DEFAULT RISK AND ASSET RETURNS

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This dissertation investigates the role of default risk on asset returns. In the first essay, I study the role of default risk spillovers on an intra-industry setting and its relevance to equity return predictability. In the second essay, I empirally explore the relationship between default risk and informed trading in the Credit Default Swap (CDS) and equity market.

In Chapter 1, I describe the two methods used for estimating the probability of default. The first one, which is used for generating the data for this thesis is named dynamic discrete-time hazard rate model with industry fixed effects as in Chava and Jarrow (2004), and the second one is a structural approach titled Merton's distance to default (DD) studied in Vassalou and Xing (2004). I go over the pros and cons of each method and the motivation of why the former is used for this study. In summary, the hazard rate method has a higher out-of-sample predictive power, does not assume that all assets of a firm trade which is an unrealistic assumption made by the structural model, and Distance to Default variable if included in the hazard rate model does not have any incremental power as shown in Campbell et al. (2008).

In Chapter 2, "Default Risk Spillovers and Intra-Industry Return Predictability", I observe that stocks *far* from the most distressed stocks in their industry earn significantly higher future returns. I connect less distressed stocks to the most distressed stocks in their industry through $\beta-$*distance* and common institutional ownership. *Disconnectedness* forecasts higher future returns, especially

when returns of the most distressed stocks are high. A one standard deviation increase in *disconnectedness* with the most distressed stocks increases next month returns by 0.53%. A strategy that buys stocks that are *far* from the distressed firms and sells stocks *near* the distressed firms yields 7.44% annualized Fama French five-factor alpha with t-statistic 3.22. I argue that this predictability arises through an intra-industry default risk propagation mechanism, which affects the liquidation value of connected firms' assets. Predictability is strongest in industries with the lowest levels of asset redeployability. Taken together, these findings suggest that intra-industry distress risk spillovers predict equity returns.

In Chapter 3 (joint with Gaurav Kankanhalli), "Default Risk and Informed Trading: Evidence from the CDS Market", in a sample of the 520 most frequently-traded single-name non-sovereign credit default swaps (CDS), we find evidence of a non-monotonic relationship between informed trading (proxied by *PIN*) and quoted CDS spreads, as a function of default risk (proxied by reduced-form estimates of default probability, or *DP*). Unconditionally, higher *PIN* is associated with higher quoted CDS spreads, as predicted by models with market makers facing an adverse selection problem. However, conditional on higher DP, the marginal effect of PIN on spreads decreases. This is consistent with the notion that at higher levels of default risk the private signals of informed traders have less value, reducing the adverse selection problem faced by the market maker and, at the margin, reducing spreads. VAR analysis confirms that the private signal of informed traders is informative about future default risk, as lagged PIN predicts lead , but only at shorter horizons. An investment strategy that buys low PIN low DP stocks and sells high PIN high DP stocks earns average daily returns of 0.13% and average daily Fama-French 3-factor alpha of 0.17% (with a t-statistic of 4.86). Taken together, our results provide new insights into the joint dynamics of informed trading and default risk, and their implications on CDS spreads and equity returns.

BIOGRAPHICAL SKETCH

Rinald Murataj was born in Vlore, Albania to Gezim and Elisabet Murataj. He has a younger brother named Genti. Rinald is a first-generation university graduate but comes from a family with a strong passion for knowledge. His parents and their families were persecuted by the Albanian communist regime and prohibited to attend university. The devastating civil war in 1997 taught Rinald how short life can be and how important it is to use time wisely. Rinald grew up in poverty but was nourished by his father's motto "Education is the most valuable treasure in life and is always with you."

At the age of 13, Rinald came across a Math Olympiad book in Russian which he studied the entire summer. He ended up winning a Gold Medal at the National Mathematics Olympiad and an Honorable Mention at the International Mathematics Olympiad in Hanoi, Vietnam during high school.

In 2012, Rinald graduated in two years with a BSc in Mathematics from Jacobs University Bremen, Germany. Afterwards, he joined the PhD program in Applied Mathematics at Cornell University and in the middle of his studies was fascinated to study Finance, an area completely out of his comfort zone. This dissertation reflects the academic journey of the last six years at Cornell University, a place close to his heart.

To my father, who vicariously lived through my successes and failures and took proper care of my academic growth. To my mother, who showed me love and comfort when things would become tough. To my brother, who always knew how to make me laugh.

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CHAPTER 1

INTRODUCTION

Default is the economic state of a firm characterized by a delayed or missing contractual debt payment. In reality we do not have access to defaults and we proxy them using bankruptcies, where a firm is declared bankrupt if it files for Chapter 7 or Chapter 11. Chapter 7 consists of the liquidiation of the assets, meaning that the assets are sold and the proceedings are distributed to its creditors, and the residual, if any, is distributed to equity holders. In case of Chapter 11, the business operations do not stop and the lenders remain in control of the business. Chapter 7 and Chapter 11 bankruptcy filings are both categorized as a bankruptcy in the data since it is difficult to get information on all the private debt restructuring between the lenders and borrowers. In the upcoming pages, when I am using the word *default* it means *bankruptcy*.

Since both essays in this thesis focus on default and its interactions with asset returns, it is of paramount importance to firstly describe the method used for the probability of default estimation used here and secondly the other method available, and comparisons between the two approaches.

There are two available procedures for the estimation of default probability. The first one is named Dynamic Hazard Rate Estimation with industry fixed effects studied in Chava and Jarrow (2004) and the second is the Distance to Default based on Merton (1974) *structural model*.

1.1 Dynamic Hazard Rate Estimation

The discrete-time dynamic rate estimation is the statistical procedure used to estimate the probabilities of default data which are used in both essays of this thesis. This estimation is identical with respect to maximization over the data to the log-likelihood of the multiple logistic regression function[1]. Assume we have a collection of $i = 1, 2, \ldots, n$ firms at times $t = 1, 2, \ldots, T$ each with bankruptcy time τ_B^i . The hazard rate for the bankruptcy time τ_B^i is a random variable and based on Kiefer (1988) is defined as:

$$\lambda_B^i(t) = \lim_{\Delta t \to 0} \frac{\mathrm{P}(t \leq \tau_B^i < t + \Delta t \mid \tau_B^i \geq t)}{\Delta t} \tag{1.1}$$

where the point process for this bankruptcy time is $N_t^i = 1$ if $\tau_B^i \leq t$ and 0 otherwise. Let $Y_i = \min(\tau_B^i, T_i)$ be the random time characterizing the last date we observe firm i in the sample, where τ_B^i is the bankruptcy time and T_i is the censoring time or the last date before the firm vanishes from the data. We assume that censoring is uninformative for bankruptcy prediction.

The conditional discrete-time hazard rate process based on Allison (1982) is:

$$\mathrm{P}_t^i = \mathrm{P}(\tau_B^i = t \mid \tau_B^i \geq t, X_{it_i}, \ldots, X_{iY_i}) \tag{1.2}$$

where $t_i + 1 \leq t \leq T_i$ and t_i is the first date we observe firm i. X_{it} are time varying covarites like market, accounting, and other variables associated with firm i at time t. We assume that the default times are indipendent which is a common assumption. The likelihood function of firm i is:

$$L(N_{Y_i}^i \mid X_{it_i}, \ldots, X_{iY_i}) = \mathrm{P}(\tau_B^i = Y_i \mid X_{it_i}, \ldots, X_{iY_i})^{N_{Y_i}^i} \mathrm{P}(\tau_B^i > Y_i \mid X_{it_i}, \ldots, X_{iY_i})^{1-N_{Y_i}^i} \tag{1.3}$$

where $N_{Y_i}^i = 1$ if $Y_i = \tau_B^i$ meaning bankruptcy happens at time τ_B^i or $N_{Y_i}^i = 0$ if $Y_i = T_i$. For simplicity assume that $\mathrm{P}(\cdot \mid X_{it_i}, \ldots, X_{iY_i}) = \mathrm{P}(\cdot)$. We can compute each

[1] Notes of this section follow closely the notation in Chava and Jarrow (2004).

of the conditional probabilities above as follows:

$$\mathrm{P}(\tau_B^i = Y_i) = \mathrm{P}_{Y_i}^i \prod_{t=t_i+1}^{Y_i-1} (1 - \mathrm{P}_t^i) \quad \text{and} \quad \mathrm{P}(\tau_B^i > Y_i) = \prod_{t=t_i+1}^{Y_i} (1 - \mathrm{P}_t^i) \tag{1.4}$$

If we substitute equation (1.4) into the likelihood function in (1.3) and calculate the log-likelihood function we obtain:

$$\log\Big(L(N_{Y_i}^i \mid X_{it_i}, \ldots, X_{iY_i})\Big) = N_{Y_i}^i \log\left(\frac{\mathrm{P}_{Y_i}^i}{1 - \mathrm{P}_{Y_i}^i}\right) + \sum_{t=t_i+1}^{Y_i} (1 - \mathrm{P}_t^i) \tag{1.5}$$

The simplification comes as a result of most terms cancelling out. Next, in order to obtain the entire log-likelihood function across all firms, we need to assume indipendence among firms. Therefore, the log-likelihood is:

$$\begin{aligned} &\log\Big(L(N_{Y_1}^1, N_{Y_2}^2, \ldots, N_{Y_n}^n \mid X_{1t_1}, \ldots, X_{1Y_1}; \ldots; X_{nt_1}, \ldots, X_{nY_n})\Big) = \\ &\sum_{i=1}^{n} \sum_{t=t_i+1}^{Y_i} [N_t^i - N_{t-1}^i] \log\left(\frac{P_{Y_i}^i}{1 - P_{Y_i}^i}\right) + \sum_{i=1}^{n} \sum_{t=t_i+1}^{Y_i} \log\Big(1 - \mathrm{P}_t^i\Big) \end{aligned} \tag{1.6}$$

The maximization of equation (1.6) is equivalent to the maximization of the multiple logistic regression. As a linkage function for the hazard rate model we use a logistic model:

$$\mathrm{P}_t^i = \frac{1}{1 + \exp(-\alpha_t - \boldsymbol{\beta_t} \cdot \boldsymbol{X_{it}})} \tag{1.7}$$

In the estimation procedure, Chava and Jarrow (2004) account for industry fixed effects which improve the out-of-sample bankruptcy prediction.

1.2 Merton's Distance to Default Estimation

Vassalou and Xing (2004) is the first paper that uses Merton (1974) methodology to estimate the likelihood of default of a firm without using information from the debt market. Since equity holders have the right on a firm's assets after all the liabilities are met, the equity of a firm is a call option the firm's assets with the strike price equal to liabilities based on Merton (1974)'s argument. In order to derive Merton's Distance to Default (DD)[2] as a proxy for probability of default, we need to assume that the asset value follows a geometric Brownian motion as:

$$dA_t = \mu A_t dt + \sigma_A A_t dW_t \tag{1.8}$$

where μ and σ_A are the instantaneous average rate of return and volatility on assets, respectively. If the value of liabilities at maturity is L_T, then the payoff to equity holders is $E_T = \max(A_T - L_T, 0)$. The Black Scholes Merton Call Option Formula gives the market value of equity at time 0 as:

$$E_0 = A_0 N(d_1) - L_0 e^{-rT} N(d_2) \tag{1.9}$$

where

$$d_1 = \frac{\ln\left(\frac{A_0}{L_0}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma_A \sqrt{T} \tag{1.10}$$

Probability of default is the probability that the value of the assets of a firm is less than the value of its liabilities.

$$\mathrm{P}_t = \mathrm{P}(A_{t+T} \leq L_t \mid A_t) = \mathrm{P}(\ln(A_{t+T}) \leq \ln(L_t) \mid A_t) \tag{1.11}$$

Since the value of the assets is a geometric Brownian motion, from equation (1.8) and equation (1.11) we have:

$$\mathrm{P}_t = \mathrm{P}\left(-\frac{\ln\left(\frac{A_t}{L_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \geq \epsilon_{t+T}\right) \tag{1.12}$$

[2]Derivation is based on Vassalou and Xing (2004)

where $\epsilon_{t+T} = \frac{W_{t+T} - W_T}{\sqrt{T}} \sim N(0,1)$. Define distance to default as:

$$DD_t = \frac{\ln\left(\frac{A_t}{L_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{1.13}$$

Then probability of default in equation (1.12) is $\mathrm{P}_t = N(-DD_t)$ where $N(\cdot)$ is the cummulative density function of the standard normal distribution.

1.3 Hazard Rate Estimation vs Merton's Distance To Default

Merton's distance to default is based on Merton (1974) and though conceptually useful it is built on a set of very stringent assumptions. It assumes that all assets of a firm trade, which is an unrealistic assumption, the term structure of default free interest rates is taken to be constant, and the liability structure is a single discount bond, which in reality it is more complex and changes over time. On the other hand, the hazard rate estimation allows more flexibility in terms of the covariates to be included in the estimation and produces higher out-of-sample prediction rates as shown in Bharath and Shumway (2008). Moreover, if distance to default is included in the hazard rate estimation as an explanatory variable it is not statistically significant (Campbell et al. (2008)). Discrete-time hazard rate method which accounts for industry fixed effects studied in Chava and Jarrow (2004) is the estimation producing the data utilized in this thesis.

CHAPTER 2

DEFAULT RISK SPILLOVERS AND INTRA-INDUSTRY RETURN PREDICTABILITY

2.1 Introduction

I show that default risk propagates among firms within the same industry, generating a predictable returns relationship between the most distressed firms and connected, but less distressed, firms. Specifically, I show that less distressed firms in a given industry that are connected to the most distressed firms within that industry show economically and statistically significant increases in future returns. I connect firms within the same industry through two main measures: (1) β*–distance*, reflecting common exposure to systematic risk factors, and (2) common institutional ownership. In doing so, I aim to capture channels through which investors gain information about the future distress risk of stocks that may not be currently distressed, based on how closely connected they are with the most distressed firms within their industry. A one standard deviation increase in *disconnectedness* with the most distressed stocks under the β*–distance* measure increases next month returns by 0.21% on average, and under the common institutional ownership measure the increase is 0.53%. A strategy that buys stocks that are *far* from the distressed firms and sells stocks *near* the distressed firms generates 7.44% annualized Fama French five-factor alpha with t-statistic 3.22 and results are not subdued by controlling for individual default risk.

The return predictability that I find between the most distressed firms and less distressed firms within an industry, rests on the idea that default risk propagates intra-industry through the asset revaluation channel. In their seminal work, Shleifer and Vishny (1992) posit that default risk can propagate among firms in a given industry, as firms in the same industry are likely to be the first-best users of the assets of other firms in that industry. Given a negative shock to cashflows of firms in an industry, the distress risk of firms in that industry is likely to increase. The default risk of firms in this industry (particularly of the most financially constrained firms) is likely to increase their need to liquidate their assets in the face of impending bankruptcy. However, the first-best users of the firms' assets are likely to be other firms in that industry which are also facing increased distress risk and, consequently, are less financially capable to purchase these assets at fair value. The liquidity in the market for these assets thus endogenously dries up, leading to an asset value decline. This asset revaluation impairs the balance sheets of firms in the industry and increases the distress risk and brings more firms in this industry closer to default. Thus, a clear mechanism is established by which default risk propagates amongst firms within an industry, following a negative shock to cashflows in that industry.

The return predictability evidence that I uncover is consistent with this asset revaluation channel. Investors who observe the increased risk of the most distressed firms can rationally infer that firms in the same industry are likely to face increased default risk in the subsequent period. Indeed, I find robust evidence that one standard deviation increase in β*–distance* forecasts an average increase of 4.4% in the default probability of the less distressed firms in the upcoming month. Since riskier firms are expected to earn higher returns, investors' activity leads to increased buying pressure for these stocks, driving up next period returns of the currently less distressed firms. [1]

[1] I rely on the asset pricing theory claim that ex-ante returns are positively related to risk (e.g. Sharpe (1964); Lintner (1965); Merton (1973)) and to default risk in this setting. The empirical relationship between default risk and returns is debatable. Vassalou and Xing (2004) find that default risk is systematic. Campbell et al. (2008) discover the low-distress anomaly. Chava

The investor inattention mechanism documented in Cohen and Frazzini (2008), may also play a role here. They show that investors fail to take into account the customer-supplier economic links, resulting in return predictability if one buys (sells) the supplier after a positive (negative) shock to its customer. I hypothesize that firm-level information about financial distress risk conveys information about the future financial distress risk of related firms measured by lower levels of the interconnectedness measure (i.e. more related firms). Specifically, for investors, the most salient stocks in a given month are those with the highest distress risk, which they expect will earn higher returns over the next month. Investors may also use the information contained in the distress probability of the highest distress risk stocks to update their beliefs about the more related firms in the industry. In particular, they may extrapolate that the most connected firms, may suffer from higher distress risk in future periods and, hence, earn higher returns. The extent of this premium is a function of the extent of the premium earned by the highly distressed stocks in that month. By this line of reasoning, the buying pressure by investors in stocks related to the most distressed firms triggers next month returns of these stocks to rise above and beyond the premium predicted by their own default probability level, generating predictability. Thus, predictability of a given stock's return in a month is a function of being correlated with: (1) average connectedness with the most distressed stocks in its industry in the previous month, and (2) the premium for distressed stocks in the previous month.

I show that higher returns on the portfolio of the most distressed stocks in a

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and Purnanandam (2010) show that realized returns are a poor proxy to study the relationship between default risk and returns. They find a positive relationship between returns and default risk by computing ex-ante returns from implied-cost of capital. Aretz et al. (2017) find a positive default risk premium in international markets, using the same methodology as in Campbell et al. (2008).

given industry predict higher future returns for all other less distressed stocks in the industry and especially for firms which are *far* from the most distressed firms based on $\beta-$*distance* and institutional ownership connectedness measures. As an additional robustness check, I show that this predictability also exists when using common analyst coverage as the measure of connectedness. To strengthen the argument, we must rule out alternate explanations.

The most poignant counter argument is that we are simply identifying the excess comovement of connected stocks as documented in Anton and Polk (2014). In order to show that it is the proposed intra-industry asset revaluation channel that is generating this predictability, I run a placebo test analysis. I connect each less distressed firm from a given industry to portfolios of the most distressed stocks from all *other* industries except its own. If we are simply capturing the effect of connected stocks, we should find equally strong evidence of predictability in this sample as in the baseline analysis, controlling for industry and time fixed effects. However, the placebo analysis reveals insignificant predictability for $\beta-$*distance*, and significant but statistically smaller predictability for common ownership. Thus, while I am unable to completely rule out the connected stocks effect, the placebo analysis provides sufficient evidence that at the very least, I have uncovered a specific channel of predictability that has incremental power over the unconditional comovement of connected stocks. The inclusion of industry and time fixed effects rules out the possibility that I am identifying industry shocks that affect all firms regardless of their distress risk or degrees of connectedness to distressed firms.

I present further evidence in favor of the proposed channel by considering how asset tangibility might moderate this phenomenon. I split the sample based on an industry-level proxy of asset tangibility, namely asset redeployability, which is measured as the ratio of used to total fixed depreciable capital expenditures. Almeida and Campello (2007) argue that firms in industries with more tangible assets, proxied by higher levels of asset redeployability, should have higher investment-cash flow sensitivities, but only for financially constrained firms. This occurs because firms with more tangible assets are able to borrow more, allowing them to invest in more tangible assets. This can provide an important counteracting force against negative cashflow shocks to an industry, which causes[2] distress risk to spread from one firm to another. Increased borrowing capacity allows firms to weather the effects of increased financial distress risk better without requiring them to sell off their existing assets at a discount to face value. Thus, balance sheets of other firms in the industry are unlikely to become impaired through this asset revaluation channel. Moreover, more redeployable assets are likely to find better uses in firms outside the current industry, which may not be suffering from negative cashflow shocks. Kim and Kung (2014) find that redeployability affects liquidation values and thus makes firms reluctant to invest under uncertainty.

Taken together, these insights imply that in industries with high asset redeployability, distress risk spillovers and return predictability should not exist, or at least be less pronounced than in industries with low asset redeployability, where this channel is likely to be stronger. Evidence of predictability is strongest in industries with the lowest tercile of asset redeployability and non-existent in industries in the highest tercile of asset redeployability. I interpret this as strong evidence in favor of the industry-specific channel of default risk propagation being distinct from the general comovement of connected stocks.

[2] I use the word cause here since Almeida and Campello (2007) study the causal effects of financing frictions on real investment decisions, using a difference-in-difference methodology.

The remainder of the chapter is organized as follows. Section 2.2 describes the related literature, Section 2.3 outlines data sources and provides details on the empirical methodology, and Section 2.4 presents the panel regression results. Section 2.5 focuses on the investment strategy built on the intra-industry default spillover phenomenon and its backtesting using minute-level data from a crowd-sourced platform and Section 2.6 concludes.

2.2 Related Literature

This study primarily draws on two extant strands of the literature, the asset pricing literature on the relationship between financial distress risk and equity returns, and the growing literature in both asset pricing and corporate finance on inter-connected firms, and firm networks. To my knowledge, this is the first study that synthesizes both these literatures by investigating whether default risk propagation between connected firms generates predictable returns patterns, and therein lies the main contribution.

One of the pioneering studies of the equity returns of financially distressed firms was conducted by Dichev (1998). Using Altman's Z-score and Ohlson's O-score as measures of bankruptcy risk, he shows that firms with higher likelihood of default measured by these scores did not go on to earn higher average returns for industrial firms over the period 1981-1995, suggesting that bankruptcy risk is not systematic. Subsequently, Vassalou and Xing (2004) find that using distance to default derived from Merton (1974) structural model, that default risk is systematic, and hence is priced in the cross-section of equity returns.

The seminal study in this area, which systematically uncovered the low distress anomaly is Campbell, Hilscher, and Szilagyi (2008). They compute probability of distress using some modification of Chava and Jarrow (2004) model and find that it performs better than the original model. They discover that cross-sectionally, firms which are more distressed have anomalously low stock returns. This is despite having higher levels of volatility and also higher Market, HML, and SMB betas than low distress stocks. Some of the possible explanations that they offer for these anomalously low returns, center around the ideas of informational and arbitrage-related frictions.

On the other hand, Chava and Purnanandam (2010) resolve the low distress anomaly of Campbell, Hilscher, and Szilagyi (2008), by saying that in a small sample it is hard to correctly estimate relationship of default risk and returns. They claim that previous studies which use ex-post realized returns as a proxy for expected returns may not be appropriate. Instead, they use ex-ante expected returns computed from implied cost-of-capital and show that this is positively related to default risk, as expected.[3]

This paper makes a contribution to this strand of literature by showing that distress risk of a firm affects not only its own equity returns, but the returns of industry peer firms. By considering only the impact of distress risk on its own firm returns, these prior studies fail to identify a significant channel by which distress risk affects equity returns, and that is through the propagation of distress risk amongst connected firms in a given industry. Thus, I provide suggestive evidence that distress risk has not only a direct effect on equity returns, but also a feedback effect through connections with industry peers.

This paper also contributes to the recent and growing literature on connected

[3]Campello, Chen, and Zhang (2008) show that realized returns are poor proxies of expected returns and construct measures of expected returns based on corporate bond yields.

stocks and firm networks. Several studies have investigated the view that firms exist in various networks. Firms may be members of supply-chain networks connected upstream and downstream to other supplier and customer firms that cause information flows between related firms and may not be promptly incorporated by investors and this in turn may generate subsequent return predictability Cohen and Frazzini (2008). Firms may also be connected in industry networks, in which managers and investors alike infer useful properties about investment, valuation, and other financial variables by studying the behavior of peer firms within the same industry Foucault and Fresard (2014). Closer to this study, Gao (2014) studies the financial policies of firms in customer-supplier networks and documents the effects of shocks to distressed firms on connected firms' capital structure, cashflow, and payout policies. Instead, I focus on how the propagation of distress risk generates comovements in returns of less distressed stocks with the returns of their most distressed industry peers. The channel captured here is thus distinct from that of Cohen and Frazzini (2008).

Earlier studies like Badrinath, Kale, and Noe (1995), Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Chordia and Swaminathan (2000), Hou and Moskowitz (2005), and Hou (2007) find that larger firms, or firms with higher levels of analyst coverage, institutional ownership, and trading volume, lead smaller firms or firms with lower levels of analyst coverage, institutional ownership, and trading volume. This study, on the other hand, investigates whether the propagation of distress risk induces returns predictability for firms from the same industry with common analyst coverage and institutional ownership.

The set of papers closest to this include Anton and Polk (2014), Gao, Moulton, and Ng (2017), and Bartram et al. (2015), who all document the effect of common institutional ownership on stock returns. Anton and Polk (2014) show that common institutional ownership forecasts cross-sectional variation in excess correlations. Whereas Gao, Moulton, and Ng (2017) document predictability across firms in economically unrelated industries through common institutional ownership. Bartram, Griffin, Lim, and Ng (2015) consider the effect of common institutional ownership of a given stock with foreign stocks and find that the return of foreign connected stocks have strong explanatory power in the cross-section of international equity returns.

While I also use common institutional ownership as one of the measures of connected firms, I do not focus on the return comovements generated by common ownership itself (which I do find, and control for). Rather, I document the effects of distress risk spillovers within industries, with connectedness determining the degree of propagation. I show that stocks that are less connected to the most distressed stocks in their industry through common ownership earn higher future returns unconditionally, especially when the most distressed stocks earn higher returns, controlling for their own level of distress risk.

2.3 Data and Methodology

2.3.1 Data Sources

I obtain data from a number of sources for the empirical analysis. I get monthly stock returns from CRSP, quarterly accounting information from Compustat, quarterly analyst information from IBES, quarterly institutional holdings data from 13F institutional holdings via Thomson Reuters, and monthly default probability estimates from Kamakura Default Probabilities (KDP) dataset from Kamakura Corporation (this source is described in further detail in a following sub-section). In addition, I obtain industry-level data on used versus new fixed depreciable capital expenditures that are used to compute the measure of asset redeployability as in Almeida and Campello (2007) from the Economic Census of the Bureau of Census. I classify all firms into the Fama-French 49 industry portfolios on the basis of their 4-digit SIC codes (Fama and French (1997). Only firms which can be matched to one of the 49 Fama-French industries in every period are included in the sample.

Sample Period and Construction

The initial constraint on the sample period is the availability of the monthly KDP data, which (after taking suitable lags) I have from January 1991 to December 2014. In order to compute β*−distance*, however, I estimate betas using 5-year rolling-window time series Fama-French 3- and 4-factor regressions for which I withhold the first 60 months of observations. Thus, I do the analysis with β*−distance* on the sample period January 1996 to December 2014. Analysis involving institutional holdings and analyst coverage are done using the entire sample period for added power, however in unreported tests I perform analysis on the shorter 1996-2014 sample period and find no significant change in results. All monthly independent variables are lagged by one month, and all quarterly independent variables are lagged by one quarter, respectively, to avoid any lookahead bias in the regressions. Amongst the universe of publicly traded US stocks available on CRSP, I consider those who have COMPUSTAT data for the past two years and strictly positive book value. On average, there-are 3266 unique firms in the sample for each month.

Default Probability Estimates

The empirical analysis is based upon a proprietary dataset of estimated default probabilities provided by Kamakura Corporation[4]. The probabilities are estimated by Kamakura monthly, using data up to the prior month. I examine US publicly traded firms which meet the sample construction criteria described above.

I use estimated probabilities of default within the next year. While the exact model used is proprietary, the Kamakura Default Probabilities (KDPs) used in this sample are calculated using the Chava-Jarrow model (from Chava and Jarrow (2004)). The model uses a hazard rate estimation with multivariate logit in which explanatory variables include firm financial ratios, industry classification, interest rates, macroeconomic factors, and information about firm and market equity price levels and behavior. In this model, firm default can occur randomly at any time with an intensity determined by the explanatory variables. As an example of the industry-wide view of the relative accuracy of this class of models, The Federal Deposit Insurance Corporation of the United States has been using the Chava-Jarrow model since 2003 to provide default estimates for its internal analysis for its funds. A large number of bank regulators around the world now subscribe to Kamakura Risk Information Services (KRIS). The default probabilities in this sample are estimated using the fifth generation

[4]More information about the dataset can be found at http://www.kamakuraco.com.

Jarrow-Chava models, which incorporate multiple equations for forecasting default at different forward time intervals, conditional on survival up to that point in time. These equations share the same inputs but they have different weightings depending on the time horizon. Since they are the industry leading default probability estimates, one can argue that they represent a reasonable proxy for a firm-level distress risk.

2.3.2 Variable Construction

Most Distressed Industry Portfolios

In each month t, in each Fama-French industry $j \in \{1, 2, ..., 49\}$, with $N_{j,t}$ firms, I form deciles based on month $t-1$ default probabilities, and the firms k which fall in the highest decile of lagged default probabilities are considered to be members of the set of the *most distressed* stocks, in industry j, in month t, namely $k \in MD_t^j$. The cardinality of MD_t^j is $K_{j,t} = \frac{N_{j,t}}{10}$ by construction. The complement firms l in the lowest 9 deciles of default probabilities, are considered to be members of the set of *less distressed* stocks, in industry j, in month t, namely $l \in LD_t^j$. The stocks in LD_t^j are the ones whose returns we predict in period $t + 1$. The cardinality of LD_t^j is $L_{j,t} = \frac{9}{10} \times N_{j,t}$ by construction.

In particular, since I am trying to measure whether connected stocks earn higher returns when the returns of the most distressed stocks in their industry are high, I form an equal-weighted portfolio of all the most distressed stocks in an industry, whose return in period t is used to predict the returns of the less distressed stocks in period $t + 1$. More formally, the most distressed industry portfolio return for industry j, in time t, is defined as:

$$R^{MD}_{j,t} = \frac{1}{K_{j,t}} \sum_{k \in MD^j_t} r^e_{k,t} \tag{2.1}$$

The interconnectedness measures described below are calculated for all firms $l \in LD^j_t$ with respect to the set of firms $k \in MD^j_t$.

β−distance

The β−*distance* measure is constructed by performing time-series regressions for the excess returns of each firm $l \in LD^j_t$, in each industry j, over a 60-month rolling window from period t to $t - 59$:

$$r_{l,j,t} = \alpha_{l,j} + \beta_{l,j}\mathbf{F}_t + \epsilon_{l,j,t} \tag{2.2}$$

where $\mathbf{F_t}$ refers to the vector of the time-series of excess returns of the 3 Fama-French Factors, Mkt, SMB, and HML (Fama and French, 1993)[5]. The beta vector $\beta_{l,j,t}$ is stored for each firm l in each industry j at each time t estimated over a five-year rolling window. Similarly, the beta vector $\beta_{k,j,t}$ is stored for each firm $k \in MD^j_t$. Then, for each pair (l, k) in each industry j at time t, I compute the β−*distance* using the L_2-norm $\left\|\beta_{l,j,t} - \beta_{k,j,t}\right\|_2$. Then, I compute an average β−*distance* for each l in each j, at time t across all $k \in MD^j_t$, and this gives the interconnectedness measure (standardized in each monthly cross-section):

$$Int^{FF3}_{l,j,t} = \frac{1}{K_{j,t}} \sum_{k \in MD^j_t} \left\|\beta_{l,j,t} - \beta_{k,j,t}\right\|_2 \tag{2.3}$$

[5]A similar measure is computed using the Fama-French-Carhart 4-factor model (Carhart, 1997) but results are not reported in this chapter.

Common Institutional Ownership

The measure of common institutional ownership is defined as follows. In each industry j, in each month t, the common institutional ownership measure for each $l \in LD_t^j$, which is denoted by $I_{l,j,t}^{OWN}$ takes the value of 1 if stock l shares a common major institutional owner (defined as an owner with a position of greater than 10,000 shares)[6], with at least one of the most distressed stocks in that industry, $k \in MD_t^j$ for the previous two quarters.

As a robustness check, I also compute a finer measure of common institutional ownership, by considering the proportion of the joint market cap of two stocks that is owned by their common institutional owners. This measure is constructed in a few steps. First, let us consider each pair $(l,k)_{j,t}$ of less distressed firms l and most distressed firms k in industry j at time t. For each pair, we compute the proportion of market capitalization owned by the common institutional owners F who own greater than 10,000 shares of l and k for the previous two quarters :

$$FCAP_{l,k,j,t} = \frac{\sum_{f=1}^{F} (s_{l,t}^{f} \cdot p_{l,t} + s_{k,t}^{f} \cdot p_{k,t})}{s_{l,t} \cdot p_{l,t} + s_{k,t} \cdot p_{k,t}} \tag{2.4}$$

where $s_{l,t}^{f}$ is the number of shares owned by common owner f of stock l at time t, $p_{l,t}$ is the price of stock l at time t, and $s_{l,t}$ is the total number of shares outstanding of stock l at time t, with analogous definitions for k. Second, this measure is averaged for each l, across all of the most distressed stocks in industry j at time t, $k \in MD_t^j$. Note that this measure takes a value of 0 for each k with which l does not share a single common major institutional owner, i.e. $F = 0$. Finally, this measure is standardized in each cross-section to give $I_{l,j,t}^{OWN*}$. Note that $I_{l,j,t}^{OWN*} = 0$

[6] Analysis is also done using the definition of major owner as owning above median number of shares amongst all institutional owners of that stock over a certain period. Results are quantitatively and qualitatively similar, although sample size and thus power is greatly reduced.

if and only if $I_{l,j,t}^{OWN} = 0$.

Common Analyst Coverage

The measure of common analyst coverage is defined as follows. In each industry j from the 49 Fama French industries, in each month t, the common analyst coverage measure for each $l \in LD_t^j$, which is denoted by $I_{l,j,t}^{A}$, takes the value of 1 if at least one analyst making an Earnings Per Share (EPS) forecast for stock l, also makes an EPS forecast for at least one member of the most distressed stocks in that industry, $k \in MD_t^j$ for the previous two quarters.

2.3.3 Empirical Methodology

For the empirical analysis, I use a panel regression framework as it allows to control for confounding observable and unobservable factors which may be driving the predictability relationship between less distressed and most distressed stocks.

Baseline Analysis

In the baseline specification, I use two measures of interconnectedness: $\beta-$distance computed from the Fama-French 3 factor model ($Int_{l,t}^{FF3}$) and common institutional ownership ($I_{l,t}^{OWN}$). We estimate the following monthly panel regression:

$$r_{l,j,t+1}^{e} = \alpha + \beta_1 R_{j,t}^{MD} + \beta_2 X_{l,j,t} + \beta_3 X_{l,j,t} \times R_{j,t}^{MD} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t} \quad (2.5)$$

where $r^e_{l,j,t+1}$ is the next month excess return of the less distressed firm l in industry j, $R^{MD}_{j,t}$ is the excess return of the portfolio of the most distressed stocks in industry j in this month, and $X \in \{Int^{FF3},\ I^{OWN}\}$, $DP1_{l,j,t}$ is the one-year ahead estimated default probability of firm l in industry j in this month. The remaining variables are log market equity, log book-to-market, industry fixed-effects and time fixed-effects, respectively. I do not include industry-time fixed effects as they would be collinear with R^{MD}.

I choose this particular specification as it allows to estimate various important dimensions of the predictability relationship and control for various confounding effects. Each of the main coefficients of interest represents a distinct and important aspect of the predictability relationship. First, by controlling for the most distressed industry portfolio return $R^{MD}_{j,t}$, we are able to control for the overall level of financial distress risk in the industry in the previous month.

By introducing both $X_{l,j,t}$ and $X_{l,j,t} \times R^{MD}_{j,t}$, we are able to derive a predictability "alpha" and "beta". This means that we are able to determine both the direct effect on next period returns of being more connected to the most distressed stocks in this period (β_2) and also the marginal effect on next period returns of being more connected to the most distressed stocks in this period (β_3) per unit increase in the most distressed industry portfolio return in this period. In other words, β_2 measures how sensitive next period returns are to being more connected to the most distressed industry portfolio, and β_3 measures the marginal returns spillover from most distressed to less distressed stocks.

I control for own firm distress risk to make sure we are not simply identifying the fact that stocks, which are most connected to the most distressed stocks are likely to have relatively higher distress risk themselves, leading to higher future returns. I control for log market cap and log book-to-market to make sure we are not capturing any size or value/growth effects. Finally, I control for industry and time fixed effects to remedy for any unobserved invariant factors that may be influencing the predictability relationship. Standard errors are double clustered by industry and year to allow for cross-correlation of errors across firms in a given industry and within firms in a given year (Petersen, 2009).

Placebo Analysis

In order to rule out the explanation that I am simply picking up on the well-documented comovement of the returns of connected stocks, as in Anton and Polk (2014), among others, I perform a placebo test in which I connect the less distressed stocks of industry j to the most distressed stocks of all other industries $i \neq j$. Each of the interconnectedness measures can be redefined accordingly, and the most distressed industry portfolio is now an equally weighted portfolio of the returns of the most distressed stocks from all other industries $i \neq j$. If we were simply picking up on a connected stock effect and not an industry-specific default risk propagation channel as I propose, then the estimates obtained from this analysis should be no different to the estimates obtained from the baseline. Furthermore, if both the true and the placebo measures are introduced into the predictability regression simultaneously, the placebo terms should remain significant and not be absorbed by the true terms, since they are capturing a general connectedness effect.

Asset Redeployability and Sub-Sample Analysis

I also split the sample into high and low asset redeployability industries to further validate my explanation. High levels of asset redeployability are likely to counteract the intra-industry default risk propagation mechanism that I argue drives the predictability result. This is because firms in industries with high levels of asset redeployability are not as reliant on other firms within the same industry to be the first-best users of their assets. Thus, the endogenous fall in liquidation value due to negative industry-wide shocks, which causes distress risk of connected firms to increase will not be as pronounced. In addition, redeployable assets tend to be more pledgeable, which should also help improve borrowing capacity and help mitigate negative shocks to cashflows. As a result, we expect default risk propagation to be lower in industries with higher asset redeployability. Therefore, the predictability evidence should be weaker in industries with higher asset redeployability than in lower asset redeployability ones.

The most recent value for the redeployability measure is available in 1992 at the 4-digit SIC code level. I assign this value to each 4-digit SIC industry and then group the 4-digit SIC industries into the Fama French 49 industries, taking an average redeployability measure for each of the 49 industries. Since this measure is computed only for manufacturing industries, I end up with 23 of the 49 Fama French industries having a valid asset redeployability measure. I assume (as do Almeida and Campello (2007)) that this measure is time invariant for the rest of the sample. I sort the 23 remaining industries into terciles based on asset redeployability and perform the analysis in the sub-samples of the lowest and highest terciles.

Robustness

As a robustness check, I repeat the baseline analysis using common analyst coverage as a measure of interconnectedness. Also, I repeat the baseline analysis for only manufacturing industries, and all industries excluding utilities and finance. In unreported robustness checks, I recompute β*−distance* using the Fama-French-Carhart 4-factor model which includes the UMD momentum risk factor (Carhart, 1997) and results do not change quantitatively and qualitatively.

2.4 Results

Table 2.1 presents summary statistics and correlations of key variables. It can be noted from the summary statistics table that the portfolio of the most distressed stocks, on average across all industries earns average monthly excess returns of 0.993%, contrary to the low distress risk anomaly documented by Campbell, Hilscher, and Szilagyi (2008).

[Table 2.1 about here]

2.4.1 Baseline Results

Table 2.2 contains baseline results in which I measure intra-industry firm interconnectedness through Fama-French 3-factor β*−distance*. I regress next month excess returns of each of the less distressed stocks $l \in LD^j, \ \forall \ j = 1, ..., 49$ on lagged predictors including the interconnectedness measure, the returns of the most distressed industry portfolio, the interaction of the two, as well as lagged controls. In almost all specifications Int^{FF3} is a significant predictor of future returns and in all specifications the interaction term is significant, indicating positive returns spillover from the current returns of the most distressed firms in each industry to the future returns of highly connected but less distressed firms in their industry. This effect remains, even after controlling for own-firm default probability, showing that the more connected stocks are not earning higher returns simply because they are more distressed. Even in specification (4), where I obtain the most conservative estimate of the return spillover after controlling for industry and time fixed effects, the magnitude is economically meaningful.

[Table 2.2 about here]

A one standard deviation increase in the interconnectedness measure is 1 by construction, and the mean return of the most distressed industry portfolio is 0.993%. Assuming the current return of the most distressed industry portfolio takes its sample mean value, a one standard deviation increase in the interconnectedness measure increases next month returns by $(0.00198 \times 1) + (0.00993 \times 1 \times 0.00798) = 0.21\%$, which leads to an annualized increase in returns of 2.5%. Excluding financial and utility companies, the annualized effect of a one standard deviation increase in the interconnectedness measure, assuming the most distressed industry portfolio return is at its mean, leads to an annualized increase in next month returns of 2.2% and concentrating on manufacturing firms, the annualized effect is 3.0%.

Table 2.3 specifies baseline results in which I measure intra-industry firm interconnectedness through common institutional ownership. I regress next month excess returns of each of the less distressed stocks $l \in LD^j, \ \forall \ j = 1, ..., 49$ on lagged predictors including the interconnectedness measure, the returns of the most distressed industry portfolio, the interaction of the two, as well as lagged controls. Across almost all specifications, I^{OWN} is a significant predictor of future returns, and in all specifications, the interaction term is significant, indicating positive returns spillover from the current returns of the most distressed firms in each industry to the future returns of highly connected but less distressed firms in their industry. This effect remains, even after controlling for own-firm default probability, once again showing that the more connected stocks are not earning higher returns simply because they are more distressed.

[Table 2.3 about here]

Since the intra-industry interconnectedness measure is now a dummy variable, the coefficients on I^{OWN} and $I^{OWN} \times R^{MD}$ have clear interpretations as the predictability "alpha" and "beta" respectively. Referring to the regression:

$$r^{e}_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 I^{OWN}_{l,j,t} + \beta_3 I^{OWN}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t} \quad (2.6)$$

If in time t, the less distressed stock l in industry j shares a common institutional owner with at least one of the most distressed stocks $k \in MD^j_t$ for the previous two quarters, I^{OWN} would take the value of 1. Thus, relative to a less distressed stock s in industry j which does NOT share a common institutional owner with at least one of the most distressed stocks $k \in MD^j_t$ in the past two quarters, the excess returns of l in the next month i.e. $t+1$ is higher than the excess returns of s by $\beta_2 + \beta_3 R^{MD}_{j,t}$. I have deliberately allowed the returns spillover effect to be dependent on the level of most distressed returns in the industry, as the higher the distressed returns are, the larger is the spillover effect to the connected stocks.

Using estimates from column (4) and assuming once again that R^{MD} takes its sample mean value of 0.993%, relative to a firm in its industry which shares no common institutional owners with the most distressed stocks in its industry ($I^{OWN} = 0$), a firm which DOES share a common institutional owner with the most distressed stocks in its industry ($I^{OWN} = 1$) earns higher returns next-month of on average $0.00482 + (0.0434 \times 0.00993) = 0.53\%$. I annualize this figure to get a sense of the economic magnitude, and I find that relative to a firm with no common institutional owners, a firm which shares at least one common institutional owner with the most distressed firms in it industry earns on average 6.4% more, annualized. The pure returns spillover part alone is also significant, increasing returns of connected firms relative to unconnected ones by $0.0434 \times R^{MD}$.

Additional analysis in which I include Firm and Time fixed effects (available on request) shows quantitatively and qualitatively similar results, suggesting not only cross-sectionally within an industry, but also within-firm over time. As the firm gets *far* from the most distressed firms in its industry, it earns significantly higher future returns.

In columns (7) and (8), I use I^{OWN*} in place of I^{OWN}, which is a finer measure of common institutional ownership that takes into account the proportion of the joint market capitalization of two stocks owned by their common institutional owner. Results remain statistically significant when using I^{OWN*} as a measure of common institutional ownership, although interpretation of magnitudes is not as clear as in the case of I^{OWN}. Nevertheless, these results show that we continue to observe returns spillovers from the most distressed stocks to the less distressed stocks with whom they share common owners, even allowing for the fact that not all stocks which share common owners with the most distressed stocks in their industry have an equivalent proportion of their joint market cap held by these common owners.

One concern that rises from the baseline results is that perhaps we are just rediscovering a connected stock effect, as documented in Anton and Polk (2014) and Cohen and Frazzini (2008), who show, respectively, that stocks connected through major institutional owners reveal excess comovement in returns and stocks connected in economically related industries, through customer-supplier links, show return predictability. While I cannot rule this out completely, I offer three reasons why it is unlikely that we are simply rediscovering this effect and instead are observing a distinct channel of predictability.

First, I am not connecting ANY two firms with a common institutional owner, or even ANY two firms which come from economically related industries. I am specifically connecting less distressed firms in each industry to most distressed firms within their own industry, and measuring how their returns evolve in future periods. Second, the inclusion of the interaction term is crucial. As even assuming the coefficient on I^{OWN} represents a general connectedness effect as in Anton and Polk (2014) and Cohen and Frazzini (2008), the interaction term allows to measure the increase in next period returns for a connected relative to an unconnected firm per unit increase in the returns of the most distressed industry portfolio. The prior studies do not account for additional predictability through this channel and as such, the fact that I obtain significant results for the interaction term provides evidence of a distinct channel. Finally, to provide stronger evidence in support of the intra-industry default spillover discovered in this paper against the notion of a general connected stocks effect, I conduct a placebo analysis.

2.4.2 Placebo Results

The proposed explanation of default risk propagation through the asset revaluation channel leading to return predictability amongst less distressed firms that are connected to the most distressed firms in their industry, should be a distinctly intra-industry phenomenon. Thus, if we connect less distressed firms from one industry to more distressed firms in all other industries, we should not be able to observe predictability as we do in baseline results. I repeat the baseline analysis, except I connect less distressed firms in industry j to most distressed firms in all industries $i \neq j$. By allowing connections between firms in industries that are not the same, but may be economically related, I am even allowing for Cohen and Frazzini's explanation. I also retain the original interconnectedness terms in the regression, in order to check whether they remain significant in the presence of the placebo terms.

[Table 2.4 about here]

Table 2.4 shows placebo results for interconnectedness based on β*–distance*. In both columns (1) and (2), with or without controls, the placebo connectedness term $PInt^{FF3}$ is insignificant and $PInt^{FF3} \times PR^{MD}$ are (marginally) significant with the opposite sign, meaning sharing common owners with the most distressed stocks in all other industries reduces future returns. The original interconnectedness terms Int^{FF3} and $Int^{FF3} \times R^{MD}$ remain significant. The magnitudes of the estimates are also extremely similar to those obtained in the baseline analysis in Table 2.2. This provides direct evidence that I am capturing a distinct predictability mechanism independent of any general connectedness effect, or even, economically related industries predictability effect.

[Table 2.5 about here]

Table 2.5 shows placebo results for interconnectedness based on common institutional ownership. Here results are weaker, although, still providing evidence that the default risk spillover effect has incremental power over the general common institutional ownership in generating excess comovement. Both I^{OWN} and PI^{OWN} are significant, and the magnitude of the coefficient on PI^{OWN} is about 5 times larger than that of I^{OWN}, suggesting that I am able to find the result of Anton and Polk in the sample, using the slightly different criterion for measuring common institutional owners, in industries other than that of a given firm. In some ways, this is a restatement of the finding of Gao, Moulton, and Ng (2017), who suggest that institutional portfolio rebalancing induces return predictability among economically unrelated stocks.

However, even controlling for this effect of having common institutional owners, the spillover term $I^{OWN} \times R^{MD}$ remains significant and larger in magnitude by almost 1.5 times than the placebo spillover term $PI^{OWN} \times PR^{MD}$. While this does not let us completely to isolate the mechanism as a solely intra-industry effect, it certainly provides evidence that I have uncovered a predictability relationship with incremental predictive power over general connected stock effects. Possible reasons why the placebo spillover term remains significant here may be due to a misspecification of industry, or the fact that distress risk spillovers may not be solely restricted to a firm in the same industry, but also to firms in economically related industries for example.

2.4.3 Common Analyst Coverage

In Table 2.6 I repeat the baseline analysis using common analyst coverage as a measure of interconnectedness. The idea behind this robustness check is twofold. First, I intend to show that distress risk spillovers generate return predictability across a wide variety of interconnectedness measures, constructed from independent data sources, based on completely different firm characteristics. Thus, I am able to show that it is not the means of connectedness itself that is important, but that the result is a robust one no matter what method of connectedness one considers.

[Table 2.6 about here]

Second, common analyst coverage is chosen as a measure of interconnectedness, as analysts study the firms they cover in detail are highly likely to be informed about their prospects and are efficient information intermediaries. Thus, if an analyst is covering one firm which is highly distressed in the current period and is also covering another firm in the same industry which is highly connected to it, but not currently distressed, they can reasonably infer that this risk may spread to the connected firm and this may reflect in their forecasts and recommendations. Assuming these affect investor behavior, this is likely to generate predictable returns patterns among firms connected in this way.

Results in Table 2.6 provide evidence of this. Using estimates from column (4), and assuming once again that R^{MD} takes its sample mean value of 0.993%, relative to a firm in its industry, which shares no common analyst coverage with the most distressed stocks in its industry (I^A =0), a firm which DOES share at least one common analyst with the most distressed stocks in its industry (I^A = 1) earns higher returns next month of on average $0.00198 + (0.0352 \times 0.00993) = 0.23\%$. I annualize this figure to get a sense of the economic magnitude, and I find that relative to a firm with no common analyst coverage, a firm which shares at least one common analyst with the most distressed firms in it industry earns on average 2.8% higher returns annualized. The pure returns spillover is also significant increasing returns of connected firms relative to unconnected ones by $0.0352 \times R^{MD}$.

2.4.4 β−*distance* Predicts Default Probability

I hypothesize that next month returns of the presently less distressed stocks rise as a result of their increased default risk in the coming month. Investors who observe higher levels of default among risky firms expect firms within the same industry to experience increased default risk in the subsequent month and therefore growth in expected returns. I test this conjecture with the following panel regression:

$$DP1_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 Int^{FF3}_{l,j,t} + \beta_3 Int^{FF3}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 Log(Size_{l,j,t}) + \beta_5 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t} \quad (2.7)$$

where the dependent variable is the next-month default probability for the coming 1 year of the less distressed firm l in industry j. R^{MD} refers to the returns of the most distressed industry portfolios. Int^{FF3} refers to the $\beta-$ *distance* calculated based upon the Fama-French 3 factor model. The $\beta-$ *distance* is standardized to reduce multicollinearity between interacting variables, resulting in Variance Inflation Factors (VIF) all below 1.5. $Size$ refers to market capitalization in thousands of US Dollars and B/M is the book-to-market ratio defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum.

Table 2.7 presents the estimates of the panel regression (7), in which column (4) shows the estimates for the entire sample, column (5) gives the estimates excluding Utilities and Financials, and column (6) focuses only on Manufacturing industries. In all of these specification tests, the $\beta-$ *distance* is a statistically and economically relevant variable in forecasting next month probability of default of the less distressed firm l. Referring to column (4), we can see that one standard deviation increase in $\beta-$ *distance* increases on average next month default probability by $0.00455 - 0.0411 \times 0.00993 = 4.4\%$. In summary, the empirical results validate the hypothesis that $\beta-$ *distance* forecasts an increase in default probability of the less distressed firms which results in higher returns in the next month.

[Table 2.7 about here]

2.4.5 Asset Redeployability Results

The final set of analysis intends to explore a source of cross-sectional industry-level heterogeneity, asset redeployability, which should affect the intra-industry distress risk propagation mechanism, and accordingly affect the extent of predictability results[7]. As suggested in Almeida and Campello (2007), we expect default risk propagation to be relatively less pronounced in industries with higher levels of asset tangibility, as the asset revaluation channel is effectively shut down. High asset redeployability implies that the set of first-best users of these assets are not necessarily restricted only to other firms within the indus-

[7] I use the asset redeployability data from Almeida and Campello (2007). This measure is constructed as the ratio of used to total (i.e., used plus new) fixed depreciable capital expenditures based on the used and new capital acquisitions data at the four-digit SIC level from the Bureau of Census' *Economic Census.*

try, but may also comprise firms in other industries which may not be suffering from a negative cashflow shock. Similarly, for firms in industries with high degree of asset redeployability, their assets are likely to be more pledgeable as collateral and, hence, liquidation values should not be as sensitive to the worsening financial position of other firms in that industry.

In order to test this, I partition the sample based on asset redeployability, sorting the 49 industries into terciles based on average asset redeployability. I repeat the baseline analysis in the subsamples of the highest and lowest terciles of asset redeployability.

Table 2.8 presents results using β*−distance* as the interconnectedness measure. Columns (1) to (4) contain results for the highest tercile of redeployability and columns (5) to (8) give results for the lowest tercile of redeployability. While interconnectedness itself is significant across both high and low redeployability industries, the returns spillover captured through the interaction term is *only* significant in low redeployability industries. Thus, being connected matters in both high and low redeployability industries, but the spillover happens only in low redeployability industries. This is broadly consistent with the predictions I have made.

[Table 2.8 about here]

Table 2.9 presents results using common institutional ownership as the interconnectedness measure. Columns (1) to (4) introduce results for the highest tercile of redeployability and columns (5) to (8) give results for the lowest tercile of redeployability. Once again, while interconnectedness itself is significant across both high and low redeployability industries, the returns spillover captured through the interaction term is only significant in low redeployability industries. The magnitude of spillover is striking even when compared to results obtained for the full sample. Compared to the overall sample where having a common institutional owner increases returns in the next period by $0.0434 \times R^{MD}$ (column (4) of Table 2.3), in the lowest tercile of asset redeployability, having a common institutional owner increase returns in the next period by $0.0650 \times R^{MD}$ (column (8) of Table 2.9). This provides further evidence in favor of my proposed explanation.

[Table 2.9 about here]

In columns (9) and (10), I repeat the same exercise, using I^{OWN*} as a common institutional ownership measure. Once again, I find that while I^{OWN*} itself is significant in both high and low redeployability industries, the interaction term is only significant in low redeployability industries, further suggesting that it is amongst the firms in these industries that the phenomenon I document is most pronounced.

2.5 Investment Strategy

In this section, I focus on the investment strategies of the intra-industry default risk spillover phenomenon, proxied by the β*−distance* measure. The *Far - Near* strategy, which buys stocks that are in the *Far* quintile of interconnectedness and sells stocks in the *Near* quintile of interconnectedness, yields monthly Fama French five-factor alpha of 0.62% and t-statistic of 3.22. The results are robust with respect to value-weighted portfolios and are not subsumed after controlling for individual default risk, pointing in the direction of a new risk premium related to intra-industry default spillovers.

2.5.1 Time Series Returns

Before analyzing the return dispersion in the univariate and bivariate analysis, I show the time series variation of the average monthly β–*distance*. Figure 2.1 displays the monthly time series of the average equal-weighted interconnectedness (IntEW.mean) and standard deviation (IntEW.sd). The grey-shaded bars represent The National Bureau of Economic Research (NBER) recessions. As a robustness check, I plot the times series of the average value-weighted interconnectedness (IntVW.mean) and standard deviation (IntVW.sd). The value-weighted interconnectedness (IntVW) is value-weighted by market capitalization of the Euclidian distances of the Fama French 3-factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is an intra-industry measure, and is computed within each of the Fama French 49 industries at the end of every month. Both the equal-weighted and the value-weighted interconnectedness track each other pretty closely in terms of means, but during recessions, the value-weighted interconnectedness exhibits higher volatility.

[Figure 2.1 about here]

Figure 2.2 shows an overlapping histogram of IntEW and IntVW, confirming the non-normality of the measure through a long left-tail. Value-weighted interconnectedness (IntVW) histogram covers the equal-weighted interconnectedness (IntEW), supporting the results that the volatility of the IntVW is higher than IntEW.

[Figure 2.2 about here]

Figure 2.3 illustrates the time series cumulative log returns of the Far - Near equal-weighted and value-weighted portfolios. A number of interesting dynamics appear: first, there is a significant spike of the Far - Near portfolio up to the dotcom bubble, a period during which the technology-dominated NASDAQ index grew from 1000 to more than 5000 from 1995 to 2000, which corresponds with the starting point of the strategy; second, both the top and the bottom graph show that the value-weighted portfolios perform better than the respective equal-weighted ones, suggesting that the returns are not driven by small stocks. The Far-Near graph in the bottom figure shows that the value-weighted portfolio formed on the value-weighted interconnectedness (IntVW.vw)significantly outperforms the equal-weighted portfolio. Based on the construction of the value-weighted interconnectedness (IntVW), this implies that a *far* firm from a large distressed firm outperforms a *far* firm from a small distressed firm, which shows that the default spillover effects are more severe the more connected you are to a large distressed firm.

[Figure 2.3 about here]

Figure 2.4 is a heat-map of the monthly value-weighted returns of the Far-Near strategy from April 1995 to December 2014. We can see that the most severe losses are during the dotcom bubble. In order to understand how default spillover ranges among industries, Figure 2.5 shows the Far-Near average monthly returns for each of the Fama French 12 industries. The bar chart reveals that the value-weighted returns are consistently larger than the equal-weighted for 6 out of 12 industries and the top performing industries are non-durables and telecommunications, whereas the worst performing are energy and utilities.

[Figure 2.4 about here]

[Figure 2.5 about here]

Lastly, I plot the long-only Far cumulative returns in Figure 2.6 and market returns, where the market portfolio includes all the NYSE, NASDAQ, and AMEX firms. We observe that long-only Far portfolio returns are independent of the construction of the interconnectedness measure. Two relevant patterns from the graphs come into view: (1) Each of the Far strategies performs significantly better than the market in terms of the cumulative log returns. (2) The equal-weighted portfolio returns are larger than the value-weighted ones. This is in contrast with the Far-Near portfolio returns, in which the value-weighted portfolio performs better, suggesting that the large Near firms are contributing more to the long-short returns than the small Near firms. This means that the next month returns of the large Near firms are affected more by the default spillovers than the returns of the small Near firms.

[Figure 2.6 about here]

2.5.2 Univariate and Bivariate Analysis

After looking at the time series results, we are interested in the return dispersion across different levels of interconnectedness, different size groups, and default risk. I accomplish these insights by analyzing a univariate sort on interconnectedness in Table 2.10 and bivariate dependent sorts among size and interconnectedness and between default risk and interconnectedness in Table 2.11. I form portfolios by sorting on the dimension of interconnectedness, measured by β*−distance*. At the end of every month, starting in April 1995, all stocks in the sample are sorted into quintiles based on the previous month's individual interconnectedness value.

[Table 2.10 about here]

The univariate results in Table 2.10 show that returns are generally monotonically increasing as we move from the lowest quintile of interconnectedness (i.e. Near firms) to the highest quintile (i.e. Far firms). The Far - Near portfolio is a zero cost long-short portfolio, which buys the stocks that are in the Far quintile and sells stocks in the Near quintile. The monthly returns of the Far - Near portfolio are 0.23% with lower volatility and highest skewness among the other quintile portfolios. High kurtosis values in the lowest quintile suggest that the conditional distribution of interconnectedness has a longer left tail. The results are significant for value-weighted portfolios showing that return dispersion based on the interconnectedness is not driven by small stocks.

In Table 2.11 I present the results of two bivariate dependent sorts, first on size and then on interconnectedness, and on default risk and interconnectedness. Through this, I aim to uncover whether the univariate returns pattern are related to cross-sectional variation in firm-level characteristics. Bivariate sorting is useful, as it allows to observe how the returns behave as these characteristics interact, without imposing a functional form or factor structure on the relationship between characteristics and returns. I form the breakpoints on interconnectedness, size, and default risk using the empirical distribution of the respective characteristics at the end of every month using one-month lagged values to form portfolios.

[Table 2.11 about here]

In Panel A, I sort conditionally, first on size and then on interconenctedness, as unconditional sorts result in unbalanced portfolios with some having very large number number of stocks and some with very few. Through the conditional sort, I am able to form evenly sized portfolios and, hence, can be sure to minimize the noise and outlier portfolios do not drive the results. The first clear pattern that emerges is: conditional on size, the Far - Near portfolio generates positive returns across different size quintiles, ranging from 0.45% monthly for small stocks to 0.21% monthly for large stocks. This result shows that the portfolio returns based on interconnectedness are present accounting for size.

Panel B presents the average monthly returns of the bivariate dependent sort on default risk and interconnectedness. At the end of the every month, I sort first on the default probability estimates and then on interconnectedness. Two patterns stand out: (1) Far - Near portfolio returns are positive for each of the default probability quintiles. (2) Far-Near average monthly returns among the distressed firms are 6.5 times larger than the average monthly returns among the safe firms. This shows that firms in the most distressed quintile are affected the most by the default spillovers, and the further away a firm is from the most distressed firms the higher its returns are compared to nearby firms. The result is in support of the proposed channel of the default risk propagation spillover, that firms with high likelihood of default in an industry reduce the value of the assets of the safer firms within the same industry in the short term.[8]

[8]As a robustness test, I analyze the univariate and bivariate dependent results using deciles as breakpoints of the empirical distribution of the variables and the results are still significant.

2.5.3 Regression Analysis

Univariate and bivariate sorting results documented above point in the direction of a new premium for intra-industry default risk spillovers. Nevertheless, the equal-weighted hedge portfolios can be dominated by tiny stocks, and the value-weighted hedge portfolio returns can be skewed by the large stocks, as revealed in Fama and French (2008). Therefore, I present the time series regression estimates of Far - Near portfolio returns to determine if the premium is explained by standard asset pricing factor models. I regress the Far-Near portfolio returns using the Fama French five-factor model, which performs better at explaining the cross sectional returns than Fama French three-factor model, as shown in Fama and French (2015).

[Table 2.12 about here]

Table 2.12 presents the alpha and beta estimates of the regression. The equal-weighted Far - Near portfolio produces 0.62% (7.44% annualized) monthly Fama-French five-factor alpha with t-statistic of 3.22, and the value-weighted portfolio alpha estimate is 0.60% monthly with t-statistic of 3.15. Statistics are computed using the methodology in Newey and West (1987), accounting for autocorrelation in the regression errors. The equal-weighted Far - Near portfolio loads positively but statistically insignificant on the market factor Mkt, positively and significantly on the size factor SMB, which is congruent with the portfolio construction method. It also loads negatively on the value factor HML and profitability factor RMW with large statistical significance. Each of the quintile portfolios has a positive exposure on the value factor except the Far and the Far-Near portfolios.

These results are in support of the arguments presented in the literature, starting with Fama and French (1993) that the HML factor is a proxy for financial distress. Since the Far portfolio, based on construction, is affected the least by the default spillovers from the distressed firms, we would expect its HML beta to be negative. Based on the risk exposures, we attest that the Far - Near strategy is characterized as an investment among firms with low short term profitability, which is congruent with the mechanism of the intra-industry spillovers, where the closer you are to the distressed firms the higher the less profitable you are in the short term. The beta estimate on the investment factor is negative and statistically insignificant. I am not claiming if the risk factor is priced or not. Non-priced risk factors are equally important for portfolio decision investments as the priced risk factors, but they are not relevant for computing expected returns. The value-weighted regression results are qualitatively and quantitatively similar.

In summary, regression results support portfolio sorting outcomes, suggesting the presence of a new intra-industry default risk spillover premium and they conform to the intuition of the Far - Near portfolio construction and the expected signs of betas.

2.5.4 Quantopian Backtesting

In this section, I backtest the investment strategy of the Far - Near and Far value-weighted portfolios in Quantopian, using minute-level data from January 2005 to December 2014. The purpose of this analysis is twofold: first, to test if the results are present using minute-level market data and are not prone to transaction costs and second, to introduce the academic community to Quantopian, a crowd-sourced quantitative platform, gaining a lot of traction recently, which allows every individual to research, develop, backtest, and live trade their investment ideas for free. Due to limitations on Quantopian's server computational power, I limit testing only to firms with market capitalization above 1 billion at the end of every month before portfolio formation to remove look-ahead bias. [9]

[Figure 2.7 about here]

Figure 2.7 presents the time series backtest results of the value-weighted Far - Near strategy from January 2005 to December 2014. The time frame for the backtest is imposed by the data availability of the platform, which starts in 2002. I perform the analysis from January 2005, since this year seems a stable starting point on the average returns, if we refer to Figure 2.3. The Far - Near Quantopian backtested strategy, even though focused on a smaller pool of stocks, is qualitatively similar to the strategy tested from April 1995 to December 2014, which included the entire dataset of stocks.

[Table 2.13 about here]

Table 2.13 gives the top 10 stocks based on portfolio weight for the Far and Near portfolios, which are both dominated by multibillion-dollar firms. In the meantime, Figure 2.8 exhibits the value-weighted Far strategy from January 2005 to December 2014, which confirms the previously long-only strategy formed based on default risk spillovers. Altogether, the backtesting results, using minute-level execution data, show that the Far - Near and Far portfolio

[9] **Disclaimer**: Quantopian reference is provided for information purposes only and does not constitute endorsement of the company and I do not have any social or economic relation with any employee from the company. For more information about the process of developing, testing strategies, and the company, please consult the contents on the webpage https://www.quantopian.com/home

results are present and not susceptible to transaction costs.

2.6 Conclusions

In this chapter, I investigate whether distress risk spillovers among connected firms within an industry generate predictable returns patterns. I find evidence that less distressed firms in a given industry that are less connected to the most distressed firms within their industry earn significantly higher future returns. This finding is robust to three interconnectedness measures: β−*distance*, common institutional ownership, and common analyst coverage and exists in the full sample, among only manufacturing firms, and among all firms except financials and utilities.

Placebo analysis provides evidence in favor of the intra-industry default risk spillover relationship I propose, being distinct to the general connected stock effect and retaining incremental predictive power when considered together with general connectedness measures.

Finally, I validate the proposed explanation by considering the moderating effect of asset redeployability and find evidence of spillovers in industries with low asset redeployability and absence of evidence in industries with high asset redeployability. An investment strategy that buys stocks *far* from the distressed stocks and sells stocks *near* the distressed stocks earns annualized Fama French five-factor alpha 7.44% with t-statistic of 3.22.

Table 2.1: Correlations and Summary Statistics

These tables provide correlations and summary statistics for the key variables from 1996-2014. $\log(Size)$ refers to the natural log of market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. Int^{FF3} refers to the β*−distance* calculated based upon the Fama-French 3 factor model (Fama and French, 1993). R^{MD} refers to the returns of the most distressed industry portfolios, averaged across all 49 industries over the sample period. $\log(B/M)$ is the natural log of the book-to-market ratio. I^{OWN} is an indicator variable which takes the value of 1 if a stock shares at least one major institutional owner (defined as owning at least 10,000 shares) in the previous two quarters, with the most distressed stocks in its industry. I^{OWN*} is the normalized value of the percentage of the joint market cap of a stock and each of the most distressed stocks in its industry in that month, owned by common major institutional owners in the previous two quarters, averaged across all distressed stocks in its industry. I^A is an indicator variable which takes the value of 1 if there is at least one common analyst who offers quarterly EPS forecasts for the stock and at least one of the most distressed stocks in its industry, over the past two quarters.

	r^e	$\log(Size)$	$DP1$	Int^{FF3}	R^{MD}	$\log(B/M)$	I^{OWN}	I^{OWN*}	I^A
r^e	1								
$\log(Size)$	0.0286	1							
$DP1$	0.0523	-0.2080	1						
Int^{FF3}	0.0199	-0.0273	0.0073	1					
R^{MD}	0.0268	0.0090	-0.0416	0.0451	1				
$\log(B/M)$	-0.1136	-0.3206	0.2258	-0.1658	-0.0326	1			
I^{OWN}	0.0123	-0.2290	0.1375	-0.0181	-0.0009	0.1026	1		
I^{OWN*}	-0.0126	-0.0847	0.0575	0.0106	-0.0000	0.0432	0.1521	1	
I^A	0.0096	-0.2184	0.1034	-0.0343	-0.0040	0.1425	0.2238	0.0742	1

VARIABLES	*Mean*	*Min*	*Max*	*Std*	*Skewness*	*Kurtosis*	25%	50%	75%
$DP1$	0.145	9.20e-05	11.38	0.401	9.139	125.3	0.0118	0.0398	0.121
R^{MD}	0.00993	-0.972	3.479	0.161	1.776	17.85	-0.0758	-0.00423	0.0765
$\log(Size)$	13.89	7.337	20.26	1.704	0.386	3.042	12.68	13.78	14.96
I^{OWN}	0.0530	0	1	0.224	3.989	16.91	0	0	0
I^A	0.0893	0	1	0.285	2.881	9.301	0	0	0
$\log(B/M)$	-0.753	-10.80	4.375	0.734	-0.961	7.243	-1.155	-0.681	-0.266
I^{OWN*}	-0.134	-0.940	16.43	0.462	14.61	262.1	-0.217	-0.176	-0.140
Int^{FF3}	3.66e-09	-3.727	25.11	1.000	1.814	24.51	-0.646	-0.118	0.510

Table 2.2: Baseline Predictability Regression Analysis using $\beta{-}distance$

In this table, I present estimates for the following predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 Int^{FF3}_{l,j,t} + \beta_3 Int^{FF3}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$ refers to market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. Int^{FF3} refers to the $\beta-$ *distance* calculated based upon the Fama-French 3 factor model (Fama and French, 1993). R^{MD} refers to the returns of the most distressed industry portfolios. B/M is the book-to-market ratio, defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum. Columns (1) and (2) present coefficient estimated using OLS for the pooled cross-section. Columns (3) and (4) are estimated using Industry and Time fixed effects. Column (5) is estimated using Industry and Time fixed effects, for all firms except financial and utility firms. Column (6) is estimated using Industry and Time fixed effects, for all firms in manufacturing industries. T-statistics are given in brackets. For columns (1) and (2), they are computed using HAC robust standard errors, and for columns (3) - (6) they are computed using industry-year double clustered standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
R^{MD}	0.0349***	0.0330***	0.0137***	0.0129**	0.00420	0.00465
	(25.66)	(24.44)	(2.79)	(2.69)	(1.14)	(0.85)
Int^{FF3}	0.00294***	0.000239	0.00308***	0.00198***	0.00171***	0.00235***
	(6.59)	(0.54)	(5.16)	(3.00)	(2.90)	(3.02)
$Int^{FF3} \times R^{MD}$	0.0110**	0.0114***	0.00830**	0.00798**	0.0125***	0.0110**
	(2.51)	(2.61)	(2.30)	(2.24)	(3.33)	(2.37)
$DP1$		0.00711***		0.00617***	0.00633***	0.00573***
		(15.59)		(8.99)	(9.00)	(5.07)
$Log(Size)$		0.00122***		0.000836*	0.000715**	0.000291
		(12.08)		(1.79)	(2.04)	(0.49)
$Log(B/M)$		-0.0198***		-0.0206***	-0.0229***	-0.0255***
		(-63.67)		(-7.77)	(-15.68)	(-14.66)
$Constant$	0.0119***	-0.0191***				
	(0.000181)	(-14.25))				
Observations	643,378	643,378	643,378	643,378	469,401	245,269
R-squared	0.002	0.016	0.121	0.133	0.145	0.154
Industry FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	No Util/Fin	Manufacturing
Cluster	No	No	Industry-Year	Industry-Year	Industry-Year	Industry-Year

Table 2.3: Regression Analysis using Common Institutional Ownership

These are estimates of the following predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 I^{OWN}_{l,j,t} + \beta_3 I^{OWN}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where r^e is the next-month excess returns and the lagged independent variables are $Size$, $DP1$, I^{OWN} which takes the value of 1 if a stock shares at least one major institutional owner (defined as owning at least 10,000 shares) in the previous two quarters, with the most distressed stocks in its industry. I^{OWN*} is the normalized value of the percentage joint market cap of a stock and each of the most distressed stocks in its industry that month, owned by common major institutional owners in the previous two quarters, averaged across all distressed stocks in its industry T-statistics are given in brackets. For columns (1), (2) and (7), they are computed using HAC robust standard errors, and for columns (3) - (6) and (8) they are computed using industry-year double clustered standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	I^{OWN*}	I^{OWN*}
R^{MD}	0.0247***	0.0228***	0.00651*	0.00541	-0.0019	-0.00217	0.0272***	0.0101***
	(16.69)	(15.62)	(1.75)	(1.48)	(-0.55)	(-0.40)	(19.17)	(2.73)
I^{OWN}	0.000935	0.00588***	0.000798	0.00482***	0.00578***	0.00709***	0.00119***	0.00108***
	(1.42)	(8.51)	(0.93)	(4.98)	(4.52)	(4.35)	(4.66)	(4.27)
$I^{OWN} \times R^{MD}$	0.0383***	0.0374***	0.0435***	0.0434***	0.0455***	0.0494***	0.00586***	0.00610***
	(6.99)	(6.88)	(5.38)	(5.45)	(4.38)	(3.86)	(3.29)	(2.89)
$DP1$		0.0142***		0.0138***	0.00632***	0.0169***	0.0141***	0.0136***
		(16.51)		(8.91)	(4.30)	(6.19)	(16.63)	(8.54)
$Log(Size)$		0.000415***		9.64E-06	-0.000538	-0.00124***	0.000138	-0.00019
		(3.84)		(0.02)	(-1.40)	(-3.28)	(1.30)	(-0.32)
$Log(B/M)$		-0.0211***		-0.0214***	-0.0246***	-0.0285***	-0.0209***	-0.0212***
		(-60.11)		(-6.60)	(-13.30)	(-13.38)	(-60.57)	(-6.60)
Constant	0.0135***	-0.0104***					-0.00576***	
	(70.68)	(-7.03)					(-4.08)	
Observations	511598	511598	511598	511598	368571	191365	509527	509527
R-squared	0.002	0.019	0.133	0.148	0.159	0.167	0.019	0.149
Industry FE	No	No	Yes	Yes	Yes	Yes	No	Yes
Month FE	No	No	Yes	Yes	Yes	Yes	No	Yes
Sample	Full	Full	Full	Full	No Util/Fin	Manufacturing	Full	Full
Cluster	No	No	Industry-Year	Industry-Year	Industry-Year	Industry-Year	No	Industry-Year

Table 2.4: Placebo Regression Analysis using β*–distance*

Regression estimates for the following predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 Int^{FF3}_{l,j,t} + \beta_3 Int^{FF3}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \beta_7 PR^{MD}_{j,,t} + \beta_8 PInt^{FF3}_{l,j,t} + \beta_9 PInt^{FF3}_{l,j,t} \times PR^{MD}_{j,t} + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$ refers to market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. Int^{FF3} refers to the β*–distance* calculated based upon the Fama-French 3 factor model (Fama and French, 1993). R^{MD} refers to the returns of the most distressed industry portfolios. $PInt^{FF3}$ refers to the placebo β*–distance* calculated based upon the Fama-French 3 factor model (Fama and French, 1993). PR^{MD} refers to the returns of the most distressed placebo industry portfolios.B/M is the book-to-market ratio, defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum. Columns (1) and (2) are estimated using Industry and Time fixed effects. T-statistics are given in brackets and are computed using industry-year double clustered standard errors.

	(1)	(2)
VARIABLES	Fixed Effects	Fixed Effects
R^{MD}	0.0102**	0.00962**
	(2.23)	(2.13)
Int^{FF3}	0.00284***	0.00175***
	(4.97)	(2.69)
$Int^{FF3} \times R^{MD}$	0.0101**	0.00979**
	(2.42)	(2.39)
$DP1$		0.00629***
		(9.35)
$Log(Size)$		0.000806*
		(1.74)
$Log(B/M)$		-0.0203***
		(-7.87)
PR^{MD}	-2.019***	-1.972***
	(-6.39)	(-6.26)
$PInt^{FF3}$	-0.000509	-0.000388
	(-1.45)	(-1.12)
$PInt^{FF3} \times PR^{MD}$	-0.0114*	-0.0104*
	(-1.92)	(-1.76)
Observations	643,378	643,378
R-squared	0.128	0.140
Industry FE	Yes	Yes
Month FE	Yes	Yes
Sample	Full	Full
Cluster	Industry-Year	Industry-Year

Table 2.5: Placebo Analysis with Common Institutional Ownership

These are estimates for the following predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 I^{OWN}_{l,j,t} + \beta_3 I^{OWN}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \beta_7 PR^{MD}_{j,,t} + \beta_8 PI^{OWN}_{l,j,t} + \beta_9 PI^{OWN}_{l,j,t} \times PR^{MD}_{j,t} + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$ refers to market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. I^{OWN} is an indicator variable which takes the value of 1 if a stock shares at least one major institutional owner (defined as owning at least 10,000 shares) in the previous two quarters, with the most distressed stocks in its industry. R^{MD} refers to the returns of the most distressed industry portfolios. PI^{OWN} is an indicator variable which takes the value of 1 if a stock shares at least one major institutional owner (defined as owning at least 10,000 shares) in the previous two quarters, with the most distressed stocks in all other industries. PR^{MD} refers to the returns of the most distressed placebo industry portfolios.B/M is the book-to-market ratio, defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum. Columns (1) and (2) are estimated using Industry and Time fixed effects. T-statistics are given in brackets and are computed using industry-year double clustered standard errors.

	(1)	(2)
VARIABLES	Fixed Effects	Fixed Effects
R^{MD}	0.00674*	0.00579
	(1.87)	(1.60)
I^{OWN}	-0.000301	0.00257***
	(-0.39)	(2.81)
$I^{OWN} \times R^{MD}$	0.0358***	0.0358***
	(4.44)	(4.49)
$DP1$		0.0139***
		(9.20)
$Log(Size)$		0.00151**
		(2.51)
$Log(B/M)$		-0.0216***
		(-6.55)
PR^{MD}	-0.0414	-0.0331
	(-1.27)	(-1.02)
PI^{OWN}	0.00144**	0.0107***
	(2.49)	(6.08)
$PI^{OWN} \times PR^{MD}$	0.0255**	0.0242**
	(2.59)	(2.45)
Observations	508,636	508,636
R-squared	0.133	0.149
Industry FE	Yes	Yes
Month FE	Yes	Yes
Sample	Full	Full
Cluster	Industry-Year	Industry-Year

Table 2.6: Regression Analysis using Common Analyst Coverage

In this table, I present estimates for the following predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 I^A_{l,j,t} + \beta_3 I^A_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$ refers to market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. I^A is an indicator variable which takes the value of 1 if there is at least one common analyst who offers quarterly EPS forecasts for the stock and at least one of the most distressed stocks in its industry, over the past two quarters. R^{MD} refers to the returns of the most distressed industry portfolios. B/M is the book-to-market ratio, defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum. Columns (1) and (2) present coefficient estimated using OLS for the pooled cross-section. Columns (3) and (4) are estimated using Industry and Time fixed effects. Column (5) is estimated using Industry and Time fixed effects, for all firms except financial and utility firms. Column (6) is estimated using Industry and Time fixed effects, for all firms in manufacturing industries. T-statistics are given in brackets. For columns (1) and (2), they are computed using HAC robust standard errors, and for columns (3) - (6) they are computed using industry-year double clustered standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
R^{MD}	0.0196***	0.0175***	0.00511	0.00394	-0.00248	-0.00209
	(12.02)	(10.87)	(1.24)	(0.98)	(-0.66)	(-0.38)
I^A	-0.00182**	0.00439***	-0.00204***	0.00198***	0.00253***	0.00239*
	(-2.32)	(5.61)	(-2.86)	(2.89)	(2.98)	(1.71)
$I^A \times R^{MD}$	0.0295***	0.0272***	0.0368***	0.0352***	0.0343***	0.0391***
	(4.41)	(4.13)	(4.38)	(4.33)	(3.50)	(3.29)
$DP1$		0.0162***		0.0155***	0.0155***	0.0155***
		(15.73)		(9.17)	(8.47)	(5.03)
$Log(Size)$		0.00116***		0.000280	0.000213	-0.000127
		(9.13)		(0.72)	(0.69)	(-0.26)
$Log(B/M)$		-0.0237***		-0.0248***	-0.0257***	-0.0277***
		(-60.46)		(-12.28)	(-15.67)	(-12.31)
Constant	0.0129***	-0.0251***				
	(61.43)	(-13.87)				
Observations	394,577	394,577	394,577	394,577	295,312	152,775
R-squared	0.001	0.022	0.163	0.181	0.189	0.195
Industry FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	No Util/Fin	Manufacturing
Cluster	No	No	Industry-Year	Industry-Year	Industry-Year	Industry-Year

Table 2.7: Predictability of Default Risk using β−*distance*

In this table, I present estimates for the following predictability regression: $DP1_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 Int^{FF3}_{l,j,t} + \beta_3 Int^{FF3}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 Log(Size_{l,j,t}) + \beta_5 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is the next-month default probability for the coming 1 year of the less distressed firm l in industry j. R^{MD} refers to the returns of the most distressed industry portfolios. Int^{FF3} refers to the $\beta-$ *distance* calculated based upon the Fama-French 3 factor model. The $\beta-$ *distance* is standardized to reduce multicollinearity between interacting variables, resulting in Variance Inflation Factors (VIF) all below 1.5. For columns (1) and (2), t-statistics are computed using HAC robust standard errors and for columns (3) - (6) they are computed using industry clustered robust standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
R^{MD}	-0.186***	-0.159***	-0.0692***	-0.0576***	-0.0505**	-0.0391*
	(-23.08)	(-21.00)	(-4.61)	(-3.92)	(-2.64)	(-1.84)
Int^{FF3}	0.0674***	0.0558***	0.0545***	0.0401***	0.0445***	0.0293***
	(50.68)	(44.29)	(6.07)	(5.24)	(5.68)	(3.11)
$Int^{FF3} \times R^{MD}$	0.00772	0.00435	-0.0391***	-0.0311***	-0.0411***	-0.0485***
	(0.83)	(0.49)	(-3.03)	(-2.8)	(-3.70)	(-3.46)
$Log(Size)$		-0.113***		-0.0923***	-0.109***	-0.111***
		(-185.55)		(-10.04	(-19.16)	(-12.56)
$Log(B/M)$		0.101***		0.115***	0.0990***	0.0711***
		(62.73)		(6.05)	(7.23)	(3.82)
$Constant$	0.337***	1.859***				
	(327.18)	(220.78)				
Observations	635680	635680	635680	635680	463661	242456
R-squared	0.008	0.121	0.161	0.24	0.257	0.241
Industry FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	No Util/Fin	Manufacturing
Cluster	No	No	Industry	Industry	Industry	Industry

Table 2.8: Regression with β−*distance* in Asset Redeployability Subsamples

Predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 Int^{FF3}_{l,j,t} + \beta_3 Int^{FF3}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$ refers to market capitalization in thousands of US Dollars. $DP1$ refers to monthly estimates of default probability for the coming 1 year. Int^{FF3} refers to the β−*distance* calculated based upon the Fama-French 3 factor model (Fama and French, 1993). R^{MD} refers to the returns of the most distressed industry portfolios. B/M is the book-to-market ratio, defined as book equity value scaled by prior six-months market equity value to avoid inadvertently capturing the effect of momentum. Asset redeployability is defined as the ratio of used to total (used plus new) fixed depreciable capital expenditures, computed using data derived from the 1992 Economic Census. Columns (1) - (4) are estimated for the subsample of firms in industries with high asset redeployability (in the highest tercile). Columns (5) - (8) are estimates for the subsample of firms in industries with low asset redeployability (in the lowest tercile).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects
R^{MD}	0.0188***	0.0155***	0.00234	0.000946	0.0421***	0.0397***	-0.00412	-0.00484
	(3.64)	(3.00)	(0.28)	(0.10)	(11.89)	(11.34)	(-1.12)	(-1.24)
Int^{FF3}	0.00596***	0.00289	0.00530***	0.00335**	0.00266***	-0.000432	0.00276**	0.00125
	(3.10)	(1.51)	(3.71)	(2.45)	(3.45)	(-0.57)	(2.34)	(1.02)
$Int^{FF3} \times R^{MD}$	0.0176	0.0183	0.0187	0.0185	0.0135**	0.0134**	0.0141***	0.0138***
	(1.02)	(1.07)	(1.35)	(1.34)	(2.17)	(2.18)	(4.21)	(4.23)
$DP1$		0.00863***		0.00547***		0.00934***		0.00758**
		(7.31)		(6.10)		(8.12)		(3.09)
$Log(Size)$		-0.000532		-0.000692*		0.00257***		0.00210**
		(-1.46)		(-2.08)		(10.71)		(2.88)
$Log(B/M)$		-0.0334***		-0.0306***		-0.0228***		-0.0228***
		(-27.38)		(-12.91)		(-29.38)		(-9.12)
Constant	0.0114***	-0.00497			0.0125***	-0.0460***		
	(18.18)	(-1.03)			(23.95)	(-13.69)		
Observations	84,925	84,925	84,925	84,925	104,088	104,088	104,088	104,088
R-squared	0.003	0.023	0.162	0.178	0.003	0.020	0.132	0.146
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
Month FE	No	No	Yes	Yes	No	No	Yes	Yes
Sample	H Red	H Red	H Red	H Red	L Red	L Red	L Red	L Red
Cluster	No	No	Industry-Year	Industry-Year	No	No	Industry-Year	Industry-Year

Table 2.9: Institutional Ownership in Asset Redeployability Subsamples

Predictability regression: $r^e_{l,j,t+1} = \alpha + \beta_1 R^{MD}_{j,t} + \beta_2 I^{OWN}_{l,j,t} + \beta_3 I^{OWN}_{l,j,t} \times R^{MD}_{j,t} + \beta_4 DP1_{l,j,t} + \beta_5 Log(Size_{l,j,t}) + \beta_6 Log(B/M_{l,j,t}) + \lambda_j + \mu_t + \epsilon_{l,j,t}$, where the dependent variable is next-month excess returns r^e, and the lagged independent variables are $Size$, $DP1$ monthly estimates of default probability for the coming 1 year, and I^{OWN} takes the value of 1 if a stock shares at least one major institutional owner in the previous two quarters, with the most distressed stocks in its industry. Asset redeployability is defined as the ratio of used to total (used plus new) fixed depreciable capital expenditures, computed using data derived from the 1992 Economic Census. Columns (1) - (4) are estimated for the subsample of firms in industries with high asset redeployability (in the highest tercile). Columns (5) - (8) are estimates for the subsample of firms in industries with low asset redeployability (in the lowest tercile). Columns (9) and (10) are estimated using I^{OWN*} in place of I^{OWN} in the subsample of firm in industries with high asset redeployability and low asset redeployability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
R^{MD}	0.0161***	0.0118***	0.000991	-0.00154	0.0206***	0.0176***	-0.0110**	-0.0126**	0.00327	-0.00555
	(4.00)	(2.96)	(0.12)	(-0.17)	(5.89)	(5.13)	(-2.80)	(-2.88)	(0.54)	(-1.39)
I^{OWN}	0.00743***	0.0101***	0.00610***	0.0103***	0.00277	0.00541**	0.00182	0.00455**	0.00133***	0.00120***
	(3.16)	(4.20)	(3.86)	(5.69)	(1.34)	(2.53)	(1.26)	(2.59)	(3.00)	(2.42)
$I^{OWN} \times R^{MD}$	0.0258	0.0296*	0.0464	0.0483	0.0683***	0.0680***	0.0648***	0.0650***	0.00442	0.01322**
	(1.56)	(1.82)	(1.55)	(1.59)	(4.81)	(4.89)	(4.53)	(4.68)	(0.84)	(2.45)
$DP1$		0.0234***		0.0208***		0.0195***		0.0192***	0.0203***	0.0183***
		(9.07)		(6.34)		(7.30)		(3.77)	(8.87)	(3.75)
$Log(Size)$		-0.00149***		-0.00135**		0.000842***		0.000474	-0.00178**	0.000234
		(-4.13)		(-3.01)		(3.37)		(0.71)	(-4.12)	(0.35)
$Log(B/M)$		-0.0365***		-0.0327***		-0.0235***		-0.0231***	-0.0321***	-0.0231***
		(-25.17)		(-13.08)		(-26.86)		(-5.93)	(-13.26)	(-5.79)
$Constant$	0.0139***	0.00321			0.0151***	-0.0240***				
	(23.76)	(0.71)			(28.87)	(-6.93)				
Observations	66,487	66,487	66,487	66,487	84,514	84,514	84,514	84,514	66,164	84,198
R-squared	0.001	0.029	0.175	0.196	0.002	0.023	0.129	0.147	0.196	0.144
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Sample	H Red	H Red	H Red	H Red	L Red	L Red	L Red	L Red	H Red	L Red
Cluster	No	No	Industry-Year	Industry-Year	No	No	Industry-Year	Industry-Year	Industry-Year	Industry-Year

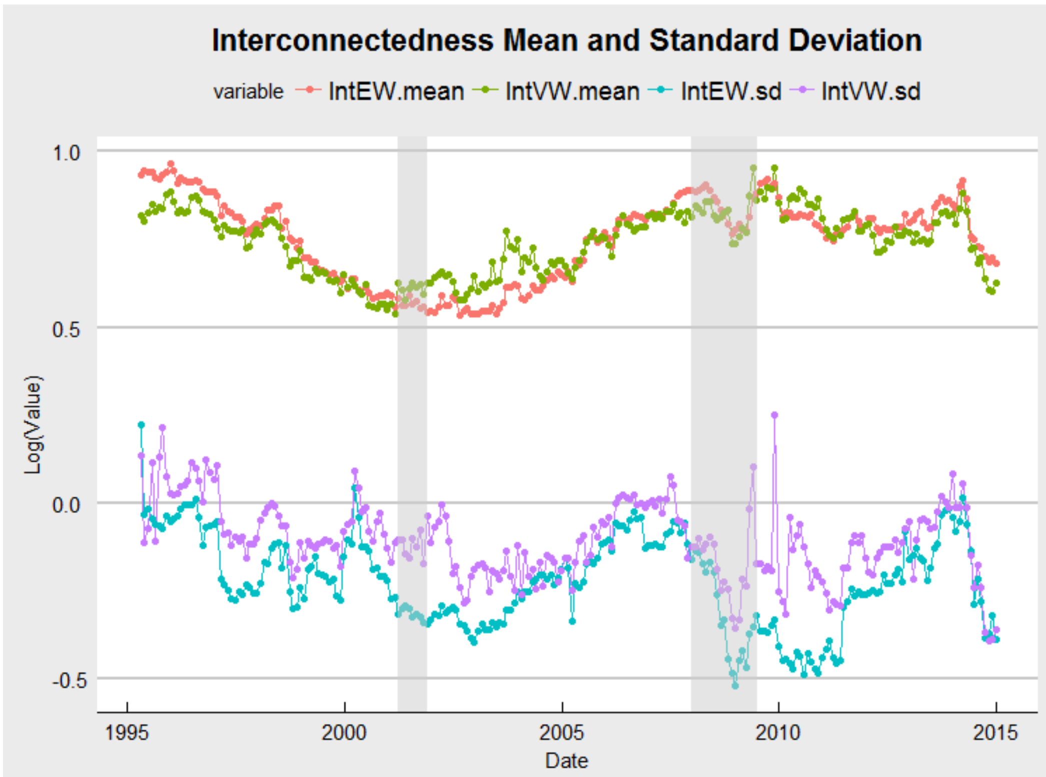


Figure 2.1: Interconnectedness Measure

Top graph shows the monthly time series of the means and standard deviations of the equal-weighted and value-weighted interconnectedness measure, respectively IntEW.mean, IntEW.sd, IntVW.mean, and IntVW.sd. The equal-weighted interconnectedness (IntEW) is the average of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The value weighted interconnectedness (IntVW) is the value weighted by market capitalization of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is computed within each of the Fama French 49 industries, at the end of every month. I estimate the Fama French 3 factor loadings for every firm that has the returns of the past 60 months, at the end of every month. The construction of variables covers the data sample from April 1991 to December 2014.

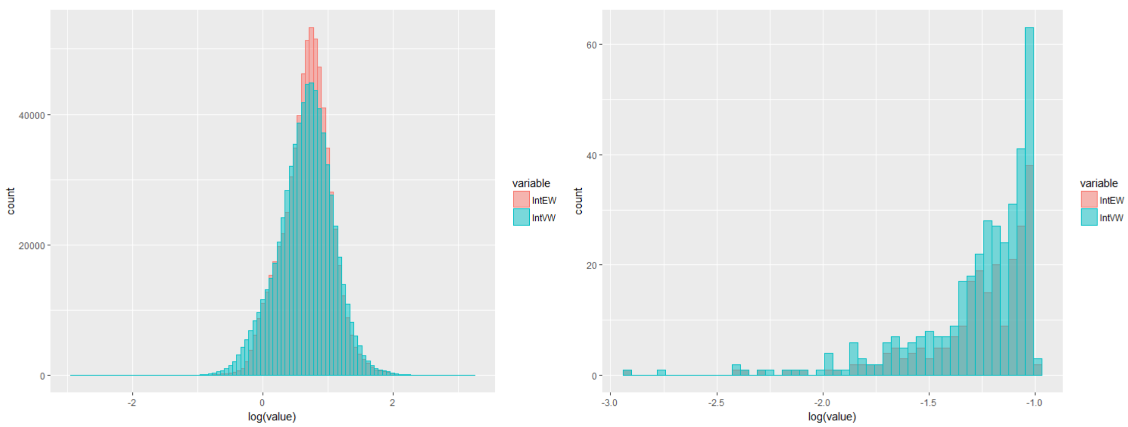
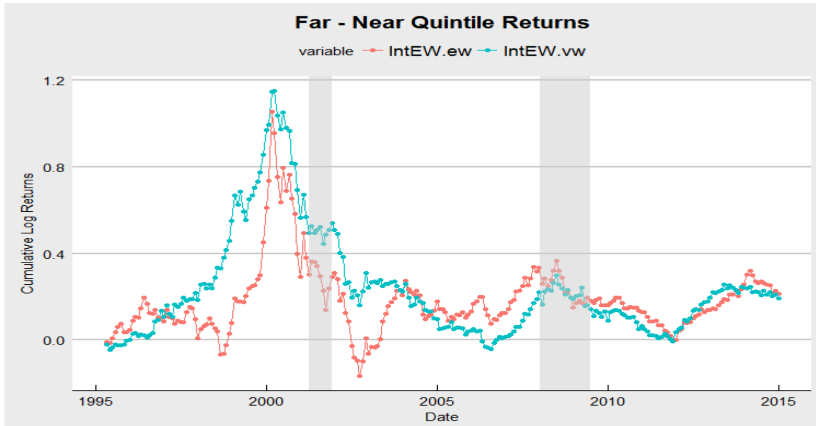


Figure 2.2: Histogram of Interconnectedness

Top figure is an overlapping histogram of the monthly equal-weighted interconnectedness (IntEW) and value-weighted interconnectedness (IntVW). The bottom figure presents the left tail of the histogram.



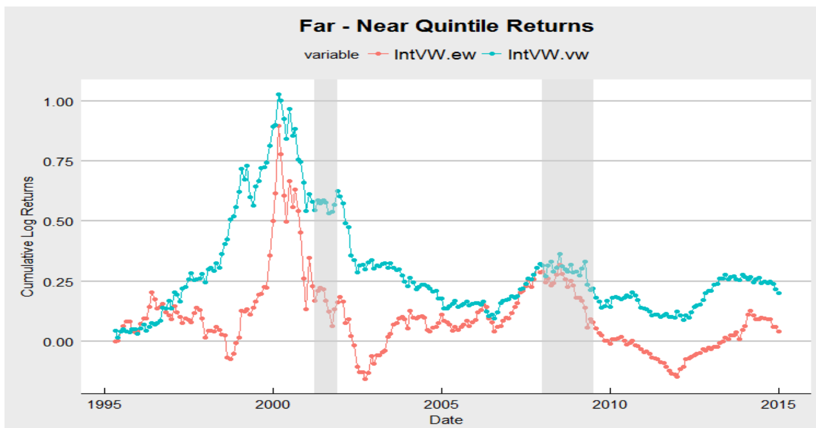


Figure 2.3: Far - Near Monthly Quintile Returns

Top graph shows the Far - Near equal weighted and value weighted monthly returns of the quintile equal weighted interconnectedness measure, respectively IntEW.ew and IntEW.vw. The equal weighted interconnectedness (IntEW) is the average of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is computed within each of the Fama French 49 industries, at the end of every month. Bottom graph presents the Far- Near equal weighted and value weighted monthly returns of the quintile value weighted interconnectedness measure (IntVW). The value weighted interconnectedness measure (IntVW) is value weighted by market capitalization of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile.

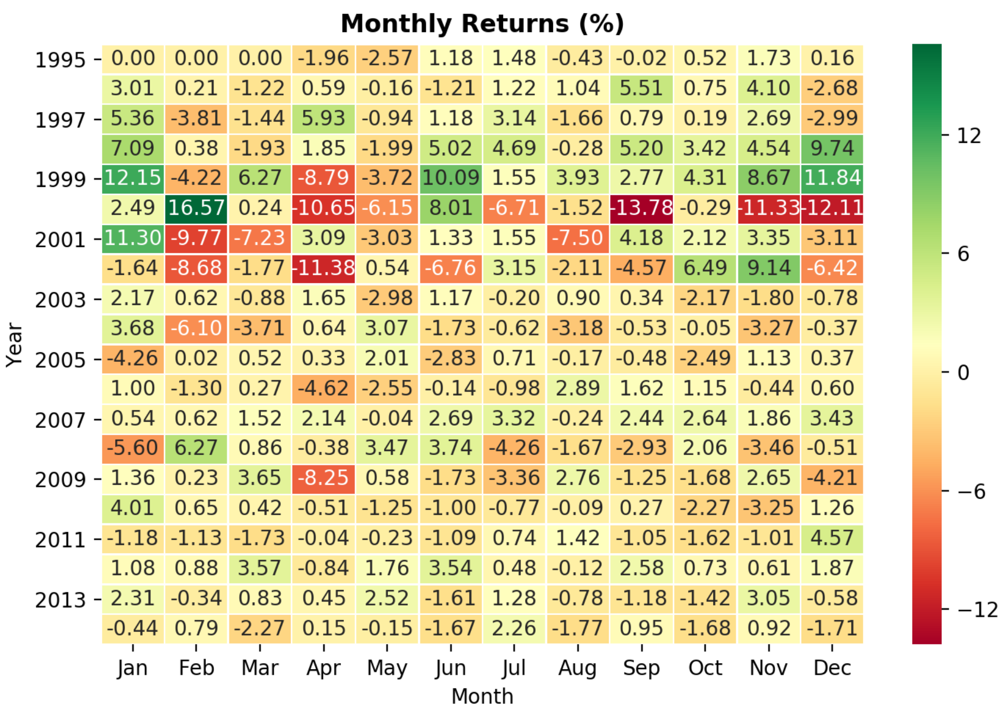


Figure 2.4: Far - Near Returns

Figure shows the individual value weighted monthly returns of the Far - Near strategy from April 1995 to December 2014. Portfolios are formed based on the quintile equal weighted interconnectedness measure at the end of every month, within each of the Fama French 49 industries.

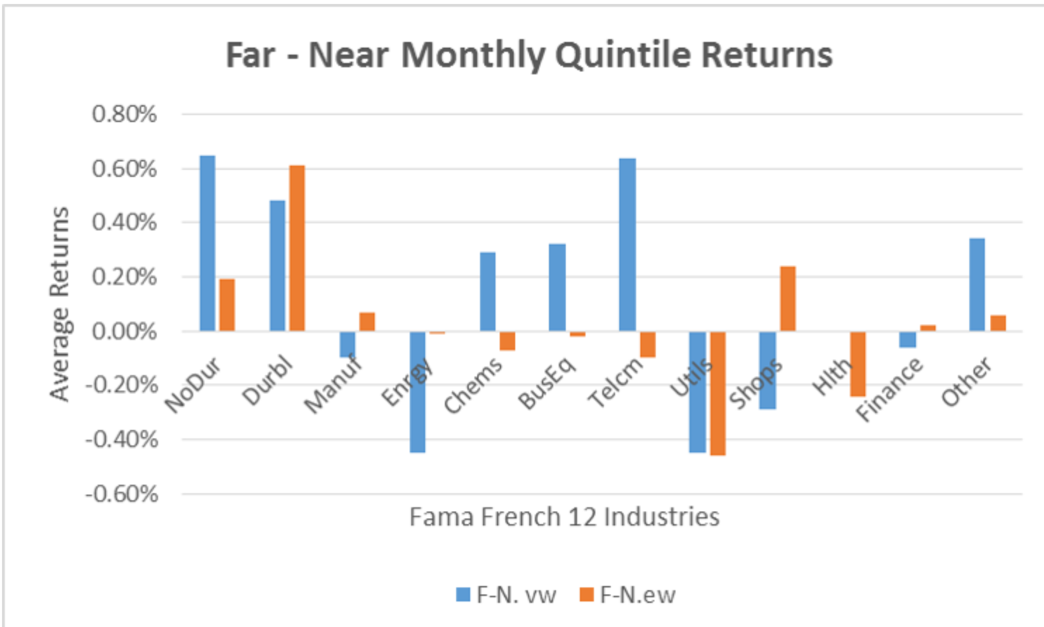


Figure 2.5: Far - Near Monthly Returns on Fama French 12 Industries

The bar charts show the average equal weighted and value weighted Far - Near portfolio returns on each of the Fama French 12 industries. Portfolios are formed on the quintile breaks of the equal weighted interconnectedness measure. The equal weighted interconnectedness (IntEW) is the average of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is computed within each of the Fama French 49 industries, at the end of every month. The returns are computed from April 1995 to December 2014, whereas the entire data used to construct the interconnectedness is from April 1991 to December 2014.

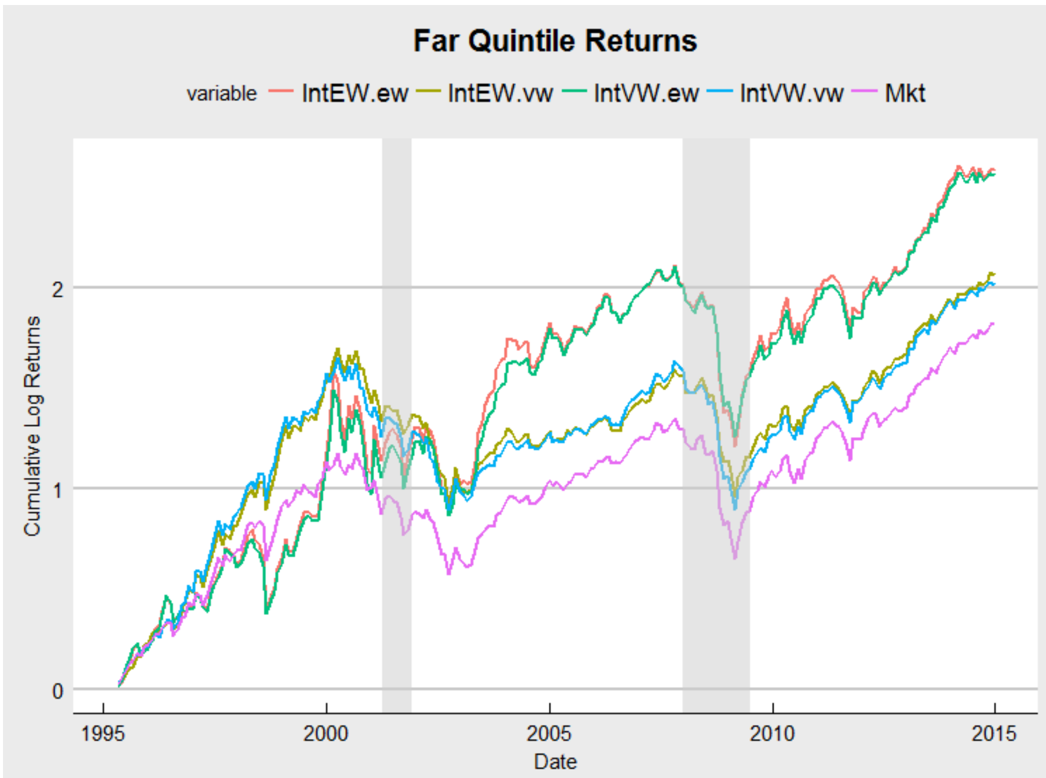


Figure 2.6: Far Quintile Monthly Returns

Figure shows the cumulative log returns of the equal weighted and value weighted Far portfolio returns based on the quintile equal weighted interconnectedness measure (IntEW.ew and IntEW.vw), and time series of portfolio returns based on the quintile value weighted interconnectedness measure (IntVW.ew and IntVW.vw). Market portfolio returns (Mkt) include all NYSE, AMEX, and NASDAQ firms. The time frame of the returns is from April 1995 to December 2014.

Table 2.10: Summary Statistics on Interconnectedness

Panel A shows the summary statistics of the equal-weighted portfolio returns formed on quintile interconnectedness and Panel B presents the results for value-weighted portfolio returns. r, Vol, Skew, Kurt, Average Int stand for monthly average returns, volatility, skewness, kurtosis, and average interconnectedness measure for each quintile, respectively. The analysis is from April 1995 to December 2014, whereas the entire sample of data to construct the signal is from April 1991 to December 2014.

Panel A: Equal-Weighted Porftolios

	r	Vol	Skew	Kurt	Average Int
Near	0.0112	0.044	-0.69	4.34	1.27
2	0.0123	0.047	-0.74	3.06	1.72
3	0.0124	0.049	-0.64	1.82	2.02
4	0.0137	0.056	-0.31	1.18	2.38
Far	0.0135	0.072	0.18	2.47	3.30
F-N	0.0023	0.054	1.51	10.49	

Panel B: Value-Weighted Portfolios

	r	Vol	Skew	Kurt	Average Int
Near	0.0083	0.040	-0.69	1.66	1.27
2	0.0101	0.046	-0.52	2.22	1.72
3	0.0086	0.047	-0.78	1.86	2.02
4	0.0085	0.050	-0.65	1.25	2.38
Far	0.0099	0.048	-0.43	0.22	3.30
F-N	0.0016	0.040	0.01	2.78	

Table 2.11: Conditional Double Sorting on Interconnectedness and Size

Panel A presents the average equal weighted monthly returns formed on sorting first on interconnectedness and then on size. The breakpoints are chosen at the quintile level for both dimensions of sorting. Panel B shows the average equal weighted monthly returns of the conditional sort of interconnectedness and default risk. The interconnectedness measure, here, is the average of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is computed within each of the Fama French 49 industries, at the end of every month. I estimate the Fama French 3 factor loadings for every firm that has the returns of the past 60 months, at the end of every month. The sample covers April 1991 to December 2014.

Panel A: Dependent-sort on Interconnectedness | Size

	Small	2	3	4	Large
Near	0.0131	0.0115	0.0116	0.0104	0.0095
2	0.0141	0.0114	0.0126	0.0123	0.0109
3	0.0173	0.0131	0.0138	0.0113	0.0100
4	0.0175	0.0131	0.0137	0.0120	0.0100
Far	0.0176	0.0144	0.0128	0.0104	0.0116
F-N	0.0045	0.0029	0.0012	-0.0001	0.0021

Panel B: Dependent-sort on Interconnectedness | Default Risk

	Safe	2	3	4	Distressed
Near	0.0107	0.0114	0.0118	0.0128	0.0114
2	0.0104	0.0113	0.0123	0.0134	0.0134
3	0.0117	0.0113	0.0129	0.0162	0.0152
4	0.0114	0.0117	0.0110	0.0153	0.0152
Far	0.0112	0.0118	0.0119	0.0162	0.0140
F-N	0.0004	0.0004	0.0000	0.0034	0.0026

Table 2.12: Fama French 5-Factor Regressions

Panel A outlines Fama French 5 factor regression results of equal weighted portfolio returns formed on quintiles of equal weighted interconnectedness measure. The interconnectedness measure, here, is the average of the Euclidian distances of the Fama French 3 factor loadings of a less distressed firm from all the factor loadings of the firms in the most distressed decile. The measure is computed within each of the Fama French 49 industries, at the end of every month. I estimate the Fama French 3 factor loadings for every firm that has the returns of the past 60 months, at the end of every month. Portfolios are formed on quintiles of interconnectedness of the less distressed firms. Panel B repeats the same procedure focused on value weighted portfolios by market capitalization. The sample covers April 1991 to December 2014. The t-statistics are computed using the Newey-West (1987) method with 6 lags accounting for autocorrelation.

Panel A: Equal-Weighted Portfolios

		FF5 alphas and factor loadings					
	r^e	α_{FF5}	$Mk-Rf$	SMB	HML	RMW	CMA
Near	0.0091	-0.0003	0.8489	0.5385	0.4371	0.3267	0.0815
	(3.18)	(-0.27)	(29.69)	(14.66)	(9.18)	(6.52)	(1.25)
2	0.0101	0.0008	0.9346	0.5533	0.4328	0.2893	-0.0479
	(3.33)	(0.83)	(39.33)	(18.13)	(10.94)	(6.95)	(-0.89)
3	0.0103	0.0020	0.9227	0.5963	0.2797	0.1543	-0.1229
	(3.22)	(1.92)	(34.73)	(17.47)	(6.33)	(3.32)	(-2.03)
4	0.0115	0.0043	0.9306	0.6300	0.1203	-0.1333	-0.0534
	(3.18)	(3.41)	(28.45)	(14.99)	(2.21)	(-2.33)	(-0.72)
Far	0.0114	0.0059	0.9404	0.7582	-0.1368	-0.6047	0.0039
	(2.44)	(3.76)	(23.00)	(14.44)	(-2.01)	(-8.45)	(0.04)
F - N	0.0023	0.0062	0.0915	0.2197	-0.5739	-0.9313	-0.0776
	(0.66)	(3.22)	(1.83)	(3.42)	(-6.89)	(-10.62)	(-0.68)

Panel B: Value-Weighted Portfolios

		FF5 alphas and factor loadings					
	r^e	α_{FF5}	$Mk-Rf$	SMB	HML	RMW	CMA
Near	0.0062	-0.0032	0.9078	0.1199	0.1590	0.4118	0.3912
	(2.40)	(-2.81)	(30.66)	(3.15)	(3.23)	(7.94)	(5.80)
2	0.0079	-0.0011	1.0218	0.0150	0.4360	0.3547	-0.0214
	(2.64)	(-0.97)	(35.25)	(0.40)	(9.04)	(6.99)	(-0.32)
3	0.0064	-0.0016	1.0471	-0.0355	0.1707	0.2152	0.0260
	(2.13)	(-1.53)	(37.75)	(-1.00)	(3.70)	(4.43)	(0.41)
4	0.0064	-0.0005	1.0693	-0.1088	0.0377	0.0499	-0.0484
	(1.98)	(-0.48)	(38.85)	(-3.08)	(0.82)	(1.03)	(-0.77)
Far	0.0077	0.0028	0.9532	-0.2435	-0.2627	-0.1621	0.1404
	(2.47)	(2.42)	(31.36)	(-6.24)	(-5.19)	(-3.04)	(2.03)
F - N	0.0016	0.0060	0.0454	-0.3634	-0.4217	-0.5739	-0.2508
	(0.61)	(3.15)	(0.91)	(-5.69)	(-5.10)	(-6.59)	(-2.21)

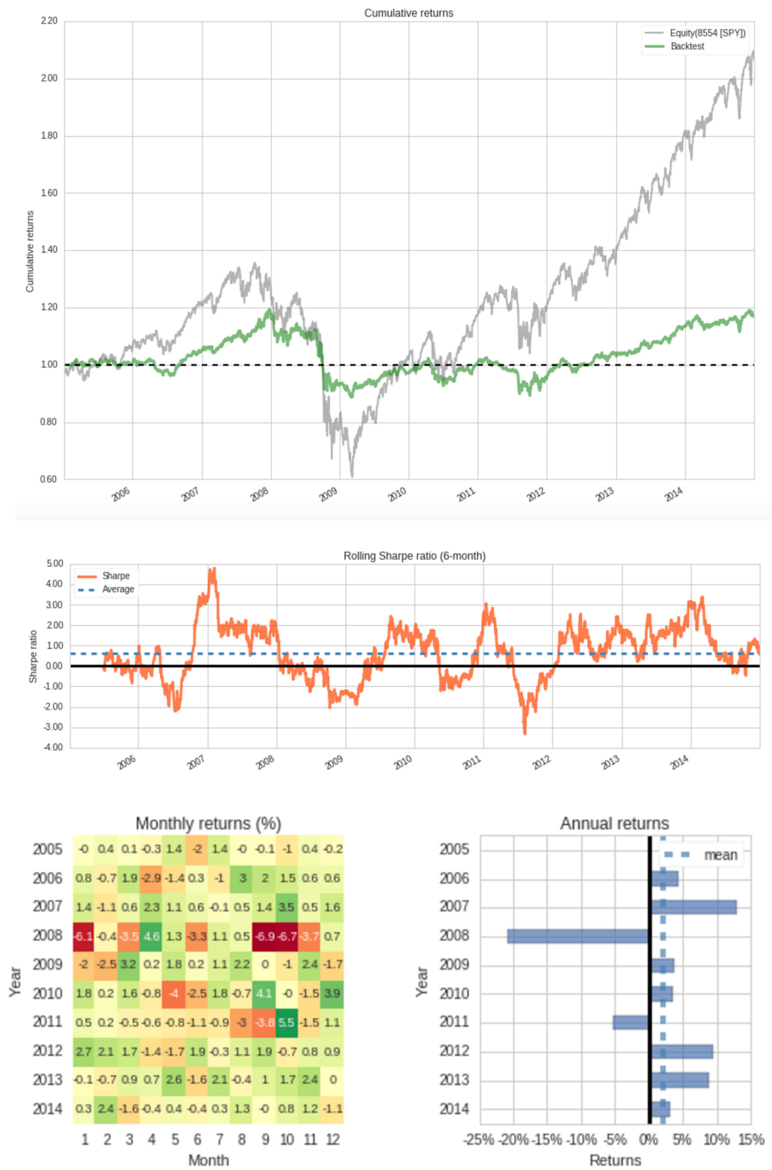


Figure 2.7: Far-Near Portfolio Backtesting on Quantopian

The graphs show the backtesting results of the value-weighted Far-Near portfolio on Quantopian on firms with market cap above 1 billion, using minute-level data from January 2005 to December 2014. Top figure shows the cumulative returns on an arithmetic scale, middle figure plots the 6-month rolling Sharpe ratio, and bottom one shows a summary of the individual monthly and yearly returns.

Table 2.13: Top 10 Far and Near Positions of All Time

Panel A shows the top 10 long positions of all time in the Far portfolio based on the Quantopian backtest from January 2005 to December 2014. Panel B shows the top 10 short positions of all time in the Near portfolio for a similar period. The Far-Near backtest strategy is a value-weighted strategy focused on firms with market capitalization above 1 billion, and orders are filled with limit orders, in which the previous closing trading price is entered as a limit order.

Pane A: Top 10 long positions of all time		
Ticker	Max (%)	Size (billions)
GE	16.62	217.66
XOM	14.49	324.44
WMT	12.95	234.11
PG	12.60	235.95
AAPL	11.94	847.61
MSFT	11.84	563.18
JNJ	8.63	351.68
IBM	7.99	134.27
T	7.75	230.13
PFE	6.91	202.24

Panel B: Top 10 short positions of all time		
Ticker	Max(%)	Size (billions)
BAC	8.71	254.16
KO	6.82	195.27
IBM	6.66	134.27
PG	5.65	235.95
PEP	5.65	165.13
MO	5.16	121.91
HPQ	4.98	32.34
WFC	4.19	253.01
WB	3.71	23.72
UTX	2.95	94.19

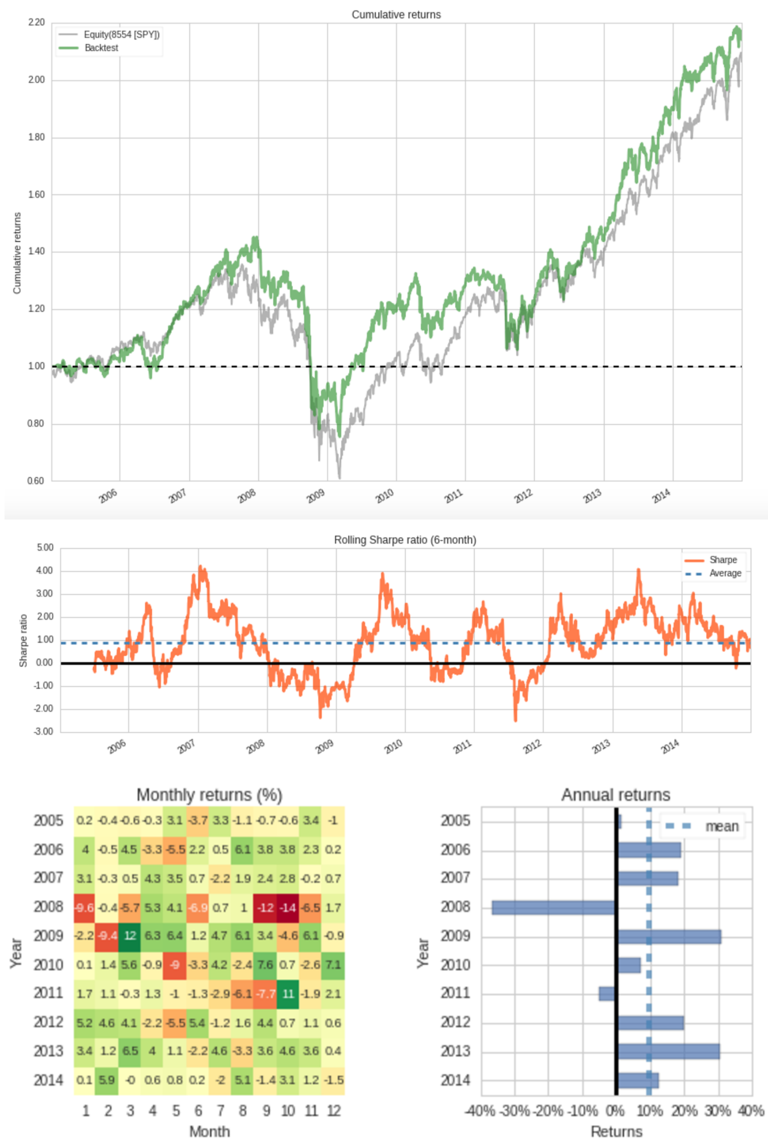


Figure 2.8: Far Portfolio Backtesting on Quantopian

The graphs show the backtesting results of the value-weighted Far portfolio on Quantopian on firms with market cap above 1 billion, using minute-level data from January 2005 to December 2014. Top figure shows the cumulative returns on an arithmetic scale, middle figure plots the 6-month rolling Sharpe ratio, and bottom one shows a summary of the individual monthly and yearly returns.

CHAPTER 3

DEFAULT RISK AND INFORMED TRADING: EVIDENCE FROM THE CDS MARKET

3.1 Introduction

In this paper, we empirically investigate the relationship between default risk and informed trading in the context of credit default swap (CDS) market. Building upon the fact that CDSs are traded in over-the-counter markets which are illiquid (relative to the corresponding names being traded in equity markets) and contain a high degree of information asymmetry, we argue that the level of informed trading may affect how fundamentals (which in the case of CDSs, consist primarily of default risk) are reflected in the pricing of these instruments. A number of possible priors motivate our study of this topic. For instance, when there are high distress risk events, the price impact on CDSs should be a function of the level of informed trading, which we find to be broadly true. Following on from this, higher levels of informed trading may be reflected in higher future default risk, which we find to be true only at shorter maturities. We investigate this and a number of related hypotheses in an attempt to understand the role of market microstructure phenomena on the pricing of credit derivatives.

CDS markets provide a uniquely suitable environment to study the joint dynamics of informed trading and default risk on the pricing of assets for a number of reasons. Specifically, the CDS market has key advantages over equity and bonds markets in this respect.

First, the price of a firm's CDSs is tied to its fundamental default risk in a way that the price of its equity is not. In the literature, there have been several studies on the link between informed trading and equity returns, such as Easley, Hvidkjaer, and O'Hara (2002). However, the complex nature of the risk exposure of a firm's equity means that any inference on the link between default risk and informed trading may be confounded. In contrast, CDS spreads are inherently linked to the default risk of a firm both theoretically (Duffie and Singleton (2003)) and empirically (Longstaff, Mithal, and Neis (2005)), and thus provide a more suitable environment in which to investigate this relationship. As noted by Acharya and Johnson (2007), "the nature of private information (the likelihood of default), is unambiguous".

Second, speculative trading has been shown to concentrate in CDS markets as compared to hedging activities which take place in both bond and CDS markets (Oehmke and Zawadowski (2016)). To the extent that we are interested in informed trading, it seems more suitable to study CDS markets, which provide a standardization and liquidity role.

Our baseline prior regarding the relationship between default risk and informed trading, and its effect on CDS pricing derives from the argument that CDS implied default probabilities do not provide reliable estimates for the actual default probability of a firm (Jarrow (2012)). The logic relies on the fact that CDS spreads not only reflect the true default risk of the firm, but also reflect the impact of risk premium, counterparty risk, market frictions, and strategic trading. Through an analogy to life insurance, Jarrow (2012) shows that the presence of transaction costs (e.g. bid-ask spreads) causes equilibrium spreads to deviate systematically from the true default probability. He also argues that in illiquid markets where the competitive market assumption does not hold, strategic trading (such as by informed traders), can lead to market prices deviating from true default probabilities.

In order to obtain directional predictions on how informed trading and default risk are likely to affect CDS pricing in the presence of such frictions, we turn to market microstructure models which explicitly endogenize such phenomena.

First, unconditionally, higher degree of informed trading should lead to higher transactions costs (bid-ask spread) and higher quoted CDS spreads. The logic follows that of Easley, Kiefer, and O'Hara (1997a), wherein the market maker charges a positive spread in response to facing an adverse selection problem. The competitive, risk-neutral market maker must balance losses made by transacting against informed traders (who only buy when they are privately informed of good news and only sell when they are privately informed of bad news), with gains made by transacting against uninformed liquidity traders to satisfy the zero-profit condition.

Second, when default risk is higher, we conjecture that the informational advantage of informed traders is diminished and the value of private signal reduces. The Easley, Kiefer, and O'Hara (1997a) model would predict that this diminishes the adverse selection problem of the market maker and thus spreads would be at the margin, lower for a given level of informed trading.

Third, by reducing the market maker's fundamental uncertainty, higher levels of default risk may lead to a decreasing relationship between informed trading and CDS spreads. This effect may be the result of market-maker risk-aversion as in Subrahmanyam (1991) (where the presence of a risk-averse market maker can generate a non-monotonic relationship between informed trading and liquidity, and as a result, prices), or with a risk-neutral market maker in the presence of information asymmetry as in Copeland and Galai (1983).

Fourth, over shorter horizons, default risk is likely to be affected more by idiosyncratic factors, increasing the value of informed traders' private signals. Thus, informed trading should predict default risk. Acharya and Johnson (2007) present evidence that is broadly consistent with trading based on non-public information in credit derivatives markets, and document significant incremental information revelation surrounding negative credit events. In particular, they show that information revelation occurs prior to adverse shocks, which would generate predictable relationship between informed trading and default risk. At longer horizons, market efficiency considerations imply that non-public information is likely to be incorporated into prices, which in turn feed into default risk estimates, and thus the variation in these estimates should be predominantly due to systematic factors. Thus, the predictive relationship between informed trading and default risk found at shorter horizons should no longer exist.

Finally, based on the short horizon predictive relationship between informed trade and default risk, and the empirically documented low distress risk anomaly of Campbell, Hilscher, and Szilagyi (2008), we expect a portfolio which buys low default risk and low informed trading stocks, and sells high default risk and high informed trading stocks to generate significantly positive abnormal returns and alphas. The reasoning behind this is as follows. At shorter horizons, higher informed trading predicts higher default risk as discussed above. Further, as documented in Campbell, Hilscher, and Szilagyi (2008), low distress risk stocks earn anomalously higher returns than high distress risk stocks. Thus, stocks with low default risk and low levels of informed trading are likely to have low levels of future default risk, and stocks with high default risk and high levels of informed trading are likely to have high levels of future default risk. A portfolio which buys stocks in the former category, and sells stocks in the latter category, thus should earn positive returns associated with the excess returns earned by low distress risk stocks as compared to high distress risk stocks.

Our analysis proceeds in three steps. First, we use panel regression techniques to characterize the cross-sectional determinants of CDS spreads using daily quotes data for 520 of the most actively-traded single-name non-sovereign CDSs. We find robust evidence of a positive unconditional effect of informed trading on CDS spreads, and a negative marginal effect of informed trading on spreads conditional on higher default risk, even after controlling for factors known to affect spreads and liquidity. Motivated by our theoretical priors and cross-sectional evidence, we use a vector-autoregression framework to analyze the time-series dynamics of informed trading and default risk for our sample of firms, and find that for shorter maturities, default probability leads informed trading, while at longer maturities, informed trading leads default probability, consistent with market efficiency at longer horizons. Finally, we develop an investment strategy based on the empirical results on the joint dynamics of informed trading and default risk that we establish in the first two parts. As conjectured, a long-short portfolio consisting of low PIN low default probability stocks minus high PIN high default probability stocks generates average daily excess returns of 0.13%, and average daily Fama-French 3-factor alpha of 0.17%, with a Newey-West t-statistic of 4.86.

3.1.1 Literature Contribution

A number of prior studies have investigated market microstructure issues in the context of CDS markets. Acharya and Johnson (2007) investigate insider trading in credit derivate markets. Using the equity market as a benchmark for public information, they find incremental information revelation in credit derivatives markets through the trades of informed parties (here banks). They, however, conclude that the there is no evidence that the degree of asymmetric information adversely affects prices or liquidity in either equity or credit markets. Our findings run counter to this, as we find that informed trading (proxied by PIN), has a non-monotonic effect on quoted spreads as a function of default risk, increasing spreads unconditionally, while having a negative marginal effect as default risk increases.

Several studies have modeled cross-market information flows between CDS markets and equity and bond markets using vector autoregressive frameworks (Hotchkiss and Ronen (2002), Blanco, Brennan, and Marsh (2005), Norden and Weber (2004), and Longstaff, Mithal, and Neis (2005)). The second part of our analysis relates to this stream of literature. In our paper, however, we use a VAR model to characterize the joint dynamics of PIN and default risk, and not market prices/price impacts of CDSs. Our cross-sectional analysis shows that CDS quoted spreads are affected not only by default risk, but also by liquidity and informed trading. Thus, by modeling the lead-lag relationship of PIN and default risk, we are able to determine the extent to which default risk reflects the private information of informed traders.

In a recent paper, using detailed CDS trading and position data, Oehmke and Zawadowski (2016) characterize trading behavior in CDS markets and find that

CDS markets serve as an alternative trading venue for bond investors. Their results show that while trading volume in both bond and CDS markets is associated with hedging motives, speculators are more likely to concentrate in CDS markets particularly for bonds traded in more fragmented and complex issues.

Our paper adds to the literature by determining the relative contribution of informed trading and default risk in explaining time-series and cross-sectional variation of quoted CDS spreads. Through our analysis, we find a non-monotonic relationship between informed trade and spreads as a function of default risk. We also analyze the time-series relationship between informed trading and default risk, to determine the extent to which private information is embedded into default risk estimates. Finally, we develop a trading strategy that exploits the predictive relationship between PIN and DP at the 1 year horizon, and find that it generates significant excess returns and alphas.

3.2 Data and Methodology

In this section, we summarize the data sources used in our empirical analysis, describe the sample selection and variable construction process, and outline the methodology used in the three parts of our main analysis.

3.2.1 Data Sources and Sample Selection

We utilize several proprietary datasets in our analysis. We obtain CDS market data from Markit, who provide daily composite quoted spreads based on market makers' official books of record, live quotes and clearing submissions and results. This dataset has been used in a number of prior studies on CDS markets including Acharya and Johnson (2007), Jarrow, Li, and Ye (2015), and Oehmke and Zawadowski (2016). We also obtain implied ratings, recovery rates, and other contractual details from the Markit dataset. We apply the same filters as Jarrow, Li, and Ye (2015), starting with the entire sample of US Dollar denominated single-name CDS contracts on non-sovereign entities, over the sample period 2003-2010 during which we have CDS data available. We focus on US corporate entities with publicly traded equity on US stock exchanges, in order to have market and accounting data available for constructing our proxy for informed trading and other control variables. We restrict our sample further to only CDS contracts written on senior unsecured issues with modified restructuring (MR) clauses, in order to obtain a sample of the most representative traded contracts in the US market. We further restrict our sample to those with complete data coverage, in particular, considering only names with above 90% non-missing observations for the 5-year maturity CDS quoted spread.

While this data completeness requirement is needed to ensure our models can be estimated, and statistically valid inferences can be drawn, it also raises the concern of sample selection bias. The presence of a more complete set of quoted spreads can be plausibly related to a contract being more liquid and more frequently traded. The relationship between liquidity and informed trading is one of the most well-studied in the field of market microstructure (starting with the seminal work of Easley, Kiefer, O'Hara, and Paperman (1996), followed by several applications including Easley, Hvidkjaer, and O'Hara (2002)). Given that informed trading is one of the two key factors we are studying in the context of CDS markets (the other being default risk), naturally the issue of selection into the sample on the basis of liquidity is one that could be concerning. Notwithstanding, we argue that this is unlikely to have a detrimental effect on our study for two reasons. First, by considering only the most liquid CDS contracts, we are in some senses abstracting away from the confounding effect of the CDS market as a whole being highly illiquid (Jarrow, Li, and Ye (2015)), which could materially affect our model estimation and our results. Second, crucially even amongst the sample of these most liquid contracts, we are able to observe substantial heterogeneity in informed trading. For instance, in Figure 3.1 we plot summary statistics of the distribution of the probability of information-based trade (or PIN) across the firms in our sample, split by implied ratings class, and observe a significant degree of variation.

[Figure 3.1 about here]

Our eventual sample consists of daily observations on 520 firms from January 2003 to December 2010, for which we observe quoted CDS spreads for maturities of 1, 2, 3, 5, 7, 15, 20, and 30 years. For the bulk of our analysis, we use the 5 year maturity contracts for each firm, since these are the most frequently traded, however for robustness we also consider 1 and 10 year maturities.

Monthly default probability estimates are obtained from Kamakura Default Probabilities (KDP) dataset from Kamakura Corporation[1]. The probabilities are estimated by Kamakura monthly, using data up to the prior month.We obtain estimates for all 520 US publicly traded firms which meet the sample construction criteria described above. The KDP dataset contains monthly estimates for probability of default within the next 1 year, within the next 5 years conditional on not defaulting in the next 1 year, and within the next 10 years conditional on not defaulting in the next 5 years. For our main analysis, to match the maturity

[1]We are grateful to Kamakura Corporation for providing us with the data. More details can be found at this link.

of the most frequently traded CDS contracts for these firms, we use the 5 year default probability estimates. However, for robustness we also consider the 1 and 10 year estimates to match with the 1 and 10 year maturity CDSs.

While the exact model used is proprietary, the Kamakura Default Probabilities (KDPs) used in our sample are calculated using the Chava-Jarrow model (from Chava and Jarrow (2004)). The Chava-Jarrow model is estimated using explanatory variables which include firm financial ratios, other firm attributes, industry classification, interest rates, macroeconomic factors, and information about firm and market equity price levels and behavior. In this model, firm default can occur randomly at any time with an intensity determined by the explanatory variables. As an example of the industry-wide view of the relative accuracy of this class of models model, The Federal Deposit Insurance Corporation of the United States has been using the Chava-Jarrow model since 2003 to provide default estimates for its internal analysis for its funds. A large number of bank regulators around the world now subscribe to KRIS. Both the fourth and fifth generation Jarrow-Chava models incorporate multiple equations for forecasting default at different forward time intervals, conditional on survival to that point in time. These equations share the same inputs but they have different weightings depending on the time horizon. Since they are the industry leading default probability estimates, we can argue that they represent a reasonable proxy for a firm-level distress risk.

We obtain daily stock data (including daily closing bid, ask, closing price, holding period return, shares outstanding, and trading volume) from CRSP for the firms in our sample. We access quarterly accounting information for the firms in our sample from Compustat.

In order to construct our proxy for informed trading, the probability of information based-trade (PIN), based on the seminal structural model developed in a series of papers by Easley, Kiefer, and O'Hara (1996), Easley, Kiefer, and O'Hara (1997a), Easley, Kiefer, and O'Hara (1997b), and Easley, Kiefer, O'Hara, and Paperman (1996), we use intra-day transaction level data from the Trade and Quote (TAQ) dataset. We provide a brief overview of the PIN model and the estimation procedure in the next section.

3.2.2 Variable Construction

Probability of Information-Based Trade (PIN)

Having described one of the two key variables of interest, the default probability estimates from the KDP dataset, we now turn to our proxy for informed trading, PIN. As outlined in Easley, Hvidkjaer, and O'Hara (2010), PIN can be derived from a structural model in which a single competitive market maker faces two types of traders, informed and uninformed, who trade a single stock in continuous time, over discrete trading days $t = 1, ..., T$. Between two days, an information event can occur with probability α. This information event at date t can contain good news, that the stock is worth $\overline{V_t}$, with probability $(1 - \delta)$, or bad news, that the stock is worth $\underline{V_t}$, with probability δ. In this model, order arrival in any given day is described by a Poisson process, and the market maker observes order flow in order to set prices at which they buy or sell.

Naturally, informed traders with bad news sell, and informed traders with good news buy. Informed trading follows a Poisson process with arrival rate μ, while trading behavior of uninformed traders who trade for liquidity reasons, are characterized by independent Poisson processes with daily arrival rates ϵ_b and ϵ_s for buys and sells respectively. The market maker cannot distinguish whether an order comes from an informed trader or an uninformed trader. All they can observe is whether the order is a buy or a sell. Thus, the market maker must use Bayes Rule to infer the probability that a given order comes from an informed trader or an uninformed trader, and accordingly set bid and ask price at which they are willing to buy or sell the stock, in order to balance the losses that are inevitably made when transacting with the informed traders, against the gains made when transacting with the uninformed traders, in order to satisfy the zero-profit perfect competition condition. The market makers inference problem can be summarized in Figure 3.2, taken from Easley, Hvidkjaer, and O'Hara (2002).

[Figure 3.2 about here]

Given the assumption that arrivals follow independent Poisson processes, the authors show that this generates a likelihood function for the total number of buys and sells on a single trading day of

$$\mathcal{L}((B,S)|\theta) = \alpha(1-\delta)e^{-(\mu+\epsilon_b+\epsilon_s)}\frac{(\mu+\epsilon_b)^B(\epsilon_s)^S}{B!S!} + \alpha\delta e^{-(\mu+\epsilon_b+\epsilon_s)}\frac{(\mu+\epsilon_S)^S(\epsilon_B)^B}{B!S!} + (1-\alpha)e^{-(\epsilon_b+\epsilon_s)}\frac{(\epsilon_b)^B(\epsilon_s)^S}{B!S!} \tag{3.1}$$

where (B,S) is the total number of buys and sells for the day and $\theta = (\mu, \epsilon_b, \epsilon_s, \alpha, \delta)$ are the structural parameters described above. The likelihood function has a relatively straightforward interpretation. The first term represents the probability of having "good news", which in turn compounds the probability of having "news" and having "good news", $\alpha(1-\delta)$, followed by the Poisson probability of observing order flow made up of random buys and sells from uninformed traders, and only buys from informed traders. The second term represents the probability of having "bad news", which in turn compounds the probability of having "news" and having "bad news", $\alpha\delta$, followed by the Poisson probability of observing order flow made up of random buys and sells from uninformed traders, and only sells from informed traders. The final term represents the probability of having "no news", $(1-\alpha)$, followed by the Poisson probability of observing order flow made up of only random buys and sells from uninformed traders, as informed traders have no incentive to trade without any information, as it costs them the spread.

By assuming independence of arrival of the information event across days, and independent and identical distribution of the parameters governing the Poisson trading process across days conditional on information events, the likelihood function for T days is simply the product of the above function. We estimate the model parameters using maximum likelihood. We classify trades into buys and sells using the Lee-Ready algorithm (Lee and Ready (1991)), and use the estimated volume of buys and sells as inputs into the maximum likelihood estimation for each stock in our sample of 520 for each quarter in our sample period (this is the shortest time period for which we can obtain reliable estimates), giving us a panel of quarterly estimates for the structural variables $\theta = (\alpha, \delta, \mu, \epsilon_b, \epsilon_s)$. We use these parameter estimates to compute quarterly estimates of PINs using the following expression:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s} \tag{3.2}$$

which can be interpreted as the share of total order flow that can be attributed to informed traders.

In addition, we construct a proxy for liquidity in order to control for this confounding effect. We compute the measure of illiquidity defined by Amihud

(2002) as:

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{DVOL_{i,t}} \tag{3.3}$$

where $r_{i,t}$ is the daily stock return for stock i, for day t, and $DVOL_{i,t}$ is the dollar volume for stock i for day t.

One major caveat to our analysis is that we use PIN calculated from equity market data, but extrapolate it to CDS markets. The reason behind this is simply data availability – we lack trading data in CDS markets, and thus are unable to estimate PIN. However, the extrapolation of equity market PIN to CDS markets may not be entirely unreasonable for the following reasons.

First, informed traders may prefer to trade in CDS markets than in stock markets as the risk of detection in equity markets is higher due to surveillance by regulatory authorities, and well defined and severe penalties for trading on non-public information (Acharya and Johnson (2007)). The legal precedent for insider trading in other markets (e.g. CDS markets) is not as clear. For instance, Thomas Newkirk, then the Associate Director of Enforcement at the SEC noted that "the classical theory of insider-trading applies only to shares (equity) because it rests on the fiduciary relationship between company officers and shareholders... the courts take the view that it's not the same relationship with bondholders", in reference to allegations of insider trading in bond markets prior to Marvel filing for Chapter 11 bankruptcy[2]. Certainly, a similar logic can be applied to credit derivatives.

Second, in over-the-counter markets, transactions costs tend to be inversely proportional to trade size, as opposed to in equity markets where they tend to

[2]Linda Sandler, "Angry traders say sale of Marvel junk bonds highlights different rules in non-stock cases", *The Wall Street Journal*, December 9, 1996

be directly proportional. Thus, it may be optimal for large informed trades to be executed in bond or CDS markets as compared to equity markets. While we proceed with this assumption, we also note that access to CDS trade data would allow us to determine whether this assumption is valid.

Finally, we compute several quarterly control variables from Compustat including profitability (revenues minus cost of goods sold, scaled by total assets), leverage ratio, book-to-market ratio, and market capitalization (both in logs, following the convention of the literature).

3.2.3 Cross-Sectional Analysis

First, we present summary statistics of the key variables of interest in Table 3.1 which shows sufficient variation in PIN. This justifies the argument made previously that sample selection bias is not likely to be an issue.

[Table 3.1 about here]

To further explore this, we plot the distribution of PIN by ratings class in Figure 3.1. We see that higher-risk proxied credit ratings classes are associated with a higher mean level of PIN. Additionally, the distribution of PIN by ratings class exhibits greater variance as we move to riskier credit ratings. For instance, the distribution of PIN amongst CCC rated firms appears to be more disperse than that of AA rated firms, and far fewer firms are estimated to have PIN equal to 0.

Second, the purpose of our cross-sectional analysis is to establish the role played by default risk and informed trading in jointly determining quoted CDS spreads. In order to test this, while to the greatest extent possible minimizing the effect of confounding variables on our inferences, we estimate a panel regression model with fixed effects. Specifically, we run the following regression at the firm-day level:

$$spread_{i,t} = \beta_1 X_{i,t} + \beta_2 DP_{i,t} + \beta_3 X_{i,t} \times DP_{i,t} + Controls + FEs + \epsilon_{i,t} \tag{3.4}$$

where *spread* refers to the quoted CDS spread (in most specifications, for the 5-year maturity contract), X refers to the proxies for informed trading and illiquidity i.e. $X \in \{PIN, Illiq\}$, DP refers to the estimate of default probability (in most specifications, at the 5-year horizon), and *Controls* include proportional bid-ask spread, size, book-to-market, and profitability. In addition, for all specifications we include day fixed effects to control for market-wide shocks. Further, we include estimates from three versions of the model, with firm fixed effects, industry fixed effects, and ratings fixed effects. This enables us to estimate the relevant effects within firm or within industry or within ratings class, and controls for any unobserved, time-invariant, firm-, industry-, and ratings-class level heterogeneity. Following Petersen (2009), we double cluster standard errors at the industry-month level. This ensures that our inferences are valid in the presence of heteroskedasticity and standard errors that are correlated across firms within an industry and across days within a month.

The coefficients of interest are β_1 and β_3. We expect β_2 to be significantly positive in all specifications, as higher probability of default, all else equal, would lead to higher CDS spreads. The coefficient β_1 identifies the marginal effect of informed trading on CDS spreads, and the coefficient β_2 identifies the interaction effect of default risk and informed trading. Per our hypotheses, we expect β_1 to be positive and β_3 to be negative, suggesting that CDS spreads are increasing in PIN, though at the margin, decreasing in PIN as default risk increases. In other words, we hypothesize that default risk and informed trading exhibit a substitution effect in terms of their impact on CDS spreads - higher levels of default risk are associated with a negative effect of informed trading on spreads and vice versa.

3.2.4 Time-Series and Portfolio Analysis

In order to further explore the joint dynamics of informed trading and default risk, we estimate vector autoregression (VAR) models for each of the 520 firms in our sample, with 3 specifications. In each specification, one of the variables is PIN, while the other variable is either $DP1$, $DP5$, or $DP10$. In each case, we estimate the following VAR(1) specification:

$$\begin{bmatrix} PIN_{t+1} \\ DP_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix} + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} PIN_t \\ DP_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \tag{3.5}$$

for each of the 520 firms in our sample. Our estimation of the covariance matrix of the errors allows for heteroskedasticity and an arbitrary correlation structure.

In the final part of our analysis, we examine the implications of the joint dynamics between informed trading and default risk on equity market returns. We double-sort our sample of 520 firms into decile portfolios based on prior quarter default probability and conditional on this, into quintile portfolios based on prior quarter PIN. We track the returns of these portfolios over the sample period 2003-2010. In addition, we form a long-short investment strategy that buys low *PIN* low *DP* stocks and sells high *PIN* high *DP* stocks, and compute its excess returns and abnormal performance relative to the Fama-French 3-factor model benchmark.

3.3 Cross-Sectional Results

In Table 3.2, we report results for our panel regression analysis. Columns (1) through (4) contain estimates from pooled OLS regressions without fixed effects. In columns (1) and (3) we consider the effect of illiquidity on 5-year CDS spreads, without and with controls respectively. The results suggest that in the cross-section, higher *Illiq* is associated with significantly higher CDS *spread* unconditionally. The cross-effect is negative, evident through significantly negative coefficient on the interaction term in both specifications. Thus, the marginal effect of *Illiq* on *spread* declines as default risk is higher. That is to say, during periods of higher default risk, higher *Illiq* decreases the *spread* rather than increases it. We find a similar substitution effect between default risk and informed trading in columns (2) and (4). While the unconditional effect of *PIN* on the CDS *spread* is to increase it, at the margin, the interaction term indicates that higher default risk is associated with a decreasing effect of *PIN* on *spread*.

[Table 3.2 about here]

This suggests that at higher degrees of default risk, there are two plausible mechanisms at play. First, the informational advantage of the informed trader diminishes at higher levels of default risk, reducing the adverse selection problem of market makers and hence diminishing the component of the quoted spread compensating the market for this adverse selection, at the margin decreasing the spread itself. This is broadly consistent with the intuition of Easley, Kiefer, and O'Hara (1997a). Second, it is also possible that the market maker themselves have less uncertainty about the fundamental probability of distress at higher levels of default risk, and hence the positive relationship between informed trade and spread is reversed (as in Subrahmanyam (1991)). The second interpretation requires some caution though, as the models that would generate this insight would have to assume risk-averse market makers, whereas PIN is computed under the assumption of market-maker risk-neutrality. Nevertheless, the empirical results are suggestive of a non-monotonic relationship between informed trading and CDS spreads, as a function of default risk.

Columns (5) through (10) contain results of the same regression estimated with fixed effects for day and industry/firm/ratings class. Fixed effects panel regressions allow us to address concerns that unobserved time- and entity (industry or firm or ratings class)-invariant heterogeneity is driving our results, by producing within-group estimates of the marginal effects. The results are supportive of the inferences drawn based on the pooled OLS regressions, as the unconditional coefficients continue to remain positively significant across most specifications, with the interaction terms remaining negatively significant across all specifications.

In Tables 3.3 and 3.4, we present results of panel regression coefficient estimates in subsamples of six ratings classes, ranging from AA to CCC. We find that results hold in general for higher ratings classes, whereas in the junk class (CCC), results seem to be reversed. While we have no clear explanation for this, we suspect that trading in junk-rated CDSs is materially different than in investment-grade ones, with a higher degree of speculative trading (as suggested in Oehmke and Zawadowski (2016)), and hence the underlying intuition and assumptions on trader and market maker behavior may not be appropriate.

[Table 3.3 about here]

[Table 3.4 about here]

In Table 3.5, we run our panel regression in subsamples of industries in order to check whether the effects found in the overall sample are heterogeneous. In columns (1) and (2) we exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999 respectively), and find that results continue to hold. In columns (3) and (4) we restrict our sample to only industrials, and find that results are reversed - this merits further investigation, but is beyond the scope of our current study.

[Table 3.5 about here]

3.4 Time-Series Results

In this section, we discuss results from our vector autoregression (VAR) analysis of the time-series dynamics of informed trading and default risk. In order to take advantage of the sample of 520 firms, we estimate our baseline VAR(1) model for each firm, for each horizon at which we have default probability estimates (1, 5, and 10 years). However, presenting results from 1,560 regressions in a way that is informative yet parsimonious, is a challenge. Thus, we have chosen to present summary statistics of the distribution of coefficient estimates obtained from the 1,560 iterations of model estimation across firms and default probability horizons. In the absence of a proper specification of the joint distribution of these test statistics, we are unable to determine overall statistical significance. However, our analysis does produce strongly suggestive non-parametric, directional results on the nature of the time-series relationship between *PIN* and *DP*.

In Table 3.6, we present the 5th, 20th, 50th, and 90th percentiles of coefficient estimates, and t-statistics, of our VAR(1) specification run on 520 firms for 1, 5, and 10 year horizons. We also report the percentage of t-statistics that exceed the critical values for 5% and 1% two-sided significance. The diagonal terms $\phi_{11,1}$ and $\phi_{22,1}$ represent the autoregressive coefficients of *PIN* and *DP* on their own lags. Results show that across all three maturities, both *PIN* and *DP* are highly persistent, with close to 100% of the t-statistics being above the threshold for 5% and 1% significance for *PIN* and over 96% and 88% of the t-statistics being above the threshold for 5% and 1% respectively for *DP*.

[Table 3.6 about here]

The off-diagonal terms $\phi_{12,1}$ and $\phi_{21,1}$ represent estimates of the lead-lag effect of lagged DP_t on lead PIN_{t+1}, and lagged PIN_t on lead DP_{t+1}. By examining these coefficients, some interesting patterns emerge. For the relatively shorter two maturities (1 and 5 years, represented by the first two panels), the effect of lagged PIN_t on lead DP_{t+1} seems to dominate the effect of lagged DP_t on lead PIN_{t+1}. For instance, in the case of 1 year, only 16.5% of the t-statistics for $\phi_{12,1}$ cross the threshold of 5% significance, while 48.7% of the t-statistics for $\phi_{21,1}$ cross the threshold of 5% significance. However, for the longer maturity of 10 years, the results are reversed, and the effect of lagged DP_t on lead PIN_{t+1} dominates the effect of lagged PIN_t on lead DP_{t+1}. Our interpretation of this is that at shorter maturities, the estimates of default probability are likely to be subject to a higher degree of idiosyncratic information, which gives an inherent advantage to informed traders who have access to private signals about the firm. Thus, at these horizons, the private signals of informed traders are likely to be informative about future default risk, and hence we find that higher degree of informed trading predicts higher future default probability. However, at longer horizons, private signals are likely to matter less for a firm's default risk. The dominant factors affecting default risk at the 10-year horizon would be related to the fundamental riskiness of the firm's cashflows and sensitivity to long-run macroeconomic factors. The informed traders' private signals are likely to be less informative about default risk, and hence informed trading follows, rather than leads default probability estimates.

In Table 3.7, we present VAR estimates of subsamples formed based on credit ratings class. As was the case in the cross-sectional analysis, our results from the whole sample generally hold in the investment-grade credit ratings classes, while they reverse in the junk class (CCC).

[Table 3.7 about here]

We formally test these hypotheses using Granger causality tests (Granger (1969)). Granger causality tests are formal hypothesis tests used in order to determine whether one time-series is useful in forecasting another. If prior values of one series are able to predict future values of another, then the first series is said to Granger cause the second. Granger causality, however, should not be confused with true economic causality. We remain silent on the question of economic causality as we are unable to isolate exogenous sources of variation in liquidity, informed trading, and default risk as they are all equilibrium outcomes. Rather, our correlational evidence is suggestive of the underlying economic mechanisms that we have discussed.

Nevertheless, the predictive inferences from the VAR models are confirmed by the Granger causality tests. The results in Table 3.8 show that for the 1 year maturity case, in 85.7% of cases, PIN Granger causes DP, while 55.6% of cases DP Granger causes PIN at the 5% significance level. For the 5 year maturity case, in 86.8% of cases, PIN Granger causes DP, while in 64.7% of cases, DP Granger causes PIN. However, in the 10 year case, in 69.4% of cases, PIN Granger causes DP, while in 84.2% of cases, DP Granger causes PIN.

[Table 3.8 about here]

In Figure 3.3 we plot the impulse response function based on the median estimates obtained from our VAR(1) specification for 1 year ahead DP and PIN. We estimate the impulse response with 12 leads, and the choice of the square root matrix of the VAR residuals is computed using the spectral decomposition (since there is no theoretical prior on the order). A shock to PIN causes a persistent positive effect on DP for the next 2 quarters, whereas a shock to DP causes a persistent but less positive effect on PIN over the same time horizon.

[Figure 3.3 about here]

Finally, in Table 3.9, we repeat the Granger causality analysis in subsamples by credit rating classes. We find that the whole sample results hold (in general) in the less risky, investment-grade credit ratings classes, while as before, they flip in the junk class (CCC). This is further suggestive evidence of substantially different trading behavior in this class as compared to others. We hope to investigate this further in future work with access to detailed CDS position and trading data.

[Table 3.9 about here]

3.5 Portfolio Results

Consistent with the idea that at shorter horizons, informed traders' private signals about default risk are more valuable, our time-series analysis results show a positive statistically significant predictive relationship between lagged PIN_t and lead DP_{t+1}. We also observe that in our sample, lower *DP* stocks earn significantly higher returns than higher *DP* stocks, evidence of the low distress risk anomaly put forward by the seminal work of Campbell, Hilscher, and Szilagyi (2008). This can be seen in Figure 3.4, where we plot the logarithm of cumulative returns of a trading strategy that is long the stocks in the lowest decile of 1-year *DP* and short the stocks in the highest decile of 1-year *DP*. As seen in the figure, this strategy earns significantly positive excess returns.

[Figure 3.4 about here]

In order to analyze the implications of these empirical facts on the equity returns of the firms in our sample, we sort them into 10 portfolios based on *DP* deciles, and then conditional on this, into 5 portfolios based on *PIN* quintiles. The mean daily excess return of each of these conditionally double-sorted portfolios is given in the first panel of Table 3.10. We find that in 7 out of 10 DP deciles, the high PIN portfolio earns higher returns than the low PIN portfolio (confirming the findings of Easley, Hvidkjaer, and O'Hara (2002)), and in all 5 of the PIN quintiles, the low DP portfolio earns higher returns that the high DP portfolio (confirming the findings of Campbell, Hilscher, and Szilagyi (2008)).

[Table 3.10 about here]

Taken together, these two empirical facts can be used to generate an investment strategy which buys stocks in the lowest decile of DP and lowest quintile of PIN, as these are expected to have low future DP (based on our VAR results), and sells stocks in the highest decile of DP and highest quintile of PIN as these are expected to have high future DP. Assuming the low distress risk anomaly of Campbell, Hilscher, and Szilagyi (2008) holds (and Figure 4 shows that it does in our sample), this strategy should generate positive excess returns and alphas as it is long low future DP stocks and short high future DP stocks.

The second panel of Table 3.10 provides the mean daily excess return of this strategy which is 0.13%, and the mean daily Fama-French 3-factor alpha is 0.17% (t-stat of 4.86, estimated using Newey-West heteroskedasticity and autocorrelation robust standard errors). Both are positive and the alpha is highly significant, as conjectured. Figure 3.5 plots the logarithm of the cumulative returns of this strategy. Thus, we find that the predictive relationship between PIN and DP found in our time-series analysis generates economically meaningful investment implications.

[Figure 3.5 about here]

3.6 Conclusions

Consistent with the notion that at higher levels of default risk, the private signals of informed traders have less value, thus reducing the adverse selection problem faced by the market maker, at the margin reducing the spread, we find a non-monotonic relationship between PIN and quoted CDS spreads as a function of probability of default. While unconditionally, higher PIN is associated with higher quoted CDS spreads, as predicted by models with market makers facing asymmetric information, conditional on higher default risk the marginal effect of *PIN* on spreads decreases. Our time-series analysis confirms that the private signal of informed traders is informative about future default risk, as lagged *PIN* predicts lead *DP*, but only at shorter horizons. Accordingly, an investment strategy that buys low *PIN* low *DP* stocks and sells high *PIN* high *DP* stocks, earns positive excess returns and alphas. Taken together, our results provide new insights into the joint dynamics of informed trading and default risk, and their implications on CDS spreads and equity returns.

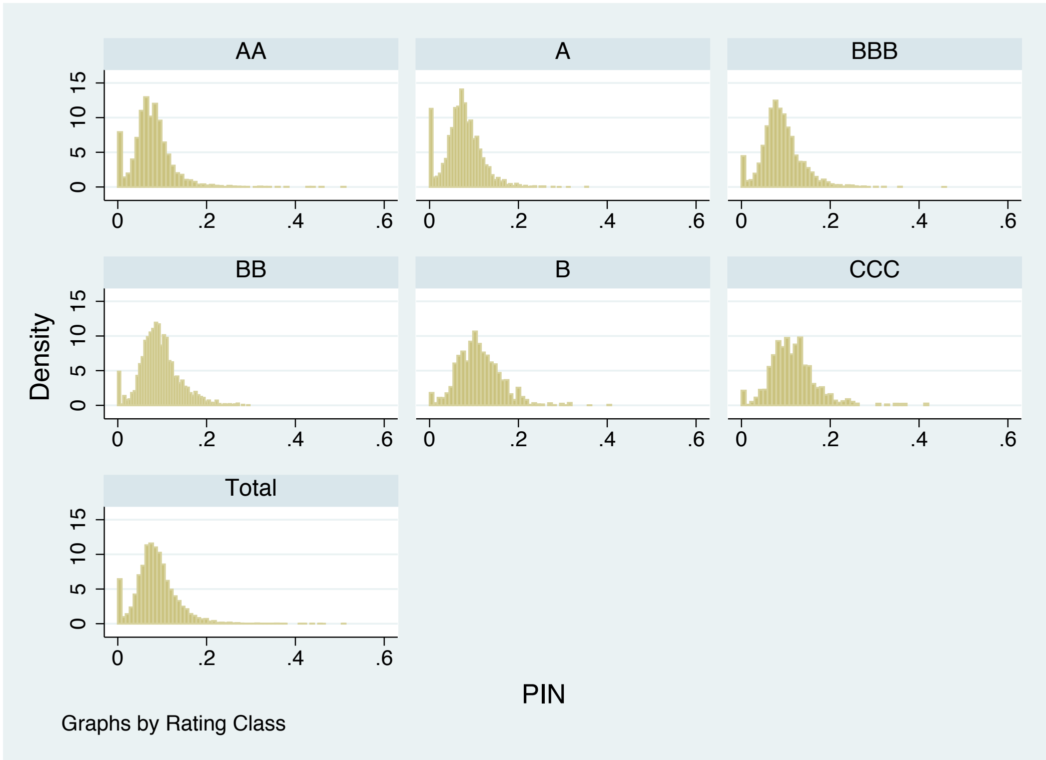


Figure 3.1: Histograms of PIN by Ratings Class

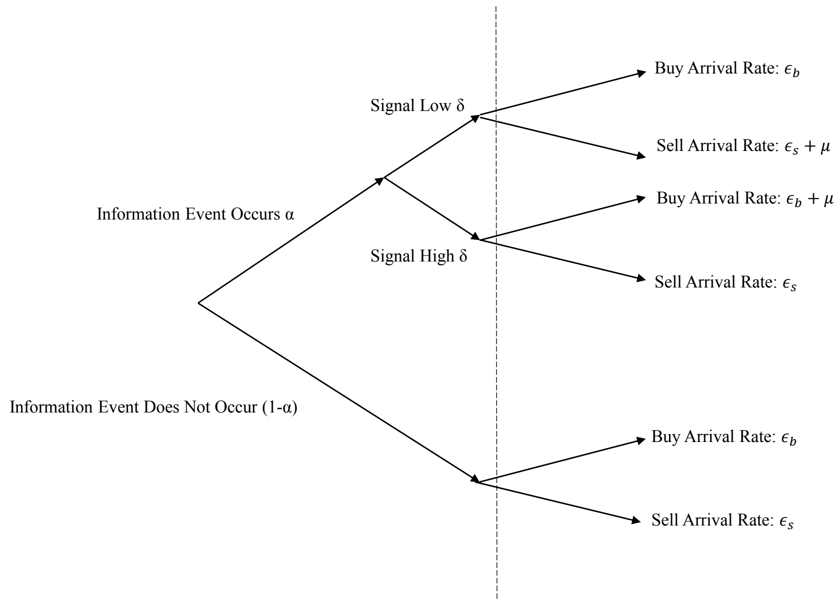


Figure 3.2: Tree Diagram of Trading Process

An information event between two days happens with probability α. It contains good news that the stock is worth $\overline{V_t}$ with probability $1 - \delta$ or bad news that the stock is worth $\underline{V_t}$ with probability δ. Informed trading order arrival follows a Poisson process with rate μ and uninformed trading buys and sells have rates of ϵ_b and ϵ_s, respecitvely.

Table 3.1: Summary Statistics of Key Variables

	N	$Mean$	Min	Max	$Std.Dev.$	$Skew$	$Kurt$	$25th$	$50th$	$75th$
$spread1y$	685357	0.620	0.000	240.640	2.929	31.092	1827.300	0.009	0.090	0.320
$spread5y$	685357	0.993	0.000	144.699	2.526	17.986	734.929	0.120	0.370	0.900
$spread10y$	685357	0.990	0.000	113.530	2.190	15.672	573.835	0.020	0.470	0.970
R	685354	0.001	-0.643	1.439	0.025	1.230	68.903	-0.009	0.000	0.010
$pspread$	685357	0.028	-0.412	1.499	0.025	7.037	155.947	0.014	0.021	0.032
PIN	685357	0.086	0.000	0.513	0.046	1.045	7.299	0.059	0.082	0.108
$DP1$	685357	0.321	0.000	67.824	1.666	15.249	345.879	0.008	0.033	0.126
$DP5$	685357	0.332	0.004	27.308	0.986	9.620	137.029	0.056	0.104	0.232
$DP10$	685357	0.625	0.028	36.852	1.593	7.705	89.297	0.111	0.200	0.446
$profit$	667277	0.067	-0.408	0.382	0.054	0.906	7.032	0.028	0.058	0.095
$log(mc)$	685357	15.772	9.049	20.083	1.402	0.125	3.282	14.840	15.663	16.680
$log(bm)$	684797	-0.819	-6.511	3.414	0.727	-0.749	7.052	-1.214	-0.772	-0.373
$Illiq$	685122	0.000	0.000	0.000	0.000	186.616	42203.300	0.000	0.000	0.000

Table 3.2: Whole Sample Cross-Sectional Results

We present coefficient estimates for the following regression $spread_{i,t} = \beta_1 X_{i,t} + \beta_2 DP_{i,t} + \beta_3 X_{i,t} \times DP_{i,t} + Controls + FEs + \epsilon_{i,t}$, where *spread* refers to the quoted CDS spread (in most specifications, for the 5-year maturity contract), X refers to the proxies for informed trading and illiquidity i.e. $X \in \{PIN, Illiq\}$, DP refers to the estimate of default probability (in most specifications, at the 5-year horizon), and *Controls* include proportional bid-ask spread, size, book-to-market, and profitability. In addition, for all specifications we include day fixed effects to control for market-wide shocks. Further, we include estimate two versions of the model, one with firm fixed effects and one with industry fixed effects. This enables us to estimate the effects within firm or within industry, and controls for any unobserved, time-invariant, firm- and industry-level heterogeneity. Following Petersen (2009), we double cluster standard errors at the industry-month level. This ensures that our inferences are valid in the presence of heteroskedasticity and standard errors that are correlated across firms within an industry, across days within a month.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
PIN		1.744***	-0.417*	0.845***	0.390	0.194	0.696***	1.463***	0.156	1.111***
		(0.0706)	(0.219)	(0.129)	(0.302)	(0.234)	(0.187)	(0.131)	(0.222)	(0.118)
$DP_5 \cdot PIN$		-3.115***		-2.394***			-0.567*	-2.201***		-1.660***
		(0.286)		(0.301)			(0.344)	(0.306)		(0.297)
$Illiq$	322,009***		332,113***	-12,728***	232,985***	336,890***	-5,691***	-15,813***	274,108***	-5,819***
	(50,708)		(50,521)	(2,767)	(38,009)	(51,357)	(1,497)	(3,041)	(42,278)	(1,610)
$DP_5 \cdot Illiq$	-340,548***		-355,103***		-244,281***	-362,650***			-287,712***	
	(55,783)		(56,799)		(41,728)	(57,972)			(46,805)	
$pspread$			23.18***	22.94***	14.94***	19.36***	14.83***	18.93***	16.29***	15.99***
			(0.685)	(0.695)	(0.751)	(0.883)	(0.767)	(0.908)	(0.845)	(0.865)
DP_5	1.237***	1.668***	0.970***	1.310***	0.798***	0.920***	0.866***	1.234***	0.772***	1.009***
	(0.0147)	(0.0375)	(0.0125)	(0.0424)	(0.0147)	(0.0126)	(0.0466)	(0.0433)	(0.0114)	(0.0426)
$log(mc)$			-0.138***	-0.122***	-0.493***	-0.142***	-0.487***	-0.126***	-0.0107**	-0.000218
			(0.00599)	(0.00465)	(0.0177)	(0.00660)	(0.0198)	(0.00495)	(0.00546)	(0.00412)
$log(bm)$			0.0564***	0.0472***	0.429***	0.0737***	0.429***	0.0609***	0.0857***	0.0765***
			(0.00961)	(0.0100)	(0.0224)	(0.00908)	(0.0231)	(0.00979)	(0.00893)	(0.00965)
$profit$			-0.813***	-0.755***	-1.085***	-1.622***	-1.036***	-1.483***	-0.194***	-0.169**
			(0.0835)	(0.0808)	(0.150)	(0.118)	(0.133)	(0.108)	(0.0732)	(0.0715)
Constant	0.584***	0.411***	2.346***	1.961***						
	(0.00378)	(0.00603)	(0.124)	(0.0935)						
Observations	685,122	685,357	667,042	667,042	667,041	663,372	667,041	663,372	663,489	663,489
R^2	0.229	0.234	0.288	0.289	0.509	0.342	0.508	0.343	0.386	0.386
Firm FE	No	No	No	No	Yes	No	Yes	No	No	No
Industry FE	No	No	No	No	No	Yes	No	Yes	No	No
Day FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Ratings FE	No	No	No	No	No	No	No	No	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full

Table 3.3: Cross-Sectional Results by Credit Ratings Subsamples

We present coefficient estimates for the following regression estimated in each credit ratings class subsample: $spread_{i,t} = \beta_1 X_{i,t} + \beta_2 DP_{i,t} + \beta_3 X_{i,t} \times DP_{i,t} + Controls + FEs + \epsilon_{i,t}$, where $spread$ refers to the quoted CDS spread (in most specifications, for the 5-year maturity contract), X refers to the proxies for informed trading and illiquidity i.e. $X \in \{PIN, Illiq\}$, DP refers to the estimate of default probability (in most specifications, at the 5-year horizon), and $Controls$ include proportional bid-ask spread, size, book-to-market, and profitability. In addition, for all specifications we include day fixed effects to control for market-wide shocks. Further, we include estimate two versions of the model, one with firm fixed effects and one with industry fixed effects. This enables us to estimate the effects within firm or within industry, and controls for any unobserved, time-invariant, firm- and industry-level heterogeneity. Following Petersen (2009), we double cluster standard errors at the industry-month level. This ensures that our inferences are valid in the presence of heteroskedasticity and standard errors that are correlated across firms within an industry, across days within a month.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
PIN	-0.330***	0.0879*	-0.239***	-0.270***	-1.947***	-1.431***
	(0.0348)	(0.0522)	(0.0300)	(0.0609)	(0.0773)	(0.0669)
$DP_5 \cdot PIN$		-1.606***		0.204		-1.074***
		(0.178)		(0.396)		(0.0855)
$Illiq$	4,018*	-2,408***	3.086e+06***	-833,219***	183,015	-317,814***
	(2,090)	(490.9)	(486,100)	(172,722)	(224,671)	(59,862)
$DP_5 \cdot Illiq$	-7,536***		-4.961e+06***		-102,244***	
	(2,310)		(834,827)		(23,196)	
$pspread$	0.411**	0.339**	2.538***	2.588***	3.264***	3.289***
	(0.161)	(0.160)	(0.165)	(0.163)	(0.314)	(0.285)
DP_5	0.578***	0.807***	0.876***	0.839***	0.234***	0.493***
	(0.0144)	(0.0275)	(0.0303)	(0.0443)	(0.0342)	(0.0458)
$log(mc)$	-0.305***	-0.287***	-0.0282***	-0.0308***	-0.147***	-0.139***
	(0.00786)	(0.00728)	(0.00550)	(0.00558)	(0.0112)	(0.0111)
$log(bm)$	-0.0366***	-0.0395***	0.125***	0.124***	0.139***	0.110***
	(0.00548)	(0.00548)	(0.00477)	(0.00477)	(0.0146)	(0.0142)
$profit$	-0.838***	-0.798***	0.413***	0.402***	-0.708***	-0.673***
	(0.0550)	(0.0531)	(0.0683)	(0.0681)	(0.107)	(0.107)
Observations	167,556	167,556	174,682	174,682	144,177	144,177
R^2	0.748	0.750	0.725	0.725	0.733	0.737
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	AA	AA	A	A	BBB	BBB

Table 3.4: Cross-Sectional Results by Credit Ratings Subsamples

We present coefficient estimates for the following regression estimated in each credit ratings class subsample: $spread_{i,t} = \beta_1 X_{i,t} + \beta_2 DP_{i,t} + \beta_3 X_{i,t} \times DP_{i,t} + Controls + FEs + \epsilon_{i,t}$, where $spread$ refers to the quoted CDS spread (in most specifications, for the 5-year maturity contract), X refers to the proxies for informed trading and illiquidity i.e. $X \in \{PIN, Illiq\}$, DP refers to the estimate of default probability (in most specifications, at the 5-year horizon), and $Controls$ include proportional bid-ask spread, size, book-to-market, and profitability. In addition, for all specifications we include day fixed effects to control for market-wide shocks. Further, we include estimate two versions of the model, one with firm fixed effects and one with industry fixed effects. This enables us to estimate the effects within firm or within industry, and controls for any unobserved, time-invariant, firm- and industry-level heterogeneity. Following Petersen (2009), we double cluster standard errors at the industry-month level. This ensures that our inferences are valid in the presence of heteroskedasticity and standard errors that are correlated across firms within an industry, across days within a month.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
PIN	-0.301***	-1.271***	-2.952***	-0.936**	-0.277	-16.17***
	(0.108)	(0.191)	(0.381)	(0.389)	(1.306)	(1.455)
$DP_5 \cdot PIN$		1.910***		-1.038***		7.800***
		(0.335)		(0.247)		(0.765)
$Illiq$	-1.623e+07***	-1.260e+07***	-6.924e+06***	-6.042e+06***	-2.077e+07***	3.289e+07***
	(2.294e+06)	(2.277e+06)	(1.931e+06)	(1.015e+06)	(4.558e+06)	(8.629e+06)
$DP_5 \cdot Illiq$	1.036e+06***		137,102		1.269e+07***	
	(251,994)		(486,510)		(1.794e+06)	
$pspread$	2.183***	2.304***	8.728***	8.447***	8.017	10.98**
	(0.382)	(0.386)	(0.727)	(0.727)	(5.160)	(5.218)
DP_5	0.596***	0.364***	0.295***	0.455***	0.342***	-0.569***
	(0.0273)	(0.0565)	(0.0147)	(0.0396)	(0.0549)	(0.0871)
$log(mc)$	-0.580***	-0.562***	-1.355***	-1.285***	-4.760***	-5.277***
	(0.0229)	(0.0189)	(0.0455)	(0.0485)	(0.158)	(0.169)
$log(bm)$	0.0534***	0.0789***	-0.325***	-0.310***	0.508***	0.534***
	(0.0163)	(0.0162)	(0.0426)	(0.0428)	(0.0549)	(0.0565)
$profit$	-1.081***	-1.048***	-1.299***	-1.093**	5.587***	5.805***
	(0.120)	(0.117)	(0.459)	(0.455)	(1.073)	(1.088)
Observations	107,703	107,703	44,936	44,936	24,397	24,397
R^2	0.759	0.760	0.833	0.834	0.699	0.698
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	BB	BB	B	B	CCC	CCC

Table 3.5: Cross-Sectional Results by Industry Subsamples

We present coefficient estimates for the following regression in industry-specific subsamples: $spread_{i,t} = \beta_1 X_{i,t} + \beta_2 DP_{i,t} + \beta_3 X_{i,t} \times DP_{i,t} + Controls + FEs + \epsilon_{i,t}$, where $spread$ refers to the quoted CDS spread (in most specifications, for the 5-year maturity contract), X refers to the proxies for informed trading and illiquidity i.e. $X \in \{PIN, Illiq\}$, DP refers to the estimate of default probability (in most specifications, at the 5-year horizon), and $Controls$ include proportional bid-ask spread, size, book-to-market, and profitability. In addition, for all specifications we include day fixed effects to control for market-wide shocks. Further, we include estimate two versions of the model, one with firm fixed effects and one with industry fixed effects. This enables us to estimate the effects within firm or within industry, and controls for any unobserved, time-invariant, firm- and industry-level heterogeneity. Following Petersen (2009), we double cluster standard errors at the industry-month level. This ensures that our inferences are valid in the presence of heteroskedasticity and standard errors that are correlated across firms within an industry, across days within a month.

	(1)	(2)	(3)	(4)
VARIABLES	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects
$pspread$	7.484***	7.295***	6.361***	5.868***
	(0.498)	(0.488)	(0.567)	(0.610)
$Illiq$	212,084***	-2,670***	-4.119e+06	4.461e+07***
	(34,982)	(806.9)	(8.328e+06)	(1.030e+07)
PIN	-1.144***	0.536***	0.450***	0.117
	(0.115)	(0.102)	(0.172)	(0.223)
DP_5	0.836***	1.168***	0.700***	0.658***
	(0.0142)	(0.0222)	(0.0421)	(0.0671)
$log(mc)$	-0.301***	-0.255***	-0.295***	-0.256***
	(0.0134)	(0.0137)	(0.0181)	(0.0220)
$log(bm)$	0.215***	0.206	-0.0792***	-0.0756***
	(0.0121)	(0.0122)	(0.0161)	(0.0172)
$profit$	-2.395***	-2.089***	0.924***	1.002***
	(0.111)	(0.107)	(0.161)	(0.158)
$DP_5 \cdot Illiq$	-221,433***		8.670e+06***	
	(38,036)		(3.039e+06)	
$DP_5 \cdot PIN$		-2.220***		0.484
		(0.139)		(0.431)
Observations	515,136	515,136	109,299	109,299
R^2	0.596	0.598	0.645	0.642
Firm FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Day FE	Yes	Yes	Yes	Yes
Ratings FE	No	No	No	No
Sample	No Fin and Util	No Fin and Util	Industrials	Industrials

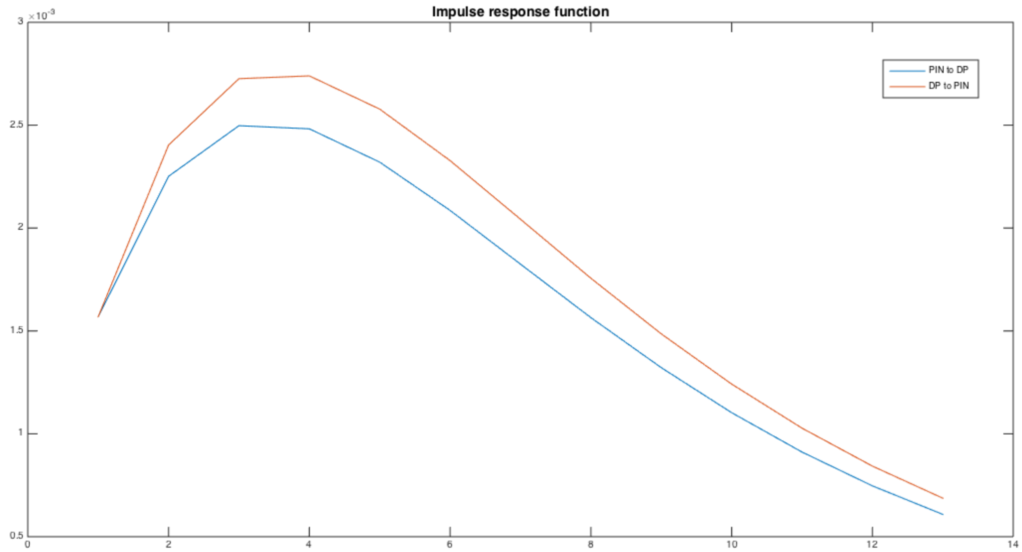


Figure 3.3: Impulse Response Function Graph

Table 3.6: Summary Statistics of Univariate VAR Results

Summary statistics of univariate VAR $\begin{bmatrix} PIN_{t+1} \\ DP_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix} + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} PIN_t \\ DP_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$, using quarterly PIN estimates and 1-, 5-, and 10-year default probability estimates. Table below shows the 5th, 20th, 50th, and 95th percentiles of the t-statistics and also the percentage of t-stats above 1.96 and 2.56, respectively the 95% and 99% confidence levels.

$PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.8	0.9	0.9	1.0	$t_{11,1}$	10.1	13.7	17.9	26.9	100.0	100.0
$\phi_{12,1}$	-0.1	0.2	2.2	37.0	$t_{12,1}$	-0.1	0.5	1.2	2.7	16.5	6.0
$\phi_{21,1}$	0.0	0.0	0.0	0.0	$t_{21,1}$	0.8	1.3	1.9	3.3	48.7	22.0
$\phi_{22,2}$	0.4	0.6	0.7	0.9	$t_{22,2}$	2.1	3.1	5.0	11.2	96.2	88.2

$PIN-DP5$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.6	0.7	0.8	0.9	$t_{11,1}$	5.1	7.9	11.8	21.8	100.0	100.0
$\phi_{12,1}$	0.1	0.6	4.7	27.9	$t_{12,1}$	0.5	1.2	2.1	3.9	27.4	11.3
$\phi_{21,1}$	-0.0	0.0	0.0	0.0	$t_{21,1}$	-0.2	0.8	1.5	2.9	38.5	16.0
$\phi_{22,2}$	0.6	0.8	0.9	1.0	$t_{22,2}$	2.9	5.5	9.7	21.2	98.9	95.9

$PIN-DP10$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.7	0.8	0.9	0.9	$t_{11,1}$	7.1	10.2	14.1	22.8	100.0	99.6
$\phi_{12,1}$	0.1	0.6	2.7	18.4	$t_{12,1}$	0.4	0.9	1.5	3.0	53.6	31.6
$\phi_{21,1}$	0.0	0.0	0.0	0.0	$t_{21,1}$	0.7	1.2	1.7	3.2	25.2	10.7
$\phi_{22,2}$	0.6	0.8	0.8	0.9	$t_{22,2}$	2.8	4.7	7.9	16.3	98.9	95.9

Table 3.7: $VAR(1)$ Results by Credit Rating Subsamples

Summary statistics of univariate VAR split by credit ratings subsamples on $\begin{bmatrix} PIN_{t+1} \\ DP_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix} + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} PIN_t \\ DP_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$, using quarterly PIN estimates and 1-, 5-, and 10-year default probability estimates. Table below shows the 5th, 20th, 50th, and 95th percentiles of the t-statistics and also the percentage of t-stats above 1.96 and 2.56, respectively the 95% and 99% confidence levels.

$AA-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.5	0.7	0.9	0.9	$t_{11,1}$	2.9	5.4	10.2	18.3	97.2	97.2
$\phi_{12,1}$	-0.1	1.1	14.5	419.5	$t_{12,1}$	-0.0	0.7	1.6	5.4	36.1	22.2
$\phi_{21,1}$	-0.0	0.0	0.0	0.0	$t_{21,1}$	-0.6	0.8	1.6	3.9	34.7	15.3
$\phi_{22,2}$	0.1	0.4	0.7	1.4	$t_{22,2}$	1.3	2.1	4.0	11.7	83.3	68.1

$A-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.5	0.7	0.9	1.0	$t_{11,1}$	3.3	6.0	10.5	19.0	98.6	97.2
$\phi_{12,1}$	-2.2	1.2	12.1	198.1	$t_{12,1}$	-0.9	0.4	1.3	3.9	26.4	19.4
$\phi_{21,1}$	-0.0	0.0	0.0	0.0	$t_{21,1}$	-0.1	0.9	1.8	3.4	41.7	22.2
$\phi_{22,2}$	0.2	0.5	0.6	1.2	$t_{22,2}$	1.3	2.5	3.5	9.9	90.3	77.8

$BBB-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.8	0.8	0.9	1.0	$t_{11,1}$	6.3	9.1	11.8	20.6	100.0	97.9
$\phi_{12,1}$	-3.7	1.9	7.1	112.7	$t_{12,1}$	-0.6	0.9	1.8	5.6	35.4	22.9
$\phi_{21,1}$	0.0	0.0	0.0	0.0	$t_{21,1}$	0.9	1.3	1.9	3.2	41.7	16.7
$\phi_{22,2}$	0.3	0.4	0.6	0.9	$t_{22,2}$	1.4	1.7	4.1	15.3	77.1	68.8

$BB-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.8	0.8	0.9	1.0	$t_{11,1}$	6.4	9.4	12.2	19.8	100.0	100.0
$\phi_{12,1}$	-0.9	0.3	1.8	68.0	$t_{12,1}$	-1.9	0.2	1.5	3.8	34.1	19.5
$\phi_{21,1}$	-0.0	0.0	0.0	0.0	$t_{21,1}$	-3.1	1.0	1.6	2.6	31.7	4.9
$\phi_{22,2}$	0.2	0.4	0.6	8.6	$t_{22,2}$	0.9	2.4	3.9	21.3	85.4	75.6

$B-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.7	0.8	0.9	1.0	$t_{11,1}$	4.7	10.0	12.6	18.8	100.0	100.0
$\phi_{12,1}$	-0.9	-0.1	0.3	33.2	$t_{12,1}$	-0.7	-0.4	0.7	2.0	7.1	0.0
$\phi_{21,1}$	0.0	0.0	0.0	0.1	$t_{21,1}$	-0.0	0.9	1.6	2.1	14.3	0.0
$\phi_{22,2}$	0.3	0.5	0.5	0.9	$t_{22,2}$	1.3	1.9	2.9	12.4	78.6	64.3

$CCC-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$t-stat$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$\phi_{11,1}$	0.8	0.9	0.9	1.0	$t_{11,1}$	9.6	10.5	12.9	19.6	100.0	100.0
$\phi_{12,1}$	-0.2	-0.1	0.1	1.5	$t_{12,1}$	-2.1	-0.2	0.4	3.4	30.0	20.0
$\phi_{21,1}$	0.0	0.0	0.0	0.3	$t_{21,1}$	0.0	0.3	1.7	2.1	20.0	0.0
$\phi_{22,2}$	0.2	0.3	0.6	0.9	$t_{22,2}$	1.3	1.8	3.2	5.8	80.0	60.0

Table 3.8: Summary Statistics of Granger Causality Results

Summary statistics of Granger Causality results based on the VAR(1) specification $\begin{bmatrix} PIN_{t+1} \\ DP_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix} + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} PIN_t \\ DP_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$, using quarterly PIN estimates and 1-, 5-, and 10-year default probability estimates. Table below shows the 5th, 20th, 50th, and 95th percentiles of the t-statistics and also the percentage of t-stats above 1.96 and 2.56, respectively the 95% and 99% confidence levels.

$PIN - DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t > 1.96)$	$\%(t > 2.58)$
$t_{11,1}$	114.9	210.5	354.5	789.2	100.0	100.0
$t_{12,1}$	0.0	0.6	2.4	15.1	55.6	47.2
$t_{21,1}$	0.9	2.6	5.4	14.6	85.7	80.3
$t_{22,2}$	10.6	25.3	57.7	250.2	99.6	99.6

$PIN - DP5$	$5th$	$20th$	$50th$	$95th$	$\%(t > 1.96)$	$\%(t > 2.58)$
$t_{11,1}$	64.0	121.2	227.4	632.6	100.0	100.0
$t_{12,1}$	0.2	1.2	3.3	13.2	64.7	58.5
$t_{21,1}$	0.9	2.8	5.4	17.1	86.8	82.1
$t_{22,2}$	20.6	49.7	122.2	464.2	99.8	99.8

$PIN - DP10$	$5th$	$20th$	$50th$	$95th$	$\%(t > 1.96)$	$\%(t > 2.58)$
$t_{11,1}$	31.3	70.7	166.9	622.7	100.0	100.0
$t_{12,1}$	0.5	2.4	5.7	18.4	84.2	78.0
$t_{21,1}$	0.1	1.1	3.8	21.7	69.4	63.0
$t_{22,2}$	25.6	71.3	164.6	672.7	100.0	99.8

Table 3.9: Summary Statistics of Granger Causality Results by Credit Ratings Subsamples

Summary statistics of Granger Causality results based on the VAR(1) specification $\begin{bmatrix} PIN_{t+1} \\ DP_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix} + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} PIN_t \\ DP_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$, using quarterly PIN estimates and 1-, 5-, and 10-year default probability estimates, reported in credit ratings subsamples. Table below shows the 5th, 20th, 50th, and 95th percentiles of the t-statistics and also the percentage of t-stats above 1.96 and 2.56, respectively the 95% and 99% confidence levels. The data is analyzed from

$AA-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	5.6	22.9	126.8	420.9	97.8	97.8
$t_{12,1}$	0.0	0.6	4.0	38.4	66.7	60.0
$t_{21,1}$	0.3	1.5	3.6	29.2	77.8	60.0
$t_{22,2}$	4.5	10.7	45.1	192.9	100.0	100.0

$A-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	20.3	41.3	164.8	419.9	100.0	100.0
$t_{12,1}$	0.1	0.7	3.1	28.8	64.2	58.5
$t_{21,1}$	0.2	1.9	4.1	17.9	79.2	75.5
$t_{22,2}$	5.1	9.9	36.3	223.0	100.0	100.0

$BBB-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	54.7	107.4	180.1	524.1	100.0	100.0
$t_{12,1}$	0.1	1.5	4.5	61.5	75.0	71.4
$t_{21,1}$	0.9	2.7	4.9	52.6	85.7	82.1
$t_{22,2}$	2.8	8.4	21.5	529.2	96.4	96.4

$BB-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	76.1	96.7	202.9	529.6	100.0	100.0
$t_{12,1}$	0.1	0.5	4.6	73.9	69.2	61.5
$t_{21,1}$	0.4	1.7	3.6	21.8	76.9	73.1
$t_{22,2}$	9.3	22.4	50.0	1476.7	100.0	100.0

$B-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	52.6	158.2	196.5	381.8	100.0	100.0
$t_{12,1}$	0.1	0.4	2.1	23.0	55.6	44.4
$t_{21,1}$	0.1	1.0	5.0	12.0	77.8	77.8
$t_{22,2}$	6.2	11.9	65.0	589.3	100.0	100.0

$CCC-PIN-DP1$	$5th$	$20th$	$50th$	$95th$	$\%(t>1.96)$	$\%(t>2.58)$
$t_{11,1}$	193.9	226.3	369.9	716.2	100.0	100.0
$t_{12,1}$	0.0	0.0	1.1	28.3	37.5	37.5
$t_{21,1}$	0.0	0.3	3.7	38.7	75.0	75.0
$t_{22,2}$	17.7	22.3	47.2	205.3	100.0	100.0

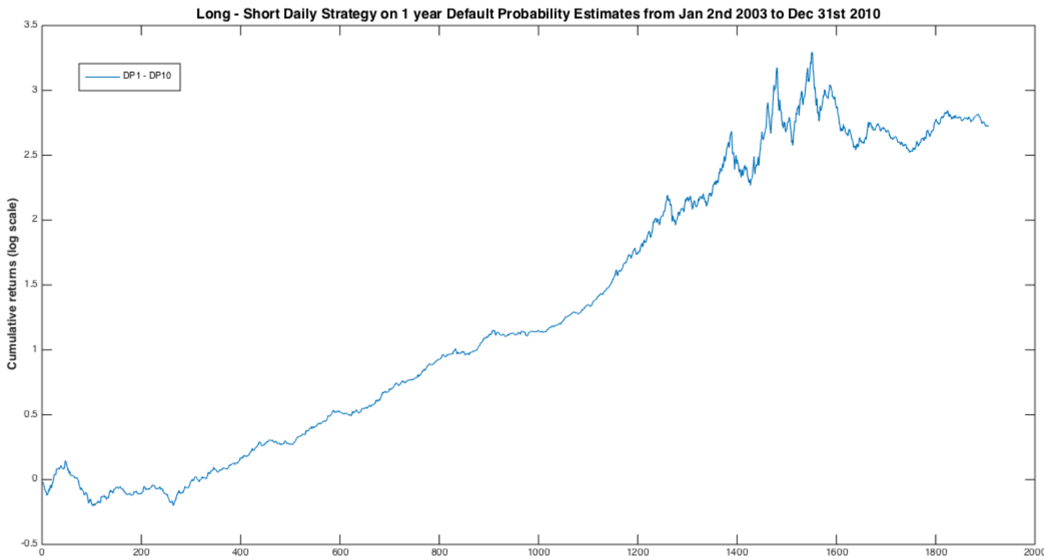


Figure 3.4: Daily Returns of Long-Short Default Probability Strategy from Jan 2nd 2003 to Dec 31st 2010

Table 3.10: Portfolio and Regression Results of the Long-Short Strategy

The upper panel contains average daily returns from January 2, 2003 to December 31, 2010, of double-conditionally sorted portfolios on 1-year ahead default probability estimates and PIN estimates. The lower panel contains summary statistics of the returns of the trading strategy which goes long the portfolio of lowest decile DP and lowest quintile PIN, and goes short the portfolio of highest decile DP and highest quintile PIN.

	Low DP	DP 2	DP 3	DP 4	DP 5	DP 6	DP 7	DP 8	DP 9	High DP	Low DP - High DP
Low PIN	0.0014	0.0007	0.0004	0.0004	0.0003	-0.0000	0.0002	-0.0003	-0.0008	0.0003	0.0011
PIN 2	0.0015	0.0007	0.0010	0.0006	0.0001	0.0003	0.0003	0.0002	0.0001	0.0003	0.0011
PIN 3	0.0018	0.0010	0.0008	0.0008	0.0008	0.0007	0.0004	0.0005	0.0002	0.0008	0.0009
PIN 4	0.0015	0.0008	0.0005	0.0005	0.0002	-0.0001	0.0001	-0.0002	-0.0005	-0.0005	0.0021
High PIN	0.0019	0.0010	0.0007	0.0010	0.0010	0.0010	0.0006	0.0005	0.0002	0.0010	0.0006
High PIN - Low PIN	0.0010	0.0007	-0.0003	0.0011	0.0004	0.0008	0.0014	-0.0002	0.0001	-0.0000	

DP10/PIN1 - DP1/PIN5

Mean R	SD	Sharpe	α_{FF3}	Mkt-Rf	SMB	HML
0.0013**	0.0193	0.0647	0.0017***	-0.4598***	-0.9216***	-1.1743***
(2.5)			(4.86)	(-8.11)	(-12.53)	(-9.53)

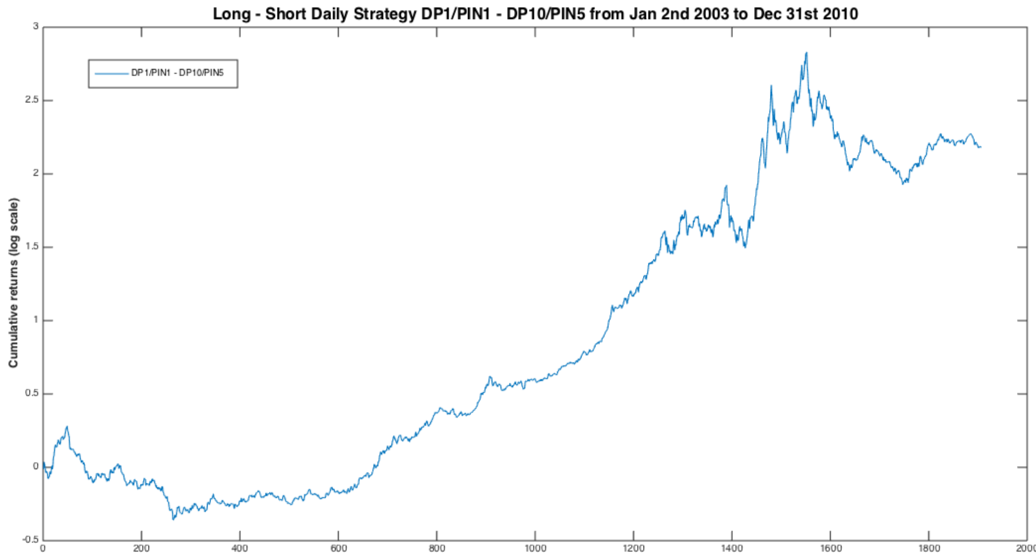


Figure 3.5: Daily Returns of Long-Short DP1/PIN1 - DP10/PIN5 Strategy from Jan 2nd 2003 to Dec 31st 2010

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