the sample time period. We observe a negative mean for Lev3 definition of leverage for years 1995 and 2001. Given the definition of total debt, we infer that a negative sign is consistent with a firm carrying negative equity. That is, during 1995 and 2001, an average company was exhibiting signs of financial distress. These dates are consistent with two stock market crashes: a stock market crash of January 1994 - June 1994 as reported by Pagen and Sossunov (2003) and a stock market crash of August 2000 - December 2001 as reported by Mishkin and White (2002). This interpretation of the data is further supported by the fact that the median in years 1995 and 2001 is positive, and not significantly different from average median; that is, only a few firms in the sample experienced extreme financial distress.

Figure 3.6 provides a visual representation of leverage ratios throughout time. Again, we see a drop in the comprehensive leverage measure, Lev3, in 1995 and 2001, consistent with abnormally poor performance associated with stock market crashes as reported during those time periods. On the other hand, Lev1 and Lev2 experience peaks during those same time periods, which is also consistent with stock market underperformance. In general, firms incur debt and liabilities during periods of economic downturn as it allows them to pursue positive NPV projects and investment opportunities in times of limited cash flow.

3.3.3 Factors Correlated with Performance

We base our selection of independent variables on current empirical models relating leverage and firm performance, as well as a meta-analysis of statistical results in the literature on industry and firm financial performance, relating results of 320 published studies of dependence between environmental, strategic and organizational factors and financial performance. The following is a discussion of factors correlated with performance and reasons for their inclusion in the model.

A. *Equity*:

Equity is an important indicator of performance. For the purposes of this study, we create a dummy variable which is equal to one if firm equity is below zero, that is, the firm is in financial distress, and is equal to zero otherwise. Because the issue of negative equity specifically affects the third measure of leverage, we also create an interaction variable of our equity dummy with Lev3.

B. *Age*:

Age of a firm is a determinant of its performance. As a firm continues to operate in a market, it gains learning-based experience and can avoid many liabilities associated with being an inexperienced start-up. However, according to Majumdar and Chhibber (1999), older firms are also likely to under-perform. Authors point out that with age, inertia and rigidities in adaptability set in, potentially leading to decreased performance. In this study, we use the number of years since first link to CRSP database as a proxy for a firm's age.

C. *Tangibility*:

The physical asset structure of the firm is expected to have a significant influence on its performance. In the real world there exist certain contractual imperfections that lead creditors to seek collateral in exchange for financing. The amount of external financing that can be supported by contracts with outside creditors is, therefore, correlated with those creditors' valuation of the firm's transferable assets in liquidation, the firm's asset tangibility.

Following Jensen and Meckling (1976) and Harris and Raviv (1991), conflicts between lenders and shareholders create incentives for shareholders to invest in a suboptimal way; therefore, lenders take actions to protect themselves by requiring tangible assets as collateral. If a firm has an excess of tangible assets that it can use as collateral it is expected to have open access to lending markets, allowing it greater opportunity to undertake value-increasing projects.

The proxy for asset tangibility is borrowed from Campello (2003) and is based on the work by Berger, Ofek and Swary (1996). Using data on proceeds from discontinued operations reported by a sample of COMPUSTAT firms over 1984-1993 time period, Berger et al. (1996) find that during liquidation, on average, a dollar invested produces 72 cents for total receivables, 55 cents for inventories, and 54 cents for fixed assets. Here, the proxy is intended to estimate the expected resale value of firm's assets in liquidation.

D. *Uniqueness*:

Uniqueness can be an indicator of success of a corporation. In this paper, we measure uniqueness as a ratio of a firm's research and development (R&D) expenses to its capital expenditures. Higher R&D spending implies more innovative processes and improved product, which is likely to advance the performance of the firm. In addition, we construct a uniqueness dummy to control for differences between firms that allocate resources to R&D activities and those that do not. Here, the uniqueness dummy is equal to one if R&D spending is greater than zero, and is equal to zero otherwise.

E. *Growth Opportunity*:

Unprofitable firms generally do not have excess resources and, as such, rarely seek to expand. Thus, it is reasonable to expect that firms with significant growth opportunities are good performers. We define growth opportunity as a bundle of capital assets that add value to a firm but cannot be collateralized, and measure it as a ratio of capital expenditures to total assets.

F. *Size*:

Firm size can be an important determinant of performance. Larger firms have a greater variety of capabilities and resources available to them then do smaller firms. They are also in a position to enjoy economies of scale. All these factors can positively impact performance. Table 3.7 shows correlation coefficients for the five types of performance measures implemented in this study for small, average, and large firms, as well as the average correlations coefficients for all firms in the sample. It becomes quite clear that the direction of the correlation coefficient is firm size-dependent.

Size can also be regarded as a proxy for information asymmetry between firm insiders and the capital markets. Large firms are more closely observed by analysts and, therefore, have more incentive to perform well. On the other hand, according to Williamson (1967), larger firms are prone to experience problems of coordination, which can negatively influence performance.

In this study, we use two approaches to capture firm size. First, following Majumdar and Chhibber (1999), we measure size as the natural log of sales. The logarithmic transformation accounts for the conjecture that small firms are particularly affected by a size effect. Second, we create a size categorical dummy variable, where size is measured as gross fixed assets. The dummy is constructed in such as way as to allow us to see what happens to very small and very large companies. That is, we create three categories where we sort all firms according to size of their gross fixed assets. The fist category represents small firms in the sample; it is composed of firms that are in the lowest 25^{th} percentile of fixed assets as compared to the sample. The second category contains the bulk of the companies; they are firms with assets between 25^{th} and 75^{th} percentiles. The last category is composed of the largest firms, those firms whose gross assets are greater than 75^{th} percentile as compared to the sample.

G. *Industry and Trend*:

In addition to determinants described above, a full set of industry (at the two-digit SIC level) and time dummies is included in the model. By introducing industry and time dummies we account for performance shifts across different industries and over time.

The computational methodology for each variable is available in Table 3.8a. Table 3.8b reports summary statistics for the dependent and independent variables included in our model.

3.4 Empirical Methodology

The objective of this study is to determine the direction of the relationship between a specific type of financing and firm performance; and, to establish whether this interaction is significant and persistent. To do so, we develop a dynamic empirical model relating firm performance and capital structure over a number of firms and years. The use of a dynamic model allows us to first, evaluate the persistence of the dependent variable and second, identify short- and long-run effects of our independent variables on the dependent variable of interest.

A common approach to estimating the impact of capital structure on firm performance consists of simply regressing the performance measure on a leverage variable. It is important to note that within the context of our model, this regression can be misspecified due to the presence of unobserved firm heterogeneity. To control for this heterogeneity we extend the model to include a firm-specific shock ω_i which accounts for the fact that firm performance is a function of internal factors in addition to external shocks.

Here, external shocks are events that can be observed by the firm as well as the econometrician analyzing its performance; the internal shocks are only visible to the firm itself. To better understand the impact that shocks have on regression coefficients consider the role of manager in firm operations. In anticipation of some macro shocks to the economy, a manager will adjust production to better reflect future demand, thereby directly affecting a firm's performance. While this internal adjustment is known to the manager, and thus the firm itself, it is unobservable to the econometrician, affecting the validity and reliability of estimates generated from an underspecified model. In order to yield precise estimates, the model must be specified in such as way as to account for the possibility of firm-specific shocks.

The model, in its general form, is as follows

$$\begin{aligned}\text{Performance}_{q,i,t} = \beta_0 &+ \beta_1\text{Performance}_{q,i,t-1} + \beta_2\text{Leverage}_{p,i,t} \\ &+ \beta_3\text{Equity Dummy}_{i,t} + \beta_4\text{Leverage*Equity}_{i,t} \\ &+ \beta_5\text{Tangibility}_{i,t} + \beta_6\text{Growth Opportunity}_{i,t} \\ &+ \beta_7\text{Uniqueness}_{i,t} + \beta_8\text{Uniqueness Dummy}_{i,t} \\ &+ \beta_9\text{Age}_{i,t} + \beta_{10}\text{Size}_{i,t}\beta_{11}\text{Size Dummy}_{i,t} \\ &+ \delta\text{Industry Dummy}_{i,t} + \gamma\text{Trend}_{i,t} + \omega_i + \eta_{i,t},\end{aligned} \tag{3.1}$$

where $q \in \{\text{ROE, Profit, Tobin's } q, \text{lnMV, lnTFP}\}$ indicates a specific performance measure for firm i at time t, $t \in \{1, 15\}$; $p \in \{\text{Lev1, Lev2, Lev3}\}$ indicates a specific leverage measure; Equity Dummy and Leverage3*Equity are only included for the 3^{rd} definition of leverage; β, δ and γ are our variable coefficients to be estimated; ω represents some firm-specific shock; and η is the error term.

We estimate out model using a variety of econometric techniques, emphasizing results obtained using general Methods of Moments technique for estimating dynamic panel data models with endogenous variables developed by Arellano and Bond (1991). The advantage of using this method lies in its efficient use of instruments. Konings and Roodhoft (1997), show that since levels of the dependent variable in time period $t-2$ are not correlated with the differenced error term in year t, they are valid instruments in year t. Table 3.9 shows how the number of available instruments increases as the panel progresses.

Arellano and Bond (1991) demonstrate that first difference-GMM (FD-GMM) results in efficient, consistent and unbiased estimates for a dynamic, panel-data model. Consider a reduced form representation of our model in Eq.(3.1)

$$y_{q,i,t} = \beta_0 + \beta_1 y_{q,i,t-1} + \beta_2 x_{p,i,t} + \lambda Z_{i,t} + \omega_i + \eta_{i,t}. \tag{3.2}$$

The first difference transformation removes both the constant term and the individual effect, eliminating the omitted-variable bias

$$\Delta y_{q,i,t} = \Delta\beta_1 y_{q,i,t-1} + \Delta\beta_2 x_{p,i,t} + \Delta\lambda Z_{i,t} + \Delta\eta_{i,t}. \tag{3.3}$$

We can now specify the model as a system of equations, one for each time period, allowing the instruments for each equation to vary. Here, the instruments include lags of the levels of the endogenous variable that enter the equation in a differenced form, as well as the strictly exogenous regressors. Arellano and Bond (1991) show that the FD-GMM approach produces efficient results by using all available lagged levels of the dependent variable and explanatory variables as instruments. The validity of the additional instruments is based on orthogonality between lagged values of the dependent variables and the error terms.

To check for the validity of our instruments we use specification tests proposed by Arellano and Bond (1991) and Arellano and Bover (1995). First, we apply the Hansen test of over-identifying restrictions to check for correlation between our instruments and the error terms. An instrument is considered to be valid if no correlation is present; that is, the instruments and the error terms are independent. Second, we test for second order serial correlation in the error terms of the differenced equation. While we expect that the differenced error term may be first order serially correlated, consistency of the GMM estimator is dependent on the error terms of the first-differenced equation being second-order serially uncorrelated, Yasar et al. (2003). That is, absence of second-order serial correlation would indicate that the error term in the levels equation is white noise, Konings and Roodhoft (1997). Thus, a test of second-order serial correlation is reported.

3.5 Empirical Results

In this section we present results of our econometric estimation for all five performance variables and three definitions of leverage. Consistent with empirical methodology presented in Section 4, we emphasize estimates generated using the difference GMM method of econometric estimation. Main results of our estimation are summarized below.

We observe in Table 3.10 that all five performance variables are persistent, consistent with the notion that performance today is to some extent correlated with yesterday's performance. The main results are such that leverage appears to have a positive relationship with forward looking measures of performance such as Tobin's q and Market Value; the relationship is statistically significant for Tobin's q measure of performance. We observe a negative and statistically significant relationship when performance is measured by ROE, Profitability and Total Factor Productivity. More generally, preliminary evidence suggests that debt appears to have a variety of performance implications for firms.

Comparing effects of leverage across performance measures we observe that an increase in debt in a firm's capital structure has the greatest impact on the firm's ROE and the least impact on the immediate financial state of the corporation. That is, change in debt has very clear implications for the managerial efficiency of the firm but not necessarily it's immediate financial position.

By decomposing the effect of leverage on performance into short- and long-run components we observe that long-run effect of leverage carries the same sign as a short-run effect but is, in general, much larger in magnitude. This finding carries several interesting implications. First, our results suggest that the market attributes positive characteristics to debt as a fraction of firm's capital structure. That is, consistent with signaling hypothesis, investors perceive higher levels of debt to be indicative of positive future performance. Second, while the market believes debt to be beneficial to corporate performance, our results show that in both the short- and the long- run, debt adversely affects firm efficiency, thereby hindering corporate performance.

We check consistency of our results by adjusting the panel for outliers. Outliers are eliminated following methodology presented in Seo (2006), using adjusted boxplot procedure for skewed distributions developed by Huberg and Vandervieren (2006). Results generated using this new panel are similar to results obtained using the full panel, and differ in magnitude only.

3.5.1 Regression Results

Results presented in this section aim at understanding the immediate relationship between capital structure and various measure of firm performance. Using ordinary least squares, fixed effects and FD-GMM estimation techniques, we find that the direction of the relationship between debt and performance does not change depending on the definition of leverage used, only the magnitude of the coefficient. The following sub-sections discuss main results for each of the dependent variables.

3.5.1.1 Return on Equity

Table 3.11 presents the results of various alternative specifications for Return on Equity measure of firm performance. Results show that leverage has a negative and statistically significant relationship with Return on Equity for all definitions of leverage. In particular, when using FD-GMM approach, the estimated coefficients associated with leverage are (-2.296), (-2.415), and (-2.202), for Lev1, Lev2, and Lev3 respectively.

To understand this result it is of use to reiterate what is actually measured by Return on Equity. In accounting, ROE measures how efficient the firm is in using resources acquired through equity issues. As firm efficiency is a function of resources available to a corporation, it is clear that higher levels of debt can lead to diminishing efficiency by creating an overabundance of resources. That is, availability of additional funds can result in adverse behavior by management, the outcome of which is that the same level of performance may have been achieved with fewer resources. This result is consistent with agency cost theories of corporate finance in that management has an incentive to borrow in an effort to alleviate resource constraints faced by the firm, thereby avoiding having to sacrifice incentive intensity.

3.5.1.2 Profitability

Table 3.12 presents results of various alternative specifications for the accounting measure of Profitability. Results demonstrate that leverage has a negative and statistically significant relationship with performance as measured by accounting Profitability. This relationship holds across all definitions of leverage.

When performance is measured based on firm financials alone, higher levels of debt in a company's capital structure imply decreased performance. This result can be attributed to the fact that a short-term increase in debt generally occurs as a result of resource constraints. That is, if a firm does not currently have the funds necessary to support its operating or investment activities it is obvious that an immediate relationship between leverage and performance should be a negative one. On the other hand, increased borrowing implies increased payouts in both principal and interest, which in the long-run eat away at corporate profits, resulting in reduced profitability, thereby perpetuating the negative long-run relationship between leverage and firm performance.

When we use difference GMM approach to econometric estimation, the estimated coefficients associated with leverage are (-0.242), (-0.305), and (-0.055), for Lev1, Lev2, and Lev3 respectively. The estimates generated using simple OLS and fixed effect estimators, are still negative and significant, although smaller in magnitude than those generated using FD-GMM approach. The coefficient on the FE estimate is smaller, in absolute value, indicating that the cross-sectional differences in the financial structure across firm play a more important role in explaining performance than the time series variability.

3.5.1.3 Tobin's q

Table 3.13 presents results of various alternative specifications based on Tobin's q measure of firm performance. Results show that leverage has a positive and statistically significant relationship with our dependent variable across all definitions of leverage. In particular, under FD-GMM approach, estimated coefficients associated with leverage are (-0.844), (0.652), and (0.241), for Lev1, Lev2, and Lev3 respectively. The estimates generated using simple OLS and fixed effect estimators are also positive and significant. The fact that the coefficient on the fixed effects estimates is greater indicates that the cross-sectional differences across firms in the financial structure play a lesser role in explaining performance than the time series variability. Still, the positive estimated coefficient on the fixed effects specification suggests that, for the same firm, an increase in leverage is associated with a higher performance.

Although a change in firm's q over time may simply reflect changes to the valuation of future growth opportunities that arise in part from factors exogenous to managerial decisions, industry dummies and trend in the regression help control for these. Overall, results suggest that investors view increased borrowing as indicative of future growth opportunities for the firm. That is, consistent with signaling theory, debt serves as a credible signal to separate firms with solid fundamentals and desirable future projects, from firms with poor prospects. As debt is costly to accrue and higher levels of debt are associated with increased outside monitoring of borrower activities, the market tends to assign a greater value to firms which are highly levered.

3.5.1.4 Market Value

Table 3.14 presents results of various alternative specifications based on firm Market Value measure of performance. Results show that leverage has a positive and statistically significant relationship with the dependent variable across all definitions of leverage. In particular, FD-GMM estimated coefficients associated with leverage are (-1.205), (2.911), and (0.222), for Lev1, Lev2, and Lev3 respectively. Note, that while the coefficient on LEV1 generated using FD-GMM methodology is negative it is not statistically significant; therefore we can not say that the relationship between leverage and performance in this case is, in fact, negative. The estimates generated using simple OLS and fixed effect estimators, are still positive for Lev1, Lev2, and Lev3 respectively. That is, for a particular firm, an increase in leverage is associated with higher performance.

Similar to Tobin's q measure of firm performance, signaling and monitoring capabilities of debt make it possible for investors to assign greater value to highly levered firms as they associate higher levels of debt with future performance.

3.5.1.5 Total Factor Productivity

Table 3.15 presents results of various alternative specifications based on economic efficiency (TFP) measure of firm performance. When it comes to the effect of debt on firm performance, results show that firms with lower leverage are, on average, more productive. In particular, FD-GMM estimated coefficients associated with leverage are (-0.393), (-0.213), and (-0.219), for Lev1, Lev2, and Lev3 respectively. FE coefficients are also negative and equal to -0.012, -0.032, and -0.003 for Lev1, Lev2, and Lev3 respectively.

A reduction in efficiency is associated with higher levels of debt in a firm's capital structure, can be explained by the fact that firms take on debt when internal cash is not available; that is, when there exists some resource constraint. It follows that an immediate effect of debt is decreased firm performance and thus, lower efficiency. In the long-run, increased borrowing obligates management to principal and interest payouts, which means that less of the profits are available to invest back into firm activities. That is, resulting resource constraints prohibit firms from investing internally, further hindering productivity and efficiency.

3.5.2 Dynamic Decomposition Results

The dynamic component of the model allows us to differentiate between short- and long-run effects of independent variables on various performance measures. Since in this study we are interested in the effect of debt on firm performance, we limit our analysis to leverage variables.

Consider our model

$$\begin{aligned}\text{Performance}_{q,i,t} = \beta_0 + \beta_1 \text{Performance}_{q,i,t-1} \\ + \beta_2 \text{Leverage}_{p,i,t} + \lambda Z_{i,t} + \omega_i + \eta_{i,t},\end{aligned} \tag{3.4}$$

where $q \in$ {ROE, Profit, Tobin's q, lnMV, lnTFP} indicates a specific performance measure for firm i at time t, $t \in \{1,15\}$; $p \in$ {Lev1, Lev2, Lev3} indicates a specific leverage measure; β and λ are our variable coefficients to be estimated; Z is a vector representing the explanatory variables as outlined in section 3.4; ω represents some firm-specific shock; and η is the error term.

The short-run effect of leverage on the dependent variable of interest is given by the coefficient on leverage, β_2. The long-run effect of leverage on performance is calculated as a ratio of the coefficient of our independent variable, β_2, over one minus the coefficient of our lagged performance variable, $(1 - \beta_1)$. That is

$$\begin{aligned} \text{Short-run effect} &= \beta_2, \\ \text{Long-run effect} &= \frac{\beta_2}{(1 - \beta_1)}. \end{aligned} \tag{3.5}$$

Table 3.16 summarizes the results of our analysis of short- and long-run effects of leverage on performance. We observe that, in general, long-run effect of leverage on performance is of the same sign as a short-run effect, but is larger in magnitude. This result is puzzling in the theoretical context as it implies that performance is both positively and negatively affected by increases in debt. A possible answer can be found in the definitions of performance measures themselves. Investor sentiment is an intrinsic factor in computation of our financial measures of performance, Tobin's q and Market Value. Therefore, markets are likely to overvalue highly levered firms, consistent with the signaling theory of debt. On the other hand, measures based on efficiency and firm fundamentals suggest that debt hinders performance as it serves as a long-run resource constraint preventing the firm from efficiently utilizing available resources.

A possible explanation could be found in the effect which the amount of external financing could have on firm performance. A study by Campello (2003) suggests that it is possible for debt financing to both boost and hurt firm performance, implying that it is not debt as such that hinders efficiency, but rather its level in the capital structure of the firm. The next logical step in determining the effect of financing decisions on business performance should involve the decomposition of sample by debt size.

Finally, a key to the puzzling relationship between different measures of firm performance and leverage could be the size of the firm itself. As mentioned previously, different measures of performance demonstrated differing time-dynamics for small, medium, and large firms. While this study focuses on estimating the "average" effect of increased amount of debt on firm performance, it is possible that this effect is actually different for different size firms.

3.6 Conclusions and Extensions

While much of theoretical literature has focused on the characterization of capital structure-performance interaction, improvements can still be made to better understand the practical features of this relationship. Research presented in this paper provides new insight into the relationship between leverage and corporate performance. Here, we use a flexible approach to model the impact of debt on performance, which allows us to accommodate a broader spectrum of theoretical predictions. While the standard empirical approach permits for debt to manifest only its immediate effect on performance, we adopt an empirical strategy which allows us to distinguish between long- and short-run effects of this relationship.

Results imply that debt is positively associated with current and future performance when performance is measured in a forward-looking fashion; that is, when investor sentiment is present. To be precise, after controlling for idiosyncratic time and industry effects, as well as relative corporate size, R&D expenditures and growth opportunities, we find that higher levels of debt in firm's capital structure serve as a strong signal of firm potential. However, the "leverage effect" becomes negative when corporate performance is based strictly on firm financials and past performance, such as Return on Equity, Profitability and Total Factor Productivity. That is, immediate effects of taking on additional debt lead to a decrease in both current profitability and efficiency of the firm.

Results also suggest that capital structure-performance interactions are highly persistent and increase in magnitude over time. This finding is puzzling as it allows us to conclude that while the market has a positive perception of an increase in a firm's leverage ratio, in reality, an increase in debt is likely to reduce firm efficiency, thereby hindering corporate performance. While this work is based on sound econometric theory, we stress that one must interpret our results with care as there are limitations to any empirical work.

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Table 3.1: Descriptive Statistics, ROE Measure of Performance, by Year

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
1988	-0.228	0.098	24.221	-519.412	880.000	2,027
1989	-0.036	0.086	3.362	-49.817	42.761	1,970
1990	0.093	0.079	11.992	-156.323	490.909	1,971
1991	-0.277	0.067	7.914	-124.000	201.792	2,034
1992	0.092	0.070	9.212	-204.500	223.000	2,175
1993	0.048	0.076	3.729	-103.551	59.936	2,296
1994	-0.410	0.097	9.964	-405.778	17.930	2,383
1995	0.148	0.102	7.505	-102.512	263.203	2,629
1996	0.177	0.088	20.442	-526.683	906.778	2,677
1997	-0.160	0.084	8.804	-382.241	157.486	2,570
1998	0.174	0.074	14.002	-113.500	494.750	2,614
1999	5.568	0.070	286.061	-263.333	14416.000	2,541
2000	-0.420	0.052	18.493	-865.250	158.494	2,417
2001	-0.199	0.017	5.510	-107.562	78.554	2,261
2002	-0.011	0.021	8.368	-111.567	261.512	2,160

Table 3.2: Descriptive Statistics, Profitability Measure of Performance, by Year

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
1988	0.016	0.106	0.388	-7.992	0.765	2,031
1989	0.013	0.107	0.420	-7.365	0.873	1,972
1990	0.015	0.105	0.361	-3.863	3.098	1,972
1991	0.010	0.101	0.437	-8.128	1.009	2,033
1992	0.014	0.107	0.457	-12.800	1.744	2,176
1993	0.016	0.106	0.376	-4.763	1.685	2,294
1994	0.000	0.116	0.533	-11.593	0.885	2,379
1995	-0.075	0.115	1.931	-76.727	0.807	2,630
1996	-0.019	0.109	0.745	-28.590	0.749	2,673
1997	-0.025	0.105	0.501	-11.264	2.041	2,569
1998	-0.119	0.089	0.934	-26.049	0.965	2,617
1999	-0.105	0.084	0.841	-18.429	4.780	2,552
2000	-0.114	0.082	0.975	-24.908	13.334	2,440
2001	-0.188	0.058	1.416	-50.400	4.305	2,275
2002	-0.231	0.060	2.575	-100.000	1.070	2,193

Table 3.3: Descriptive Statistics, Tobin's q Measure of Performance, by Year

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
1988	0.561	0.498	0.511	0.008	12.197	1,740
1989	0.590	0.510	0.677	0.008	15.916	1,656
1990	0.579	0.502	0.726	0.007	18.985	1,617
1991	0.548	0.471	0.639	0.011	16.569	1,653
1992	0.512	0.450	0.648	0.011	21.317	1,751
1993	0.494	0.429	0.568	0.017	14.160	1,895
1994	0.510	0.437	1.142	0.017	47.244	1,968
1995	0.596	0.440	2.659	0.020	120.544	2,193
1996	0.527	0.415	1.061	0.009	41.635	2,383
1997	0.594	0.431	1.775	0.018	59.118	2,381
1998	0.660	0.474	1.159	0.021	21.755	2,319
1999	0.693	0.481	1.491	0.027	42.274	2,233
2000	0.681	0.454	1.755	0.007	53.571	2,226
2001	0.851	0.445	6.301	0.014	278.551	2,095
2002	0.827	0.443	3.163	0.017	108.814	1,966

Table 3.4: Descriptive Statistics, lnMV Measure of Performance, by Year

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
1988	8.958	9.041	2.987	-1.457	18.315	1,740
1989	9.013	9.070	3.082	-0.623	18.389	1,656
1990	9.031	9.116	3.157	-1.343	18.411	1,618
1991	8.981	9.029	3.154	-1.586	18.418	1,652
1992	8.913	8.915	3.125	-2.300	18.440	1,750
1993	8.864	8.796	3.102	-0.391	18.564	1,893
1994	8.898	8.939	3.168	-2.393	18.716	1,964
1995	8.868	8.761	3.138	-1.476	18.824	2,188
1996	8.821	8.704	3.186	-0.227	18.889	2,374
1997	8.931	8.936	3.199	-1.173	18.949	2,373
1998	9.123	9.118	3.277	-1.761	18.706	2,312
1999	9.264	9.217	3.239	-4.249	18.846	2,227
2000	9.216	9.211	3.288	-0.468	18.929	2,221
2001	9.208	9.202	3.391	-1.120	18.940	2,089
2002	9.104	9.113	3.547	-2.022	19.124	1,960

Table 3.5: Descriptive Statistics, lnTFP Measure of Performance, by Year

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
1988	2.329	2.675	1.782	-3.391	6.014	1,643
1989	2.345	2.708	1.786	-5.217	5.405	1,612
1990	2.359	2.662	1.775	-2.521	5.482	1,618
1991	2.402	2.826	1.769	-2.517	5.759	1,686
1992	2.426	2.842	1.758	-2.914	5.454	1,800
1993	2.428	2.771	1.762	-2.663	5.933	1,853
1994	2.424	2.726	1.759	-4.167	5.759	1,934
1995	2.399	2.758	1.773	-3.381	6.077	2,050
1996	2.421	2.88	1.787	-3.891	5.529	2,048
1997	2.412	2.938	1.786	-3.975	5.739	1,951
1998	2.385	2.922	1.794	-4.686	5.381	1,901
1999	2.368	2.911	1.821	-3.7	5.617	1,859
2000	2.298	2.849	1.86	-3.573	7.332	1,811
2001	2.341	2.947	1.853	-5.052	6.769	1,730
2002	2.329	2.675	1.782	-3.391	6.014	1,643

Table 3.6: Descriptive Statistics, Leverage Variables, by Year

	Lev1		*Lev2*		*Lev3*	
	Mean (%)	*Median (%)*	*Mean (%)*	*Median (%)*	*Mean (%)*	*Median (%)*
1988	57.231	52.372	28.679	23.999	48.102	32.098
1989	58.745	53.890	29.836	24.728	42.512	32.322
1990	59.513	53.380	29.943	23.934	18.041	30.673
1991	59.471	50.753	28.950	21.431	3.801	27.027
1992	56.559	49.696	26.699	19.495	27.575	25.132
1993	53.926	47.334	24.426	17.130	20.146	22.455
1994	55.712	47.757	23.736	16.864	25.641	21.165
1995	70.760	47.197	31.954	17.061	-12.391	20.483
1996	52.292	44.145	24.119	15.736	32.522	19.636
1997	52.913	44.053	24.311	15.518	17.642	19.036
1998	58.540	47.330	27.580	18.192	28.398	21.832
1999	60.284	47.758	27.914	18.755	37.558	22.492
2000	62.350	46.367	30.260	17.367	36.731	21.783
2001	75.610	46.051	31.105	17.159	-10.086	19.867
2002	67.032	45.406	30.513	16.260	37.394	17.471
Observations	35,041		35,014		34,782	

Table 3.7: Performance Measures Correlation Coefficients

Panel A: Full Sample

	ROE	*Profitability*	*Tobin's q*	*lnMV*	*lnTFP*
ROE	**1**				
Profitability	-0.01	**1**			
Tobin's q	0.009	-0.399	**1**		
lnMV	0.009	0.157	0.099	1	
lnTFP	-0.001	0.073	-0.034	-0.104	**1**

Panel B: Small Firms

	ROE	*Profitability*	*Tobin's q*	*lnMV*	*lnTFP*
ROE	**1**				
Profitability	-0.015	**1**			
Tobin's q	0.009	-0.394	**1**		
lnMV	0.024	-0.036	0.227	**1**	
lnTFP	0	0.177	-0.091	-0.086	**1**

Panel C: Medium Firms

	ROE	*Profitability*	*Tobin's q*	*lnMV*	*lnTFP*
ROE	**1**				
Profitability	0.005	**1**			
Tobin's q	0.009	-0.206	**1**		
lnMV	0.002	0.085	0.496	**1**	
lnTFP	-0.002	0.128	-0.043	-0.022	**1**

Panel D: Large Firms

	ROE	*Profitability*	*Tobin's q*	*lnMV*	*lnTFP*
ROE	**1**				
Profitability	0.016	**1**			
Tobin's q	0.015	-0.218	**1**		
lnMV	0.001	-0.087	0.468	**1**	
lnTFP	0.001	0.094	0.045	-0.051	**1**

Table 3.8a: Variable Definitions and Sources

Below, variable definitions and sources are reported for all variables used in the regression estimations. The data are collected from COMPUSTAT Annual (Industrial) database.

Panel A: Performance Variables

Return On Equity	Net income (COMPUSTAT item #172) divided by book value of equity, where book value of equity is measured as total common equity (item #60) + deferred tax (item #35) − liquidation value of preferred stock (item #10).
Profitability	Ratio of operating income before depreciation (item #13) over total assets (item #6).
Tobin's q	Sum of book value of debt and market value of equity, divided by total assets; where book value of debt is total assets minus book value of equity, and market value of equity is the number of common shares outstanding (item #25) multiplied by fiscal year closing price (item #199).
Market Value	Market value of equity plus preferred stock, plus long term debt (item #9) plus debt in current liabilities (item #34).
Total Factor Productivity	Total Factor Productivity is calculated using the Olley and Pakes (1996) estimation method; we then generate the final variable form by performing a log-transform. Details are available upon request.

Panel B: Leverage Variables

Lev1	Liabilities (COMPUSTAT item #181) over total assets (item #6).
Lev2	Ratio of total debt, calculated as the sum of long term debt (item #9) and debt in current liabilities (item #34), over assets.
Lev3	Total debt over capital, where capital is total debt plus book value of equity, calculated as total common equity (item #60) + deferred tax (item #35) − liquidation value of preferred stock (item #10).

Panel C: Main Regression Variables

Equity Dummy	Variable is equal to 1 if total common equity (COMPUSTAT item #60) is below zero, and is 0 otherwise.
Age	Age is calculated from the date of first link to CRSP until current time period.
Tangibility	Weighted sum of cash holdings, accounts receivables, inventories, and net fixed capital, divided by total assets ([item #1 + (0.715 × item #2) + (0.547 × item #3) + (0.535 × item #8)] divided by item #6).
Uniqueness	Ratio of R&D expense (item #46) over capital expenditures (item #128).
Uniqueness Dummy	Variable is equal to 1 if R&D expense is greater than 0, variable is equal to 0 otherwise.
Growth Opportunity	Capital expenditures divided by total assets (item #6).
Size	Log-transform of net sales (item 12).
Size Dummy	Size is measured as gross fixed assets; we create three categories in which we sort the firms according to the size of their gross fixed assets. The fist category represents the small firms in the sample; it is composed of firms which are in the lowest 25^{th} percentile of fixed assets as compared to the sample. The second category contains the bulk of the companies; they are the firms with assets between 25^{th} and 75^{th} percentiles. The last category is composed of the largest firms, those firms whose gross assets are greater than the 75^{th} percentile as compared to the sample.
Industry Dummy	Industry dummy at the two-digit SIC level.
Trend	Variable is constructed by subtracting 1987 from current time period.

Table 3.8b: Sample Descriptive Statistics

Panel A: Summary statistics for performance measures variables

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
ROE	0.345	0.074	78.324	-865.25	14416	34,725
Profitability	-0.055	0.0987	1.077	-100	13.334	34,806
Tobin's q	0.619	0.459	2.236	0.007	278.551	30,076
lnMV	9.016	9.013	3.214	-4.249	19.124	30,017
lnTFP	2.383	2.838	1.79	-5.217	7.332	25,496

Panel B: Summary statistics for leverage variables, by firm size

	Lev1		*Lev2*		*Lev3*	
	Mean (%)	*Median (%)*	*Mean (%)*	*Median (%)*	*Mean (%)*	*Median(%)*
Small	94.609	50.082	41.913	17.572	16.618	12.252
Medium	45.137	39.356	21.399	13.683	16.32	16.763
Large	60.242	59.558	28.931	26.482	42.652	38.233
Observations	35,041		35,014		34,782	

Panel C: Summary statistics for independent variables

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
Age	19.012	17	10.97	1	55	27,604
Tangibility	0.564	0.556	0.156	0	1	34,918
Uniqueness	2.92	0	37.966	0	7277.667	78,560
Growth Opportunity	0.057	0.041	0.06	0.001	2.2	34,297
Size	11.086	11.055	2.684	0	19.143	35,038

Table 3.9: FD-GMM Instruments

Observation Year	*Instrument(s) Available*
Δx_{p1990}	x_{p1988}
Δx_{p1991}	x_{p1988}, x_{p1989}
Δx_{p1992}	x_{p1988}, x_{p1989}, x_{p1990}
Δx_{p1993}	x_{p1988}, x_{p1989}, x_{p1990}, x_{p1991}
$\cdots$	$\cdots$
Δx_{p2002}	x_{p1988}, $\cdots$, x_{p2000}

Table 3.10: Partial Regression Analysis

Panel A: Debt-ROE Interactions, FD-GMM

	Lev1	*Lev2*	*Lev3*
l.ROE	0.004	0.007	0.009
	(0.001)***	(0.001)***	(0.001)***
lev	-2.296	-2.415	-2.202
	(0.191)***	(0.264)***	(0.169)***
LR lev	-2.305	-2.432	-2.221

Panel B: Debt-Profitability Interactions, FD-GMM

	Lev1	*Lev2*	*Lev3*
l.Profitability	0.253	0.138	-0.052
	(0.037)***	(0.032)***	(0.019)***
lev	-0.242	-0.305	-0.055
	(0.035)***	(0.080)***	(0.017)***
LR lev	-0.323	-0.4	-0.052

Panel C: Debt-Tobin's q Interactions, FD-GMM

	Lev1	*Lev2*	*Lev3*
l.Tobin's q	0.287	0.270	0.189
	(0.052)***	(0.081)***	(0.003)***
lev	0.844	0.652	0.241
	(0.043)***	(0.157)***	(0.028)***
LR lev	1.183	0.893	0.297

Panel D: Debt-Market Value Interactions, FD-GMM

	Lev1	*Lev2*	*Lev3*
l.lnMV	0.349	0.286	0.359
	(0.143)**	(0.100)***	(0.028)***
lev	-1.205	2.911	0.222
	(0.872)	(0.703)***	(0.067)***
LR lev	-1.85	4.077	0.346

Panel E: Debt-TFP Interactions, FD-GMM

	Lev1	*Lev2*	*Lev3*
l.lnTFP	0.197	0.138	-0.219
	(0.109)*	(0.048)***	(0.066)***
lev	-0.393	-0.213	-0.219
	(0.096)***	(0.047)***	(0.081)***
LR lev	-0.489	-0.247	-0.179

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.11: Debt-ROE Interactions, OLS, FE, and FD-GMM Estimation

	Lev1			*Lev2*			*Lev3*		
	OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
Constant	-1.836	-5.373	...	-1.719	-5.305	...	-2.916	-8.067	...
	(0.678)***	(1.303)***		(0.683)**	(1.322)***		(0.666)***	(1.306)***	
l.ROE	0.012	-0.051	0.004	0.012	-0.051	0.007	0.012	-0.051	0.009
	(0.007)*	(0.007)***	(0.001)***	(-0.007)	(0.007)***	(0.001)***	(0.007)*	(0.007)***	(0.001)***
Lev	0.138	0.469	-2.296	0.044	0.153	-2.415	-0.114	-0.037	-2.202
	(-0.135)	(0.181)***	(0.191)***	(-0.194)	(-0.255)	(0.264)***	(0.061)*	(-0.061)	(0.169)***
Equity Dummy	...	...	...	...	...	...	3.193	5.223	4.689
							(0.260)***	(0.324)***	(0.365)***
Lev3 × Equity	...	...	...	...	...	...	0.116	0.037	2.204
							(0.062)*	(-0.061)	(0.169)***
Age	-0.011	-0.043	0.021	-0.011	0.000	-0.013	-0.011	0.000	-0.073
	(-0.007)	(0.018)**	(-0.015)	(-0.007)	(0.000)	(-0.014)	(0.007)*	(0.000)	(0.019)***
Tangibility	-0.549	-0.263	-0.800	-0.649	-0.482	-1.211	0.114	0.295	-1.362
	(-0.511)	(-0.737)	(0.387)**	(-0.515)	(-0.742)	(0.428)***	(-0.499)	(-0.725)	(0.397)***
Uniqueness	0.002	0.002	0.003	0.002	0.003	0.004	0.000	0.001	0.002
	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(0.002)*	(-0.002)	(-0.002)	(-0.002)
Uniqueness Dummy	0.150	0.027	0.242	0.146	0.022	0.119	0.180	0.110	-0.101
	(-0.166)	(-0.375)	(0.132)*	(-0.166)	(-0.375)	(-0.124)	(-0.165)	(-0.372)	(-0.117)
Growth Opportunity	-2.396	-2.505	0.257	-2.333	-2.346	-0.169	-2.686	-2.241	-0.391
	(1.235)*	(1.482)*	(-0.842)	(1.236)*	(-1.483)	(-0.801)	(1.228)**	(-1.468)	(-0.741)
Size	0.246	0.621	-0.074	0.247	0.602	0.065	0.296	0.768	0.470
	(0.050)***	(0.111)***	(-0.087)	(0.051)***	(0.111)***	(-0.089)	(0.050)***	(0.111)***	(0.096)***
Size Dummy 2	-0.420	-1.214	-0.577	-0.445	-1.276	-0.305	-0.192	-0.954	0.082
	(0.203)**	(0.303)***	(0.200)***	(0.202)**	(0.302)***	(0.168)*	(-0.202)	(0.300)***	(-0.215)
Size Dummy 3	-0.939	-1.544	-0.450	-0.962	-1.620	-0.091	-0.736	-1.118	0.454
	(0.333)***	(0.462)***	(0.240)*	(0.332)***	(0.461)***	(-0.224)	(0.331)**	(0.458)**	(0.257)*
Trend	-0.018	0.000	...	-0.018	-0.039	...	-0.023	-0.071	...
	(-0.016)	(0.000)		(-0.016)	(0.018)**		(-0.016)	(0.018)***	
R-squared	0	0.01	...	0	0.01	...	0.01	0.02	...
Number of Groups	...	1,708	1,594	...	1,708	1,593	...	1,708	1,593
Observations	16,317	16,317	14,441	16,303	16,303	14,426	16,303	16,303	14,426

FD Instruments: (2 7,3 5), Hansen test of overid. restrictions: $\chi^2(94) = 81.22$ Prob $> \chi^2 = 0.824$
Arellano-Bond test for AR(1) in first differences: z = -2.03 Pr > z = 0.042
Arellano-Bond test for AR(2) in first differences: z = -0.49 Pr > z = 0.627

FD Instruments: (2 7,3 5), Hansen test of overid. restrictions: $\chi^2(94) = 70.39$ Prob $> \chi^2 = 0.967$
Arellano-Bond test for AR(1) in first differences: z = -2.02 Pr > z = 0.043
Arellano-Bond test for AR(2) in first differences: z = -0.27 Pr > z = 0.783

FD Instruments: (2 7,4 5), Hansen test of overid. restrictions: $\chi^2(82) = 75.95$ Prob $> \chi^2 = 0.667$
Arellano-Bond test for AR(1) in first differences: z = -2.19 Pr > z = 0.028
Arellano-Bond test for AR(2) in first differences: z = -0.70 Pr > z = 0.482

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.12: Debt-Profitability Interactions, OLS, FE, and FD-GMM Estimation

	Lev1			*Lev2*			*Lev3*		
	OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
Constant	-0.292	-0.872	...	-0.308	-0.950	...	-0.367	-0.979	...
	(0.017)***	(0.030)***		(0.018)***	(0.031)***		(0.018)***	(0.031)***	
l.Profitability	0.479	0.183	0.253	0.512	0.205	0.138	0.528	0.223	-0.052
	(0.006)***	(0.007)***	(0.037)***	(0.006)***	(0.007)***	(0.032)***	(0.006)***	(0.007)***	(0.019)***
Lev	-0.151	-0.171	-0.242	-0.155	-0.181	-0.305	-0.006	-0.005	-0.055
	(0.004)***	(0.004)***	(0.035)***	(0.005)***	(0.006)***	(0.080)***	(0.002)***	(0.001)***	(0.017)***
Equity Dummy	...	...	...	...	...	...	-0.170	-0.185	-0.216
							(0.007)***	(0.008)***	(0.017)***
Lev3 × Equity	...	...	...	...	...	...	0.006	0.005	0.055
							(0.002)***	(0.001)***	(0.017)***
Age	0.000	0.000	-0.010	0.000	0.000	-0.013	0.000	0.000	-0.013
	(0.000)	(0.000)	(0.001)***	(0.000)**	0.000	(0.001)***	(0.000)*	(0.000)	(0.001)***
Tangibility	0.009	0.199	0.197	0.035	0.206	0.186	0.098	0.266	0.291
	-0.013)	(0.016)***	(0.035)***	(0.013)***	(0.017)***	(0.041)***	(0.013)***	(0.017)***	(0.036)***
Uniqueness	-0.001	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000
	(0.000)***	(0.000)**	(0.000)	(0.000)***	(0.000)***	(0.000)	(0.000)***	(0.000)***	(0.000)
Uniqueness Dummy	-0.038	-0.042	-0.011	-0.037	-0.038	-0.005	-0.032	-0.043	0.003
	(0.004)***	(0.008)***	(-0.013)	(0.004)***	(0.009)***	(-0.012)	(0.004)***	(0.009)***	(-0.011)
Growth Opportunity	-0.310	-0.326	-0.354	-0.336	-0.359	-0.391	-0.393	-0.424	-0.440
	(0.031)***	(0.033)***	(0.048)***	(0.032)***	(0.034)***	(0.087)***	(0.032)***	(0.034)***	(0.063)***
Size	0.041	0.085	0.124	0.036	0.086	0.125	0.036	0.084	0.133
	(0.001)***	(0.003)***	(0.008)***	(0.001)***	(0.003)***	(0.009)***	(0.001)***	(0.003)***	(0.007)***
Size Dummy 2	-0.001	0.030	0.041	0.017	0.048	0.078	0.012	0.041	0.084
	(-0.005)	(0.007)***	(0.014)***	(0.005)***	(0.007)***	(0.015)***	(0.005)**	(0.007)***	(0.013)***
Size Dummy 3	-0.079	-0.006	0.020	-0.054	0.021	0.070	-0.061	0.003	0.067
	(0.008)***	(-0.010)	(-0.016)	(0.008)***	(0.010)*	(0.017)***	(0.009)***	(-0.011)	(0.015)***
Trend	-0.003	-0.007	...	-0.002	-0.009	...	-0.002	-0.008	...
	(0.000)***	(0.000)***		(0.000)***	(0.000)***		(0.000)***	(0.000)***	
R-squared	0.57	0.3	...	0.54	0.27	...	0.54	0.25	...
Number of Groups	...	1,707	1,595	...	1,707	1,594	...	1,707	1,594
Observations	16,310	16,310	14,435	16,296	16,296	14,420	16,275	16,275	14,394

FD Instruments: (10 15,7 15), Hansen test of overid. restrictions: $\chi^2(49) = 60.02$ Prob $> \chi^2 = 0.134$
Arellano-Bond test for AR(1) in first differences: z = -6.41 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = -0.87 Pr > z = 0.384

FD Instruments: (2 3,6 7), Hansen test of overid. restrictions: $\chi^2(40) = 46.95$ Prob $> \chi^2 = 0.209$
Arellano-Bond test for AR(1) in first differences: z = -7.10 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = -1.52 Pr > z = 0.129

FD Instruments: (4 5,2 4), Hansen test of overid. restrictions: $\chi^2(55) = 66.43$ Prob $> \chi^2 = 0.139$
Arellano-Bond test for AR(1) in first differences: z = -2.39 Pr > z = 0.017
Arellano-Bond test for AR(2) in first differences: z = -1.48 Pr > z = 0.138

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.13: **Debt-Tobin's q Interactions**, OLS, FE, and FD-GMM Estimation

	Lev1			*Lev2*			*Lev3*		
	OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
Constant	-0.179	-0.026	...	-0.194	0.242	...	0.186	0.611	...
	(0.033)***	(-0.056)		(0.035)***	(0.061)***		(0.039)***	(0.076)***	
l.Tobins q	0.681	0.392	0.287	0.746	0.464	0.27	0.912	0.661	0.189
	(0.006)***	(0.006)***	(0.052)***	(0.006)***	(0.007)***	(0.081)***	(0.006)***	(0.008)***	(0.003)***
Lev	0.823	1.120	0.844	0.960	1.323	0.652	0.012	0.012	0.241
	(0.009)***	(0.009)***	(0.043)***	(0.013)***	(0.014)***	(0.157)***	(0.004)***	(0.004)***	(0.028)***
Equity Dummy	...	...	...	...	...	...	0.570	0.692	0.709
							(0.018)***	(0.021)***	(0.027)***
Lev3 × Equity	...	...	...	...	...	...	-0.012	-0.011	-0.241
							(0.004)***	(0.004)***	(0.028)***
Age	0.000	0.003	0.006	0.001	0.009	0.013	0.000	0.004	0.012
	(0.000)	(0.001)***	(0.001)***	(0.000)***	(0.001)***	(0.003)***	(0.000)	(0.001)***	(0.002)***
Tangibility	0.123	0.001	-0.092	0.124	0.044	-0.251	-0.257	-0.441	-0.259
	(0.025)***	(-0.031)	(0.040)**	(0.026)***	(-0.035)	(0.090)***	(0.029)***	(0.043)***	(0.058)***
Uniqueness	0.001	0.000	0.000	0.001	0.001	0.000	0.002	0.002	0.001
	(0.000)***	(0.000)	(0.000)	(0.000)***	(0.000)***	(0.000)	(0.000)***	(0.000)***	(-0.001)
Uniqueness Dummy	0.028	0.013	0.004	0.040	-0.006	-0.005	0.008	0.032	-0.006
	(0.008)***	(-0.016)	(-0.008)	(0.009)***	(-0.018)	(-0.014)	(-0.010)	(-0.022)	(-0.015)
Growth Opportunity	1.306	0.922	0.640	1.400	1.075	0.690	1.618	1.623	0.556
	(0.060)***	(0.063)***	(0.177)***	(0.063)***	(0.070)***	(-0.452)	(0.071)***	(0.087)***	(0.174)***
Size	-0.025	-0.031	-0.031	-0.009	-0.037	-0.045	-0.010	-0.032	-0.042
	(0.002)***	(0.005)***	(0.008)***	(0.003)***	(0.005)***	(0.014)***	(0.003)***	(0.006)***	(0.010)***
Size Dummy 2	0.019	0.033	-0.038	-0.067	-0.074	-0.113	-0.039	-0.044	-0.093
	(0.010)*	(0.013)**	(0.014)***	(0.011)***	(0.014)***	(0.024)***	(0.012)***	(0.018)**	(0.019)***
Size Dummy 3	0.046	0.047	-0.027	-0.063	-0.114	-0.104	-0.025	-0.020	-0.076
	(0.016)***	(0.019)**	(0.016)*	(0.017)***	(0.021)***	(0.025)***	(-0.019)	(-0.027)	(0.025)***
Trend	0.003	0.000	...	0.003	0.000	...	0.001	0.000	...
	(0.001)***	(0.000)		(0.001)***	(0.000)		(-0.001)	(0.000)	
R-squared	0.78	0.71	...	0.76	0.64	...	0.69	0.45	...
Number of Groups	...	1,678	1,545	...	1,678	1,544	...	1,678	1,544
Observations	15,606	15,606	13,724	15,592	15,592	13,709	15,592	15,592	13,709

FD Instruments: (9 15,6 7), Hansen test of overid. restrictions: $\chi^2(36) = 31.23$ Prob $> \chi^2 = 0.695$
Arellano-Bond test for AR(1) in first differences: z = -1.35 Pr > z = 0.178
Arellano-Bond test for AR(2) in first differences: z = 0.64 Pr > z = 0.520

FD Instruments: (9 13,12 15), Hansen test of overid. restrictions: $\chi^2(24) = 16.48$ Prob $> \chi^2 = 0.870$
Arellano-Bond test for AR(1) in first differences: z = -1.37 Pr > z = 0.171
Arellano-Bond test for AR(2) in first differences: z = 0.83 Pr > z = 0.408

FD Instruments: (6 7,3 5), Hansen test of overid. restrictions: $\chi^2(48) = 44.09$ Prob $> \chi^2 = 0.634$
Arellano-Bond test for AR(1) in first differences: z = -1.85 Pr > z = 0.064
Arellano-Bond test for AR(2) in first differences: z = 1.14 Pr > z = 0.253

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.14: **Debt-lnMV Interactions**, OLS, FE, and FD-GMM Estimation

	Lev1			*Lev2*			*Lev3*		
	OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
Constant	0.766	1.948	...	0.406	1.770	...	1.021	2.281	...
	(0.096)***	(0.189)***		(0.093)***	(0.182)***		(0.095)***	(0.194)***	
l.lnMV	0.757	0.527	0.349	0.714	0.491	0.286	0.779	0.552	0.359
	(0.005)***	(0.007)***	(0.143)**	(0.005)***	(0.007)***	(0.100)***	(0.005)***	(0.007)***	(0.028)***
Lev	0.471	0.638	-1.205	1.176	1.500	2.911	0.099	0.082	0.222
	(0.023)***	(0.029)***	(-0.872)	(0.032)***	(0.038)***	(0.703)***	(0.009)***	(0.009)***	(0.067)***
Equity Dummy	...	...	...	...	...	...	0.359	0.362	0.191
							(0.041)***	(0.050)***	(0.017)***
Lev3 × Equity	...	...	...	...	...	...	-0.099	-0.083	-0.222
							(0.009)***	(0.009)***	(0.067)***
Age	-0.003	-0.016	0.002	-0.002	-0.014	-0.027	-0.003	0.000	-0.015
	(0.001)***	(0.003)***	(-0.018)	(0.001)**	(0.002)***	(0.008)***	(0.001)***	(0.000)	(0.005)***
Tangibility	-1.522	-2.697	-3.650	-1.323	-2.412	-2.347	-1.683	-2.922	-3.086
	(0.074)***	(0.108)***	(0.421)***	(0.072)***	(0.104)***	(0.299)***	(0.074)***	(0.109)***	(0.211)***
Uniqueness	0.000	-0.002	0.001	-0.001	-0.002	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)***	(-0.001)	(0.000)**	(0.000)***	(-0.001)	(0.000)	(0.000)	(-0.001)
Uniqueness Dummy	0.015	0.121	0.181	0.045	0.105	0.126	0.008	0.120	0.157
	(-0.024)	(0.055)**	(0.093)*	(0.023)**	(0.053)**	(0.076)*	(-0.024)	(0.055)**	(0.084)*
Growth Opportunity	1.833	1.385	2.061	1.579	1.061	0.391	2.176	1.839	1.211
	(0.174)***	(0.216)***	(0.780)***	(0.169)***	(0.208)***	(-0.700)	(0.174)***	(0.218)***	(0.305)***
Size	0.147	0.278	0.213	0.195	0.308	0.351	0.136	0.249	0.246
	(0.008)***	(0.016)***	(0.064)***	(0.008)***	(0.016)***	(0.049)***	(0.008)***	(0.016)***	(0.030)***
Size Dummy 2	0.323	0.562	0.507	0.308	0.527	0.671	0.258	0.488	0.649
	(0.029)***	(0.044)***	(0.138)***	(0.028)***	(0.042)***	(0.086)***	(0.029)***	(0.044)***	(0.074)***
Size Dummy 3	0.739	0.994	1.046	0.746	0.921	1.095	0.649	0.909	1.137
	(0.047)***	(0.066)***	(0.159)***	(0.046)***	(0.063)***	(0.117)***	(0.048)***	(0.067)***	(0.114)***
Trend	-0.008	0.000	...	-0.009	0.000	...	-0.007	-0.013	...
	(0.002)***	(0.000)		(0.002)***	(0.000)		(0.002)***	(0.003)***	
R-squared	0.9	0.49	...	0.91	0.52	...	0.9	0.47	...
Number of Groups	...	1,678	1,545	...	1,678	1,545	...	1,678	1,545
Observations	15,594	15,594	13,713	15,594	15,594	13,713	15,588	15,588	13,706

FD Instruments: (11 15,11 12), Hansen test of overid. restrictions: $\chi^2(15) = 9.81$ Prob $> \chi^2 = 0.831$
Arellano-Bond test for AR(1) in first differences: z = -3.36 Pr > z = 0.001
Arellano-Bond test for AR(2) in first differences: z = 0.24 Pr > z = 0.813

FD Instruments: (11 15,6 7), Hansen test of overid. restrictions: $\chi^2(25) = 25.17$ Prob $> \chi^2 = 0.453$
Arellano-Bond test for AR(1) in first differences: z = -4.15 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = 0.85 Pr > z = 0.396

FD Instruments: (12 15,3 7), Hansen test of overid. restrictions: $\chi^2(54) = 60.74$ Prob $> \chi^2 = 0.246$
Arellano-Bond test for AR(1) in first differences: z = -8.77 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = 0.97 Pr > z = 0.331

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.15: **Debt-lnTFP Interactions**, OLS, FE, and FD-GMM Estimation with Lev1

	Lev1			*Lev2*			*Lev3*		
	OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
Constant	0.332	-0.153	...	0.333	-0.252	...	0.322	-0.266	...
	(0.030)***	(0.049)***		(0.030)***	(0.049)***		(0.030)***	(0.049)***	
l.lnTFP	0.891	0.610	0.197	0.891	0.610	0.138	0.891	0.610	-0.219
	(0.004)***	(0.007)***	(0.109)*	(0.004)***	(0.007)***	(0.048)***	(0.004)***	(0.007)***	(0.066)***
Lev	-0.012	-0.012	-0.393	-0.018	-0.032	-0.213	-0.003	-0.003	-0.219
	(0.005)**	(0.007)*	(0.096)***	(0.007)**	(0.009)***	(0.047)***	(-0.002)	(0.002)*	(0.081)***
Equity Dummy	...	...	...	...	...	...	-0.017	-0.023	-0.182
							(0.009)*	(0.010)**	(0.062)***
Lev3 × Equity	...	...	...	...	...	...	0.003	0.003	0.219
							(-0.002)	(0.002)**	(0.081)***
Age	-0.001	-0.009	-0.015	-0.001	0.000	-0.018	-0.001	0.000	-0.025
	(0.000)***	(0.001)***	(0.003)***	(0.000)***	(0.000)	(0.002)***	(0.000)***	(0.000)	(0.003)***
Tangibility	0.085	0.116	0.044	0.083	0.107	0.113	0.09	0.118	-0.023
	(0.017)***	(0.023)***	(-0.058)	(0.017)***	(0.023)***	(0.036)***	(0.017)***	(0.023)***	(-0.083)
Uniqueness	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)**	(0.000)*	(0.000)***	(0.000)**	(0.000)***	(0.000)***	(0.000)**	(0.000)**
Uniqueness Dummy	-0.006	-0.057	-0.058	-0.006	-0.056	-0.014	-0.005	-0.057	-0.058
	(-0.005)	(0.012)***	(0.027)**	(-0.005)	(0.012)***	(-0.018)	(-0.005)	(0.012)***	(0.023)**
Growth Opportunity	-0.142	-0.187	0.181	-0.144	-0.189	0.108	-0.146	-0.190	0.228
	(0.041)***	(0.047)***	(0.077)**	(0.042)***	(0.047)***	(0.047)**	(0.042)***	(0.047)***	(0.052)***
Size	0.016	0.120	0.292	0.016	0.119	0.264	0.016	0.120	0.341
	(0.002)***	(0.004)***	(0.035)***	(0.002)***	(0.004)***	(0.020)***	(0.002)***	(0.004)***	(0.035)***
Size Dummy 2	-0.078	-0.175	-0.223	-0.078	-0.174	-0.171	-0.078	-0.174	-0.156
	(0.007)***	(0.010)***	(0.029)***	(0.007)***	(0.010)***	(0.017)***	(0.007)***	(0.010)***	(0.021)***
Size Dummy 3	-0.144	-0.292	-0.326	-0.143	-0.290	-0.262	-0.143	-0.292	-0.236
	(0.011)***	(0.015)***	(0.035)***	(0.011)***	(0.015)***	(0.024)***	(0.011)***	(0.015)***	(0.031)***
Trend	-0.001	0.000	...	-0.001	-0.009	...	0.000	-0.009	...
	(-0.001)	(0.000)		(-0.001)	(0.001)***		(-0.001)	(0.001)***	
R-squared	0.99	0.48	...	0.99	0.48	...	0.99	0.48	...
Number of Groups	...	1,496	1,409	...	1,496	1,408	...	1,496	1,408
Observations	13,112	13,112	11,475	13,100	13,100	11,462	13,096	13,096	11,457

FD Instruments: (14 15,2 3), Hansen test of overid. restrictions: $\chi^2(22) = 30.65$ Prob $> \chi^2 = 0.103$
Arellano-Bond test for AR(1) in first differences: z = -1.89 Pr > z = 0.059
Arellano-Bond test for AR(2) in first differences: z = 0.42 Pr > z = 0.678

FD Instruments: (2 5,3 7), Hansen test of overid. restrictions: $\chi^2(90) = 100.81$ Prob $> \chi^2 = 0.205$
Arellano-Bond test for AR(1) in first differences: z = -2.63 Pr > z = 0.008
Arellano-Bond test for AR(2) in first differences: z = 0.21 Pr > z = 0.838

FD Instruments: (13 15,8 9), Hansen test of overid. restrictions: $\chi^2(12) = 13.55$ Prob $> \chi^2 = 0.331$
Arellano-Bond test for AR(1) in first differences: z = -0.92 Pr > z = 0.357
Arellano-Bond test for AR(2) in first differences: z = 1.36 Pr > z = 0.175

Standard errors in parentheses

* significant at 10%
** significant at 5%
*** significant at 1%

Table 3.16: Short-run and Long-run Effects of Leverage on Performance

		Lev1			*Lev2*			*Lev3*		
		OLS	FE	FD	OLS	FE	FD	OLS	FE	FD
ROE	SR	0.138	0.469	-2.296	0.044	0.153	-2.415	-0.114	-0.037	-2.202
	LR	0.139	0.446	-2.305	0.044	0.145	-2.432	-0.115	-0.035	-2.221
	diff +/-	0.001	-0.023	0.009	0.000	-0.008	0.017	0.001	-0.002	0.019
Profitability	SR	-0.151	-0.171	-0.242	-0.155	-0.181	-0.305	-0.006	-0.005	-0.055
	LR	-0.289	-0.209	-0.323	-0.317	-0.227	-0.400	-0.012	-0.006	-0.052
	diff +/-	0.138	0.038	0.081	0.162	0.046	0.096	0.006	0.001	-0.003
Tobin's q	SR	0.823	1.120	0.844	0.960	1.323	0.652	0.012	0.012	0.241
	LR	2.579	1.842	1.183	3.779	2.468	0.893	0.136	0.035	0.297
	diff +/-	1.756	0.722	0.339	2.819	1.145	0.241	0.124	0.023	0.056
lnMV	SR	0.471	0.638	-1.205 ∧	1.176	1.500	2.911	0.099	0.082	0.222
	LR	1.938	1.348	-1.850 ∧	4.111	2.946	4.077	0.447	0.183	0.346
	diff +/-	1.467	0.710	0.645 ∧	2.935	1.446	1.166	0.348	0.101	0.124
lnTFP	SR	-0.012	-0.012	-0.393	-0.018	-0.032	-0.213	-0.003	-0.003	-0.219
	LR	-0.110	-0.030	-0.489	-0.165	-0.082	-0.247	-0.027	-0.007	-0.179
	diff +/-	0.098	0.018	0.096	0.147	0.050	0.034	0.024	0.004	-0.040

diff +/- refers to the difference between Long-run (LR) and Short-run (SR) effects of leverage on performance; if LR>SR then we have a positive value, if LR<SR, then the difference value is negative.

∧ signifies statistical insignificance.

Figure 3.1: ROE, Sample Dynamics over Time, by Firm Size

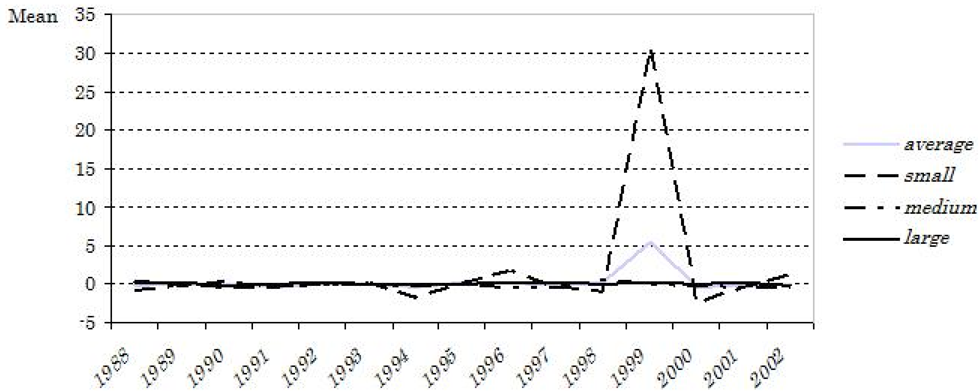


Figure 3.2: Profitability, Sample Dynamics over Time, by Firm Size

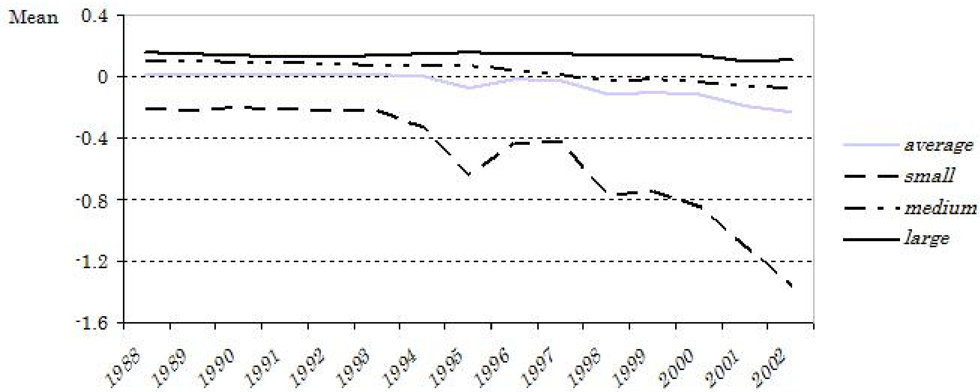


Figure 3.3: Tobin's q, Sample Dynamics over Time, by Firm Size

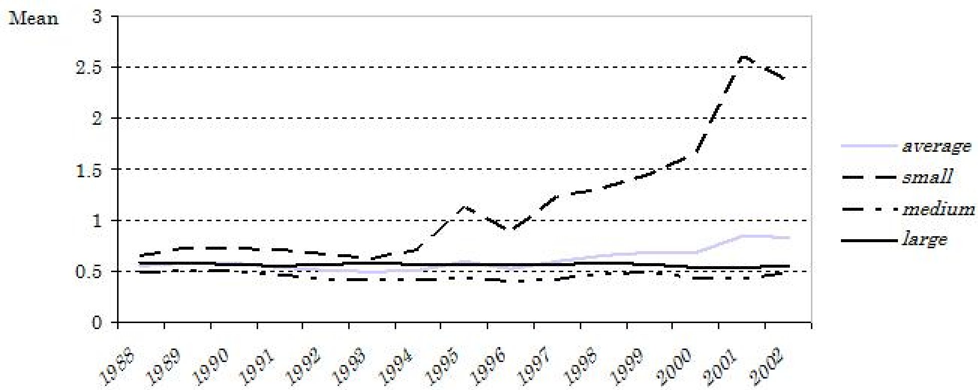


Figure 3.4: lnMV, Sample Dynamics over Time, by Firm Size

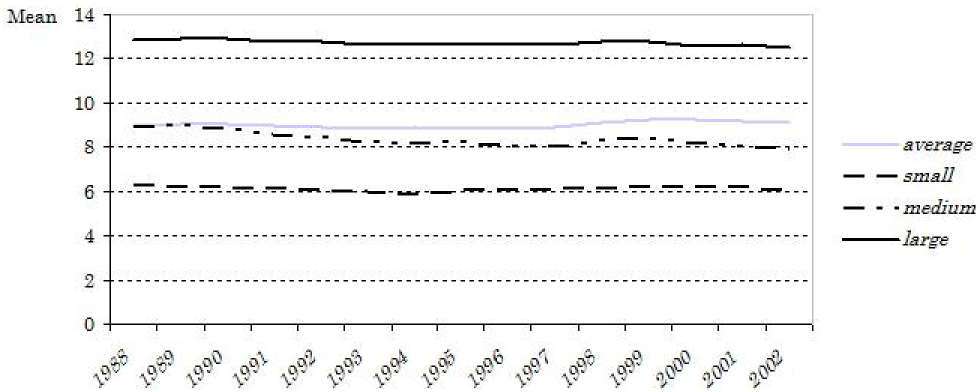


Figure 3.5: lnTFP, Sample Dynamics over Time, by Firm Size

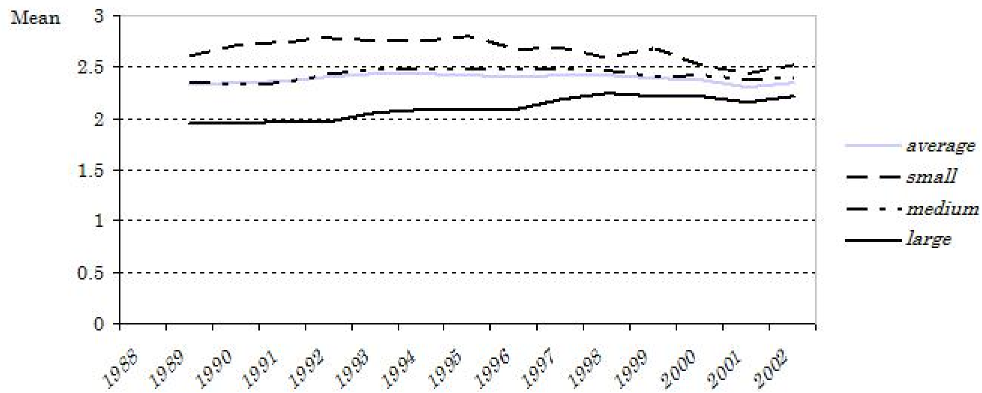
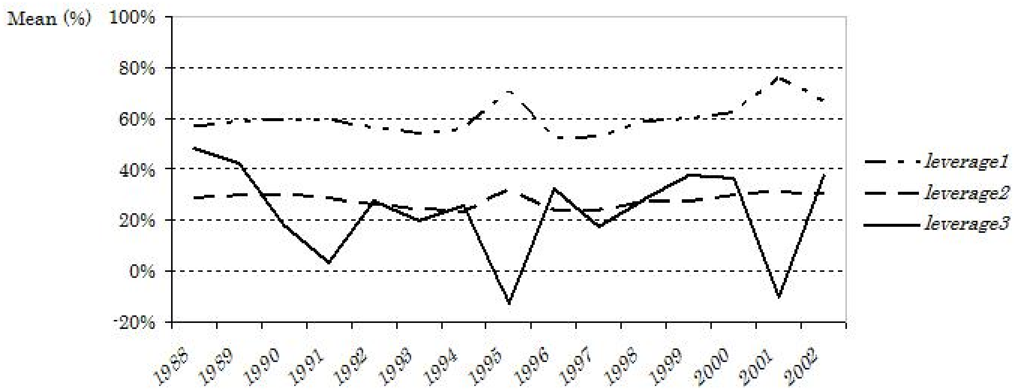


Figure 3.6: Leverage Ratios, Sample Dynamics over Time, by Firm Size



Appendix

Firm-level estimates of total factor productivity (TFP) used in this study are computed using ordinary least squares (OLS), fixed effects (FE), and Olley and Pakes (OP) methodologies. The following sections describe the OLS, FE and OP approaches to firm-level TFP estimation. Advantages and disadvantages of each estimation technique are discussed.

A.1 Variable Definitions

In computing total factor productivity, we measure output (Y) using log of net sales, deflated by the two-digit SIC industry-level price index aggregated up from Bartelsman and Gray (2001). Firm employment records are used to capture the labor (L) component. Materials component (M) is calculated following Keller and Yeaple (2003), and is deflated using Bartelsman and Gray. Capital stock measure (K) is constructed using the Perpetual Inventory Method, outlined in Olley and Pakes (1996)

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{A.1}$$

where K is gross fixed assets deflated using Bartelsman and Gray; δ is the depreciation rate; and I is the investment level, deflated using the Bartelsman and Gray index. We rely on the assumption that current capital stock is a reflection of past investment and depreciated capital form a prior time-period. In this study, depreciation rates are constructed at the four-digit SIC industry-level using the U.S. Producer Price Index.

Definitions of key variables used to generate accurate estimates of firm-level TFP are available in Appendix Table A.1a. Appendix Table A.1b provides summary statistics for the key variables in our total factor productivity estimation.

A.2 OLS Estimation Approach

The most common technique used in productivity estimation is ordinary least squares (OLS). The OLS approach can be reduced to a two-step process; the first step consists of estimating output (Y) as a function of inputs (K, L, M); the second step requires subtracting the estimated output from the actual output, thereby generating a residual which captures the productivity of a particular firm. Although attractive because of simplicity of its implementation, it has been shown that results generated using ordinary least squares estimation technique are inconsistent, and the technique itself suffers from simultaneity (see Marshack and Andrews 1944), and selection bias (see Olley and Pakes 1996).

Suppose we have a random sample of firms with information on output, capital, labor and materials for each firm. Also, suppose that production technology is represented by a production function of the following form

$$y_{i,t} = \beta_k k_{i,t}, + \beta_l l_{i,t} + \beta_m m_{i,t} + \omega_{i,t} + \eta_{i,t}, \tag{A.2}$$

where $y_{i,t}$ is the log-transformed measure of output for firm i at time t; $l_{i,t}$ and $m_{i,t}$, are logs of freely variable inputs of labor and materials respectively; $k_{i,t}$ is the state variable, which needs some time to adjust, and represents the log of capital inputs; $\omega_{i,t}$ is the productivity shock; and $\eta_{i,t}$ is the measurement error, or unforeseeable productivity shock for which inputs can not be immediately adjusted.

Estimating Eq.(A.2) allows us to calculate the total factor productivity, which is measured as follows

$$lnTFP_{i,t} = y_{i,t} - \hat{\beta}_k k_{i,t} - \hat{\beta}_l l_{i,t} - \hat{\beta}_m m_{i,t}, \tag{A.3}$$

where $\hat{\beta}_x$ is the estimated coefficient of an input x, $x \in$ {capital, labor, materials} indicates a specific input for firm i at time t.

The firm specific shock $\omega_{i,t}$, Eq.(A.2), is the source of the simultaneity and selection biases mentioned above. It is important to note that while both $\omega_{i,t}$ and $\eta_{i,t}$ are unobserved shocks $\omega_{i,t}$ is a state variable in the firm's decision problem, while $\eta_{i,t}$ is not. The term $\omega_{i,t}$ represents productivity shocks known to the firm but unobserved by the econometrician. Since $\omega_{i,t}$ is part of the firm's decision making model it is a determinant of both liquidation and input demand decisions. The error term $\eta_{i,t}$, on the other hand, represents all disturbances unknown to both the firm and the econometrician.

The empirical goal of this study is to analyze changes in firm-level productivity that accompanied the firm-specific changes in capital structure, as discussed in the body of the paper. To accomplish this we need to estimate the parameters of our production function, introduced above in Eq.(A.2). To accurately estimate the parameters we must take into account two factors: first, the cause of and pattern associated with entry and exit of firms from the industry and our sample; second, the change in productivity which is related to change in the quantities of inputs used by firms choosing to remain in production.

Consider again shock $\omega_{i,t}$ discussed previously. In 1994, Marshack and Andrews emphasized that since inputs are chosen by the firm based on some optimizing behavior which is not known to the econometrician, there exists endogeneity in the equation which the econometrician is attempting to estimate. Authors argued that the nature of inconsistency of OLS estimates comes from the fact that a firm chooses its inputs based on a model consistent with some future goal, the firm's output is thus determined by that model and is directly correlated with its inputs in a way which is unobserved by the econometrician. Generally speaking, while producers observe private information about their own productivity, this information is unavailable to outside observers and as such, unknown to the econometrician. This information asymmetry introduces a simultaneity bias since the information which is unknown to the econometrician will, in a forward-looking firm, affect that firm's labor policies and investment decisions such that a firm can alter its factor input decision in order to compensate for anticipated shocks.

Suppose we have a firm which is productive, then that firm will have the resources necessary to hire more workers and invest in capital in order to further improve performance. The simultaneity, in this case, may cause ordinary least squares estimation of the production function to generate upwardly biased coefficient estimates. This is because OLS treats factor quantities as exogenous while we just demonstrated that it is likely that they are, in fact, endogenously determined. Thus, we can say that the simple OLS estimates of the production function may suffer from simultaneity bias and be inconsistent because the productivity of a firm could be correlated with its inputs.

The second problem with consistency of ordinary least squares estimates has to do with the selection bias. The econometrician can only observe firms that stay in the market during each time period and not of the ones that exit the industry. On the other hand, producers make much more informed decisions based on information about their productivity and current level of capital stock which allows the firm to adjust the quantity of inputs. This lack of transparency creates a problem because if there exists a correlation between a firm's exit from the market and quantity of inputs used, then this correlation will result in a biased coefficient for the input estimate.

Often, firm-level data sets are incomplete, where missing values can be attributed to a firm exiting the market. If these firms are selected in a non-random manner, then the sample may become biased. Suppose that total factor productivity is influenced by the capital stock in such as way that low performing, low TFP firms generally have lower capital stock levels. If firms which tend to exit more often are the ones with low levels of total factor productivity then the selection bias in the ordinary least squares estimation will overemphasize the coefficient on capital for non-exiting firms, generating an upward bias.

One way to avoid the simultaneity and selection bias associated with ordinary least squares is to estimate the production function using fixed effects methodology. Suppose we assume that the part of TFP that influences firm behavior, $\omega_{i,t}$, is a firm-specific attribute and is invariant over time. In that case, we can include firm dummies into the regression, thereby creating a fixed-effect panel regression, mitigate the problem created by the unobserved shock $\omega_{i,t}$, and derive consistent estimates of model parameters.

A.3 FE Estimation Approach

Consider again our log-transformed production function

$$y_{i,t} = \beta_k k_{i,t}, + \beta_l l_{i,t} + \beta_m m_{i,t} + \omega_{i,t} + \eta_{i,t}, \tag{A.4}$$

where $y_{i,t}$ is the logarithm of output for firm i at time t; $k_{i,t}$, $l_{i,t}$, and $m_{i,t}$ are the logs of capital, labor and materials; and $\omega_{i,t}$ and $\eta_{i,t}$ are shocks.

The estimation of Eq.(A.4) without consideration of possible firm-specific effects can generate misleading results for OLS regressions. That is, when the unobservable firm-specific variables (shocks) are correlated with the included right-hand-side variables OLS estimation produces inconsistent and biased estimates.

The problems associated with OLS estimation can be addressed by using the fixed effects method of econometric estimation. Suppose that the error term $\omega_{i,t}$ represents productivity which is firm specific and is invariant over time such that $\omega_{i,t} = \omega_i$. Our model suggests that we may have omitted firm-specific variables. To correct for the omission of firm-specific variables we adjust all variables first by subtracting their respective means over time. Since the unobserved firm-specific variables and the intercept are time invariant, the adjustment drops these variables out of the regression equations. Estimating the resulting model produces coefficients which are both unbiased and consistent.

It is important to note that while parameters generated using the FE methodology are consistent and unbiased, the technique may still not produce the optimal results. Specifically, in the model above we assume that $\omega_{i,t}$ denotes firm specific productivity but here we are interested in how firm productivity changes in relation to corporate financial structure; that is change over time. Hence, assuming that $\omega_{i,t}$ is constant over time would imply that the results generated by using fixed effects estimation are invalid.

As an alternative to fixed effects estimation, Olley and Pakes (1996) develop a consistent semi-parametric estimator which eliminates the simultaneity problem by using a firm's investment decision to proxy for unobserved productivity shocks (see Arnold 2005). In essence, the Olley and Pakes approach relies on the theory of firm dynamics, which shows that investment can be modeled as a positive and monotonically increasing function of the productivity shock, ω, and capital (see Ericson and Pakes 1995). The investment function is used to identify the productivity shock. Inverting the investment function allows the productivity shock to be substituted out, which leads to consistent estimation of labor and materials coefficients. In each period, the firm decides whether to continue operations or to exit, depending on the productivity shock it experiences. The introduction of the exit decision into the estimation procedure allows Olley and Pakes to correctly determine the coefficient on capital.

A.4 OP Estimation Approach

In their 1996 paper, Olley and Pakes use an innovative approach to estimate the effects of restructuring on firm productivity, specifically addressing the issue of simultaneity and the selection bias. Recall from our earlier discussion that the existence of firm-specific productivity shocks which are unobserved by the econometrician can result in correlation between the error term and the quantity of inputs used, leading to simultaneity, a problem first addressed by Marshack and Andrews (1944). Olley and Pakes develop a model where they use investment as a proxy to control for the correlation between the error term and the quantity of inputs used, thereby mitigating the simultaneity problem. Authors obtain consistent estimates of capital, and then use these estimates to generate survival probabilities of each firm which, in turn, controls for the selection bias.

Consider again our production function, in its general form

$$y_{i,t} = \beta_k k_{i,t,} + \beta_l l_{i,t} + \beta_m m_{i,t} + v_{i,t}, \tag{A.5}$$

where $y_{i,t}$ is the logarithm of output for firm i at time t; $k_{i,t}$, $l_{i,t}$, and $m_{i,t}$ are the logs of capital, labor and materials. The last term, $v_{i,t}$, is the error term which represents all shocks that prevent Eq.(A.5) form holding exactly. Assume the error term to have the following form

$$v_{i,t} = \omega_{i,t,} + \eta_{i,t,}. \tag{A.6}$$

We further assume that $\omega_{i,t}$ is a firm-specific shock; that is, it contains information observable by the firm but unknown to the econometrician. On the other hand, $\eta_{i,t}$ represents a shock which is not known to either the firm or the econometrician. Conceptually, one can think about this is as if the term $\eta_{i,t}$, could be capturing unpredictable macro-related shocks, while $\omega_{i,t}$ could be measuring firm productivity. If $\omega_{i,t}$ is known to the firm, the optimal choice of inputs will be a function of ?it, and simple OLS estimation will result in a simultaneity bias because of the correlation between the error term $v_{i,t}$ and variable inputs. That is, $E[v_{i,t}|X_{i,t}] \neq 0$, where $X \in \{k_{i,t}, l_{i,t}, m_{i,t}\}$.

Similarly, using fixed effects method of estimation will also result in poor estimates of model parameters. Suppose the term $\omega_{i,t}$ is constant over time such that $\omega_{i,t} = \omega_i$, for all t. As discussed in Section A.2 of this appendix, performing fixed effects regression analysis can lead to consistent parameter estimates. However, within our framework this strategy is not optimal and although parameter estimates will be consistent they are likely to be invalid. Because we assume that $\omega_{i,t}$ denotes firm productivity and we are specifically interested in how it changes in relation to corporate financial structure, assuming that $\omega_{i,t}$ is constant over time will lead to poor estimates. We can, however, following Olley and Pakes (1996) methodology, construct $\omega_{i,t}$ from the firm's investment choices. Once we know $\omega_{i,t}$, the simultaneity of input choices can be modeled and the bias avoided.

Having now discussed the methodology for addressing the problem of simultaneity, we must turn to the selection problem. It is rational to assume that the firm maximizes the expected discounted value of its future net cash flows. At the beginning of the period, the firm learns its productivity, $\omega_{i,t}$, which is assumed to evolve according to some exogenous Markov process. Then, the firm has to make three choices. First, it decides whether it wants to stay in the market or exit. Second, the firm chooses some amount of its variable inputs, in our case labor and materials. Finally, it has to make a decision about how much to invest in capital. The Olley and Pakes approach generates an exit rule, which allows us to account for the self-selection associated with the firm's decision to exit, and avid the associated bias.

The following describes our methodology for econometric estimation of total factor productivity coefficients based on OP approach.

In Eq.(A.5) and (A.6), we assume that labor and materials are variable inputs so that their choice is affected by $\omega_{i,t}$, whereas capital $k_{i,t}$ is only determined by past values of ω, not the current one. Dropping the firm subscript for ease of notation let i_t be the firm's optimal investment choice at time t. Provided that $i_t > 0$, it is possible to show that investment is strictly increasing in ω_t for any k_t. This means that the investment function can be inverted to yield

$$\omega_t = h(i_t, k_t). \tag{A.7}$$

Substituting Eq.(A.6) and (A.7) into Eq.(A.5) gives

$$y_{i,t} = \beta_l l_t + \beta_m m_t + \phi_t(i_t, k_t) + \eta_t, \tag{A.8}$$

with $\phi_t(i_t, k_t) = \beta_0 + \beta_k k_t + h_t(i_t, k_t)$. Because $\phi_t(\cdot)$ contains the productivity term $\omega_t = h(\cdot)$ that is the source of the simultaneity bias, Eq.(A.8) can be estimated to obtain consistent estimates β_l and β_m on the variable inputs, labor and materials. We use a fourth-order polynomial in investment and capital to capture the unknown function $\phi_t(\cdot)$.

Having generated consistent estimates of β_l and β_m, we proceed to estimating the effect of capital on output, β_k, which is not identified in Eq.(A.8) because it is combined with capital's effect on investment. We assume for simplicity that k_t is uncorrelated with the innovation in ω_t, $\xi_t = \omega_t - \omega_{t-1}$, or, ω_t is a random walk. Substituting this into Eq.(A.8) gives

$$y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \hat{\beta}_k k_t + \hat{\phi}_{t-1} - \beta_k k_{t-1} + \xi_t + \eta_t \tag{A.9}$$

where $\hat{\phi}_{t-1}$ comes from estimating Eq.(A.8), and $\hat{\phi}_{t-1} - \beta_k k_{t-1}$ is an estimate of ω_{t-1}.

The probability of survival to period t depends on ω_{t-1} and $\underline{\omega_{t-1}}$, the unobserved level of productivity that would make a firm shut down its operations, which can be shown to depend only on capital and investment at time $t-1$. We generate an estimate of the survival probability by running a probit regression on a fourth-order polynomial in capital and investment (lagged by one period); the estimated survival probability is denoted by $\hat{P}_t$. The final step is to estimate β_k from the resulting equation

$$y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \hat{\beta}_k k_t + g(\hat{\phi}_{t-1} - \beta_k k_{t-1}, \hat{P}_t) + \xi_t + \eta_t. \tag{A.10}$$

Here we approximate the unknown function $g(\cdot)$ by a fourth-order polynomial in $\hat{\phi}_{t-1} - \beta_k k_{t-1}$ and $\hat{P}_t$; β_k is then estimated non-linearly across all terms that contain it.

Using the estimates of coefficients of labor, materials, and capital, we estimate total factor productivity as follows

$$TFP_{i,t} = y_{i,t} - \hat{\beta}_l l_t - \hat{\beta}_m m_t - \hat{\beta}_k k_t. \tag{A.11}$$

The log-transformed TFP, $lnTFP$, becomes our measure of firm productivity.

Appendix Table A.2 compares the coefficients generated using OLS, FE and OP methodologies. We can observe from our results that Olley and Pakes (1996) econometric approach, which allows for exit and entry, generates the “best” coefficients in terms of consistency with existing literature. Note that the coefficient on the capital tends to be underestimated by OLS and FE methods of econometric estimation since firms with higher capital stocks remain in the market even with a lower productivity shock. Appendix Table A.3 displays estimates of labor, materials, and capital coefficients generated at the two-digit SIC level, as well as by OLS, FE, and OP methodology.

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Table A.1a: Total Factor Productivity (TFP) Estimation Variables

Below, variable definitions and sources are reported for all variables used in total factor productivity (TFP) estimation, adapted from Keller and Yeaple (2003). The data are collected from COMPUSTAT Annual (Industrial) database and Wayne Grays NBER-CES Manufacturing Industry database.

Panel A: Sales

denoted Y — Net sales (COMPUSTAT item #12); deflated by industry-level price index aggregated up from Bartelsman and Gray (2001).

Panel B: Labor

denoted L — Number of employees (item #29).

Panel C: Capital

denoted K — Value of property, plant and equipments, net of depreciation, from (item #8); deflators are from Bartelsman and Gray (2001).

The construction of the actual capital variable (K_{OP}) follows perpetual inventory method as outlined in Olley and Pakes (1996) such that next period capital is equal to $(1-\delta)$ multiplied by current capital plus current investment, where d is depreciation rate constructed from the Producer Price Index at the 4-digit SIC code level, and investment is capital expenditures (COMPUSTAT item #128); deflators are from Bartelsman and Gray (2001).

Panel D: Materials

denoted M — Cost of goods sold (item #41), plus administrative and selling expenses (item #189) minus depreciation (item #14) and wage expenditures.

Wage expenditures are calculated by multiplying L by average industry wage, from Annual Survey of Manufacturers; deflators from Bartelsman and Gray (2001).

Table A.1b: Descriptive Statistics for Total Factor Productivity Variables

	Mean	*Median*	*Std. Dev.*	*Min*	*Max*	Observations
Output (Y)	1.06E+07	64216.69	1729474	0.856	4.51E+08	35,038
Capital (K)	949751.2	20892.83	5740441	0.879	1.54E+08	32,139
Labor (L)	6.222	0.43	28.069	0.000	775.1	32,031
Materials (M)	1015800	56428.75	5468138	8.842	1.22E+08	28,732

Table A.2: Total Factor Productivity Coefficients, OLS, FE and OP Approach

		Coef.	*Std. Err.*	*t*	*P > t*	*[95% Conf. Interval]*	
OLS	lnL	0.255	0.006	43	0.000	0.243	0.267
	lnM	0.717	0.005	139	0.000	0.707	0.727
Observations = 25,496	lnK$_{OP}$	0.088	0.005	19	0.000	0.080	0.097
Fixed Effects	lnL	0.378	0.006	59.95	0.000	0.365	0.390
	lnM	0.633	0.006	109.48	0.000	0.622	0.645
Observations = 25,496	lnK$_{OP}$	0.034	0.005	7.150	0.000	0.025	0.044
Olley and Pakes	lnL	0.243	0.006	40	0.000	0.232	0.255
(no age/with selection)	lnM	0.718	0.005	134.03	0.000	0.708	0.729
Observations = 21,890	lnK$_{OP}$	0.197	0.007	29	0.000	0.184	0.210

Table A.3: Total Factor Productivity Coefficients

Coefficients below were estimated Using OLS, FE and OP Approach, computed by Two-Digit SIC Code.

	OLS			Fixed Effects			Olley and Pakes (no age/with selection)			Observations
	*ln*L	*ln*M	*ln*K_{OP}	*ln*L	*ln*M	*ln*K_{OP}	*ln*L	*ln*M	*ln*K_{OP}	OLS,FE(OP)
SIC 20 + SIC 21	0.237 ***	0.648 ***	0.079 ***	0.305 ***	0.576 ***	0.002	0.229 ***	0.639 ***	0.048 ***	951(815)
SIC 22	0.218 ***	0.760 ***	0.022 **	0.202 ***	0.801 ***	-0.025 **	0.171 ***	0.753 ***	-0.054 **	358(315)
SIC 24	0.162 ***	0.689 ***	0.125 ***	0.304 ***	0.681 ***	0.008	0.145 ***	0.691 ***	-0.005	286(253)
SIC 25	0.294 ***	0.681 ***	-0.008	0.285 ***	0.676 ***	-0.037 ***	0.261 ***	0.645 ***	-0.063 **	297(265)
SIC 26	0.374 ***	0.412 ***	0.207 ***	0.542 ***	0.377 ***	0.016	0.354 ***	0.408 ***	0.298 ***	442(384)
SIC 27	0.155 ***	0.709 ***	0.114 ***	0.441 ***	0.584 ***	-0.009	0.149 ***	0.724 ***	0.193 ***	485(414)
SIC 28	0.468 ***	0.556 ***	0.074 ***	0.425 ***	0.570 ***	0.096 ***	0.499 ***	0.586 ***	0.170 ***	3,087(2,638)
SIC 29	0.175 ***	0.716 ***	0.128 ***	0.228 ***	0.536 ***	0.080 ***	0.197 ***	0.707 ***	0.276 ***	461(395)
SIC 30	0.244 ***	0.738 ***	0.070 ***	0.302 ***	0.660 ***	0.011	0.253 ***	0.754 ***	0.131 ***	769(659)
SIC 32	0.458 ***	0.441 ***	0.138 ***	0.415 ***	0.419 ***	-0.027	0.502 ***	0.411 ***	0.150 ***	205(175)
SIC 33	0.279 ***	0.631 ***	0.094 ***	0.406 ***	0.584 ***	0.031 **	0.261 ***	0.623 ***	0.143 ***	800(696)
SIC 34	0.219 ***	0.726 ***	0.096 ***	0.221 ***	0.758 ***	0.011	0.223 ***	0.703 ***	-0.021 **	591(510)
SIC 35	0.082 ***	0.958 ***	0.030 ***	0.315 ***	0.815 ***	0.000	0.082 ***	0.947 ***	0.146 ***	3,900(3,345)
SIC 36	0.160 ***	0.600 ***	0.197 ***	0.410 ***	0.600 ***	-0.010	0.129 ***	0.553 ***	0.359 ***	5,316(4,554)
SIC 37	0.388 ***	0.512 ***	0.098 ***	0.396 ***	0.499 ***	0.063 ***	0.377 ***	0.484 ***	0.166 ***	1,533(1,321)
SIC 38	0.471 ***	0.579 ***	0.059 ***	0.442 ***	0.586 ***	0.011 ***	0.497 ***	0.604 ***	0.113 ***	5,410(4,647)
SIC 39	0.323 ***	0.687 ***	0.025	0.376 ***	0.492 ***	0.018	0.329 ***	0.664 ***	0.130 ***	605(504)

* indicates significance at the .10 level
** indicates significance at the .05 level
*** indicates significance at the .01 level