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Market Frictions and the Efficiency of Capital Allocation

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Market Frictions and the Efficiency of Capital Allocation

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Foreword

This dissertation contains two articles in seemingly unrelated areas of Financial Economics: financial markets and institutions and mutual funds. While these two areas may not appear to be directly related, there are some common themes and empirical findings that echo some of the most important concepts in the field. In many ways, the main goal of finance is to reduce market frictions that hinder the efficient flow of capital in the economy, and a major friction involves information problems in the economy. Accordingly, A main goal of the finance discipline is to design mechanisms that reduce market frictions and solve problems of incomplete, asymmetric, and uncertain information in the financial markets that, if left unchecked, can hinder the flow of capital and, consequently, reduce real economic productivity. Undoubtedly, the biggest economic failure in recent times has been the financial crisis of 2008. The inability of the financial markets to efficiently price complicated new financial instruments led to a period of increased risk and uncertainty in the financial markets and, as a result, financial activity fell dramatically, resulting in massive financial losses and unemployment.

The first chapter of this dissertation analyzes the financial sector leading up to the financial crisis. The reason financial firms are so heavily regulated in the U.S. is in order to ensure that investors feel confident in the financial system and that they have enough information to make beneficial economic decisions. However, recent trends in financial intermediation including the use of largely unregulated derivative products and the growth of a new set of less-regulated financial companies can pose significant problems for the efficient flow of information in the economy. In an empirical analysis, this chapter provides interesting evidence that highlights the role that these trends played in the stability of the U.S. financial sector leading up to the financial crisis, and it has implications regarding policy changes that may improve information flows in the financial markets.

The second chapter examines the relative efficiency of mutual funds in terms of how quickly they are able to adjust portfolios in order to achieve better performance. Mutual funds have become an important investment vehicle and have seen tremendous growth over the past several decades. Mutual funds offer lay investors the ability to instantly hold a diversified portfolio and, as a result, mutual funds owned by smaller investors in retirement accounts and the like have provided a significant amount of capital to the financial markets. Due to the prominence of mutual funds, it is important to know whether they are efficiently investing their clients' funds. In particular, mutual fund managers are charged with making investments on behalf of their clients, and a key element of this charge is gathering and efficiently using information about investment opportunities in order to make the best investment decisions. There has been much debate on this subject; however, this chapter applies a novel empirical methodology in order to address a new aspect of mutual fund efficiency.

This dissertation, while investigating topics in two different areas of finance, shows empirical results related to the importance of information and its efficient and productive use. Whether it is used to insure that investors are trading securities that are transparent enough for investors to understand their underlying risks, or whether it is used by fund managers to acquire specialized information to yield high returns for their clients, information is the key to efficiently operating financial markets, and it is imperative to design frameworks that promote the efficient use of information and reduce other market frictions. The two chapters presented in this dissertation provide unique empirical analyses that significantly contribute to the literature in the field, and the results have significant implications regarding financial reform, regulatory policy, financial institutions and mutual fund governance, and optimal investing behavior.

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Abstract

The following dissertation contains two unique empirical studies that contribute to the overall literature in the field of Financial Economics in the areas of mutual fund investing and financial intermediation and regulation. The first Chapter, entitled "The Impact of Macroeconomic Stress on the U.S. Financial Sector", examines the relative impact of macroeconomic stress on financial and non-financial U.S. firms. Empirical results show that macroeconomic shocks appear to have a larger impact on financial firms. Additionally, the sensitivity of financial firms to macroeconomic events can be traced to the influence of non-depository institutions, or "shadow banks", like finance and investment companies, which are less regulated than depository institutions. The results coincide with several trends in the financial sector including increased competition, complexity and interconnectedness and highlight the need for governance mechanisms that account for the risks associated with these factors. The second chapter, entitled "Partial Adjustment Towards Equilibrium Mutual Fund Allocations: Evidence from U.S.-based Equity Mutual Funds", examines the relative efficiency of equity mutual funds in terms of speed of portfolio adjustment by applying a partial adjustment model. Empirical results show that mutual fund managers are able and willing to quickly adjust their portfolios when results have been sub-optimal, implying that the cost of persistent poor performance is perceived as being high. Managers can offset about 106 percent of the deviation within one period. Additionally, results show that funds that typically engage in the costly production of specialized information, like emerging market and sector funds have more efficient speeds of portfolio adjustment than more passive funds, like market index funds. The results imply that actively managed funds may have efficiency advantages that have been previously ignored in the empirical literature.

Keywords: Financial crises, Financial institutions, Policy, Regulation, Financial markets, Mutual Funds, Partial Adjustment Models, Active Portfolio Management, Mutual Fund Performance and Efficiency

1. The Impact of Macroeconomic Stress on the U.S. Financial Sector

1.1 Introduction

The stability and efficiency of the financial sector has gained increased scrutiny in light of the 2008 financial crisis and corresponding "Great Recession". The consequences of the collapse of many financial institutions were not confined to Wall Street. The failure of the financial sector in handling increasing financial stress contributed to a worldwide economic slowdown. As a result, countless investors, pension funds, and corporations realized losses in the trillions of dollars, and millions of people became unemployed. The effects of this downturn are still being felt years later. The real sector consequences of the financial crisis of 2008 illustrate the important role that financial intermediaries play in ensuring a stable and efficient economy. Not surprisingly, there has been an increased focus on the financial sector in the wake of the global financial crisis, as stakeholders around the world study the causes of the crisis and contemplate which solutions, if any, could be employed to prevent similar occurrences in the future.

Efficiently functioning capital markets are paramount to generating and sustaining real economic growth, and financial intermediaries play an important role in developing and maintaining healthy capital markets. The consequences of a financial system collapse became apparent in the aftermath of the Global Financial Crisis of 2008. Accordingly, there have been continued efforts over many years to increase the efficiency and stability of the financial services sector. Since the 1980s, deregulation in the U.S. markets and liberalization policies in emerging markets have coincided with a growing degree of international market integration and robust growth in emerging economies. Proponents of many of these financial reforms that favor open and less restrictive markets may take credit for some of the successes of what seems to be improved international market efficiency and growth. However, the recent financial crisis points to the fact that the increasingly integrated and complex financial system appears to carry with it a great deal of risk that is still perhaps not yet fully recognized.

The typical financial intermediary holds assets that are funded with liabilities of a different maturity. Accordingly, the majority of risk in the financial sector stems from the uncertainty surrounding the value of the firm's assets relative to its liabilities as economic variables such as interest and exchange rates fluctuate. Additionally, since many financial firms leverage their liabilities by making risky investments, they often also face significant liquidity and default risks. To avoid excess losses from these and other sources of risk, many financial intermediaries have increasingly relied on the use derivative securities to hedge their asset portfolios. Additionally, the financial sector has faced an increasingly friendly regulatory environment with regards to the designing and implementation of derivative securities. On one hand, the use of derivatives allows financial intermediaries to transfer risk and insure against both default and price risk, resulting in less uncertainty in the capital markets. On the other hand, trading in redundant securities may not lead to any economic benefits, and may in fact only be serving to skirt regulations aimed at controlling financial asset risk through the use of off balance sheet activities. In addition, the difficulty in pricing complex derivatives may add yet another level of unanticipated risk to a financial institution's balance sheet.

The potential risks posed by the failure of the financial system are compounded by the unprecedented consolidation that has taken place within the financial sector over the past several decades. Regulations limiting commercial banking branching across state lines were relaxed in the 1990s, resulting in increased mergers and acquisitions in commercial banking activities. Additionally, regulations such as the Financial Services Modernization Act of 1999 allowed for the creation of bank holding companies, which are allowed to hold both depository and non-depository institutions. The increased consolidation in the financial sector can allow financial firms to become more efficient. Larger financial institutions are able to more easily diversify and can benefit from economies of scale and scope. On the other hand, consolidating financial assets also poses significant risks, because the failure of an individual financial institution has a much larger potential impact on the real sector[1].

This chapter focuses on the impact of macroeconomic shocks and financial market stress on the financial services sector. The translation of macroeconomic events into corporate earnings or asset price appreciation or depreciation is a complex and dynamic process. However, we use previous studies as a guide to building an empirical model that generalizes that process. Through the use of univariate tests as well as static and dynamic panel data techniques, we use both firm-specific and macroeconomic data to study the degree to which the financial sector is sensitive to macroeconomic distress. The fragility of the financial sector relative to other sectors of the economy has important implications for financial sector governance. Financial firms in general are subject to a much deeper set of regulations, the purpose of which is to reduce risk-taking and ensure stable and trustworthy institutions. From this perspective, we may expect that financial services firms should be relatively immune from financial shocks in the economy. Regulatory requirements ensuring proper capitalization as well as their use of complex derivative products for hedging risk should ensure the stability of financial intermediaries.

However, the recent financial crisis begs the question as to whether this is indeed the case. The loosening of many regulations over the past several decades may have worked to offset some of the risk reduction benefits established by previous legislation. Additionally, innovations in the financial sector may contribute to an increasingly risky financial environment. The most highly regulated institutions, depository institutions, have traditionally been a major source of financial activity. However, financial innovations and practices have

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[1] Jiménez, Lopez, and Saurina (2013) use data from the Spanish banking system to show empirical support for a convex relationship between bank competition and risk, indicating that there is an optimal level of banking competition that minimizes risk.

shifted much of this activity to the non-depository or "shadow" banks. These trends induced risks into the financial system that were some of the major causes of the global financial crisis, and it is questionable as to whether current regulations and governance practices have evolved to sufficiently offset these risks.

The severe moral hazard issues perpetuating financial institutions that lead to the dramatic failures seen during the financial crisis have brought about a renewed scrutiny from public policy makers in the United States. For example, The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 aims to improve the stability of the financial system in the United States through reforms to the regulatory mechanisms that govern financial institutions. The act aims to improve the financial regulatory regime by taking a more holistic or macro-prudential approach to regulation. Among the many changes taking place under the Dodd-Frank Act are the consolidation and collaboration of regulatory agencies, an increased focus on the risks posed by derivative securities, transparency requirements with regards to consumer financial products, and a focus on overall systemic risk. Accordingly, the Act gives supervisors the authority to regulate financial institutions that have historically been left relatively unregulated by substantial external governance, such as finance companies and investment banks. This paper contributes to the literature in this area, as the results presented highlight several key facets of the financial services industry that have motivated such attempts at increased regulatory scrutiny.

We analyze the relative performance of the financial sector in order to determine whether firm performance is more consistent with a financial sector that is robust to economic conditions or is consistent with an increasingly complex and risky financial market. In light of the results, the fragility of the financial sector seen during the recent financial crises is not surprising. The study significantly contributes to the literature in several ways. Previous studies have separately analyzed the impact of financial stress on financial and real sector firms. Additionally, there has been previous literature describing the causes of real and financial sector instability. This study extends this literature by directly comparing the relative impact of economic distress on financial and nonfinancial institutions. This allows us to link changes in the comparative sensitivity of financial sector firms to economic stress to recent trends in the global financial markets. Furthermore, in a more detailed analysis of the financial sector, we identify the types of financial firms that are driving financial market instability. The results presented are of particular interest to academics and practitioners interested in evaluating and designing regulatory and governance mechanisms aimed at more accurately measuring and controlling the risks taken by financial intermediaries.

The results show that financial sector profitability is extremely sensitive to the macroeconomic regime. The average profitability of a financial firm is significantly higher than the average real sector firm in normal economic times. However, the results show that the specific impact of a recession or financial market stress on financial firms can be significantly worse than that of other industries. Furthermore, we trace the source of this sensitivity to non-depository financial institutions such as financial services firms, investment companies, insurance, and finance companies. This has implications as to the effectiveness of the current risk management and corporate governance mechanisms in place within the finance industry as well as the regulatory bodies aimed at ensuring stable markets. The results are consistent with many of the goals of the recent Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, which, among other things, focuses on the reduction of risks posed by exotic financial products and the systemic risks posed by non-depository financial institutions.

This chapter proceeds as follows. In Section 1.2, we provide a review of the literature regarding the impact of macroeconomic news on firm and stock performance of both financial and non-financial firms, including the impact of financial crises. Section 1.3 describes the methodology used in the empirical analysis. Section 1.4 describes the data used in the empirical models. Section 1.5 describes the relative impact of financial distress on financial firm profitability.

Section 1.6 extends the analysis to the effect of financial distress on the cross-section of stock returns. Section 1.7 conducts a further examination of the financial services industry. Section 1.8 discuses robustness issues and presents potential areas of future research. Section 1.9 concludes.

1.2 Literature Review

This paper combines several lines of literature that relate to the determinants of firm and economic growth in both the financial and real sectors and examines how they are affected by economic downturns and financial crises. Past research has attempted to describe the process by which economic fundamentals are transmitted through the financial system and their impact on real and financial sector asset prices and performance. Additionally, much recent literature has focused on the impact of financial market distress in light of increasing international market interdependency. The following review of the literature on these topics illustrates the current state of empirical research.

1.2.1 Macroeconomic conditions and interest/exchange rates

The driving force behind efficiently operating financial markets is the ability of financial intermediaries to properly price and transfer capital to the real economy through the supply and demand for domestic and foreign currencies. As interest and exchange rates adjust to equilibrium, financial intermediaries must adjust their positions to reflect new information imputed into the supply and demand for real capital. In this sense, the essential mechanism upon which the financial sector relies is influenced by the macroeconomic conditions underlying the real economy. This relationship illustrates the importance of identifying the relationship between real economic activity and the supply and demand for capital, and an extensive literature has focused on the impact of macroeconomic events on domestic and foreign interest and exchange rates. As the largest economy in the world, economic progress in the United States has been a key driver of global capital demand, and many studies focus on the impact of U.S. macroeconomic news on domestic and foreign interest and exchange rates.

Among the many studies along this line, Frenkel (1981)[2] examines the effect of "news" on interest and exchange rates in the wake of the establishment of the modern, floating exchange rate system developed in the 1970s and finds that macroeconomic news is essential in the determination of foreign exchange and interest rates. Important economic events like unexpected inflation are implied to be the type of news that determines the size and direction of interest rate changes. More recent studies have extended the literature to more accurately define the relationship between economic news and its impact on the cost of funds. For example, measures that reflect underlying economic growth such as GDP growth, retail sales, inflation, and monetary policy stance are positively related to interest rate changes (Faust *et al.* (2003)[3]). Along similar lines, Neely and Dey (2010) provide a review of the literature showing that macroeconomic news from several major economies similarly effect foreign exchange rates as well[4]. Additionally, Bellas, Papaioannou, and Petrova (2010) find that financial stress can have a significant impact on sovereign bond yields.

1.2.2 The Determinants of financial sector stock prices and profitability

Aside from having an impact on overall economic growth, macroeconomic news has also been shown to impact the operating and stock performance of financial intermediaries. Due to the important role of financial intermediaries in matching the supply and demand for money at correct prices, firms in the financial sector are particularly affected by changes in underlying macroeconomic conditions.

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[2] While "news" in this model is defined as innovations in interest rates, the model is general enough to define "news" as any significant, unanticipated change in a key economic variable that will affect asset prices or cash flows.
[3] They find that the effect of price "surprises on interest rates has declined over the period of 1987 to 2002.
[4] Other studies also show the impact of U.S. and international fundamental news on foreign exchange rates in the context of emerging markets (Özataya, Özmenb, & Şahinbeyoğluc (2007), Emir, Özatay, and Şahinbeyoğluc (2005).

This fact underscores the importance of a financial firm's ability to anticipate, react to, and hedge against both expected and unexpected changes in real economic production. The literature shows that both idiosyncratic factors and macroeconomic factors influence financial sector performance. One such line relates to the stock price performance of financial firms, while another relates to the performance of financial firms, typically measured by some ratio such as profit margin or return on assets (ROA).

The effect of interest rate changes on the stock price performance of financial firms is tested empirically by Flannery and James (1984). They find that the common stock returns of financial companies are associated with unanticipated changes in key interest rates. A positive coefficient between unanticipated interest rate changes and the return on bank stock indexes is consistent with the idea that the decrease in equity capital caused by maturity mismatch increases the investors' required return. An alternative explanation is that increased interest rates are also associated with the contractionary monetary policies indicative of good overall economic performance. Flannery and James (1984) find a link between of the magnitude of this affect and the maturity mismatch of assets and liabilities that tend to occur in the financial sector. Claire and Courtenay (2002) also show that changes in interest rate policy and monetary actions are incorporated into financial contract prices[5]. Staikouras (2005) extends similar results to the sample of U.K. firms. Similarly, Ewing (2002) develops an impulse response model to measure the sensitivity of the NASDAQ Financial 100 to changes in key macroeconomic variables. Key variables used to explain financial firm performance are the Fed Funds rate, as a proxy for monetary policy position, the spread between Baa and Aaa bonds, as a measure of default risk, and the Consumer Price Index. Additionally, Bernoth and Pick (2011) find that the long-term rate of interest is consistently found to be an important factor in distance to default for both banks and insurance companies.

[5] They show, however, that the announcement effect has weakened over time.

Real macroeconomic variables also influence the operating performance of financial firms. Williams (2003) shows that return on assets (ROA) is associated with GDP growth. Athanasoglou, Brissimis, and Delis (2005) find that business cycle effects and inflation are important determinants of bank profits as well. Bernoth and Pick (2011) extend their study to include both banks and insurance companies in a model that also includes the long term bond rate, inflation, industrial production growth, equity market growth, unemployment, and GDP growth.

A final piece in accurately modeling the cross-section of financial firm performance is firm-specific or idiosyncratic factors. While macroeconomic conditions like GDP and inflation affect the overall business environment in which financial firms operate, the decisions of management can influence how well the financial institution is able to anticipate and take advantage of the external economic conditions. Individual firm decisions like capital structure and payout policy can affect the firm's ability to operate efficiently in a given economy. Hoffman (2011) finds that a higher capital ratio is associated with lower profitability and lower firm size, measured by the log of assets. The literature relating to the profitability and stock returns for financial sector firms presents several theoretical motivations for both macroeconomic and firm-specific factors determining profitability and stock return. The empirical results throughout the world show strong evidence that these effects are significant in the observed data. Accordingly, many researchers incorporate both effects into models of bank profitability. For example, Athanasoglou, Brissimis, and Delis (2005) model bank profitability as a function of firm-specific, industry-specific and macroeconomic factors.

1.2.3 Macroeconomic news and stock returns

The literature also documents a similar relationship between macroeconomic fundamentals and the stock performance of firms in the real economy. Fama (1990) concludes that nearly half of the return variance of NYSE stocks is explained by variables intended to measure macroeconomic growth prospects. Schwert (1990) extends the Fama (1990) results to include data ranging from 1889 to 1988. Their extension shows the persistent effect of anticipated economic fundamentals on real sector stock returns. The consistent finding over such a long sample period makes it unlikely that the results are a product of sample selection. Model specifications by Chen, Roll and Ross (1986) show that the long and short-term interest rate spread, inflation, industrial production, and high-low grade bond spread have an important impact on the performance of NYSE stocks[6]. Their findings notably show a positive relationship in stock price reactions to changes in industrial production as well as increases in the risk premium, as traditional financial theories suggest.

McQueen and Roley (1993) find a relationship between daily returns and economic news when significant macroeconomic events like the position within the business cycle are taken into account[7]. More recently, Funke and Matsuda (2006) study the impact of macroeconomic events on the stock returns of U.S. and German stocks. Similar to Ewing (2002), they use current data relating to the state of the economy, such as growth in the gross domestic product to explain stock returns. Additionally, they use supposed leading indicators of economic activity such as consumer confidence indices, interest rates, and consumer prices. The main findings of the paper suggest that monetary policy news such as changes in consumer prices and interest rates have the largest impact on real stock price movements. In addition, similar to McQueen and Roley (1993), they also find evidence of some asymmetric reaction of the stock market to certain types of news, conditional upon the state of the economy. For example, the authors find that real economic news has a larger impact on stock prices during times of recession than in

[6] They do not find that consumption has much explanatory power.

[7] In general, McQueen and Roley (1993) do not ascribe the same direct link between macroeconomic news and daily stock returns and point to other studies that show daily asset prices seem unresponsive to most macroeconomic news. They find a very state-dependent relationship between economic news and stock prices. Stock prices react positively to positive economic news when the economy is weak, but the relationship is reversed then the economy is already experiencing growth. State-invariant discount rates are one explanation as to why this relationship is observed.

expansionary periods. Flannery and Protopapadakis (2002) also include real GDP, consumer prices, money supply, and employment in a model describing stock prices[8].

1.2.4 Financial Crisis, Contagion, and the Real economy

There is also a line of literature that establishes the relationship between financial crises and recessions and the performance of financial and real sector firms. Allen and Carletti (2013) point out that very little attention had been paid on the role of financial crises in financial sector performance leading up to the financial crisis of 2008. The lack of focus on the banking and macro-prudential systems and their impact on systemic economic stability leading up to the financial crisis can be viewed as one of the major precipitators of the recent crisis. There is a line of research that provides empirical evidence on the impact of crisis events on financial and real sector performance and stability.

Several studies look at the effects of the Asian crisis on financial firm performance. Kutan, Muradoglu, and Sudjana (2012) look at IMF news and the impact on the real and financial sectors during the Asian crisis. They find that IMF news impacts the returns of the financial sector significantly, but that the real sector economy was less responsive. Borensztein and Lee (2002) show that profitability is a key factor in the ability of financial sector firms to access credit during the Korean credit crisis. Sufian and Habibullah (2010) focus on the performance of Indonesian banks during the Indonesian financial crisis. They utilize a panel data model, and the main dependent performance variable in their model is Return on Assets (ROA). Another bank-specific measure used in this study is the size of the bank. Naturally, external factors affecting bank profitability are also included. They include measures of economic growth such as GDP, bank asset concentration, and crisis dummy variables. It is determined that larger banks tend

[8] The authors find that several inflation measures, including the CPI, balance of trade, unemployment, and money supply, significantly affect aggregate stock returns.

to make lower profits. Not surprisingly, they find that financial crises have a significant, negative impact on bank performance.

There is also a growing literature examining the effects of the recent global recession. Recent evidence from the Global Financial Crisis of 2008 shows the increasing impact of financial market failures on the real economies across the world. Virtually no economy or sector was spared the reach of the recent recession (Baur (2011)[9]). Bernoth and Pick (2011) point out the importance of the inter-linkages between firms in the financial sector. The inter-linkages not only between commercial banks, but also between commercial banks and other financial firms, such as insurance companies, have a significant impact on the systemic risk of the global financial system.

Bolt *et al.* (2010) look at bank profitability in light of the recent 2008 financial crisis and find a pro-cyclical link between bank profits and the economy. However, they find that the relationship is nonlinear in that severe recessions have a pronounced impact on bank profitability. They argue that higher-than-expected asset value and loan losses account for this affect. Dietrich and Wanzenried (2010) examine Swiss banks during the recent crisis and find that better capitalized banks tend to be more profitable. They do not find a significant relation between bank profitability and GDP, but do find that stock market capitalization and the term structure of interest rates are important. Van den End and Tabbae (2012) show that liquidity plays an important role in the banking system during a financial crisis. When faced with liquidity problems, banks typically follow a "pecking order" in which they adjust the most liquid, or short-term, assets on the balance sheet first. However, the study shows that, during the recent financial crisis, banks did not engage in this behavior and often opted to adjust less liquid assets, which can have a systemic affect on the flow of capital to the economy.

[9] Baur (2011) shows that the Healthcare, Telecommunications, and Technology sectors were relatively less affected by the recent Global Financial Crisis.

The cyclical nature of bank profits may be exacerbated by current banking regulatory paradigms as well as the increased interdependence of the global financial system (Blejer (2006)). Specifically, Nijskens and Wagner (2011) document a significant increase in financial stock betas with the advent of new methods of transferring credit risk, such as mortgage backed securities, CDSs and CLOs. These instruments essentially transfer credit risk from individual lenders to the financial system as a whole. The increased betas may be a reflection of the market's anticipation of the increased risk inherent in the financial system due to the use of these new securities, some of which pose significant off balance sheet risk. They also point to the possible need for more comprehensive regulations that take into account an institution's impact on systemic risk. Similar evidence linking financial product innovations to banking sector instability is provided by Dewally and Shao (2013). They find an empirical link between a bank's use of interest rate and foreign exchange derivatives and co-movement between the firm's stock returns and those of the market, an indication of increased systematic risk. In addition, they also link a financial firm's use of financial derivatives with the risk of a future stock price crash. Finally, López-Espinosa *et al.* (2013) examine how different types of banking activities affect institutional as well as systemic risk. They recommend a strong balance between micro and macro-prudential oversight in order to ensure a stable banking system. In addition, Masciandaro, Pansini, and Quintyn (2013) link regulatory regime with financial sector risk and conclude that supervision needs to be "more intrusive, proactive, risk-based, and result oriented" in order to avoid the risks seen during the financial crisis. Overall, the empirical evidence relating bank risk-taking behaviors to systemic financial and economic risk shows that industry trends, such as consolidation and financial innovation, as well as the regulatory environment can have a significant impact on the spillover of financial risk to the banking industry and the real economy.

1.3 Methodology

A main goal of this study is to compare the degree to which financial and non-financial firms are affected by macroeconomic shocks and financial crises. We expect all firms to be significantly affected by economic slowdowns and credit crises. However, their impact on financial firms is of particular importance, since a stagnant financial sector can have dramatic real sector implications, because financial sector weakness impedes the efficient allocation of real capital. We seek to develop a framework that compares the impact of financial distress on the performance of different types of firms. Significant results showing that macroeconomic stress impacts the financial sector differently than it affects non-financial firms has important regulatory and governance implications as well.

As part of this framework, we first present an analysis that examines the impact of macroeconomic shocks on firm profitability in section 1.5. As part of this initial analysis, a univariate analysis is conducted that examines the impact of a macroeconomic recession on several key firm fundamentals and compare the level differences in performance caused by a recession between financial and non-financial firms. The univariate analysis is followed by a series of multivariate regression estimations that attempt to more accurately define the role that financial shocks play in firm profitability. The baseline multivariate model is one that models firm performance as a combination of firm-specific and macroeconomic variables, along the lines of Sufian and Habibullah (2010). However, a set of variables aimed at examining the specific impact of financial market distress on certain types of firms is added to the specification. The econometric estimation utilizes a panel data approach of the general form:

$$Profitability_{i,t} = \alpha_i + \beta' FirmSpecific_{i,t} + \gamma' Macroeconomic_{i,t} + \theta' Distress_{i,t} + \varepsilon_{i,t} \quad (1.1)$$

In section 1.5, static fixed-effect as well as dynamic panel estimation procedures are employed to allow for significant cross-sectional differences among firms. A test for different intercepts rejects the hypothesis of a pooled panel data approach at the one percent level. Additionally, a series of Hausman tests show that a random effects estimation procedure is likely inappropriate for the parameter estimation.

In our baseline multivariate model, it is assumed that firm performance, measured by profit margin, is a function of several key firm-specific and macroeconomic determinants. The firm-specific factors included in the model are the log of total assets, the debt ratio (total assets divided by total liabilities), and lagged profit margin. The macroeconomic factors include inflation, measured by the CPI for all urban consumers, real GDP growth, the Fed Funds rate, the spread between the Fed Funds rate and the 10-year constant-maturity treasury bond, and a set of quarterly dummy variables. Also included are a set of distress or crisis variables, namely a recession dummy variable and the Chicago Federal Reserve's Financial Conditions Index. It is the sign and significance of these two variables and their interactions with firm-type dummy variables that drive many of the conclusions in this chapter.

In section 1.6, as a robustness check, the analysis is extended to the cross-section of stock returns. It is assumed that, if the firm profitability model presented in section 1.5 is correctly specified, then the influence of the deterministic factors should also be significant in explaining the cross-section of stock returns. However, it is expected that the results should be weaker for a model of stock returns, because the market should be able to more efficiently adjust to changes in perceived risk than the individual firm. Additionally, investors should also be able to diversify away firm and industry specific risks. In the stock returns analysis, the same panel ordinary least squares (OLS) fixed effect methodology described above is employed.

In section 1.7, the empirical analysis continues with a more detailed accounting of the financial firm results. In this section, the financial sector firms are divided by SIC code into 6 sub-industries: depository institutions, finance companies, financial services, insurance, real estate, and investment companies. The multivariate, panel data regression framework is applied to the financial sub-sectors in order to examine how different types of financial institutions react to financial stress. The analysis compares the results of the same regressions for different types of financial institutions. In addition, a set of industry interaction dummy variables is utilized in order to directly compare the effects of economic distress across the sub-sectors in a nested model. Here, the signs and significance of the coefficients that compare different types of financial sector firms to their non-financial counterparts are directly observable.

1.4 The Data

Following the literature, we collect data on the variables commonly found to be associated with the profitability and stock performance of financial and real sector firms. As in Sufian and Habibullah (2010) and others, we include both firm-specific data and well as macroeconomic variables.

All firm-level data are collected from COMPUSTAT. These data include information on firm size, profitability, and leverage. Likewise, all macroeconomic time series data are collected from the St. Louis Federal Reserve's FRED database. These data include real gross domestic product growth, inflation, measured by the Consumer Price Index (CPI), the Fed Funds interest rate, and the rate on the ten year U.S. constant-maturity Treasury bond. Also included are measures that proxy for macroeconomic and financial crises. A dummy variable indicates whether the given observation falls under an NBER-defined recession. The National Bureau of Economic Research does not have a precise definition for a recession, but an NBER-defined recession is a period ranging from a few months to a year whereby economic productivity falls enough to have a significant impact on the U.S. economy. This measure is less restrictive than the formal definition of a recession. Therefore, it can account for periods of distress that will significantly affect firm performance, but may not fit the technical definition of a recession. The Federal Reserve's Financial

Condition Index another measure of macroeconomic stress. The Federal Reserve's Financial Condition Index measures the overall financial status of the economy, including risk and liquidity. It considers stock and bond market conditions, as well as liquidity and conditions within the shadow banking system. Normal financial conditions are represented by a value of zero, while a level above zero represents higher than average stress, and a level below zero represents lower than average stress. Hence, a negative regression coefficient for this variable can be interpreted as increasing financial stress being associated with a decrease in firm performance.

The firm-level data are filtered to reduce the impact of outliers and data errors. All firm-level data are sampled quarterly from 1980Q1 through 2010Q4. Sample firms are required to have revenues greater than $500 thousand and total assets greater than $1 million. Also, all firm-quarter observations must contain the complete set of variables used in our baseline model on order to be included in the sample. For example, an observation with a missing value for the debt ratio is excluded. Each sample firm must also have at least eight quarters of complete data. As a final measure of ensuring a representative sample, the data are windsorized at the one percent level of the dependent variable, profit margin, for each tail every year. This has the effect of eliminating many extreme observations that are likely the result of extraordinary performance or errors in the data.

The final sample contains 607,588 firm-quarter observations for a sample of 17,591 firms. Table 1.1 presents some sample statistics for the U.S. firms in the COMPUSTAT sample. Summary statistics are presented for several key variables for the entire sample, each decade, and for each single-digit SIC-classification industry. The data show that financial firms average a higher level of total assets with a sample average of $16.2 billion, compared with the full sample average of $3.7 billion. The standard deviation of total assets is higher for financial firms, however. Financial firms on average also have higher revenues with $487 million, compared with the full sample average of $444 million. However, the standard deviation of financial firm revenues is lower than that of the full sample. Financial firms are able to generate an average net income of about $36 million on revenues for a profit margin of 11.2 percent, compared with 3.01 percent for the full sample. Financial firms have higher average debt ratios than the full sample with 63.3 percent and 53.6 percent, respectively. Financial firms also exhibit higher average ROE, retained earnings, and cash, but lower levels of capital expenditures.

Table 1.1 also divides the full sample into decades. Profit margins for all firms appear to decrease over time from an average margin of 4.97 percent during the 1980s to 1.52 percent during the 2000s. There are similar uniform decreases in both ROE and ROA. Conversely, the market-to-book values for the full sample of firms increase from 1.02 in the 1980s to 1.52 in the 2000s. This reflects the dramatic increase in average profits earned, from $12 million in the 1980s to $44 million in the 2000s.

The dependent variable in our main profitability analysis is profit margin. Figure 1.1 compares the profit margins of financial firms, defined as firms having SIC codes between 6000 and 6999, with those of non-financial firms over the 1980Q1 to 2010Q4 sample period. The figure illustrates the fact that financial firm profit margins are consistently higher than those of non-financial firms, as previously implied by Table 1.1. There is also a significant degree of variation in the profit margin time series for financial firms, compared with that of non-financial firms, especially around the recent global financial crisis. The figure also shows a significant amount of seasonality in the data. We incorporate lagged profit margin and quarterly dummy variables in our multivariate regressions to account for seasonality and persistence.

For the stock returns analysis presented in section 1.6, monthly stock return data from the CRSP database over the same 1980 through 2010 period are analyzed. Accordingly, monthly observations of the key macroeconomic variables, GDP growth, Fed Funds, *etc.*, and distress variables, NBER recession dummy and Financial Condition Index, are collected. The monthly data is then matched with

Table 1.1: Summary Statistics

The following are descriptive statistics on a sample of COMPUSTAT firms, sampled quarterly from 1980Q1 through 2010Q4. The data includes all firms with revenues of more than $500K and is windsorized in each tail at the one percentile. The sample also requires each firm to have at least 8 quarters of complete data.

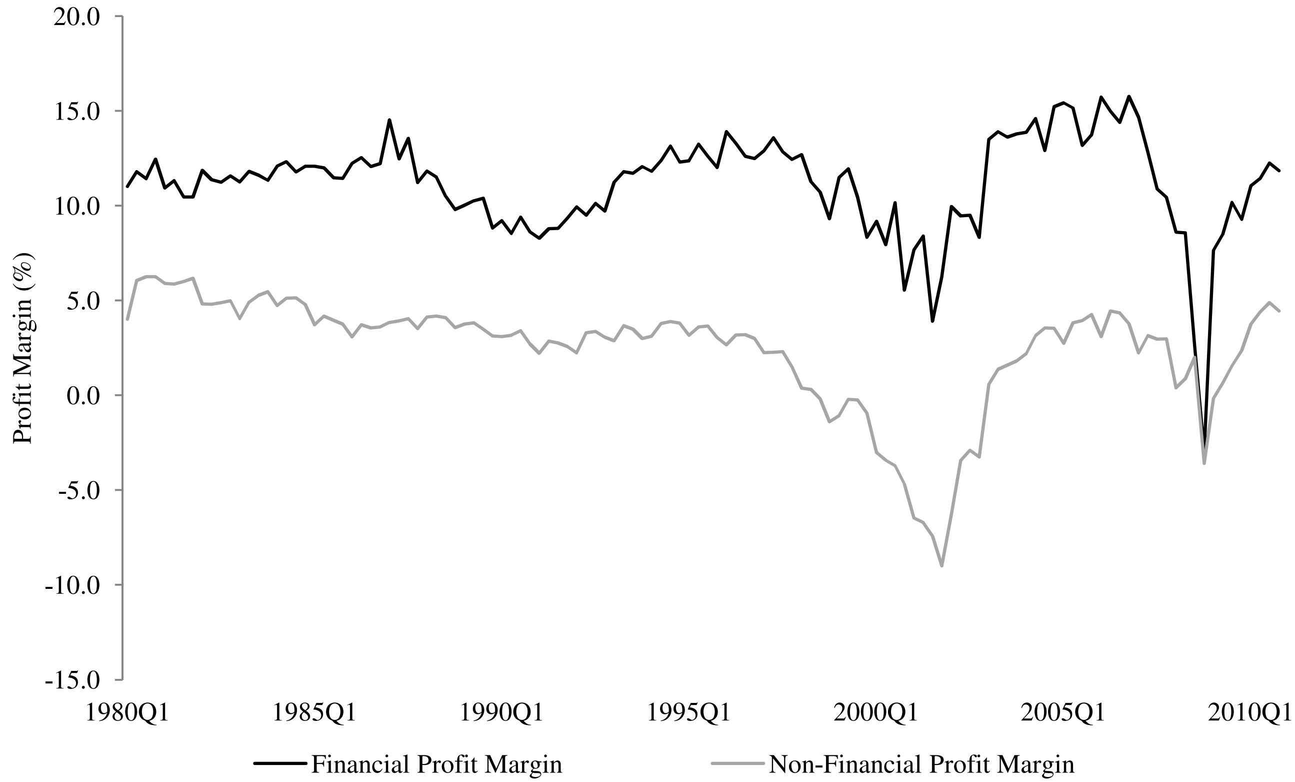
	Full Sample	1980s	1990s	2000s	SIC Industry 000-999	SIC Industry 1000-1999	SIC Industry 2000-2999
Total Assets							
Mean	3,708	1,147	2,129	6,865	795	1,287	3,045
Std. Dev.	33,965	5,073	13,138	52,944	1,928	4,081	13,398
Revenue							
Mean	444	227	299	723	195	191	771
Std. Dev.	2,213	946	1,325	3,218	402	588	3,678
Net Income							
Mean	25	12	15	44	7	18	54
Std. Dev.	200	59	98	303	65	116	354
Profit Margin (%)							
Mean	3.01	4.97	3.27	1.52	2.65	4.25	2.00
Std. Dev.	17.94	10.31	15.05	23.38	23.51	22.77	16.89
ROA (%)							
Mean	0.82	1.25	0.86	0.50	1.00	0.86	1.05
Std. Dev.	2.80	2.09	2.72	3.21	2.89	2.53	2.84
ROE (%)							
Mean	2.37	2.97	2.40	1.96	2.37	2.05	2.77
Std. Dev.	8.84	6.54	8.60	10.22	8.80	7.47	9.06
Debt Ratio (%)							
Mean	53.63	54.05	54.01	52.99	48.28	49.02	51.82
Std. Dev.	26.04	22.08	26.44	27.90	23.60	23.00	24.93
Market Cap							
Mean	1,906	533	1,288	3,304	965	1,284	3,576
Std. Dev.	10,645	2,228	7,156	15,244	4,227	5,006	17,037
Market-to-Book Ratio							
Mean	1.52	1.02	1.97	1.52	1.15	1.45	1.61
Std. Dev.	1.13	0.26	1.39	1.13	0.59	0.91	1.11
Capital Expenditures							
Mean	84	40	57	127	20	102	129
Std. Dev.	581	228	409	780	59	419	858
Retained Earnings							
Mean	404	218	250	670	66	234	947
Std. Dev.	3,559	1,076	1,454	5,471	366	1,343	6,553
Cash							
Mean	336	22	47	426	108	181	522
Std. Dev.	2,190	61	143	2,485	314	571	2,043

Table 1.1 (cont.): Summary Statistics

	SIC Industry						
	3000-3999	4000-4999	5000-5999	**6000-6999**	7000-7999	8000-8999	9000-9999
Total Assets							
Mean	1,556	4,693	1,158	**16,215**	846	512	13,713
Std. Dev.	10,876	12,829	5,220	**95,149**	4,478	1,653	72,499
Revenue							
Mean	352	582	568	**487**	158	133	1,282
Std. Dev.	2,013	1,587	2,615	**1,963**	922	434	5,306
Net Income							
Mean	14	39	14	**36**	10	5	98
Std. Dev.	135	186	96	**243**	123	30	554
Profit Margin (%)							
Mean	1.42	4.94	1.36	**11.20**	-0.36	1.54	-1.50
Std. Dev.	15.71	16.90	8.43	**21.84**	22.02	15.06	20.82
ROA (%)							
Mean	0.85	0.76	0.86	**0.84**	0.48	0.83	-0.06
Std. Dev.	3.05	2.02	2.57	**2.02**	3.65	2.94	3.49
ROE (%)							
Mean	2.13	2.75	2.58	**2.70**	1.74	2.46	1.49
Std. Dev.	8.65	8.41	9.52	**6.83**	10.49	9.71	12.00
Debt Ratio (%)							
Mean	47.30	63.45	57.27	**63.78**	49.17	52.87	56.37
Std. Dev.	26.26	20.20	24.39	**26.50**	28.24	26.90	27.73
Market Cap							
Mean	1,300	2,900	1,241	**2,087**	1,354	545	8,671
Std. Dev.	7,244	9,828	7,431	**9,273**	10,874	1,744	42,482
Market-to-Book Ratio							
Mean	1.51	1.31	1.54	**1.30**	1.87	1.73	1.27
Std. Dev.	0.96	0.68	1.53	**1.01**	1.53	1.19	0.76
Capital Expenditures							
Mean	54	244	45	**63**	33	17	241
Std. Dev.	558	749	260	**642**	235	68	1,210
Retained Earnings							
Mean	269	350	270	**722**	73	40	2,493
Std. Dev.	2,502	3,080	1,747	**3,981**	1,651	457	12,480
Cash							
Mean	382	131	206	**1,195**	211	94	6,512
Std. Dev.	1,581	548	814	**5,775**	838	286	14,923

Figure 1.1: Firm Profitability

This figure depicts the average profitability of our sample firms from 1980Q1 to 2010Q4. Average Profit margin (NI/Sales) per quarter for non-financial firms are compared with those of financial firms.



the firm-specific, COMPUSTAT quarterly data. The same filtering procedure is applied in order to ensure the stock return data are free from the influence of outliers and data entry errors. The final sample for the stock returns analysis contains 1,631,313 firm-month observations over 15,676 firms.

1.5 The Impact of Economic Stress on Profitability

In this section, The results pertaining to the determinants of firm profitability are presented, and the focus is on the differences between financial firms and non-financial firms in times of economic distress. Several statistical analyses are used to compare the operating results of financial firms with those of non-financial firms. Different methodologies, including univariate difference of means tests, static fixed effect multivariate regression estimation, and dynamic panel data estimation are employed.

1.5.1 Univariate Analysis

A difference of means analysis is presented in Table 1.2. The table splits the firm-level sample into two groups: financial firms and non-financial firms, as defined by SIC code. The recession means are compared with the non-recession means for key firm statistics for each sample across the entire sample period. We compare the magnitude of the differences between the financial firms and those of non-financial firms as an indicator of the effect of a recession across these sectors of the economy.

Two interesting results are presented in Table 1.2. Firstly, we again note the fact that firm profitability measured by profit margin is typically higher for financial firms. During non-recession periods, financial firms have an average quarterly profit margin of 11.8 percent, while the non-financial firm average profit margin is 2.3 percent. Not surprisingly, both financial and non-financial firms experience significant decreases in profitability during periods of recession, as profit margin, ROE and ROA are all significantly lower. Another key result, however, is

Table 1.2: Difference of means during Recessions

The following are difference of means tests on the sample of COMPUSTAT firms, sampled quarterly from 1980Q1 through 2010Q4. The data includes all firms with revenues of more than $500K and total assets greater than $1M. The sample is windsorized in each tail at the one percentile. The sample also requires each firm to have at least 8 quarters of complete data. Recession means are compared with non-recession means

	Non-Financial Firms				Financial Firms (SIC 6000-6999)			
Variable	Non-Recession Mean	Recession Mean	Difference	P-value	Non-Recession Mean	Recession Mean	Difference	P-value
Total Assets	2053.9	2710.1	656.2	<.0001	15444.3	21564.4	6120.1	<.0001
Revenue	423.3	542.7	119.4	<.0001	470.6	597.6	127.0	<.0001
Net Income	23.9	25.2	1.3	0.1758	39.3	14.2	-25.1	<.0001
Profit Margin	2.261	0.210	-2.052	<.0001	11.772	7.236	-4.536	<.0001
ROA	0.856	0.529	-0.328	<.0001	0.879	0.578	-0.301	<.0001
ROE	2.399	1.884	-0.516	<.0001	2.809	1.957	-0.852	<.0001
Debt Ratio	52.305	52.675	0.370	0.0001	63.637	64.766	1.129	<.0001
Market Cap	1849.3	2096.3	247	<.0001	2066.1	2232.5	166.4	0.1242
Market-to-Book	1.62	1.37	-0.26	<.0001	1.33	1.19	-0.14	<.0001
Capital Expenditures	79.5	128.1	48.6	<.0001	60.0	78.6	18.6	<.0001
Retained Earnings	342.8	506.0	163.2	<.0001	704.5	842.0	137.5	0.0040
Cash	238.4	273.7	35.3	0.0001	1186.8	1207.4	20.6	0.8607

that the magnitude of the differences is much larger for the sample of financial firms. During a recession, a typical non-financial firm experiences a 2.05 percentage point reduction in quarterly profit margin, while the typical financial firms sees a 4.54 percentage point decrease. We also show a significant increase in the debt ratio for financial firms; however the debt ratio for non-financial firms is not statistically different during a recession. For financial firms the debt ratio tends to increase by roughly 1 percentage point during a recession. This result is not surprising, but is of particular concern for financial institutions, which may have regulatory capital structure requirements. As expected, other key financial ratios such as ROA, ROE, and market-to-book are all significantly lower during recessions for all firms. We would not necessarily expect raw financial variables such as total assets and net income to show significant deterioration during recessions, due to the long time dimension of our sample.

The results of Table 1.2 provide some preliminary results showing a pronounced impact of a recession on financial sector firms. While both financial and non-financial firms experience a decline in profit margin, the decrease for financial firms is on average more than twice that of non-financial firms. We also find a significantly more pronounced decrease in ROA and a significantly pronounced increase in the debt ratio for financial firms.

1.5.2 Multivariate Regression Analysis

We now turn to a multivariate framework and attempt to more precisely measure the determinants of firm profitability and the effect of financial distress across firm types. Panels A and B of Table 1.3 present the results for the baseline model of firm profitability across the three decades in our sample. We divide the sample into decades in order to observe any changes in the responsiveness of firms to financial shocks over time. Table 1.3, Panel A presents the results for non-financial firms, while Panel B presents the results for financial firms. Two alternative specifications are presented. The dependent variable in all specifications is profitability as defined by profit margin - total net income divided by total revenues. We use the previously defined set of firm-specific and macroeconomic factors in each specification, but alternate the measures of macroeconomic distress. In specification (1), we include the recession dummy variable to measure macroeconomic stress, while the Financial Conditions Index is used in specification (2). For each specification, we present the results of two estimation methods. The first method utilizes a panel OLS estimation with firm-level fixed effects to account for cross-sectional variation among firms. These models can be applied to unbalanced panel data sets provided that the explanatory variables are strictly exogenous. However, if this criterion is not met, it is possible that the estimated coefficients will not be consistent. When applying an empirical model that relates firm performance to macroeconomic variables, it is possible that there is endogeneity between the dependent and explanatory variables. For example, it is possible that the state of the economy is influenced by firm performance. In this case, the endogeneity of the independent variables means that a more dynamic econometric methodology should be used. Additionally, if there is reason to believe that the dependent variable, profit margin, is highly persistent, then traditional static models become inappropriate as well. In order to ensure our estimates are robust to these issues, we also estimate the model of firm performance using a dynamic panel data approach in the style of Arellano and Bond (1991). This model utilizes the Generalized Method of Moments (GMM) and uses differenced lagged dependent and state variables as instruments to derive consistent dynamic panel coefficient estimates. Both static panel OLS and dynamic panel estimates are provided, along with panel-robust p-values.

The results in Table 1.3 are consistent with previous studies with regards to the macroeconomic and firm-specific factors that influence firm profitability and stock performance. For the non-financial sample, *Inflation* is significant and positive across almost all specifications. This is in contrast with the financial sector sample results, where *Inflation* is mostly insignificant in the 1980s and 1990s samples, but positive in the 2000s sample. A positive relationship between inflation and profit margin may be explained by the fact that inflation can be associated with times of high demand and good firm performance. The dynamic panel estimate of the impact of the Federal funds rate on firm profitability is also significant and positive across decades for the sample of non-financial firms. However, we again only find a statistically significant relationship for financial firms in the 2000s sample. A positive relationship between short-term interest rates and firm profitability can be explained by the contractionary monetary policy that is often implemented in response to recent positive economic performance. Overall, the set of macroeconomic variables, *Inflation*, *Real GDP Growth*, *FedFunds*, and *Spread* are highly significant across all specifications for non-financial firms, while they only become consistently significant in the 2000s sample for financial firms. The fact that the macroeconomic factors in our model are only consistently significant in the more recent sample indicates that financial firms may have become more influenced by macroeconomic forces since the year 2000. Furthermore, this is consistent with our *a priori* expectations, given associated changes in the regulatory framework and trends within the financial sector.

The results also highlight other potential differences between the financial and non-financial samples. *Debt Ratio* exhibits a significantly negative and significant impact on firm profitability in all specifications for both financial and non-financial firms, as expected. Leverage increases fixed costs, thus reducing profit margin. However, the impact on financial institutions appears to be larger. For example, in the 2000s sample, at the means, the dynamic panel estimate indicates that an increase in the debt ratio of a non-financial firm by 1 percentage point has the effect of reducing quarterly profit margin by about 0.25 percentage points, compared with a decrease of roughly 0.44 percentage points for financial firms. The dynamic panel estimates also show a significant negative relationship between the current quarter's profit margin and the change in the previous quarter's profit margin, indicating that there is reversal in the time series. The difference between the panel OLS and dynamic panel estimates of *Profit Margin*$_{-1}$ can be explained by the fact that the lagged level is used in the panel OLS model, while that of the dynamic model is differenced. The presence of the quarterly dummy variables also adds explanatory power to the model.

The most important results presented in Table 1.3 measure the impact of the financial distress variables, *Recession Dummy* and *Financial Condition* on firm profitability. We find, consistent with Table 1.2, that recessions and financial stress have a significant impact on the cross-section of firm profitability. Both the *Recession Dummy* and *Financial Condition* coefficients are negative and significant in the 2000s for the dynamic panel estimations. This is consistent with the *a priori* expectation that increasing financial stress causes a reduction in firm profit margins. In addition, the effects of financial stress appear to be more pronounced in the later sample periods, indicating that the sensitivity of firm profitability to financial stress has increased over time for *all* firms. For example, the *Recession Dummy* coefficients are not significant for the non-financial firms in the 1980s and both the *Recession Dummy* and *Financial Condition* variables are insignificant in the 1980s for the financial firms.

Table 1.3 also begins to show an increasing marginal sensitivity of financial firms to financial stress. For example, the dynamic panel estimate of the impact of a recession on non-financial firm profit margin for the 2000s sample is -0.82, compared with -1.1 for financial firms. Therefore, during a recession, we can expect the profit margin of a non-financial firm to decline by 0.8 percentage points, while that of a financial firm will decline by more than one percentage point. In addition, the coefficient estimating of the impact of *Financial Condition* on non-financial performance is -0.47, compared with -1.8 for financial firms. These results point to the fact that financial firms react more to changes in financial stress, and this sensitivity is pronounced in the later sample period. While we may expect that financial firms are more affected by the factors included in the Financial Conditions Index, the intended function of many financial regulations and the goals of

Table 1.3: The Impact of Financial Stress on Real Sector and Financial Firm Profit Margin

Multiple regression estimates of the effect of a set of macroeconomic and firm-specific factors on firm profitability, as defined by net income divided by total revenue (profit margin). The panel OLS coefficients are measured using firm-level, cross-sectional fixed-effects, and panel robust standard errors are used to compute p-values. Dynamic panel estimates are measured using a dynamic GMM estimation procedure along the lines of Arellano and Bond (1991). Panel robust standard errors are used to compute standard errors. P-values are reported below each coefficient.

	1980s							
	Panel A: Non-Financial Firms				*Panel B: Financial Firms*			
	Panel OLS		Dynamic Panel		Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Inflation	0.302	0.312	0.205	0.256	-0.167	-0.157	-0.078	-0.036
	0.000	*0.000*	*0.000*	*0.000*	*0.378*	*0.410*	*0.731*	*0.874*
Real GDP Growth	0.021	0.035	-0.046	-0.049	-0.186	-0.194	0.188	0.096
	0.382	*0.062*	*0.113*	*0.143*	*0.173*	*0.069*	*0.108*	*0.478*
Fed Funds Rate	0.211	0.223	0.450	0.555	0.049	0.058	0.058	0.079
	0.000	*0.000*	*0.000*	*0.000*	*0.471*	*0.375*	*0.747*	*0.688*
Recession Dummy	-0.101		0.040		0.006		0.484	
	0.142		*0.719*		*0.988*		*0.411*	
Financial Condition		-0.134		-0.353		-0.072		-0.113
		0.000		*0.000*		*0.603*		*0.590*
Total Assets	-0.498	-0.476	-3.321	-3.208	-0.260	-0.255	-0.988	-1.197
	0.000	*0.000*	*0.000*	*0.000*	*0.266*	*0.276*	*0.225*	*0.146*
Debt Ratio	-0.081	-0.081	-0.105	-0.106	-0.253	-0.253	-0.178	-0.177
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.002	0.002	-0.366	-0.367	0.001	0.001	-0.396	-0.396
	0.009	*0.009*	*0.000*	*0.000*	*0.213*	*0.213*	*0.000*	*0.000*
Spread	0.236	0.253	0.403	0.507	0.412	0.426	0.353	0.385
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.134*	*0.107*
Q2 Dummy	0.232	0.262	0.191	0.273	-0.342	-0.324	0.129	0.183
	0.000	*0.000*	*0.000*	*0.000*	*0.147*	*0.172*	*0.437*	*0.275*
Q3 Dummy	0.216	0.252	0.279	0.401	-0.552	-0.531	-0.271	-0.196
	0.000	*0.000*	*0.000*	*0.000*	*0.019*	*0.026*	*0.228*	*0.391*
Q4 Dummy	-0.015	0.023	-0.170	-0.022	-0.973	-0.948	-0.932	-0.834
	0.780	*0.675*	*0.004*	*0.725*	*0.000*	*0.000*	*0.000*	*0.000*
No. of Firms	7,042	7,042	6,609	6,609	761	761	714	714
Obs.	152,945	152,945	127,248	127,248	14,370	14,370	11,532	11,532

Table 1.3 (cont.): The Impact of Financial Stress on Real Sector and Financial Firm Profit Margin

	1990s							
	Panel A: Non-Financial Firms				*Panel B: Financial Firms*			
	Panel OLS		Dynamic Panel		Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Inflation	0.468	0.017	0.591	0.156	-0.093	-0.639	0.056	-0.081
	0.000	*0.865*	*0.000*	*0.137*	*0.788*	*0.072*	*0.877*	*0.819*
Real GDP Growth	-0.283	0.231	-0.704	-0.004	-0.454	0.128	-0.633	-0.297
	0.000	*0.000*	*0.000*	*0.952*	*0.038*	*0.535*	*0.007*	*0.184*
Fed Funds Rate	0.412	0.309	1.191	1.377	-0.102	-0.215	0.035	0.216
	0.000	*0.000*	*0.000*	*0.000*	*0.394*	*0.066*	*0.868*	*0.322*
Recession Dummy	-1.239		-0.074		-1.357		0.284	
	0.000		*0.516*		*0.004*		*0.489*	
Financial Condition		-0.630		-3.194		-0.826		-2.142
		0.000		*0.000*		*0.004*		*0.000*
Total Assets	-0.907	-0.846	-2.910	-1.374	0.346	0.442	-2.747	-1.621
	0.000	*0.000*	*0.000*	*0.000*	*0.135*	*0.068*	*0.000*	*0.032*
Debt Ratio	-0.082	-0.082	-0.151	-0.153	-0.237	-0.237	-0.265	-0.270
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.001	0.001	-0.375	-0.377	0.003	0.003	-0.404	-0.404
	0.023	*0.023*	*0.000*	*0.000*	*0.106*	*0.109*	*0.000*	*0.000*
Spread	0.534	0.335	1.194	1.025	-0.127	-0.368	0.347	0.314
	0.000	*0.000*	*0.000*	*0.000*	*0.348*	*0.009*	*0.131*	*0.171*
Q2 Dummy	0.405	0.404	0.651	0.674	-0.054	-0.060	0.697	0.697
	0.000	*0.000*	*0.000*	*0.000*	*0.804*	*0.782*	*0.000*	*0.000*
Q3 Dummy	0.590	0.580	0.859	1.063	-0.495	-0.489	0.299	0.427
	0.000	*0.000*	*0.000*	*0.000*	*0.018*	*0.019*	*0.162*	*0.049*
Q4 Dummy	-0.144	-0.056	-0.131	0.763	-1.385	-1.258	-1.040	-0.444
	0.033	*0.418*	*0.058*	*0.000*	*0.000*	*0.000*	*0.000*	*0.068*
No. of Firms	10,773	10,773	9,811	9,811	1,411	1,411	1,317	1,317
Obs.	224,737	224,737	182,709	182,709	28,997	28,997	23,830	23,830

Table 1.3 (cont.): The Impact of Financial Stress on Real Sector and Financial Firm Profit Margin

	2000s							
	Panel A: Non-Financial Firms				*Panel B: Financial Firms*			
	Panel OLS		Dynamic Panel		Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Inflation	1.071	1.121	0.443	0.305	0.682	0.244	1.134	0.580
	0.000	*0.000*	*0.000*	*0.000*	*0.007*	*0.332*	*0.000*	*0.012*
Real GDP Growth	0.514	1.895	0.230	0.276	1.991	2.474	1.310	1.040
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Fed Funds Rate	-2.810	-2.818	1.362	1.740	-0.354	-0.344	3.008	3.704
	0.000	*0.000*	*0.000*	*0.000*	*0.100*	*0.110*	*0.000*	*0.000*
Recession Dummy	-3.662		-0.819		-4.028		-1.061	
	0.000		*0.000*		*0.000*		*0.066*	
Financial Condition		0.106		-0.473		-1.962		-1.763
		0.133		*0.000*		*0.000*		*0.000*
Total Assets	-1.358	-1.432	0.719	0.547	0.226	0.632	-3.701	-3.911
	0.000	*0.000*	*0.164*	*0.290*	*0.469*	*0.045*	*0.008*	*0.005*
Debt Ratio	-0.018	-0.019	-0.253	-0.253	-0.199	-0.200	-0.442	-0.436
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.000	0.000	-0.338	-0.338	0.000	0.000	-0.395	-0.398
	0.063	*0.062*	*0.000*	*0.000*	*0.281*	*0.288*	*0.000*	*0.000*
Spread	-3.646	-3.738	0.230	0.564	-0.707	-0.960	1.940	2.425
	0.000	*0.000*	*0.057*	*0.000*	*0.012*	*0.001*	*0.000*	*0.000*
Q2 Dummy	1.406	0.540	0.813	0.633	-0.328	-0.851	0.188	0.084
	0.000	*0.000*	*0.000*	*0.000*	*0.254*	*0.003*	*0.439*	*0.702*
Q3 Dummy	0.772	0.598	1.013	0.965	-1.519	-1.571	-0.925	-0.906
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*
Q4 Dummy	-0.434	-0.530	-0.211	-0.197	-1.847	-1.797	-1.328	-1.224
	0.000	*0.000*	*0.013*	*0.021*	*0.000*	*0.000*	*0.000*	*0.000*
No. of Firms	9,520	9,520	8,956	8,956	1,323	1,323	1,257	1,257
Obs.	229,906	229,906	192,629	192,629	32,775	32,775	27,753	27,753

innovative financial products like swaps are to immunize financial firms from many of these risks.

In the previous analyses, we compare the determinants of firm profitability of financial and non-financial firms by comparing the results of regressions performed on separate samples. A more robust analysis is one that allows for a more direct statistical comparison. Accordingly, we present a nested model, whereby we test the impact of the financial distress measures on financial companies with the use of dummy variables and associated interaction terms. We create a dummy variable that indicates whether the firm is a financial firm, defined by SIC code, and interact this variable with the financial distress variables. This allows us to analyze the marginal impact of the financial distress variables on financial companies over time without the need to compare coefficients from different samples. Table 1.4 presents the results for the two specifications of firm profitability defined previously. There is an added set of interaction terms that test the relationship between financial firms and financial stress. For example, the variable *Financial*Recession* measures the marginal impact of a recession on the profitability of financial firms.

The results of Table 1.4 are consistent with those of Table 1.3. For example, the coefficients of *Debt Ratio*, *Profit Margin*$_{-1}$ and *Total Assets* remain negative. Likewise, the coefficients for *Inflation*, *FedFunds Rate,* and *Spread* remain positive. The results of Table 1.4 also coincide with previous results suggesting financial firms have become increasingly more affected by financial distress. The significant negative coefficients for *Financial*Recession* and *Financial*Condition* in the 2000s sample imply that financial firms experience a greater decrease in profit margin as a result of financial distress, compared with non-financial firms. The results from the dynamic panel estimation for the most recent sample imply that a recession will cause the profit margin of a financial firm to fall by approximately 1.2 percentage points more than that of a non-financial firm. An analogous argument holds for an increase in the Financial Conditions Index. An increase in the Financial Conditions Index of one (which is a large movement), results in the profit margin of financial firms decreasing by 1.1 percentage points more than that of the average non-financial firm. In addition, there is also evidence that this sensitivity has increased over time. For example, in the 1980s sample, *Financial*Recession* is positive at 1.2 and *Financial*Condition* is insignificant. In the 1990s sample, the positive coefficient *Financial*Recession* falls to 0.82, while *Financial*Condition* becomes negative and significant. Finally, in the 2000s sample, both financial distress interaction terms become negative and significant. This implies that, during the 1980s, financial firms had profit margins that were 1.2 percentage points higher than non-financial firms as a result of a recession, and there was no difference between the performance of financial and non-financial firms as a result of a change in the Financial Conditions Index. However, by the 2000s, financial firm margins were 1.2 percentage points worse than those of non-financial firms as a result of a recession, and financial firms performed worse than non-financial firms as a result of changes in the Financial Conditions Index as well.

1.6 Stock Return Effect

In this section, as a robustness check, we utilize the panel data regression framework to analyze the impact of financial distress on the cross-section of stock returns. We begin by applying the multivariable regression model used in Section 1.5 to the cross section of stock returns. The dependent variable in this framework is the total monthly excess stock return. The independent variables remain the same set of firm-specific and macroeconomic variables used in Section 1.5, but lagged profit margin is replaced by the lagged monthly excess return, and real GDP growth is replaced by the CRSP equal weighted market return. It is likely that investors are able to quickly anticipate changes in true firm fundamentals, and they also have horizons beyond the current quarterly results. Thus, the *a priori* expectation is that the impact of the distress variables on firm performance as measured by stock returns will be diluted significantly.

Table 1.4: The Marginal Impact of Financial Stress on Financial Sector Profit Margin

Multiple regression estimates of the effect of a set of macroeconomic and firm-specific factors on firm profitability, as defined by net income divided by total revenue (profit margin). The panel OLS coefficients are measured using firm-level, cross-sectional fixed-effects, and panel robust standard errors are used to compute p-values. Dynamic panel estimates are measured using a dynamic GMM estimation procedure along the lines of Arellano and Bond (1991). Panel robust standard errors are used to compute standard errors. P-values are reported below each coefficient.

	1980s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
Inflation	0.2698	0.2810	0.1808	0.2331
	0.000	*0.000*	*0.000*	*0.000*
Real GDP Growth	0.0060	0.0228	-0.0132	-0.0143
	0.808	*0.233*	*0.633*	*0.667*
Fed Funds Rate	0.1916	0.2000	0.4032	0.4911
	0.000	*0.000*	*0.000*	*0.000*
Recession Dummy	-0.0580		-0.0809	
	0.405		*0.463*	
Financial Condition		-0.1037		-0.3258
		0.000		*0.000*
Total Assets	-0.5442	-0.5228	-2.4873	-2.4277
	0.000	*0.000*	*0.000*	*0.000*
Debt Ratio	-0.0926	-0.0926	-0.1146	-0.1151
	0.000	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.0022	0.0022	-0.3758	-0.3766
	0.003	*0.003*	*0.000*	*0.000*
Spread	0.2392	0.2536	0.4252	0.5080
	0.000	*0.000*	*0.000*	*0.000*
*Financial*Recession*	-0.7819		1.2208	
	0.003		*0.001*	
*Financial*Condition*		-0.2262		-0.0316
		0.068		*0.804*
Q2 Dummy	0.1843	0.2108	0.1873	0.2645
	0.000	*0.000*	*0.000*	*0.000*
Q3 Dummy	0.1542	0.1847	0.2239	0.3363
	0.003	*0.000*	*0.001*	*0.000*
Q4 Dummy	-0.0965	-0.0639	-0.2454	-0.1082
	0.075	*0.241*	*0.000*	*0.071*
No. of Firms	7,803	7,803	7,323	7,323
Obs.	167,315	167,315	138,780	138,780

Table 1.4 (cont.): The Marginal Impact of Financial Stress on Financial Sector Profit Margin

	1990s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
Inflation	0.3963	-0.0564	0.5516	0.1355
	0.000	*0.557*	*0.000*	*0.180*
Real GDP Growth	-0.2987	0.2133	-0.7085	-0.0622
	0.000	*0.000*	*0.000*	*0.324*
Fed Funds Rate	0.3496	0.2443	1.0120	1.1963
	0.000	*0.000*	*0.000*	*0.000*
Recession Dummy	-1.0888		-0.1373	
	0.000		*0.210*	
Financial Condition		-0.7362		-2.5114
		0.000		*0.000*
Total Assets	-0.8100	-0.7587	-2.8565	-1.3621
	0.000	*0.000*	*0.000*	*0.000*
Debt Ratio	-0.0952	-0.0950	-0.1651	-0.1672
	0.000	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.0011	0.0011	-0.3838	-0.3862
	0.019	*0.019*	*0.000*	*0.000*
Spread	0.4435	0.2425	1.0865	0.9351
	0.000	*0.000*	*0.000*	*0.000*
*Financial*Recession*	-1.4873		0.8189	
	0.000		*0.014*	
*Financial*Condition*		0.9601		-3.9096
		0.000		*0.000*
Q2 Dummy	0.3522	0.3506	0.6631	0.6823
	0.000	*0.000*	*0.000*	*0.000*
Q3 Dummy	0.4663	0.4579	0.8039	0.9915
	0.000	*0.000*	*0.000*	*0.000*
Q4 Dummy	-0.2889	-0.2028	-0.2268	0.6021
	0.000	*0.002*	*0.001*	*0.000*
No. of Firms	12,184	12,184	11,128	11,128
Obs.	253,734	253,734	206,539	206,539

Table 1.4: The Marginal Impact of Financial Stress on Financial Sector Profit Margin

	2000s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
Inflation	1.0297	1.0149	0.5230	0.3288
	0.000	*0.000*	*0.000*	*0.000*
Real GDP Growth	0.6982	1.9759	0.3295	0.3319
	0.000	*0.000*	*0.000*	*0.000*
Fed Funds Rate	-2.5596	-2.5646	1.5896	2.0087
	0.000	*0.000*	*0.000*	*0.000*
Recession Dummy	-3.3963		-0.6647	
	0.000		*0.000*	
Financial Condition		0.1449		-0.5070
		0.037		*0.000*
Total Assets	-1.3219	-1.3193	-0.1861	-0.3716
	0.000	*0.000*	*0.699*	*0.441*
Debt Ratio	-0.0322	-0.0324	-0.2734	-0.2724
	0.000	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	0.0001	0.0001	-0.3503	-0.3506
	0.031	*0.030*	*0.000*	*0.000*
Spread	-3.3501	-3.4629	0.4582	0.8135
	0.000	*0.000*	*0.000*	*0.000*
*Financial*Recession*	-2.6886		-1.2293	
	0.000		*0.009*	
*Financial*Condition*		-2.3992		-1.0702
		0.000		*0.000*
Q2 Dummy	1.1937	0.3678	0.7215	0.5543
	0.000	*0.000*	*0.000*	*0.000*
Q3 Dummy	0.4846	0.3277	0.7668	0.7269
	0.000	*0.001*	*0.000*	*0.000*
Q4 Dummy	-0.6213	-0.6984	-0.3452	-0.3195
	0.000	*0.000*	*0.000*	*0.000*
No. of Firms	10,843	10,843	10,213	10,213
Obs.	262,681	262,681	220,382	220,382

To compare the effect of financial distress on the stock returns of financial and non-financial firms, we again divide the sample into financial and non-financial firm samples based on SIC code. We run the firm performance specifications from the previous section on the financial and non-financial samples and utilize a firm-level fixed-effect panel OLS estimation procedure. The longer time series nature of the monthly stock returns reduces the need to employ the dynamic panel estimates used in the previous section. Results for the stock performance regressions are presented in Table 1.5.

The results show that the larger magnitude of the impact of the distress variables on financial firms is echoed in the cross-section of stock returns. The *Financial Condition* and the *Recession Dummy* coefficient estimates are negative and significant at the five percent level in all specifications for both financial and non-financial firms in the 2000s sample. The macroeconomic stress variables that have caused an increasingly large reduction in profit margin also negatively impact the stock returns of firms as well. In addition, there is evidence supporting an increasing sensitivity of financial sector stock returns to financial distress. The coefficient estimates for the 2000s sample show that a recession is associated with a -0.01 percentage point decrease in excess monthly return for financial stocks, but there is only a -0.001 percentage point decrease in excess monthly return for non-financial stocks. The Financial Conditions Index shows a similar result, with a *Financial Condition* coefficient of -0.006 for financial firms, compared with -0.003 for non-financial firms.

For a more direct comparison of the effects of financial distress, we again apply the nested model with the financial dummy variable interaction terms. The results are presented in Table 1.6. We find results that are less consistent with the results presented in Section 1.5; however there is still a marginal difference with regards to the impact of financial distress on financial firm stock returns. The signs of *Financial*Recession* and *Financial*Condition* are positive in the 1980s sample, but *Financial*Financial Condition* turns negative in the 1990s sample, while

Table 1.5: The Impact of Financial Stress on Stock Returns

Panel-OLS estimates of the effect of a set of macroeconomic and firm-specific factors on firm stock return. The panel OLS coefficients are measured using firm-level, cross-sectional fixed-effects, and panel robust standard errors are used to compute p-values. P-values are reported below each coefficient.

	Non-Financial Firms					
	1980s		1990s		2000s	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Return$_{t-1}$	-0.05908	-0.05868	-0.04549	-0.04556	-0.04075	-0.04125
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Market Return	0.95518	0.95886	0.94435	0.94345	0.95454	0.95001
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Fed Funds Rate	0.00005	0.00010	0.00205	0.00179	0.00145	0.00101
	0.657	*0.374*	*0.000*	*0.000*	*0.000*	*0.002*
Spread	-0.00001	0.00003	0.00201	0.00157	0.00193	0.00115
	0.965	*0.866*	*0.000*	*0.000*	*0.000*	*0.008*
Inflation	-0.00643	-0.00644	-0.00215	-0.00260	0.00258	0.00174
	0.000	*0.000*	*0.135*	*0.075*	*0.000*	*0.009*
Recession Dummy	0.00221		-0.00019		-0.00124	
	0.000		*0.833*		*0.033*	
Financial Condition		0.00087		-0.00105		-0.00324
		0.000		*0.027*		*0.000*
Total Assets	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	0.411	*0.327*	*0.108*	*0.137*	*0.004*	*0.020*
Debt Ratio	-0.00448	-0.00450	0.00350	0.00372	0.02149	0.02227
	0.059	*0.058*	*0.109*	*0.088*	*0.000*	*0.000*
Q2 Dummy	0.00459	0.00448	0.00483	0.00498	0.00469	0.00458
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Q3 Dummy	0.00352	0.00344	0.00288	0.00301	0.00162	0.00134
	0.000	*0.000*	*0.000*	*0.000*	*0.004*	*0.017*
Q4 Dummy	0.00508	0.00499	0.00583	0.00614	0.00615	0.00617
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
No. of Firms	396,643	396,643	9,380	9,380	7,645	7,645
N	6,480	6,480	548,702	548,702	511,300	511,300

Table 1.5 (cont.): The Impact of Financial Stress on Stock Returns

	Financial Firms					
	1980s		1990s		2000s	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Return$_{t-1}$	-0.05584	-0.05656	-0.06330	-0.06628	-0.04230	-0.04302
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Market Return	0.86165	0.85993	0.70658	0.69761	0.66660	0.66373
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Fed Funds Rate	0.00207	0.00244	0.00123	-0.00092	-0.00025	0.00000
	0.000	*0.000*	*0.035*	*0.114*	*0.713*	*0.996*
Spread	0.00148	0.00174	0.00257	-0.00261	-0.00119	-0.00139
	0.002	*0.000*	*0.000*	*0.000*	*0.182*	*0.119*
Inflation	-0.01165	-0.01179	-0.02753	-0.03248	-0.00571	-0.00603
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Recession Dummy	0.00262		0.01054		-0.01008	
	0.186		*0.000*		*0.000*	
Financial Condition		-0.00114		-0.01492		-0.00555
		0.178		*0.000*		*0.000*
Total Assets	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	0.357	*0.353*	*0.872*	*0.066*	*0.015*	*0.035*
Debt Ratio	0.00531	0.00548	-0.00545	-0.00265	-0.01285	-0.01164
	0.405	*0.389*	*0.327*	*0.629*	*0.040*	*0.060*
Q2 Dummy	0.00089	0.00116	0.00195	0.00292	0.01107	0.01007
	0.588	*0.480*	*0.105*	*0.016*	*0.000*	*0.000*
Q3 Dummy	0.00261	0.00291	0.00090	0.00233	0.01354	0.01326
	0.096	*0.066*	*0.455*	*0.055*	*0.000*	*0.000*
Q4 Dummy	0.00508	0.00549	0.00205	0.00675	0.00624	0.00701
	0.004	*0.002*	*0.132*	*0.000*	*0.000*	*0.000*
No. of Firms	676	676	1,208	1,208	1,030	1,030
N	34,675	34,675	68,761	68,761	71,302	71,302

*Financial*Recession* becomes negative in the 2000s sample. This supports the results of Section 1.5 that show financial stress has had an increasingly negative impact on the performance of financial firms. However, the *Financial*Condition* coefficient is positive and significant for the 2000s sample. As expected, the signs and magnitude of the stock return estimation imply that stock prices are efficient enough to remove much of the impact of macroeconomic news when sampled at the frequency under consideration. The economic significance of the distress variables as well as the financial interaction terms in explaining stock returns is fairly small, when compared with their impact on quarterly profit margin.

1.7 Further Analysis of the Finance Industry

It is shown in previous sections that there is evidence supporting the idea that financial sector companies are more affected by changes in key financial distress variables than their real sector counterparts, and this result has many important governance implications. Expanding upon these results, we compare the impact of financial distress across sub-industries within the financial sector, as this is an important factor in identifying the potential sources of the increased susceptibility of the financial sector to economic distress. As a final analysis of the impact of financial distress on financial firms, we provide a more detailed analysis of the financial services industry. We begin by dividing the sample of financial firms into six sub-industries based on SIC code: depository institutions, finance companies, financial services, insurance, real estate, and investment companies. Table 1.7 presents the descriptive statistics for these subsamples of financial firms.

Depository institutions have the highest average total assets with an average of $63.0 billion, and they also have the highest average revenues and net income per quarter at $1.1 billion and $116.0 million, respectively. For the average financial firm, profit margins are 7.7 percent for depository institutions, 11.6 percent for finance companies, 7.4 percent for financial services firms, 7.8 percent for insurance companies, 4.6 percent for real estate companies and 18.9 percent for investment

Table 1.6: The Marginal Impact of Financial Stress on Financial Sector Stock Returns

Panel-OLS estimates of the effect of a set of macroeconomic and firm-specific factors on firm stock return. The panel OLS coefficients are measured using firm-level, cross-sectional fixed-effects, and panel robust standard errors are used to compute p-values. P-values are reported below each coefficient.

	1980s		1990s		2000s	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Return$_{t-1}$	-0.05879	-0.05843	-0.04653	-0.04677	-0.04054	-0.04107
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Market Return	0.94753	0.95079	0.91753	0.91571	0.92007	0.91569
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Fed Funds Rate	0.00019	0.00026	0.00201	0.00152	0.00132	0.00094
	0.054	*0.005*	*0.000*	*0.000*	*0.000*	*0.004*
Spread	0.00010	0.00014	0.00212	0.00113	0.00164	0.00090
	0.462	*0.290*	*0.000*	*0.000*	*0.000*	*0.031*
Inflation	-0.00683	-0.00688	-0.00514	-0.00610	0.00152	0.00076
	0.000	*0.000*	*0.000*	*0.000*	*0.009*	*0.188*
Recession Dummy	0.00190		0.00039		-0.00194	
	0.001		*0.689*		*0.001*	
Financial Condition		0.00061		-0.00189		-0.00375
		0.010		*0.000*		*0.000*
Total Assets	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	0.655	*0.399*	*0.475*	*0.520*	*0.003*	*0.007*
Debt Ratio	-0.00359	-0.00349	0.00246	0.00294	0.01849	0.01924
	0.091	*0.100*	*0.200*	*0.126*	*0.000*	*0.000*
Q2 Dummy	0.00431	0.00424	0.00447	0.00471	0.00546	0.00523
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Q3 Dummy	0.00346	0.00342	0.00264	0.00291	0.00305	0.00275
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Q4 Dummy	0.00513	0.00509	0.00540	0.00621	0.00616	0.00625
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
*Financial*Recession*	0.00510		0.00544		-0.00292	
	0.005		*0.030*		*0.040*	
*Financial*Financial Condition*		0.00140		-0.00668		0.00184
		0.054		*0.000*		*0.012*
No. of Firms	7,152	7,152	10,588	10,588	8,672	8,672
Obs.	431,318	431,318	617,463	617,463	582,602	582,602

firms. Financial service firms have the highest average ROA and ROE at 1.2 and 3.4 percent, respectively. Investment firms have the lowest average debt ratio of 52.2 percent, while finance companies have the highest at 76.7 percent.

We continue the analysis of financial firms by applying the firm profitability model presented in section 1.5 to the subsample of financial firms. The Dynamic panel coefficients are estimated from the 2000s sample of financial firms, and the results are reported in Table 1.8. We focus on the later sample of firms due to the fact that the negative impact of financial stress on the financial sector is most pronounced in the latest sample. In addition, the effect of financial stress on financial firms in the most recent sample is the most relevant for making current governance and policy decisions.

The model describing the profitability across financial sector sub-groups behaves similarly to that of the full sample of financial firms. *Inflation*, *Real GDP Growth*, *FedFunds Rate*, and *Spread* are consistently positive and significant, while *Total Assets*, *Debt Ratio*, and *Profit Margin*$_{-1}$ have a consistent negative impact on profit margin. However, the major result of this analysis is that both the *Financial Condition* and *Recession Dummy* coefficients are insignificant for depository institutions. This implies that the pronounced effects of these variables on financial firm profitability and stock returns is likely driven by the non-depository sectors of the financial industry, or the "shadow" banking system. Conversely, for the remainder of the industries, at least one of the financial distress variables is negative and significant at the five percent level. For the financial services sub-industry, both *Recession Dummy* and *Financial Condition* are negative and significant at the five percent level. Non-depository financial institutions appear to be particularly sensitive to changes in the Financial Conditions Index, with all coefficients for *Financial Condition* being negative and significant at the five percent level, except for the real estate sub-sector, where it is only marginally significant (p-value=0.124). Table 1.8 suggests that the most sensitive sector to financial distress is financial services. An economic recession is associated with a

Table 1.7: Financial firm Summary Statistics

The following are descriptive statistics on a sample of COMPUSTAT Financial firms (SIC code 6000-6999), sampled quarterly from 1980Q1 through 2010Q4. The data includes all firms with revenues of more than$ 500K and is windsorized in each tail at the one percentile. The sample also requires each firm to have at least 8 quarters of complete data.

	All Financial Firms			
	Full sample	1980s	1990s	2000s
Total Assets				
Mean	16,215	3,156	7,774	29,408
Std. Dev.	95,149	10,949	32,735	140,429
Revenue				
Mean	487	200	289	787
Std. Dev.	1,963	632	976	2,788
Net Income				
Mean	36	11	23	59
Std. Dev.	243	33	90	359
Profit Margin (%)				
Mean	11.20	11.55	11.41	10.86
Std. Dev.	21.84	17.00	19.05	25.70
ROA (%)				
Mean	0.84	1.01	0.85	0.76
Std. Dev.	2.02	1.75	1.87	2.24
ROE (%)				
Mean	2.70	3.31	2.73	2.41
Std. Dev.	6.83	6.19	6.17	7.59
Debt Ratio (%)				
Mean	63.78	64.98	63.50	63.50
Std. Dev.	26.50	25.33	27.26	26.30
Market Cap				
Mean	2,087	406	1,133	3,511
Std. Dev.	9,273	1,063	4,872	12,867
Market-to-Book Ratio				
Mean	1.30	0.95	1.00	1.30
Std. Dev.	1.01	0.01	0.01	1.01
Capital Expenditures				
Mean	63	16	50	88
Std. Dev.	642	116	597	765
Retained Earnings				
Mean	722	218	401	1,218
Std. Dev.	3,981	584	1,561	5,807
Cash				
Mean	1,195	26	-	1,196
Std. Dev.	5,775	31	-	5,777

Table 1.7 (cont.): Financial firm Summary Statistics

	SIC Industry					
	Depository	Finance	Services	Insurance	Real Estate	Investment
Total Assets						
Mean	63,040	28,891	34,375	18,863	751	1,455
Std. Dev.	126,855	141,061	153,460	93,147	3,375	3,455
Revenue						
Mean	1,109	738	687	807	54	70
Std. Dev.	1,885	2,709	2,459	2,456	195	277
Net Income						
Mean	116	64	51	49	3	8
Std. Dev.	259	412	323	248	24	29
Profit Margin (%)						
Mean	7.67	11.55	7.39	7.76	4.62	18.85
Std. Dev.	15.20	19.05	18.13	15.07	21.41	27.92
ROA (%)						
Mean	0.66	0.60	1.18	0.82	0.63	0.94
Std. Dev.	2.29	1.42	3.06	1.70	2.15	1.90
ROE (%)						
Mean	3.32	3.18	3.36	3.03	2.05	2.06
Std. Dev.	7.90	6.19	7.65	6.51	8.44	6.18
Debt Ratio (%)						
Mean	71.32	76.74	59.77	70.61	61.79	52.24
Std. Dev.	29.44	22.11	29.35	20.83	27.53	26.38
Market Cap						
Mean	6,665	3,637	3,067	2,779	317	755
Std. Dev.	13,410	18,702	10,123	9,674	1,192	1,649
Market-to-Book Ratio						
Mean	1.44	1.06	1.71	1.07	1.19	1.37
Std. Dev.	0.87	0.36	1.48	0.44	0.51	1.23
Capital Expenditures						
Mean	50	317	36	26	23	6
Std. Dev.	115	1,625	148	255	180	51
Retained Earnings						
Mean	1,862	1,350	1,056	1,167	49	-65
Std. Dev.	3,792	7,298	4,364	3,907	418	255
Cash						
Mean	5,348	2,926	2,005	1,212	70	105
Std. Dev.	16,338	8,896	7,819	3,819	210	319

2.5 percentage point drop in profit margin for financial services companies. The percentage point decrease in profit margin associated with a recession for insurance companies is likewise 3.7 percent; however the *Financial Condition* coefficient is not significant for insurance companies. The results suggest that the pronounced impact of financial distress on financial firms is likely driven by non-depository institutions like financial services, finance companies, real estate, insurance, and investment firms.

Following the framework presented in previous sections, we continue our analysis of financial companies by directly comparing the determinants of financial sector profits across sub-sectors using a nested model framework. We begin by constructing several dummy variables that represent each sub-sector within the financial industry: Depository, Finance, Insurance, Investment, Real Estate, and Services. We then use the sub-sector dummies to create an interaction term with the financial distress variables. In this estimation, non-financial firms are the baseline firm, and the interaction terms describe the marginal impact of the financial distress measures on the average firm in each sub-sector. For example, *Deposit*Recession* represents the marginal impact of a recession on the profit margin of a depository institution, compared with that of a non-financial firm. The results of this analysis are presented in Table 1.9.

The conclusion that the recent financial sector sensitivity to macroeconomic distress is driven by non-depository institutions is supported by the results reported in Table 1.9. The dynamic panel estimate of the impact of a recession on the performance of depository institutions, *Deposit*Recession*, is insignificant in the 2000s sample, and the panel OLS estimate is positive and significant. Additionally, both the dynamic and panel OLS estimates are positive and significant for the 1980s sample. Additionally, dynamic estimates for *Deposit*Condition* are insignificant across the samples, while the panel OLS estimates are positive and

Table 1.8: The Impact of Financial Stress on Profit Margin across Financial Institutions

Multiple regression estimates of the effect of a set of macroeconomic and firm-specific factors on firm profitability, as defined by net income divided by total revenue (profit margin). The estimates are dynamic panel estimates measured using a dynamic GMM estimation procedure along the lines of Arellano and Bond (1991). Panel robust standard errors are used to compute standard errors. P-values are reported below each coefficient.

	Depository		Finance		Services	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Inflation	-0.5364	-0.7756	1.4034	0.6198	1.5047	0.6244
	0.572	*0.332*	*0.041*	*0.365*	*0.011*	*0.302*
Real GDP Growth	-0.1508	-1.0603	1.6272	1.1740	2.6781	2.3008
	0.884	*0.385*	*0.023*	*0.109*	*0.000*	*0.000*
Fed Funds Rate	2.3484	2.2144	3.4670	4.2591	3.5001	4.6702
	0.186	*0.172*	*0.011*	*0.002*	*0.000*	*0.000*
Recession Dummy	2.6919		-1.1321		-2.5314	
	0.362		*0.478*		*0.022*	
Financial Condition		-0.8470		-2.7281		-2.9424
		0.523		*0.019*		*0.000*
Total Assets	-8.0372	-8.0627	-6.7314	-7.0306	1.6993	1.4442
	0.137	*0.114*	*0.161*	*0.141*	*0.429*	*0.495*
Debt Ratio	-0.4197	-0.4019	-0.3428	-0.3182	-0.1722	-0.1639
	0.028	*0.031*	*0.009*	*0.014*	*0.017*	*0.024*
Profit Margin$_{-1}$	-0.2055	-0.2086	-0.3087	-0.3128	-0.3542	-0.3587
	0.002	*0.001*	*0.000*	*0.000*	*0.000*	*0.000*
Spread	3.1713	3.1438	3.7923	4.3385	2.4067	3.2104
	0.109	*0.083*	*0.016*	*0.005*	*0.014*	*0.001*
Q2 Dummy	-1.2646	-0.7726	-0.5360	-0.6032	-0.5883	-0.7740
	0.276	*0.448*	*0.443*	*0.359*	*0.238*	*0.113*
Q3 Dummy	0.1186	0.2275	-1.2852	-1.2498	-0.9155	-0.7555
	0.871	*0.740*	*0.087*	*0.099*	*0.100*	*0.180*
Q4 Dummy	-2.1630	-2.1306	-1.7010	-1.5316	-0.5123	-0.1600
	0.022	*0.021*	*0.009*	*0.017*	*0.331*	*0.753*
No. of Firms	38	38	154	154	175	175
Obs.	887	887	3,384	3,384	3,629	3,629

Table 1.8 (cont.): The Impact of Financial Stress on Profit Margin across Financial Institutions

	Insurance		Real Estate		Investment	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Inflation	0.0499	-0.0410	2.6463	2.2278	1.3909	0.5929
	0.854	*0.897*	*0.002*	*0.005*	*0.002*	*0.207*
Real GDP Growth	1.6002	1.9864	1.3301	1.3364	0.6691	-0.0012
	0.000	*0.000*	*0.080*	*0.105*	*0.103*	*0.998*
Fed Funds Rate	0.2332	1.2102	1.6954	2.6555	4.0697	4.3965
	0.686	*0.025*	*0.251*	*0.053*	*0.000*	*0.000*
Recession Dummy	-3.7394		-2.2287		1.2249	
	0.000		*0.302*		*0.342*	
Financial Condition		-0.3352		-1.3670		-2.3422
		0.544		*0.124*		*0.000*
Total Assets	-7.7831	-7.9803	4.0868	3.6601	-9.0099	-8.8876
	0.004	*0.005*	*0.344*	*0.394*	*0.001*	*0.001*
Debt Ratio	-0.6611	-0.6803	-0.6611	-0.6560	-0.5831	-0.5674
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Profit Margin$_{-1}$	-0.3127	-0.3115	-0.3689	-0.3696	-0.4101	-0.4126
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Spread	-0.4930	0.1881	0.6755	1.3763	2.4745	2.7202
	0.429	*0.750*	*0.667*	*0.359*	*0.003*	*0.001*
Q2 Dummy	0.6687	0.0384	0.8904	0.4777	0.1325	0.4415
	0.025	*0.888*	*0.336*	*0.569*	*0.809*	*0.359*
Q3 Dummy	-2.0985	-2.2754	0.4356	0.2985	-0.3583	-0.1969
	0.000	*0.000*	*0.728*	*0.810*	*0.554*	*0.742*
Q4 Dummy	-2.2929	-2.3400	1.0150	1.0437	-1.3323	-1.1867
	0.000	*0.000*	*0.424*	*0.412*	*0.006*	*0.014*
No. of Firms	332	332	136	136	422	422
Obs.	8,291	8,291	2,668	2,668	8,894	8,894

significant for the later samples. The insignificant interaction terms for the dynamic estimates in the later samples means that from 2000 to 2010, the performance response from depository institutions to a recession or change in the Financial Conditions Index is no different than that of an average non-financial firm. This result supports the efficacy of regulations and internal controls aimed at controlling risk within depository institutions. At least one of the dynamic panel and many of the panel OLS interaction term estimates are negative and significant for all other non-depository institutions in the most recent sample, indicating that these firms have greater sensitivity to financial distress than the average non-financial firm. In addition, consistent with the results of Table 1.8, both *Services*Recession* and *Services*Condition* are negative and significant, implying that financial service firms are the most sensitive to economic distress, having a decrease in profit margin of almost three percentage points more than the average non-financial firm during a recession. The relatively high risks of the financial services sub-sector is feasible given that this sub-sector also yields the highest average ROE and ROA. For the other non-depository sub-sectors, the dynamic estimates for the 2000s sample report a negative and significant recession interaction term for insurance and real estate companies, while the Financial Conditions Index interaction term is negative and significant for finance and investment companies. In addition, many of the interaction terms weaken in economic significance or change signs in the two earlier samples, indicating that the sensitivity of these firms to economic distress has increased over time. This finding is consistent with the heightened risks associated with the increased use of financial products that expose non-depository financial intermediaries to greater systemic risk.

The results of a nested model that examines the marginal effect of financial stress on different types of financial institutions mirror the findings from Table 1.8 that non-depository firms drive the pronounced impact of economic stress on financial firm profit margins found in sections 1.5 and 1.6. This result is expected

Table 1.9: The Marginal Impact of Financial Stress on Profit Margin across Financial Firms

Multiple regression estimates of the effect of a set of macroeconomic and firm-specific factors on firm profitability, as defined by net income divided by total revenue (profit margin). The panel OLS coefficients are measured using firm-level, cross-sectional fixed-effects, and panel robust standard errors are used to compute p-values. Dynamic panel estimates are measured using a dynamic GMM estimation procedure along the lines of Arellano and Bond (1991). Panel robust standard errors are used to compute standard errors. P-values are reported below each coefficient.

	1980s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
*Deposit*Recession*	3.8111		3.5128	
	0.055		*0.087*	
*Deposit*Condition*		0.7298		-0.5389
		0.441		*0.470*
*Finance*Recession*	-0.8244		2.5137	
	0.013		*0.000*	
*Finance*Condition*		-0.6120		-0.1757
		0.000		*0.418*
*Insurance*Recession*	-1.0713		-1.0699	
	0.001		*0.017*	
*Insurance*Condition*		-0.5621		-0.5816
		0.000		*0.000*
*Investment*Recession*	-3.3813		2.3201	
	0.000		*0.039*	
*Investment*Condition*		-0.0600		0.7578
		0.870		*0.037*
*RealEstate*Recession*	1.9276		1.5659	
	0.005		*0.122*	
*RealEstate*Condition*		0.6203		0.3678
		0.072		*0.327*
*Services*Recession*	0.5689		1.0876	
	0.252		*0.190*	
*Services*Condition*		-0.5019		-0.4877
		0.051		*0.078*
Control Variables?	*Yes*	*Yes*	*Yes*	*Yes*
No. of Firms	7,803	7,803	7,323	7,323
Obs.	167,315	167,315	138,780	138,780

Table 1.9 (cont.): The Marginal Impact of Financial Stress on Profit Margin across Financial Firms

	1990s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
*Deposit*Recession*	0.5824		1.4891	
	0.762		*0.433*	
*Deposit*Condition*		4.1204		0.0964
		0.000		*0.951*
*Finance*Recession*	-1.7174		1.4369	
	0.003		*0.010*	
*Finance*Condition*		-0.0166		-4.9673
		0.969		*0.000*
*Insurance*Recession*	-1.3163		0.9046	
	0.002		*0.018*	
*Insurance*Condition*		0.3637		-2.8033
		0.120		*0.000*
*Investment*Recession*	-0.7738		1.6122	
	0.430		*0.095*	
*Investment*Condition*		1.4421		-6.5409
		0.001		*0.000*
*RealEstate*Recession*	-2.4265		-1.8232	
	0.069		*0.092*	
*RealEstate*Condition*		3.0341		-1.7208
		0.000		*0.194*
*Services*Recession*	-2.4955		0.1151	
	0.000		*0.861*	
*Services*Condition*		0.0458		-1.7383
		0.906		*0.082*
Control Variables?	*Yes*	*Yes*	*Yes*	*Yes*
No. of Firms	12,184	12,184	11,128	11,128
Obs.	253,734	253,734	206,539	206,539

Table 1.9 (cont.): The Marginal Impact of Financial Stress on Profit Margin across Financial Firms

	2000s			
	Panel OLS		Dynamic Panel	
Variable	(1)	(2)	(1)	(2)
*Deposit*Recession*	3.2919		3.1164	
	0.015		*0.129*	
*Deposit*Condition*		1.3330		1.1139
		0.075		*0.423*
*Finance*Recession*	-4.3760		-0.3916	
	0.000		*0.764*	
*Finance*Condition*		-4.9321		-1.5974
		0.000		*0.081*
*Insurance*Recession*	-2.3121		-2.0685	
	0.000		*0.000*	
*Insurance*Condition*		-0.9696		-0.3918
		0.002		*0.291*
*Investment*Recession*	-2.1004		-0.0093	
	0.003		*0.992*	
*Investment*Condition*		-2.6274		-1.0237
		0.000		*0.069*
*RealEstate*Recession*	-3.3123		-2.8576	
	0.003		*0.088*	
*RealEstate*Condition*		-3.1392		-1.3881
		0.000		*0.197*
*Services*Recession*	-4.3184		-2.9596	
	0.000		*0.002*	
*Services*Condition*		-3.0422		-2.4697
		0.000		*0.001*
Control Variables?	*Yes*	*Yes*	*Yes*	*Yes*
No. of Firms	10,843	10,843	10,213	10,213
Obs.	262,681	262,681	220,382	220,382

given the recent trend toward non-depository financial intermediation, because these firms are subject to less regulations aimed at reducing risk, and they have become increasingly engaged in the use of more complicated financial products.

1.8 Robustness and Areas of Future Research

This section discusses some issues with the robustness of the presented results, ways in which the paper could be improved, and areas for future research.

The models presented here are based on those used in the literature. Accordingly, there are many complex variations that can be used as robustness checks for these results. Naturally, when determining which model to run and which variables to include, some variations are left out. Including more complex models may yield more robust estimates with higher explanatory power. For example, using alternative measures of profitability may show support for the results presented. In unreported regressions, the alternative performance measures return on equity (ROE) and return on assets (ROA) are used as the dependent variable in the models describing firm profitability. While the economic significance of the results are diminished somewhat by using these measures, the conclusions are not substantially different.

This study provides evidence supporting the hypothesis that financial firms are impacted more substantially by macroeconomic shocks using evidence on both profitability and stock return. However, many studies also focus on the speed at which macroeconomic news affects stock prices. Accordingly, different frequency data may be used to both add robustness to the results presented as well as to determine the more precise persistence of the effects.

A final way in which this study can be improved is to include a similar analysis using a sample of non-financial firms that may be affected by similar macroeconomic conditions. Financial sector firms are chosen, because they are likely to be the firms most affected by the macroeconomic events affecting the financial markets. However, there are many other firms that also fit this category. For example, firms that pay large dividends, international firms, and highly leveraged firms may also be more sensitive to macroeconomic shocks.

1.9 Conclusion

In the aftermath of one of the biggest financial collapses in recent history, it is natural to question the sensitivity of the financial sector to extreme macroeconomic distress. There are several ways to measure firm sensitivity. One line of literature looks at the stock price reaction surrounding economic news. Another focuses on how the macroeconomic regime affects the profitability of firms. This study contributes significantly along this line. We utilize a panel data set with a long time dimension and show that, while all firms seem to exhibit increased sensitivity to measures of financial distress, firms in the financial sector have become relatively more sensitive than their non-financial counterparts. In addition, we identify that the increased sensitivity is caused by the influence of non-depository financial institutions, which has very important policy and governance implications given recent trends in the financial sector.

We utilize a combination of firm specific and macroeconomic variables to build a model of firm profitability and stock returns. Using a robust series of univariate and multivariate techniques, it is shown that financial sector firms are more sensitive to changes in financial stress, measured by a recession dummy variable and the Federal Reserve's Financial Conditions Index, than their real sector counterparts. We also find evidence consistent with the idea that this sensitivity has increased over the past three decades.

Results showing financial firms seem to be disproportionately affected by economic shocks contrasts starkly with the goals of many regulations imposed upon the industry. The financial sector, and depository institutions in particular, has been historically one of the most highly regulated. The goal of many of these regulations is to provide confidence and stability in the financial system in order to avoid economic disasters, like that of the Great Depression in the 1930s. Over the past thirty years, however, relaxing regulations in the U.S. have allowed for the consolidation of financial service firms that are engaging in increasingly interrelated transactions. Additionally, there has been increasing complexity in the practices and products within the financial sector. Among these has been the development of sophisticated financial products like derivatives and an increase in the importance of non-depository financial institutions, or "shadow" banking.

The evidence pointing to increased systemic fragility in the financial sectors surrounding the recent financial crisis brings into question the soundness of these recent trends in regulation and financial product engineering. Indeed, our results support the idea that the source of financial sector firm risk lies in non-depository institutions, and this effect appears to have presented after the year 2000. The increased riskiness of financial institutions is consistent with the risks associated with the global financial market trends of consolidation, globalization, deregulation, financial product innovation, and the shift to shadow banking activities. Increases in financial sector risk have motivated policy makers to increase the scrutiny of external regulators in the United States. The Dodd-Frank Wall Street Reform Act of 2010 aims to offset many of the risks posed by the increased reliance on complex financial instruments and non-depository "shadow banking". For example, The Act creates The Financial Stability Oversight Council with the specific goal of monitoring the risks of bank holding companies and other non-depository institutions in order to prevent excessive systemic exposure. Many of the goals of this legislation are consistent with policy makers attempting to identify and control the risks evidenced by our results. It is unlikely, however, that any individual provision is sufficient to completely offset the exposure seen during the financial crisis. It may be necessary for all stakeholders to evaluate both the regulatory and governance mechanisms of financial firms, given the apparent impact of recent trends on financial sector risk.

2. Partial Adjustment Towards Equilibrium Mutual Fund Allocations: Evidence from U.S.-based Equity Mutual Funds

2.1 Introduction

The development and implementation of mutual funds and other pooling arrangements has been a major trend in the financial markets over the past several decades. The economies of scale present in these arrangements lower the costs of diversification for smaller investors. Additionally, arrangements like mutual funds can provide lay investors with cheaper access to professional, active portfolio management. As a consequence, smaller investors have become more active in the financial markets through retirement and other investment accounts that utilize mutual funds as a main conduit for low-cost diversification.

The cost efficiencies and active management benefits of mutual funds come at a cost, however. For example, there remains significant debate as to whether actively managed mutual funds actually outperform the overall market index on a risk adjusted basis after management fees are deducted. For this reason, more passive pooling arrangements have been developed to answer the concerns that active management provides very little additional risk-adjusted return. Index and sector-mimicking funds, for example, allow smaller investors to reap the benefits of low cost diversification, while taking a more passive market stance, thus lowering the management fees associated with active management.

With the development of different types of pooling arrangements, it is important for investors to know which types of funds are most efficient. While passive funds may be more cost efficient, it is possible that more actively managed funds can more efficiently rebalance their portfolios due to the informational advantages captured by active managers. While the literature in the area of mutual funds has often focused on the efficiency of funds in terms of return efficiency, there is currently no evidence showing the time dimension of mutual fund efficiency.

Specifically, the literature lacks empirical evidence regarding how quickly different types of mutual funds are able to adjust their portfolios to the equilibrium return. The ability of managers to quickly adjust, especially to suboptimal allocations or adverse market conditions, is of particular importance to investors displaying a significant amount of loss or risk aversion. Therefore, this important dimension of efficiency is an important issue that has been left largely unanswered, since longer adjustment times for passively managed funds may represent additional fund risk that has previously been left un-quantified.

Mutual fund managers are charged with selecting a portfolio of securities consistent with the fund's objective in order to maximize the investors' risk-adjusted return. The fund managers make these selections based on a set of publically available information. It is safe to assume that portfolio managers are rational and thus have correct market expectations, given their information set. However, the set of information available to managers may be limited by the characteristics of the fund. Often times, funds specifically set out to gain informational advantages in certain markets, such as international markets or specific sectors of the economy. Fund that focus on particular markets are able to extract more or better information than those that are limited to more passive management; however the more actively managed funds face higher costs to produce the information advantage and pass this costs to investors in the form of higher management fees. A key question remains as to which approach is the most efficient for mutual fund investors, and the empirical literature on the topic has provided mixed results. The speed of adjustment may play a significant role in this debate, as the relatively low management fees of more passive funds may be offset by the ability of active funds more efficiently manage information through faster portfolio adjustment.

In this paper, we apply a partial adjustment econometric estimation procedure to the CRSP mutual fund database in order to analyze how quickly mutual funds adjust to measures of the equilibrium risk-adjusted return. In section 2.6, we apply the model to the full sample of U.S. equity mutual funds, and find that underperforming funds adjust relatively quickly to deviations in measures of risk-adjusted return, which is consistent with the idea that managers face significant costs for underperformance. Then, in section 2.7, we apply the model to eight sub-samples of funds based on their investment focus. We show that the speed of adjustment is heterogeneous across different types of funds, consistent with the idea that managers of different types of funds have heterogeneous information costs. In section 2.8, we show how the speed of adjustment for mutual funds appears to be consistent over time, but does exhibit some cyclicality, consistent with changes in the market information set under different macroeconomic regimes. Section 2.9 discusses robustness issues as well as areas in which we hope to expand the paper. Section 2.10 concludes.

2.2 Previous Empirical Findings

The previous empirical literature on mutual fund performance and management show a wide range of often-conflicting results. While some studies find that active mutual fund managers are able to provide abnormal returns to investors, others find that, net of the expenses charged for active management, mutual funds actually underperform passively managed indexes. Other studies find that the abnormal return earned by mutual fund managers are essentially offset by management fees, essentially leaving investors with a net return equivalent to those of passively managed pooling arrangements. The performance of highly active equity mutual funds, relative to that of more passive funds, has important implications as to the informational efficiency of the stock market. Severe underperformance of mutual funds implies that investors are either irrational, because they fail to take advantage of better performing assets, or misinformed in that they are unaware that they are achieving suboptimal returns. Consistent positive abnormal performance, on the other hand, implies that mutual fund managers have superior information and pass that advantage to investors in the form of higher returns. However, as arbitrage occurs and the mutual fund market matures, it can be expected that both fund managers and investors become increasingly competitive, and the aggregate equilibrium net returns for actively managed mutual funds equal those of alternative investments, such as index funds.

The seminal work of Sharpe (1966) pioneered the use of empirical techniques to evaluate mutual fund performance. Among other contributions, Sharpe developed a measure of mutual fund performance that evaluates return, relative to the risk undertaken. The theoretical motivation for developing a risk-adjusted performance measure is to eliminate performance differences caused by fund idiosyncrasies such as investment style and risk tolerance. In an efficient market, one expects all funds to achieve the same risk-return tradeoff, as measured in this manner. However, the results of his study show that, even when using a measure that takes into consideration risk-adjusted returns, mutual fund performance differs among funds. The discrepancy in performance among mutual funds may be driven by differences in expenses and management fees, among other factors. The interesting results of Sharpe drive a line of literature dealing with relative mutual fund performance.

Among the earlier studies responding to evidence presented by Sharpe (1966) and others is Ippolito (1989), which examines the role of information costs in the context of U.S. mutual funds. In an empirical study using data from 143 mutual funds over the 1965 to 1984 time period, the study finds that the returns of mutual funds are commensurate with those of passive funds, or the overall market, even after considering information costs in the form of management fees and expenses. The results showing that active management is worth its cost is consistent with market efficiency, because the fees charged by managers offset the cost of acquiring specialized information. Net of the fees charged for information acquisition and management, investors receive net returns that are equivalent to those of other available asset portfolios, such as index funds. In addition, Ippolito (1989) finds no relationship between management fees and turnover and fund performance.

Supporting the idea that active management provides value to investors, Daniel *et al.* (1997) examine the ability of equity mutual fund managers in terms of selection and timing abilities. The authors develop measures of performance based on fund characteristics, such as book-to-market, market capitalization, style, *etc*. They find that actively managed funds achieve performance advantages over passively managed funds; however, the magnitude of the advantage is small and roughly offset by management fees. For example, aggressive and momentum based funds tend to have the highest performance advantages, but they also have higher associated management expenses as well.

There are also empirical studies that find active managers are able to achieve abnormal returns that are worth the increased expense, but that advantage is only realized by a minority of fund managers. For example, Kosowski *et al.* (2006) use a bootstrap methodology[10] to analyze the returns of U.S. open-ended funds from 1975 to 2002. The bootstrap methodology is necessary to circumvent problems with non-normality of alphas in the distribution of mutual fund returns[11]. In light of the bootstrap methodology, the authors find that there are some managers who are able to generate returns that offset the associated fees charged. In addition, they find that the ability of some active mutual funds managers to achieve abnormal returns persists over time[12]. In addition, Volkman (1999) investigates the performance of mutual funds in the context of increased market volatility and finds that active mutual funds, in aggregate, do not possess superior stock selection ability, but some managers are able to consistently select undervalued securities. In addition, even though some managers exhibit superior stock selection skill, their ability to time the market is often not optimal.[13]

[10] They argue that this methodology is necessary to eliminate biases due to non-normal distributions caused by *ex post* sorting on mutual fund performance.
[11] Other studies, such as Fama and French (2010) also advocate the use of bootstrapping methodologies in dealing with distribution issues.
[12] They find that this result holds mostly for managers of growth-oriented funds, but find no evidence that income-oriented funds achieve persistent abnormal returns.
[13] The results also suggest a negative relationship between management compensation and selection ability – a puzzling result. In addition, the results find that larger funds tend to have better stock selection ability.

Barras *et al.* (2010) provide further evidence that mutual funds do not consistently provide abnormal returns in aggregate. They attribute previous findings that mutual funds experience persistent positive alpha as "false discoveries". In their methodology, they divide funds based on whether their managers are skilled or unskilled and find that 75 percent of funds do not exhibit positive alpha. In a related finding, they show that there were significantly more "skilled" funds in existence in 1996 than in 2006[14], which supports the idea that increased competition and access to information has removed the ability of mutual fund managers to yield abnormal returns, net of expenses. They argue that, although there is a minority of "skilled" managers who can achieve a relatively high return, actively managed funds underperform (net of expenses) in aggregate due to the persistence of underperforming funds.

There is also a line of literature which argues that results showing persistent positive abnormal returns for active managers are driven by specific biases and methodological issues that, when corrected, question the efficiency of actively managed mutual funds. In an early empirical study along this line, Lehmann and Modest (1987) examine 130 U.S. mutual funds from 1968 to 1982. The empirical results indicate that estimates of mutual fund performance are sensitive to the pricing model and estimation method used to compute abnormal returns. The authors use various specifications of the CAPM and APT and different estimation techniques and find significantly different estimates of mutual fund abnormal performance. However, despite this fact, they still find that both CAPM and APT estimates show that mutual funds experience negative abnormal returns, which the authors find difficult to explain in an information efficient market. In addition, Kothari and Warner (2001) point to evidence suggesting that typical empirical tests of mutual fund performance are of low power. They use simulated funds that mimic the behavior of actual funds, and the results show that typical empirical tests are very weak in detecting skill-based abnormal portfolio returns, especially when the

[14] They also cite that this trend makes identification of the skilled funds more accurate in later years.

characteristics of funds differ greatly from the market portfolio. As an alternative, the authors suggest that the power of tests can be improved by conducting event studies on mutual fund trading behavior[15].

Further evidence by Elton *et al.* (1993) show that early evidence claiming the persistence of mutual fund abnormal performance was primarily driven by the portfolio used in deriving the abnormal performance measures. The authors show using a sample spanning from 1965 to 1984 that estimated risk-adjusted measures of performance for mutual funds imply that mutual funds are not efficient enough to justify their expenses. The authors attribute most of the cost of active management their associated information costs and conclude that previous literature implying positive alphas or abnormal returns is due to the exclusion of non-S&P assets in the calculation of performance evaluation measures. They find that accounting for these assets shows that actively managed funds underperform more mechanical or passive funds. In addition, funds with high fees and turnover underperform those with low fees and turnover. These results imply that actively managed funds are inefficient.

Additional evidence by Wermers (2000) evaluates the ability of managers to select stocks that outperform enough to cover costs. Their results show that, while managers tend to select stocks that outperform the market index by over one percentage point per year, the net returns underperform by roughly one percentage point per year. The authors attribute the majority of this discrepancy to expenses and transaction costs. However, they show that high turnover funds tend to perform well, which suggests that active management may add some value to investors. They also draw attention to the negative impact on mutual fund performance of cash and bond holdings that must be maintained to account for the uncertain cash flows into and out of funds. Bollen and Busse (2005) examine the ability of managers to attain persistent abnormal returns by sorting mutual funds into

[15] This study focuses on the ability to identify if a particular fund is able to achieve abnormal returns.

percentiles based on performance and find that the highest percentile performance funds are unable to maintain high levels of abnormal performance over time.

In a more recent study, Fama and French (2010) concur with many previous studies that actively managed mutual funds rarely have abnormal returns high enough to overcome their significantly higher expenses. As a result, the real returns to mutual fund investors tend to be below those that are expected from the market portfolio. The authors use CRSP data from 1984 to 2006 and a bootstrap methodology to differentiate skill from luck in the cross section of mutual fund returns. Consistent with earlier findings, the results show that a small percentage of managers appear to outperform the market, but that their good performance is offset in the cross section by those that do not meet performance expectations, net of costs. In addition, they find evidence that even the top performing active funds do not seem to outperform efficiently managed passive funds.

There is also a line of empirical literature that relates the manager characteristics of mutual funds to performance. In one such study, Sirri and Tufano (1998) analyze the flows into and out of mutual funds. They find that investors tend to funnel money into mutual funds with good prior performance. However, they document that this trend is asymmetric in that investors fail to flee worse performing funds. They find a significant relationship between expenses and fund inflows, which the authors attribute to more aggressive marketing efforts, which present as higher fees. In addition, funds that are part of a large fund family exhibit higher inflows as well. These results are consistent with the explanation that funds with lower search costs for investors can realize significantly more cash inflows.

An empirical analysis that more directly ties manager characteristics with mutual fund performance is Chevalier and Ellison (1999). Chevalier and Ellison examine manager characteristics such as age, SAT score, and undergraduate institution and find that there is little relationship between fund performance and manager characteristics. However, there is a significant relationship between managers who attended high-SAT undergraduate institution and mutual fund performance[16]. They suggest this is due to the innate ability of the manager, better education, better access to social networks, or some combination of effects. The results are consistent with a market having incomplete information and increased competition, whereby only slight advantages can be maintained. In a related study, Khorana (1996) shows that well performing funds are less likely to experience managerial turnover[17]. This finding shows that managers have good reason to be concerned about relative performance, as deviation from optimal performance levels may result in their replacement.

Our study contributes to the mutual fund literature by applying a partial adjustment methodology to the mutual fund performance characteristics in an attempt to estimate the efficiency of mutual fund managers. Measuring the adjustment speed not only has important implications with regards to the efficiency of actively managed funds, but also provides insights into how fund managers weigh the various costs associated with portfolio rebalancing. The insights gained from this analysis fills an important gap in the current literature.

2.3 The Model

Mutual fund managers are charged with using the available information in the financial markets in order to maximize risk-adjusted return. Since the risk-adjusted return is based on economic fundamentals, there should exist an equilibrium or target level of risk-adjusted return. Thus, the mutual fund manager aims to achieve at least the equilibrium risk-adjusted return. Failure to do so can lead to cash outflows, as investors funnel capital into competing funds, which, if not corrected, will result in the manager's replacement. The realized return of mutual funds should equal the equilibrium return over the long-run. However, in any given

[16] They also find that younger managers tend to make higher risk-adjusted returns than older managers.
[17] Managerial turnover is also found to be correlated with fund turnover, expenses, and overall portfolio risk.

period, individual returns will deviate from the equilibrium due to both poor investment decisions and random price movements. When the fund returns are below those of other funds of equivalent risk, the managers will have an incentive to rebalance the portfolio with securities that will close the deviation from the equilibrium. However, portfolio rebalancing is costly. The costs of rebalancing include the search and information costs necessary to insure the selected securities will achieve the desired risk and return trade-off. Thus, the mutual fund manager faces a rebalancing decision where he or she must balance the benefits of retaining investors through a more efficient allocation with the costs of rebalancing.

The mutual fund manager's problem of balancing the costs and benefits of portfolio reallocation are consistent with a model of partial adjustment towards a target or equilibrium. Partial adjustment models can be applied in cases where there is a long-run equilibrium or optimal level for a variable of interest. Such models have been commonly applied to describe key relationships in Economics and Finance, such as the optimal level of leverage in a corporate finance context or the long-run equilibrium GDP growth of a country. Kennan (1979) describes the application of partial adjustment models to optimal behavior decisions in economic contexts and shows that, provided expectations are rational, the observed variables in question can be used in a partial adjustment model without having to directly observe the (unobservable) beliefs of the agents. As a result, the partial adjustment estimation will produce consistent estimates of the adjustment parameters. In the context of mutual fund performance, Cho and Shin (2011) develop a partial adjustment model based on a model whereby investors identify funds based on the past ability of managers to achieve returns and the assumption that there is partial adjustment in mutual fund portfolios. In the context of the paper, the authors show that a "smart money effect" exists for younger funds in Korea, because investors are uncertain as to the manager's ability[18].

[18] Consequently, the cash flow adjustment to and from these funds is higher, and these funds tend to outperform older funds. Additionally, the effect diminishes as funds age.

In a partial adjustment model, the economic relationship of interest can generalized as:

$$y_t^* = \mu + \beta \boldsymbol{X}_t + \varepsilon_t \tag{2.1}$$

In (1), y_t^* is the equilibrium or optimal value of some variable of interest. In this study, we focus on the long-run risk-adjusted returns of equity mutual funds, such as measures calculated using a Sharpe or Treynor ratio, or the abnormal returns from an asset-pricing model. The parameter μ is the long-run equilibrium measure of risk-adjusted return, and $\boldsymbol{X}_t$ is a vector of variables that affect the long-run equilibrium return. Factors influencing the optimal risk-adjusted return of a mutual fund include the risk-adjusted return of the market index and the risk-adjusted return of a fund of a similar risk or style, among others.

Due to the costs of adjustment, mutual fund managers may choose to not continuously adjust their portfolios towards the equilibrium. Instead, the manager may choose to only attempt to offset some of the deviation. Thus, the change in the risk-adjusted return from one period to the next is given by:

$$y_t - y_{t-1} = \lambda(y_t^* - y_{t-1}) \tag{2.2}$$

The parameter λ in (2) represents the proportion of the deviation from the optimum in one period that is reversed in the following period, or speed of adjustment. In the case of observed mutual fund returns, λ will express both the amount of deviation that is offset due to purposeful managerial portfolio rebalancing, plus a component that is due to random variation or mean reversion.

In order to model the partial adjustment that mutual fund managers undergo in rebalancing portfolios, we can plug (1) into (2), rearrange, and simplify, to yield:

$$y_t = \lambda\mu + \lambda\beta \boldsymbol{X}_t + (1 - \lambda)y_{t-1} + \lambda\varepsilon_t \tag{2.3}$$

The parameters in Equation (3) can be estimated using the regression model:

$$y_t = \alpha + \theta \boldsymbol{X}_t + \gamma y_{t-1} + \nu_t \tag{2.4}$$

The estimation of (4) will yield the parameter estimate $\hat{\gamma}$, which can be used to estimate $\hat{\lambda}$ as $\hat{\lambda} = 1 - \hat{\gamma}$. $\hat{\lambda}$ describes the percentage deviation from the optimal or target risk-adjusted return that is offset in one period. If there is partial adjustment towards a target, $\hat{\lambda}$ is bounded between 0 and 1. The other parameters of interest can be estimated similarly as, $\hat{\beta} = \frac{\hat{\theta}}{(1-\hat{\gamma})}$ and $\hat{\mu} = \frac{\hat{\alpha}}{(1-\hat{\gamma})}$.

In the above representation of the partial adjustment model, we note that the estimate of adjustment speed, $\hat{\lambda}$, has two components: rebalancing decisions of the fund managers and random price movements. Additionally, $\hat{\lambda}$ is assumed to be equal whether adjustment is taking place from either below or above the target or equilibrium. However, this is not likely to apply in the case of mutual fund portfolio rebalancing. A mutual fund manager who achieves a return below the target has a great deal of incentive to rebalance toward the optimum. This has become increasingly true over time, as competition among mutual funds has increased and investors realizing sub-optimal returns will abandon their funds for more successful funds or other pooling arrangements. Conversely, a mutual fund manager who achieves a return above the target equilibrium (whether through superior security selection or luck) has less incentive to expend the cost necessary to significantly rebalance the portfolio. In fact, remaining above the equilibrium, or over-performing, while likely not feasible in an efficient market over the long run, may be a short-term goal of mutual fund managers. As a result, we expect very little incentive for adjustment when performance exceeds that of the equilibrium.

In the case where the speed of adjustment, $\hat{\lambda}$, changes with the direction of the deviation from the optimum, the Asymmetric Partial Adjustment Model is more appropriate. In the asymmetric partial adjustment model, the econometric specification in (4) is modified into:

$$y_t = \alpha + \theta \boldsymbol{X}_t + \gamma_1 High \times y_{t-1} + \gamma_2 Low \times y_{t-1} + \nu_t \tag{2.5}$$

High in (5) is a dummy variable equal to one if the level of risk-adjusted return is above that of the previous period (and, hence, the equilibrium), and zero if not. Similarly, *Low* is an indicator equal to one if the return is below that of the previous period, and zero if not. Therefore, the asymmetric partial adjustment model in (5) estimates two separate adjustment speeds. γ_1 measures the speed of adjustment parameter when the level of return is above the equilibrium and γ_2 measures the speed when the return is below the optimum. The associated speed of adjustments can be measured by $\hat{\lambda}_1 = 1 - \hat{\gamma}_1$ and $\hat{\lambda}_2 = 1 - \hat{\gamma}_2$, respectively. *A priori*, given the competitive mutual fund environment and the lack of incentives for correcting deviations when performance is abnormally good, we expect managers to have an incentive to adjust as quickly as possible when fund performance is bad. Thus, we expect $\hat{\lambda}_2 > \hat{\lambda}_1$, or $\hat{\gamma}_1 > \hat{\gamma}_2$.

2.4 Estimation Methodology

We apply the asymmetric partial adjustment framework in a panel data setting using a fixed effect estimation procedure. The dependent variable in our empirical framework is a risk-adjusted measure of mutual fund return. In our study we compute three measures of risk-adjusted return. The first is a modified version of the ratio defined by Sharpe (1966),

$$Sharpe_{i,t} = \frac{r_{i,t}}{\sigma_{(r_{i,t})}}, \tag{2.6}$$

which is the average return, scaled by its standard deviation. In (6), $r_{i,t}$ is the average return for mutual fund i across the time period t, and $\sigma_{(r_{i,t})}$ is the standard deviation of the return for mutual fund i across period t. The Sharpe ratio essentially measures the return achieved by a mutual fund per unit of risk taken. This ratio should be determined by financial market and economic conditions, and there should be an optimal or target Sharpe ratio that is achievable in the financial markets. Therefore, the partial adjust model that measures the degree to which fund managers balance the costs and benefits of rebalancing portfolios towards the optimal ratio can be appropriately measured by the asymmetric partial adjustment model. The second risk-adjusted measure of return is similar to that defined by Treynor (1966):

$$Treynor_{i,t} = \frac{r_{i,t}}{\beta_{(r_{i,t})}}, \tag{2.7}$$

where $r_{i,t}$ is the average return for mutual fund i across period t, and $\beta_{(r_{i,t})}$ is the beta coefficient calculated using the CAPM single factor model for mutual fund i across period t. This is another measure of risk-adjusted return that, unlike the Sharpe ratio, scales the fund's return by the amount of risk that that particular fund will contribute to a diversified portfolio. Again, economic conditions should dictate a long-run equilibrium level of the Treynor ratio that is attainable by investors. The third and final measure of risk-adjusted return is the alpha defined by Jensen (1968), which is the intercept term from the single factor CAPM. Alpha measures the fund's abnormal return, or the amount of return investors yield from the mutual fund manager's skill. A positive value of alpha is an indication that the manager is efficient; however, expenses and transaction costs can offset benefits attained by realizing a positive alpha.

The general econometric specifications we use to estimate how quickly mutual funds adjust to their respective optimal portfolio allocations are represented by:

$$\begin{aligned} Sharpe_{i,t} = \alpha_i + \gamma_1 High \times Sharpe_{t-1} + \gamma_{12} High \times Sharpe_{t-2} + \\ \gamma_2 Low \times Sharpe_{t-1} + \gamma_{22} Low \times Sharpe_{t-2} + \theta \boldsymbol{X}_t + +\nu_t \end{aligned} \tag{2.8}$$

$$\begin{aligned} Treynor_{i,t} = \alpha_i + \gamma_1 High \times Treynor_{t-1} + \gamma_{12} High \times Treynor_{t-2} + \\ \gamma_2 Low \times Treynor_{t-1} + \gamma_{22} Low \times Treynor_{t-2} + \theta \boldsymbol{X}_t + +\nu_t \end{aligned} \tag{2.9}$$

$$\begin{aligned} Alpha_{i,t} = \alpha_i + \gamma_1 High \times Alpha_{t-1} + \gamma_{12} High \times Alpha_{t-2} + \\ \gamma_2 Low \times Alpha_{t-1} + \gamma_{22} Low \times Alpha_{t-2} + \theta \boldsymbol{X}_t + +\nu_t \end{aligned} \tag{2.10}$$

The empirical specification in (2.8) – (2.10) is the same as that presented in (2.5) with the addition of a second set of asymmetric adjustment parameters that measure the degree to which the deviation from the equilibrium return is reversed by the next *two* periods. These adjustment parameters are estimated by the γ_{12} and γ_{22} parameters. These coefficients can have important implications with regards to the time series properties of the variable and, thus, help to ensure the proper specification of the model. The vector of variables that determine the target or equilibrium risk-adjusted return achievable by each respective fund, $\boldsymbol{X}_t$, are the market Sharpe Ratio (*Market Sharpe*) and the average Sharpe ratio for a mutual fund within the same Lipper Classification (*Classification Sharpe*) as denoted by the CRSP Mutual Fund dataset for (8), the market return (market beta is unity) (*Market Treynor*) and the average Treynor ratio for a mutual fund within the same Lipper Classification (*Classification Treynor*) for (9), and the average alpha for a mutual fund within the same Lipper Classification (*Classification Alpha*) for (10). The Lipper Classification classifies mutual funds by the types of securities they are chartered to purchase.

2.5 The Data

The data for this study are from the CRSP U.S.-based Mutual Fund dataset. Daily and monthly mutual fund returns from January 2000 through December 2013 are analyzed. Daily data are used to compute monthly and quarterly performance measures for each mutual fund, and monthly data are used to compute yearly measures. Market index returns and the U.S. risk free rate data are from the website of Kenneth French. The data are windsorized at the one percent level for each performance measure under study in order to reduce the influence of outliers and data errors. In addition, daily observations displaying a zero return are omitted in order to remove any bias due to illiquidity. The mutual fund return data are merged with annual summary information from CRSP, which includes information describing the fund, including net asset value, fund family, management fees, age of the fund, fund management group*, etc*.

Additionally, in an extension of our basic results, in Section 2.7 we test whether the speed of adjustment is heterogeneous among different types of mutual funds. For this purpose, we divide the sample of U.S. equity funds into eight "styles", based on their Lipper Objective defined in the CRSP dataset. The eight styles differ in terms of the range of securities that are considered for inclusion in the fund; thus, information costs should be heterogeneous across several of the fund styles. In our analysis, we exclude all funds that focus primarily on purchasing debt and other fixed income securities and consider funds that primarily invest in equities. The sample of equity mutual funds is divided into the following styles categories: General Equity Funds, International Funds, International Focused Funds, Global Funds, Global Focused Funds, Sector Funds, Emerging Market Funds, and Market Index Funds. General Equity Funds are funds that primarily purchase the equities of U.S. firms through a variety of strategies, but are not focused on any specific market or sector. International Funds are funds that primarily focus on investing in international assets, but are not focused on specific international sectors or markets, while International Focused Funds invest in international assets that are located in more specific international sectors or markets. Likewise, Global Funds are those that invest in a portfolio of global assets, but are not focused a specific region or industry, while Global Focused Funds purchase global assets that are concentrated in specific markets or sectors. Sector funds are those that are focused on purchasing equities from specific sectors of the U.S. economy. Emerging Market funds are those that focus on purchasing assets in emerging markets, which are typically more informationally opaque, and, consequently, more risky. Finally, Market Index Funds are those that are designed to mimic the returns of the overall market, as defined by a market benchmark such as the S&P 500. Funds are assigned to each group based on their respective Lipper Objectives. Table 2.1 presents the mapping of the Lipper Objectives to the eight styles defined by this analysis.

Table 2.1: Equity Style Designation by Lipper Objective

We divide the CRSP sample of U.S.-based mutual funds into different classes, or "styles" of equity funds. This paper analyzes U.S. equity funds, so funds focused on purchasing debt securities and other fixed income securities are omitted from the sample. The remaining sample of equity funds are divided into eight categories, based on the fund's Lipper Objective, as defined in the CRSP database.

Style	Lipper Objective	
Sector	Basic Materials Funds	Natural Resources Funds
	Consumer Goods Funds	Science & Technology Funds
	Consumer Services Funds	Specialty/Miscellaneous Funds
	Financial Services Funds	Real Estate Funds
	Gold Oriented Funds	Telecommunication Funds
	Health/Biotechnology Funds	Utility Funds
	Industrials Funds	
International	International Funds	International Small-Cap Funds
	International Income Funds	
International Focused	International Real Estate Funds	Japanese Funds
	China Region Funds	Pacific Ex Japan Funds
	European Region Funds	Pacific Region Funds
Emerging Markets	Emerging Markets Funds	Latin American Funds
General Equity	Equity Market Neutral Funds	Income Funds
	Long/Short Equity Funds	Flexible Portfolio Funds
	Flexible Income Funds	Balanced Funds
	Growth and Income Funds	Multi-Sector Income Funds
	Growth Funds	High Current Yield Funds
	Mid-Cap Funds	Equity Income Funds
	Small-cap Funds	
Global	Global Funds	Global Income Funds
	Global Small-Cap Funds	
Global Focused	Global Financial Services Funds	Global Natural Resources Funds
	Global Health/Biotechnology Funds	Global Science/Technology Funds
	Global Flexible Port Funds	Global Real Estate Funds
Market	S&P 500 Index Objective Funds	

Table 2.2 presents the summary statistics of several key variables for the sample of U.S. equity funds under observation from January 2000 to December 2012. The first column presents the summary statistics for the full sample of U.S. equity funds, which consists of 1,885,540 observations for approximately 22,900 U.S.-based equity mutual funds. The average monthly return for a fund in the sample is approximately 0.6 percent. The average monthly Sharpe ratio for the full sample is 0.074 with a standard deviation of 0.226. A positive Sharpe ratio indicates a positive relationship between risk and return, as expected. The relatively small value of the average Sharpe ratio indicates that, when computed using daily observations, daily returns are small, compared with the standard deviation of daily returns. The average Treynor ratio is also positive, with an average value of 0.048 and a standard deviation of 0.416. In addition, the average value of alpha is slightly positive, at 0.007. The average mutual fund in the sample has a net asset value (NAV) of $16.38 and total net assets (TNA) of $443 million. The average fund also charges average management fees of 0.67 percent per year and has an average turnover ratio of 1.67 times per year.

Table 2.2 also shows summary statistics for the style subsamples of equity mutual funds previously defined by their Lipper Objective Codes. The statistics show that Emerging Market Funds yield the highest average monthly returns of 1.69 percent per month, followed by Sector funds with 0.97 percent. The Market Index Funds have the lowest monthly returns of about 0.3 percent per month. However, emerging markets also appear to be the most risky, as emerging market funds have a monthly return standard deviation of 6.75 percent, followed by Sector funds with a standard deviation of 6.17 percent. Market Index funds have the lowest monthly return standard deviation of 4.67 percent. The summary statistics of U.S. equity funds display the key property that funds that invest in markets that yield higher returns are subject to higher risk. In addition, since market index and funds are more passively managed, the summary statistics are consistent with prior literature that actively managed funds yield higher returns. However, whether

Table 2.2: U.S. Equity Fund Summary Statistics

Summary Statistics for the sample of CRSP mutual funds from January 2000 to December 2012. The CRSP sample of mutual funds is divided into different styles of U.S.-based equity funds. Funds focused on purchasing debt securities and other fixed income securities are omitted, and the remaining sample of equity funds are divided into eight categories, based on the fund's Lipper Objective, as defined in the CRSP database (See Table 2.1). The return data are sampled monthly. Daily data are used to report monthly measures of risk-adjusted return (Sharpe Ratio, Treynor Ratio, and Alpha). Fund characteristics (NAV, TNA, Turnover, Fees, etc.) are reported annually. The data are windsorized at the 1% tails for each performance ratio (Sharpe Ratio, Treynor Ratio, and Alpha).

Variable		Full Sample	Emerging Markets	General Equity	Global
Monthly Return (%)					
	Mean	0.589	1.693	0.496	0.604
	Std. Dev.	5.154	6.751	4.889	4.847
Sharpe Ratio					
	Mean	0.074	0.113	0.074	0.083
	Std. Dev.	0.226	0.264	0.227	0.235
Treynor Ratio					
	Mean	0.048	0.144	0.041	0.036
	Std. Dev.	0.416	0.565	0.377	0.512
Alpha					
	Mean	0.007	0.053	0.003	0.007
	Std. Dev.	0.126	0.216	0.105	0.122
Net Asset Value ($)					
	Mean	16.38	20.29	15.77	15.89
	Std. Dev.	15.45	15.47	15.77	10.01
Totoal Net Assets ($ millions)					
	Mean	443	543	431	462
	Std. Dev.	2,436	2,481	2,287	2,732
12-1b Fees					
	Mean	0.006	0.006	0.006	0.006
	Std. Dev.	0.004	0.004	0.004	0.003
Management Fees (%)					
	Mean	0.667	0.996	0.632	0.716
	Std. Dev.	0.320	0.348	0.310	0.306
Turnover					
	Mean	1.67	0.87	1.95	0.88
	Std. Dev.	291.45	1.69	351.08	0.99
N		1,885,540	40,536	1,303,178	87,690

Table 2.2 (cont.): U.S. Equity Fund Summary Statistics

Variable		Global Focused	International	International Focused	Market	Sector
Monthly Return (%)						
	Mean	0.650	0.614	0.929	0.296	0.972
	Std. Dev.	5.454	5.474	5.945	4.670	6.173
Sharpe Ratio						
	Mean	0.078	0.070	0.070	0.055	0.072
	Std. Dev.	0.224	0.221	0.221	0.197	0.214
Treynor Ratio						
	Mean	0.058	0.054	0.114	0.022	0.068
	Std. Dev.	0.379	0.517	0.673	0.234	0.426
Alpha						
	Mean	0.007	0.005	0.026	-0.001	0.025
	Std. Dev.	0.134	0.149	0.193	0.047	0.189
Net Asset Value ($)						
	Mean	15.25	14.86	17.92	24.10	20.78
	Std. Dev.	11.36	9.72	13.17	27.13	17.72
Totoal Net Assets ($ millions)						
	Mean	438	496	257	2,029	223
	Std. Dev.	1,476	2,343	985	8,838	921
12-1b Fees						
	Mean	0.006	0.006	0.006	0.005	0.006
	Std. Dev.	0.003	0.004	0.004	0.003	0.004
Management Fees (%)						
	Mean	0.684	0.782	0.789	0.193	0.736
	Std. Dev.	0.314	0.286	0.315	0.127	0.302
Turnover						
	Mean	0.90	0.85	1.06	0.11	1.62
	Std. Dev.	1.29	0.95	2.81	0.23	3.67
N		43,471	178,128	42,295	27,424	162,818

these higher returns are high enough to offset their expenses is another question. Indeed, Emerging Market Funds also have the highest management fees of approximately 1 percent per year, while Market focused funds have the lowest of 0.19 percent. The summary statistics show that Market Index Funds have the lowest Sharpe ratio of 0.055, followed by International and International Focused Funds (0.070), Sector Funds (0.072), General Equity (0.074), Global Focused Funds (0.078), Global Funds (0.083), and Emerging Markets (0.113). Similar trends are revealed for the Treynor ratios and alphas. Additionally, General Equity funds have the highest turnover of 1.95 times, while Market funds have the lowest of 0.11 times. In general, the summary statistics support the idea that focused funds appear to show some efficiency advantages over passive, or non-focused, funds, as evidenced by higher average risk-adjusted returns. Whether the higher risk-adjusted returns of more focused funds adequately offset their higher management fees has often been debated. We shed further light on this issue by examining the speed at which mutual fund managers of different types of firms are able to adjust their portfolios.

2.6 Partial Adjustment in U.S.-based Equity Mutual Funds

The results of the fixed effect econometric estimation of the asymmetric partial adjustment model using monthly measures of risk-adjusted returns are presented in Table 2.3. Panels A, B, and C of Table 2.3 represent the partial adjustment estimations using the Sharpe Ratio, Treynor Ratio, and Alpha, as dependent variables, respectively. In Panel A, the coefficient *highadjust1* measures the speed of adjustment parameter when the Sharpe ratio is above the target or equilibrium ratio. A coefficient of 0.205 implies that, when a fund achieves higher than optimal performance, as measured by the Sharpe Ratio, approximately 80 percent (1-0.205) of that deviation is offset in the next period (month). Correspondingly, the coefficient *lowadjust1* of -0.0471 implies that when a mutual fund is below its equilibrium risk return tradeoff, approximately 105 percent of the deviation is offset within one month. The coefficients for the second lag of Sharpe ratio, *highasjust2* and *lowasjust2*, are either not statistically significant or very close to zero, implying that equilibrium is restored within the next two periods. The *Market Sharpe* ratio and *Classification Sharpe* coefficients are both positive and significant at the one percent level, as expected *a priori*. The standard asymmetric partial adjustment model appears to fit the data well. The R-squared value for the model presented in Panel A, using the Sharpe Ratio as the dependent variable, is 0.706.

Panel B shows the results of the asymmetric partial adjustment model when the Treynor Ratio is used as the dependent variable. The coefficient 0.12 for *highadjust1* implies that, when a fund's Treynor Ratio is above above equilibrium, approximately 88 percent of the deviation will be offset in the next period. The coefficient *lowadjust1* is insignificant, however, which implies that, when a mutual fund's Treynor Ratio is below that of the equilibrium, there is no partial adjustment. In other words, managers fully adjust the portfolio to the equilibrium. Again, the coefficients for the second lag of the dependent variable, *highasjust2* and *lowasjust2*, are either not statistically significant or very close to zero. In addition, the coefficients for *Market Return* and *Classification Treynor* are positive and significant at the five percent level, as expected. The R-squared value for the model presented in Panel B, where the Treynor Ratio is the dependent variable, is 0.422. Similar results are reported in Panel C, where Jensen's alpha is used as the dependent value. The *highadjust1* coefficient is 0.12, similar to that of Panel B, while the *lowadjust1* coefficient is -0.036 in Panel C, implying the a fund making less than the equilibrium alpha is able to more than offset the deviation in the next period by making a single-period adjustment of 103.6 percent.

The results presented in Panels A, B, and C of Table 2.3 provide consistent evidence with regards to the speed at which mutual funds are able to adjust their portfolios in order to achieve equilibrium (or higher) levels of risk-adjusted return. The resulting coefficients for *highadjust1* are positive and significant across the

Table 2.3: Monthly Asymmetric Partial Adjustment Estimation

Monthly fixed effect estimations of the asymmetric partial adjustment model presented in Eqs. (8)-(10) for U.S.-based equity mutual funds from January 2000 to December 2012. Results are presented using several measures of risk-adjusted return, Sharpe Ratio, Treynor Ratio, and Alpha. Independent variables are associated measures of the market risk-adjusted return and the risk-adjusted return of an average fund in the same Lipper Class. Second order lags of the dependent variable are also included to ensure proper specification of the model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable - Sharpe Ratio

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0242***	0.0044	5.472	0.000
highadjust1	0.2050***	0.0296	6.924	0.000
highadjust2	0.0004***	0.0001	2.750	0.006
lowadjust1	-0.0471**	0.0181	-2.593	0.010
lowadjust2	0.0000	0.0001	0.220	0.826
Market Sharpe	0.9104***	0.0196	46.353	0.000
Classification Sharpe	0.0185***	0.0047	3.906	0.000
R-Square	0.706			
No. of Funds	22,939			
N	1,865,715			

Panel B: Dependent Variable - Treynor Ratio

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0291***	0.0062	4.725	0.000
highadjust1	0.1182***	0.0306	3.861	0.000
highadjust2	0.0000*	0.0000	1.959	0.050
lowadjust1	-0.0094	0.0198	-0.474	0.635
lowadjust2	-0.0000	0.0000	-0.111	0.912
Market Return	0.0541***	0.0012	46.202	0.000
Classification Treynor	0.0001**	0.0000	2.116	0.034
R-Square	0.422			
No. of Funds	22,939			
N	1,865,715			

Table 2.3 (cont.): Monthly Asymmetric Partial Adjustment Estimation

Panel C: Dependent Variable - Alpha				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0071***	0.0002	32.376	0.000
highadjust1	0.1169***	0.0054	21.645	0.000
highadjust2	0.0016	0.0011	1.481	0.139
lowadjust1	-0.036***	0.0034	-10.526	0.000
lowadjust2	0.0126***	0.0027	4.609	0.000
Classification Alpha	0.6966***	0.0106	65.723	0.000
R-Square	0.452			
No. of Funds	22,939			
N	1,866,031			

three specifications in Table 2.3, which implies that there is some persistence, or relatively little adjustment, when fund performance is relatively good. The coefficient *lowadjust1* is negative across specifications and significant in two out of the three specifications of Table 2.3. While a negative adjustment coefficient normally violates an assumption of the partial adjustment model, it does not in the case of asymmetric adjustment in mutual funds. A negative *lowadjust1* coefficient implies that funds completely offset the deviation and are able to reverse their performance in one period. In cases where there is a definitive "target" level of some variable, the partial adjustment model assumes that there are costs for a deviation in either direction, which implies that adjustment coefficients should theoretically be between 0 and 1. However, in the context of mutual fund performance, a negative adjustment parameter represents an underperforming fund becoming an over performing one in the next period – a situation that a mutual fund manager would welcome, especially in a highly competitive environment.

The use of the asymmetric adjustment model makes a significant difference in terms of interpreting the overall efficiency of mutual funds. The relatively low adjustment speed when a fund is above the equilibrium value is consistent with the fact that there is no incentive for managers to adjust when the fund is outperforming and adds support for the implementation of the asymmetrical partial adjustment model. Particularly good outcomes tend to be transitory and the effects are short lived, as the market naturally restores equilibrium. However, the relatively high adjustment speed when the performance measures are below the equilibrium value indicates that poorly performing fund managers are able and willing to adjust portfolios quickly in order to bring fund performance back to (or above) the equilibrium level. This is consistent with prior evidence that managers are sensitive to poor performance. Managers may perceive the costs of adjustment to be low, relative to the benefits of keeping current investors and attracting new investors through the realization of high relative returns. These results imply that managers are fairly efficient in that they are able to quickly offset deviations in fund performance.

2.7 Heterogeneous Adjustment Across Mutual Fund Styles

One of the benefits of actively managed mutual funds is that they allow lay investors to benefit from the information gathering ability and expertise of professional managers who are familiar with specific areas of the financial markets. However, mutual funds often have different objectives that may require gathering different types of information. Thus, there may be differences in the costs of portfolio adjustment across different fund types. As a result, the estimated speed of adjustment may be different across fund types as well. In this section, we divide the sample based on the eight previously defined styles and examine the speed of adjustment estimates across fund types.

Each fund style in our sample is focused on purchasing equity securities; however, some funds are more specific with regards to the geographical locations and industries of the assets under consideration. As a consequence, managers will face heterogeneous information costs across fund styles, which may have important implications with regards to their willingness and ability to quickly adjust their funds' portfolios. For example, managers investing in emerging markets face relatively high information costs, because emerging markets are less integrated with developed markets and are subject to greater uncertainty. In order to succeed in emerging markets, the managers must expend more resources in order to acquire accurate information, which makes them competitive in this market. As a result, the managers of emerging market funds should capitalize on the information advantage (that they paid for) through more efficient portfolio adjustment, either in the form of higher risk-adjusted returns, or more optimal portfolio adjustment. Consequently, in the context of this paper, *a priori*, we expect the speed of adjustment for Emerging Market Funds and the like to be more optimal than that of Market and General Equity Funds, due to differences in information costs and advantages. The monthly fixed effect estimations of the asymmetric partial adjustment model are presented for each style subsample of mutual funds in Tables 2.4, 2.5, and 2.6.

Table 2.4 presents the fixed effect estimation for the asymmetric partial adjustment model across different fund styles using the Sharpe ratio as the dependent variable. A major result is consistent with the full sample estimation of asymmetric adjustment – the adjustment speed when the Sharpe ratio is above the equilibrium value is relatively slow, when compared to when the Sharpe ratio is below the equilibrium value. This result is consistent across all styles of U.S. equity mutual funds specified in this study. Additionally, The *Market Sharpe* and *Classification Sharpe* coefficients are all positive and consistently statistically significant across all fund types, which is consistent with *a priori* expectations. The partial adjustment model applied in this study best describes the behavior of Market Index Funds, as this specification has an R-squared value of 0.994. This is not surprising, since the measures used to estimate adjustment speed are based on statistics derived from market data. The model consistently explains the adjustment dynamics across funds styles, with R-squared values of 0.76, 0.72, 0.66, 0.61, 0.58, 0.55, 0.52 for General Equity, Global Focused, International, Global, Emerging Markets, International Focused, and Sector funds, respectively.

More importantly, Table 2.4 provides further results regarding the relative efficiency of mutual funds that are charged with purchasing different types of securities. We begin by analyzing the speed of adjustment when the Sharpe Ratio is above that of the equilibrium, or the fund is performing relatively well. The *highadjust1* coefficient is highest (adjustment is slowest) for Emerging Market Funds at 0.33, meaning 67 percent (1-0.33) of the deviation is offset in one period. Global, International Focused, International, and Sector Funds adjust more quickly, with coefficients of 0.27, 0.30, 0.27, and 0.23, respectively. On the other hand, Market and General Equity Funds adjust among the fastest with coefficients of 0.0148 and 0.1739, respectively. In the context of mutual fund performance, this means funds that focus on more specialized markets and typically acquire more specific market information are able to achieve more prolonged above average performance. Therefore, in the context of adjustment from above the equilibrium, slower adjustment is good from the perspective of mutual fund managers and investors. The results in Table 2.4 imply that funds that have a more focused style are more efficient at maintaining high levels of risk-adjusted returns. We find similar results when the Sharpe Ratio is below the equilibrium value, implying a suboptimal portfolio. The *lowadjust1* coefficient of -0.11 is relatively lowest (faster adjustment) for Sector Funds, implying that Sector Funds offset 111 percent of the deviation from the equilibrium Sharpe ratio in one period. Also among the fund styles that adjust relatively quickly are Emerging Market, Global, Global Focused, and International Funds, with coefficients of -0.11, -0.08, -0.06, and -0.06, respectively. The highest coefficient (lowest adjustment speed) is that of Market Funds (*lowadjust1* is insignificant), followed by General Equity Funds, with a coefficient of -0.033. The results indicate that more specialized funds are able to improve performance more quickly when the fund underperforms, which gives investors in these funds an advantage.

Table 2.5 presents the fixed effect estimation for the asymmetric partial adjustment model across different fund styles using the Treynor ratio as the

Table 2.4: Monthly Asymmetric Partial Adjustment Estimation Across Fund Styles: Sharpe Ratio

Monthly Fixed Effect estimations of the asymmetric partial adjustment model for each U.S. equity mutual fund style subsample (See Table 2.1) from January 2000 to December 2012. The Dependent variable is the Sharpe Ratio. Independent variables include the Market Sharpe Ratio and the average Sharpe Ratio for a mutual fund having a similar Lipper Classification. Second order lags of the dependent variable are also included to ensure proper specification of the model. T-stats are reported below each coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Emerging Markets	General Equity	Global	Global Focused	Inter-national	Inter-national Focused	Market	Sector
Intercept	0.0799***	0.0199***	0.0405***	0.0359***	0.0229**	0.0539***	0.0020**	0.0426***
	4.65	*5.40*	*5.15*	*3.56*	*2.23*	*4.82*	*2.16*	*8.08*
highadjust1	0.3304***	0.1739***	0.2659***	0.1435***	0.2720***	0.2979***	0.0148***	0.2302***
	5.23	*6.37*	*6.14*	*3.35*	*4.19*	*4.70*	*2.64*	*7.24*
highadjust2	0.0001	0.0006**	0.1026**	0.0001	0.0936	0.2020***	-0.0025	0.0003***
	1.42	*2.15*	*2.45*	*0.67*	*1.52*	*3.38*	*-0.77*	*3.51*
lowadjust1	-0.1072**	-0.0324*	-0.0824***	-0.0609**	-0.0677*	-0.0410	-0.0036	-0.1126***
	-1.97	*-1.87*	*-2.90*	*-2.05*	*-1.65*	*-1.08*	*-1.34*	*-4.67*
lowadjust2	-0.0878	-0.0002*	0.0003**	-0.1152***	0.0010***	-0.1205***	-0.0055*	-0.0001
	-1.59	*-1.80*	*2.12*	*-3.92*	*3.73*	*-3.23*	*-1.82*	*-0.74*
Market Sharpe	0.8990***	0.9539***	0.8664***	0.9042***	0.7727***	0.7101***	0.0014	0.7113***
	13.55	*58.75*	*26.49*	*22.78*	*15.14*	*13.21*	*0.11*	*27.21*
Classification Sharpe	0.0320	0.0171***	0.0038	0.0184**	0.0958***	0.0282	0.9871***	0.0224*
	1.60	*2.83*	*0.58*	*2.46*	*2.85*	*1.28*	*78.62*	*1.94*
R-Square	0.579	0.759	0.605	0.719	0.661	0.545	0.994	0.516
No. of Funds	559	15,893	1,337	928	2,212	603	284	2,222
N	40,100	1,289,108	86,781	43,121	176,418	41,935	27,159	161,093

dependent variable. Again, we see results that are consistent with the full sample estimation of asymmetric adjustment – adjustment speed when the Treynor ratio is above the equilibrium value is relatively lower than when the Sharpe ratio is below the equilibrium value, which justifies the use of the asymmetric version of the partial adjustment model in the context of mutual fund performance. This result is consistent across all types of equity mutual funds specified in this study. Also consistent with the results in Table 2.4, the *Market Return* and *Classification Treynor* coefficients are consistently positive and significant across fund styles, which is coincides with *a priori* expectations. Due to the construction of the testing methodology, we again find a very high R-squared value for Market Index Funds of 0.965. R-squared values for other fund types range from 0.256 for International Focused Funds to 0.588 for Global Focused Funds.

Most importantly, we find similar to those presented in Table 2.4 when comparing speeds of adjustment across fund styles when using the Treynor ratio as the dependent variable. When funds over perform, more specialized firms that typically charge higher fees and produce more information are able to maintain a performance advantage in terms of the speed of adjustment. Recall that, in the context of mutual fund adjustment, when the fund is performing well, statistically significant slower adjustment speed indicates better managerial skill. Table 2.5 shows that the highest *highadjust1* coefficient (slowest adjustment speed) is reported for Emerging Market Funds at 0.23, implying that 77 percent of the deviation is offset in one period. International, International Focused, Sector, and Global Funds are also among the slowest to adjust, with coefficients of 0.15, 0.16, 0.13, and 0.10, respectively. The fact that adjustment speeds for specialized types of funds like Emerging Market and International Focused Funds are lower when the funds over perform implies that these fund managers have some advantage in portfolio allocation, and information advantages have long been cited in the literature as a potential explanation.

Table 2.5: Monthly Asymmetric Partial Adjustment Estimation Across Fund Styles: Treynor Ratio

Monthly Fixed Effect estimations of the asymmetric partial adjustment model for each U.S. equity mutual fund style subsample (See Table 2.1) from January 2000 to December 2012. The Dependent variable is the Treynor Ratio. Independent variables include the Market Return (market beta is zero) and the average Treynor Ratio for a mutual fund having a similar Lipper Classification. Second order lags of the dependent variable are also included to ensure proper specification of the model. T-stats are reported below each coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Emerging Markets	General Equity	Global	Global Focused	International	International Focused	Market	Sector
Intercept	0.1003***	0.0225***	0.0037	0.0282**	0.0247	0.1030***	0.0032	0.0534***
	3.26	*4.24*	*0.33*	*2.41*	*1.25*	*4.56*	*0.80*	*6.64*
highadjust1	0.2333***	0.0942***	0.0973**	0.0770	0.1534***	0.1618***	-0.0138	0.1270***
	2.68	*2.89*	*2.39*	*1.54*	*2.74*	*2.85*	*-0.83*	*3.88*
highadjust2	0.0047	0.0000	0.0001***	0.0088	0.0002	-0.0020***	-0.0088	0.0000
	0.98	*1.60*	*2.81*	*1.60*	*0.61*	*-2.73*	*-0.70*	*-0.69*
lowadjust1	-0.0260	-0.0061	0.0488	0.0091	-0.0075	-0.0764**	-0.0042	-0.0311
	-0.53	*-0.26*	*1.53*	*0.24*	*-0.17*	*-2.22*	*-0.20*	*-1.17*
lowadjust2	0.0000	0.0000	0.0002	-0.0005***	-0.0001	0.0009***	-0.0186	0.0001***
	-1.01	*-0.65*	*0.64*	*-6.20*	*-0.38*	*4.32*	*-1.33*	*2.85*
Market Return	0.0740***	0.0522***	0.0550***	0.0562***	0.0651***	0.0669***	0.0266***	0.0470***
	14.14	*53.99*	*30.62*	*30.26*	*17.03*	*15.43*	*2.64*	*30.33*
Classification Treynor	0.0162***	0.0001**	0.0020*	0.0038	0.0085	0.0026	0.4210**	0.0074**
	3.91	*2.55*	*1.72*	*0.86*	*1.50*	*0.47*	*2.04*	*2.49*
R-Square	0.431	0.477	0.304	0.588	0.406	0.256	0.965	0.303
No. of Funds	559	15,893	1,337	928	2,212	603	284	2,222
N	40,100	1,289,108	86,781	43,121	176,418	41,935	27,159	161,093

The speed of adjustment results when the Treynor Ratio is below the equilibrium value are somewhat different than the results presented in Table 2.4. The *lowadjust1* coefficient is insignificant for all style subsamples except one (International Focused), which implies that there is full adjustment within one period. When using the Treynor Ratio as the dependent variable, Table 2.5 shows that focused funds, who typically acquire more information, seem to be better able to sustain relatively good fund performance; however, there is no statistically significant evidence that there are differences in the speed of adjustment across fund styles when the funds underperform, relative to the equilibrium. However, consistent with the results in Table 2.4, full adjustment within one period when funds underperform is consistent low costs of portfolio rebalancing, relative to the benefits of maintaining a competitive portfolio in a saturated market for mutual funds.

Table 2.6 presents the fixed effect estimation for the asymmetric partial adjustment model across different fund styles with alpha as the dependent variable. In general, we see results that are consistent with the full sample estimation, as well as those of Tables 2.4 and 2.5. The speed of adjustment when alpha is above the equilibrium is lower than when alpha is above the equilibrium. Also, certain types of funds that typically engage in more information producing activities exhibit more optimal adjustment behavior than those who are typically more passive and less focused on producing information advantages. The *highadjust1* coefficient for the Market Funds is much higher (0.40) than in previous estimations. This is likely an erroneous result, because the application of the partial adjustment model with alpha as the dependent variable is questionable for market index funds, since these funds should not exhibit abnormal returns. Similar to previous results, we find that the *lowadjust1* coefficient is lowest for Emerging Market, Global, and Sector Funds at -0.12, -0.09, and -0.06, respectively, implying faster adjustment. On the other hand, the *lowadjust1* coefficient is insignificant for Market Funds.

Table 2.6: Monthly Asymmetric Partial Adjustment Estimation Across Fund Styles: Alpha

Monthly Fixed Effect estimations of the asymmetric partial adjustment model for each U.S. equity mutual fund style subsample (See Table 2.1) from January 2000 to December 2012. The Dependent variable is Jensen's alpha. Independent variables include the average alpha for a mutual fund having a similar Lipper Classification. Second order lags of the dependent variable are also included to ensure proper specification of the model. T-stats are reported below each coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Emerging Markets	General Equity	Global	Global Focused	Inter-national	Inter-national Focused	Market	Sector
Intercept	0.0340***	0.0041***	0.0094**	0.0081***	0.0053**	0.0116***	0.0027	0.0303***
	2.59	*4.12*	*2.10*	*3.60*	*2.11*	*4.80*	*1.55*	*3.50*
highadjust1	0.1389***	0.0997***	0.1814**	0.0530**	0.0740**	0.0632***	0.4059***	0.1318***
	2.65	*3.58*	*2.28*	*1.98*	*2.24*	*3.15*	*2.81*	*4.07*
highadjust2	0.0006	0.0026	0.0361	0.0104	-0.0010	0.0005	-0.0738	0.0613
	0.95	*0.51*	*0.85*	*0.38*	*-0.17*	*0.03*	*-0.83*	*1.59*
lowadjust1	-0.1154***	-0.0245*	-0.0874**	-0.0479**	-0.0409**	-0.0262**	-0.0786	-0.0566*
	-2.65	*-1.92*	*-2.53*	*-2.00*	*-2.15*	*-2.38*	*-1.07*	*-1.81*
lowadjust2	0.0327	0.0167	0.0053	-0.0241	0.0098	-0.0170	0.1213	-0.0442*
	0.63	*0.91*	*0.15*	*-1.20*	*0.67*	*-1.50*	*1.21*	*-1.75*
Classification Alpha	0.7327***	0.8917***	0.8163***	0.9156***	0.9286***	0.9043***	1.0789***	0.4104**
	5.14	*57.53*	*24.38*	*53.56*	*79.28*	*79.17*	*13.24*	*2.41*
R-Square	0.630	0.411	0.552	0.606	0.758	0.755	0.708	0.343
No. of Funds	559	15,898	1,337	928	2,212	603	284	2,223
N	40,105	1,289,325	86,789	43,136	176,438	41,945	27,159	161,134

In general, we find consistent evidence of heterogeneity in adjustment speeds when estimating an asymmetric partial adjustment model across different fund styles using three different measures of risk-adjusted return. We find that mutual funds adjust more slowly when outperforming on a risk-adjusted basis then when underperforming – a result that makes intuitive sense, given the lack of incentive for managers to adjust when results are good. In contrast, when funds underperform, managers appear to quickly offset (and perhaps reverse) the deviation from equilibrium, indicating the costs of underperformance are high. Additionally, firms that exhibit higher returns and charge higher fees, like emerging market and sector funds, tend to be relatively more efficient. These results are consistent with active managers who expend resources in order to gain informational advantages that allow them to not only achieve higher returns, but also allow them to rebalance in a timelier manner. As shown in previous literature, active managers seem to demand a premium for these advantages in the form of higher expenses.

2.8 Time-Varying Mutual Fund Adjustment Speeds

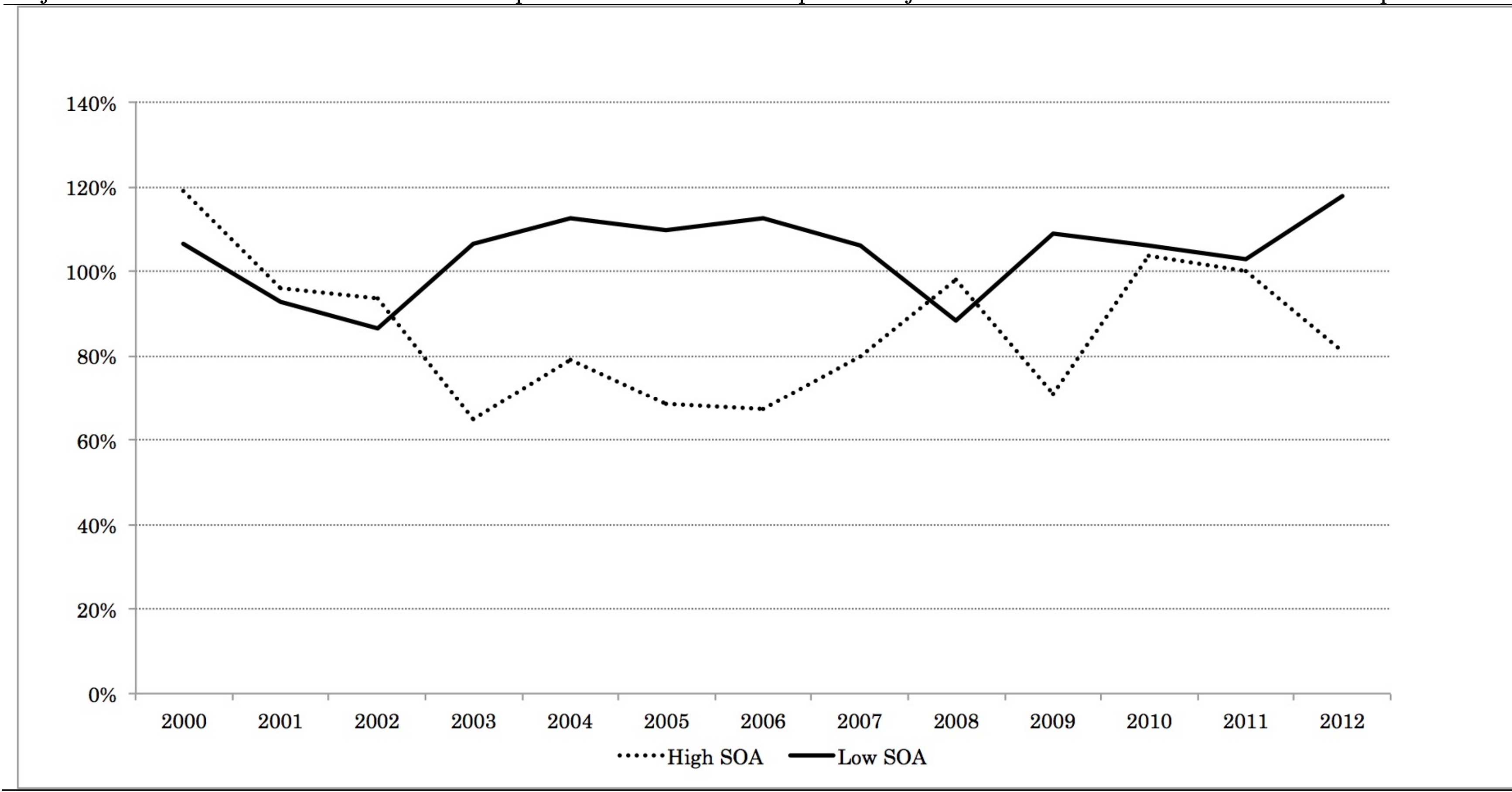
In Sections 2.6 and 2.7, we provide evidence that mutual fund managers quickly adjust their portfolios when portfolio performance is below that of the market equilibrium, and that the speeds at which funds adjust is heterogeneous across different styles of funds. We link the differences in adjustment speeds across fund styles to information advantage acquired by more actively managed, focused funds; however, there have been significant changes in information production costs over the past several decades. In particular, the efficiency of information dissemination and production has significantly increased with the use of technology, and this trend has been driving increasingly open and integrated financial markets.

Based on the fact that information has become more efficient over time, we expect that mutual funds have become more efficient at producing information, and, thus, we should observe an increase in speed of adjustment over time. To test this hypothesis, we estimate the monthly fixed effect asymmetric partial adjustment model from (8) for the full U.S.-based equity mutual fund sample for each year. We then capture the speed of adjustment coefficients (one minus the *lowadjust1* and *highadjust1* coefficients) and examine the trend from 2000 to 2012.

Figure 2.1 presents the speed of adjustment estimates for the full mutual fund sample over time using the Sharpe ratio as the measure of risk adjusted return. The results show that the speeds of adjustment remain mostly consistent over the sample period under study. *Highadjust1* is generally lower than *lowadjust1*, which is consistent with the benefits of active management. Active or more informationally efficient managers are able to succeed in quickly offsetting deviations when the fund underperforms, while maintaining the good performance (for a short while) when the fund does well. More relevant to the information hypothesis, there also appears to be some cyclicality in the speeds of adjustment. For example, the speed of adjustment when funds underperform tends to increase when the economy is good and decline during a recession. This can be seen in Figure 2.1 as reductions in *Low SOA* around 2001 and 2008. Conversely, the speed of adjustment when funds perform well tends to decrease during good economic times and increase during a recession. Figure 2.1 shows that *High SOA* tends to increase around 2001 and 2008, but decreases afterwards. The yearly trends in speed of adjustment are consistent with mutual fund managers being more efficient during good economic times. The most likely explanation of this result is consistent with the information production ability mutual funds. In Section 2.7 of this study, we show that certain funds that tend to focus on producing and utilizing more specific information tend to be more efficient in terms of portfolio rebalancing. Figure 2.1 supports the role that information plays in mutual fund portfolio adjustment ability by showing that, during times when information becomes more uncertain and costly to acquire for all funds, like during an economic recession, mutual funds are not able to rebalance their portfolios as efficiently.

Figure 2.1: Asymmetric Speeds of Adjustment, 2000 - 2012

Estimates of the speed of adjustment parameters from the asymmetric partial adjustment model for the full sample of U.S.-based equity mutual funds from January 2000 to December 2012. The dependent variable is the monthly Sharpe Ratio. *High SOA* is the speed of adjustment when fund returns are above the optimum. *Low SOA* is the speed of adjustment when fund returns are below the optimum.



2.9 Robustness and Possible Extensions

In previous sections, we provide empirical results using several monthly performance ratios that are computed using daily data. However, the use of daily data and the short estimation window can bias the calculation of the performance measures, and, hence, the speed of adjustment estimation. In order to ensure robustness of the results presented, the frequency of the data can be expanded to include the calculation of the risk-adjusted measures of return over a longer time period in order to ensure consistent results. In Tables 2.7 and 2.8, we provide results supporting the robustness of the previous results by estimating the speed of adjustment using measures of risk-adjusted return that are computed over a longer time period. Table 2.7 reports results for the speed of adjustment estimation using the Sharpe ratio computed on a quarterly and yearly basis as the dependent variable for the full sample of U.S. equity funds. In Panel A of Table 2.7, daily data is used to compute quarterly estimates of the Sharpe ratio, and in Panel B, the CRSP monthly return data are used to compute yearly measures of risk-adjusted return. The dependent variable used in Table 2.7 is the Sharpe Ratio, because this ratio is less dependent on correctly specifying a correct asset pricing model[19]. *A priori*, we expect that our results should weaken when the models are estimated using longer estimation windows when calculating the performance measures, because, over longer horizons, the equilibrium return should hold. As a consequence, a manager's ability to maintain long-run advantages should diminish, so funds should exhibit full adjustment in the long run. Additionally, we also expect the model to show a better fit over longer time horizons, since the impact of fund idiosyncrasies and random movements are diminished in the long-run. The results in Table 2.7 support these expectations and confirm the results presented in previous sections.

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[19] Failure to properly account for the correct market model specification in calculating risk-adjusted returns, as in the Treynor ratio and Jensen's alpha, can bias the speed of adjustment estimation. Although, previous results show results that are generally consistent across performance measures. In addition, unreported regressions using additional measures of risk-adjusted return show no appreciable difference in the inferences provided in Table 7.

The *highadjust1* coefficient for the estimation utilizing quarterly estimates of the Sharpe ratio reported in Panel A is 0.103, compared with that reported for the estimation using yearly estimates in Panel B of 0.013. An increase in adjustment speed when funds surpass the equilibrium return implies that any advantage that mutual fund managers may have in generating persistently above average results diminishes over time. On the other hand, the *lowadjust1* coefficients appear to remain consistent over time, having reported values of -0.035 (not statistically significant) in Panel A and -0.062 (p-value=0.076) in Panel B, which are similar to that reported in Panel A of Table 2.3 of -0.047. Therefore, we find consistent evidence showing mutual funds exhibiting sub-optimal Sharpe Ratios tend to offset and reverse the deviation by approximately 105 percent over the next period, and this result is consistent across several estimation horizons. Consistently significant, negative coefficients for *lowadjust1* also give support to previous results showing that mutual funds managers actively strive to quickly reverse negative performance. In addition, over longer time horizons, the R-squared values from the estimations increase from 0.752 in Panel A to 0.834 in Panel B (compared with 0.706 in Table 2.3, Panel A), because performance measures converge to the equilibrium over longer horizons.

In a second set of results presented in Section 2.7, we examine the speed of adjustment across funds of different styles and show that mutual fund adjustment speeds are heterogeneous across fund types. As a robustness check of this result, we estimate the speed of adjustment using Sharpe ratios calculated over quarterly intervals, and the results are presented in Table 2.8[20]. The results are generally consistent with those reported in Section 2.7. The *highadjust1* coefficients are highest for International Focused and Sector Funds, meaning that these funds have the slowest adjustment when performance is above the optimum. Conversely, Market Funds have the lowest *highadjust1* coefficient, and it is also insignificant.

[20] In unreported regressions, we also estimate the speed of adjustment across fund styles using Treynor Ratios and Alpha as the measure of return as well as using yearly estimates calculated using monthly data. Results are generally consistent.

Table 2.7: Quarterly and Yearly Asymmetric Partial Adjustment Estimation

Quarterly and yearly fixed effect estimations of the asymmetric partial adjustment model presented in Eqs. (8)-(10) for U.S.-based equity mutual funds from January 2000 to December 2012. The Dependent variable is the Sharpe Ratio. Independent variables are the market Sharpe Ratio and the Sharpe Ratio of the average fund in the same Lipper Class. Second order lags of the dependent variable are also included to ensure proper specification of the model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Quarterly Estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0126***	0.0048	2.641	0.008
highadjust1	0.1032**	0.0448	2.305	0.021
highadjust2	0.0007	0.0006	1.226	0.220
lowadjust1	-0.0346	0.0341	-1.015	0.310
lowadjust2	-0.0001	0.0002	-0.275	0.783
Market Sharpe	0.9421***	0.0387	24.318	0.000
Classification Sharpe	0.0057	0.0036	1.597	0.110
R-Square	0.752			
No. of Funds	23,198			
N	602,017			

Panel B: Yearly Estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0469**	0.0230	2.042	0.041
highadjust1	0.0133	0.0823	0.161	0.872
highadjust2	0.0754	0.0537	1.405	0.160
lowadjust1	-0.0628*	0.0354	-1.776	0.076
lowadjust2	-0.0537*	0.0302	-1.777	0.076
Market Sharpe	0.8922***	0.0510	17.479	0.000
Classification Sharpe	0.0001	0.0025	0.037	0.971
R-Square	0.834			
No. of Funds	24,158			
N	123,302			

Additionally, *lowadjust1* is lowest for Sector and Global Focused funds, which means that these types of funds can most quickly reverse their fortunes after achieving suboptimal results. Market Funds, on the other hand, have a high coefficient value, implying that they are less efficient than their peers. The results presented in Table 2.8 support the robustness of those presented in Section 2.7. Mutual funds that typically specialize in expending resources for the purpose of producing information advantages, like Sector and Global Focused Funds, are able to more efficiently rebalance their portfolios than more passive, Market Funds. The ability of funds that produce more information to achieve more optimal portfolio adjustment is an advantage to actively managed funds that has previously been unaddressed in the mutual fund literature.

There are other areas of robustness and potential extensions of the results shown here that may expand the mutual fund literature in future research. For example, the dependent variables in our main estimations of adjustment speed are measures of risk-adjusted mutual fund returns defined by the Sharp ratio, Treynor ratio, and alpha. There are, however, several other measures that may be used in order to ensure robustness of the results presented. For example, a multi-factor model like that of Fama and French (1993) could be used to calculate expected returns. An advantage of these measures is that they incorporate more complex asset-pricing models into the measurement of risk-adjusted return. However, a drawback of such a methodology is that, if these asset pricing models are not correctly specified, which has been an area of contention in empirical research, then the resulting speed of adjustment estimates may be biased. Additionally, using rolling estimation windows may also provide robustness to the results presented.

Finally, the results presented in this analysis focus mostly on macroeconomic and fund-style characteristics as determining the long-run risk-adjusted fund equilibrium. By using the fixed effect methodology, we ignore the impact of any idiosyncratic, fund-specific characteristics. These characteristics are captured in the intercept and error terms of the models, and the errors are not correlated with the

Table 2.8: Quarterly Asymmetric Partial Adjustment Estimation Across Fund Styles : Sharpe Ratio

Quarterly Fixed Effect estimations of the asymmetric partial adjustment model for each U.S. equity mutual fund style subsample (See Table 1) from January 2000 to December. The Dependent variable is the Sharpe Ratio. Independent variables are the market Sharpe Ratio and the Sharpe Ratio of the average fund in the same Lipper Class. Second order lags of the dependent variable are also included to ensure proper specification of the model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Emerging Markets	General Equity	Global	Global Focused	Inter-national	Inter-national Focused	Market	Sector
Intercept	0.0109***	0.0107***	0.0324***	0.0198**	0.0082	0.0138**	0.0012*	0.0314***
	3.40	*2.65*	*3.06*	*2.24*	*0.72*	*2.39*	*1.72*	*5.32*
highadjust1	0.0516***	0.0834**	0.1466**	0.0925	0.1243	0.1491***	0.0030	0.1390***
	2.74	*2.17*	*2.27*	*1.44*	*1.18*	*2.67*	*0.88*	*3.07*
highadjust2	0.0325	0.0005	0.2340***	0.2296***	0.2237**	0.1012**	-0.0031	0.2096***
	1.58	*1.28*	*3.89*	*4.00*	*2.02*	*2.02*	*-0.49*	*3.97*
lowadjust1	-0.0378**	-0.0285	-0.0209	-0.0606	0.0140	-0.0272	-0.0057	-0.0712*
	-2.42	*-0.99*	*-0.36*	*-1.31*	*0.18*	*-1.46*	*-1.27*	*-1.75*
lowadjust2	-0.0404***	-0.0002	-0.1371***	-0.0800*	0.0004***	-0.0568**	-0.0028	-0.1020***
	-2.89	*-1.58*	*-3.43*	*-1.70*	*2.60*	*-2.04*	*-1.06*	*-3.70*
Market Sharpe	0.0325	0.9771***	0.8925***	0.7708***	0.9312***	0.2566*	0.0524	0.4995***
	1.30	*34.29*	*14.13*	*7.97*	*11.09*	*1.77*	*1.52*	*4.13*
Classification Sharpe	0.9495***	0.0037	0.0175	0.1848***	0.0235	0.6682***	0.9389***	0.2942*
	46.11	*1.39*	*0.82*	*2.61*	*1.27*	*4.02*	*25.24*	*1.85*
R-Square	0.936	0.808	0.671	0.779	0.681	0.845	0.998	0.683
No. of Funds	564	16,036	1,346	936	2,235	610	285	2,231
N	13,120	414,658	27,833	14,339	56,822	13,534	8,774	52,937

independent variables. Thus, our speed of adjustment estimates are consistent; however, we cannot examine the relationship between individual fund characteristics and speed of adjustment. The CRSP mutual fund dataset provides data on certain fund-specific characteristics such as information regarding management fees, manager tenure, fund age, and turnover. This data can be used in an extension of this study to analyze the relationship between key fund-specific variables and the speed of adjustment. An analysis of the fund-specific determinants of adjustment speed will expand on the efficacy of the results of this paper, as it will provide additional implications for mutual fund governance. In unreported regressions, we test for potential firm-specific determinants of speed of adjustment, but have yet to find conclusive results.

2.10 Conclusion

Mutual Funds and other pooling arrangements have become increasingly important instruments in the financial markets over the past several decades. The benefits of low cost diversification and the ability of lay investors to receive active, professional portfolio management has allowed many more investors to access the capital markets. The resulting increase in available capital has helped fuel the increasingly expanding financial markets. It is, therefore, important to analyze and understand how efficiently mutual funds are able to allocate funds for their investors, thereby giving them the best risk-adjusted return.

The mutual fund manager plays a key role in the ability of mutual funds to allocate assets to create the most efficient portfolios. The managers are charged with achieving the highest risk-adjusted level of return for their investors, given their fund's objective. Overall market fundamentals drive the equilibrium level of risk-adjusted return attainable in the financial markets, but a manager's allocation decisions can determine whether an individual fund will fall below or above the market equilibrium in any given period. When a fund's performance is below that of the equilibrium level, the fund manager has an incentive the rebalance the portfolio in an attempt to close the performance gap. The consequence of not re-allocating quickly enough is a flow of funds away from the fund. However, portfolio rebalancing is costly. Trading costs as well as information costs, which must be passed on to the investors, make the manager reluctant to engage in unnecessary rebalancing, especially when random price changes may offset his or her actions. Thus, the mutual fund manager faces a problem of tradeoff. He or she must balance the benefits of quickly reversing poor fund performance by rebalancing the portfolio with the trading and information costs necessary to engage in that rebalancing. As a result, mutual fund managers may only choose to partially adjust to deviations from the risk-adjusted equilibrium return.

We apply an asymmetric partial adjustment model to a panel data set of U.S.-based, equity mutual funds from January of 2000 through December of 2012. We estimate the speed at which mutual funds adjust to the equilibrium risk-adjusted return as a measure of mutual fund efficiency and report several significant results. Firstly, we show that when fund performance is below the equilibrium, the average fund offsets the performance gap by roughly 105 percent within one period, implying that firms that underperform in one period tend to outperform in the next period. In contrast, when a mutual fund's performance exceeds the equilibrium return, only 80 percent of the deviation is offset within one period, which reflects the fund manager's lack of incentive to adjust the portfolio when performance is good. These results imply that mutual funds appear to be relatively efficient in terms of portfolio rebalancing, as mangers appear to be willing and able to rebalance towards (or above) the equilibrium risk-adjusted return. Additionally, a fast adjustment speed when funds underperform implies that managers view the cost of persistent underperformance as being high – a result that is supported by related literature.

Secondly, we divide the sample into eight sub-categories based on the mutual fund's style or focus. The results show that funds that typically focus on producing more specialized information and purchasing securities in specific markets or industries, like emerging market and sector funds, have more efficient adjustment speeds than those that invest in broader categories of securities, like market index and generic equity funds. This result is consistent with the idea that more active mutual fund managers are able to take advantage of the information they are paying to produce. The evidence presented supports the idea that more active managers have information advantages that help them achieve above average returns as well as more efficient portfolio rebalancing. It is also shown that investors pay a premium for this advantage in the form of higher expense ratios. Finally, by applying the partial adjustment model to the sample of mutual funds over time, we show that mutual fund managers tend to more efficiently rebalance portfolios during good economic times. This evidence implies that portfolio managers (and possibly all inventors) lose some information advantages during times when uncertainty is high in the financial markets.

The results shown in this paper have significant implications for investors, mutual fund managers, and mutual fund governance. We contribute significantly to the literature by looking at the time dimension of the fund manager's rebalancing decision. The efficiency with which fund managers are able to adjust to deviations from the equilibrium risk-adjusted return may represent a benefit of active portfolio management that has previously been left un-quantified. We show that the higher costs and turnover ratios for mutual funds that focus on more specific market segments may be offset not only by higher realized returns, but also by more efficient portfolio rebalancing.

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