Theoretical and empirical evidence of the influence of economic linkages on stock returns

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Author's Declaration

This thesis is submitted according to the requirements of the Degree Committee of the Department of Land Economy. It does not exceed the regulation length of 80,000 words including footnotes, references and appendices.

It is the result of my own work and includes nothing that is the outcome of work done in collaboration.

Ramona Meyricke
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Abstract

Inter-linkages between suppliers and customers are a channel by which shocks can spread between firms. When firms buy and sell intermediate goods from one another, they may rely on each other for the supply of input goods or for cash-flow from sales. This is a problem because financially distressed suppliers can pose significant risk to the economic activity of customers that rely on them for goods and services. A case in point is the heavy loss suffered by General Motors when its equipment and parts supplier Delphi went on strike in 1998. Vice-versa, distressed customers can negatively impact suppliers' business operations.

Real economic activities are highly related to major stock pricing factors. The main hypothesis of this thesis is that shocks to a firm's direct and indirect suppliers and customers influence its stock price. There is a large amount of research addressing how shocks spread between international financial markets and asset classes influence stock prices during financial crises (financial contagion). Past research has identified the macroeconomic conditions and the types of linkages between markets and assets that make a country or market vulnerable to financial contagion.

Little is known, however, about how shocks spread via economic linkages influence firm-level stock returns. Studies find that significant movements in a firm's stock price forecast subsequent movements in the stock price of its major suppliers. Several questions remain open, however, regarding how shocks spread via economic linkages influence stock returns, such as: how shocks spread via economic linkages influence return volatility and correlation; what characteristics of economic linkages (e.g. the degree or the concentration of linkage) are most important in the process of contagion; and whether the spread of shocks via economic linkages increases during recessions.

The main objective of this thesis is to increase knowledge of *how* economic linkages between firms influence stock returns. My approach is to examine how a firm's economic linkages influence three dimensions of its stock returns: volatility, pairwise correlation between linked firms' returns and the cross-sectional distribution of average returns. The research questions addressed are:

1. How does the structure of a firm's economic linkages influence the volatility of its stock returns?
2. How do shocks transmitted via economic linkages increase correlation between linked firms' returns?
3. How do shocks transmitted via economic linkages affect average returns, cross-sectionally and over time?

For each dimension of stock returns (volatility, pairwise correlation and average returns) I examine what characteristics of economic linkages are most influential, and whether the influence of economic linkages increases in recessions.

I develop a theoretical model explaining how the spread of cash-flow shocks via economic linkages between firms influences the volatility, pairwise correlation and average level of stock returns. The reduced form of the theoretical model corresponds to a factor model of stock returns (based on Arbitrage Pricing Theory), with an additional factor added to allow for non-diversifiable risk created by economic linkages. This model describes the relationship between economic linkages and return volatility, pairwise correlation and average returns.

To answer the first research question, I apply the Lindeberg-Feller theorem to derive an explicit relationship between a firm's stock return volatility and the structure of its linkages to other firms. I prove that when the distribution a firm's economic linkages is heavy-tailed (such that it has an extremely high degree of economic linkage to a few firms and a far lower degree of economic linkage to all others), shocks to the firm's key suppliers and/or customers can significantly influence its return volatility. Intuitively, shocks to the most connected suppliers and/or customers are not offset by shocks to less connected suppliers and/or customers, so they can significantly influence a firm's cash-flow and therefore stock returns. Monte Carlo simulations confirm that shocks transmitted via economic linkages are diversified away at rate much slower than the $\frac{1}{\sqrt{N}}$ rate implied by the law of large numbers in many common supply chain structures. In these 'concentrated' supply chain structures, shocks transmitted via economic linkages can create portfolio return volatility in excess of that explained by systematic risk factors, even in large portfolios.

To answer the second and third research questions, I use monthly stock return data and annual accounting data on the major customers of all listed US firms between 1990 and 2010 from the CRSP/Compustat database. To investigate how shocks transmitted via economic linkages influence correlation between linked firms' returns, I test the hypothesis that an increase in the degree of linkage between two firms increases the pairwise correlation between their stock returns. First, I adapt correlation-based tests of contagion to test whether pairwise return correlation is higher when two firms are linked than when they are not linked. Second, I develop measures of the strength of pairwise linkage between firms (using principles from network theory and economic input-output modeling). I then estimate regressions of firm-pairs' return correlation against the strength of their linkage and a number of controls (such as industry-pair fixed-effects and credit usage along the supply chain). The regression results show that an increase in the economic linkage between two firms is associated with increased correlation between their stock returns. Linked firms' returns are more correlated when credit is involved in the supplier-customer relationship and in recessions, implying that it is harder to replace a supplier or customer in these situations.

Finally, I test whether shocks spread via economic linkages influence average stock returns over and above other factors that have been shown to influence stock returns. My method is to develop measures of the degree and concentration of a firm's supplier and customer linkages. I include these measures in a factor model of stock returns alongside a number of other factors that have been shown to explain stock returns. Cross-sectional regressions show that, in a given time-period, firms with more concentrated supplier bases have higher average returns than firms with less concentrated supplier bases. Second, time-series regressions showed that an increase in the concentration of a firm's supplier-base lowered realized returns in the following period. These results suggest that investors demand a positive risk premium (higher expected return) for holding the stock of firms whose supplier-base is concentrated. This places downward pressure on prices following an increase in supplier-base concentration. While concentration of a firm's supplier and customer linkages has a significant influence on stock returns, the magnitude of this effect is small compared to the influence of systematic risk factors. The influence of economic linkages on stock returns, however, increases in recessions.

Together the results in this thesis provide solid evidence that shocks spread via economic linkages can affect the volatility, correlation and average level of stock returns. The thesis establishes a robust framework for modeling the returns of portfolios in which the underlying securities or firms are linked via economic relationships. This is an important extension to existing models that ignore the potential impact of shocks spread via linkages between firms on stock prices. The model can be used for pricing securities with concentrated supply chain exposures or to identify stock portfolios that are susceptible to contagion.

Contents

Chapter 1

Introduction and overview

1.1 Research background

Over the past thirty years, interdependence in financial markets has increased as a result of many factors including globalization and technological developments (Brock, 1999; Farrell, Lund, Folster, Bick, Pierce, and Atkins, 2008). At the same time, the interdependence between firms' economic activities has also increased (Jarrow and Yu, 2001). For example, changes in production processes like 'lean' and 'just-in-time' manufacturing mean that firms are increasingly reliant on their suppliers. Such economic linkages between firms along a supply chain are a channel by which shocks can spread between supplier and customer firms (Dornbusch, Park, and Claessens, 2000). This is a problem because financially distressed suppliers pose significant risk to the economic activity of customers that rely on them for goods and services (Wagner, Bode, and Koziol, 2011). A case in point is the heavy loss suffered by General Motors when its equipment and parts supplier Delphi went on strike in 1998. Vice-versa, distressed customers can negatively impact suppliers' business operations (Hertzel, Li, Officer, and Rodgers, 2008). For example, in 2008/2009 the chief executive of Ford requested emergency government support for General Motors and Chrysler from the US Senate. He argued that given the significant overlap in the suppliers and dealers of Ford, General Motors and Chrysler, the collapse of either General Motors or Chrysler could create serious operational and financial distress for Ford (Mulally, 2008).

Given that real economic activities are highly related to major stock pricing factors, market volatility and to investors' attitudes toward risk (Fama, 1990), the spread of distress between suppliers and customers may have a significant influence on stock returns. If interdependence between firms' economic activities has increased, it is therefore important to assess whether this has increased interdependence between stock returns. However, very little is known about how the economic linkages between firms (that issue equity stocks) influence their stock returns[1].

Ignoring the potential impact of shocks spread via economic linkages on asset prices is problematic for two reasons. First, if investors are aware of the linkages between assets, asset prices will reflect the market's assessment of the counterparty risk created by these linkages (Jarrow and Yu, 2001); therefore ignoring economic linkages may result in mispricing. Second, even if investors are unaware or unconcerned by counterparty risk, when firms are linked to each other, shocks can spread between firms. I show that shocks spread via inter-firm linkages can increase the volatility of asset returns and the correlation between assets, and may create aggregate fluctuations in financial markets. So ignoring shocks spread via economic linkages may lead to an underestimation of risk.

1.2 Previous research and gaps

Currently, there is no comprehensive study of how shocks spread via economic linkages influence stock prices. Recent financial crises, however, show that firm-level events, such as the failure of Lehman Brothers in 2008, can spread far beyond the firm, market and country in which they originate[2]. Contagion is defined as an increase in return dependence during periods of crisis and/or during volatile markets. Most tests of contagion are performed at the level of an entire market

[1] The small number of studies is partly due to a lack of reliable data on the supply linkages between firms.

[2] Other examples include the effect that the potential default of Long Term Capital Management had on other major investment banks in 1998, and the effect that the collapse of the Thai Baht in 1997 had on stock prices throughout most East Asian stock markets.

or asset class, by testing whether there is a statistically significant increase in return correlation between markets or assets during a crisis period (Dungey, Fry, Gonzlez-Hermosillo, and Martin, 2005). Research on contagion has identified the types of links and other macroeconomic conditions that can make a country or asset class vulnerable to contagion during crisis periods. Extant research concludes that the most important channels by which firm-level shocks spread in financial crises are credit linkages and investor behavior (Kaminsky, Reinhart, and Vegh, 2003). Very few studies, however, have been undertaken at the firm-level and very few studies explicitly test whether economic linkages may be a channel of contagion.

Some empirical studies shed light on how shocks spread between customers and suppliers influence stock prices. Hertzel, Li, Officer, and Rodgers (2008) find that financial distress of customer firms (as indicated by bankruptcy filings) is associated with significant negative effects on the stock price of their suppliers. Similarly, Cohen and Frazzini (2008) find that the returns of customer firms' stock predict their suppliers' subsequent returns. Both of these studies indicate that the connection between customers and their suppliers has a significant influence on stock returns; however, they are both limited in two respects. First, both studies focus on pairwise linkages and ignore the potential influence of shocks transmitted from further up or down a firm's supply chain (e.g. customers' customers, or suppliers' suppliers etc.). Second, both studies focus on stock price movements surrounding a significant event, such as bankruptcy or a significant news announcement by the customer firm. The narrow focus on direct linkages and significant events means that these studies do not fully answer the question of how shocks spread via economic linkages between suppliers and customers affect stock returns, as they do not address the influence of both direct and indirect economic linkages on stock returns, on average over time.

Research investigating how production linkages between the sectors of an economy affect the volatility of economic activity shed light on how economic linkages between firms may influence their stock returns. Recent papers show that the structure of economic linkages between sectors and/or firms affects volatility in

GDP(Gabaix, 2011; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010; Carvalho, 2008). Similar intuition underpins all of these models: when sectors are linked, a shock to one sector can spread via linkages to other sectors and can create aggregate fluctuations in the economy. Horvath (2000); Carvalho (2008); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010); Dupor (1999) all show that sectoral shocks, propagated via inter-sector linkages, can create fluctuations in GDP.

The theoretical explanation of this effect is clarified in Gabaix (2011) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010). They prove that sector-level shocks are not diversified away when the distribution of each sector's total influence on the aggregate is heavy-tailed, i.e. when a few firms have a very large influence, while most firms have a negligible influence on the aggregate economy. This is because the law of large numbers does not hold when a few sectors (or firms) have an extremely large influence on the aggregate, while most have a small influence on the aggregate[3]. While these studies explain how *sector-level* economic linkages influence *economic activity*, the theory can be adapted to explain how *firm-level* economic linkages influence *stock returns*.

1.3 Research questions and rationale

This thesis focusses on whether or not, and on how, shocks spread via economic linkages between supplier and customer firms affect stock returns. The main objective of this thesis is to establish how economic linkages between firms influence stock returns. My approach is to examine how a firm's economic linkages influence three dimensions of its stock returns: the volatility of stock returns, pairwise correlation between linked firms' returns and the cross-sectional distribution of average returns. The research questions addressed are:

[3] The law of large numbers predicts that the sum of N i.i.d. shocks, $S = \sum_{i=1}^{N} Y_i$ where $Y_i \sim (0, \sigma^2)$ will have variance $\frac{\sigma^2}{N}$. Now let the shocks have different influence on the aggregate, such that $S_w = \sum_{i=1}^{N} w_i Y_i$ where $\sum_{i=1}^{N} w_i = 1$. Gabaix (2011) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) show that when the distribution of the weights w_i is heavy-tailed, aggregate volatility decays much more slowly than the $\frac{1}{\sqrt{N}}$ rate predicted by the law of large numbers.

1. How does the structure of economic linkages influence the volatility of stock returns? (Chapter 3)

2. How do shocks transmitted via economic linkages increase correlation between linked firms' returns? (Chapter 5)

3. How do shocks transmitted via economic linkages affect average returns, cross-sectionally and/or over time? (Chapter 6)

For each dimension of stock returns (volatility, pairwise correlation and average returns) I examine what characteristics of economic linkages are most influential, and whether the influence of economic linkages increases in recessions. Together the answers to these questions elucidate the influence of shocks spread via economic linkages on the volatility, pairwise correlation and cross-sectional distribution of stock returns. The results offer insights for a range of asset pricing and risk management problems, including portfolio risk management and assessing financial stability.

The methodology extends existing models of stock returns to allow for shocks transmitted via linkages between firms. First, I develop a theoretical model explaining how the spread of cash-flow shocks via economic linkages between firms influences the pairwise correlation, mean and volatility of stock returns. By applying the Lindeberg-Feller theorem, I prove that diversification occurs significantly slower than the $\frac{1}{\sqrt{N}}$ rate predicted by the law of large numbers if the distribution of firms' degree of economic linkage is heavy-tailed (such that a few firms have an extremely high degree of economic linkage while the majority have a far lower degree of economic linkage). I derive an expression explicitly linking the structure of linkages between firms and the rate at which shocks are diversified away. Importantly, economic network structures are identified in which shocks to a single firm may not be diversified away, and can have a significant influence on aggregate volatility even in large portfolios. This has wide-ranging implications because the assumption that diversification occurs at rate $\frac{1}{\sqrt{N}}$ is frequently used to support the assumption that a set of common, systematic risk factors adequately explains stock returns. In cases where shocks are not diversified away at rate $\frac{1}{\sqrt{N}}$ there is a strong case to allow for exposure to shocks transmitted via inter-firm linkages in asset pricing models.

In Section 3.3 I derive a reduced form model (corresponding to the theory) of how shocks transmitted via economic linkages affect stock returns. An approximate factor model is the correct reduced form representation of returns in a portfolio where residual returns may be correlated. However, the standard approximate factor model assumes that in large portfolios the proportion of non-zero correlations between assets approaches zero (Chamberlain and Rothschild, 1983). I prove that when the distribution of economic linkages is heavy-tailed (i.e. there are a few extremely connected firms while the majority of firms have limited connectivity), the contribution of firm-level volatility to aggregate volatility is non-zero, even in extremely large portfolios. This implies that rather than using an approximate factor model, standard factor models of asset prices should be extended to allow for inter-firm linkages if the distribution of inter-firm connectivity is heavy-tailed. To test the significance of inter-firm linkages within this framework, I develop factors that measure the pervasive influence of shocks transmitted via linkages and include these factors in an asset pricing model to capture the influence of economic linkages on stock returns.

In summary, the theoretical model implies testable hypotheses concerning how economic linkages between firms influence the pairwise correlation, mean and volatility of stock returns. The reduced form of the theoretical model corresponds to a factor model of returns. Therefore I extend a factor model of returns to allow for economic linkages, and then investigate how shocks spread via economic linkages between suppliers and customers affect stock returns. To empirically test the implications of the theory I use annual account data containing the significant customer-supplier links of all listed US firms on the CRSP/Compustat database from 1990 to 2010, and monthly data on the stock returns all listed US firms on the CRSP/Compustat database from 1990 to 2010.

1.4 Overview of results and contributions

In Chapter 3 I show that if the distribution of firms' connectivity, measured by the number of customers and/or suppliers that rely on the firm, has heavy-tails (i.e. there are a few extremely connected firms while the majority of firms have limited connectivity) then aggregate variance decays much slower than the $\frac{1}{\sqrt{N}}$ rate predicted by the law of large numbers. This implies that when the distribution of firms' connectivity is heavy-tailed shocks to the most connected firms can significantly influence the variance of stock returns.

In Chapter 4 I analyze annual accounting data on the economic linkages between all listed US firms on the Compustat database from 1990 to 2010. I show that the distribution of US listed firms' connectivity (number of dependent suppliers and customers) follows a power law distribution, with a very small chance that a randomly selected firm is a key customer of an extremely large number of suppliers. The data analysis identifies an increasing trend in the degree of linkage between firms from 1990 to 2010, implying firms have become more inter-dependent on their suppliers and on their customers over this period. These findings support the assumptions of the theory in Chapter 3, and suggest that analyzing the influence of inter-firm connectivity on asset prices is of increasing importance in modern financial markets.

Using accounting data and monthly stock price data for all listed US firms on the Compustat/CRSP database from 1990 to 2010, in Chapter 5 I test whether economic linkages increase the correlation between linked firms' stock returns. I show that there is a direct relationship between the strength of linkage between firms and the correlation of their stock returns. An increase in the economic linkage between two firms (i.e. the proportion of total production inputs and/or outputs bought and/or sold from one another) is associated with increased correlation in those firms' stock returns. The influence of economic linkages on return correlation is stronger when trade credit is used along the supply chain connecting the firms and is stronger in recessions. This is consistent with economic theory and intuition, as a supplier (customer) is harder to replace when there are credit contracts involved in the relationship and/or when the economy is in recession. Pairwise return correlation is a central component of portfolio return variance, so this finding suggests linkages may have a significant influence on stock returns.

In Chapter 6, therefore, I test whether shocks transmitted via economic linkages influence average stock returns, over and above systematic risk factors (such as the market return) and firm-specific characteristics (such as size and book-to-market ratio) that have been shown to influence returns. I show that when firms' connectivity is heavy-tailed, the proportion of non-zero correlations between assets remains greater than zero, even in large portfolios; so factor models of stock returns should be extended to allow for inter-firm linkages. I develop factors that represent connectivity and the level of risk transmission between linked firms. These factors are included in a factor model of asset returns in order to test the influence of inter-firm linkages on average returns.

The results show that shocks spread via economic linkages can have a significant negative influence on average stock returns over time. I find that there is a significant positive risk premium attached to the concentration of a firm's supply chain, in addition to the factors commonly accepted as explaining equity risk premiums. This positive contemporaneous risk premium is consistent with the finding of lower average lagged stock returns following an increase in the concentration of a firm's supplier-base (as higher expected returns place downward pressure on prices over time). While shocks spread via economic linkages can significantly influence stock returns, their influence is small compared to that of systematic risk factors; although the influence of shocks spread via economic linkages on stock returns increases in recessions.

In summary, the theoretical and empirical results in this thesis advance knowledge of how shocks spread via economic linkages affect stock returns and when this effect is most significant. To the best of my knowledge, this is the first study of how economic linkages influence average asset prices over time. This is an important contribution because it is a first step towards extending asset pricing theory to allow for episodes of financial contagion and/or interdependence.

1.5 Structure of thesis

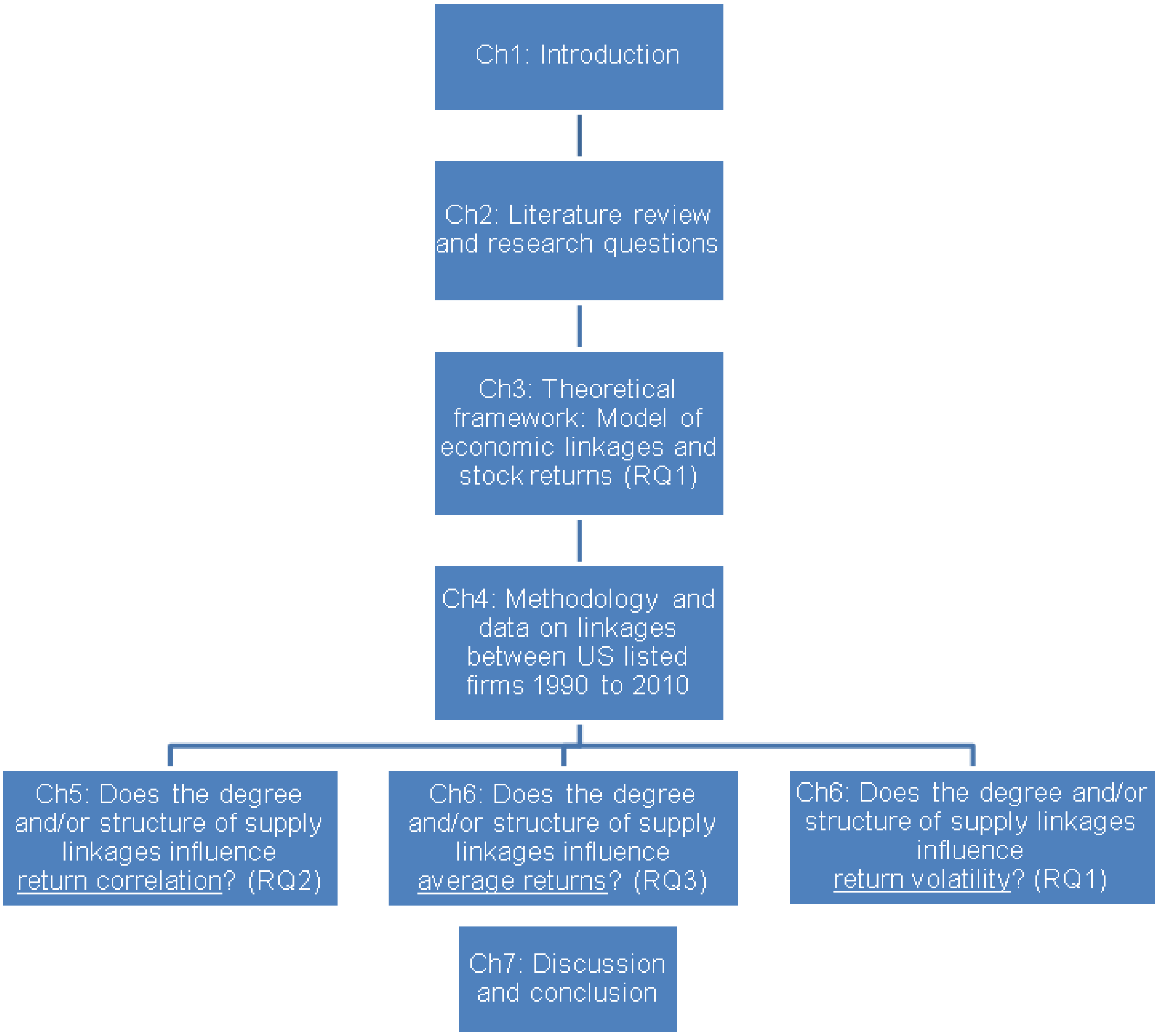

Figure 1.1: Schematic diagram of thesis structure.

Chapter 2 contains a critical review of the existing literature in economics and finance which considers the relationship between inter-firm linkages, economic activity and stock returns. Three substantial bodies of literature offer insight into the influence of economic linkages between firms on stock returns:

- Literature on how shocks spread within and between equity markets during a financial crisis (financial contagion)
- Literature that explains how shocks spread via credit and counterparty linkages and create default correlation
- Economic theory on how shocks spread via production linkages between economic sectors effect aggregate output and can explain business cycles.

The main gaps in this literature are identified and formulated into research questions. Drawing upon the existing literature, hypotheses are developed to answer the research questions.

In Chapter 3 I develop a theoretical model of the way in which shocks transmitted via inter-firm linkages affect returns. I derive two key results on the relationship between the structure of inter-firm linkages and the distribution and volatility of stock returns. I derive the implications of these results for asset pricing models.

In Chapter 4 I describe the methodology used to test the implications of the theory and the data source on economic linkages (which covers all firms with stocks listed on North American stock exchanges recorded on the Compustat/CRSP database from 1990 to 2010). I show how accounting disclosures on 'key customers' can be used to characterize the supply chain network underlying the US stock markets. Furthermore, I develop statistical measures of the degree and structure of the economic linkages between all stocks listed on North American exchanges and summarize how these linkages have changed between 1990 and 2010.

Chapter 5 presents empirical tests of the hypothesis that inter-firm linkages increase the correlation between linked firms stock returns. I also test whether the influence of economic linkages on return correlation is stronger when trade credit is used along the supply chain connecting the firms and/or in a recession (as suggested by economic theory in which a supplier (customer) is harder to replace when there are credit contracts involved in the relationship and/or when the economy is in recession). Chapter 6 contains empirical tests of the relationship between economic linkages and the cross-sectional and time-series variation in stock returns, after controlling for systematic and industry-level risk factors.

Chapter 7 concludes by summarizing the answers to the research questions. The implications of the results for portfolio risk management and financial stability are discussed.

1.6 Terminology

Groups of firms or assets, such as an entire market or a portfolio, may exhibit *contagion* and/or *interdependence*. Contagion is defined as contemporaneous transmission of shocks between firms, assets, sectors or markets after conditioning on common factors. A similar definition is used in Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005). Forbes and Rigobon (2002) distinguish interdependence from contagion, defining interdependence to be comovement in outcomes caused by linkages which exists during crisis and non-crisis periods. The distinction between contagion and interdependence is that the former implies that linkages (which cause comovement) change during a crisis, whereas the latter implies that linkages remain the same in all states of the world. As the primary focus of this thesis is to establish how economic linkages between firms influence stock returns, this distinction is not necessary and the term *contagion* is used in this thesis to refer to the transmission of shocks between firms (after conditioning on common factors) in both crisis and non-crisis periods.

Shocks are the realization of underlying random variables or *risk factors*. The terms *systematic* and *idiosyncratic* are used when referring to the *initial impact of a shock*. A systematic shock is one that immediately affects all units in the economy. For example, monetary policy shocks are systematic as they immediately affect a large number of exposed securities and firms. Idiosyncratic shocks only initially affect one firm. For example, internal fraud by an employee is an idiosyncratic shock.

When referring to the affect of a shock on stock returns (rather than the initial point of impact of a shock) I use the terms *pervasive* and *asset-specific*. A pervasive risk factor has an economically significant aggregate effect on returns in large portfolios. In contrast, an asset-specific risk factor affects a single or limited number of units in the economy, and has a negligible aggregate effect as the number of units in the portfolio being considered grows. By definition, a pervasive risk factor is non-diversifiable, whereas an asset-specific risk factor is diversifiable[4] (Ross, 1976). This terminology is consistent with the terminology used the Arbitrage Pricing Theory of Ross (1976), and in the factor models derived from this theory developed in Chamberlain and Rothschild (1983); Chen, Roll, and Ross (1986); Connor (1995)[5].

Finally, it is important to note the difference between a *link* and a *linkage*. A link is used to refer to a one-step or direct, point to point connection. For example, if A is linked to B, it is possible to travel from A to B in one step. A linkage is a chain of two or more links. If A buys directly from B, and B buys directly from C, there is an indirect linkage between A and C. (The terms inter-linkage, inter-firm linkage and linkage are used inter-changeably.)

[4] In the exact words of Ross (1976), an asset specific risk factor must be 'sufficiently independent to permit the law of large numbers to hold'.

[5] The distinction between the initial impact of a shock and its aggregate effect on returns is crucial in Chapter 3. In Chapter 3 it is shown that a shock initially affecting one firm may spread via inter-linkages and have an economically significant aggregate effect on returns in large portfolios. This occurs because shocks transmitted via inter-linkages create sufficient dependence between linked firms returns such that the law of large numbers does not hold.

Chapter 2

Literature review and research questions

2.1 Introduction

This thesis focusses on whether or not, and on how, shocks spread via economic linkages between supplier and customer firms affect stock returns. The main objective of this thesis is to establish how economic linkages between firms influence stock returns. Three separate bodies of literature offer insight into the influence of economic linkages between firms on stock returns:

- Literature on how shocks spread within and between equity markets during a financial crisis (financial contagion)
- Literature that explains how shocks spread via credit and counterparty linkages (corporate default and credit contagion)
- Economic theory on how shocks spread via production linkages between economic sectors can create fluctuations in aggregate economic activity (economic linkages and business cycles).

In this chapter I analyze each of these bodies of literature from the following angles:

- What underlying theories did they apply?

- What empirical methodologies do they use?
- What are the main empirical findings?
- What are the gaps in theory, empirical methodology and findings (regarding how economic linkages between firms influence stock returns) that need to be addressed?

I conclude by formulating research questions and hypotheses that address some of the gaps identified in the literature regarding how economic linkages between firms influence stock returns.

2.2 Overview of literature

In recent years, there has been an increasing recognition of the importance of networks and inter-linkages in both finance and economic literature. In finance, the role of networks and inter-linkages is most commonly examined within the context of financial crises or the spread of financial distress through asset markets. In economics, research has analyzed salient features of networks and their effects on pricing, economic fluctuations (or volatility) and market structure. In order to understand how shocks spread via economic linkages (arising from the trade of goods between suppliers and customers) might influence stock returns, I draw on key findings and methodologies from both finance and economics.

By way of introduction, financial contagion is defined as 'the contemporaneous transmission of local shocks to another country or market after conditioning on common factors that exist over a non-crisis period' (Dungey, Fry, Gonzlez-Hermosillo, and Martin, 2005). Several financial crises in the past decade have highlighted the importance of inter-linkages in process of contagion. In these crises, financial contracts, such as bank loans or credit contracts that linked banks, were the main channel by which initially country-specific shocks spread between international stock markets (Kaminsky, Reinhart, and Vegh, 2003; Kaufman, 1994). There is a large body of literature exploring the role of *financial linkages* in contagion, which offers insights into how shocks spread via economic linkages may influence stock returns.

Contagion is also a major concern in credit portfolios, particularly following corporate default (or bankruptcy). Egloff and Leippold (2007) define 'credit contagion' as the transmission of shocks via interdependencies between debtors that go beyond their exposure to common factors. Like financial contagion, credit contagion involves the transmission of shocks via channels involving a finite number of firms (e.g., supply chain or legal interdependencies) rather than via systematic channels affecting all firms. In credit portfolios, linkages between the assets can create significant credit risk (Schonbucher, 2000). In contrast to financial contagion, which is mainly at the market-level, research on corporate default and credit contagion is mostly at the firm-level or asset-level. In addition, in the most commonly used model of default, the Merton (1974) model, stock price is one of the main inputs driving default risk. Therefore the literature on corporate default and credit contagion contains many results that may be adapted and extended to model how shocks spread via economic linkages between firms influence stock prices.

In particular, the empirical methodology for modeling contagion is well developed and unified (Dungey, Fry, Gonzlez-Hermosillo, and Martin, 2005). Almost all empirical models of contagion and interdependence in asset markets are specified as factor models of asset returns (Dungey, Fry, Gonzlez-Hermosillo, and Martin, 2005). The theoretical basis of factor models of asset returns is the Arbitrage Pricing Theory (APT) developed by Ross (1976). Under APT, asset returns are determined exclusively by common factors representing non-diversifiable risk, as idiosyncratic factors are assumed to be diversified away (Ross, 1976). Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005) extend factor models to include a latent factor that captures the transmission of local shocks between asset markets, after conditioning on common factors. The methodology for modeling credit contagion proposed by Egloff and Leippold (2007) also augments standard factor models of asset returns with a term that captures microstructural dependence between creditors and debtors. The key difference between these two approaches is that Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005) assume that the linkages between assets are unobservable and allow for them using a latent factor, whereas Egloff and Leippold (2007) assume that the linkages between assets are observable and explicitly include them in a factor model.

Traditional models of stock returns assume that idiosyncratic shocks do not influence stock returns because they are fully diversified away in large portfolios. Importantly, however, recent economic literature demonstrates two situations in which the law of large numbers does not hold and firm-level shocks have a significant influence on aggregate outcomes. First, Gabaix (2011) shows that shocks to individual firms may not average out in aggregate when the distribution of firm sizes is heavy-tailed. Modern economies are dominated by large firms and shocks to these firms can trigger significant fluctuations in stock market indices (Gabaix, 2011). Second, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) proved that shocks to individual firms do not average out in aggregate when firms are linked and the distribution of firms' total influence via these linkages is heavy-tailed. In an inter-linked economy, a firm's influence on the aggregate is determined by its connectivity as well as its size. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) prove that the structure of inter-sector linkages determines how shocks propagate through an economy and influence GDP volatility. These papers highlight a significant gap in the previous research that has assumed that the law of large numbers applies in all situation and has therefore ignored idiosyncratic shocks.

In light of this new evidence it is crucial to reconsider whether shocks spread via economic linkages affect stock returns. I do so by synthesizing key empirical methodologies and results from the contagion literature with the theoretical results from the economic literature. The key theoretical findings, empirical methodologies and results from the literature are reviewed in detail in the rest of this chapter. I analyze the main theoretical findings, and then the empirical methods and results for each of the following bodies of literature in turn: financial contagion, corporate default and credit contagion, economic linkages and aggregate fluctuations.

2.3 Financial contagion

'Contagion' is defined as a change in the contemporaneous transmission of shocks during a crisis period (after conditioning on common factors that exist over a non-crisis period). Contagion results in increased correlation between asset classes and/or asset markets during crisis periods. There is a large body of research into methods of modeling this phenomenon (see Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005) for a review). The focus of this literature is on identifying transmission channels at the aggregate market level. This literature does not directly address whether shocks transmitted via economic linkages influence stock returns, but many of the theories and empirical tests can easily be modified in order to investigate this question.

2.3.1 Theoretical literature

It is widely accepted that common exposure to macroeconomic factors (such as interest rates or GDP) creates correlation in asset prices because these factors simultaneously affect many assets and firms (Allen and Saunders, 2003). While common macroeconomic and industry conditions are important causes of default correlation, Das, Duffie, Kapadia, and Saita (2007) and Duffie, Eckner, Horel, and Saita (2009) show that observable firm-specific, industry-level and macroeconomic conditions do not fully explain the degree to which failures are correlated across firms. Consistently, three explanations have been proposed for contagion: common observable risk factors (macroeconomic conditions), contagion via direct linkages and contagion via common unobservable risk factors (frailty or informational contagion)(Elizalde, 2012). In this section I review the theory of contagion due to direct linkages and contagion due to unobserved information effects.

Contagion via direct links

Direct contagion operates if there is a direct link between two firms that leads to a causal relationship between an initial default (A) and a subsequent default (B). Jarrow and Yu (2001) cite the example of the automotive industry where A is a major car producer and B is a small supplier who only sells to A and who will have to close if A fails. In contrast, informational contagion (frailty) describes the situation where the bankruptcy of firm A conveys bad news about other firms that have an unobservable risk factor in common with A. Contagion may occur via direct linkages such as supply or purchase contracts for goods, financial contracts such as bank loans or trade credit and/or ownership contracts. For example, in vertically integrated manufacturing processes, intermediate goods flow between many pairs of suppliers and customers along a supply chain.

In relation to financial firms, the first significant paper to focus on contagion in financial networks was Allen and Gale (2001). In an equilibrium economic model, they showed how 'liquidity preference' shocks can trigger contagion in a network of financial claims. Their key finding was that the possibility of contagion depends strongly on the *completeness* of the inter-firm network (i.e. on the degree of connectivity between banks generated by the cross holdings of deposits and other inter-bank claims). If the interbank market is complete and each region is connected to all the other regions, the initial impact of a shock in one region may be attenuated. On the other hand, if the interbank market is incomplete, each region is connected with a small number of other regions. The initial impact of the financial crisis may be felt strongly in a few neighboring regions, with the result that they too succumb to a crisis. Complete claims structures are shown to be more robust than incomplete structures because the initial impact of a shock in one region is spread over a greater number of firms.

An important issue not considered in the paper by Allen and Gale (2001) is that for a fixed level of *completeness*, different network structures have different potential for *positive feedback*. If increasing the completeness of the claims structures sets up one or more significant positive feedback loops in the claims network, then increasing completeness may *increase* the possibility of contagion. This idea is developed in Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2009).

Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2009) develop a model that characterizes the network of credit relations among financial agents as a system of coupled stochastic processes. Each stochastic process describes the dynamics of individual financial robustness, while the coupling results from a network of liabilities among agents. Resembling the conclusion of Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010), Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2009) find that the average level of default risk diversification across firms in a financial network is related to the *distribution* of links in the network (i.e. the pattern of connectivity as distinct from the degree of connectivity). They show that the correlation of output and default risk can be explained by local interaction among firms connected by production and credit ties. The framework can yield avalanches of bankruptcies in the presence of delayed payments (trade credit) and costs due to failures in supply.

In contrast to Allen and Gale (2001) they find that when there is positive feedback (in this particular model feedback takes the form of a *financial accelerator*), the aggregate risk of a portfolio of firms *does not* decrease monotonically as the degree of connection in the network increases. In most conditions there is an optimal level of connectivity, beyond which aggregate risk increases non-linearly (Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz, 2009). That is, diversification works when connectivity is low, but increasing connectivity beyond the optimal point may have the effect of amplifying shocks due to propagation through the network and the positive feedback mechanism.

These studies conclude that linkages between businesses are a channel by which shocks flow from one firm or sector to another, resulting in comovement between linked firms' or sectors' output. There is no consensus, however, on whether it is the degree or the distribution (or structure) of inter-linkages that influences the extent of contagion.

Informational contagion

Default correlation can also arise from information effects if investors are imperfectly informed about common factors affecting the true riskiness of an asset or debtor. The basic idea is that a default event reveals information to the market about unobserved risk factors, which may influence the market's assessment of the risk of any other firms that are affected by the same risk factors; so investors update their beliefs whenever defaults arrive with a timing that is more or less clustered than expected based solely on the observable risk factors (Duffie, Eckner, Horel, and Saita, 2009). Frailty explains why the spreads of unlinked, competing firms can widen significantly upon a default (Schonbucher, 2000; Jorion and Zhang, 2009). For example, Schonbucher (2000) argues that the failure of Enron reduced trust in accounting information and this 'frailty' raised the failure risk premium priced into credit spreads for all firms related to Enron or Arthur Anderson. Other examples of increases in market-perceived risk could be observed for example in the widening of credit spreads in the telecom sector upon the frequent failures between 2000 and 2002, or in the airline sector in the period after September 11th 2001. These spread moves were associated with a change in market perceptions rather than a change of the underlying business fundamentals (Schonbucher, 2000; Giesecke and Weber, 2003). Similarly, corporate bankruptcy can decrease the market value of competitors by conveying information that affects a firm's dealings with customers, investors, creditors, regulators, and/or suppliers (Lang and Stulz, 1992). Information about one or more firms in an industry adversely affects all other firms in the industry, including firms that may have little in common with the first firms other than being in the same industry (Hertzel, Li, Officer, and Rodgers, 2008).

Frailty effects are strongest when firms are viewed by the market as being more or less homogeneous (Kaufman, 1994). Vice versa, heterogeneity of firms has a negative effect on the likelihood of contagion (Hertzel, Li, Officer, and Rodgers, 2008). This is consistent with theories of financial contagion which suggests that contagion is more widespread when firms or products are homogenous (Kaufman, 1994). This can occur when investors are not able to distinguish between products because they are too complex (as in the case of complex financial products) or because the information is not publicly available. Informational contagion, therefore, is also more likely to occur between firms in the same industry, as they have the same operating environment and produce similar products.

The strength of contagion is also influenced by factors affecting the extent of informational asymmetry. High levels of uncertainty, poor disclosure, incomplete information, and incentives to withhold information can mean that firms are viewed by the market as being homogeneous because investors do not have enough information to distinguish individual firms or products from one another (Duffie, Eckner, Horel, and Saita, 2009). In conclusion, frailty is likely to be more significant in the following circumstances: during periods of uncertainty, when information is costly or scarce, when market values change quickly or liabilities are short term, and/or when firms or products are homogenous.

Finally, theoretical models generally imply that both types of contagion (direct and informational) are more prevalent during a recession, when firms are closer to their default thresholds (due to high levels of debt and/or low net worth) and/or when firms have more contractual links with one another (Lang and Stulz, 1992).

2.3.2 Empirical studies

Empirical studies use a number of alternative methods to test for the presence of contagion during financial market crises. Most statistical tests of contagion test whether the correlation in returns is significantly higher in crisis periods than in non-crisis periods (Dungey and Martin, 2004; Dungey, Fry, Gonzalez-Hermosillo, and Martin, 2006; Forbes and Rigobon, 2002). Billio and Pelizzon (2003) show that the methodologies proposed by Forbes and Rigobon (2002) are highly affected by the time windows used and by the presence of omitted variables. They propose some analyzes to strengthen the robustness of these tests. Correlation based tests focus on pairs of asset returns, but it is possible to test contagion in multiple directions using factor models. Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005) show that factor-based models and correlation-based models of contagion can be united within the general framework of latent factor models (because financial contagion occurs via unobservable, or latent, channels). These findings suggest that it should be possible to extend factor models of stock returns to allow for contagion via observable economic linkages between firms.

Empirical studies find that the correlation in asset returns is higher during recessions than in growth periods (Erb, Harvey, and Viskanta, 1994; Das, Duffie, Kapadia, and Saita, 2007)[1]. Similarly, a large number of studies show that correlation in stock markets is higher during more volatile markets (i.e. that the dependence of assets or markets is asymmetric). Importantly, Longin and Solnik (2001) show that correlation between international equity markets increases in volatile times, but only when the market trend is positive. They find that correlation is not related to market volatility per se but to the market trend, so correlation increases in bear markets, but not in bull markets. The finding that equity returns are more correlated in bear markets than in bull markets is confirmed by Ang and Chen (2002) and Ang and Bekaert (2002). Ang and Chen (2002) find significantly higher correlations between equity portfolios and equity markets. These findings suggest that contagion via economic linkages may be stronger in recessions and/or volatile market regimes.

The usual tool for investigating whether correlation is significantly higher in volatile markets is the 'exceedance correlation' (correlation between returns conditional upon returns exceeding a threshold) developed by Longin and Solnik (2001). Ang and Chen (2002) develop a statistic for testing asymmetries in conditional exceedance correlations and find that correlations between US stocks and the aggregate US market are much greater for downside moves, especially for extreme downside moves, than for upside moves. Their test is a joint test of the model used to predict returns and of whether or not return correlation is asymmetric. Hong, Zhou, and Tu (2007) develop a model-free test for asymmetric correlations, and also find that stocks tend to have greater correlations with the market when the market goes down than when it goes up. They find that stock return asymmetries over crisis periods are statistically significant and are of substantial economic importance.

Regime shifting models can also capture asymmetric dependence in returns. Ang and Chen (2002) and Ang and Bekaert (2002) show that regime switching models can reproduce the fact that large negative returns are more correlated than large

[1] Das, Duffie, Kapadia, and Saita (2007) find that the correlation between corporate default risk is significantly higher in recession periods.

positive returns. Das, Duffie, Kapadia, and Saita (2007) also use a regime shifting model to capture how default correlation increases in recessions, and finds that a model that allows default correlation to increase in recessions (when marginal default probabilities are also higher) is able to predict out-of-sample aggregate default rates much better than a model with a single regime.

Summary Contagion is defined as an increase in return dependence during periods of crisis and/or during volatile markets. Theoretical models identify production, trade and/or credit linkages between firms as a source of contagion. In addition, higher levels of correlation are associated with higher levels of linkage between firms (Raddatz, 2010). Most tests of contagion are performed at the level of an entire market or asset class, by testing whether there is a statistically significant increase in return correlation in a recession or a bear market (Dungey, Fry, Gonzlez-Hermosillo, and Martin, 2005). Very few studies have been undertaken at the firm-level and very few studies explicitly test whether inter-firm linkages may be a source of contagion. This is partly due to the difficulty obtaining data on inter-firm linkages, and partly because the informational linkages that have been proposed as a cause of contagion are unobservable (Egloff and Leippold, 2007). However, there is a unified empirical methodology for testing for contagion between markets which can be adapted to test for contagion between economically linked firms.

2.4 Corporate default and credit contagion

Corporate defaults tend to cluster in time (Allen and Saunders, 2003). This is problematic because even small levels of default dependence (credit contagion) have significant effects on the price and risk of credit portfolios (Schonbucher, 2000). Due to the economic significance of this problem, much effort has been put into modeling corporate default and credit contagion. This body of research contains several insights for understanding and modeling linked firms' asset prices. A major advantage of this literature, for the purposes of understanding how economic linkages between firms influence stock prices, is that default is typically modeled at the firm-level.

2.4.1 Theoretical literature

The probability that a borrower defaults (PD) is the major driver of the credit risk borne by lenders. This fact has motivated a large amount of research on default risk, mostly at the level of the individual borrower. The standard structural model of default assumes that a firm defaults when its asset value (V_t) falls below a default threshold (Merton, 1974). The default threshold is typically related to the value of a firm's liabilities. It is not possible to observe V_t continuously in time (Jarrow and Protter, 2004). In practice, therefore, stock prices are used as a proxy for the firm's asset value. Within the Merton (1974) framework, any factors that simultaneously influence, or reveal information about, the condition of many firms' asset values may create default correlation. It is necessary to identify and control for key drivers of default correlation when testing whether contagion occurs via economic linkages in addition to these other causes. In the following sections, therefore, we review empirical research that identifies the key drivers of default correlation.

2.4.2 Empirical studies

Corporate default and macroeconomic conditions

Time-series of corporate default rates exhibit two important characteristics. First, aggregate default rates vary over time in a way that is related to macroeconomic conditions. Second, defaults tend to cluster because, on average, correlation between corporate defaults is positive across firms (Allen and Saunders, 2003). Several strands of theory explain these stylized facts.

There is consensus in the economic and credit risk literature that macroeconomic growth impacts corporate default risk (that is, the likelihood a firm will become bankrupt in the US or insolvent in the UK) (Jarrow and Turnbull, 2000; Allen and Saunders, 2003). Corporate failure rates are related to macroeconomic conditions (such as investment and output) in several ways. Wilson (1998) found that macroeconomic factors explain much of the overall variation in the aggregate corporate failure rates. Studies linking corporate failure and macroeconomic conditions show that, in addition to firm-level financial position, macroeconomic factors influence firm failure risk (Duffie, Saita, and Wang, 2007; Jacobson, Lind, and Roszbach, Forthcoming; Carling, Jacobson, Lind, and Roszbach, 2007).

Many studies suggest that macroeconomic factors such as nominal interest rates, output growth or deviation from trend, aggregate levels of indebtedness, and real exchange rates, profits, price, and corporate birth rates explain the majority of variation in aggregate failure rates in both the short run and in the long run (Wilson, 1998; Jokivuolle, Virolainen, and Vhmaa, 2008; Liu, 2009). Of these macroeconomic variables, interest rate appears to be an important factor influencing failure rates. Hunter and Isachenkova (2006) model default risk of UK listed firms between 1989 and 1991 and find evidence that in addition to financial statement variables, shocks in the nominal interest rate and the real exchange rate are key factors in causing large firms to fail. These results underscore the significant influence of macroeconomic conditions on corporate default risk.

Duffie, Eckner, Horel, and Saita (2009) find that the three month Treasury bill rate and the annual return on the S&P 500 are significant predictors of corporate bond default rates. Lando and Nielsen (2010) find that, in addition to the aforementioned factors, US industrial production and the Treasury interest rate spread are also significant predictors of default rates. At an aggregate level, the probability of default (PD) is positively correlated across firms and macroeconomic risk factors explain the majority of the positive correlation of PD across firms (Das, Duffie, Kapadia, and Saita, 2007). However, this relationship is dynamic as cyclical effects in asset valuations and shifts in market regimes due to structural, regulatory, or economic factors may change PD and PD correlation (Das, Duffie, Kapadia, and Saita, 2007; Liu, 2009).

Structural changes, however, affect the way that firms react to macroeconomic shocks. For example, Liu (2009) shows that UK firms were more affected by net lending to the corporate sector and less affected by interest rates prior to the 1980s (when market-oriented economic reforms in the UK made it easier for firms to access non-bank credit and increased the importance of interest rates as a monetary policy tool (Liu, 2009). Another structural influence on default rates is bankruptcy law (Allen and Saunders, 2003)[2]. Finally, in an interconnected economy, business cycles in other regions or sectors may be significant determinants of business exit (Bhattacharjee, Higson, Holly, and Kattuman, 2009).

Macroeconomic conditions affect many firms and many assets at the same time. It follows that, macroeconomic conditions that explain an individual firm's PD are also crucial drivers of default correlation. Therefore, in adverse macro conditions, such as a recession, clusters of defaults are more likely and aggregate credit risk increases (Allen and Saunders, 2003). However, models only allowing for dependence caused by macroeconomic factors under-predict levels of default correlation and cannot reproduce the high degree of correlation found in empirical data on defaults (Das, Duffie, Kapadia, and Saita, 2007; Egloff and Leippold, 2007).

Summary Adverse macroeconomic conditions tend to increase corporate default rates. Examples of adverse macroeconomic conditions include low growth in terms of GDP or stock market returns and/or tight monetary conditions. The relationship between macroeconomic conditions and default risk may change over time as a result of average levels of leverage, structural factors or changes in the way firms react to shocks.

Macro factors are a significant source of default correlation, but models only allowing for macro factors are insufficient for modeling the aggregate return of both equity and credit portfolios. I.e. pure macro models cannot reproduce the high degree of correlation found in empirical data on defaults (Das, Duffie, Kapadia, and Saita, 2007; Egloff and Leippold, 2007). Models that ignore contagion understate the joint failure risk and the probability of large losses (Duffie, Eck-

[2] Bhattacharjee, Higson, Holly, and Kattuman (2009) find significant differences in the way that US and UK firms react to changes in the macroeconomic environment related to differences in bankruptcy legislation. In particular, firms in the US are able to enter into Chapter 11 bankruptcy, which allows the firm protection from creditors while it reorganizes itself. Protective bankruptcy laws can allow firms to survive a period of macroeconomic disturbance and have been related to lower failure rates and lower sensitivity of failure rates to macroeconomic volatility (Bhattacharjee, Higson, Holly, and Kattuman, 2009).

ner, Horel, and Saita, 2009). Therefore, it is crucial that credit risk models are extended to allow for other factors that explain default correlation. Finally, as stock prices are a key driver of default risk, these findings imply that factors other than systematic risk factors can create correlation in stock prices.

Corporate default and industry-level conditions

Several models of corporate default allow for industry-level factors that explain default correlation in excess of that explained by SRFs, in order to generate observed levels of dependence between default events.

There may be differences in the way different types of firms, or different industries, respond to macroeconomic conditions. In the academic literature industry effects on corporate default have received significantly less attention than macroeconomic risk factors. Relationships are often modeled at an aggregate level, despite the issues of aggregation bias or the fact that aggregation may obscure heterogeneity in relationships between different units (Bond, 2002). Few studies allow for industry heterogeneity in the relationship between corporate failure and macroeconomic factors. Chava and Jarrow (2004) suggest this is due to the limited number of bankruptcies in the databases previously available. Yet, economic intuition, theory and empirical evidence suggest that industry effects are an important component in bankruptcy prediction.

Firms in different industries respond differently to macroeconomic and financial market conditions (Wilson, 1998). For example, heavy exporters are more impacted by the real terms of trade than firms that do not export their products and services; demand for non-durables and services is less sensitive to interest rates than demand for durable goods (Mankiw, 1985); industries with greater dependence on external finance grow disproportionately faster when credit is available (Rajan and Zingales, 1998). Different industries also have different levels of competition and operating environments that influence default rates (Opler and Titman, 1994). On the other hand, firms in the same industry share similar structural characteristics such as inputs, dependence on external financial, capital needs and the nature of the production process (La Porta, Lopez-de Silanes, Shleifer, and Vishny, 1997; Carling, Jacobson, Lind, and Roszbach, 2007; Booth, Aivazian, Kunt, and Maksimovic, 2001). This means that firms in the same industry are likely to be influenced in a similar way by macroeconomic and financial market conditions. So industry effects should be controlled for when testing for contagion via economic linkages.

Empirical evidence supports the hypothesis that industry linkages are a significant channel of credit contagion. Lang and Stulz (1992) and others find that bankruptcy announcements have significant contagious and competitive intra-industry effects on stock prices. Cheung and Levy (1998) found statistically significant inter-industry linkages among bankruptcy rates in Australia, with high rates in one industry positively related to an increase in default in other industries in subsequent periods. In addition, a number of other industry-specific variables were also found to be significantly associated with business bankruptcy rates, including the number of industrial disputes, housing prices and manufacturing wage rate. Shleifer and Vishny (1992) argue that when a firm in financial distress needs to sell assets, its industry peers are likely to be experiencing problems themselves; they show how this 'fire-sale' of assets places downward pressure on prices, leading to sales at prices below fair value. Supporting this argument, Acharya, Bharath, and Srinivasan (2003) find that industry conditions at the time of default are important determinants of recovery rates, in addition to seniority and security of the defaulted securities. These studies support the view that default risk can spread between industries or through firms within an industry via business relationships, and that industry conditions can significantly affect the spread of financial distress between firms.

Summary It appears that industry-level risk factors (such as capital needs of production, the stage in industry life-cycle and industry concentration) have a significant influence on joint default risk in addition to macroeconomic and firm-specific risk factors. There are also interacting effects between industry concentration, leverage and macroeconomic conditions that determine the strength of contagion effects (following a bankruptcy or default) by affecting the ability of the firm to substitute its suppliers and customers. As default risk is closely linked to a firm's asset value and stock price, these findings suggest that industry factors, leverage and macroeconomic conditions should be controlled for when testing for contagion between economically linked firms[3].

Corporate default and firm-level conditions

In addition to the degree and structure of linkages, the influence of linkages is determined by firm-level characteristics and firm-level counterparty relationships. Several studies report that the influence of inter-linkages on correlation between firm value depends on the extent of linkages and the degree to which linked firms are substitutable (Lang and Stulz, 1992; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010). In turn, the substitutability of a counterparty is a function of specialized product nature, industry structure, and the degree of leverage of affected firms. Product specificity affects the spread of contagion because it is more difficult to replace a supplier (customer) if the goods made by (for) the supplier (customer) are highly specialized or custom made (Titman and Wessels, 1988). Titman and Wessels (1988) find that suppliers of unique or specialized products (as measured by research and development intensity) are more likely to suffer distress when an important customer is in distress.

Substitutability of a supplier (customer) is also affected by whether or not the supplier's (customer's) own industry is highly concentrated. This is because a) in a concentrated industry there are not many alternative firms, and b) in a concentrated industry, the default of a firm would be of greater significance to that industry, which could make it harder for suppliers and customers to find a replacement (Lang and Stulz, 1992; Hertzel, Li, Officer, and Rodgers, 2008). On the other hand, Lang and Stulz (1992) argue that competitive benefits to intra-industry rivals are more prominent in concentrated industries, whereas intra-industry 'informational' contagion dominates in competitive industries. They also note that competitive benefits can only be realized if intra-industry competitors have spare

[3] I.e. it is important to control for factors other than economic linkages that have been shown to influence stock returns and return correlation, in order to make sure that the significance of economic linkages is not due to an omitted factor.

debt capacity and can access external finance, as expansion and acquisition require investment funded by internal or external finance. The ability to realize competitor benefits will be limited for firms that are highly leveraged and cannot access additional external finance even when a good opportunity arises because they have reached the limit of investors' willingness to lend. Supporting the hypothesis that a firm's spare debt capacity and/or leverage affects its counterparty risk, many studies note that spare debt capacity is important in capital structure decisions of the firm, because firms reserve spare debt capacity to maintain financial flexibility and to avoid having to pass up profitable investment opportunities (Graham and Harvey, 2001).

Finally it is important to note that macroeconomic conditions interact with industry-level and firm-level factors driving contagion. For example, spare debt capacity is influenced by macroeconomic conditions and the current stage of the credit cycle; in a bull market, firms are more likely to be able to access external finance because leverage ratios tend to increase as asset prices increase (Chen and Wang, 2007). In addition, in a recession, when more firms are in distress, it is more difficult to replace a supplier or customer should they fail.

Summary The theory above suggests that the market-level, industry-level and firm-level risk factors shown in Table 2.1 influence default correlation. The substitutability of a counterparty is a function of specialized product nature, industry structure, and the degree of leverage of affected firms. The influence of interlinkages on firm value is likely to be greater when firms are more reliant on counterparties because they cannot easily substitute them should they fail. Therefore shocks are more likely to spread between suppliers and customers: when spare debt capacity and access external finance are lower, or in a recession.

Credit contagion

The previous sections have focussed on literature relating to corporate default. Additional insights regarding how shocks spread between firms may be gained by analyzing literature on contagion in credit markets and from studies that examine the impact of bankruptcy on the stock price of a firm's suppliers and customers.

Table 2.1: Market-level, industry-level and firm-level risk factors documented as having an influence on default correlation

	Theoretical variable	Model covariate
Market-level	Measure of market uncertainty	Volatility of stock price index (Duffie, Eckner, Horel, and Saita, 2009)
Industry-level	Product specificity	Industry pair dummies (Raddatz, 2010)
	Capital needs of production	Measure of dependence on external finance (Rajan and Zingales, 1998)
	Industry concentration	Herfindahl index (Lang and Stulz, 1992)
	Stage in industry life-cycle	Industry growth rate and/or rate of new entrants (Caves, 1998)
Firm-level	Trade credit	Ratio of trade credit to total sales (Raddatz, 2010)
	Leverage	Ratio of bank debt to assets (Raddatz, 2010); Book or market leverage (Duffie, Eckner, Horel, and Saita, 2009)

The empirical methodology for modeling credit contagion proposed by Egloff and Leippold (2007) also augments standard factor models of asset returns with a term that captures microstructural dependence between creditors and debtors. The key difference between this model and the approaches for modeling financial contagion are that Egloff and Leippold (2007) assume that the linkages between assets are observable and explicitly include them in a factor model, whereas in models of financial contagion the linkages between assets are unobservable and are allowed for using a latent factor. By calibrating this model, Egloff and Leippold (2007) conclude that even small levels of inter-dependence between debtors in a credit portfolio has a significant impact on the tails of the portfolio loss distribution.

In regards to how bankruptcy events may impact the stock price of a firm's suppliers and customers, Lang and Stulz (1992) investigated the effect of bankruptcy announcements on the equity value of other firms in the same industry as the bankrupt firm. On average, bankruptcy announcements decreased the equity value of (a value-weighted portfolio of) competitors by 1%. Negative effects on equity value were significantly larger for: a) highly levered industries and b) industries where the unconditional stock returns of the non-bankrupt and bankrupt firms are highly correlated[4]. These negative effects on other firms within the same industry may be offset by positive 'competitor' effects. Lang and Stulz (1992) suggest that positive competitor effects are only realized when other firms are able to increase their market share following the bankruptcy of a competitor, or to acquire the bankrupt firm's assets. In summary, the effects of a bankruptcy on the equity value of rival firms within the same industry may be negative (contagion) or positive (competitive benefits). Competitive benefits are more prominent in concentrated industries, with low leverage, whereas contagion dominates in competitive industries, with high leverage.

Jorion and Zhang (2009) extend the work of Lang and Stulz (1992) and examine intra-industry effects of bankruptcy announcements using credit spread and stock price data. They find that the response of credit spreads and stock prices varies significantly across industry and by the type of default (anticipated versus non-anticipated); default correlation effects are significantly related to industry characteristics such as concentration, leverage and correlation of stock prices. Contagion effects are greater amongst industries in which firms have very similar cash flows (or equity correlations) or are highly leveraged. Whereas, in highly concentrated industries, the default of a competitor is likely to strengthen the position of surviving firms, or reduce default intensity.

More recently, innovative sources of data on direct linkages have been used to examine inter-industry contagion between linked firms. Using bankruptcy an-

[4] A high degree of correlation in returns suggests that all firms within an industry are similar to one another, or homogenous, in terms of cash flows and other factors that influence market price.

nouncements that detail the major creditors of bankrupt companies, Jorion and Zhang (2009) examine the effect of unexpected bankruptcy events on creditors' stock returns, and subsequent default probabilities. Using bankruptcy filings and credit spread data, they find that creditors experience negative abnormal returns if a debtor becomes bankrupt, and that losses reflect both direct exposure and the loss of customer relationships (or present value of loss of future profits and income). Creditors with large exposures are more likely to suffer financial distress. These effects are stronger for non-financial companies than for financial companies. Finally, they illustrate that default clustering can be explained by counterparty connections in this data set.

Hertzel, Li, Officer, and Rodgers (2008) test for abnormal returns following bankruptcy filings of major suppliers and customers. The main finding is that a supplier's abnormal returns are significantly negative on average around both the distress and bankruptcy filing of a major customer, especially when the filing firm's industry experiences intra-industry contagion (Hertzel, Li, Officer, and Rodgers, 2008). In some cases contagion effects spread beyond reliant suppliers and major customers to firms in their respective industries. Hertzel, Li, Officer, and Rodgers (2008) do not find any significant contagion effects on customers, nor do they find any significant contagion effects on suppliers when intra-industry contagion is not present in the bankrupt firm's industry[5]. Wagner, Bode, and Koziol (2011) also find significant levels of default dependency in auto firms' supplier portfolios using detailed industry reviews of major suppliers in the automobile industry. They show that supplier default dependency can have significant consequences.

Summary Most of the studies testing for contagion effects following default (or bankruptcy) look for effects over reasonably short periods (e.g. around financial distress filing events). Many of the effects of financial distress build up over

[5] They were also not able to find a significant relationship between contagion (measured by abnormal stock returns following default of a customer/ supplier) and industry concentration, specialized product nature or leverage, due to the small size of their sample, the considerable cross-sectional variation in customer and supplier returns, and the coarseness of proxies used to capture the characteristics.

time and occur simultaneously, therefore a continuous time methodology is often more appropriate than an event study for studies of default risk (Duffie, Saita, and Wang, 2007). With regard to the impact of linkages on stock prices, these findings suggest that an unexplored area is the influence of shocks spread via economic linkages on average stock returns over time.

2.5 Economic linkages and business cycle fluctuations

The question of how shocks spread via linkages between sectors of the economy influence aggregate outcomes (such as movements in Gross Domestic Product) has been analyzed in the economic literature, and contains significant results that shed light on how shocks spread between supplier and customer firms.

2.5.1 Theoretical literature

Economic business cycles are marked by distinct periods in which volatility and correlation in economic aggregates increases (Lucas, 1981). Early attempts to understand business cycles focussed exclusively on macroeconomic shocks, arguing that micro shocks could not generate the aggregate movements observed in markets (Lucas, 1981). The traditional argument against the relevance of idiosyncratic shocks for aggregate fluctuations in economic and/or financial markets invokes the law of large numbers (see Gabaix (2011) and Ross (1976) for discussion in context of economic markets and financial markets respectively). The law of large numbers implies that when idiosyncratic shocks are independent of one another, they will have a negligible aggregate affect in large portfolios. This argument underpins the exclusive use of SRFs to aggregate fluctuations in economic aggregates Lucas (1981)[6]. For a long time, almost no research refuted this assumption, or considered situations in which idiosyncratic shocks might influence asset prices or create aggregate market fluctuations.

[6] The law of large numbers also underpins the exclusive use of SRFs to explain asset prices in almost all asset pricing models (Ross, 1976).

Two recent papers, however, show that idiosyncratic shocks can cause fluctuations in economic aggregates when the influence of different units in the economy is very uneven (Gabaix, 2011; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010). These papers show that idiosyncratic shocks do not average out in the aggregate when a few firms have extremely high influence, but most have low influence (i.e. the distribution of units' influence, across the aggregate, is heavy-tailed). First, Gabaix (2011) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) demonstrate two separate sets of conditions in which the law of large numbers does not hold. Gabaix (2011) shows that individual firm shocks do not average out in aggregate when the distribution of firm sizes is heavy-tailed. As pointed out by Gabaix (2011), modern economies are dominated by large firms, so shocks to these firms can trigger non-trivial aggregate fluctuations. Second, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) prove that individual firm shocks do not average out in aggregate when firms are linked and the distribution of firms' total influence via these linkages is heavy-tailed. In an inter-linked economy, a firm's influence on the aggregate is determined by its connectivity as well as its size, so the results of Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) are most useful when considering the spread of shocks between linked firms and/or assets. These papers highlight that firm-level shocks to very large or very connected firms can create aggregate economic fluctuations.

Empirical evidence on aggregate economic fluctuations also supports the hypothesis that firm-level (or micro) shocks can create aggregate economic fluctuations. Horvath (2000) and Shea (2002) find that micro shocks can cause aggregate fluctuations. Dupor (1999) debates the evidence put forward by Horvath (2000) (that sectoral shocks, propagated via inter-sector linkages, can cause aggregate fluctuations), arguing that the variance of aggregates in multi-sector models is the same as the variance of aggregates in their single-sector counterparts so sector-specific shocks cannot cause aggregate fluctuations.

The crux of the debate between Dupor (1999) and Horvath (2000) is whether or not the Central Limit Theorem (CLT) applies, so that idiosyncratic shocks average out in aggregate portfolios of size N at rate $\frac{1}{\sqrt{N}}$. Dupor (1999) assumes that the distribution of linkages across sectors is balanced[7]. Horvath (2000), on the other hand, noted that actual US input-use matrices are not balanced; the number of sectors supplying inputs increases much slower than the total number of sectors upon disaggregation. This implies that a few central 'hub' sectors provide most of the inputs supporting production across a range of sectors, while most sectors act as producers rather than input suppliers. In unbalanced economies, the diversification of sector-specific shocks is affected by inter-sector linkages; and the rate at which the law of large numbers applies is controlled by the rate of increase in the number of full rows in the input-use matrix rather than by the rate of increases in the total number of sectors (Horvath, 2000). In the types of structures observed in the US economy, aggregate volatility from sector shocks declines at less than half the rate implied by the law of large numbers, suggesting that a sizable portion of aggregate volatility could be caused by shocks to individual sectors(Horvath, 2000). Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) formally proves that the structure of inter-sector linkages in an economy determines whether or not the CLT applies, and therefore whether or not sector-specific shocks can cause aggregate fluctuations.

Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) provide a general framework for understanding how linkages affect the spread of shocks between firms. The intuition is as follows. The structure of inter-sector linkages determines the way in which sector-specific shocks average out over the whole network of linked firms. In the class of balanced economies considered by Dupor (1999) shocks to all sectors have equal weight, so aggregate volatility decays in line with the law of large numbers. When an economy is unbalanced (or heavily reliant on a few 'hub' sectors so that the distribution of linkages across sectors is uneven), however, aggregate volatility decays much slower than the law of large numbers. This is because adding unconnected (low influence) sectors to an economy does very little to offset the effect of shocks to the high influence sectors in the economy. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) develop an expression for the lower bounds on aggregate volatility in terms of the linkages between sectors. They

[7] Balanced economies are those in which each sector's output is used to approximately the same extent, such that the structure of linkages for each sector is approximately symmetrical.

show that aggregate volatility converges to zero (i.e. the CLT applies) only if the share of sales (or output) of the largest sector approaches zero as the number of sectors increases. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) and Horvath (2000) both provide empirical evidence from US input-output tables that correlation between outputs across sectors is highest when a few non-substitutable sectors supply inputs (such that their share of aggregate output is bound away from zero even as the number of sectors increases).

2.5.2 Empirical studies

In the theoretical literature above, the transmission of shocks via linkages (production linkages and credit linkages respectively) amplifies shocks, meaning that shocks that are initially small can have a significant effect on aggregate outcomes[8]. Similarly, multi-sector models of economic production imply that the output of sectors that buy goods from (sell goods to) each other will be correlated (Raddatz, 2010; di Giovanni and Levchenko, 2010). The comovement of economically linked businesses has been empirically verified at the country-level and at the sector-level. Countries that trade more with each other exhibit higher business cycle correlation(di Giovanni and Levchenko, 2010). At the sector-level, Shea (2002) finds that input-output linkages between US manufacturing sectors are important to sector-level comovement in output and employment. Likewise, Raddatz (2010) finds that comovement in output across sector-pairs in 43 countries are related to the strength of input-output relationships and also to the use of trade credit in these relationships.

Recent empirical studies have shown that inter-sector (input-output) linkages do explain correlation in output at an industry level e.g. Horvath (2000), Shea (2002) and Raddatz (2010). Shea (2002)finds that input-output linkages and local activity spill-overs are important to comovement in aggregate output of US

[8] Financial crises provide plenty of examples of shocks spreading far beyond the firm, market and country in which they originate. For example, the potential default of Long Term Capital Management in 1998 created financial difficulties for several other major investment banks, and the collapse of the Thai Baht in 1997 had a wide-spread effect on prices throughout East Asian stock markets.

manufacturing industries, whereas aggregate activity spill-overs are not important. Raddatz (2010) focuses on production networks in which firms are linked by supplier-customer relationships involving extension of trade credit. Specifically, he investigates the relationship between the correlations and input-output relations of 378 manufacturing industry-pairs across 44 countries (with different degrees of use of trade credit) and finds that an increase in the use of trade-credit along the input-output chain linking two industries increases the correlation of their output.

Very few studies, however, consider how shocks are transmitted along supply chains at the firm-level [9]. The transmission of shocks through supplier-customer linkages has been investigated at the sector-level by Lang and Stulz (1992) and Raddatz (2010). Lang and Stulz (1992) investigated the effect of bankruptcy on the equity value of firms in the same industry as the bankrupt firm. On average, bankruptcy announcements decreased the returns of same-industry competitors by 1%. Negative effects on equity value were significantly larger for highly levered and homogenous industries (where the stock returns of the non-bankrupt and bankrupt firms were highly correlated). Within the same industry, negative contagion may be offset by positive 'competition' effects when firms are able to increase their market share following the bankruptcy of a competitor (Lang and Stulz, 1992). Competition effects are stronger in highly concentrated industries with low leverage(Lang and Stulz, 1992), where a bankruptcy is likely to free up more market share and where fewer firms subsequently compete to secure the available market share. In addition to the industry environment, the use of trade credit amplifies contagion, as it increases the spread of shocks along supply chains (Raddatz, 2010). In summary, contagion is strongest in competitive (not concentrated) industries with high leverage.

Other studies also show that the spread of shocks via economic linkages influences stock returns. Jorion and Zhang (2009) and Hertzel, Li, Officer, and Rodgers (2008) use bankruptcy announcements and filings to identify contagion

[9] The small number of studies is partly because detailed data on supplier-customer linkages is not readily available.

between suppliers and customers following the bankruptcy of a major supplier (customer). Jorion and Zhang (2009) find that the response of credit spreads and stock prices varies significantly across industry and by the type of default (anticipated versus non-anticipated). Default correlation effects are significantly related to industry characteristics such as concentration, leverage and correlation of stock prices. Like Lang and Stulz (1992), they show that contagion effects are greater amongst industries in which firms have very similar cash flows or are highly leveraged. There is evidence that a firm's stock returns respond to significant events to its key customers (Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008). Hertzel, Li, Officer, and Rodgers (2008) examine suppliers and customers of distressed firms using bankruptcy filings and find that the stock prices of a firm's suppliers, but not customers, are affected by its bankruptcy, but the average effect for suppliers is less than 2% of the market value of equity. Similarly, Cohen and Frazzini (2008) show that customer firms' returns predict their suppliers' subsequent returns.

In summary, several studies find statistically significant counterparty effects on suppliers' stock prices, but the magnitude of the effects is small (Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008; Jorion and Zhang, 2009). These studies, however, are limited in three ways. First, event studies focusing on a time window around a bankruptcy filing or significant stock price movement shed little light on how counterparty effects can influence returns over medium to long term periods. Second, these studies focus on how the direct links between suppliers and customers explain correlation in returns, and neglect the potential influence of shocks transmitted via indirect linkages on returns. As shown in Chapter 4, shocks from suppliers (customers) multiple steps upstream (downstream) along a supply chain can be a non-diversifiable source of risk. If shocks transmitted from suppliers (customers) multiple steps upstream (downstream) are significant, this will increase the economic significance of counterparty effects. Finally, these studies do not test the hypothesis that the magnitude of counterparty effects is higher in recessions.

Supplier-customer relationships are affected by dynamic factors such as shifts in market regimes, and structural, regulatory, or economic factors (Das, Duffie, Kapadia, and Saita, 2007; Liu, 2009). It is widely noted in the credit risk literature that default correlation and default probabilities are higher in recessions (Allen and Saunders, 2003). Jarrow and Yu (2001) show that default correlation arises because of both a SRF and a counterparty risk factor (exposure to other firms' risk). Counterparty risk is a significant factor driving the default clustering in recessions (Jarrow and Yu, 2001), suggesting counterparty effects are stronger in recessions. Furthermore, there are economic reasons to expect that the transmission of shocks via economic linkages is stronger in recessions. The influence of inter-linkages on firm value depends on the extent of linkages and the degree to which linked firms are substitutable (Lang and Stulz, 1992). The influence of economic linkages is stronger in recessions as it is harder to replace a counterparty in a recession, and because more firms are in distress in a recessionLang and Stulz (1992). Hence, an important but unexplored question is whether the magnitude of counterparty effects on stock returns is larger when indirect linkages are considered and/or during recessions.

Summary The structure of linkages between sectors in the economy can have a significant impact on the correlation and volatility of aggregate output (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010; Raddatz, 2010). Specifically, when the economy is dominated by a few 'hub' sectors (so the distribution of economic output across sectors is heavy-tailed), aggregate volatility decays much slower than the law of large numbers predicts. This is because adding additional sectors to the economy does very little to offset the effect of shocks to the 'hub' sectors in the economy. While Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) notes that his framework could be down-scaled to the firm-level, as yet there is no general framework for analyzing the relationship between inter-firm linkages and asset prices. Both theoretical and empirical evidence exists that firm-level shocks, transmitted via economic linkages, have a significant influence on economic aggregates. This effect may be influenced by the use of credit.

2.6 Summary and research gaps

The financial contagion literature has successfully identified channels relevant in the spread of financial crises, many of which are unobservable factors associated with investment behavior. There is a unified empirical methodology for modeling and testing for contagion between markets. Far less is known about how firm-level linkages influence contagion. In particular, there is a disagreement about whether the degree or the structure of financial linkages is more important in the process of financial contagion.

The literature on corporate default and credit contagion is helpful because unlike studies of financial contagion, a lot of this research and modeling has been done at the firm-level. Studies of corporate default are instructive in understanding the factors that influence stock returns, and as a whole this literature suggests that it is important to control for the market-level, industry-level and firm-level risk factors shown in Table 2.1 when modeling firms' asset values or stock prices. In addition this literature highlights the potential for regime shifting behavior in the way that firms' asset values respond to shocks to their suppliers, customers or industry. In particular, the influence of inter-linkages on firms' net worth is likely to be greater when firms are more reliant on counterparties because they cannot easily substitute them should they fail. Therefore shocks are more likely to spread between suppliers and customers: when spare debt capacity and access external finance are lower, or in a recession.

Finally, there are also a range of economic models of the way that shocks spread through economic networks, and the impacts that shocks spread through inter-sector economic linkages have on aggregate volatility in GDP (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010; Gabaix, 2011). Gaps remain, however, in the broad area of inter-firm contagion (not specifically via economic linkages). The most relevant gaps in the existing research may be summarized as follows:

- The existing literature focuses on financial linkages between firms. Limited consideration has been given to the way in which shocks spread through production and economic linkages influence asset prices and/or aggregate market outcomes. These shocks can potentially affect asset prices if they change the expected future cash-flow stream of any firms.

- There are very few firm-level studies that assess the effect of inter-firm linkages on asset prices (partly due to the lack of detailed information on inter-firm linkages). Most studies focus on inter-linkages that influence output and asset prices at the sector-level or market-level. For example, most studies of contagion are at the level of international financial markets, or across asset classes within the same national market.

- Finally, there has been a focus on the spread of shocks during crisis periods, but comparatively little is known about how shocks may spread in non-crisis periods through channels associated with production and economic activity.

2.7 Research questions and hypotheses

In order to address some of these gaps, the research questions (RQs) addressed in this thesis are:

1. How does the structure of economic linkages influence the volatility of stock returns? (Chapters 3 and 6)

2. How do shocks transmitted via economic linkages increase correlation between linked firms' returns? (Chapter 5)

3. How do shocks transmitted via economic linkages affect average returns, cross-sectionally and/or over time? (Chapter 6)

In particular, RQ 1 addresses whether shocks transmitted via inter-firm linkages are diversifiable. To answer this question I test the hypothesis that return volatility increases as the structure of upstream and/or downstream linkages becomes more concentrated (i.e. as the distribution of inter-firm linkages becomes heavy-tailed). My rationale (based on the work of Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) and the theoretical model presented in Chapter 3) is that the structure of upstream and downstream linkages determines the way in which firm-level shocks average out and influence return volatility. As shown in Chapter

3, return volatility is influenced by direct and transmitted (systematic and firm-level) shocks; when the structure of the linkages by which shocks are transmitted is concentrated (such that a few firms are highly connected while most are not) the law of large numbers does not apply, so return volatility will decay slower than rate $\frac{1}{\sqrt{N}}$ as a firm adds customers and/or suppliers.

RQ 2 focuses on the correlation between the returns of pairs of assets. I investigate the relationship between economic linkages and stock return correlation, and ask: *do shocks transmitted via supply chains increase correlation between linked firms' returns?*. If so, a secondary question is whether the influence of inter-firm linkages on return correlation (i.e. stock price dependence between linked firms) is different in bear markets than in bull markets (as suggested by numerous studies including Longin and Solnik (2001)).

By adapting correlation-based tests of contagion (see Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005)), I test the hypothesis that as the degree of linkage between two firms increases, so does the strength of transmission of shocks from one firm to the other. When there is significant transmission of shocks from one firm to another, the two firms' returns will be correlated because they are exposed to the same shocks. My rationale is that the degree of linkage between two firms determines the strength of transmission of idiosyncratic shocks from one firm to the other. Finally, I test whether the sensitivity of return correlation to inter-firm linkages is higher in recession and/or high correlation regimes or for more leveraged firms (as suggested by the work of Lang and Stulz (1992) and Raddatz (2010)).

To the extent that the public is aware of the linkages between assets, the prices of traded securities will reflect the public's assessment of the importance of risk that may be transmitted through these linkages (counterparty risk) (Jarrow and Yu, 2001). Therefore, RQ 3 is whether the cross-section of stock returns reflects a premium for exposure to shocks to economically linked suppliers and/or customers, in addition to SRFs. If so, a secondary test is whether this premium (i.e. stock price dependence between linked firms) is higher during economic recessions than it is during economic expansions.

My rationale is that the degree of upstream and downstream linkages determines firms' exposure to shocks to linked firms and in turn influences return volatility. Investors will demand compensation for this higher risk exposure and/or volatility via a risk premium. Furthermore, the premium for the degree and/or structure of upstream and/or downstream linkages should be higher in recessions when it is hard to replace or substitute linked firms.

In addition to informing the RQs, I use the literature reviewed above to develop a theoretical framework and methodology (in Chapters 3 and 4) which is used to empirically investigate the RQs (in Chapters 5 and 6).

Chapter 3

Theoretical framework

3.1 Introduction

In this chapter, I develop a theoretical framework for modeling how inter-linkages between firms influence stock returns. I develop a model of stock returns that shows how the structure of inter-linkages between firms determines whether or not shocks transmitted via linkages influence stock returns. The reduced form of the model corresponds to a factor model of stock returns. I prove that factor model of stock returns should be extended to include a factor representing the portion of shocks transmitted via linkages that is non-diversifiable.

Section 2 presents an original firm-level model that illustrates how inter-firm linkages affect returns. The main results in Section 2 specify the relationship between inter-linkages, return variance and return correlation in a portfolio of stocks. Section 3 outlines the implications of these results for factor models of stock returns.

3.2 Model of economic linkages and returns

In firm-level economic networks, shocks may be transmitted between customers and suppliers. For example, during 2008 Ford Motor Co. was concerned about the failure of its competitors, General Motors and Chrysler, because such an event could trigger the failure of upstream suppliers that they all share. Multi-sector models of economic activity model the influence of shocks transmitted between different sectors of the economy on aggregate economic activity[1] (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010). One way to develop a model of how economic linkages influence stock returns is to note that multi-sector models can be downscaled to apply to a set of firms (rather than a set of economic sectors).

There are fundamental differences, however, between the influence of economic linkages on *economic activity* and the influence of economic linkages on *financial asset prices*. In this thesis I focus on modeling the influence of firm-level economic linkages on stock prices. For the purposes of asset pricing studies, it is important that the linkages reflect the *cash-flow between firms* (rather than the flow of intermediate input and output goods between firms, as in economic models). Furthermore, at the firm-level *substitution* of suppliers and customers needs to be modeled. As shown in Chapter 2, substitution possibilities might be different in different economic conditions. For example, firms might be beholden to their suppliers in a recession, but can switch suppliers with sufficient advance planning outside of recession periods. I develop a framework which addresses these fundamental issues.

The analysis of the influence of economic linkages on stock returns is based on the relation between stock returns and cash-flows noted in Chen, Roll, and Ross (1986). I.e. stock prices can be written as discounted expected cash-flows,

$$P = \frac{E(c)}{k}$$

where p is the price of the stock, $E(c)$ is the expected stream of future cash-flows associated with the stock and k is the discount rate. Ignoring dividend pay-outs, this implies that the actual return of the stock in any period (R) is given by

$$\frac{dP}{P} = R = \frac{dE(c)}{E(c)} - \frac{dk}{k}.$$

[1] The mathematical tools and economic models that underpin this framework are reviewed in Appendix 3.B.

Holding the discount rate constant, $R \approx \frac{dE(c)}{E(c)}$ i.e. factors which change a firm's expected future cash-flows will affect its stock returns. If economic linkages between firms affect correlation and volatility in firm-level cash-flows[2], therefore, it is reasonable to expect that these linkages will in turn affect stock returns.

The basic intuition of the model in this section is that if expectations fully incorporate available information, so that changes in expectations are driven by shocks only, then when firms are linked the one-period, equilibrium change in expected cash-flows for firms $i = 1, ..., n$ is given by:

$$\mathbf{R} \approx \frac{\mathbf{dE(c)}}{\mathbf{E(c)}} \approx \mathbf{CS}\eta + \beta\mathbf{F}$$

Where $\mathbf{CS}$[3] is a matrix capturing direct and indirect inter-firm linkages, whose ij'th element CS_{ij} is the share of firm j in providing firm i's total sales revenue through direct and indirect linkages; η is a vector of firm-specific cash-flow shocks (which may be transmitted via inter-firm linkages); and $\beta\mathbf{F}$ is a weighted summed of common, systematic cash-flow shocks.

I now formalize this intuition and develop a model which shows how the structure of economic linkages (supply chains) influences the marginal and joint distribution of stock returns. I show that in certain structures of inter-linkage the proportion of aggregate risk explained by shocks transmitted via economic linkages is non-diversifiable and significantly influences returns, even in large portfolios.

Let $\mathbf{W}$ denote a (n by n) matrix whose elements w_{ij} represent the strength of the business interdependence between i and j. Let w_{ij} be defined as the share of i's

[2] Research reviewed in Chapter 2 shows that economic linkages between sectors affect the correlation and volatility of sector-level income and output (Shea, 2002; Horvath, 2000; Raddatz, 2010).

[3] The notation used from now on is: matrices are denoted by bold, capital letters (e.g. **F**). Vectors are denoted by bold, lower case letters (e.g. **f**). Scalars are represented by plain, lower case letters (e.g. f). Vectors are columns by definition, so row vectors are obtained by taking the transpose of a column vector, which is denoted by a prime (e.g. **f'**). **I** is a unit matrix, which is a square matrix with ones on the diagonal, and zeros elsewhere.

revenue received from j[4]. The matrix $\mathbf{W}$ captures the structure of a weighted, directed inter-firm network. By definition, the row sums of W are less than or equal to one[5], so W acts as the transition matrix of a Markov Chain describing the movement of shocks across firms. w_{ij} represents the probability of a shock to firm j moving to firm i in one step. The probability of a shock moving from j to i in m steps is given by the ij'th element of the m'th power of W, i.e. $(W^m)_{ij}$. When firms are inter-linked, shocks initially hitting only one firm can feed back between firms. The structure of W determines how transmitted shocks affect returns.

In Figure 3.1 the firm j is influenced by all shocks that enter the circle labeled j. Allowing for feedback, the total effect of a shock to firm i (η_i) on firm j can be represented as the sum over all paths, of any length, from i to j or $\eta_i(w_{ji} + w_{ji}^2 w_{kj} w_{ik} + w_{ji}^3 w_{kj}^2 w_{ik}^2 \cdots)$. The total effect of the vector of shocks, $\eta = [\eta_i, \eta_j, \eta_k]$, on firm j is the sum over all paths, of any length, that the shocks can take to firm j[6].

As shocks circulate the inter-firm network specified by W, I assume that each link independently has the same probability $0 \leq \alpha \leq 1$ of passing on a shock. This means that a k-step chain has probability a α^k of passing on a shock from start to finish . $\alpha = 1$ corresponds to complete pass-through, and $\alpha = 0$ to absence of any pass-through. Allowing for the influence of linkages, the total effect of a shock directly to firm j (η_j) on firm i is the α-weighted sum of all transition

[4] In a supply network w_{ij} represents the average cost of goods firm i must purchase from firm j to produce one unit of its own output. w_{ii} may be greater than zero as firm's can use their own output to as an input into production.

[5] In a closed model, W includes *all* suppliers of *all* firms so the $\sum_j w_{ij} = 1$; in an open model, W includes only some of a firm's suppliers so $\sum_j w_{ij} < 1$.

[6] So in Figure 3.1, the total effect of the vector of shocks, $\eta = [\eta_i, \eta_j, \eta_k]$, on firm j is given by

$$\begin{aligned} \varepsilon_j &= \eta_i(w_{ji} + w_{ji}^2 w_{kj} w_{ik} + w_{ji}^3 w_{kj}^2 w_{ik}^2 \cdots) \\ &+ \eta_j(1 + w_{kj} w_{ik} w_{ji} + w_{kj}^2 w_{ik}^2 w_{ji}^2 \cdots) \\ &+ \eta_k(w_{ik} w_{ji} + w_{ik}^2 w_{ji}^2 w_{kj} \cdots). \end{aligned}$$

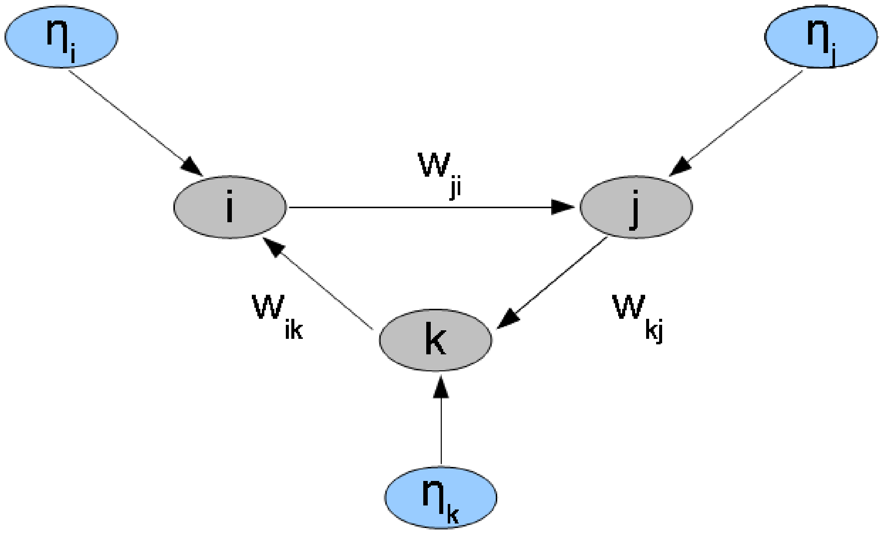

Figure 3.1: Illustration of the return model with linkages. *The return is the cumulative sum of all shocks passing through the inner circles representing firms i, j and k. The inter-linkages are the lines marked w_{ji}, w_{kj} and w_{ik} connecting the inner circles. The inter-linkages between firms mean that shocks hitting each firm (η_i, η_j, η_k) have an indirect impact on all firms connected through one or more inter-linkages to the initial shock. Feedback occurs over looping paths e.g. the shock to firm i will travel to j, then k, then back to i etc.*

probabilities from j to i or

$$\sum_{m=0}^{\infty} \alpha^m (W^m)_{ij} \eta_j,$$

and the total effect of all transmitted shocks on firm i is the sum of the total effect of *all* shocks $\eta_1 \cdots \eta_n$

$$\sum_{j=1}^{n} \sum_{m=0}^{\infty} \alpha^m (W^m)_{ij} \eta_j.$$

Assuming that returns are proportional to the sum of all (direct and indirect) cash-flow shocks, stacking this model for $i = 1, \cdots, n$ yields the following system of equations for the total effect of transmitted shocks, $\eta = [\eta_i, \eta_j, \eta_n]$, on returns

$$\begin{aligned} \mathbf{R} &\approx \sum_{m=0}^{\infty} \alpha^m \mathbf{W^m} \eta \\ &= (\mathbf{I} - \alpha \mathbf{W})^{-1} \eta \\ &= \mathbf{CS}\eta, \end{aligned} \tag{3.1}$$

where $\mathbf{R}$ is a vector consisting of the one-period return for firms $i = 1, ..., n$; $\mathbf{I}$ is an n by n identity matrix; α is a constant between zero and one; $\mathbf{W}$ is the n by n matrix of inter-firm linkage weights and η is a vector of independent firm-level shocks. As above, the parameter α is the probability of a single link passing on a shock.

The elements CS_{ij}, of the square matrix $\mathbf{CS}$, denote the total effect of a shock to firm j on firm i, or the total connectivity of firm i to firm j (via all 1-step, 2-step, 3-step etc. paths from firm j to firm i). In (3.1), η is the effect of shocks direct to the firm and $(\mathbf{CS} - \mathbf{I})\eta$ is the indirect effect of shocks transmitted via inter-linkages on returns. The indirect effects, $(\mathbf{CS} - \mathbf{I})\eta$, may be non-linear and capture the effect of any feedback on returns.

In the model above, α is assumed to be exogenous, time-invariant and the same for all firms. (In section 3.2.4, however, I simulate a situation in which α is an endogenous function of the average level of shocks. I specify α to be higher when shocks are negative than when shocks are positive, to simulate a scenario in which it is much harder for firms to substitute or replace a counterparty during recessions.) It is also assumed that the network of inter-linkages is deterministic and exogenous[7]. Necessary and sufficient conditions for the existence of a solution to (3.1) are included in Appendix 3.A.

One assumption of (3.1) is that the shocks directly hitting each firm are independent of one another. Put another way, model (3.1) does not allow for common

[7] If shocks spread rapidly through asset markets, firms are unlikely to have time to alter linkages before they are affected; so a static network is appropriate in this context.

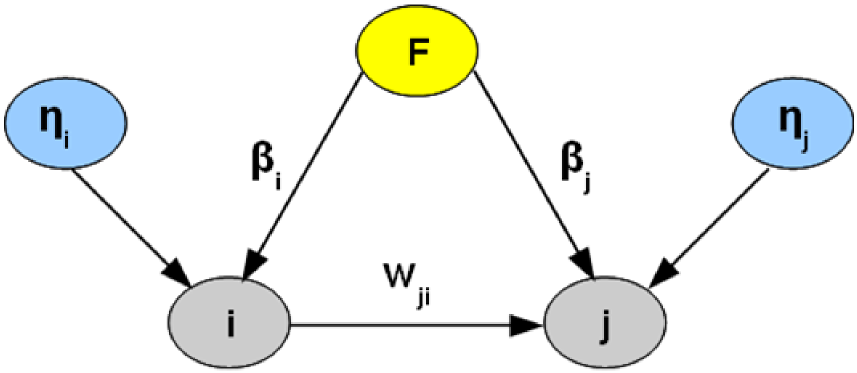

Figure 3.2: Illustration of the return model with linkages and common shocks. *The return is the cumulative sum of all shocks passing through the inner circles representing firms i and j. The inter-linkage is the line marked w_{ji} connecting the inner circles. Because of w_{ji}, firm j is exposed to a portion of the common shock F passed on via firm i. This indirect exposure to the common shock changes j's return by $\beta_i F w_{ji}$.*

systematic shocks, such as monetary policy shocks or shocks to the general state of the economy, that hit each firm. This situation is shown in Figure 3.2.

Let $\mathbf{F}$ be a vector of K systematic shocks and β be a matrix of asset-specific exposure weights, the return relationship allowing for systematic shocks becomes:

$$\begin{aligned} \mathbf{R} &= (\mathbf{I} - \alpha\mathbf{W})^{-\mathbf{1}}(\beta\mathbf{F} + \eta) \\ &= \mathbf{CS}(\beta\mathbf{F} + \eta) \\ &= \mathbf{CS}\beta\mathbf{F} + \mathbf{CS}\eta, \end{aligned} \tag{3.2}$$

And equivalently the firm level model becomes,

$$R_i = \sum_{j=1}^{N}\sum_{k=1}^{K} CS_{ij}\beta_{jk}F_k + \sum_{j=1}^{N} CS_{ij}\eta_j. \tag{3.3}$$

The systematic shocks F_k $(k = 1, \cdots, K)$ are non-diversifiable because they affect all firms. Whether or not the total (direct and indirect) effect of the shock η_j is diversifiable depends on the distribution of CS_{ij} over $j = 1, \cdots, N$ as proven in Section 3.2.3.

Model 3.2 illustrates that economic linkages can amplify the effect of systematic shocks on asset returns, as firm i's exposure to systematic risk factor F_k increases from $\beta_{ik}F_k$ to $\sum_{j=1}^{N} CS_{ij}\beta_{jk}F_k$. Most tests for financial contagion (to identify the transmission of shock between markets) condition on common factors, because common exposure to systematic shocks is not evidence of contagion. Provided each firm $i = 1, \cdots, N$ is allowed its own firm-specific sensitivity to common factors ($\beta^*_{ik} \approx \sum_{j=1}^{N} CS_{ij}\beta_{jk}$), the residual returns after controlling for common factors is given by (3.1). To theoretically study how inter-linkages influence diversification, it is important that the shocks that are transmitted via linkages are independent of one another; therefore, in the following sections I retain the assumption that systematic shocks directly hitting the firm have been controlled for, so equation (3.1) only captures the portion of stock returns associated with (direct and transmitted) idiosyncratic shocks.

3.2.1 Mean and variance of returns

The mean and variance of returns in (3.1) depend upon the total exposure implied by inter-linkages, measured by CS. E.g., assuming shocks are independent and identically distributed (i.i.d.), all firms with first order exposure of 90% (i.e. $\sum_j w_{ij} = 0.9$) will have the same mean return if their total exposure to higher order effects is the same (such that $\sum_j CS_{ij} = \sum_j CS_{lj}$), and will have the same variance if $\sum_j CS^2_{ij} = \sum_j CS^2_{lj}$.

Given **CS**, if firm-level shocks ($\eta_1, \cdots, \eta_n$) are independent r.v.s with finite mean and variance $E(\eta_j) = \mu_j$ and $Var(\eta_j) = \sigma^2_j < \infty$ for $j = 1, ..., n$ and $Cov(\eta_j, \eta_k) = 0$ for $j \neq k$, then the mean, variance and covariance of returns ($R_i = \sum_j CS_{ij}\eta_j$) are:

$$\begin{aligned}
E(R_i) &= \sum_{j=1}^{n} CS_{ij}E(\eta_j) = \sum_{j=1}^{n} CS_{ij}\mu_j \\
Var(R_i) &= \sum_{j=1}^{n} CS^2_{ij}Var(\eta_j) = \sum_{j=1}^{n} CS^2_{ij}\sigma^2_j \\
Cov(R_i, R_l) &= \sum_{j=1}^{n}\sum_{k=1}^{n} CS_{ij}CS_{lk}Cov(\eta_j, \eta_k) = \sum_{j=1}^{n} CS_{ij}CS_{lj}\sigma^2_j. \qquad (3.4)
\end{aligned}$$

The expected return, $E(R_i)$, is driven by the i'th row sum of the matrix of total exposures $\mathbf{CS}$, or $||CS_i|| = \sum_j CS_{ij}$. Similarly, the variance returns is a weighted sum of the variance of the firm-level shocks, which scales with $||CS_i||_2^2$; where $||CS_i||_2 = \sqrt{\sum_{j=1}^{n} CS_{ij}^2}$ is the norm of the i'th row of $\mathbf{CS}$. Thus the total exposure implied by firm i's linkages, $||CS_i||$, drives the mean and variance of its returns, as distinct from first order exposure implied by firm i's direct links, $||W_i||$.

Diversification of W_i reduces risk so long as it either reduces or diversifies total connectivity (i.e. $||CS_i||$). For example, in all structures in Figure 3.3, firm 4 has the same total first order exposure ($||W_4|| = 0.9$) but different combinations of total connectivity ($||CS_4||$) and total risk exposure ($||CS_4||_2$). As return variance is proportional to $||CS_i||_2^2$, variance reduces as $||CS_i||$ becomes more disaggregated. In Figure 3.3, moving from A to B reduces the variance of returns, as $||CS_4||_2^2$ drops from 3 to 2.5 because the 100% first order exposure to η_3 has been split into two 50% exposures to η_2 and η_3. It is also possible to reduce risk by reducing total exposure while maintaining the same first order exposure. In Panels C and D of Figure 3.3 the second order influence of firm 1 on firm 4 (i.e. the product of the weights along all 2 step paths lead from firm 1 to firm 4) is lower than in A and B; so $||CS_4|| = 3$ in A and B, but $||CS_4|| = 2.5$ in C and D. Finally, firm 4's return variance will be lower in D than in C as the total exposure to η_1 is reduced in D by linking to firm 5 rather than firm 1 (i.e. in C: $CS_{41} = 1$, $CS_{51} = 0$ and $||CS_i||_2^2 = 2.25$ but in D: $CS_{41} = CS_{51} = 0.5$ and $||CS_i||_2^2 = 1.75$).

In summary, it is possible to reduce risk by diversifying first order linkages (W_i) across an increasing number of firms if the total exposure to transmitted shocks ($||CS_i||$) is reduced or spread across more firms. Diversification fails to reduce risk if changing first order linkages increases or concentrates higher order exposures. Diversification of an investment portfolio follows the same principles since portfolio returns and variances are weighted averages of the corresponding measures for the component assets[8].

[8] That is, the variance of portfolio returns is given by $\mathbf{pCS\Sigma CS'p'}$, where $p = [p_1, \cdots, p_n]$ is a row-vector of portfolio weights summing to 100%; $\mathbf{CS}$ is the (n by n) connectivity matrix; $\mathbf{\Sigma}$ denotes the (n by n) diagonal covariance matrix of η. The investor must minimize $\mathbf{pCS\Sigma CS'p'}$ subject to a fixed level of expected returns, by choosing p conditional upon the

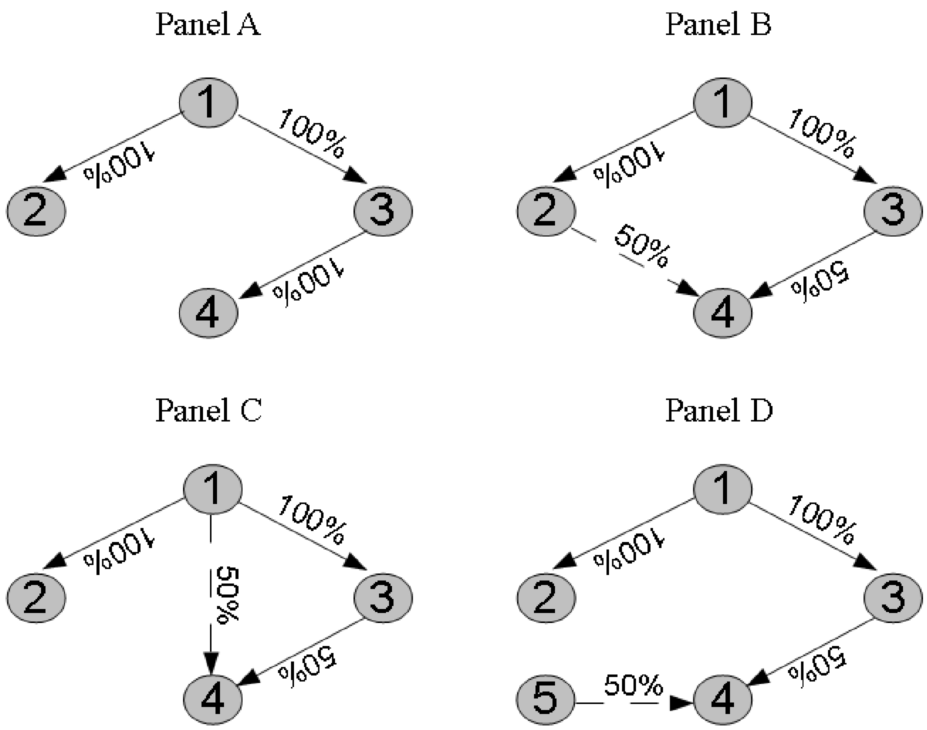

Figure 3.3: Networks with identical first-order connections that have different levels of aggregate volatility resulting from higher-order connections. *In all four structures, firm 4 has the same total first order exposure ($||W_4|| = 1$) but different volatility (Panel A: $||CS_4|| = 3$, $||CS_4||_2^2 = 3$; Panel B: $||CS_4|| = 3$, $||CS_4|_2^2 = 2.5$; Panel C: $||CS_4|| = 2.5$, $||CS_4||_2^2 = 2.25$; Panel D: $||CS_4|| = 2.5$, $||CS_4||_2^2 = 1.75$). Volatility may be reduced by reducing or diversifying total connectivity. When total exposure is constant ($||CS_4|| = 3$ in both A and B), diversification of first order exposure reduces risk. In Panel B firm 4's 100% exposure to firm 3 has been split into two 50% exposures so $||CS_4||_2^2$ drops from 3 to 2.5. In Panel C and D, firm 4's risk is lower than in A or B because second order exposure to firm 1 has been reduced so $||CS_4||$ drops from 3 to 2.5. Finally, Panel D has the lowest risk ($||CS_4||_2^2 = 1.75$) as second order exposure is reduced and diversified.*

3.2.2 The asymptotic distribution and variance of returns

The assumption of multivariate normally distributed returns is central to many asset pricing and risk management models (Embrechts, McNeil, and Straumann, 1999). Therefore, it is crucial to understand how inter-linkages affect the shape of the return distribution. First note that if η has a multivariate normal distribution, then returns in (3.1) will also be normally distributed. In most financial applications, however, the distribution of firm-level shocks is not precisely known, so neither is the exact distribution of returns in (3.1).

To obtain general results regarding how inter-linkages affect returns I consider a sequence of portfolios of increasing size, corresponding to increasing disaggregation of first order exposure as portfolio size increases. As R_i is a weighted sum of independent r.v.s, $[\eta_1, \cdots, \eta_n]$, its asymptotic behavior can be derived using central limit theorems. Namely, the Lindeberg-Feller (LF) theorem can be used to derive the asymptotic behavior of R_i. The LF theorem says that so long as each r.v. accounts for an infinitely small proportion of aggregate variance as $n \to \infty$, the normalized sum of the r.v.s will be normally distributed. Formally, the asymptotic distribution of returns can be characterized as follows:

Proposition 1: Asymptotic return distribution *Let R_i be a random variable (r.v.) defined as*

$$R_i = CS_i\eta = \sum_{j=1}^{n} CS_{ij}\eta_j, \tag{3.5}$$

where $CS_i = [CS_{i1}, \cdots, CS_{in}]$ is the i'th row of the matrix $\mathbf{CS} = (\mathbf{I} - \alpha\mathbf{W})^{-\mathbf{1}}$; $\eta = [\eta_1, \cdots, \eta_n]$ is a vector of i.i.d. shocks, centered so that $E(\eta_i) = 0$, with finite variance $E(\eta_i^2) = \sigma^2 < \infty$. Then, as proven in Appendix 3.C

- If $\frac{max_j(CS_{ij})}{||CS_i||_2} \to 0$ as $n \to \infty$ then $\frac{R_i}{||CS_i||_2} \to N(0, \sigma^2)$
- If $\frac{max_j(CS_{ij})}{||CS_i||_2} \nrightarrow 0$ as $n \to \infty$, and η is a vector of independent, non-normal r.v.s, then the distribution of R_i, when it exists, is not normal.

first order exposures of other firms (W_j $j \neq i$) and $\mathbf{\Sigma}$. This situation is depicted in Figure 3.3 if 4 represents a portfolio allocating $p = [p_1, \cdots, p_n]$ across assets.

Proposition 1 establishes that returns, when normalized by $||CS_i||_2$, are asymptotically normal so long as each shock affecting firm i accounts for a negligible fraction of the total standard deviation of i's returns as $n \to \infty$ (i.e. $\frac{max_j(CS_{ij})}{||CS_i||_2} \to 0$). On the other hand, if one or more shocks accounts for a positive proportion of aggregate variance as $n \to \infty$ then returns will not have a normal distribution unless the shocks themselves are normal. The firm corresponding to the largest term in $CS_i = [CS_{i1}, \cdots, CS_{in}]$ is referred to as the *dominant* firm in i's network. Note that a dominant customer (supplier) may be several steps downstream or upstream the firm's supply chain. If the dominant firm does not account for a diminishing proportion of total risk as firm i spreads its exposure over more firms, then the distribution of returns will not be normal. Instead it will reflect the distribution of shocks to the dominant firm (Gnedenko and Kolmogorov, 1954).

Dominant firms are characteristic of 'Star' networks (see Figure 3.8). In a Star network regardless of how an investor chooses assets from the pool of assets shown, shocks to the central firm 2 will have a significant influence on the aggregate risk of the portfolio. If the Star network in Figure 3.8 is expanded by adding more spokes out from firm 2, then the influence of shocks to firm 2 on the aggregate return will be significant even in very large portfolios. In contrast, if the idiosyncratic risk exposure of i was spread evenly over $j = 1, ...n$ (as in the Balanced network in Figure 3.8) then $\frac{max_j(CS_{ij})}{||CS_i||_2} \to 0$ as $n \to \infty$.

Networks with dominant firms can arise in real world business structures. For example, say a major source of revenue for Allegheny Technologies is the sale of metals to electronics companies producing semiconductors. If all of the electronics companies buying metals from Allegheny Technologies sell semiconductors to Apple and IBM, then by adding more customers Allegheny Technologies is not reducing its exposure to negative events that may affect Apple and IBM. In this case Apple and IBM are dominant customers of Allegheny Technologies, and shocks to these customers may not be diversified away. The returns of Allegheny Technologies are unlikely to be normally distributed and may have higher volatility because of exposure to transmitted risk from its dominant customers.

When there are dominant firms the summands of $||CS_i||_2$ are not uniformly distributed, as one entry in CS_i must be larger than the others. So the variation across CS_i is an indicator of whether or not returns converge to normality[9]. If there is a dominant firm in row i then $(CS_{ij} - \overline{CS_i})$ will be large for that firm, which will increase $Var(CS_i)$. Conversely, small variance across the rows of **CS** implies that returns are more likely to be asymptotically normally distributed.

3.2.3 Diversification of return volatility

It is also of interest to determine the rate at which return volatility decays (i.e. the rate at which transmitted shocks are diversified away) as a firm increases the number of linkages it has to other firms. Several studies show that when the distribution of firm sizes is heavy-tailed, the volatility of total market returns (or any weighted sum of individual firms' returns, such as the return on a stock market index) converges to zero at a rate that is slower than the $\frac{1}{\sqrt{n}}$ rate predicted by the law of large numbers (Malevergne, P., and Sornette, 2009; Gabaix, 2011). Intuitively, the influence of the largest firms on the aggregate cannot be diversified away even when the number of firms in the aggregate is very large. I show that a similar result holds at the firm-level when firms are inter-linked. That is, I show that when the distribution of i's total risk exposure across the n firms to which it is linked $(CS_{i1}, \cdots, CS_{in})$ is heavy-tailed, the volatility of i's return decays slower than $\frac{1}{\sqrt{n}}$ as n increases. Intuitively, the influence of dominant suppliers and customers on firm i cannot be diversified away even when i increases the number of linkages it has to other firms.

If returns are weighted sums of independent shocks, as in (3.1), return volatility should be higher for firms with concentrated exposure to a few shocks, because shocks will not average out in this case. That is, risk should be higher for firms whose total risk exposure across $j = 1, ..., n$ $(CS_{i1}, \cdots, CS_{in})$ has a heavy-tailed

[9] To see this note that the variance of entries along CS_i is

$$Var(CS_i) = s_{in}^2 = n^{-1}\sum_j (CS_{ij} - \overline{CS_i})^2 = n^{-1}\sum_j CS_{ij}^2 - \overline{CS_i}^2,$$

where $\overline{CS_i} = n^{-1}\sum_j CS_{ij}$ is the average row entry.

distribution. It has been shown that the distribution of sector-level connectivity is heavy-tailed and can be characterized by a power law (Carvalho, 2008; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010; Focardi and Fabozzi, 2004). In Chapter 4 I show that the distribution of firm-level connectivity between listed US firms is also heavy-tailed and can be characterized by a power law. To define this situation formally, total connectivity has power law tails if the probability that firm i has total connectivity $||CS_i||$ greater than k is proportional to $k^{-\zeta_i}$ for $\zeta_i > 0$. That is

$$Pr(||CS_i|| > k) = P_k = ck^{-\zeta_i}, \tag{3.6}$$

where c is a positive constant; k is an integer ≥ 1 and $0 < \zeta_i \leq 2$ is the tail index. If the distribution of total connectivity across firms can be approximated by a power law, and returns are given by $R_i = \sum_j CS_{ij}\eta_j$, then the rate at which return volatility decays as portfolio size increases is given by Proposition 2:

Proposition 2: Lower bound on return volatility

Let firm i be linked to n other firms with connectivity weights $CS_{i1}, ..., CS_{in}$ that follow a power law such that $Pr(||CS_i|| > k) = P_k = ck^{-\zeta_i}$. If $\eta = [\eta_1, \cdots, \eta_n]$ is a vector of i.i.d. shocks with $E(\eta_j) = 0$ and $E(\eta_j^2) = \sigma^2 < \infty$, then as proven in Appendix 3.C

$$\sqrt{Var(R_i)} \geq \frac{\sigma}{n^{1-\frac{1}{\zeta_i}}}. \tag{3.7}$$

Proposition 2 shows that the volatility of firm i's returns is directly related to the structure of its linkages to other firms. Specifically, the tail parameter of the distribution of firm i's connectivity (ζ_i) determines the rate at which shocks directly and indirectly hitting[10] firm i are diversified away. It sets a lower bound for the return volatility of the form $\frac{\sigma}{f(n)}$, where the denominator $f(n)$ controls the rate of decay in return volatility. Higher ζ_i means that returns converge to a lower variance distribution as $n \to \infty$. For example, if the distribution of total exposure to transmitted shocks across $j = 1, ..., n$ (i.e. $CS_{i1}, \cdots, CS_{in}$) has finite variance ($\zeta_i = 2$), then return volatility decays according to $\frac{1}{\sqrt{n}}$. In contrast, if the distribution of total exposure has heavy-tails, and $0 < \zeta_i < 2$, return volatility

[10] Indirect shocks are those that initially hit a firm other than firm i, but are transmitted to firm i via its economic linkages.

decays much slower than $\frac{1}{\sqrt{n}}$, at the rate $n^{1-\frac{1}{\zeta_i}}$.

Similar results have been proven by Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) and Carvalho (2008) in the context of GDP volatility in a multi-sector economy. Their estimates of the distribution of connectivity across sectors of the US economy using Bureau of Economic Analysis's input-output accounts from 1972 to 2002 show that $\zeta \approx 1.2$ (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2011). The magnitude of this difference is economically significant. For example, if a portfolio expands from 5 to 500 firms, under a Gaussian assumption one would expect a ten-fold decrease in return volatility. However, if the distribution of the weights is heavy-tailed with $\zeta = 1.2$ there will only be a two-fold decrease in volatility. Thus, Proposition 2 shows that volatility decays significantly slower when the distribution of total risk exposure has heavy-tails. For $\zeta < 2$ a small number of firms (assets) emerge as dominant risk exposures, and shocks to these firms (assets) may be non-diversifiable.

Summary Transmitted idiosyncratic shocks are only likely to be diversifiable if a firm does not have any dominant suppliers or customers; where a firm has a dominant supplier (customer) if the share of input supply (sales revenue) from the largest supplier (customer) remains bounded away from zero as the firm adds more suppliers (customers). The theory above shows that economic linkages can influence returns via a process of shocks passed on from suppliers and/or customers failing to average out.

3.2.4 Simulation of returns in common networks

Proposition 1 and Proposition 2 show how the structure of inter-linkages determines the way in which independent firm-level shocks to linked firms affect residual returns. In particular, if the distribution of both the total connectivity $(CS_{i1}, \cdots, CS_{in})$ and firm-level shocks have finite variance, then returns will be normally distributed and return volatility decays at the rate $\frac{1}{\sqrt{n}}$. On the other hand, if either total connectivity or the shocks follow a heavy-tailed distribution, then returns may not be normally distributed, and return volatility is likely to decay much slower than $\frac{1}{\sqrt{n}}$.

I use Monte Carlo simulation to analyze the effect of different structures of interlinkage on the shape and the volatility of the return distribution. I also investigate the affect that changing the influence of linkages has on return correlation. Specifically, I assess whether Proposition 1 and 2 predict the shape of the return distribution and the rate at which firm-level shocks are diversified away in three common networks. The different networks shown in Figure 3.8 represent stylized market arrangements.

A *Star network* consists of one central firm to which all other firms are connected. This central firm provides a common connection point through which shocks spread to all firms. This structure arises when the central firm is a very large firm, with dominant market share in an industry or product crucial to other firms in the portfolio. For example, within a large credit portfolio, Egloff and Leippold (2007) find that Star-type structures are common in the retail and real estate industries, as a few large retail companies (real estate firms) act as hubs to many suppliers (renters). In a *Ring network* each firm has one supplier and one customer, such that there is a single continuous pathway between any two firms in the network. This structure arises when firms rely on a single supplier, rather than a diversified supplier network, for example in a vertically integrated company or a conglomerate. Finally, in a *Balanced network* each firm is equally connected to all other firms in the network. The Balanced structure corresponds to a situation where firms have a diversified supplier network, with multiple suppliers, rather than a single supplier. Importantly, the distribution of risk exposure across $j = 1, ..., n$ $(CS_{i1}, \cdots, CS_{in})$ is different in each case. The networks in Figure 3.8 are ordered from most heavy-tailed to least heavy-tailed, i.e. $\zeta_{Star} < \zeta_{Ring} < \zeta_{Balanced}$. In the Star exposure is heavily concentrated on firm 2 so the distribution of risk exposure is heavy-tailed and $\zeta_{Star} \ll 2$. In the Ring and Balanced network the distribution of risk exposure is more uniform, so ζ is closer to 2.

I simulate returns using (3.1) and measuring the sensitivity of the return distribution to: the size of the portfolio, the network structure and the distribution of firm-level shocks. Star, Ring and Balanced networks representing portfolios with 4, 10, 20, 40, 70 and 100 firms are constructed[11]. To imitate diversification of a fixed dollar amount across an increasing number of counter-parties, the total first-order exposure is held constant ($\sum_j w_{ij} = 0.9$) as the portfolio size is increased. For example, in the Balanced network with 4 firms, all entries are equal to $\frac{0.9}{4}$ but with forty firms, all entries are equal to $\frac{0.9}{40}$. Initially I set $\alpha = 1$ to explore sensitivity to W, n and η. In the section below titled 'Asymmetric correlations', however, α is allowed to vary.

For each network returns are simulated for three different distributions of η, all with $E(\eta) = 0$:

- A standard normal distribution, i.e. $\eta \sim N(0, 1)$
- A uniform distribution with mean zero and unit variance, i.e. $\eta \sim U(-1.732, 1.732)$
- A Student's t distribution with 1.5 degrees of freedom, i.e. $\eta \sim t(1.5)$

Note that the first two distributions have variance of 1, while the Student's t distribution with 1.5 degrees of freedom has infinite variance[12].

Chi-square goodness-of-fit and Jarque-Bera test statistics are used to test the null hypothesis that returns are normally distributed. These tests complement each other as the Chi-square test is based on mean and variance of the observed distribution, while the Jarque-Bera test is based on skewness and kurtosis. For finite variance shocks, the results are based on 10^4 simulated vectors of length n. The robustness of results to the number of simulations was tested by using $10^2/10^3/10^4/10^6$ simulated vectors. The results of the Chi-square and Jarque-Bera tests are robust to the size of the simulated error vector. For infinite variance shocks (i.e. Student's t distribution with $v = 1.5$ degrees of freedom) 10^6 simulations were used for each firm, as 10^6 or more observations are required to

[11] Campbell et al. 2001 find that in the period 1986 to 1997 reducing idiosyncratic risk to 5% of excess standard deviation required almost 50 stocks.

[12] As, if Y follows a t distribution with n degrees of freedom, $E(Y^k)$ exists only for $k < n$ degrees of freedom.

observe the tail behavior in heavy-tailed data sets (Borak, Wolfgang, and Weron, 2005).

Simulation of finite variance shocks

Normal and uniform shocks were simulated for networks, with 4, 10, 20, 40, 70 and 100 firms. I calculated returns using (3.1) and tested whether returns were normally distributed and whether return volatility and diversification of risk varied across different networks. The qqplots in 3.4 and the Chi-square and

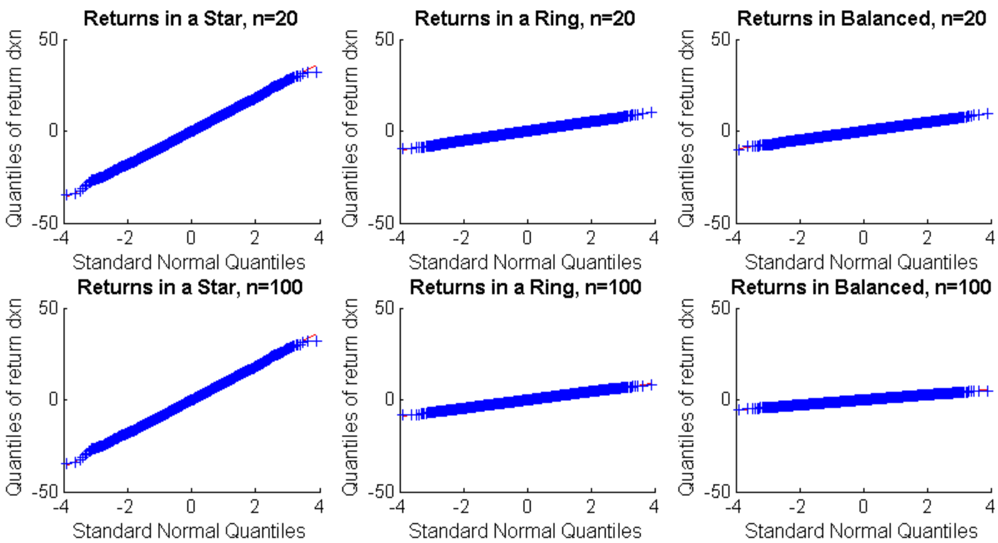

Figure 3.4: qqplots for Star, Ring and Balanced networks of size $n = 20$ and $n = 100$ with normal shocks $\eta \sim N(0, 1)$. *The qqplots show that when the idiosyncratic errors shocks are normally distributed, returns are normally distributed in all network structures.*

Jarque-Bera tests confirmed that when firm-level shocks are normally distributed, returns are normally distributed regardless of the network structure or size. The variance of returns, however, is noticeably higher in the Star network, even when $n = 100$. Figure 3.5 contains qqplots of returns generated by (3.1) when the firm-level shocks have a uniform distribution on $(-1.732, 1.732)$. The statistical tests of normality corresponding to these qqplots confirm that when firm-level shocks have a uniform distribution, returns are not normally distributed in any of the networks. Returns are closest to being normally distributed in the Ring and

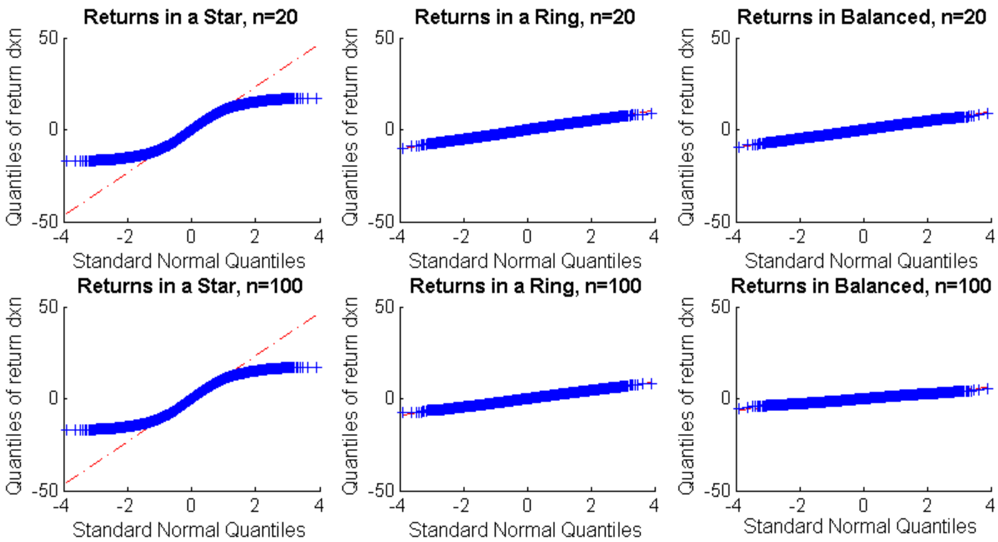

Figure 3.5: qqplots for Star, Ring and Balanced networks of size $n = 20$ and $n = 100$ with uniform shocks $\eta \sim U(-1.732, 1.732)$. *The qqplots show that when the idiosyncratic errors shocks are uniformly distributed, returns appear normally distributed in the Ring and the Balanced networks, but not in the Star network. Deviations from normality are most noticeable in the tails of the return distribution.*

Balanced structures, and least so in the Star structure. These results support the mathematical reasoning in Proposition 1 because the Star has the highest ratio of $Max(CS_{ij})$ to $||CS_i||_2$. The qqplots in Figure 3.5 illustrate that when the idiosyncratic errors have a uniform distribution, the largest deviations from normality occur in the tails of the return distribution. The Jarque-Bera test and Chi-square tests both reject the null hypothesis of normality, with p-values well below 0.05 in almost all cases.

Table 3.1: Moments of the return distribution for Star, Ring and Balanced networks of size n=20, 40 and 100 uniform shocks. Entries report the first four moments of the return distribution and risk-adjusted returns for firm 1 and firm 2 in three different network structures (Star, Ring and Balanced). The returns are based on a simulation of uniformly distributed shocks, $\eta \sim U(-1.732, 1.732)$, with 10^4 samples.

	Mean		Variance		Skew		Kurtosis		Sharpe Ratio	
Network	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**
ε_1 **and** ε_2 **when n=20,** $\eta \sim U(-1.732, 1.732)$:										
Star	-0.03	-0.04	83.08	101.56	0.00	0.00	1.81	1.78	-0.32%	-0.42%
Ring	0.00	-0.01	6.72	6.71	-0.03	-0.05	2.81	2.84	-0.16%	-0.31%
Balanced	0.01	0.00	5.85	5.92	-0.02	-0.04	2.80	2.83	0.49%	-0.05%
ε_1 **and** ε_2 **when n=40,** $\eta \sim U(-1.732, 1.732)$:										
Star	-0.03	-0.04	83.08	101.56	0.00	0.00	1.81	1.78	-0.32%	-0.42%
Ring	0.03	0.03	5.37	5.39	-0.01	-0.01	2.86	2.90	1.42%	1.09%
Balanced	0.02	0.01	3.38	3.42	0.01	-0.02	2.76	2.77	1.28%	0.54%
ε_1 **and** ε_2 **when n=100,** $\eta \sim U(-1.732, 1.732)$:										
Star	-0.03	-0.04	83.08	101.56	0.00	0.00	1.81	1.78	-0.32%	-0.42%
Ring	0.04	0.03	5.26	5.32	0.00	0.01	2.81	2.71	1.67%	1.31%
Balanced	0.02	0.01	1.95	2.00	0.01	-0.02	2.59	2.59	1.40%	0.41%

Table 3.1 shows the mean, variance, skewness and kurtosis of the return distribution for firms 1 and 2 in each network when $\eta$is a uniform r.v. with mean 0 and standard deviation of 1 (i.e. $\eta \sim U(-1.732, 1.732)$). The mean return is approximately the same in all networks because all of the row sums in W (and therefore all of the row sums in CS) are equal[13]. However, the variance is significantly higher in the Star network than in the Ring or the Balanced networks. The difference in return variance between the Star and the Ring and Balanced networks becomes larger as n increases. In the Star, adding more firms connected to the same hub does not reduce the return variance at all. On the other hand, adding more firms to the Ring reduces variance by a factor of 1.25 (from 6.72 to 5.37) as n increases from 20 to 40, and by a factor of 1.28 (from 6.72 to 5.26) as n increases from 20 to 100. In the Balanced structures, variance reduces by a factor of 1.73 (from 5.85 to 3.38) as n increases from 20 to 40, and by a factor of 3 (from 5.85 to 1.95) as n increases from 20 to 100. As a result, risk adjusted returns are lower in the Star network than in the Ring or Balanced networks.

Figure 3.6 show the standard deviation of residual returns in the three network for portfolios with $4, 10, 20, 40, 70$ and 100 firms. As n increases, return variance declines significantly slower in the Star network than in the Ring or Balanced networks. The unmarked solid line in Figure 3.6 shows the volatility predicted by the law of large numbers. In the Balanced network returns decline very close to the rate predicted by the law of large numbers. In the Star network, however, return volatility decays slower than the rate predicted by the law of large numbers. Figure 3.6 confirms the result of Proposition 2, as it shows that volatility decays significantly slower in structures, like the Star, where the distribution of connectivity is heavy-tailed.

Simulation of heavy-tailed shocks

The simulations were repeated for heavy-tailed shocks, in particular $\eta \sim t(1.5)$. For simulating heavy-tailed r.v.s, it is appropriate to use 10^6 simulations (Borak, Wolfgang, and Weron, 2005). I observed returns in networks of size 4 and 20

[13] Only when $s_i = \sum_j w_{ij}$ is the same for $i = 1, \cdots, n$ will $||CS_i||$ be the same for $i = 1, \cdots, n$.

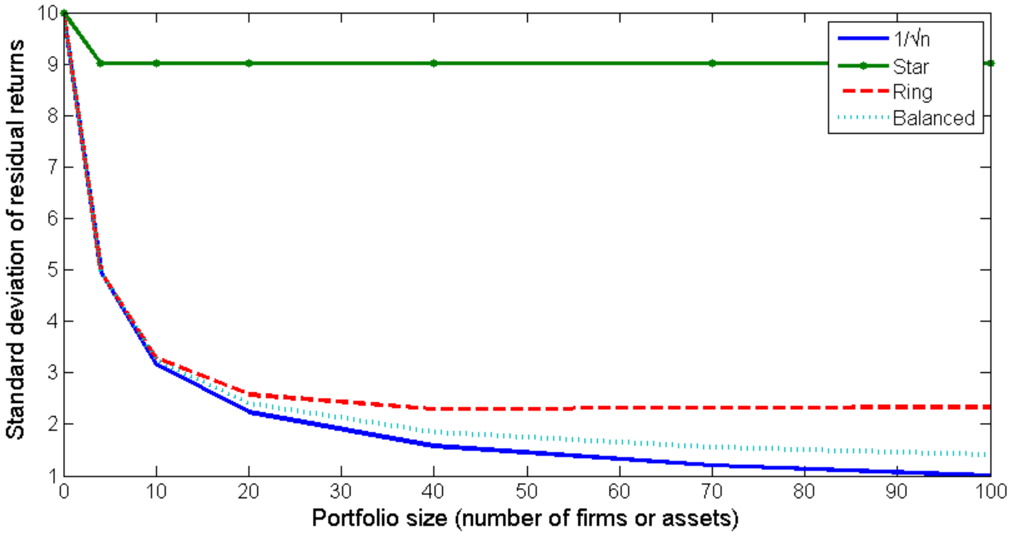

Figure 3.6: Standard deviation of returns against number of stocks in different networks. *This figure shows the rate at which return volatility declines in the Star, Ring and Balanced networks vs. the rate predicted by the law of large numbers (shown by the unmarked solid line). In the Balanced network, risk is diversified away at a rate that is close to the rate predicted by the law of large numbers. In the Star network, however, return volatility decays much slower than the rate predicted by the law of large numbers.*

firms. Panel A of Table 3.2 contains the sample moments of the shock distribution for four different firms, η_1 to η_4. These firm-level shocks have a Student's t distribution with 1.5 degrees of freedom. While the mean shock is still zero, the variance, skewness and kurtosis are much higher than the previously simulated normal and uniform distributions, due to the occurrence of tail events. The variance, skewness and kurtosis are also significantly different across firms. For example, η_1 and η_3 have long positive tails (high variance and positive skew), while η_4 has a long negative tail (high variance and negative skew).

Table 3.2: **Moments of the return distribution for Star, Ring and Balanced networks of size n=4 and 20 heavy-tailed shocks.** Panel B: Entries report the mean, variance and Sharpe ratio of the residual return distribution for firm 1 to firm 4 in three different network structures (Star, Ring and Balanced). The returns are based on simulations of Student's t distributed shocks, $\eta \sim t(1.5)$, with 10^6 samples as shown in Panel A. Due to significant differences in the tails of the shock distribution to firms 1 to 4, the hub of the Star is changed from firm 2 to firm 3 to firm 4 in order to illustrate that the occurrence of tail events dominates the return distribution.

Panel A: Shocks distributions

	η_1	η_2	η_3	η_4
Mean	0.00	0.00	0.00	0.00
Variance	619.50	189.00	358.60	523.60
Skewness	303.60	99.30	171.90	-121.50
Kurtosis	247,001.30	54,612.50	162,666.30	198,474.20

Panel B: Return distributions

	Mean				Variance				Sharpe Ratio			
Network	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**
ε_1 **to** ε_4 **when n=4,** $\eta \sim t(1.5)$												
Star	0.02	0.03	0.06	0.02	15,932.62	18,903.14	15,668.87	15,834.91	0.02%	0.02%	0.05%	0.02%
Ring	0.05	0.04	0.07	0.05	6,459.47	5,474.41	4,891.81	4,630.93	0.06%	0.06%	0.10%	0.07%
Balanced	0.10	0.11	0.13	0.10	9,322.26	8,505.07	8,825.92	9,139.93	0.10%	0.12%	0.14%	0.10%
ε_1 **to** ε_4 **when n=4,** $\eta \sim t(1.5)$												
Star (firm 2 hub)	0.02	0.03	0.06	0.02	15,932.62	18,903.14	15,668.87	15,834.91	0.02%	0.02%	0.05%	0.02%
Star (firm 3 hub)	0.24	0.25	0.27	0.23	29,668.39	29,237.30	35,863.69	29,573.00	0.14%	0.14%	0.14%	0.14%
Star (firm 4 hub)	-0.09	-0.08	-0.06	-0.10	43,031.67	42,601.90	42,771.56	52,361.88	-0.04%	-0.04%	-0.03%	-0.04%
ε_1 **to** ε_4 **when n=20,** $\eta \sim t(1.5)$												
Star	0.02	0.03	0.06	0.02	15,932.62	18,903.14	15,668.87	15,834.91	0.02%	0.02%	0.05%	0.02%
Ring	0.03	0.03	0.05	0.04	11,661.86	10,356.51	10,115.23	10,714.56	0.03%	0.03%	0.05%	0.04%
Balanced	0.03	0.04	0.06	0.02	11,965.53	9,598.14	10,530.41	11,438.01	0.03%	0.04%	0.06%	0.02%

Table 3.2 contains the mean, sample variance and risk adjusted return when shocks have a t distribution with 1.5 degrees of freedom. Even with 10^6 simulations in each firm-specific shock vector, there are significant differences in the second, third and fourth moment of the distribution of shocks across firms (e.g. η_1 has a large positive skew of 303.6, while η_4 has a large negative skew of -121.5). Tests of normality rejected the null hypothesis that returns were normally distributed in all cases. Table 2 shows that deviations from normality are highest in the tails of the distribution. When firm 2 is the central firm in the star, variance is highest in the Star and risk-adjusted returns are the lowest. However, when the central firm in the Star has a large positive tail event (e.g. firm 3 in Table 3.2 has a large positive tail event, as the skewness of η_3 is 171.9 and the kurtosis of η_3 is 162666), risk adjusted returns are higher in the Star than in the Ring and Balanced structures. As illustrated in Table 3.2, changing the central firm in the Star from firm 2 to firm 3 (shock distribution with a longer positive tail) increases the risk adjusted return from 0.02% to 0.14%. On the other hand, when the central firm is shifted from firm 2 to firm 4 variance increases drastically from 15933 to 43031, as η_4 has a longer negative tail than η_2. Depending on the tail properties of the shock to the central firm in the Star, it can either exhibit higher or lower risk adjusted returns than the Ring and Balanced structures.

In summary, when the variance of firm-specific shocks is infinite, the occurrence of tail events dominates the return distribution. Table 3.2 shows that there is a large range in the sample variance of returns across firms in all structures, because tail events mean that the distribution of shocks to each firm is highly variable. As proven in Ibragimov and Walden (2007), when shocks are heavy-tailed, diversification may increase value at risk. Similarly, the simulation results imply that when shocks are heavy-tailed less diversified structures, such as the Star, may reduce value at risk. The simulations imply that Proposition 1 and 2 only apply when shocks have finite variance.

Asymmetric correlations

In this section, I examine return correlation asymmetry in Star, Ring and Balanced networks. Importantly, I illustrate that the network structure can explain shifts in conditional correlation that are as significant as those related to downside market movements. Correlations in stock returns conditional on 'downside' market movements are, on average, higher than correlations implied by a normal distribution; while correlations conditional on 'upside' market movements are not significantly different from those implied by a normal distribution (Ang and Chen, 2002; Longin and Solnik, 2001). Proposition 2 implies that exceedance correlations will be higher when the distribution of a portfolio's connectivity to its counterparties is heavy-tailed (because return volatility will be higher that of a normal distribution).

Regime-shifting (RS) models best replicate empirically observed stock correlations (Ang and Chen, 2002). In order to model changes in the substitutability of linkages, therefore, a RS specification of the joint return distribution in (3.1) is simulated as follows. If α is low, the W matrix has little influence on returns in (3.1); if α is high, W has a large influence on the outcome of (3.1). In the simulations above, α was set equal to 1 in order to explore the issue of network structure and the distribution of η for fixed levels of α. In order to simulate RS influence of linkages, I set α equal to a function of the average level of risk, such that:

$$\alpha = \begin{cases} .99 & \bar{\eta} \leq E(\eta) = 0 \\ .01 & \bar{\eta} > E(\eta) = 0 \end{cases}$$

Where $\bar{\eta}$ is the average firm-specific shock or $\bar{\eta} = n^{-1} \sum_{j=1}^{n} \eta_j$. As firm-level shocks are assumed to be i.i.d. with $E(\eta) = 0$, $\bar{\eta} \leq 0$ represents a 'bear' market as shocks are more negative than the mean. In a bear market I assume that shocks are transmitted strongly through links, so $\alpha = .99$. Conversely if $\bar{\eta} > 0$, this represents a 'bull' market in which linkages are substitutable so shocks are not transmitted strongly, so $\alpha = .01$. This specification of α is also consistent with situations where firms are more likely to pass on negative shocks to their customers and/or suppliers than to pass on positive shocks. To quantify how

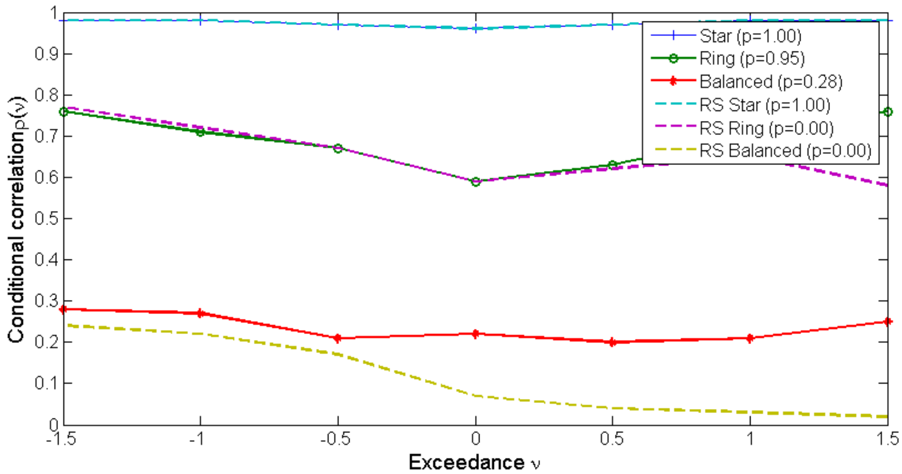

Figure 3.7: Exceedance correlations of firm 1 and firm 2 returns in the Star, Ring and Balanced networks of size $n = 100$, with regime switching weights ($\alpha = .99$ if $\bar{\eta} \leq E(\eta) = 0$; $\alpha = .01$ if $\bar{\eta} > E(\eta) = 0$) and normal shocks $\eta \sim N(0,1)$. The plot contains exceedance correlations between firms in each of the different networks, defined as $corr(x, y|x > \nu, y > \nu)$ for $\nu > 0$; and $corr(x, y|x < \nu, y > \nu)$ for $\nu < 0$. The p-value in the legend is from the test of correlation asymmetry proposed by Hong, Tu and Zhou (2007). $p < 0.05$ indicates significant correlation asymmetry.

RS affects return correlations in different networks, I calculated the correlation between returns conditional on returns being above or below a certain level using the conditional correlation proposed in Ang and Chen (2002). I.e. a correlation at an exceedance level ν is defined as the correlation between two variables when both variables register increases or decreases of more than ν standard deviations away from their means, such that

$$\rho_c^+(\nu) = corr(x, y|x > \nu, y > \nu); \nu > 0 \rho_c^-(\nu) = corr(x, y|x < \nu, y > \nu); \nu < 0$$

I also test whether the conditional correlations are symmetric using the test proposed by Hong, Tu, and Zhou (2007) [14] with null hypothesis

$$H_0 : \rho_c^+(\nu) = \rho_c^-(\nu).$$

[14] These tests were performed using code written by Andrew Patton, available at: http://econ.duke.edu/ ap172/code.html

Figure 3.7 plots the exceedance correlation between ε_1 and ε_2 in the Star, Ring and Balanced networks of size 100, when firm-level shocks follow a standard normal distribution. The results show that *in both regimes* return correlation is highest in the Star and lowest in the Balanced structure.

In addition, the Ring and Balanced structures display regime switching, with correlation being significantly lower in the Ring and Balanced structures when $\alpha = 0.01$ ($\nu > 0$). The drop in correlation in the 'bull' regime is most noticeable in the Balanced structure. This is because the Balanced structure offers the best averaging out of shocks; so when the portion of shocks passed on is small, shocks are almost fully diversified away.

Put another way, the higher influence of inter-linkages in bear markets ($\alpha = 0.99$ if $\nu < 0$) creates a significant increase in correlation in the Ring ($p = 0.00$) and Balanced ($p = 0.00$) networks, but not in the Star network ($p = 1.00$). In the Star, correlation between outer firms and the central 'hub' firm is high at all times because there is almost no averaging out of shocks to the central firm (firm 2 in Figure 3.8). So even if shocks to the central firm are only passed on with probability $\alpha = 0.01$, correlation between all firms and the hub is high.

Summary of regime switching simulations

In summary, both the economic regime and the structure of linkages affects the level of return correlation; so shifts in either the regime and the structure of linkages can cause correlation between asset returns to increase or decrease sharply. It is important to note that the increase in correlation that occurs moving from a Balanced structure to a Star structure, in either regime, is much larger than the increase in correlation in 'bear' markets within a fixed structure. The results highlight the over-arching effect of the structure of inter-linkages on return volatility and dependence.

The simulation results illustrate that correlation *increases* when: a) there is a shift from less concentrated to more concentrated structure in any regime or b) there is a regime shift from bull to bear market regimes, but only in structures that are not highly concentrated. Vice versa, correlation drops when a) there is a shift from a highly concentrated structure to a less concentrated structure in any regime or b) the regime shifts from bear to bull markets in structures where there are no dominant firms.

These results provide some insight into why correlation may drop suddenly in financial crises (as noted in Gai and Kapadia (2010)). In a financial crisis, links between assets (such as credit provision or trade links) frequently break down due to non-linear changes in asset values, default events and/or abrupt changes in liquidity. Many of these events 'break' trade linkages. For example, in periods of high volatility trading often stops abruptly due to fear or externally imposed market restrictions. This 'breaking' of trade linkages can change the structure of links between assets from concentrated to unlinked. As explained above, unlinked structures offer better averaging out of shocks than concentrated structures (the law of large number applies in unlinked structures) so correlation falls.

3.3 The influence of linkages on asset prices

A fundamental principle of asset pricing is that competitive markets do not permit profitable arbitrage opportunities to remain unexploited (Ross, 1976). In the Arbitrage Pricing Theory (APT) developed by Ross (1976), the asset market has a K factor structure if

$$R_i = E(R_i) + \beta_{i1} f_1 + ... + \beta_{iK} f_K + \upsilon_i \tag{3.8}$$

where $E(R_i)$ is the mean return on asset i and the factors $f_1, \cdots, f_K$ are uncorrelated with the residual return υ_i, which is uncorrelated across firms.

If the market does have a K factor structure then the covariance matrix of the total returns (not just the idiosyncratic component of returns), $\mathbf{\Sigma_N}$, may be decomposed as follows

$$\mathbf{\Sigma_N} = \mathbf{B_N B_N'} + \mathbf{D_N}$$

where $\mathbf{B_N}$ is the N by K matrix of factor loadings and $\mathbf{D_N}$ is a diagonal matrix.

In addition, Ross (1976) proved that if (3.8) holds, and residual returns are strictly uncorrelated, then the mean returns are approximately linear functions of the factor loadings, i.e.

$$E(R_i) \approx R_{rf} + \tau_1\beta_{i1} + ... + \tau_K\beta_{iK} \tag{3.9}$$

where R_{rf} is the risk-free rate.

In practice however there is usually some correlation between residual returns after allowing for systematic factors affecting all assets. For example, a few firms in the same industry might have industry-specific components to their returns which are not pervasive sources of uncertainty for the whole economy. For example, awarding a defense contract to one aerospace firm might affect the stock prices of several firms in the industry. The requirements for a strict factor structure, as proposed by Ross (1976), are not met in this case. Chamberlain and Rothschild (1983), however, develop an 'approximate factor model' and show that the pricing equation (3.9) holds so long as there is a sequence $[\beta_{i1}, ..., \beta_{iK}]_{i=1}^{\infty}$ such that for any N,

$$\mathbf{\Sigma_N} = \mathbf{B_N}\mathbf{B'_N} + \mathbf{R_N}$$

where $\mathbf{R_N}$ is a sequence of matrices with uniformly bounded eigenvalues. In other words, as the number of assets N approaches ∞, the portion of the variance of returns not explained by the K factors becomes negligible (as it is a finite number, bound above, divided by a total that is approaching ∞). That is, for pricing purposes the stochastic structure of returns is determined by K factors and everything else may be ignored. Approximate factor models only require that the law of large numbers applies, so the proportion of the correlations that are different from zero approaches zero as the number of assets increases (Connor and Korajczyk, 1993). If idiosyncratic risk averages out in this way, returns are well-represented by a linear combination of systematic risk factors (Ingersoll, 1984). On the other hand, when the proportion of aggregate risk explained by idiosyncratic sources is not negligible, idiosyncratic risk does not average out and can significantly contribute to aggregate risk.

When firms are linked however, there are cases in which the weaker approximate factor model condition is not met. To show this I will prove that Proposition 2 implies that for some structures of linkage, shocks (initially hitting only one firm and then) transmitted via linkages can explain a significant proportion of aggregate variance, even in large portfolios. Equation (3.7) shows that for some network structures $\mathbf{R_N}$ is not bound above, implying that mean returns are not necessarily linear functions of only the loadings on systematic factors.

To begin, recall Equation (3.4) defines the elements of the variance-covariance matrix of residual returns. That is, if the idiosyncratic shocks are independent but not necessarily identical, with variance $E(\eta_i^2) = \sigma_i^2$ for all $i = 1, ..., n$ then:

$$Cov(y_i, y_l) = \sum_{j=1}^{n} CS_{ij} CS_{lj} \sigma_j^2.$$

In matrix form this is

$$\mathbf{\Sigma} = \mathbf{CS\Psi CS'}$$

where $\mathbf{CS} = (\mathbf{I} - \alpha\mathbf{W})^{-\mathbf{1}}$ and $\mathbf{\Psi}$ is the diagonal variance-covariance matrix of idiosyncratic shocks, with elements σ_j^2 along the diagonal. I now show that Proposition 2 implies that the lower bound on $\mathbf{\Sigma}$ is $\Psi n^{\frac{2}{\zeta}-2}$ and that this in turn implies that for some values of ζ (i.e. for some heavy-tailed structures of connectivity) the eigenvalues of $\mathbf{\Sigma}$ (the covariance matrix of returns) are unbounded above.

To see this note that,

$$\mathbf{\Sigma} \geq \mathbf{\Psi n^{\frac{2}{\zeta}-2}} \Longrightarrow \mathbf{\Sigma v} = \lambda \mathbf{v} \geq \mathbf{\Psi v n^{\frac{2}{\zeta}-2}}. \tag{3.10}$$

where $\mathbf{v}$ is an eigenvector of $\mathbf{\Sigma}$ and λ the corresponding eigenvalue. So if $\zeta < 1$, then $\lambda v \geq \Psi v n^c$ where $n^c > 1$ and is increasing, so terms in the covariance matrix and the corresponding eigenvalues are not bounded above, because they will keep increasing so long as n increases. On the other hand, if $\zeta \geq 2$, the law of large numbers implies reduction of aggregate variance at rate at least n^{-1} as $n \to \infty$. In this case the covariance matrix and corresponding eigenvalues are bounded above, because as $n \to \infty$, $n^{-1} \to 0$, so $\mathbf{\Sigma}$ will converge to a finite number. For values of $1 \leq \zeta < 2$, there is some averaging out of idiosyncratic shocks, but at a rate slower than the law of large numbers. In these cases the upper bound on the eigenvalues is large and dependent on n.

Summary In some structures of inter-linkage, shocks transmitted via inter-linkages can affect a significant number of units, even in large portfolios. This means that it is not reasonable to ignore this source of risk when pricing assets. This transmitted risk can be considered to be a half-way case between systematic risk factors (which affect all units) and idiosyncratic risk factors which only affect one unit. Therefore the theory builds the case for including a factor capturing exposure to transmitted shocks into factor models of assets prices.

That is, the APT pricing equation (3.9) will not hold when the distribution of connectivity in inter-firm networks is heavy-tailed because this induces significant cross-sectional dependence in residual returns. By pulling this source of cross-sectional dependence out of the residual term, however, the results from APT will apply as the new residuals will be independent. The testable hypothesis that follows from this theory is that the structure of inter-firm connectivity (which is captured by the **CS** matrix) influences asset returns. In other words, the results in Section 3.2 imply that $\beta_{i,K+1} \neq 0$ in the following equation [15]

$$R_i = E(R_i) + \beta_{i1} f_1 + \cdots + \beta_{iK} f_K + \beta_{i,K+1} f(CS) + \tau_i. \tag{3.12}$$

3.4 Summary

The crux of the theory in this chapter is that when firms are inter-linked, the shocks transmitted via inter-firm linkages may be non-diversifiable in some network structures. This means that economic linkages can influence returns via a process of shocks passed on from suppliers and/or customers failing to average out. I prove that it is the structure of inter-linkages between firms that determines whether or not shocks transmitted via linkages influence returns. I show that transmitted shocks are only diversifiable if a firm does not have any dominant suppliers or customers[16].

The testable hypotheses arising from the theory developed in this chapter (in particular from Equation (3.4), Proposition 1 and Proposition 2) are that the structure of a firm's linkages significantly affects its mean returns, return volatility and return correlation. Equation (3.4) implies that the degree of a firm's

[15] Another way to frame this problem is to note that a strict factor model can be used if it is possible to extract the cross-sectional dependence from the residual returns, so that the transformed residual returns are independent. This is possible because the covariance of residual returns can be expressed as

$$\mathbf{\Sigma} = \mathbf{CS\Psi CS'} = (\mathbf{CS} - \mathbf{I})\mathbf{\Psi}(\mathbf{CS} - \mathbf{I})' + \mathbf{\Psi}$$

where $\mathbf{\Psi}$ is a diagonal matrix. Therefore if $(\mathbf{CS} - \mathbf{I})\mathbf{\Psi}(\mathbf{CS} - \mathbf{I})'$ is removed from the residual term, the return equation becomes:

$$\mathbf{R} = \mathbf{E(R_i)} + \beta\mathbf{F} + \gamma(\mathbf{CS} - \mathbf{I})(\mathbf{CS} - \mathbf{I})' + \tau. \tag{3.11}$$

[16] A firm has a dominant customer (supplier) if the share of sales revenue from the largest customer (input supplied by the largest supplier) remains large as the firm adds more customers (suppliers). For example, Walmart is likely to be a dominant customer of many US firms due to their large share of the retail market. Therefore the theory would predict that shocks to Walmart will influence the stock returns of those firms that rely on Walmart for a large share of their sales revenue because these shocks will not average out in the cash-flow of the supplier firms.

linkages affects its mean returns, that the concentration of a firm's total connectivity affects its return volatility and that the linkage 'distance' between two firms affects their return correlation. Proposition 2 implies that the tail parameter of a firm's degree distribution determines the rate at which shocks to linked firms are diversified away. Finally, the reduced form of the theoretical model corresponds to a factor model of stock returns; and the theory implies that factor models of returns should be extended to include a factor representing the portion of shocks transmitted via linkages that is non-diversifiable.

In the next chapter I describe the methodology and data used to empirically test these hypotheses. In chapters 5 and 6 I develop statistical measures and models of linked firms' returns (that follow directly from the theory developed in this chapter) and formally test these hypotheses.

3.A Necessary and sufficient conditions for a solution

Necessary and sufficient conditions for the existence of a unique solution to (4) are those that guarantee a unique solution to $\mathbf{CS} = (\mathbf{I} - \alpha\mathbf{W})^{-\mathbf{1}}$. This problem has been studied extensively in the economic literature, in the context of necessary and sufficient conditions for the existence of the inverse of $(I - A)^{-1}$, where I denotes the identity matrix and A is a matrix of Minkowski-Leontief type, i.e. with row sums less than one (Rosenblatt, 1957). A simple extension of the Theorem of Rosenblatt (1957) is used to prove necessary and sufficient conditions for the existence of a unique solution to (4).

Recall, at the firm level, CS_{ij} expresses the aggregate influence of a shock to firm j on firm i, transmitted via the links w_{ij}, over an infinite number of iterations through the network. Specifically

$$\begin{aligned} CS_{ij} &= \sum_{m=0}^{\infty} \alpha^m (W^m)_{ij} \\ &= \sum_{m=0}^{\infty} \alpha^m \sum_{r=1}^{n} (W^{m-1})_{ir} w_{rj}, \end{aligned} \tag{3.13}$$

where all elements of **CS** are greater than or equal to zero, as $0 \leq \alpha \leq 1$ and $0 \leq w_{ij} \leq 1$ for all pairs (i, j). Existence of the inverse matrix CS, is equivalent to the condition that the infinite sum above converges to a finite number. Note that CS_{ij} will approach ∞ in situations where $(W_{ij}^m$ does not converge to zero as m increases. The only way the series $\sum_{m=0}^{\infty} \alpha^m (W^m)_{ij}$ can diverge is if there are one or more transition paths [17] from i to j where all of the weights along the path are equal to one. For example, if firm i is connected to firm j via the path $w_{is}, w_{sr}, w_{rj}, w_{ji}$, and all of these weights are all equal to one, $CS_{ij} = \infty$ because $(W^m)_{ij}$ does not converge to zero as m increases. Conversely, the above infinite series will converge if the terms $\alpha^m (W^m)_{ij}$ are zero for m sufficiently large.

[17] E.g. if $w_{is}, w_{sr}, w_{rj}, w_{ji} > 0$, there is a transition path from i to j via s and r.

Mathematically, this condition is satisfied when either $\alpha < 1$ or $(W^m)_{ij} < 1$. From Theorem 1 from Rosenblatt (1957), it follows that $(W^m)_{ij} < 1$ so long as $w_{kl} < 1$ for at least one firm along each possible transition path between i and j. Essentially this condition guarantees that the infinite geometric series $\sum_{m=0}^{\infty} \alpha^m (W^m)_{ij}$ converges to a finite number because $(W^m)_{ij}$ converges to zero as m increases, for all pairs (i, j). Thus the inverse of the matrix $(I - \alpha W)$ exists.

A sufficient condition for the existence of CS is that all of the row sums of W are less than one. Alternatively, the necessary and sufficient condition is that $w_{kl} < 1$ for at least one firm along each possible transition path between i and j; which can be checked by scanning the W matrix for elements equal to one, and checking sequentially:

- if $w_{ik} = 1$, then $w_{ki} < 1$ and either:
  - all terms in row k of W are less than one, or
  - if row k of W contains one entry $w_{kl} = 1$, then:
    - if $w_{kl} = 1$, then $w_{lk} < 1$ and either:
      - all terms in row l of W are less than one, or
      - if row l of W contains one entry $w_{lm} = 1$ etc.

This guarantees that the necessary condition that $w_{kl} < 1$ for at least one firm along each possible transition path between every pair of firms (i,j). Theoretically, this is a more restrictive condition, but it is unlikely to be restrictive in practice as in real business networks it is very rare to encounter a firm i that is completely dependent on a supplier s such that $w_{is} = 1$. More realistic levels of inter-connection might be in the range of 10% to 50%. Taking the upper limit of that range, one can see that idiosyncratic shocks will dampen quite quickly, as $.5^2 = .25$, $.5^3 = .125$ and $.5^4 = .0625$. This 'back of the envelope' reasoning suggests a second order approximation to CS should be reasonably accurate. This implies that the influence weights αw_{sj} would most likely be much less than one for all j. Furthermore, the sufficient condition for the existence of CS, that the row sums of W are *less than one*, almost surely holds in most portfolios; because a firm cannot get more that 100% of its revenue from other firms in the portfolio, and that if firms are linked to any firms outside of the portfolio then the row sums of W should be *less than one*.

3.B Network theory and economic modeling

This Appendix introduces the basic mathematical concepts and notation required to model the transmission of shocks between linked sectors, firms and/or assets. First I show how graph theory and matrix algebra can be used to model how shocks are transmitted through a network. I explain how concepts from input-output modeling (used to analyze the flow of intermediate goods throughout the economy) can be down-scaled to the firm level. The final section presents original work showing how inter-firm supply networks can be usefully described using these concepts. I build a dataset of firms' principal customers using account disclosures to identify the network of economically related firms that have listed stock on North American exchanges. I analyze the dynamic structural properties of these inter-firm networks from 1990 to 2010 and show that the distribution of firms' supply chain connectivity is fat-tailed.

3.B.1 Basic network theory

Graph theory is a type of mathematics used to model pairwise relations between objects. A *graph* in this context is a collection of *nodes* connected by *vertices* (or *edges*). A graph may be *undirected*, meaning that there is no distinction between the two vertices associated with each edge, or its edges may be *directed* such that the vertex indicates a flow from one node to another. Vertices may also be *weighted* in order to indicate the strength of a connection between two nodes e.g. weights can represent the volume of a flow between two nodes. A directed graph with weighted vertices is called a *network*.

Networks and adjacency matrices

Formally, a network is defined as follows. Let N be a set of n nodes $i = 1, \cdots, n$ and $\mathbf{W}$ be an n by n matrix containing the vertex set of all relations w_{ij} where $w_{ij} > 0$ if node i is connected to node j, and $w_{ij} = 0$ otherwise. Note that $w_{ij} \neq w_{ji}$ as the graph is directed. In this case, $\mathbf{W}$ defines the network (or weighted directed graph) of the set of nodes $i = 1, \cdots, n$.

In a network there is a weight associated with each edge. For example, if the nodes represent firms then w_{ij} could be the percentage of firm i's total sales revenue that comes from firm j in one year, rather than just a binary indicator that j is a customer of i. $\mathbf{W}$, a square matrix with entries w_{ij} is called the weight matrix. Three different weight matrices and the corresponding graphs are shown below.

Another useful representation of the network defined by $\mathbf{W}$ is its adjacency matrix, indicating which of the vertices are linked (adjacent). For a weighted directed network defined by $\mathbf{W}$ the adjacency matrix $\mathbf{A}$ is a n by n matrix with elements

$$a_{ij} = \begin{cases} 1 & w_{ij} > 0 \\ 0 & w_{ij} = 0. \end{cases}$$

So for a group of n nodes the adjacency matrix $\mathbf{A}$ is a n by n matrix where a_{ij} is 1 if unit i is linked to unit j and zero otherwise. The adjacency matrix defines the unweighted graph which is a representation of the network. (As networks are directed graphs, the adjacency matrix is usually asymmetric; however, for undirected graphs the adjacency matrix is symmetric.)

3.B.2 Measures of network structure

Measures of network structure describe connectivity within a network at the unit, pairwise or network level. The properties of any network are determined by $\mathbf{W}$. $\mathbf{W}$ is the basis for most measures of connectivity, however the adjacency matrix $\mathbf{A}$ is also used to describe network structure. I now review common measures of network structure.

The *degree* of a node is the number of edges it has linking it to other nodes. In a directed graph, *in-degree* is the number of edges in to the node, and *out-*

0	W_{12}	0	0
0	W_{22}	0	0
0	W_{32}	0	0
0	W_{42}	0	0

0	0	0	W_{14}
W_{21}	0	0	0
0	W_{32}	0	0
0	0	W_{43}	0

W_{11}	W_{12}	W_{13}	W_{14}
W_{21}	W_{22}	W_{23}	W_{24}
W_{31}	W_{32}	W_{33}	W_{34}
W_{41}	W_{42}	W_{43}	W_{44}

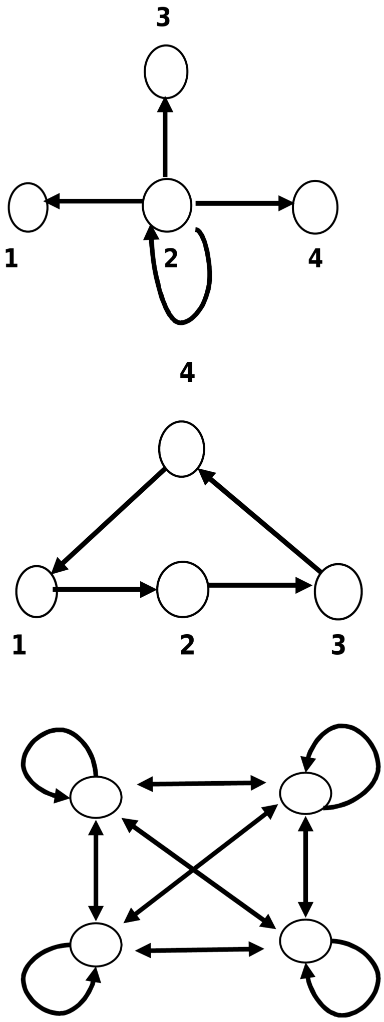

Figure 3.8: The weight matrices and graphs for Star, Ring, and Balanced networks, each with four firms.

degree is the number of edges out of the node. That is

$$d_{in}(i) = \sum_j a_{ij}$$

and

$$d_{out}(i) = \sum_j a_{ji}$$

In this thesis, the units in the network represent economic sectors or firms and the edges represent the flow of intermediate goods between sectors, or the flow of cash between firms. In an inter-firm network, firm i's in-degree can be thought of as the number of units paying cash (in) to firm i, and firm i's out-degree can be thought of as the number of units to which firm i pays cash (out). In a supply chain, it is assumed that goods and services flow in the opposite direction to cash, so cash is assumed to flow from customers to suppliers. So in-degree represents the number of key customers paying cash to the (supplier) firm, and out-degree represents the number of key suppliers requiring payment via cash-flow out of the (customer) firm. Second order degree is defined as

$$d_{in}^2(i) = \sum_j a_{ij} d_{in}(j)$$

And nth order degree, which counts how many firms are linked in n steps, as

$$d_{in}^n(i) = \sum_j a_{ij} d_{in}^{n-1}(j).$$

The degree distribution $P(k)$ is a discrete probability distribution of degrees across nodes i.e. $P(k)$ is the probability that a randomly chosen node has degree k. The mean of the degree distribution is sometimes used as a measure of total connectivity in a network. However, degree is a property that belongs to one node. In contrast distance is a property relating to two nodes. In directed networks the net-degree is given by $d_{out}(i) - d_{in}(i) = \sum_j a_{ji} - \sum_j a_{ij}$.

The *distance* between two nodes i and j, is the smallest number of edges between i and j. In a weighted network, the entries in the weight matrix $\mathbf{W}$ measure the one-step distance between i and j. The ij'th entry of $\mathbf{W}^n$ measures the n-step distance between i and j.

Finally, different measures have been proposed for how *central* each node is in a network and for identifying the most central (or influential) node or group of nodes. These measures include centralities of degree, centralities based on the column sums of the Leontief matrix (i.e. the status measure or rank prestige index in Katz (1953) or eigenvector based centrality measure in Bonacich (1987). Note that these measures are also based on manipulations of $\mathbf{A}$ or $\mathbf{W}$. So, once the adjacency matrix of an economic or financial network has been mapped out, measures of centrality can be adapted and used to identify the most influential nodes within a network. Theory-based measures of structure for firm level networks are developed in Chapter 5.

3.B.3 Input-output modeling of economic networks

The outputs of one economic sector (e.g. agriculture, mining, manufacturing) are often used as inputs in the production of other sectors. For instance, the retail sector relies heavily on the wholesale sector to provide the goods they sell onto end customers. These linkages between sectors provide a mechanism for transmission of shocks across sectors. A number of papers have considered the importance of such inter-linkages between sectors on the volatility of aggregate output and the correlation between different sectors' output (Horvath, 2000; Dupor, 1999; Schonbucher, 2000; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010). This papers all used multi-sector models of production (input-output models) to investigate the relationship between inter-sector linkages and fluctuations in aggregate output.

Input-output (IO) models represent the flow of intermediate goods between sectors within an economy using tools from graph theory. The general set-up of these models involves n sectors. The linkages in IO models are the directed flow of intermediate input and output goods between the n sectors. These linkages are captured in the matrix $\mathbf{W}$. $\mathbf{W}$ (with elements w_{ij}) captures the structure of a weighted, directed inter-sector network. w_{ij} corresponds to the value of units from sector j that sector i must use in order to produce 1 unit of its own output[18] (or the share of sector i's total output that is supported by input supplied by sector j.) Alternatively, the weights may be defined in terms of revenue or cost share. For example, w_{ij}, can be defined as the share of sector i's total revenue (operating expense) received from (attributed to) sector j.

The expected input-use matrix $\bar{\mathbf{W}}$ can be decomposed into an adjacency matrix $\mathbf{A}$ and a diagonal matrix $\mathbf{D}$ which defines the average scale of all of i's supplier transactions. That is, if $\mathbf{W}$ and $\mathbf{A}$ are n by n matrices defined as above, then:

$$\bar{\mathbf{W}} = \mathbf{A} * \mathbf{D}$$

where $\mathbf{A}$ is the adjacency matrix and $\mathbf{D}$ is a diagonal matrix with diagonal elements $\gamma_j = \frac{\sum_{i=1}^{n} w_{ij}}{\sum_{i=1}^{n} a_{ij}}$. $\mathbf{W}$ and $\bar{W}$ have the same column sums. For example, if sector j had 5 key inputs and $\mathbf{W_j} = \sum_{i=1}^{n} w_{ij} = 0.9$ (i.e. the degree of returns to scale in inputs for sector j is 90%), then $\gamma_j = \frac{0.9}{5}$.

Aggregate output in an input-output model Static IO models produce equilibrium solutions for output of the form[19]:

$$\mathbf{y} = \mathbf{W}\mathbf{y} + \varepsilon$$

where y is a vector consisting of an aggregate outcome, such as output, value added or income, for the n sectors $i = 1, ..., n$; $\mathbf{W}$ is a matrix capturing the direct interactions between units, as above, and ε is a vector of independent, idiosyncratic shocks to each sector $i = 1, ..., n$.

In order to ensure a solution in equilibrium, the matrix $(I - W)$ must be invertible. The common assumption made in these models is that the total of all input shares (the row sums) in $\mathbf{W}$ are less than or equal to one, i.e. $\sum_j w_{ij} \leq 1$.

[18] Firm i a said to be *downstream* of firm j if $w_{ij} > 0$ because a negative shock to firm j will raise the price of j's output and have consequences for all sectors downstream that rely on j to supply them with input goods (Long and Plosser, 1987).

[19] A detailed proof of the competitive equilibrium in the economy is provided in Shea (1991), Section II.

In this case, models of this form may be re-arranged to form the solution:

$$\mathbf{y} = (\mathbf{I} - \mathbf{W})^{-\mathbf{1}}\varepsilon \tag{3.14}$$

Where the vector of aggregate outcomes $y = [y_1, \cdots, y_n]$ for $i = 1, ..., n$ is a weighted sum of the independent, idiosyncratic shocks to units $i = 1, ..., n$, and the matrix $(I - W)^{-1}$ is referred to as the Leontief matrix. The Leontief matrix represents the total direct and indirect effects of shocks on production, which can be seen by expanding the Leontief matrix as follows

$$(\mathbf{I} - \mathbf{W})^{-\mathbf{1}} = \mathbf{I} + \mathbf{W} + \mathbf{W^2} + \cdots .$$

So $(\mathbf{I} - \mathbf{W})^{-\mathbf{1}}$ can be decomposed into: initial effects ($\mathbf{I}$), the direct effect ($\mathbf{W}$) and indirect effects ($\mathbf{W^2} + \mathbf{W^3}$).)

Equation (3.14) establishes a clear relationship between aggregate output, $\mathbf{y}$, and the structure of input-output linkages, captured by $\mathbf{W}$. It is possible to generalize the model so that the shocks have an aggregate and an idiosyncratic component. For example (3.14) could be reframed as

$$\mathbf{y} = \beta f + (\mathbf{I} - \mathbf{W})^{-\mathbf{1}}\varepsilon$$

where β is a vector of each sectors exposure to the aggregate shock f. It is important to note that the structure of input-output linkages becomes less significant as aggregate shocks become more important relative to idiosyncratic shocks (Shea, 1991). For this reason it is crucial to *condition on aggregate variables* in order to empirically assess the significance of inter-linkages for aggregate outcomes (Shea, 1991).

The matrices $\mathbf{A}$, $\mathbf{W}$ and $(\mathbf{I} - \mathbf{W})^{-\mathbf{1}}$ can be used to characterize sectors by the number of distinct inputs they use and/or supply. For example, Carvalho (2008) characterizes sectors by the number of distinct inputs they use. The number of inputs used by sector j is the sum of the elements in the jth column of $\mathbf{A}$: $\sum_{i=1}^{n} a_{ij}$, i.e. the out-degree of sector j.

In the framework an IO model, each sector has two kinds of economic effects on other sectors in the economy: demand and supply effects. When sector i increases its own production, this increases the demand for inputs from other sectors. This demand is referred to as *customer linkage*. Increased production in sectors with higher than average customer linkages induces the most demand for production from other sectors. Vice versa, an increase in production by other sectors leads to additional output required from sector i in its role as a supplier of inputs to these sectors. This supply function is referred to as *supplier linkage*. High degree of supplier linkage means that the sectors production is more sensitive to changes in other industries' output (Guo and Planting, 2000).

The simplest measure of customer linkage is the sum of the elements in the jth column of $\mathbf{W}$. Since the elements of $\mathbf{W}$ are measures of *direct* effects only, this is called *direct* customer linkage:

$$\gamma_{CL}(j) = \sum_{i=1}^{n} w_{ij}$$

where $1 > w_{ij} \geq 0$ are the elements of the n by n matrix $\mathbf{W}$. In terms of monetary transactions, $\gamma_{CL}(j)$ is equal to the value of total intermediate inputs for sector j divided by the value of j's total output. In matrix form, the row vector $CL = [\gamma_{CL}(1), \cdots, \gamma_{CL}(n)]$ is

$$CL = i'W$$

Where i' is a 1 by n row vector of ones.

Second, since the elements of $\mathbf{L} = (\mathbf{I} - \mathbf{W})^{\mathbf{-1}}$ are measures of total (direct and indirect) effects, the sum of the elements in the jth column of L measures total customer linkage of j:

$$\gamma_{TBL}(j) = \sum_{i=1}^{n} l_{ij}$$

Table 3.3: Measures of direct and total linkage derived from the weight matrix

	Customer linkage (in-degree)	supplier linkage (out-degree)
Direct	$\mathbf{i'W}$	$\mathbf{i'W'}$
Total	$\mathbf{i'L}$	$\mathbf{i'L'}$

where l_{ij} is the ij'th element of $(\mathbf{I}-\mathbf{W})^{-\mathbf{1}}$. The customer linkage measures quantify the exposure of a sector j to sector-specific shocks to the sectors from which it purchases inputs.

The corresponding measures of supplier linkage are comprised of the *row* sums of $\mathbf{W}$ and $(\mathbf{I}-\mathbf{W})^{-\mathbf{1}}$ as shown in Table 3.3. Table 3.3 illustrates that linkage measures based on a Leontief matrix are fundamentally different to distance measures based on (weighted or unweighted) adjacency matrices, because they represent *total* connectedness, rather than *direct* connectedness. (As $\mathbf{L}=\mathbf{I}+\mathbf{W}+\mathbf{W^2}+\mathbf{W^3}+\cdots$ which can be decomposed into: initial effects ($\mathbf{I}$), the direct effect ($\mathbf{W}$) and indirect effects ($\mathbf{W^2}+\mathbf{W^3}$).)

Various normalizations of these linkage measures have been proposed. The most straightforward normalization involves dividing each sectors linkage measure by the simple average of the corresponding measure across all sectors. Sectors with above average linkage will have measures of $\bar{\mathbf{CL}}$ or $\bar{\mathbf{SL}}$ greater than one. Finally, there is no consensus in the literature as to whether or not diagonal elements of $\mathbf{W}$ or $\mathbf{L}$ should be included or netted out of calculations (Miller and Blair, 2009). This depends to a large extent on the purpose of the investigation. If the research question relates to the units linkages to the rest of the economy, then it is appropriate to subtract or exclude the diagonal 'self-linkages'. However, if some measure of total linkage, including self-linkages is being studied, then the diagonal elements should be included.

In summary, IO analysis uses standard measures of connectedness from graph theory (in-degree and out-degree) to measure the economic connectedness of sectors (supplier linkage and customer linkage). Measures of direct connectedness can be derived using the adjacency matrix $\mathbf{A}$ or the weight matrix $\mathbf{W}$ matrix, whereas measures of total connectedness are derived from the Leontief matrix $(\mathbf{I} - \mathbf{W})^{-\mathbf{1}}$.

3.C Mathematical proofs of main results

Proof of Proposition 1 If η is a vector of n i.i.d. idiosyncratic shocks with $E(\eta_i) = 0$ and $E(\eta_i^2) = \sigma^2 < \infty$, then $E(\varepsilon_i) = 0$, and $E(\varepsilon_i^2) = \sum_{j=1}^n CS_{ij}^2 E(\eta_j^2) = \sum_{j=1}^n CS_{ij}^2 \sigma^2$.

Define $z_i = \frac{\varepsilon_i}{||CS_i||_2} = \sum_{j=1}^n \frac{CS_{ij}}{||CS_i||_2}\eta_j$; where $||CS_i||_2 = \sqrt{\sum_j CS_{ij}^2}$. Then by the LF Theorem, z_i converges to a normal distribution if the following expression approaches zero, as n approaches infinity:

$$\begin{aligned}
&\lim_{n\to\infty} \sum_{j=1}^n E\left[\frac{CS_{ij}^2}{||CS_i||_2^2}\eta_j^2; |\frac{CS_{ij}}{||CS_i||_2}\eta_j| > \delta\right] \\
&= \lim_{n\to\infty} \sum_{j=1}^n \frac{CS_{ij}^2}{||CS_i||_2^2} E\left[\eta_j^2; |\eta_j| > \frac{\delta||CS_i||_2}{CS_{ij}}\right]
\end{aligned} \tag{3.15}$$

As $Pr(|\eta_j| > \infty) = 0$, the limit of the above expression will be zero as n approaches infinity if $\frac{\delta||CS_i||_2}{CS_{ij}}$ approaches infinity so (3.15) approaches zero and the LF condition holds.

Given $\frac{\delta||CS_i||_2}{CS_{ij}} \to \infty$ iff $\frac{CS_{ij}}{||CS_i||_2} \to 0$, it follows that: if $\frac{CS_{ij}}{||CS_i||_2} \to 0$ as $n \to \infty$ for **all** $j = 1, ..., n$, then $\frac{\varepsilon_i}{||CS_i||_2} \to N(0, \sigma^2)$.

For a single firm i, the condition above must hold for **all** firms $j = 1, ..., n$. Rather than checking the condition for each firm $j = 1, ..., n$ individually, note that the returns of firm i are asymptotically normal (i.e. $\frac{\varepsilon_i}{||CS_i||_2} \to N(0, \sigma^2)$) if the following condition holds:

$\frac{max_j(CS_{ij})}{||CS_i||_2} \to 0$ as $n \to \infty$

Because if $\frac{CS_{ij}}{||CS_i||_2} < a$ and a approaches zero, then $0 \leq \frac{CS_{ij}}{||CS_i||_2} < a \to 0$. Finally, for multi-variate normality across the entire portfolio, the above condition must hold for each firm $i = 1, ..., n$.

To prove the situations in which the distribution of returns is *not* normal, I apply Proposition 1 to the distribution of $z_i = \frac{\varepsilon_i}{||CS_i||_2}$.
Recall z_i has an asymptotically normal distribution if and only if:

$$\lim_{n\to\infty} z_i^2 \frac{\int_{|z_i|>Z} p(z)dz}{\int_{|z_i|>Z} z_i^2 p(z)dz} = 0$$

Next note that z_i has an asymptotically normal distribution if and only if:

$$\lim_{n\to\infty} \int_{|z_i|>Z} p(z)dz = 0$$

As $z_i = \sum_{j=1}^n \frac{CS_{ij}}{||CS_i||_2}\eta_j$ this condition is equivalent to

$$\lim_{n\to\infty} \int \sum_{j=1}^n \frac{CS_{ij}}{||CS_i||_2}\eta_j \mathbf{1}\left[\frac{CS_{ij}}{||CS_i||_2}\eta_j > Z\right] dz = 0$$

Where $\mathbf{1}$ is the indicator function, taking value 1 if $\frac{CS_{ij}}{||CS_i||_2}\eta_j > Z$ and 0 otherwise. So, as above, in situations where $\frac{max_j(CS_{ij})}{||CS_i||_2} \nrightarrow 0$ as $n \to \infty$ then the distribution of ε_i, when it exists, is not normal. QED.

Proof of Proposition 2 Let η be a vector of i.i.d. shocks with $E(\eta_i) = 0$, $Var(\eta_i) = E(\eta_i^2) = \sigma^2 < \infty$ and $Cov(\eta_i, \eta_j) = 0$ for $i \neq j$. Let $CS_{ij} \in [0, \infty)$ be the ij'th element of the matrix $\mathbf{CS} = (\mathbf{I} - \alpha\mathbf{W})^{-1}$ where the elements of $\mathbf{W}$, w_{ij} are r.v.s $\in [0, 1)$ and $\sum_j w_{ij} \leq 1$. W is independent of η, i.e. $Cov(w_{ij}, \eta_k) = 0$ for all i, j, k. As in (3.1), $R_i = \sum_{j=1}^{n} CS_{ij}\eta_j$ so

$$\begin{aligned} Var(R_i) &= Var(\sum_{j=1}^{n} CS_{ij}\eta_j) \\ &= \sum_{j=1}^{n} Var(CS_{ij}\eta_j) \\ &= \sum_{j=1}^{n} E(CS_{ij}^2)E(\eta_j^2) \\ &= \sigma^2 E(||CS_i||_2^2) \\ &\geq \frac{\sigma^2}{n} E(||CS_i||^2), \end{aligned}$$

where the third expression follows from the fact η and **CS** are independent and $E(\eta_i) = 0$, and the last inequality follows from $||CS_i||_2 \geq \frac{||CS_i||}{\sqrt{n}}$. Assume $||CS_i||$ has power law tails such that

$$Pr(||CS_i|| > k) = P(k) = ck^{-\zeta},$$

where c is a positive constant, k is an integer $k \geq 1$ and $\zeta > 0$ is the tail index. Let $B = b_1, \cdots, b_m$ be the set of values that $||CS_i||^2$ can take, ordered such that $b_{k+1} > b_k$ for all k. It follows that:

$$\begin{aligned} E(||CS_i||^2) &= \sum_{n=1}^{m} b_n Pr(||CS_i||^2 = b_n) \\ &= \sum_{n=1}^{m} b_n \left[Pr(||CS_i||^2 > b_{n-1}) - Pr(||CS_i||^2 > b_n) \right] \\ &= \sum_{n=0}^{m-1} (b_{n+1} - b_n) Pr(||CS_i||^2 > b_n) \\ &= \int_0^{m-1} \hat{P}(b)\,\mathrm{d}b \end{aligned}$$

Where $\hat{P}(b) = Pr(||CS_i||^2 > b) = P(\sqrt{b}) = c(\sqrt{b})^{-\zeta}$. Substituting $t = \sqrt{b}$ gives:

$$\begin{aligned} E(||CS_i||^2) &= 2\int_0^{a_n} tP(t)\,\mathrm{d}t \\ &= 2c\int_0^{a_n} t^{1-\zeta}\,\mathrm{d}t \\ &\geq \frac{a_n^{2-\zeta}}{2-\zeta}, \end{aligned}$$

where $a_n = inf(y : Pr(||CS_i|| > y) \leq n^{-1})$ is the largest term in the range of $||CS_i||$. The probability that any realization is greater than the largest of n possible realizations is $\approx n^{-1}$. I.e. $Pr(||CS_i|| > a_n) = ca_n^{-\zeta} = n^{-1}$; therefore $a_n \propto n^{\frac{1}{\zeta}}$ and $\frac{a_n^{2-\zeta}}{2-\zeta} \propto n^{\frac{2-\zeta}{\zeta}}$.

Proposition 2 follows by inserting this expression into the first inequality. That is:

$$\begin{aligned} Var(R_i) &\geq \frac{\sigma^2}{n}E(||CS_i||^2) \\ &\geq \sigma^2 n^{\frac{2-\zeta}{\zeta}-1} = \sigma^2 n^{\frac{2}{\zeta}-2} \end{aligned} \quad (3.16)$$

So $\sqrt{Var(R_i)} \geq \sigma n^{\frac{1}{\zeta}-1}$ if $1 < \zeta < 2$ and $\sqrt{Var(R_i)} \geq \sigma n^{-\frac{1}{2}}$ if $\zeta \geq 2$. QED.

Chapter 4

Research methodology and data

4.1 Introduction

In Chapter 3, I developed a theoretical model of how inter-linkages between firms influence the mean, variance and correlation of stock returns. I showed that the structure of economic linkages influences the volatility of returns in certain inter-firm network structures. That is, when the structure of economic linkages is very concentrated, such that a few firms are much more connected than all others, shocks to the most connected firms dominate the distribution of aggregate returns. I also showed that the reduced form of this model was a factor model of stock returns extended to include a factor capturing non-diversifiable transmitted shocks.

In this Chapter I present the research methodology and data used to answer the second and third research questions. Section 2 outlines the research methodology used in Chapters 5 and 6. Section 3 and 4 outline the source of the data on economic linkages and the procedures for extracting this data from the Compustat/CRSP database. Section 5 summarizes the main characteristics of economic linkages between the firms on the Compustat/CRSP database and how the structure of economic linkages has changed over the period 1990 to 2010.

4.2 Research methodology

I develop a general framework for identifying and modeling situations in which shocks spread via inter-firm linkages influence asset prices and/or aggregate market fluctuations. I show that the 'diversification' argument supporting the irrelevance of idiosyncratic shocks (initially hitting only one firm) does not hold in certain network structures when shocks can be transmitted via linkages. The central theoretical result in Proposition 2 establishes a direct relationship between the rate at which shocks are diversified away as portfolio size increases, and the structure of links between units in the portfolio. Second, I develop the implications of this result for asset pricing by showing that the conditions of Approximate Factor Models (i.e. upper bounds on the eigenvalues of the covariance matrix of idiosyncratic shocks) can be directly translated into conditions on the structure of inter-linkages.

The modeling of inter-linkages is achieved through an extension of factor models of stock returns. I extend Equation (3.1) to allow for the transmission of systematic shocks directly hitting each firm, as well as direct idiosyncratic shocks, and derive the following structural model of returns when assets are inter-linked

$$\mathbf{R} = \mathbf{CS}(\beta\mathbf{F} + \eta) = \mathbf{CS}\beta\mathbf{F} + (\mathbf{CS} - \mathbf{I})\eta + \eta \tag{4.1}$$

Where $\mathbf{R}$ is a vector of returns for assets $i = 1, \cdots, n$, $\mathbf{F}$ is a vector of K systematic risk factors with N by K loading vector β; $\mathbf{CS}$ is a N by N matrix of total (direct and indirect) inter-firm linkages with entry $CS_{ij} = c$ if firm j provides $c\%$ of firm i's cash-flow through direct and indirect sources; and η is a vector of direct idiosyncratic shocks to assets for assets $i = 1, ..., n$.

I test whether an increase in the strength of the economic linkages between firms increases the pairwise correlation between linked firms' returns after controlling for systematic risk factors. Assuming that idiosyncratic shocks are i.i.d. Equation (4.1) implies that the correlation between two firms' returns, after controlling for systematic risk factors is:

$$\rho_{ik} \approx \frac{\sum_j (CS - I)_{ij}(CS - I)_{kj}}{\sqrt{\sum_j (CS - I)^2_{ij}(CS - I)^2_{kj}}} \tag{4.2}$$

So the influence of linkages on return correlation can be empirically assessed by estimating the parameters of the following equation:

$$\rho_{ik} = c_{ik} + \beta_F F + \beta_{DIST} DIST_{ik} \tag{4.3}$$

where c_{ik} represents industry pair fixed effects, F is other common factors causing correlation, and $DIST_{ik}$ is linkage distance between i and k, measured by the ik'th term of $(CS - I)$.

Second, I extend a factor model of asset returns (as in Fama and French (1993); Daniel and Titman (1997)) to test whether the risk exposure from inter-firm linkages is priced with a risk premium. Similar to (4.1), I assume that asset returns are generated by

$$R_{it} = E_{t-1}(R_{it}) + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \varepsilon_{it} \tag{4.4}$$

where R_{it}, $i = 1, \cdots, N$ and $t = 1, \cdots, T$ is the excess return (over the risk-free rate) of stock i at time t; $E_{t-1}(R_{it})$ is the risk premium of asset i; $\beta_{i,k}$ is firm i's loading on factor F_k, where $F_{k,t}$ is the realization of factor[1] $k = 1, \cdots, K$ at time t; and the noise terms ε_{it} are assumed to be mean zero, i.i.d. over time, but are allowed to be cross-sectionally correlated across stocks.

If the errors are mean zero and i.i.d., and all relevant factors have been correctly identified, it follows under the Arbitrage Pricing Theory (APT) Ross (1976) that the risk premium of asset i is a linear function of stock i's betas, that is

$$E(R_i) = \alpha + \sum_{k=1}^{K} \beta_{i,k} \gamma_k \tag{4.5}$$

[1] Common specifications of factors include: MKT_t, the excess return on the market portfolio (S&P 500) at time t, and the Fama-French SMB_t and HML_t factors.

where $\beta_{i,k}$ is firm i's loading on factor F_k, and γ_k is the risk premium associated with factor k. As argued in Section 3.3, however, when $\mathbf{\Sigma} = \mathbf{R_N}$ is not bound above, equation (4.5) should be extended as follows:

$$E_{t-1}(R_{it}) = \alpha + \sum_{k=1}^{K} \beta_{i,k}\gamma_k + CONC_{i,t-1}\gamma_{CONC} + DEG_{i,t-1}\gamma_{DEG}. \tag{4.6}$$

where $CONC_{i,t-1}$ is a measure of the concentration of firm i's total connectivity and $DEG_{i,t-1}$ is a measure of the degree of firm i's total connectivity. By including these proxies for exposure to transmitted shocks in the pricing equation (in addition to exposure to K common factors) I test the hypothesis that linkages are significant in addition to systematic factors by testing the null hypothesis

$$\gamma_{CONC} = \gamma_{DEG} = 0.$$

I also examine how the concentration of firm i's total connectivity and the degree of firm i's total connectivity influence average returns over time. The hypothesis that structure of a firm's supply linkages influences its returns over time is tested by fitting the following time-series regression for each portfolio:

$$R_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \sum_{m=1}^{M} \beta_{i,m} X^m_{i,t-1} + \beta_{i,CONC} CONC_{i,t-1} + \beta_{i,DEG} DEG_{i,t-1} + \varepsilon_{i,t} \tag{4.7}$$

where R_{it} is the excess return for stock i at time t; α_i is the time-fixed non-systematic premium; $\beta_{i,k}$ is firm i's loading on systematic factor $F_k \in \mathbf{F}$; $\beta_{i,m}$ is firm i's loading on firm characteristic $X^m_{i,t-1}$ e.g. $\beta_{i,CONC}$ is firm i's loading on the concentration of economic linkages $CONC_{i,t-1}$ and $\beta_{i,DEG}$ is firm i's loading on the degree of economic linkages $DEG_{i,t-1}$. To check whether time series variation in returns depends on the concentration of a firms supply linkages, I estimate Equation (6.2) and test the null hypothesis $\beta_{i,CONC} = \beta_{i,DEG} = 0$. A full explanation of the return generating process and justification of this methodology is provided in Chapter 6.

4.3 Data on inter-firm linkages

The key measure of inter-firm linkages developed in Chapter 3 and in the previous section was the matrix $\mathbf{CS} = (\mathbf{I} - \alpha\mathbf{W})^{-\mathbf{1}}$, a matrix capturing direct and indirect inter-firm linkages, whose ij'th element CS_{ij} is the share of firm j in providing firm i's total sales revenue through direct and indirect linkages. In this section I outline the data that I use to construct the total connectivity matrix **CS**.

Data on the economic linkages between firms is obtained from the Compustat Segment files. These files contain annual account disclosures under FAS 131 which list the identity of all customers that account for 10% or more of the firm's total sales revenue. In 1997, the Financial Accounting Standards Board (FASB) issued FAS No.131 to mend the shortcoming of FAS No.14. Both of these standard relate to breaking total account items into major business segments. Under both standards, reportable segments are operating segments that report any of the following:

- Revenues (including inter-segment revenues) of at least 10% of total revenues (including inter-segment revenues) of all reported operating segments
- Profit (loss) of at least 10% of the combined profit (loss) of all operating segments reporting a profit (loss)
- Assets of at least 10 percent of the combined revenues, profit or loss, or assets of all operating segments.

A reportable segment may aggregate two or more operating segments if their products and services, production processes, type of customer, distribution, and regulatory environments are similar. Reportable segments must total at least 75% of external revenues. Under both standards, revenues from each external customer accounting for 10% or more of the enterprize's revenues must be disclosed; however the identity of the customer firm need not be disclosed. In summary, whenever 10% or more of a company's revenues is derived from a single customer the company must disclose that it has a 'major' customer. The identity of the 'major' customer need not be disclosed. This information is only required in annual statements not interim statements.

Major differences between FAS 131 and FAS 14 was a shift from defining segments based on Standard industry classifications to defining operating segments on the basis that is used internally for decision-making (i.e., "the management approach"). Some argue that FAS 131 increased both the quantity and quality of segment disclosure because management style reporting better reflects business risk and has improved future earnings prediction (Ettredge, Kwon, Smith, and Zarowin, 2005). On the other hand, others argue that the management approach is less consistent and more easily manipulated (Springsteel, 1998). Companies are likely to manipulate the rules in order to avoid disclosing information that would threaten their competitive advantage in any way (Springsteel, 1998). To avoid complications that may arise from the change in disclosure rules, the sample period starts in 1990 because Compustat has restated key customer disclosures back to this date under FAS131.

Figure 4.1 shows the 'key customer' linkages between listed US firms recorded on the Compuststat/CRSP database in 1990. The arrow is in the direction of cash-flow, from customer to supplier. The figure illustrates that there is significant heterogeneity in the role of individual firms as key customers. There are a few 'hub' firms, that are major customers to a lot of different suppliers (i.e. about 10 customer firms with links to around 100 suppliers each) but the majority of supplier firms have the same number of key customers (i.e. the vast majority of firms shown have only 1 or 2 connections). For example, in the graph above from 1990, the major customer firms had up to 110 suppliers. The 5 firms with the greatest number of reliant suppliers were:

- AT&T INC, 110 reliant suppliers
- GENERAL MOTORS CO, 99 reliant suppliers
- SEARS HOLDINGS CORP, 97 reliant suppliers
- WALMART STORES INC, 93 reliant suppliers
- FORD MOTOR CO, 91 reliant suppliers

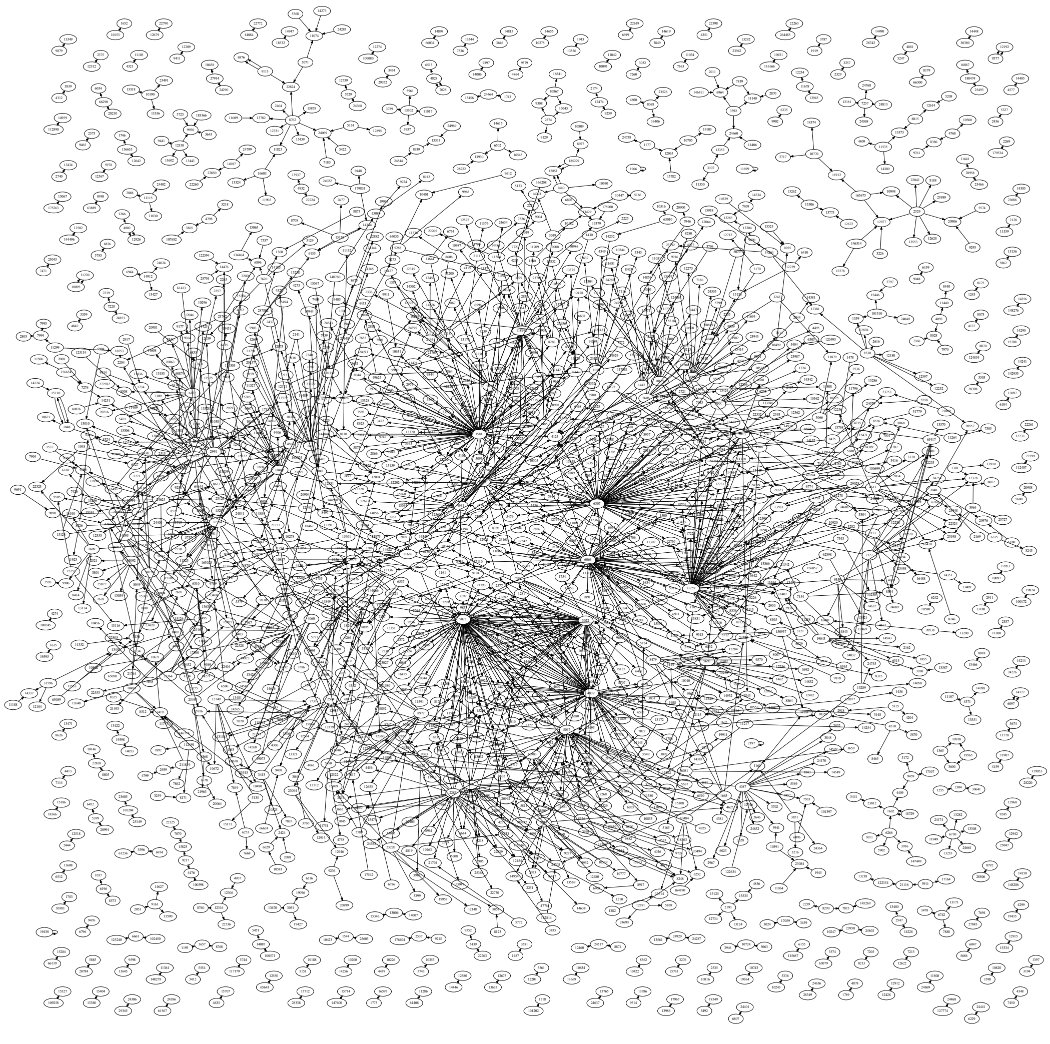

Figure 4.1: The major economic linkages between the stocks in the CRSP/Compustat sample in 1990. The arrow points from key customer to supplier in the direction of cash-flow.

In contrast, in 1990 the greatest number of key customers disclosed was 10. These observations suggest that the firms disclosed as key customers are larger on average than the subset of reliant suppliers. And that a few large customer firms tend to dominate suppliers customer base.

4.4 Procedure for extracting data on key customers

Key customer disclosures under FAS 131 are contained in the Compustat industry segment files, but not in an immediately usable format. What is generally listed is an abbreviation of the customer's name, which can vary across reporting firms and/or years. For example, the listed company 'Royal Dutch Shell PLC' was listed by different firms, 'Shell Oil', 'Shell PLC', 'Shell PLC' and 'Royal Shell CMB'. Abbreviations typically took one or more of the following forms:

- Vowels or endings were removed from words
- Suffixes 'PLC', 'LTD' etc. were frequently dropped off words
- A key word was used rather than the full name e.g. 'Shell' rather than 'Royal Dutch Shell PLC'.

To link the customer abbreviations with full company data, I used a multi-step procedure which proceeded as follows:

- Exact matches were removed from the data
- Punctuation marks and company endings such as 'PLC', 'LTD' etc. were removed from words. The next set of matches were removed
- An algorithm was run that compares the number and order of the letters in the abbreviation to those in the standardized company names listed on Compustat, the five company names from Compustat most likely to correspond to the abbreviation

- A second algorithm was run that compares the Levenshtein distance between abbreviated names the standardized company names Levenshtein distance is a metric for measuring the amount of difference between two sequences (i.e. an edit distance). The Levenshtein distance between two strings is defined as the minimum number of edits needed to transform one string into the other, with the allowable edits being insertion, deletion, or substitution of a single character. The five company names from Compustat most likely to correspond to the abbreviation were returned.

- Finally, visual inspection of the abbreviated records compared to closest 10 matches was used to manually link records where there is an almost certain, distinct match.

In instances where more than one company name could correspond with the abbreviation, I identify the customers using the Compustat industry segment information as follows: a) if one company had disclosed the same supplier in several consecutive years, it was often the case that the full name had been disclosed in at least one of the years b) alternatively, it was also possible to identify the customers using the industry segment information and the other type of customers disclosed by the firm. For example, 'General Nutrition Centers' or 'GNC' is a Pittsburgh, Pennsylvania-based American commercial enterprize focused on the retail sale of health and nutrition related products. Several firms listed 'Gen Nut' or 'GNC' in their customer disclosures. To be sure this referred to General Nutrition Centers the other customer disclosures of the firms were examined. They included 'Tree of Life' (A health food distribution company); General Nutrition Center; 'Hollister' (Hollister Incorporated is an independently-owned global company that develops, manufactures and markets healthcare products, servicing over 90 countries) and 'Maersk'.

Abbreviations still without matches using the above methods fell into one of the following categories:

- The company was a subsidiary of a larger parent company

- The company had undergone a merger, acquisitions or name change

- The company was government owned, privately owned or overseas listed.

If one or more of these conditions applied, the abbreviated name could not be linked to an official name by either of the text matching algorithms.

To identify matched within these groups, it was necessary to research the company information and history to identify its ownership structure, the international exchanges on which its stock were listed and/or any mergers or acquisitions in the companies history. This process was time consuming as it involved researching one or more sources of information: the company's website, Bloomberg Businessweek records and/or SEC filings. For this reason, only companies with more than 5 entries were followed up, and the following actions were taken:

- If the company was a subsidiary of a parent company, it was linked to the name of the parent
- If the company had undergone a merger or acquisition its historical account data may be changed, and the company it is linked to will depend on the type of merger as explained in the next section
- If the company had undergone a name change, it was linked to the Compustat record for the new name
- If the company was government owned, privately owned or overseas listed it was assigned a code to this effect (i.e. govt, private or overseas).
- If it was not possible to be almost certain that two records matched they were not linked.

Disclosed links that could not be matched

It is necessary to make some assumptions regarding the existing links. A necessary assumption is that the accounting information is accurate, such that where a link is disclosed it exists, and where the information indicates no links none exist. Table 4.1 shows the number of successful matches in each year. For example, in 1990 the customer segment files contained 6,249 key customer disclosures, for

Table 4.1: Total number of records on the Compustat FAS 131 Customer Files from 1989 to 2010, broken down into those matched to other listed firms and those that could not be matched to other listed firms.

Year	Unmatched	Matched	Total
1990	3940	2309	6249
1991	4214	2518	6732
1992	4711	2704	7415
1993	5118	2865	7983
1994	5382	2959	8341
1995	6067	3231	9298
1996	6123	3405	9528
1997	5716	3078	8794
1998	5881	2949	8830
1999	4931	2545	7476
2000	5373	3081	8454
2001	5133	2932	8065
2002	5184	3042	8226
2003	5075	2792	7867
2004	4994	2860	7854
2005	4877	2811	7688
2006	5012	2726	7738
2007	4977	2602	7579
2008	5204	2523	7727
2009	5287	2426	7713
2010	5603	2161	7764

Table 4.2: Summary statistics for cleaned (1% winsorised account values) book equity, sales revenue and key account ratios for supplier firms on the Compustat FAS 131 Customer Files

	Book equity	Sales	Book leverage	Payables ratio	EBITDA :TA	Sales: TA
Unmatched						
Mean	389	717	5.24	0.32	0.01	1.10
S.d.	2,468	4,070	296.37	5.31	0.42	0.94
Matched						
Mean	577	1,071	4.95	0.25	0.04	1.09
S.d.	3,521	4,691	112.16	2.13	0.63	0.84
Total						
Mean	455	841	5.14	0.30	0.02	1.10
S.d.	2,884	4,302	247.66	4.45	0.50	0.91

firms in the Compustat sample. I was able to match 2,309 (or 37%) of them to other firms alive in the merged CRSP / Compustat database in the same year, however 3,940 (or 63%) of these links could not be matched. Many firms did not disclose the name of the supplier or were linked to a firm that was company was government owned, privately owned or overseas listed[2].

In order to check that these missing links did not bias the results, I checked that the average characteristics (firm size, industry etc.) of firm for which I was able to match links was not significantly different from the firms for which I could not match the links. This is to check that by only including firms for which links could be identified, I am not introducing sampling bias. This table shows that, on average, the suppliers with matches to other listed firms in the merged CRSP / Compustat database had higher Book Equity and Sales than the suppliers whose key customers could not be matched (because they were unlisted firms, overseas listed firms, privately owned, not disclosed, or government departments). The accounting ratios were similar however. T-tests between the two sample means

[2] By ignoring links to government owned, privately owned or overseas firms the results are likely to under-estimate the economic impact of linkages on listed US firms, as shocks transmitted via these third parties may be influential. This under-estimation should be less pronounced for links to government because the default risk of the government is lower than that of private firms, so government links are less likely to be a channel of contagion.

showed the difference in suppliers' average BE, sales and EBITDA: TA was significant, however the difference between suppliers' book leverage, payables financing and sales: total assets was not. This suggested that larger firms are more likely than small firms to have customers that are listed firms; conversely this may be because listed firms prefer to choose larger, more profitable firms as their suppliers.

In summary, the procedure for identifying matches should not bias the regression results because the matching procedure was comprehensive, the explanatory accounting ratios were not significantly different amongst the matched sub-sample and I also control for firm size in the regressions. However, the results need to be interpreted in light of the fact that as the sub-sample is pairs of listed suppliers with listed customers, and this sample does not necessarily reflect the broader set of supplier firms (e.g. servicing government or unlisted clients).

Reasonableness checks on economic linkage measures extracted from the accounts

While FAS 131 disclosures identify important customers, it is not necessarily the case that these customers are, conversely, reliant on the supplier. That is the text-matching process cannot necessarily be reversed to identify dependent suppliers. For example, a small primary production firm may derive a large portion of its revenue from a larger upstream customer; however the larger customer is unlikely to be reliant on the small supplier. Because of the asymmetry in firm size, just because A sells goods to B worth more that 10% of A's revenue, this does not mean that the goods sold are a significant proportion of B's total inputs. If B is much larger than A, goods worth 10% of A's revenue could be a very small portion of B's total inputs. Alternatively, if B is much smaller than A, and A supplies a significant proportion of B's total inputs, the value of 10% of B's total inputs may be less than 10% of A's revenue so A will not report B as a significant customer and this information will not be reported under FAS 131.

Therefore FAS 131 disclosures are only reliable for measuring upstream effects (i.e. the economic activity induced by the expenditure of certain firms in their role as major customers) because firms are required to disclose information on customers to which sales represent more than 10% of total sales revenue or profits, but not significant supplier linkages. Downstream effects were estimated by inverting the key customer disclosures. However, since FAS 131 require firms to report major customers but not major suppliers inverting the links generates an incomplete sample of 'key suppliers'. I.e. downstream effects of shocks to firms' suppliers cannot be reliably measured for the whole sample using the Compustat data because there is asymmetry in the way that customer and supplier effects are reported. I address this issue by using the ratio of supplier sales to a given customer to the customer's cost of goods sold to identify 'dependent customers'. Customer firms in which the supplier sales received are a large proportion of total cost of goods sold should, all other things being equal, have cash flows more affected by shocks to these 'major' suppliers[3].

Like Hertzel, Li, Officer, and Rodgers (2008) and Fee and Thomas (2004), I define a 'dependent customer' as a firm with a single supplier representing more than 1% of its total cost of good sold. In order to test the robustness of the results and whether the affect of linkages on real activity and stock returns runs just from customers to their suppliers or both ways, I create sub-samples of 'dependent customer' and their key suppliers using two alternative thresholds for sales/cogs (1% and 5% of the customer's total cost of goods sold). The results are re-run using these sub-samples to test if the relationship between linkages and correlation is affected by removing the 'weaker' economic links.

[3] Cohen and Frazzini (2008) identify 'key suppliers' by identifying customer firms in which the supplier sales received are a large proportion of market equity. They reason that, ceteris paribus, cash flows should be more affected by shocks to suppliers that are a large proportion of market equity. They fit models with an indicator (equal to one) if the ratio of total sales from the supplier to the customer's total market capitalization at the end of the previous month is greater than the 75th percentile of all firms in that calendar month. This approach sets a threshold for suppliers that is not consistent with the threshold for customers because it is relative to other firms, whereas the threshold for customers is absolute as it is fixed at 10 percent of the revenues, profit or loss or assets.(Specifically the segment files contain discloses the monetary value of the transaction (salescs) between A and B when salescs is more than 10% of A's revenue).

Table 4.3: Summary statistics for 1st order customer linkages (CLs), 1st order supplier linkages (SLs), total CLs, total SLs, and the concentration of SLs and CLs

1990 to 2010	**Mean**	**S.D.**	**Skew**	**Kurt**	**Min**	**Max**
1st-order CL	0.83	1.55	4.56	44.18	0	34.0
1st-order SL	1.36	6.52	16.15	396.64	0	247.0
Total CL	1.18	0.34	4.58	41.99	1	7.8
Total SL	1.30	1.46	15.90	383.26	1	58.0
Conc. CL	0.31	0.40	0.72	1.80	0	1.0
Conc. SL	0.22	0.37	1.34	3.10	0	1.0

The main criteria for the sub-sample of dependent customers was that cost of goods bought from the supplier is greater than 1% (or 5%) of the customers' cost of goods sold[4]. In summary, the sub sample of dependent customers was extracted from the final matched set of customers and suppliers by calculating the ratio of customer purchases from the supplier (salecs) to the customers' cost of goods sold. All entries where salecs was missing or less than 1% of cost of goods sold were deleted, in addition all firms with book equity less than zero and all financial firms were deleted. The resulting sub-sample of dependent customers had 9,616 annual observations for 2,180 unique firms. The linkage measures for this sample are summarized in Table 4.3.

Table 4.3 shows that the sub-sample of dependent customer firms has higher average degree of first-order and total customer and supplier linkage (CL and SL respectively), and that their linkages are more concentrated than the sample based on dependent suppliers (p=0.000 in all pairwise t-tests comparing the means from the full sample to the mean from the sub-sample). However, the shape of the distribution of the linkage measures (1st-order CL, 1st-order SL, Total CL, Total SL) is similar in both samples. Significantly, even in the sub-sample of dependent customers the distribution of the number of supplier linkages

[4] In addition, the selection criteria also included: a) the supplier must disclose the amount of sales to the supplier and the customer firms must disclose cost of goods sold, b) customer firms with negative Book Equity were excluded in order to eliminate firms in financial distress from the sample.

(out-degree) is more heavy-tailed than the distribution of the number of customer linkages (in-degree). These summary statistics tend to support the finding that a small number of extremely large 'customer' firms dominate the sources of revenue of most listed firms. In other words, the source of revenue for listed firms (in their role as suppliers of intermediate inputs to other firms) are concentrated.

4.5 The structure of linkages between firms with securities listed on US exchanges 1990 to 2010

In this section I characterize the structure of cash flows along supply chains between the U.S. listed firms on the intersection of Compustat and CRSP between 1990 and 2010. I analyze the degree and structure of customer linkages (the source of a firm's sales revenue) and the degree and structure of supplier linkages (the source of a firm's sales expense).

The pairwise linkages between supplier and customer firms available in the Compustat/CRSP database can be mapped onto a network where each node is a firm and each edge represents cash flow from customers to their suppliers. The annual disclosures made between 1990 and 2010 to calculate an adjacency matrix $\mathbf{A_t}$ for each of these years ($t = 1990, \cdots, 2010$). The (i, j)'th entry of $\mathbf{A_t}$, $a_{ij,t}$, is 1 if i disclosed j as a key customer in year t and 0 otherwise. In a firm-level network, the set of nodes that make up the network is comprised of n *firms*, and the edge set is the subset of all ordered pairs of vertices f_i, f_j, with $f_i, f_j \in F$. $\mathbf{A_t}$ gives the set of all adjacency relations, $f_i \rightarrow f_j$ between elements of the set of all *firms* that defines a directed inter-firm network.

To analyze the characteristics of economic linkages more formally, concepts from network theory can be adapted to measure the degree of connectivity between firms along supply chains. Let the units in the network represent firms and the edges represent cash-flow between firms. In this sense, firm i's in-degree can be thought of as the number of units paying cash (in) to firm i, and firm i's out-degree can be thought of as the number of units to which firm i pays cash (out). In a supply chain, it is assumed that goods and services flow in the opposite direction to cash, so cash is assumed to flow from customers to suppliers. The *in-degree* represents the number of key customers paying cash to the (supplier) firm, and *out-degree* represents the number of key suppliers requiring payment via cash-flow out of the (customer) firm. In addition the term *supplier linkage* is used to indicate the connection of a firm to another firm to which it purchases inputs and pays money (customer to supplier) and *customer linkage* is used to indicate the connection of a firm to another firm to which it supplies inputs and receives money (supplier to customer) or the number of key customers.

Figure 4.2 gives a snapshot of the adjacency matrices describing supplier-customer linkages in 1995, 2000, 2005 and 2010. Dots in the figure correspond to a significant link between supplier i and customer j (or a flow of cash from j to i), provided firm j represents 10% or more of firm i's total sales. These matrices are sparse as the majority of firms in the CRSP/Compustat intersection have no key customers that are listed firms. The axes contain the full set of all firms in the sample alive at any time within 1990 to 2010. The matrix for 1995 appears concentrated in the upper left hand corner because the supplier firms at the bottom of the y axis are not alive yet. The progression from 1995 to 2010 shows that as new supplier firms start disclosing key customers, they tend to sell to the same customer firms. To complement these plots, Tables 4.4 to Table 4.7 summarize the first four moments of the first-order and second-order in-degree and out-degree distributions in each year from 1989 to 2010.

Tables 4.4 to 4.7 illustrate an increasing trend in both the average first-order and second-order in-degree, and both the average first-order and second-order out-degree over the period 1990 to 2010. That is, the average number of key customers and reliant suppliers that a randomly chosen firm is likely to have has increased over the last twenty years. This indicates an increasing dependence of the cash-flow of listed firms in the sample on particular customers and suppliers. In addition the tails of first-order out-degree, the first-order in-degree and the second-order in-degree have become more positively skewed and heavier, as

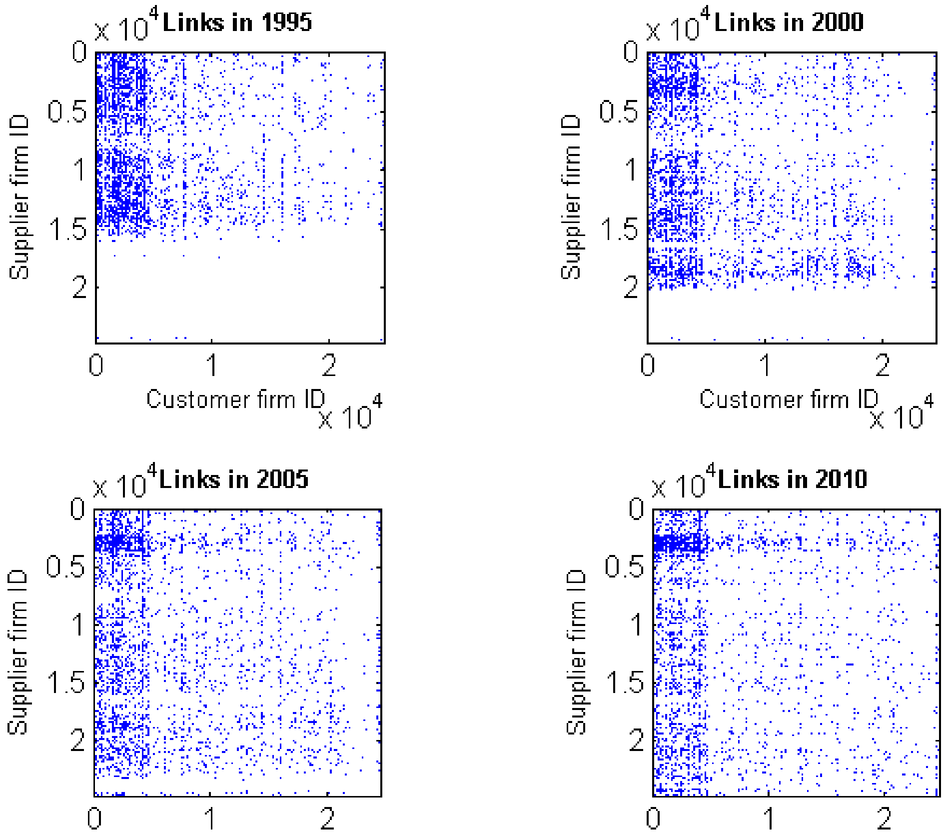

Figure 4.2: Plots of the adjacency matrices for the supplier-customer connections between listed firms on the Compustat/CRSP database in 1995, 2000, 2005 and 2010. *Each dot corresponds to a significant cash-flow (over 10% of the supplier's total sales revenue) from the row (supplier) firm i to the column (customer) firm j.*

Table 4.4: Summary statistics from the distribution of the 1st order out-degree (number of dependent suppliers)

	Mean	Std Dev	Skew	Kurt	Min	Max
1989	0.12	1.69	45.72	2,914.52	0	136
1990	0.12	1.79	41.93	2,135.94	0	110
1991	0.12	1.8	42.54	2,208.65	0	111
1992	0.12	1.85	45.22	2,494.55	0	126
1993	0.12	1.81	44.13	2,397.12	0	125
1994	0.12	1.83	45.29	2,570.31	0	137
1995	0.13	1.87	43.00	2,319.18	0	130
1996	0.14	1.88	43.46	2,577.02	0	151
1997	0.14	1.93	44.63	2,742.90	0	159
1998	0.14	1.91	43.59	2,672.45	0	158
1999	0.14	1.88	45.30	2,991.97	0	164
2000	0.14	1.77	41.94	2,614.90	0	149
2001	0.14	1.87	49.07	3,650.63	0	175
2002	0.14	1.83	47.73	3,499.33	0	170
2003	0.14	1.94	52.40	4,320.00	0	193
2004	0.14	1.83	53.37	4,549.62	0	186
2005	0.14	1.82	53.22	4,567.39	0	185
2006	0.14	1.88	57.52	5,233.97	0	198
2007	0.14	1.93	60.72	5,746.62	0	209
2008	0.14	2.01	64.81	6,399.86	0	223
2009	0.14	2.03	63.81	6,230.63	0	224
2010	0.14	2.18	68.15	6,966.05	0	248

indicated by the increasing skewness and kurtosis over the period 1990 to 2010. This suggests the supply chains are becoming more concentrated via a process of the largest firms accruing more customers and suppliers, while small and medium size firms retain the same number of customers and suppliers.

In all years the average number of dependent suppliers (out-degree) is equal to the average number of key customers (in-degree)[5]; however, the out-degree distributions have much heavier tails (higher kurtosis) than the in-degree dis-

[5] This is because the data on dependent suppliers was generated by reversing FAS 131 disclosures of key customers.

Table 4.5: Summary statistics from the distribution of the 2nd order out-degree (number of dependent suppliers)

	Mean	Std Dev	Skew	Kurt	Min	Max
1989	0.03	1.74	143.36	21,703.69	0	265
1990	0.03	1.37	127.42	18,292.32	0	200
1991	0.03	1.31	115.11	15,646.74	0	184
1992	0.03	1.26	122.74	17,262.76	0	181
1993	0.03	1.29	125.1	17,737.96	0	186
1994	0.03	1.15	124.13	17,576.98	0	166
1995	0.03	0.77	71.86	6,642.86	0	84
1996	0.03	0.65	70.84	7,034.42	0	73
1997	0.03	0.87	75.27	7,784.58	0	101
1998	0.03	0.85	62.26	5,289.95	0	88
1999	0.03	0.83	41.53	1,989.57	0	52
2000	0.04	1.01	46.74	2,622.79	0	79
2001	0.04	1.13	47.77	2,592.02	0	78
2002	0.04	1.13	40.99	1,931.24	0	69
2003	0.07	2.10	48.88	2,803.36	0	156
2004	0.07	1.96	53.21	3,501.87	0	170
2005	0.06	1.59	46.73	2,609.39	0	116
2006	0.07	1.74	33.92	1,272.11	0	91
2007	0.08	1.92	35.96	1,457.31	0	106
2008	0.07	1.81	45.61	2,511.01	0	134
2009	0.06	1.94	54.26	3,517.46	0	159
2010	0.07	2.49	59.66	4,103.30	0	210

Table 4.6: Summary statistics from the distribution of the 1st order in-degree (number of key customers)

	Mean	Std Dev	Skew	Kurt	Min	Max
1989	0.12	0.49	5.79	55.40	0	13
1990	0.12	0.52	6.02	51.37	0	10
1991	0.12	0.52	5.99	50.13	0	10
1992	0.12	0.51	5.62	43.37	0	9
1993	0.12	0.49	5.24	36.95	0	8
1994	0.12	0.49	5.89	64.97	0	15
1995	0.13	0.51	4.77	30.45	0	8
1996	0.14	0.52	4.69	29.23	0	8
1997	0.14	0.56	5.77	51.35	0	13
1998	0.14	0.59	6.41	62.59	0	13
1999	0.14	0.70	8.60	109.87	0	17
2000	0.14	0.65	8.17	109.20	0	16
2001	0.14	0.65	7.48	86.20	0	17
2002	0.14	0.63	7.07	74.94	0	14
2003	0.14	0.68	8.26	101.51	0	15
2004	0.14	0.67	7.91	91.77	0	14
2005	0.14	0.68	8.10	97.94	0	16
2006	0.14	0.73	10.13	165.46	0	24
2007	0.14	0.76	10.71	176.20	0	22
2008	0.14	0.79	11.74	209.72	0	24
2009	0.14	0.84	12.72	243.88	0	29
2010	0.14	0.93	13.86	275.02	0	34

Table 4.7: Summary statistics from the distribution of the 2nd order in-degree (number of key customers)

	Mean	Std Dev	Skew	Kurt	Min	Max
1989	0.03	0.24	11.76	178.34	0	7
1990	0.03	0.30	16.18	356.04	0	11
1991	0.03	0.31	16.31	375.87	0	11
1992	0.03	0.28	14.76	303.06	0	10
1993	0.03	0.25	12.35	196.94	0	7
1994	0.03	0.24	12.23	195.46	0	8
1995	0.03	0.25	14.17	289.72	0	9
1996	0.03	0.26	15.03	323.94	0	10
1997	0.03	0.30	13.94	245.12	0	9
1998	0.03	0.33	18.05	488.09	0	16
1999	0.03	0.47	30.94	1,434.89	0	32
2000	0.04	0.43	23.32	758.00	0	20
2001	0.04	0.44	20.13	651.79	0	25
2002	0.04	0.47	17.51	416.90	0	19
2003	0.07	0.83	20.60	583.60	0	40
2004	0.07	0.84	26.78	1,092.10	0	51
2005	0.06	0.64	22.25	737.18	0	31
2006	0.07	0.92	28.49	1,205.97	0	52
2007	0.08	1.02	29.25	1,243.81	0	56
2008	0.07	0.83	23.35	773.45	0	42
2009	0.06	0.88	25.61	877.59	0	44
2010	0.07	1.16	35.61	1,848.60	0	87

tributions. This strong heterogeneity (fat tailed behavior) along the out-degree dimension is a feature in every year of the data. It is the counterpart to the empirically documented heavy-tailed input supply distribution in sector-level analyzes (i.e. the fact that input-use matrices have a few full rows but mostly empty rows) (Carvalho, 2008; Horvath, 2000). The heterogeneity in firms' out-degrees indicates that a few 'hub' firms have a large number of dependent suppliers, while the vast majority of firms have no dependent suppliers. In contrast, there is far less heterogeneity in firms' in-degrees because almost all firms have zero or one key customer.

Figures 4.3 and 4.4 illustrate this by plotting the empirical out-degree counter-cumulative distribution in the input-use data. The empirical CDFs indicate that the distribution of out-degrees (i.e. number of supplier linkages) is much more heavy-tailed than the distribution of in-degrees (i.e. number of customer linkages), with over 90% of matched firms having a first order out-degree of zero, but one or two firms having an out-degree of 140 to 250 firms over the sample period. As above, the difference between average and highest degree is less pronounced for in-degrees, with about 70% of matched firms having a first order in-degree of zero, about 25% having in-degree between 1 and 10 and about 5% having in-degree of at most 40, even with links to unlisted firms included.

Heavy-tailed distribution of connectivity

Extremely heavy-tails in a distribution are usually associated with power law behavior. Mathematically, a quantity X obeys a power law if it is drawn from a probability distribution where the cumulative distribution function (CDF) follows

$$Pr(X > x) = cx^{-\zeta} \tag{4.8}$$

where c is a constant and $\zeta > 1$ is a parameter of the distribution known as the scaling parameter[6]. In practice, few empirical phenomena obey power laws for all

[6] The special case of $\zeta = 1$ is known as the Zipf distribution and has somewhat unusual properties as its moments do not exist. Therefore in this thesis, I focus on structures in which $\zeta > 1$. This assumption is also made by Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010); Gabaix (2011)

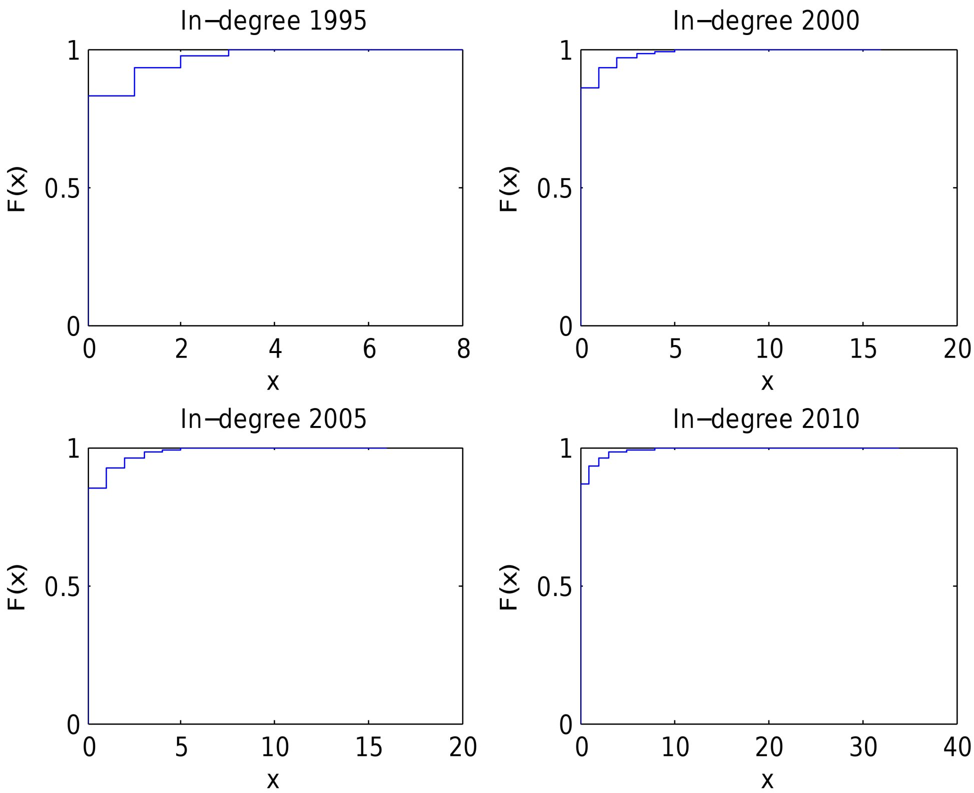

Figure 4.3: Empirical cumulative distribution of first-order in-degrees (number of key customers)

values of X, more often the power law applies only for values greater than some minimum value of X (Clauset, Shalizi, and Newman, 2009). For example, firm sizes in industrial countries are highly skew, such that small numbers of large firms coexist alongside larger numbers of smaller firms. The upper tail of the firm size distribution has often been described by a power law (Axtell, 2001; Zipf, 1949). For example, recent analysis of data on the largest 500 U.S. firms gives $\zeta \approx 1.25$, whereas it is closer to 1 for many other countries (Axtell, 2001).

In the context of a supply network, let $P(k) = \sum_{k'} p_{k'}$ be the counter-cumulative

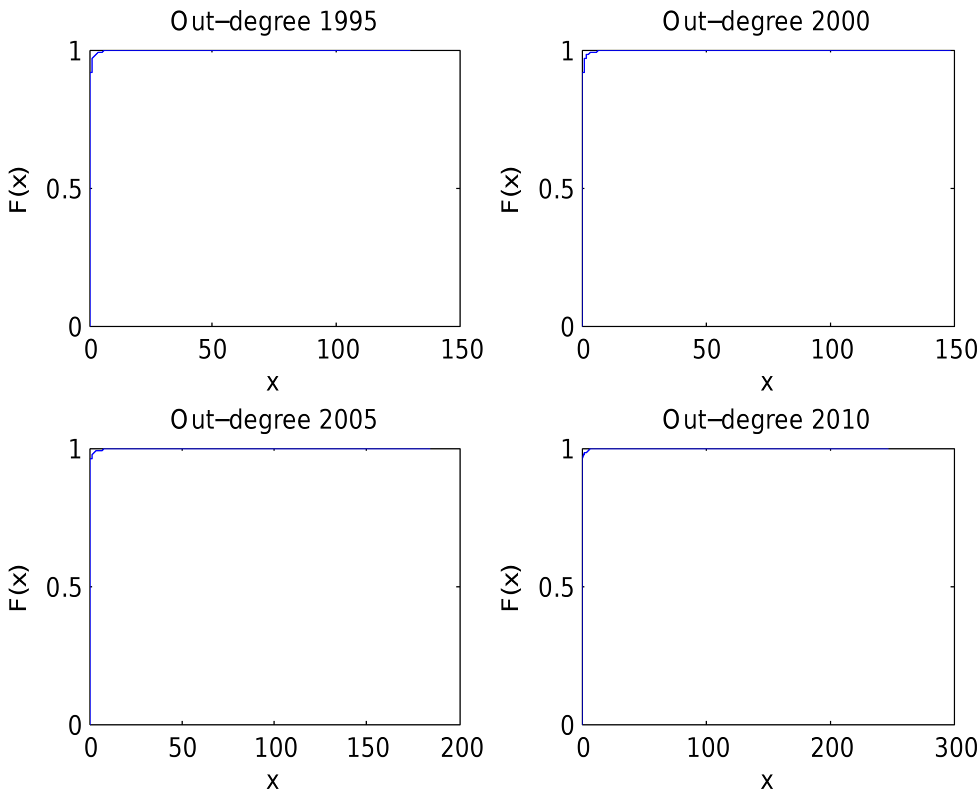

Figure 4.4: Empirical cumulative distribution of first-order out-degrees (number of dependent suppliers)

distribution (CCDF) of out-degrees, i.e. the probability that a sector selected at random from the population supplies to k or more sectors. I say that the number of sectors supplied (i.e. the out-degree), k, follows a power law distribution if, the p.d.f. giving the frequency of sectors that supply to exactly k sectors in the economy is given by $P(k) = ck^{-\zeta}$ for $\zeta > 1$, and k integer, $k > 1$. Empirical evidence from recent work showing that the tails of the out-degree distribution of economic sectors are well described by power laws, with scaling parameters in the range of $\zeta = 1.5$ (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2010).

In Chapter 4 (Proposition 2) I show that if the distribution of a firm's connectivity across its suppliers (customers), i.e. the firm's out-degree (in-degree) distribution, has power law tails then aggregate volatility in its cash-flow decreases much slower than $\frac{1}{\sqrt{n}}$[7] as the firm increases the number of suppliers (customers) it has. Conversely, for a fixed number of suppliers (customers), as the tail parameter of the out-degree (in-degree) distribution drops (so that a small numbers of its suppliers (customers) are extremely influential while most have no influence) the volatility of cash-flow is likely to increase.

Tests of heavy-tailedness

In this section I test whether the distribution of the out-degree distributions in the firm-level supply network data follows a power law. Linear regression (or least squares) methods for estimating the parameters of a power-law distribution tend to provide biased estimates for the tail parameter (Goldstein, Morris, and Yen, 2004). The maximum likelihood estimator (MLE), commonly known as the Hill estimator[8] is asymptotically normal and consistent and produces more accurate and robust estimates (Goldstein, Morris, and Yen, 2004; Clauset, Shalizi, and Newman, 2009). MLE permits the use of a Kolmogorov-Smirnov (KS) test to assess goodness-of-fit. The KS statistic assesses the accuracy of the goodness of fit of the power law distribution to the data by calculating the maximum distance between the CDFs of the data and the fitted model. I.e.

$$D = max_{x \geq x_{min}} |S(x) - P(x)|$$

where $S(x)$ is the CDF of the data for the observations with value at least x_{min}, and $P(x)$ is the CDF for the power-law model that best fits the data in the region $x \geq x_{min}$. The estimate $\hat{x_{min}}$ is the value of x_{min} that minimizes D.

There are a number of ways to assess whether a power law is a good descrip-

[7] The rate predicted by the law of large numbers.

[8] Given x_{min}, the MLE of ζ is $\hat{\zeta} = 1 + n[\sum_i ln \frac{x_i}{x_{min}}]^{-1}$. Clauset, Shalizi, and Newman (2009) outlines the following procedure for estimating x_{min}: choose the value of $\hat{x_{min}}$ that makes the probability distributions of the measured data and the best-fit power-law model as similar as possible above $\hat{x_{min}}$. For more details see Clauset, Shalizi, and Newman (2009).

tion of the tail behavior of the out-degree distribution. First, note that taking the logarithm of both sides of Equation (4.8) shows that a if X follows a power-law distribution

$$lnP(x) = -\zeta lnx + constant$$

implying that it follows a straight line on a doubly logarithmic plot.

Figure 4.5 plots the logarithm of the empirical counter-cumulative distribution function for first-order out-degrees (i.e., one minus the empirical cumulative distribution function) against the logarithm of first-order out-degrees in the years 1995, 2000, 2005 and 2010. In all cases, the tail of the log-log plot of the CCDF is approximately linear, indicating that the tails of out-degree distribution of firms on the Compustat/CRSP database are well-approximated by a power law distribution.

Formal statistical tests have also been developed to assess whether a power law is an accurate representation of empirical data. Clauset, Shalizi, and Newman (2009) outlines the following procedure for assessing whether empirical data follows a power law. First, fit a power-law model to the data using MLE and calculate the KS statistic for this fit. Next, generate a large number of power-law distributed synthetic data sets with the same tail parameter using Monte Carlo simulation. Fit each synthetic data set individually to its own power-law model and calculate the KS statistic for each one relative to its own model. The p-value is the fraction of the time the resulting KS statistic is larger than the value for the empirical data. Table shows the results of this procedure implemented on the empirical data on the first-order and second-order out-degree distributions of the sample of US listed firms by year 1990 to 2010. In Table 4.8, the null hypothesis of a power law being reasonable fit to the data is rejected at the 5% level if $p < 0.05$. That is, it is ruled out if there is a probability of 1 in 20 or less that we would merely by chance get data that agree as poorly with the model as the data we have. In many years a power law provides a reasonable fit to the data. It is interesting to note that there is considerable variation in the heavy-tailedness of supplier-customer dependencies over time, and also a considerable difference

Table 4.8: Kolmogorov-Smirnov (KS) test to assess goodness-of-fit of power law to the degree distribution

	1st order out-degree		**2nd order out-degree**	
	p-value	**gof**	**p-value**	**gof**
1989	0.07	0.02	0.06	0.06
1990	0.00	0.06	0.00	0.09
1991	0.00	0.04	0.01	0.08
1992	0.00	0.04	0.06	0.05
1993	0.00	0.04	0.39	0.04
1994	0.03	0.02	0.00	0.08
1995	0.00	0.03	0.04	0.06
1996	0.00	0.03	0.00	0.07
1997	0.00	0.04	0.05	0.05
1998	0.00	0.03	0.00	0.10
1999	0.00	0.03	0.01	0.07
2000	0.24	0.01	0.44	0.04
2001	0.06	0.02	0.13	0.05
2002	0.05	0.02	0.00	0.07
2003	0.13	0.02	0.00	0.08
2004	0.01	0.02	0.00	0.12
2005	0.09	0.02	0.00	0.09
2006	0.06	0.02	0.01	0.07
2007	0.01	0.03	0.01	0.07
2008	0.00	0.03	0.00	0.13
2009	0.11	0.02	0.03	0.06
2010	0.00	0.03	0.17	0.05

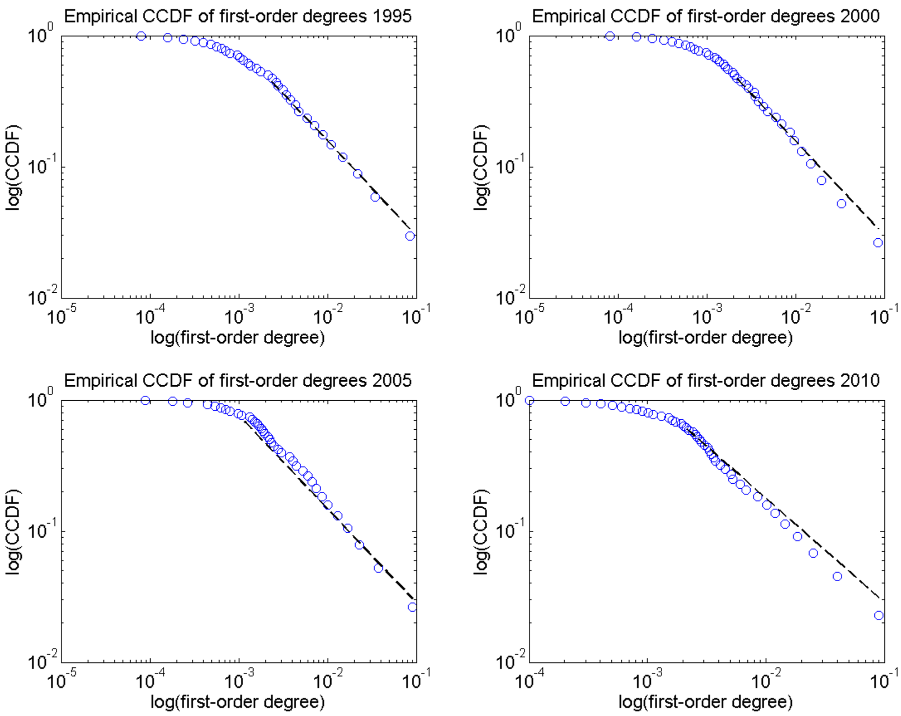

Figure 4.5: Counter-cumulative out-degree distribution. *Log-log plots of the CCDF of first-order out-degrees amongst all firms listed on the Compustat/CRSP intersection 1995, 2000, 2005 and 2010. The straight line in each panel is of slope $\hat{\zeta}$, the MLE of ζ shown in Column 3 of Table 4.9.*

between first order and second order measures.

As a power law provides a reasonable description of out-degree distributions in over half of the years in the data, it is reasonable to estimate the tail parameter and scaling cut-off. Table 4.9 contains the MLE estimates of the tail parameter (ζ) and the scaling cut-off (x_{min}). The power law tail coefficients for the second order out-degree distribution are slightly higher on average than the tail coefficients for the first order out-degree distribution (1.811 vs 1.736 respectively). This suggests that the distribution of first-order linkages is more heavy-tailed than the distribution of second-order linkages. However, in both cases there is reason to suspect that linkages interfere with diversification as the tail coefficient of both the first and second order degree distribution is less than 2 (see Acemoglu,

Table 4.9: Power law coefficients (x_{min} and ζ) fit to 1st order and 2nd order out-degree

	1st order $\hat{x_{min}}$	**1st order $\hat{\zeta}$**	**2nd order $\hat{x_{min}}$**	**2nd order $\hat{\zeta}$**
1989	0.007	1.782	0.002	1.719
1990	0.001	1.650	0.001	1.788
1991	0.002	1.722	0.001	1.743
1992	0.003	1.691	0.001	1.729
1993	0.001	1.626	0.001	1.708
1994	0.002	1.685	0.001	1.733
1995	0.002	1.720	0.001	1.659
1996	0.003	1.764	0.001	1.650
1997	0.002	1.693	0.001	1.765
1998	0.002	1.724	0.001	1.792
1999	0.002	1.751	0.001	1.863
2000	0.002	1.721	0.001	1.793
2001	0.003	1.755	0.001	1.798
2002	0.004	1.792	0.001	1.841
2003	0.004	1.810	0.001	1.900
2004	0.004	1.793	0.001	1.884
2005	0.001	1.714	0.001	1.871
2006	0.002	1.748	0.001	1.996
2007	0.002	1.756	0.003	1.929
2008	0.002	1.731	0.004	1.902
2009	0.002	1.770	0.003	1.851
2010	0.002	1.793	0.002	1.939
Min	**0.001**	**1.626**	**0.001**	**1.650**
Max	**0.007**	**1.810**	**0.004**	**1.996**
Avg	**0.002**	**1.736**	**0.001**	**1.811**
S.d.	**0.001**	**0.048**	**0.001**	**0.094**

Carvalho, Ozdaglar, and Tahbaz-Salehi (2011)).

4.6 Summary

This chapter outlined the research methodology and the data used to answer the research questions that were formulated in Chapter 2. I outline a unique source of data on economic linkages (FAS 131 accounting disclosures of key customers) and the procedures for extracting this data from the Compustat/CRSP database.

Analysis of the main characteristics of economic linkages between the firms on the Compustat/CRSP database showed that in all years 1990 to 2010 there were a small number of extremely connected 'hub' firms (e.g. Walmart and General Motors) that were the key customers of many different (dependent supplier) firms. Consistent with this observation, I showed that distribution of listed US firms' out-degree (or number of dependent suppliers) follows a power law distribution, with a very small chance that a randomly selected firm is a key customer of an extremely large number of supplier firms.

In addition, the moments of the data and the estimated power law parameters both indicate an increasing trend in the degree of economic linkage between listed US firms over the period 1990 to 2010. These findings support the assumptions of the theory in Chapter 3, and suggest that analyzing the influence of inter-firm connectivity on asset prices is of increasing importance in modern financial markets.

Chapter 5

Economic linkages and return correlation

5.1 Introduction

As shown in Chapter 3, if economic linkages are a channel through which shocks are transmitted between firms, the transmitted shocks can create correlation in linked firms' returns (as customer firms will be exposed to shocks to their suppliers, and vice versa). Studies have shown that economic linkages increase sectoral output correlation (Raddatz, 2010) and correlation in counterparties' credit spreads (Jorion and Zhang, 2009). In relation to stock returns, however, the importance of economic linkages as a source of return correlation has not been comprehensively established.

Understanding sources of correlation in returns is crucial to portfolio risk management. Return correlation may be caused by both macro and micro factors. The returns of different assets are positively correlated due to common exposure to macro factors such as interest rates. Models that include only macro factors, however, cannot replicate the levels of correlation found in empirical data on defaults (Egloff and Leippold, 2007) or the high levels of correlation in stock returns during financial crises (Longin and Solnik, 2001). Micro channels, such as economic linkages between firms, can create correlation in excess of that caused by macro factors (Egloff and Leippold, 2007). As such, economic linkages may be important in explaining situations in which observed levels of return correlation are higher than the expected level of correlation based on macro factors alone.

Most asset pricing studies neglect the economic links between firms underlying the assets under consideration. Two event studies, however, have established that economically linked firms have correlated returns following significant news announcements and bankruptcy filings. Cohen and Frazzini (2008) show that significant news announcements generate return predictability for suppliers; while Hertzel, Li, Officer, and Rodgers (2008) show that bankruptcy filings are associated with significant negative stock price movements for suppliers. The studies by Cohen and Frazzini (2008) and Hertzel, Li, Officer, and Rodgers (2008) are limited, however, as they only take into account direct links between suppliers and customers, not indirect links to firms further up or down a supply chain (e.g. from customers' customers). Also they only examine stock price response in a narrow event window. This approach does not allow for the possibility that economic linkages may create interdependence in stock returns that exists in general market conditions, or the possibility that indirect linkages to suppliers and customers may be important.

The central hypothesis tested in this chapter is that an increase in the strength of the economic linkage between two firms, as measured by cash-flow along the supply chain connecting two firms (i.e. via all direct and indirect linkages between two firms), results in an increase in their stock return correlation. I test for the presence and significance of shock transmission via economic linkages by testing the implications for return correlation based on the theoretical model in Chapter 3. First, I show that the shocks transmitted via inter-firm linkages increase correlation between linked firms' returns. Second, I show that as the use of trade credit along the supply chain between two firms increases, so does correlation in their returns. The significance of this effect remains after controlling for macro factors, industry effects and firm-level characteristics that have been shown to influence contagion. Finally, I show that the influence of shocks transmitted via economic linkages on stock returns is significantly higher during recessions.

5.2 Research method

In Chapter 3, it was shown that the transmission of shocks via economic linkages can increase the correlation between linked firms' stock prices. In this chapter I empirically test the hypothesis that the transmission of shocks via economic linkages affects stock returns, by testing whether an increase in the strength of the linkage between two firms raises their return correlation. I also test whether this relationship is stronger in a recession.

Regression of correlation on input-output distance

In Chapter 3 I developed a model of stock returns in a market where the underlying firms are linked and there is transmission of shocks through economic linkages between firms. To recap, let

$$\mathbf{R_t} = (\mathbf{I} - \alpha \mathbf{W_t})^{-1} \eta_{\mathbf{t}} = \mathbf{CS_t} \eta_{\mathbf{t}} \tag{5.1}$$

where $\mathbf{R_t}$ is a vector of excess returns in period t, α is a constant, $\mathbf{W_t} = c\mathbf{A_t}$ is an N by N weight matrix, equal to c times the adjacency matrix $\mathbf{A_t}$ describing the links between N firms in period t, and $\eta_{\mathbf{t}}$ is a vector of shocks hitting each firm directly in period t. As in Chapter 3, at the firm-level this model is

$$R_{it} = \sum_{j \neq i} CS_{ijt} \eta_{jt} + \eta_{it} \tag{5.2}$$

where R_{it} is the excess return on the stock of firm i in period t; CS_t is a matrix of the total economic linkages in period t, whose ij'th element, CS_{ijt}, is the share of firm j in the total demand for firm i's goods through direct and indirect linkages; and $\eta_t = (\eta_{1t}, ..., \eta_{Nt})$ is a vector of i.i.d. idiosyncratic shocks for firms 1 to N.

Assuming that idiosyncratic shocks are i.i.d. Equation (5.2) implies that the correlation between two firms' returns, after controlling for systematic risk factors is:

$$\rho_{ik} \approx \frac{\sum_j (CS - I)_{ij} (CS - I)_{kj}}{\sqrt{\sum_j (CS - I)^2_{ij} (CS - I)^2_{kj}}} \tag{5.3}$$

A simple modification to equations (5.2) and (5.3) allows for the possibility that trade credit may affect the transmission of shocks via inter-firm linkages. Let P_{ij} be the fraction of the supplier-customer transaction financed via trade credit (in empirical work, P_{ij} is set equal to i's ratio of accounts payable to total cost of goods sold for all of i's customers). If this fraction has an additional effect on the transmission of shocks, then the transmission via each direct linkage w_{ij} would be scaled up to $w_{ij}(1+\beta P_{ij})$, with β parameterizing the importance of trade credit.

Assuming, for data availability reasons, that P_{ij} is constant across suppliers ($P_{ij} = P_i \forall$ i), then equation (5.2) becomes

$$R_{it} = \sum_{j \neq i} CS^{*}_{ijt} \eta_{jt} + \eta_{it} \tag{5.4}$$

where $\mathbf{CS}^{*} = (\mathbf{I} - \alpha \mathbf{W}(\mathbf{I} + \beta \mathbf{P}))^{-\mathbf{1}}$, and the matrix $\mathbf{P}$ is a diagonal matrix with each firms trade credit ratio, $P_{ij} = P_i$, on the diagonal.

The first order linear approximation of CS^{*} about $\beta = 0$ is $\mathbf{CS}^{*} \approx \mathbf{CS} + \beta \mathbf{CD}$, where $\mathbf{CS}$ measures the strength of *economic linkage* between firms, and $\mathbf{CD} = \mathbf{CS}(\mathbf{WP})\mathbf{CS}$ measures the *credit distance* between two firms (i.e. use of trade credit along the supply chain connecting i and j). Using this approximation, the expression for return correlation becomes

$$\rho_{ik} \approx \frac{\sum_j CS_{ij} CS_{kj}}{\sqrt{\sum_j CS^2_{ij} CS^2_{kj}}} + \beta \sum_j \frac{CS_{ij} CS_{kj} (\grave{c_{ij}} + \grave{c_{kj}})}{\sqrt{\sum_l CS^2_{il} CS^2_{kl}}}, \tag{5.5}$$

where $\grave{c_{ij}} = \frac{CS_{ij} CD_{ij}}{CS^2_{ij}} - \frac{\sum_l CS_{il} CD_{il}}{CS^2_{il}}$, where CD_{ij} is the (i, j) element of $\mathbf{CD} = \mathbf{CS}(\mathbf{WP})\mathbf{CS}$, which measures the use of trade credit the full length along the chain connecting i and j[1].

The first term of equation (5.5) corresponds to the correlation between i and

[1] Raddatz (2010) proves a similar result in the context of sector-level input-output models.

k in the absence of trade credit amplification; the second term is a weighted average of the relative use of trade credit across all j linking i and k, where the weights are determined by the product of the direct and indirect linkages between j, i, and k. Shocks to firm j increase the correlation between firms i and k most when the linkages between j and i and j and k are a significant percentage of each firm's total cash-flow, and when the use of trade credit along the chain linking i and k (via j) is high.

I test whether economic linkages and/or the use of trade credit affect returns by estimating the following equation

$$\rho_{ik} \approx c+\beta_{CS}CS_{ik}+\beta_{CD}CD_{ik}+\sum_{m=1}^{M}\beta_m F_m+\sum_{l=1}^{L}\beta_{l,(s)}X_{il}+\sum_{l=1}^{L}\beta_{l,(c)}X_{kl}+\varepsilon_{ik}. \quad (5.6)$$

where ρ_{ik} is the correlation between R_i and R_k, the excess return of stock i and stock k; CS_{ik}, the measure of supply-chain distance between i and k, is the (i,k)'th element of $\mathbf{CSCS'}$; CD_{ik}, the measure of credit distance between i and k, is the (i,k)'th element of $\mathbf{CD} = \mathbf{CS}(\mathbf{WP})\mathbf{CS}$; β_m is the sensitivity of return correlation to common factor F_m; $\beta_{l,(s)}$ and $\beta_{l,(c)}$ are the sensitivity of return correlation to supplier and customer firm-specific characteristic l, i.e. X_{il} and X_{kl} respectively; and the noise terms ε_{ik} are assumed to be mean zero, i.i.d.

The null hypothesis that neither economic linkages nor the use of trade credit along supply chains affect return correlation is

$$H_0 : \beta_{CS} = \beta_{CD} = 0$$

And the alternative hypothesis that economic linkages and/or the use of trade credit along supply chains does influence return correlation is

$$H_A : \beta_{CS} \neq \beta_{CD} \neq 0.$$

Regime shifts

The model above assumes that linkages and trade credit amplify positive and negative shocks equally. However, transmission of shocks between suppliers and customers may be stronger in a recession, when shocks are often negative (Lang and Stulz, 1992; Escaith and Gonguet, 2009). Neglecting asymmetry could result in downward biased coefficient estimates (Raddatz, 2010). I test whether the stock returns of linked firms are more correlated in a recession than in normal times in two ways. First, equation (5.6) was estimated using only data from the NBER recession subperiods. T-tests were used to test whether the coefficients for the production and credit distance were significantly higher in recessions than in the full period (growth periods). Second, I estimated (5.6) over different quantiles of the correlation distribution via quantile regression to test whether the coefficients for the production and credit distance were higher in high correlation regimes than in low correlation regimes. The quantiles can be interpreted as a states or a regimes; i.e. lower quantiles (lower correlation) are consistent with a good state and higher quantiles (higher correlation) are consistent with a bad state or regime (Baur and Schulze, 2005). A conditional correlation approach (used in the quantile regressions) allows for asymmetry, whereas an unconditional OLS approach (used to fit Equation (5.5)) has the advantage that it avoids endogeneity issues (Raddatz, 2010). I use both OLS and quantile regression approaches to test for robustness to asymmetry and endogeneity issues.

5.3 Data and measurement of variables

5.3.1 Sample selection

The sample was selected from the set of all nonfinancial firms in the intersection of the CRSP return files and the Compustat annual files using selection criteria identical to Fama and French (1992). These files contain return and account information on all firms with listed securities on the NYSE, AMEX and/or NASDAQ exchanges. The sample was selected from the full intersection of CRSP and Compustat according to the following criteria:

- The firm must have a record in both Compustat Fundamental Annual and CRSP files between 1989 and 2010. (1989 is the start date because disclosures under FAS 131 were only restated back to 1990, but one year of extra information is included to calculate lagged variables.)
- There must be at least 2 years or 24 months of return data on CRSP. (As at least 20 observations should be used to calculate beta and correlation between firms return series. Furthermore, this controls for the potential survival/selection bias inherent in the way COMPUSTAT adds firms to its tapes (Banz and Breen, 1986).
- Financial firms were excluded based on SIC divisions 6000-6900 i.e. firms from the financial service industry because disclosure requirements and accounting rules are significantly different for these industries (Collins et al., 2003) and because the use and influence of leverage is not comparable between financial and non-financial companies (Fama and French, 1992).

In order to test the hypothesis of supply chain contagion, the sample is further limited to firms that have disclosed a key customer, or have been disclosed as a key customer, at any point during the sample period 1990 to 2010. This approach allows me to test whether the time series variation in pairwise return correlation is related to the time series variation in pairwise inter-firm linkages.

The final sample contained 305,500 monthly firm-pair return observations, between 15,417 unique pairs, each with an average of 20 overlapping monthly observations each[2]. The panel was unbalanced.

5.3.2 Dependent variable: Return correlation

To test whether inter-firm linkages are related to the pairwise correlation in stock prices I use two alternative response variables:

[2] The sample selection criteria were applied to individual firms, and ensured that individually, each firm had 24 months of return data on CRSP. Only periods in which both firms were alive were included in the final dataset, however. This is not problematic as 20 observations is still OK to calculate correlations.

- pairwise correlation in excess stock returns (**Corr(ER)) and**
- **pairwise correlation in residual returns from the CAPM (Corr(RR)).**

The first response ρ_{ij} is the sample correlation between the last 24 monthly observations of $R_i - R_f$ and $R_j - R_f$. The second response ρ_{ij}^{ε} controls for exposure to the market risk factor i.e. ρ_{ij}^{ε} is the sample correlation between the last 24 monthly observations of the residual returns

$$\hat{\varepsilon_{it}} = R_{it} - \hat{\beta_{it}} R_{Mt}$$

where $\hat{\beta_{it}}$ is calculated by taking the sample correlation between R_i and R_m over the past 24 monthly observations (similar to Fama and French (1992) who estimate β using the past 24 to 60 monthly returns, as available)[3].

5.3.3 Independent variables

Accounting variables

The firm-level linkage measures and control variables are taken from the annual financial accounts recorded in Compustat. To ensure that the explanatory accounting variables relate to the same historical period over which the return correlation is calculated, I match the (past 2 year) return correlation for July of year t to June of $t+1$ with accounting data for fiscal years ending in calendar year $t-1$. This matching rules ensures that there is at least a six month gap

[3] It is appropriate to use rolling betas in this case to allow for time-variation in the sensitivity of assets to common factors that may be caused if linkages transmit macro shocks. To see this note that (5.2) implies

$$\begin{aligned} R_{it} &= \beta_i R_{Mt} + \sum_{j \neq i} CS_{ijt}(\eta_j + \beta_j R_{Mt}) + \eta_i \qquad (5.7) \\ &= (\beta_i + \sum_{j \neq i} CS_{ijt}\beta_j) R_{Mt} + \sum_{j \neq i} CS_{ij}\eta_j + \eta_i. \end{aligned}$$

so beta will be time varying if transmitted macro shocks ($\sum_{j \neq i} CS_{ijt}\beta_j R_{Mt}$) are significant and the linkages CS_{ijt} are time varying. This construction of residual returns is also consistent with the proxy for idiosyncratic volatility, which is calculated as the standard deviation of the $\hat{\varepsilon}_{it}$ as in R. and Duffee (1995); Cheung and Ng (1992); Chava and Purnanandam (2010).

between the accounting data and the return correlation it is supposed to explain, and that the entire year to which the account information relates overlaps the two year period during which the return correlation is calculated. That is, using the standard matching rule proposed in Fama and French (1992) ensures that the response and accounting variables relate to the same historical period[4].

Adjacency matrix

Data on economic linkages between firms is obtained from the Compustat Segment files. These files contain annual account disclosures under FAS 131 which list the identity of all customers that account for 10% or more of the firm's total sales revenue (described in detail in Section 4.3). These disclosures pertained to a set of 25,595 unique firm IDs. I the annual disclosures made between 1990 and 2010 to calculate an adjacency matrix $\mathbf{A_t}$ for each of these years ($t = 1990, \cdots, 2010$). The (i, j)'th entry of $\mathbf{A_t}$, $a_{ij,t}$, is 1 if i disclosed j as a key customer in year t and 0 otherwise. (The process for determining whether i disclosed j as a key customer in year t is described in detail in Section 4.4).

The FAS 131 disclosures were used to form series of adjacency matrices describing the supplier-customer links between listed firms each year from 1990 to 2010[5] Calculating aggregate measures of linkage from the adjacency matrices is done via the matrix manipulations explained in detail in Chapter 3. For example, the first and second order in-degree and out-degree distributions for all firms on the Compustat/CRSP database each year from 1990 to 2010 are calculated by summing the entries in the rows and columns of $\mathbf{A_t}$ and $\mathbf{A_t^2}$ respectively[6].

[4] I also tested the regression results using last available accounting information as explanatory variables, and the main results and conclusions were not significantly different.

[5] The list of pairs describes the entries in a $25,595$ by $25,595$ square adjacency matrix which specifies the structure of the network of supply linkages between all listed firms on the CRSP/Compustat database in each year. The construction and manipulation of these matrices was based on standard principles from graph theory and economic input-output analysis reviewed in Chapter 3.

[6] Self-linkages, where firms have disclosed themselves as key customers, are removed from the matrix by setting the diagonal elements of $\mathbf{A_t}$ to zero. Self-linkages may arise in parent-subsidiary relationships, mergers and acquisitions or conglomerate firms. I remove self-linkages in order to focus on shocks transmitted from other firms (rather than purely idiosyncratic shocks hitting the firm directly).

Economic distance and credit chain distance

Return correlation relates to the connection between pairs of firms. Note that firm i may be connected to j directly, or through one or more other firms e.g. if i is connected to k, and k is connected to j etc. The direct links between i and j are the entries in the adjacency matrix $\mathbf{A_t}$ (which may take the values 0 or 1) , the two steps links between i and j are the entries in the matrix $\mathbf{A_t^2}$ (which may take the values $0, 1, 2, \cdots$) and so on. The total degree of linkage is the weighted sum of all possible paths from i to j, or

$$\mathbf{CS_t} = (\mathbf{I} - \alpha\mathbf{W_t})^{-\mathbf{1}}$$

where α is an influence weight, and $\mathbf{W_t} = \mathbf{cA_t}$ is the matrix of weighted connections. To convert the adjacency matrix $\mathbf{A_t}$ into the total connectivity matrix $\mathbf{CS_t}$ I need to assume values for α and c.

FAS 131 requires listed firms disclose details of any customer accounting for 10% or more of the enterprize's total sales revenue in the notes to the accounts. While not all firms provide the exact percentage of sales attributable to each key customer, many firms did. Of the 61,246 matched records, 49,767 had disclosed the amount of sales revenue received from each key customer. Of the firms that disclosed this information, the ratio of key customer sales to total sales across these firms had a mean of 19.74% and a standard deviation of 0.20%. As shown in Figure 5.1 the percentage of sales attributable to key customers is relatively constant over time in all industries. In most industries, suppliers get about 20% of total sales from one key customer. In the Healthcare industry (10) this ratio is slightly higher at around 30% of total sales.

Therefore, I assume that the percentage of sales attributable to each key customer is constant at $\alpha c = 0.2$ over firms and over time. This simplifying assumption is a reasonable first step for the current purpose of testing whether these transmitted shocks influence stock returns. But I test sensitivity of the regression results using 3 values of $\alpha c = 0.1, 0.2, 0.3$ to construct the total connectivity matrix $\mathbf{CS_t} = (\mathbf{I} - \alpha\mathbf{cA_t})^{-\mathbf{1}}$.

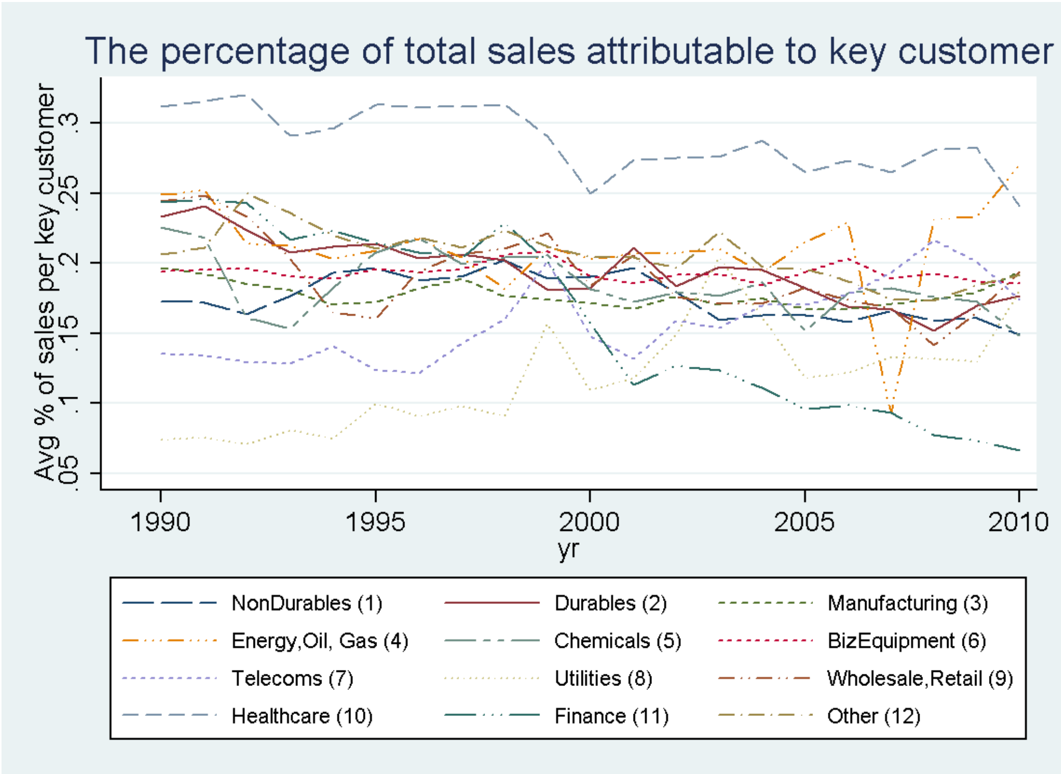

Figure 5.1: The average disclosed percentage of total sales attributable to the key customer by industry.

Macro, industry and firm-level controls

Return correlation can be caused by shocks that are transmitted via economic, financial or informational linkages (Chan, Chao, and Chou, 2001). In order to test whether increased correlation is associated with economic linkages, it is important to control for other economic, financial and informational factors that have been shown to influence return correlation. Several studies have found that the main macroeconomic factors that explain stock returns are the index returns on the stock market and interest rates (Fama and French, 1992; Aretz, Bartram, and Pope, 2010). Therefore I include the following macro controls in the regressions:

- MktRF: The excess return on the S&P 500 index (from Kenneth French's website)

- RF: The term spread, or the difference between, the 10-year constant maturity Treasury bond rate (series GS10 from the Federal Reserve Board website) and the 1-month Treasury bill rate (from Ibbotson Associates)).

In terms of economic linkages, an industry's production and financing needs and operating environment (concentration and stage in life-cycle) influence the likelihood of contagion (Raddatz, 2010; Lang and Stulz, 1992). In addition, the correlation between two stocks may be affected by the relationship between their underlying industries (i.e. how reliant one is upon the other due to 'technical' factors). Therefore, I control for own industry and industry-pair fixed effects on returns, as well as for the market return (the systematic factor influencing asset prices in the CAPM).

Firm financial characteristics affecting return correlation include: trade credit and leverage. Raddatz (2010) shows that the use of trade credit, along the input-output chain linking two industries, results in an increase in their output correlation. In a similar manner, it is widely recognized that leverage amplifies contagion (Kiyotaki and Moore, 2002; Lang and Stulz, 1992). In addition to leverage, I include controls for the following firm characteristics shown to influence returns (based on the following Compustat account items):

- Firm size (market capitalization at last fiscal year end)
- Book-to-market ratio (the ratio of book value of equity to market capitalization at last fiscal year end)
- Profitability (the ratio of sales to total assets at last fiscal year end)
- Book leverage (the ratio of total debt to the book value of equity)
- Trade credit ratio (the ratio of accounts payable to total cost of goods sold).

In relation to information linkages, these may arise because stock prices are affected by changing expectations about both dividends and required returns (i.e. the unexpected stock return may be expressed as the sum of news about dividends and news about future returns) (Campbell and Hentschel, 1992) . This implies that return correlation may be caused by common factors which simultaneously affect either the stock's fundamentals (expected future dividends) or

Table 5.1: Summary statistics for the response and explanatory variables

	Mean	**S.d.**	**Skew**	**Kurt**	**Min**	**Max**
Response:						
Corr(ER)	0.21	0.26	0.00	2.67	-0.74	0.97
Corr(RR)	0.17	0.26	0.03	2.71	-0.76	0.97
Linkage:						
Economic (CS)	0.06	0.10	2.67	18.90	0.00	1.80
Credit (CD)	0.00	0.02	13.15	274.28	0.00	0.86
Suppliers:						
Size	2,219.76	12,312.47	16.17	371.70	0.17	460,767.94
BTM	0.59	6.03	-146.50	22,042.14	-906.64	110.69
Leverage	2.20	2.51	1.42	17.67	-9.05	15.93
Payables	0.19	0.28	4.74	28.61	0.01	2.08
Profit	1.03	0.74	1.45	6.03	0.00	4.05
Customers:						
Size	44,896.50	69,963.44	2.39	9.62	0.48	508,329.47
BTM	0.45	1.77	-467.33	239,497.52	-906.64	13.11
Leverage	2.74	2.01	0.82	11.98	-6.15	11.92
Payables	0.17	0.14	3.18	14.82	0.02	0.90
Profit	1.41	1.08	1.42	4.60	0.16	4.85
Variance:						
Var(Supp)	0.03	0.02	1.93	8.54	0.00	0.33
Var(Cust)	0.01	0.01	3.36	19.26	0.00	0.18
Var(Mkt)	0.00	0.00	0.73	2.76	0.00	0.01

expectations across financial markets (investors required returns). Volatility and liquidity are widely recognized to be related to investors' required returns (Campbell and Hentschel, 1992). Therefore, I include a proxy for each stock's liquidity and proxies for market-wide and idiosyncratic volatility as controls in the regression of return correlation on economic linkages.

5.3.4 Summary statistics

The summary statistics for the response and explanatory variables are shown in Table 5.1. Compared to the supplier firms in the sample, the customer firms are have larger market capitalization, higher leverage, and are more profitable.

5.4 Empirical results

5.4.1 Preliminary test of return correlation

To establish whether the transmission of shocks via economic linkages influences stock returns, I start by testing whether the correlation between firms' returns is significantly larger in years in which they are linked versus years in which they are not linked. Testing for significant changes in bivariate correlation in crisis periods relative to non-crisis periods is commonly used in the finance literature as a test for the existence of contagion (see e.g. Bond, Dungey, and Fry (2006); Forbes and Rigobon (2002)). The transmission of shocks via economic linkages is similar to contagion, but there are some important differences. First, the channel through which shocks spread is not a market-wide factor, it exists only between the firms that are linked along a supply chain. Second, the transmission of the effects of shocks from one firm to another may occur in non-crisis periods if the channel through which the shocks passes (the chain of supplier-customer relationships) exists in both crisis and non-crisis periods. In contrast to studies of financial contagion, therefore, I test for an increase in correlation during periods during which two firm are linked (rather than in crisis periods) relative to periods during which they are not linked.

The most direct way to test for significant differences in correlation across linked and non-linked period is to exploit the time-series dimension of the data. I take a sub-sample of all firms linked at any point during 1990 to 2010. I split the sample into years during which pairs are linked and years in which pairs are not linked, and I estimate:

$$R_S = \beta_{NL}(I_{NL}R_C) + \beta_L(I_LR_C) + I_{NL}c_{NL} + I_Lc_L + \varepsilon$$

where R_S is the supplier's monthly return, I_{NL} is an indicator that is 1 if the customer was not linked to the supplier in a given month and zero otherwise, R_C is the customer's monthly return, I_L is an indicator that is 1 if the customer was linked to the supplier in a given month and zero otherwise, c_{NL} and c_L are constants and ε is the residual error. To test whether economic linkages increase pairwise return correlation I test whether $\beta_{NL} = \beta_L$. This test is equivalent to a Chow test for a structural break of the regression slope across linked and non-linked years[7].

The linked sub-sample is defined for each customer-supplier pair as the 12 monthly observations preceding the annual disclosure date (i.e. the annual reporting period) on which a link is disclosed. These observations are placed in the 'linked' sub-sample. A non-link year is a year when the customer and supplier are not linked in the data. The 12 monthly observations corresponding to the annual reporting period in which no link is disclosed are placed in the 'linked' sub-sample.

In Table 5.2, Panel A shows the two year rolling correlation between excess returns (ER(c)) and between residual returns (RR(c)) along with one-year lagged customers' excess returns (L.ER(c)) and residual returns (L.RR(c)) in linked years. Panel B shows the correlation between excess returns and residual returns, along with one-year lagged customers' excess returns and residual returns, in non-linked years. Panel C reports differences between link year and non-link year correlations and the results of the Chow test of the significance of the difference.

The results confirm that there is significant increase in correlation between customer and supplier returns in years in which they are linked. There is some evidence of persistence in this relationship as lagged suppliers returns (L.ER(s)) significantly affect customers following period returns (ER(c)).

As a cross-check, t-tests comparing the average two year rolling correlations between linked and non-linked firms also clearly rejected the null hypothesis that correlation between linked and non-linked firms was equal, in favor of the alternative that correlation between linked firms was significantly higher than the correlation between non-linked firms (p=0.000).

[7] This test is also equivalent to the adjusted correlation test for contagion proposed by Forbes and Rigobon (2002), comparing correlations on crisis and non-crisis periods. The Forbes and Rigobon (2002) can be implemented within a regression framework using OLS as above, as noted in Dungey, Fry, Gonzalez-Hermosillo, and Martin (2011).

Table 5.2: Return correlation and bivariate contagion tests in linked and non-linked years. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The Chow test p-values are shown in brackets under the coefficients.*

Panel A: Linked							
Correlation of excess returns				**Correlation of residual returns**			
	ER(c)	ER(s)	L.ER(c)		RR(c)	RR(s)	L.RR(c)
ER(c)	-			RR(c)	-		
ER(s)	0.210	-		RR(s)	0.170	-	
L.ER(c)	0.009	0.022	-	L.RR(c)	-0.009	0.009	-
L.ER(s)	0.045	0.006	0.210	L.RR(s)	0.033	0.001	0.170

Panel B: Not-linked							
Correlation of excess returns				**Correlation of residual returns**			
	ER(c)	ER(s)	L.ER(c)		RR(c)	RR(s)	L.RR(c)
ER(c)	-			RR(c)	-		
ER(s)	0.188	-		RR(s)	0.151	-	
L.ER(c)	0.005	0.016	-	L.RR(c)	0.001	0.007	-
L.ER(s)	0.045	0.019	0.188	L.RR(s)	0.033	0.006	0.153

Panel C: Difference							
Difference and Chow test				**Difference and Chow test**			
	ER(c)	ER(s)	L.ER(c)		RR(c)	RR(s)	L.RR(c)
ER(c)	-			RR(c)	-		
	-				-		
ER(s)	0.022***	-		RR(s)	0.019***	-	
	(0.000)	-			(0.000)	-	
L.ER(c)	0.004	0.006**	-	L.RR(c)	-0.010	0.002	-
	(0.817)	(0.014)	-		(0.063)	(0.337)	-
L.ER(s)	0.001	-0.013*	0.021***	L.RR(s)	0.001	-0.006	0.017***
	(0.656)	(0.042)	(0.000)		(0.809)	(0.469)	(0.000)

5.4.2 Regression results

This section presents the results of the test of the hypotheses that a) increasing the total degree of linkage along the supply chain between two firms increases their return correlation and b) that, in addition, increasing the use of trade credit along the supply chain between two firms increases their return correlation. OLS regression was used to estimate equation(5.6)[8]. Robust standard error estimates were used to control for potential heteroscedasticity and autocorrelation in the model residuals.

Table 5.2 shows the robust coefficient estimates for equation (5.6), i.e. for the correlation in **excess returns** of pairs of firms regressed on (1) contemporaneous degree of supply chain and credit linkage (2) contemporaneous and lagged degree of supply chain and credit linkage. In the final column, (3), the model with contemporaneous and lagged degree of supply chain and credit linkage is fit using only data from recession periods. All regressions include the full set of controls for macroeconomic factors, firm-specific characteristics and systematic and idiosyncratic volatility. Table 5.4 shows the corresponding results for the correlation in **residual returns** of pairs of firms.

The results are similar when the response variable is the correlation in residual returns (from the CAPM). That is, return correlation increases as the cash-flow along the supply chain connecting two firms increases. In addition, an increase in the use of trade credit along this supply chain is related to a further incremental increase in return correlation. Regression models of the correlation in residual returns against the supply chain distance, credit chain distance and control variables produced very similar results. The main result is that measures of economic linkage are significantly positively related to correlation in both excess returns and residual returns. This effect is amplified by the use of trade credit, as indi-

[8] Fixed or random effect panel models could be used to estimate equation (5.6) but the interpretation of a pairwise fixed effect is difficult to interpret. Unlike an individual fixed (or random) effect, a pairwise fixed (or random) effect implies that some element of the business relationship between two firms remains fundamentally unchanged over time. Such technical production relationships should be captured by the industry-pair dummies in the OLS regression, so a pairwise individual effect was required.

Table 5.3: Regressions of pairwise correlation in excess returns on economic linkage (CS) and credit chain distance (CD), in the full period and in recessions only. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

	Full period		Recessions
	(1)	**(2)**	**(3)**
	b/t	**b/t**	**b/t**
	b/t	b/t	b/t
MktRF	-0.001	-0.002	-0.033
	(-0.11)	(-0.12)	(-0.42)
RF	-13.547***	-13.598***	8.25
	(-22.42)	(-22.51)	(-0.47)
CS	**0.031*** **	**-0.008**	**0.078**
	(-4.80)	**(-0.95)**	**(-1.83)**
L.CS		**0.061*** **	**-0.112** **
		(-6.90)	**(-2.72)**
CD	**0.231*** **	**0.323*** **	**0.456**
	(-5.25)	**(-7.07)**	**(-1.69)**
L.CD		**-0.223*** **	**0.737*** **
		(-4.53)	**(-4.49)**
L.MktRF	-0.006	-0.006	0.073
	(-0.45)	(-0.46)	(-0.68)
L.RF	-15.095***	-15.003***	16.997
	(-28.18)	(-28.01)	(-1.27)
Var(s)	-0.655***	-0.655***	-1.660***
	(-23.90)	(-23.90)	(-8.93)
Var (c)	1.459***	1.463***	0.280
	(-30.19)	(-30.29)	(-1.13)
Var(MktRF)	26.719***	26.699***	37.918***
	(-47.47)	(-47.44)	(-4.61)
Bidask(s)	-0.011***	-0.011***	-0.073***
	(-4.11)	(-4.11)	(-3.64)
Bidask(c)	-0.003*	-0.003*	0.011
	(-2.32)	(-2.30)	(-0.31)
Size(s)	0.000***	0.000***	0.000***
	(-33.58)	(-33.57)	(-5.96)
BTM(s)	0.000	0.000	-0.008**
	(-1.91)	(-1.94)	(-2.89)
Leverage(s)	0.000**	0.000**	0.000
	(-2.99)	(-3.14)	(-0.37)
Trade credit(s)	-0.004***	-0.003**	-0.009
	(-3.88)	(-3.16)	(-1.82)
Profit(s)	-0.023***	-0.023***	-0.014***
	(-26.19)	(-26.43)	(-3.75)
Size(c)	-0.000***	-0.000***	-0.000***
	(-26.81)	(-26.91)	(-10.29)
BTM(c)	-0.016***	-0.016***	-0.006
	(-7.58)	(-7.59)	(-1.77)
Leverage(c)	0.000	0.000	0.000
	(-1.11)	(-1.08)	(-1.78)
Trade credit(c)	-0.003	-0.003	0.009
	(-1.57)	(-1.42)	(-1.04)
Profit(c)	-0.016***	-0.016***	-0.027***
Constant	0.211***	0.209***	0.199**
	(-31.55)	(-31.43)	(-3.12)
Rsq	19.6%	19.6%	29.5%
Industry indicators	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes

Table 5.4: Regression results for pairwise correlation in **residual returns** in the full period and in recessions only. **,**,*** indicate significance with * for p < .05, ** for p < .01, and *** for p < .001. The t-statistics are shown in brackets under the coefficients.*

	Full period		Recessions
	(1)	**(2)**	**(3)**
	b/t	**b/t**	**b/t**
	b/t	b/t	b/t
MktRF	-0.018	-0.019	0.006
	(-1.28)	(-1.29)	(-0.06)
RF	-11.912***	-11.958***	4.425
	(-17.30)	(-17.37)	(-0.23)
CS	0.052***	0.011	0.042
	(-6.74)	(-1.08)	(-0.86)
L.CS		0.058***	-0.016
		(-5.44)	(-0.31)
CD	0.144*	0.225**	0.257
	(-2.06)	(-2.97)	(-0.89)
L.CD		-0.148*	1.012**
		(-2.12)	(-3.20)
L.MktRF	-0.055***	-0.056***	0.038
	(-3.67)	(-3.70)	(-0.31)
L.RF	-9.866***	-9.782***	13.53
	(-16.13)	(-15.99)	(-0.90)
Var(s)	-0.349***	-0.350***	-1.068***
	(-9.76)	(-9.79)	(-4.87)
Var (c)	2.732***	2.741***	2.656***
	(-39.73)	(-39.82)	(-8.70)
Var(MktRF)	3.885***	3.863***	3.368
	(-5.79)	(-5.76)	(-0.36)
Bidask(s)	-0.010***	-0.010***	-0.075**
	(-3.93)	(-3.93)	(-3.25)
Bidask(c)	-0.002	-0.002	0.003
	(-1.84)	(-1.82)	(-0.08)
Size(s)	0.000***	0.000***	0.000***
	(-31.47)	(-31.46)	(-3.60)
BTM(s)	-0.012***	-0.012***	-0.004
	(-12.74)	(-12.75)	(-1.26)
Leverage(s)	0.000	0.000	0.000***
	(-0.19)	(-0.24)	(-3.87)
Trade credit(s)	-0.006***	-0.005***	-0.007*
	(-3.88)	(-3.60)	(-2.11)
Profit(s)	-0.025***	-0.025***	-0.015***
	(-22.74)	(-22.92)	(-3.49)
Size(c)	-0.000***	-0.000***	-0.000***
	(-40.09)	(-40.12)	(-13.17)
BTM(c)	-0.018***	-0.018***	0.005
	(-6.47)	(-6.49)	(-1.25)
Leverage(c)	0.000	0.000	-0.000**
	(-0.41)	(-0.45)	(-3.14)
Trade credit(c)	-0.003	-0.002	0.015
	(-1.17)	(-1.06)	(-1.35)
Profit(c)	-0.023***	-0.023***	-0.027***
	(-21.17)	(-21.13)	(-5.36)
Constant	0.179***	0.178***	0.106
	(-23.58)	(-23.44)	(-1.50)
Rsq	18.0%	18.0%	33.7%
Industry indicators	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes

cated by the significant positive coefficients on the CD measures. For both the excess return correlation and the residual return correlation t-tests of the null that recession and full period coefficients were the same had p-values of 0.00, indicating strong support for alternative that recession coefficients were higher than full period coefficients.

The coefficient estimates for the controls were also consistent with previous research and the theory discussed in the introduction. That is, in the full sample lower risk-free rates are associated with higher return correlation. However, this effect is not robust to the split sample regressions and does not hold in recessions. Over 1990 to 2010 lower interest rates followed recession periods; i.e. therefore it is possible that this negative relation is related to higher correlation during recessions (Ireland, 2000).

There is a strong positive relationship between the variability of the market and correlation. This is reasonable given volatile markets mean that supplier-customer relationships are less substitutable, and at the same time there are more shocks which may spread via these links (Egloff and Leippold, 2007).

There were mixed results for the influence of idiosyncratic volatility on pairwise return correlation. Higher levels of customer volatility (Var(c)) increased return correlation, but higher levels of supplier volatility (Var(s)) decreased return correlation. The same relationship persists when Var(s) and Var(c) are split into expected and unexpected components as in Campbell and Hentschel (1992) (see the results in Appendix 5.A). This result is partially explained by the data generating process. In the FAS 131 disclosures, firms are required to disclosure key customers, but not key suppliers. Therefore, in the data the suppliers are dependent on customers, but the customers are not necessarily dependent on the suppliers. This implies that suppliers are less able to restructure business agreements if their customer experiences distress, whereas customers are more able to restructure business agreements if their supplier experiences distress. Hence supplier volatility has less influence on return correlation, because customer firms are more likely to restructure business agreements. Cohen and Frazzini (2008) and

Hertzel, Li, Officer, and Rodgers (2008) found similar asymmetry in their results (i.e. that significant customer distress is associated with negative and significant stock price effects for suppliers, but that supplier distress had no impact on customers) and also attributed it to the FAS 131 requirements which require that firms disclose significant customers but not dependent suppliers. In addition, in the current sample, customer firms are much larger than the supplier firms as in Table 5.1. Gabaix (2011) argues that shocks to the largest firms in the economy act as a form of systematic risk, as they have widespread effect, whereas shocks to the smaller firms have a far less widespread effect. It is possible that the positive relationship between customer firm volatility and correlation arises because shocks to the larger customer firms increase comovement in returns more than shocks to smaller supplier firms, however customer and supplier size is controlled for in the regressions, so this effect is secondary.

In terms of firm characteristics, profitable and value (high BTM) firms exhibit lower correlation on average than unprofitable and growth (low BTM) firms. These results are consistent with work showing that growth stocks are more affected by common factors than value stocks whose returns are more driven by firm-specific factors (Ohlson, 1995). A similar argument explains why more profitable firms have lower correlation with trading partners on average, as a greater portion of their returns are more driven their own earnings, rather than common factors (Ohlson, 1995).

Economic significance Regressions of the correlation in excess returns showed a positive relationship between both supply chain distance and credit chain distance. In general firms with a higher degree of connectivity have a higher degree of correlation with their counterparties in periods during which they are economically linked. The point estimates indicate that if firm i adds one key customer, j (so that lagged CS increases by ≈ 0.2, or more if the additional customer has its own linkages) then the correlation between R_i and R_j will increase by $\approx 1\%$, as the coefficient on $L.CS$ was in the order of 0.05 in all of the runs above and

$0.01 = 0.05 * 0.2)$[9].

5.4.3 Quantile regressions

In the context of economic linkages, there is reason to believe that shocks transmitted via economic linkages are more influential in recessions (see e.g. Lang and Stulz (1992)). Neglecting asymmetry could result in downward biased coefficient estimates (Raddatz, 2010). Using a conditional correlation approach, such as quantile regression, is one way to allow for asymmetry. I estimated 5.6 over different quantiles of the correlation distribution (via quantile regression) to test whether the coefficients for the production and credit distance were higher in high correlation regimes than in low correlation regimes. Quantile regression provides a flexible modeling and estimation method to identify the dependence of two random variables in cases where the dependence structure may vary across different realizations of the response variable (Baur and Schulze, 2005). The quantiles can be interpreted as a states or a regimes; i.e. lower quantiles (lower correlation) are consistent with a good state and higher quantiles (higher correlation) are consistent with a bad state or regime (Baur and Schulze, 2005; Longin and Solnik, 2001).

Table 5.5 shows the results of estimation of the following simple quantile regression model corresponding to equation (5.6) i.e.:

$$Q(\tau|\mathbf{X}) \approx \mathbf{c} + \beta\mathbf{X} + \varepsilon \tag{5.8}$$

where $Q(\tau|\mathbf{X})$ denotes the τ-th conditional quantile of ρ, assumed to be linearly dependent on a vector of exogenous variables $\mathbf{X}$; and $\beta(\tau)$ is a parameter estimating the effect of the factors within the τ-th conditional quantile of ρ.

The estimated parameters $\beta(\tau)$ reveals information about the behavior of return correlations during the crisis period. If, for example, the coefficients $\beta(\tau)$ are significantly lower for small quantiles (e.g. $\tau \in (0.25, 0.5)$) than high quan-

[9] I have chosen numbers at the lower end of a reasonable range of possibility. For example, if firm i adds one key customer, j, that has one key customer of its own, CS will increase by $0.24 = 0.2 + 0.2 * 0.2$, and so on.

tiles (e.g. $\tau \in (0.75, 0.95)$) this indicates the comovement related to linkages is significantly higher during crisis periods in which correlation is higher.

Economic significance The results in Table 5.5 support the conclusion that the return correlation induced by economic linkages is higher in a recession. For example, the coefficient on one year lagged economic distance (L.CS) is 0.042 for the bottom 25% of the return correlation distribution, but increases to 0.123 in the top 5% of the return correlation distribution. The quantile regressions show that in crisis periods, when return variance is higher, increases in correlation will increase portfolio variance by up to three times more (dividing the high regime and lower regime L.CS coefficients from Table 5.5 gives 2.93 = 0.123/0.042).

5.4.4 Model specification

I assess whether the OLS assumptions are met by analyzing the model residuals and the covariance of the independent variables. The mean of the residuals was zero. Residual plots from the standard regression models suggested the model specification was reasonable, as most residuals were randomly scattered about zero. There are a few outliers on the left hand side of the residual plot, and there is a slight narrowing of variance in the right hand tail of the residual plot. The estimator used (described in White (1982)) is robust to heteroscedasticity, autocorrelation and firm-effects. To ensure the results are robust to potential outliers, I re-run the regressions after winsorizing extreme observations of the linkage measures, to ensure the results are not attributable only to extreme observations. That is, to avoid giving extreme observations heavy weight, the smallest and largest 1% (5%) of observations for the IO distance and the Credit Distance are set equal to the 1% and 99% quantiles (5% and 95%). The results are shown in Table 5.7.

Other than the correlation between the linkage measures, the correlation between all other explanatory variables was below 20%. Higher correlations were recorded for the linkages measures, however, with the correlation between the supply chain distance (CS_2) and one year lagged supply chain distance ($L_{12}.CS_2$)

Table 5.5: Quantile regression of return correlation on economic linkage and credit linkages **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

	Q(0.25) **b/t**	**Q(0.5)** **b/t**	**Q(0.75)** **b/t**	**Q(0.95)** **b/t**
MktRF	0.026	-0.027	-0.031	-0.017
	(-1.47)	(-1.55)	(-1.77)	(-0.69)
RF	-10.088***	-13.690***	-17.090***	-17.752***
	(-11.78)	(-16.97)	(-21.27)	(-16.29)
CS	-0.016	0.002	0.007	0.005
	(-1.32)	(-0.15)	(-0.55)	(-0.33)
L.CS	0.042**	0.052***	0.084***	0.123***
	(-3.23)	(-4.22)	(-6.92)	(-7.86)
CD	0.229***	0.392***	0.405***	0.189*
	(-3.44)	(-5.97)	(-6.14)	(-2.32)
L.CD	-0.141*	-0.216**	-0.152*	-0.045
	(-2.03)	(-3.26)	(-2.39)	(-0.57)
L.MktRF	0.012	0.004	-0.029	-0.022
	(-0.63)	(-0.25)	(-1.61)	(-0.95)
L.RF	-15.384***	-15.860***	-14.480***	-13.046***
	(-20.11)	(-21.85)	(-20.00)	(-13.63)
Var(s)	-0.795***	-0.684***	-0.589***	-0.312***
	(-20.76)	(-18.50)	(-16.02)	(-6.39)
Var (c)	1.225***	1.249***	1.740***	1.877***
	(-17.53)	(-19.67)	(-30.14)	(-28.38)
Var(MktRF)	30.338***	28.668***	25.494***	20.188***
	(-37.21)	(-36.94)	(-33.19)	(-20.09)
Bidask(s)	-0.027***	-0.020***	-0.009***	-0.006
	(-23.64)	(-13.23)	(-4.31)	(-1.46)
Bidask(c)	-0.024***	-0.011***	-0.002	-0.001
	(-38.07)	(-11.24)	(-1.59)	(-0.53)
Size(s)	0.000***	0.000***	0.000***	0.000***
	(-21.22)	(-34.75)	(-67.24)	(-98.71)
BTM(s)	0.000	0.000	-0.007***	-0.015***
	(-0.78)	(-0.47)	(-88.41)	(-329.03)
Leverage(s)	-0.000**	0.000**	0.000***	0.000
	(-3.02)	(-3.24)	(-7.33)	(-0.77)
Trade credit(s)	-0.002	-0.003*	-0.001	-0.003**
	(-1.90)	(-2.52)	(-1.12)	(-2.81)
Profit(s)	-0.021***	-0.026***	-0.024***	-0.024***
	(-18.18)	(-22.93)	(-20.48)	(-12.23)
Size(c)	-0.000***	-0.000***	-0.000***	-0.000***
	(-20.55)	(-23.31)	(-21.92)	(-18.31)
BTM(c)	-0.016***	-0.019***	-0.017***	-0.022***
	(-6.99)	(-10.79)	(-11.32)	(-12.08)
Leverage(c)	0.000***	0.000	0.000	0.000***
	(-4.19)	(-0.55)	(-0.87)	(-5.52)
Trade credit(c)	0.001	0.003	-0.001	-0.006
	(-0.22)	(-1.13)	(-0.42)	(-1.60)
Profit(c)	-0.008***	-0.013***	-0.018***	-0.019***
	(-7.10)	(-11.42)	(-15.70)	(-11.37)
Constant	0.027***	0.206***	0.356***	0.594***
	(-4.33)	(-34.38)	(-59.74)	(-72.20)
Rsq	7.19%	9.20%	11.58%	13.76%

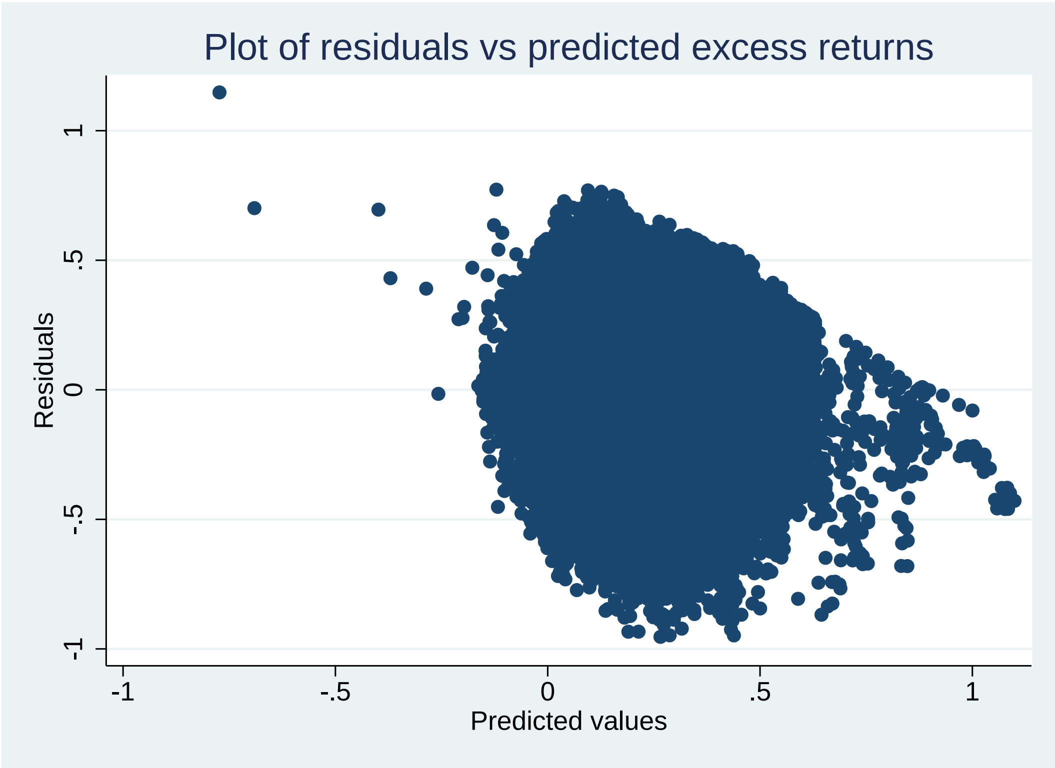

Table 5.6: Correlation between linkage measures and lagged linkage measures.

	CS_2	$L_{12}.CS_2$	CD_2	$L_{12}.CD_2$
CS_2	-			
$L_{12}.CS_2$	0.7	-		
CD_2	0.5	0.3	-	
$L_{12}.CD_2$	0.3	0.5	0.4	-

being 70%. To investigate whether this collinearity affects the main results I estimated a series of models, including the full set of macro and firm-level controls and:

- Each of the covariates: $CS_2, L_{12}.CS_2, CD_2, L_{12}.CD_2$ separately
- Contemporaneous economic and credit linkages only (CS_2, CD_2)
- Lagged linkages only $(L_{12}.CS_2, L_{12}.CD_2)$
- First difference of covariates $(D_{12}.CS_2, D_{12}.CD_2)$ and lagged linkages $(L_{12}.CS_2, L_{12}.CD_2)$

The overall conclusion is that a positive relationship between economic linkage and stock return correlation is robust to potential collinearity in the data. This is most clearly indicated by the model results in Table 5.7 showing a clear positive relationship between CS_2 and CD_2 and return correlation in all model specifications.

5.4.5 Robustness checks

The main result, that an increase in the cash-flow between customers and suppliers increases their stock price correlation, was robust to the estimation across different market regimes (as measured by quantiles of the correlation distribution). Furthermore, I also check the robustness of this result to estimation issues, measurement issues and sample issues as follows. I control for the potential effects of clustering across time and/or across firms by using standard error estimates robust to these effects (in the benchmark model, the s.e. estimate is robust to heteroscedasticity and autocorrelation.)

Another potential issue with the results is that I use a constructed measure of supply chain connectedness that relies on an assumed value of α (the influence or effectiveness of each linkage). The benchmark model, and all results above assumed a value of $\alpha = 0.2$ based on the sample average of disclosed percentage of sales revenue attributed to each key customer. I also run the full model, using values of $\alpha = 0.1$ and $\alpha = 0.3$.

Table 5.7 illustrates that the significant positive relationship between linkages and return correlation is robust to all of these checks. The mean credit distance is much lower than the IO distance because it is weighted by the trade credit fraction, which is in the order of 15%, as well as the influence factor $\alpha = 0.2$; in any case the net effect of contemporaneous and lagged credit links is positive (i.e. $0.323 - 0.223 = 0.100$).

Table 5.7: Robustness checks of the main results. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

Specification:	Supply chain dist(t) β/t-stat	Credit dist(t) β/t-stat	Supply chain dist (t-1) β/t-stat	Credit dist(t-1) β/t-stat
A. Estimation				
1) Pair fixed effects	-0.008	0.334**	0.059*	-0.228
	(-0.3)	*(-2.7)*	*(-2.1)*	*(-1.5)*
2) Time fixed effects	-0.008	0.334*	0.059	-0.228
	(-0.3)	*(-2.6)*	*(-2.0)*	*(-1.7)*
B. Measurement				
3) Using $\alpha = 0.1$	-0.010	0.334***	0.120***	-0.223***
	(-0.6)	*(-7.1)*	*(-6.7)*	*(-4.4)*
4) Using $\alpha = 0.3$	-0.007	0.327***	0.038***	-0.226***
	(-1.24)	*(-7.28)*	*(-6.54)*	*(-4.67)*
C. Sample issues				
5) Winsorized 1 %	0.015	0.226**	0.056***	-0.219**
	(-1.5)	*(-2.9)*	*(-5.5)*	*(-2.9)*
6) Winsorized 5 %	0.008	0.348**	0.048***	-0.098
	(-0.7)	*(-2.8)*	*(-4.1)*	*(-0.8)*
D. Benchmark	-0.008	0.323***	0.061***	-0.223***
	(-0.95)	*(-7.07)*	*(-6.90)*	(-4.53)

5.5 Discussion

Consistent with the hypothesis that shocks spread between firms via economic linkages influence stock returns, I show that there is a direct relationship between the strength of linkage between firms and the correlation of their stock returns. An increase in the economic linkage[10] between two firms is associated with increased correlation in those firms' stock returns. On average, if a supplier establishes a new relationship with a customer providing 20% of their sales revenue, the return correlation between the stocks of these two firms would increase by 1%. The influence of economic linkages on return correlation is stronger when trade credit is used along the supply chain connecting the firms and also in recessions. This is consistent with economic theory and intuition that a supplier (customer) is harder to replace when there are credit contracts involved in the relationship and/or when the economy is in recession. These results are significant after controlling for macro factors, industry effects and firm-level characteristics that have been shown to influence contagion. The results are also robust to changes in the data sample, the measure of return correlation used, and the estimation method used.

Pairwise return correlation is a central component of portfolio return variance, so this finding suggests linkages may have a significant influence on return volatility. That is, when stocks are correlated, the portfolio return variance depends on the correlation between individual stocks in a portfolio, as $\sigma_P^2 = \sum_i \sum_j w_i w_i Cov(R_i, R_j)$. In a portfolio of size N there are N variance terms in this equation, and $N(N-1)$ covariance terms, so small increases in the pairwise correlation between units in a portfolio can increase the portfolio variance. For example, in an equally weighted portfolio of 50 stocks, with i.i.d. returns each with variance of 10% p.a. the portfolio variance is 0.2% (=50 x $\frac{1}{50^2}$ x 10%); however if individual stocks are not independent but all pairs have covariance of 1% the portfolio variance is 1% (=0.2% + 50 x 49 x $\frac{1}{50^2}$ x 1%).

[10] To recap, the strength of economic linkage is defined as the proportion of total production outputs sold by a supplier to a customer firm, as measured by the proportion of the supplier's sales revenue attributable to the customer.

The results imply that economic linkages are a potential influence on asset prices, as certain structures of linkage are associated with significant return correlation across linked firms. It is widely acknowledged that returns do not follow a strict factor structure and that there is often some degree of correlation between the residual components of returns after allowing for systematic risk factors (residual returns) (Connor and Korajczyk, 1993). Stocks can still be priced ignoring economic linkages, however, provided that the proportion of the correlations between residual returns that are significantly different from zero is close to zero in large portfolios (Chamberlain and Rothschild, 1983). I show that economic linkages induce non-zero correlations between stocks. In the universe of US listed firms on the Compustat/CRSP database, on average 10% of these stocks were linked to other listed firms during the period 1990 to 2010. The results in this chapter therefore suggest that a large proportion of the correlations between the residual returns of US stocks may be significantly different from zero. The evidence presented in this thesis so far, therefore, suggests that economic linkages may influence asset prices. The influence of economic linkages on asset prices is directly addressed in the next chapter.

5.A Results with expected and unexpected variance

Table 5.8: Regression results for pairwise correlation in **excess returns** in the full period and in recessions. **,**,*** indicate significance at 0.05, 0.01 and 0.001 levels. T-statistics are shown under the coefficients.*

	Full period		Recessions
	(1)	(2)	(3)
MktRF	0.059***	0.059***	0.015
	-4.51	-4.51	-0.1
RF	-13.604***	-13.654***	6.715
	-22.43	-22.52	-0.34
CS_2	**0.029*** **	**-0.008**	**0.086***
	-4.6	**-0.91**	**-2.02**
CD_2	**0.240*** **	**0.334*** **	**0.44**
	-5.4	**-7.22**	**-1.66**
$L_{12}.CS_2$		**0.059*** **	**-0.123** **
		-6.65	**-2.97**
$L_{12}.CD_2$		**-0.228*** **	**0.753*** **
		-4.59	**-4.51**
L_{12}.**MktRF**	-0.018	-0.018	0.048
	-1.43	-1.44	-0.4
L_{12}.**RF**	-16.529***	-16.437***	7.273
	-30.35	-30.17	-0.34
D.Var(s)	-0.134	-0.137	1.216
	-0.86	-0.88	-1.81
D.Var(c)	2.120***	2.128***	3.096**
	-7.01	-7.04	-3.28
D.Var(MktRF)	65.989***	66.015***	4.587
	-24.11	-24.12	-0.08
L.Var(s)	-0.646***	-0.646***	-1.986***
	-23.17	-23.17	-10.09
L.Var(c)	1.506***	1.511***	-0.083
	-30.53	-30.62	-0.29
L.Var(MktRF)	25.269***	25.247***	34.889*
	-43.97	-43.93	-2.24
Bidask(c)	-0.011***	-0.011***	-0.073***
	-4.06	-4.06	-3.65
Bidask(s)	-0.003*	-0.003*	0.023
	-2.49	-2.47	-0.66
Size (s)	0.000***	0.000***	0.000***
	-33.56	-33.55	-5.99
BTM (s)	0.000	0.000	-0.008**
	-1.93	-1.96	-2.85
Leverage (s)	0.000**	0.000**	0.000
	-3.08	-3.23	-0.3
Trade credit (s)	-0.004***	-0.003**	-0.008
	-3.84	-3.18	-1.71
Profit (s)	-0.023	-0.024***	-0.014***
	-26.27	-26.52	-3.53
Size (c)	-0.000***	-0.000***	-0.000***
	-26.46	-26.56	-10.34
BTM (c)	-0.017***	-0.017***	-0.007
	-7.91	-7.92	-1.93
Leverage (c)	0.000	0.000	0.000
	-1.27	-1.24	-1.46
Trade credit (c)	-0.004	-0.003	0.01
	-1.90	-1.74	-1.24
Profit (c)	-0.017***	-0.017***	-0.027***
	-19.00	-18.89	-6.2
cons	0.216***	0.215***	0.237*
	-32.17	-32.05	-2.13
Industry indicators	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes
Adj R-sq	19.8%	19.8%	29.9%
AIC	-8,789	-8,833	-1,458

Table 5.9: Regression results for pairwise correlation in residual returns in the full period and in recessions only. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. T-statistics are shown under the coefficients.*

	Full period		Recessions
	(1)	**(2)**	**(3)**
	b/t	**b/t**	**b/t**
MktRF	0.033*	0.033*	0.015
	-2.18	-2.18	-0.10
RF	-11.869***	-11.915***	6.715
	-17.26	-17.32	-0.34
CS_2	**0.050*****	**0.010**	**0.086***
	-6.56	-0.92	-2.02
CD_2	**0.152***	**0.234****	**0.440**
	-2.18	-3.11	-1.66
$L_{12}.CS_2$		**0.058*****	**-0.123****
		-5.47	-2.97
$L_{12}.CD_2$		**-0.151***	**0.753*****
		-2.17	-4.51
L_{12}.**MktRF**	-0.067***	-0.067***	0.048
	-4.42	-4.45	-0.40
L_{12}.**RF**	-11.029***	-10.946***	7.273
	-17.79	-17.65	-0.34
D.Var(s)	-0.144	-0.153	1.216
	-0.71	-0.76	-1.81
D.Var(c)	2.940***	2.960***	3.096**
	-7.06	-7.10	-3.28
D.Var(MktRF)	38.702***	38.732***	4.587
	-12.03	-12.04	-0.08
L.Var(s)	-0.331***	-0.331***	-1.986***
	-9.18	-9.20	-10.09
L.Var(c)	2.786***	2.795***	-0.083
	-40.19	-40.27	-0.29
L.Var(MktRF)	2.556***	2.531***	34.889*
	-3.75	-3.72	-2.24
Bidask(s)	-0.010***	-0.010***	-0.073***
	-3.90	-3.90	-3.65
Bidask(c)	-0.002*	-0.002*	0.023
	-2.02	-2.00	-0.66
Size (s)	0.000***	0.000***	0.000***
	-31.53	-31.51	-5.99
BTM (s)	-0.013***	-0.013***	-0.008**
	-12.82	-12.83	-2.85
Leverage (s)	0.000	0.000	0.000
	-0.22	-0.27	-0.30
Trade Credit (s)	-0.006***	-0.006***	-0.008
	-3.97	-3.67	-1.71
Profit (s)	-0.025***	-0.025***	-0.014***
	-22.82	-23.00	-3.53
Size (c)	-0.000***	-0.000***	-0.000***
	-39.42	-39.45	-10.34
BTM (c)	-0.019***	-0.019***	-0.007
	-6.63	-6.65	-1.93
Leverage (c)	0.000	0.000	0.000
	-0.26	-0.29	-1.46
Trade Credit (c)	-0.003	-0.003	0.010
	-1.37	-1.25	-1.24
Profit (c)	-0.023***	-0.023***	-0.027***
	-21.33	-21.29	-6.20
cons	0.184***	0.183***	0.237*
	-24.21	-24.07	-2.13
Industry indicators	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes
Adj R-sq	0.18	0.18	0.30
AIC	-4,834	-4,861	-1,458

Table 5.10: Quantile regression of return correlation on economic linkage and credit linkages **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

	Q(0.25)	**Q(0.5)**	**Q(0.75)**	**Q(0.95)**
MktRF	0.092***	0.044*	0.027	0.012
	-4.85	-2.47	-1.50	-0.52
RF	-10.070***	-14.145***	-17.044***	-17.957***
	-11.77	-17.75	-21.12	-17.46
CS_2	-0.018	0.003	0.01	0.004
	-1.45	-0.26	-0.81	-0.28
L_{12} CS_2	0.037**	0.051***	0.081***	0.123***
	-2.84	-4.25	-6.58	-8.35
CD_2	0.269***	0.399***	0.420***	0.182*
	-4.02	-6.13	-6.22	-2.36
L_{12} CD_2	-0.139*	-0.217***	-0.163*	-0.062
	-1.99	-3.32	-2.54	-0.83
L_{12}MktRF	-0.001	-0.009	-0.043*	-0.035
	-0.07	-0.52	-2.40	-1.60
L_{12}RF	-17.079***	-17.182***	-15.824***	-14.109***
	-22.07	-23.72	-21.53	-15.52
D.Var(s)	-0.156	-0.098	-0.037	0.345
	-0.68	-0.47	-0.18	-1.35
D.Var(c)	1.720***	1.773***	2.061***	2.648***
	-3.8	-4.32	-5.23	-5.64
D.Var(MktRF)	79.956***	72.380***	57.218***	36.332***
	-20.7	-19.57	-14.96	-7.25
L.Var(s)	-0.794***	-0.668***	-0.573***	-0.319***
	-20.51	-18.09	-15.33	-6.85
L.Var(c)	1.262***	1.335***	1.811***	1.922***
	-17.81	-21.04	-30.87	-30.33
L.Var(MktRF)	28.521***	26.668***	23.998***	19.381***
	-34.55	-34.33	-30.66	-20.15
Bidask(s)	-0.028***	-0.019***	-0.008***	-0.006
	-23.87	-12.96	-3.83	-1.54
Bidask(c)	-0.023***	-0.010***	-0.002	-0.001
	-37.1	-11.08	-1.76	-0.54
Size(s)	0.000***	0.000***	0.000***	0.000***
	-21.79	-35.39	-67.62	-104.15
BTM(s)	0.000	0.000	-0.007***	-0.015***
	-0.86	-0.57	-89.81	-348.86
Leverage(s)	-0.000**	0.000**	0.000***	0.000
	-2.75	-3.17	-6.95	-0.43
Trade credit(s)	-0.003*	-0.003*	-0.001	-0.003*
	-2.57	-2.51	-0.97	-2.53
Profit(s)	-0.021***	-0.027***	-0.025***	-0.024***
	-18.19	-23.53	-20.63	-12.86
Size(c)	-0.000***	-0.000***	-0.000***	-0.000***
	-20.4	-23.16	-21.39	-19.65
BTM(c)	-0.017***	-0.020***	-0.018***	-0.023***
	-7.50	-11.73	-12.31	-13.83
Leverage(c)	0.000***	0.000	0.000	0.000***
	-4.10	-0.53	-0.91	-6.00
Trade credit(c)	0.000	0.003	-0.003	-0.007
	-0.07	-0.99	-0.93	-1.89
Profit(c)	-0.008***	-0.013***	-0.019***	-0.020***
	-7.07	-11.97	-15.74	-12.39
cons	0.034***	0.215***	0.361***	0.596***
	-5.4	-36.14	-59.99	-76.78
Rsq	**7.30%**	**9.32%**	**11.69%**	**13.86%**

Chapter 6

Economic linkages and expected returns

6.1 Introduction

Modern financial theory generally concludes that returns should carry a premium for non-diversifiable sources of risk, but that no return can be earned by holding diversifiable risk (Ross, 1976). In Chapter 3, I show that if firm i's total supply chain exposure[1] is concentrated, such that a few firms supply (buy) a large portion of a firm i's inputs (outputs), then the shocks transmitted to firm i from its suppliers (customers) may not be diversifiable. In Chapter 4, I show that the linkages between US listed firms are highly concentrated. Together the results in Chapters 3 and 4 suggest that shocks transmitted via the economic linkages between US listed firms may be not diversifiable. If investors are unable to diversify this risk, they will want to be compensated for it with a higher return.

The finding that shocks transmitted via inter-firm linkages may be non-diversifiable naturally leads to the question: do shocks transmitted via economic linkages affect expected stock returns? In this chapter I test the hypothesis that there is a positive relationship between shocks transmitted via economic linkages (transmitted

[1] I.e. the sum of exposure over all direct (1-step away) and indirect (2-step away, 3-step away etc.) suppliers and/or customers.

volatility) and expected return. The primary test of a factor model is whether it explains differences in average returns (Davis and Fama, 2000). Therefore I test whether the degree and concentration of a firm's economic linkages (i.e. exposure to transmitted volatility from suppliers and/or customers) explain average stock returns, cross-sectionally and over time.

Sections 2 and 3 discuss the method and the data used to test how transmitted volatility affects returns. Section 4 contains the main results, supplementary results and robustness checks. Section 5 concludes by discussing the implications of this finding for asset pricing and modeling stock returns.

6.2 Research method

To empirically test whether shocks transmitted via inter-firm linkages (hereafter transmitted volatility) influence stock returns, I augment a multi-factor model of returns with a proxy for exposure to transmitted volatility. The methodology consists of two main components: i) specifying a factor model of average returns allowing for transmitted volatility, and ii) developing measures of the exposure to transmitted volatility to be included in the factor model. These are now addressed in turn.

6.2.1 Factor models of economic linkages and returns

Multi-factor models of returns can be broadly classified as either: macroeconomic, fundamental or statistical factor models. In all factor models, returns are assumed to be a linear function of exposure to pervasive risk factors (or systematic shocks) plus an assets-specific return unrelated to the systematic shocks (Connor, 1995). Linear sensitivities to the pervasive factors are called the 'factor betas' of the security. Macroeconomic and statistical factor models estimate a firm's factor beta by time series regression. Macroeconomic factor models use observable economic time series as measures of the pervasive factors influencing security returns. Fundamental factor models do not require time series regression. A fundamental factor model uses observed company attributes as factor betas (Connor, 1995).

A factor model implies that common risk factors should capture variation in returns that is not explained by other factors. I.e. there should be a contemporaneous comovement between returns and factor betas, that is robust to the inclusion of stock characteristics and other factor betas (Ang, Hodrick, Xing, and Zhang, 2006). Therefore, my approach is to test whether there are significant loadings on factors that capture the structure of economic linkages, after controlling for a range of stock characteristics and other factors that have been shown to influence stock returns, such as firm size, book-to-market ratio, leverage and stock price volatility and liquidity (Fama and French, 1992; Ang, Hodrick, Xing, and Zhang, 2006).

I extend a factor model of asset returns to allow for transmitted volatility. Fama and French (1992) propose that stock returns are generated by the following factor structure:

$$R_{i,t} = E_{t-1}(R_{i,t}) + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \theta_{i,t-1} F_{D,t} + \varepsilon_{i,t} \tag{6.1}$$

where $R_{i,t}$ is the excess return (over the risk-free rate) of stock i at time t ($i = 1, \cdots, N$ and $t = 1, \cdots, T$); $E_{t-1}(R_{i,t})$ is the expected return of asset i at time t, based on information available at time $t-1$; $\beta_{i,k}$ is firm i's loading on factor F_k, where $F_{k,t}$ is the realization of factor[2] k at time t; $\theta_{i,t-1}$ is firm i's loading on the distress factor of interest, $F_{D,t}$; and the noise terms ε_{it} are assumed to be mean zero, i.i.d. over time.

As shown in Section 3.4, transmitted volatility can be non-diversifiable when the distribution of connectivity between assets in a portfolio is heavy-tailed. Therefore to test whether transmitted volatility influences stock returns, (6.1) should be extended as follows:

$$R_{i,t} = E_{t-1}(R_{i,t}) + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + CONC_{i,t-1} F_{CONC,t} + DEG_{i,t-1} F_{DEG,t} + \varepsilon_{i,t} \tag{6.2}$$

[2] Common specifications of factors include: MKT_t, the excess return on the market portfolio (S&P 500) at time t, and the Fama-French SMB_t and HML_t factors.

where $CONC_{i,t-1}$ is a measure of the concentration of firm i's total connectivity and $DEG_{i,t-1}$ is a measure of the degree of firm i's total connectivity; $F_{CONC,t}$ and $F_{DEG,t}$ are pervasive factors associated with shocks transmitted via economic linkages[3].

Observable account data on economic linkages can be used to develop proxies for $CONC_{i,t-1}$ and $DEG_{i,t-1}$. As in Fama and French (1992), variables based on account information are lagged in order to ensure that the account information is available before the returns that it is used to explain. It is also important to note that $CONC_{i,t-1}$ and $DEG_{i,t-1}$ can vary over time as firms form and break economic linkages[4].

If the errors are mean zero and i.i.d., then it follows from (6.2) (under the Arbitrage Pricing Theory (APT) of Ross (1976)) that the risk premium of asset i is a linear function of stock i's betas, such that

$$E_{t-1}(R_{i,t}) = \sum_{k=1}^{K} \beta_{i,k}\gamma_k + CONC_{i,t-1}\gamma_{CONC} + DEG_{i,t-1}\gamma_{DEG} \tag{6.3}$$

where γ_k is the risk premium associated with exposure to factor k (i.e. $\beta_{i,k}$), and γ_{CONC} and γ_{DEG} measure the risk premium associated with the concentration and degree of firm i's total connectivity respectively. In this model $CONC_{i,t-1}$ and $DEG_{i,t-1}$ should be interpreted as exposure to pervasive transmitted volatility, and γ_{CONC} and γ_{DEG} are the associated return premiums.

In the cross-sectional regressions represented by equation (6.3), the observed de-

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3 Note that $F_{CONC,t}$ and $F_{DEG,t}$ are unobservable. This is not a problem in the cross-sectional tests because the factor exposures (betas) $CONC_{i,t-1}$ and $DEG_{i,t-1}$ are observable from account information and can be included directly. In the time series tests, however, it is not possible to fit (6.2). Instead, in the time-series tests, $CONC_{i,t-1}$ and $DEG_{i,t-1}$ are included alongside other pervasive factors (e.g. the three Fama French factors, or macroeconomic factors) as firm characteristics that may influence returns, as in Daniel and Titman (1997). This is explained in greater detail below.

4 Thus, purely statistical factor analysis is not a suitable method to use as it looks for associations over time, and will average across years in which there are economic linkages and years in which there are not.

gree and the concentration of linkages are included alongside the factor betas for the systematic risk factors (e.g. the three Fama French factors). The observed degree and concentration of linkages are the factor betas for transmitted volatility. The estimated coefficients on the degree and concentration of linkages represent the premium for bearing transmitted volatility risk.

A characteristics-based pricing model As noted in Daniel and Titman (1997), it is possible that return premia attach themselves to firm-level or asset-level characteristics rather than to loadings upon pervasive risk factors. For example, Daniel and Titman (1997) find that the return premia assigned to small size and high book-to-market firms does not arise because of covariance of these firms' returns with the market index, but rather because their firm-level characteristics (rather than the covariance structure of returns) explain cross-sectional variation in stock returns. In other words, firm characteristics reliably predict the future covariance structure of returns.

This alternative return generating process is represented as follows:

$$\begin{aligned} R_{i,t} &= E_{t-1}(R_{i,t}) + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \varepsilon_{i,t} \\ E_{t-1}(R_{i,t}) &= a + b_1 \theta_{i,t-1} \end{aligned} \tag{6.4}$$

where $R_{i,t}$ is the excess return (over the risk-free rate) of stock i at time t ($i = 1, \cdots, N$ and $t = 1, \cdots, T$); $E_{t-1}(R_{i,t})$ is the expected return of asset i at time t, based on information available at time $(t-1)$; $\beta_{i,k}$ is firm i's loading on factor F_k, where $F_{k,t}$ is the realization of factor k at time t; and $\theta_{i,t-1}$ is the firm characteristic of interest (in this case the degree and structure of a firm's economic linkages). As in Daniel and Titman (1997), in contrast to (6.1), expected returns are a function of the firm characteristic, $\theta_{i,t-1}$, and are not affected by firm i's loading on a distress factor (i.e. $F_{D,t}$ does not appear in this model)[5].

Consistent with (6.4), in the time-series tests $CONC_{i,t-1}$ and $DEG_{i,t-1}$ are in-

[5] Another possible return generating process is a combination of (6.2) and (6.4) in which expected returns are a function of both loadings on pervasive factors and firm-specific char-

cluded alongside other pervasive factors (e.g. the three Fama French factors, or macroeconomic factors) as firm characteristics that may influence returns[6], as in

$$R_{i,t} = b_{CONC}CONC_{i,t-1} + b_{DEG}DEG_{i,t-1} + \sum_{k=1}^{K} \beta_{i,k}F_{k,t} + \varepsilon_{i,t}. \tag{6.5}$$

6.2.2 Hypotheses tests

The models above suggests two testable hypotheses

- H1: There is a relationship between transmitted volatility and expected return i.e. transmitted volatility carries a non-zero price of risk (H_{Null}: $\gamma_{CONC} = \gamma_{DEG} = 0$)
- H2: There is a relationship between the concentration of a firm's economic linkages and its average return over time (H_{Null}: $b_{CONC} = b_{DEG} = 0$).

In order to estimate the hypothesis test statistics (γ_{CONC}, γ_{DEG} and b_{CONC}, b_{DEG}) I use Fama Macbeth (1973) (FM) cross-sectional regressions and Fama and French (1993) (FF) time-series regressions respectively. The FF times-series and FM cross-sectional regressions complement each other[7] (Fama and French, 1993) and results from both methods suggest that transmitted volatility does significantly affect the cross-sectional and time series variance of stock returns, after allowing for systematic risk factors and firm-specific characteristics.

acteristics, i.e.

$$\begin{aligned} R_{i,t} &= E_{t-1}(R_{i,t}) + \sum_{k=1}^{K} \beta_{i,k}F_{k,t} + \varepsilon_{i,t} \\ E_{t-1}(R_{i,t}) &= \sum_{k=1}^{K} \beta_{i,k}\gamma_k + b_1\theta_{i,t-1}. \end{aligned}$$

[6] It is not possible to distinguish between different return generating processes unless all of the factors in (6.2) and (6.4) are observable. $F_{CONC,t}$ and $F_{DEG,t}$ are unobservable because it is not possible to observe the shocks transmitted to a firm from its suppliers and customers (outside of an event study setting). Therefore it is not possible to fit (6.2).

[7] FM allow for time varying beta but FF do not; however FF regressions do not suffer from error-in-variables issues that are an issues in FM regressions (Welsh, 2008).

6.2.3 Cross-sectional tests

FM regressions are fit in order to check whether transmitted volatility is priced in the cross-section of returns. The first step in FM regressions is to estimate the factor betas[8]. For each portfolio I regress portfolio returns on the market excess return (MktRF) to get the CAPM beta, and on the FF three factors (MktRF, SMB and HML) to estimate the factor exposures to the FF factors.

Second, I perform T cross-sectional regressions of the portfolio returns on the estimated betas *plus* measures of exposure to transmitted volatility. That is, for each portfolio I estimate (6.3). Then I collect the time-series of all these regression slopes $(\gamma_{\mathbf{1}}, \cdots, \gamma_{\mathbf{T}})$ and average these over time to get the final gamma estimates:

$$\hat{\gamma_k} = \frac{\sum_{t=1}^{T} \gamma_{kt}}{T}.$$

Rejection of the null hypothesis that $\gamma_{C\hat{O}NC} = \gamma_{D\hat{E}G} = 0$ implies that transmitted volatility explains a significant part of the relative prices of stock returns[9].

[8] The betas used in the results that are presented below are estimated based on the full (January 1990 to December 2010) sample of returns for each portfolio. I also performed the tests using betas estimated on the past two years historical returns for each portfolio. The sample period over which betas were calculated did not affect the results regarding whether transmitted risk is influential over and above other common factors. So I used the full period estimates for consistency with the time-series results, and because they had lower standard errors. The use of rolling betas (based on historical information) is most useful in return prediction studies.

[9] Equilibrium models, such as the CAPM, impose tighter restrictions on equation (6.3) than the APT. Under the CAPM, equation (6.3) must satisfy

$$H_0^{\alpha} : \alpha = 0$$

This hypothesis implies that the zero-beta expected return should equal the risk-free rate. A rejection of H_0^{α} means that the factor cannot explain the average level of stock returns. This is often the case for factors based on consumption-based asset pricing models because a very high implied risk aversion is necessary to match the overall equity premium (Ang, Liu, and Schwarz, 2008). However, even though a factor cannot price the overall market, it could still explain the relative prices of assets if it carries a non-zero price of risk. A simultaneous rejection of H_0^{α} and H_0^{γ} implies that while the model cannot fully explain the overall level of returns, exposure to F_k accounts for some of the expected returns of assets relative to each other.

6.2.4 Time-series tests

As in Fama French (1993) a second way to test whether the proxies for counterparty risk exposure (F_{CONC} and F_{DEG}) explain common variation in returns is to estimate (6.2) for each portfolio. It is then possible to test whether transmitted volatility can explain average returns by testing the null hypothesis

$$H_{Null} : b_{CONC} = b_{DEG} = 0$$

Where b_{CONC} and b_{DEG} are the slopes of time series regressions of excess returns on common risk factors (including F_{CONC} and F_{DEG}).

In the time-series regressions in Section 6.4.4 and the macroeconomic factor model in Section 6.4.5, therefore, the observed degree and concentration of company linkages is included alongside the systematic factors (excess returns on the risk-factor mimicking portfolios in the FF regression or macroeconomic variables in the macroeconomic factor model) and I test whether this firm specific characteristic explains returns over time, in addition to the systematic factors.

6.2.5 Portfolio formation

As explained in Daniel and Titman (2012) and Lo and MacKinlay (1999), by grouping all of the assets with similar size and BTM together, any variation in factor loadings that is independent of size or BTM is largely eliminated, so the sorting procedure will result in a set of portfolios that exhibit a stronger relationship between loadings on size and BTM. Fama and French (1993) find that the estimates of the CAPM intercepts deviate from zero for portfolios formed on the basis of BTM as well as for portfolios formed on size. On finding that the intercepts for these portfolios with a three-factor model are closer to zero, they conclude that missing risk factors in the CAPM are the source of the deviations. However, another explanation consistent is that on an ex post basis deviations from the CAPM, considered in a group, will appear statistically significant but may just be a result of grouping assets with common disturbance terms (Lo and MacKinlay, 1999). Lo and MacKinlay (1999) conclude that using theoretically motivated out-of-sample factors to sort portfolios is a good way to reduce such ‘data-snooping bias’.

I form portfolios based on theoretically motivated ‘linkage’ factors so that induced ordering and data-snooping bias are not likely to be serious in this study[10]. The single sorted portfolios are formed yearly by ranking stocks according to one of four annual measures of exposure to transmitted volatility:

- the degree of supplier linkage
- the degree of customer linkage
- the concentration of supplier linkage
- the concentration of customer linkage.

The distribution of linkages was uneven with most firms disclosing zero or one significant customers (a single customer accounting for at least 10% of annual sales revenue). Quartiles on the full dataset did not span a broad range of the factor values. Therefore those firms with no linkages formed the first group (1), firms with a single linkage formed the second group (2), and the remaining firms, with one or more linkages, were split into two groups based on the 50th percentile of firms with at least one linkage. In order the four ‘degree’ portfolios rank firms from least to most connected.

Similarly, the distribution of concentration of linkages was uneven. Firms disclosing zero key customers[11] (suppliers) had customer (supplier) concentration of 0%, while firms with one significant customer had customer (supplier) concentration of 100%. All other firms had values in between 0% and 100%, however, quartiles did not span a broad range of the factor values. Therefore those firms with no linkages formed the lowest concentration group (1), firms with a single linkage formed the highest concentration group (4), and the remaining firms, with

[10] In addition, I use out-of-sample Fama Macbeth (FM) regressions (where current period returns are regressed on factor exposures based on historical data) to avoid issues associated with data-snooping bias.
[11] As defined in FAS 131, a single customer accounting for at least 10% of annual sales revenue.

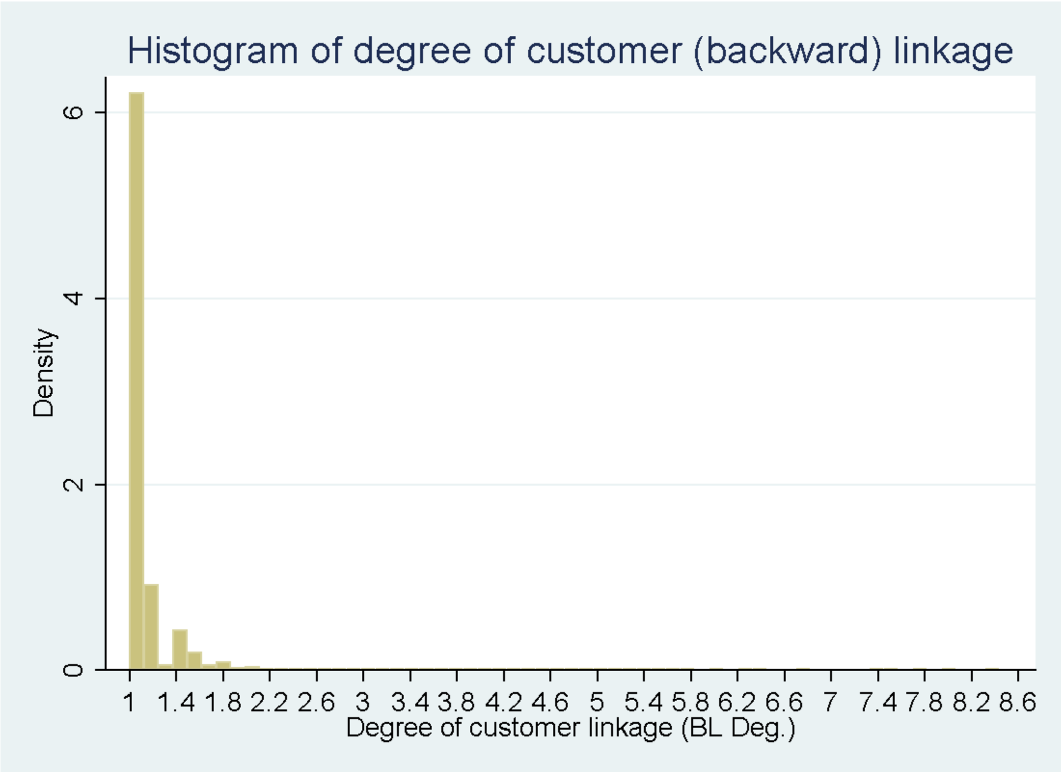

Figure 6.1: Histogram of the degree of customer (backward) linkage for firms with at least one significant customer exposure. *The total degree is calculated as the row sum of* $CS = (I - \alpha cA)^{-1}$; where $\alpha = 0.2$, and **A** is the adjacency matrix with entries $a_{ij} = 1$ if i is a key customer of j and zero otherwise.

one or more linkages, were split into two groups based on whether concentration was greater than 0% and less than 50% (group 2) or greater than or equal to 50% and less than 100% (group 3). In order, the four 'concentration' portfolios rank firms from least to most concentrated supply chain structure.

Shanken and Weinstein (2006) suggest that results from tests of the APT are sensitive to the method of portfolio formation. To check the results in this chapter are robust to the method of portfolio formation, the tests were performed using the four different portfolios outlined above, and also portfolios that are double sorted on size and the exposure to transmitted volatility (the degree of supplier linkage, the degree of customer linkage, the concentration of supplier linkage, the concentration of customer linkage).

6.3 Data and measurement of variables

6.3.1 Data source and sample selection

I examine the relationship between transmitted volatility and returns using a large unbalanced panel of observations on $10,850$ firms over 252 months, from January 1990 to December 2010. The dataset contains monthly stock return information from Center for Research in Security Prices (CRSP) and associated annual account information from Compustat. The sample period begins in January 1990 because this first year from which reliable disclosures of 'key customers' were available[12].

The sample was selected from the set of all nonfinancial firms in the intersection of the CRSP return files and the Compustat annual files. These files contain return and account information on all firms with listed securities on the NYSE,

[12] On June 30, 1997, the Financial Accounting Standards Board (FASB) issued the Statement of Financial Accounting Standards No. 131, Disclosure about Segments of an Enterprise and Related Information (FAS 131). Prior to 1997, similar information was collected under FAS 14. When the accounting standards changed Compustat restated past 'key customer' disclosures under FAS 14 so that they were consistent with under FAS 131, but only back to 1990.

AMEX and/or NASDAQ exchanges. The sample was selected from the full intersection of CRSP and Compustat according to the following criteria, identical to Fama and French (1992):

- The firm must have a record in both Compustat Fundamental Annual and CRSP files between 1990 and 2010.
- There must be at least 2 years or 24 months of return data on CRSP. (As at least 20 observations should be used to calculate beta and correlation between firms return series. Furthermore, this controls for the potential survival/selection bias inherent in the way COMPUSTAT adds firms to its tapes (Banz and Breen, 1986).
- Financial firms were excluded based on SIC divisions 6000-6900 (because disclosure requirements and accounting rules are significantly different for these industries (Collins et al., 2003) and because the use and influence of leverage is not comparable between financial and non-financial companies (Fama and French, 1992)).

The final (unbalanced) panel, contained return information for 10,853 stock for whom I had account information for the underlying firms, each with up to 252 monthly observations. Only 5% of firms were alive for the whole period. The average number of months of observations per firm was 160 (75% of firms had at least 50 months of observations).

6.3.2 Dependent variable: Excess returns

The standard response in asset pricing studies is the return on a stock in excess of the risk-free rate (Fama and French, 1992). Given the time-series nature of the data is it appropriate to use the log excess return defined as

$$r_{it} = ln(R_{it} + 1)ln(R_{ft} + 1).$$

where R_{it} is the return in percentage (i.e. $R_{it} = \frac{R_{i,t}}{R_{i,t-1}} - 1$) and R_{ft} is the risk-free rate of return for the corresponding period. I also test the results are unchanged if the untransformed excess return (i.e. $R_{it} - R_{ft}$) is used as the response.

Table 6.1: Summary statistics for monthly excess returns by year. *Excess return is each firm's monthly with-dividend return (RET) less the one-month Treasury bill rate (from Ibbotson Associates). The sample period is 1989: 1 to 2010:12. The monthly data are scaled by 1200 to express returns in percent per annum.*

Year	No. Obs	Mean	Sd	Skewness	Kurtosis
1990	(n=47,568)	-0.02%	0.16%	0.68%	7.16%
1991	(n=49,124)	0.03%	0.18%	1.05%	7.63%
1992	(n=51,315)	0.01%	0.16%	1.01%	8.17%
1993	(n=54,592)	0.01%	0.15%	1.04%	8.43%
1994	(n=59,869)	-0.01%	0.14%	0.67%	8.02%
1995	(n=62,462)	0.02%	0.15%	0.91%	8.06%
1996	(n=66,863)	0.01%	0.16%	0.82%	7.26%
1997	(n=70,400)	0.01%	0.17%	0.72%	6.81%
1998	(n=70,151)	-0.01%	0.19%	0.60%	5.92%
1999	(n=66,173)	0.02%	0.20%	1.08%	6.25%
2000	(n=64,929)	-0.02%	0.23%	0.55%	5.11%
2001	(n=60,836)	0.01%	0.22%	0.63%	5.31%
2002	(n=57,046)	-0.02%	0.19%	0.52%	6.15%
2003	(n=53,293)	0.05%	0.17%	1.15%	7.59%
2004	(n=52,256)	0.02%	0.14%	0.83%	8.13%
2005	(n=52,248)	0.00%	0.13%	0.68%	8.08%
2006	(n=52,061)	0.01%	0.13%	0.81%	8.65%
2007	(n=51,552)	0.00%	0.13%	0.51%	8.80%
2008	(n=50,450)	-0.05%	0.19%	0.09%	5.47%
2009	(n=47,030)	0.04%	0.20%	0.84%	6.11%
2010	(n=44,023)	0.02%	0.14%	0.72%	7.10%
Total	(n=1,228,688)	0.00%	0.17%	0.72%	7.18%

Table 6.1 reports summary statistics of the excess returns of the sample by year. The financial crises in the early and late 1990s, as well as the recent global financial crisis are likely explanations for negative returns in the years 1990, 2000, 2002 and 2008. Over the entire period 1990 to 2010 the average excess return was 0.00%. There is no obvious time trend in the mean, skewness or kurtosis of excess returns in this sample.

6.3.3 Independent variables: Systematic covariates

The aim of this study is to test whether the shocks transmitted via economic linkages affect the relative prices over and above systematic risk factors (SRFs).

The FF three factor model is the benchmark for asset pricing studies (Ernstberger, Haupt, and Vogler, 2011), so I use the three FF factors

- Excess return on the S&P 500 index (from Kenneth French's website).
- SMB, the average return on the three small portfolios minus the average return on the three big portfolios (from Kenneth French's website).
- HML, is the average return on the two value portfolios minus the average return on the two growth portfolios (from Kenneth French's website)

in the main model specification.

Previous studies show that the market return, average dividend yield and the term spread (or long term government bond yield and short term bill rate) are the key macroeconomic risk factors driving returns (Shanken and Weinstein, 2006; Bekaert and Hodrick, 1992). Aretz, Bartram, and Pope (2010) show the three Fama French factors above capture the cross-sectional variation in exposures to a broad set of macroeconomic factors potentially important for pricing equities[13]. Therefore in Section 6.4.5 I cross-check the results of the regressions by using the following macroeconomic risk factors instead of the FF factors:

- Excess return on the S&P 500 index (from Kenneth French's website)
- The average market dividend yield on the S&P 500 index (from Robert Schiller's website)
- The term spread defined as the difference between the 10-year, constant maturity, Treasury bond rate (series GS10 from the Federal Reserve Board website) and the 1-month Treasury bill rate (from Ibbotson Associates).

Time series properties: Unit root and structural break tests

In time-series and panel studies it is important to test whether the macroeconomic series and systematic risk factors are stationary. Non-stationary series, that follow a unit root process violate several regression assumptions and can lead to

[13] The FF factors capture the cross-sectional variation in exposures to: innovations in economic growth expectations, inflation, bankruptcy rates, the term structure of interest rates and the exchange rate (Aretz, Bartram, and Pope, 2010).

Table 6.2: Unit root tests. *Dickey-Fuller (DF) and Phillips-Perron (PP) Unit root tests include a constant and a trend; the optimal lag length is chosen by the Akaike information criterion and the Likelihood ratio test statistic.*

Panel A: Unit root tests in levels								
	Jan 1990 - Dec 1994		**Jan 1995 - Dec 1999**		**Jan 2000 - Dec 2004**		**Jan 2005 - Dec 2009**	
	DF	PP	DF	PP	DF	PP	DF	PP
MktRF	-4.566	-8.073	-5.332	-7.651	-4.414	-7.752	-2.211	-5.192
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
SMB	-3.996	-6.132	-3.660	-6.357	-5.566	-9.958	-4.806	-7.867
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
HML	-4.077	-4.784	-2.341	-6.357	-3.833	-8.786	-3.610	-8.786
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
DivYield	-2.337	-3.429	-0.192	-0.069	-0.499	0.544	-1.874	4.861
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
Spread	-1.31	-1.076	-2.034	-1.969	-2.268	-2.388	-2.33	-2.551
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
Panel B: Unit root tests in first differences								
	Jan 1990 - Dec 1994		**Jan 1995 - Dec 1999**		**Jan 2000 - Dec 2004**		**Jan 2005 - Dec 2009**	
	DF	PP	DF	PP	DF	PP	DF	PP
D.DivYield	-2.881	-2.847	-5.983	-4.271	-3.389	-3.084	-1.601	-1.736
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490
D.Spread	-4.487	-5.096	-3.237	-5.927	-4.881	-6.445	-4.456	-7.05
	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490	-3.490

spurious regression results. I.e. if two variables are trending over time, a regression of one on the other could have a high R^2 even if the two series are unrelated. To address this concern, I test whether each macroeconomic series contains a unit root using the Dickey Fuller (DF) test and the Phillips Perron (PP) test. The unit root tests include constant and trend; the optimal lag length was chosen by optimizing the Akaike's information criterion (AIC), Bayesian information criterion (BIC), and the likelihood-ratio test statistics for the auto-regressive models for each series.

Table 6.2 shows the tests of stationarity for the systematic risk factors. The tests in levels, shown in Panel A, confirm that for the three FF factors, in all cases there is a strong rejection of the null hypothesis that the variable contains a unit root, in favor of the alternative that the variable was generated by a stationary process. For the Dividend Yield and the spread however, the test fail to reject the null hypothesis that the variable contains a unit root. For these two series therefore, a second set of unit root test was performed on the variable in levels. These tests are shown in Panel B of Table 6.2 show that for the Dividend Yield and the Spread, the series are first difference stationary. In summary, in the macroeconomic specification, I fit the variables MktRF, SMB and HML in levels, but I fit the Dividend Yield and the spread as first differenced series to avoid the problems involved with non-stationary explanatory variables.

6.3.4 Independent variables: Measures of transmitted volatility

In this section I develop measures of exposure to transmitted volatility. Transmitted risk is frequently unobservable and/or hard to distinguish from direct shocks to the firm (Dungey, Fry, Gonzalez-Hermosillo, and Martin, 2011). However, while the portion of return volatility caused by transmitted risk is unobservable, I have information on the economic linkages that hypothetically transmit shocks. Therefore, in order to test whether risk transmitted via economic linkages affects asset returns, I develop measures of the *exposure* to transmitted volatility via economic linkages. Estimating exposure rather than the shocks themselves circumvents the errors-in-variables bias that is created when estimates of shocks themselves are used in subsequent regressions to derive factor loadings[14] (Hahn and Lee, 2009).

I use available information of inter-firm linkages to develop measures of the degree (DEG) and the concentration (CONC) of transmitted risk exposure. To recap, the *in-degree* of a firm in a supply network is the number of significant connections it has to customers (i.e. customer linkages or CL), while the *out-degree* of a firm in a supply network is the number of significant connections it has to suppliers[15](i.e. supplier linkages or SL). High in-degree means that the firm is influential in its role as a supplier (receiving cash 'in' from its customers); high

[14] Because aggregate exposure to transmitted shocks involves summing across both systematic and idiosyncratic shocks to all customers and suppliers directly and indirectly linked to firm i, even small estimation errors in estimates of individual shocks could compound to create significant estimation bias.

[15] These measures indicate the direction of cash-flow involved in the relationship, i.e. cash is paid out to suppliers, and in from customers.

out-degree means that the firm is influential in its role as a customer (paying cash 'out' to its suppliers).

Firms are exposed to shocks to their customers' customers, and suppliers' suppliers and so on. So, as in Chapter 3, the total degree of a firm is a weighted sum across all possible n-step linkages. The 'total in-degree' ('total out-degree') measures represent aggregate exposure to shocks from a firm's customers (suppliers).

In model (6.6) I include the total degree of customer and supplier linkages (CL DEG and SL DEG), which are based on the row and column sums of the matrix:

$$\mathbf{CS_t} = (\mathbf{I} - \alpha\mathbf{c}\mathbf{A_t})^{\mathbf{-1}}$$

where $\mathbf{A_t}$ is the adjacency matrix constructed as described in section 5.3.3 which captures all direct links between suppliers and customers in year t. For these calculations I use three different scaling weights αc: $\alpha c = 0.1$, $\alpha c = 0.2$ and $\alpha c = 0.3$ (based on the average percentage of a firm's total revenue associated with a single link, as explained in Section 5.3.3).

As in Table 3.3, measures of the total degree of linkage to customers and suppliers can be derived from $\mathbf{CS_t}$ as $\mathbf{i'CS_t}$ and $\mathbf{i'CS'_t}$ respectively. I.e. the total degree of linkage to customer i is the i'th row sum of $\mathbf{CS_t}$ and the total degree of linkage to supplier j is the j'th column sum of $\mathbf{CS_t}$.

In addition to measures of total degree, I also construct measures of the structure of total connectivity based on the theory in Chapter 4. Three measures of network structure are proposed:

- 1. $Var(CS_i)$ (i.e. CS row variance)
- 2. $\frac{max(CS_i)}{||CS_i||_2}$
- 3. $\frac{||CS_i||_2}{||CS_i||_1}$.

These are all measures of the concentration (or 'heavy-tailedness') of a firm's links either upstream or downstream of the firm. As explained in Chapter 4, the variance of the i'th row of the CS matrix is a measure of the concentration of the distribution of firm i's linkages across its counterparties. To see this note that the variance of entries along CS_i is

$$Var(CS_i) = s_{in}^2 = n^{-1}\sum_j (CS_{ij} - \overline{CS_i})^2 = n^{-1}\sum_j CS_{ij}^2 - \overline{CS_i}^2,$$

where $\overline{CS_i} = n^{-1}\sum_j CS_{ij}$ is the average row entry. So if the distribution of firm i's linkages is concentrated on firm j then $(CS_{ij} - \overline{CS_i})$ will be large for j, which will increase $Var(CS_i)$. The second measure is derived from Proposition 1 in Chapter 4. The ratio $\frac{max(CS_i)}{||CS_i||_2}$ is the fraction of the standard deviation of i's return explained by the most dominant (or influential) counterparty. The last measure is a 'Herfindahl index'. The Herfindahl index is a commonly used measure of concentration in economics (Gabaix, 2011). When firms are linked it is their total influence, rather than their size, which determines the contribution of their idiosyncratic risk to the aggregate. So in the context of network structure, the Herfindahl index translates into the ratio of the 1-row-norm over the 2-row-norm from the CS matrix. The row Herfindahl $\frac{\sqrt{\sum_j CS_{ij}^2}}{\sum_j CS_{ij}}$ represents concentration of customer base, while the column Herfindahl $\frac{\sqrt{\sum_i CS_{ij}^2}}{\sum_i CS_{ij}}$ represents concentration of supplier base.

These measures are highly collinear (for example, when all elements in a row of CS are equal, measures 2 and 3 are identical) so they are used alternatively as measures of exposure to transmitted volatility in equation (6.6).

Aggregate and idiosyncratic volatility

Market-level and firm-level volatility may affect returns (Bekaert and Wu, 2000). Similarly, market-level and firm-level shocks can influence returns directly and indirectly via linkages. To test whether *transmitted* volatility affects returns, therefore, it is important to control for direct exposure to market-level and firm-level volatility. I do this by including proxies for market volatility and firm-level volatility in equation (6.6).

As in French, Schwert, and Stambaugh (1987); Campbell and Hentschel (1992); Bekaert and Wu (2000), the proxy for market volatility is the variance of the market return (the monthly return on the S&P 500 index) over the past 24 months. Consistent with Gabaix (2011) the proxy used for firm-level volatility is the variance of the firm's return series over the past 24 months[16]

I include the one month lagged proxies (i.e. at time t I use $Var_{t-1}(R_i)$ and $Var_{t-1}(R_M)$) to control for predicted volatility. This is reasonable given that past 24-month volatility is based on information that is available to investors at the start of each period, and is one way in which an investor might rationally measure volatility. I include first difference in the volatility proxy to allow for unpredicted volatility. If it is assumed that volatility follows an $AR(1)$ process then this is exactly the method recommended in Christiano, Eichenbaum, and Evans (1999) for separating (monetary policy) shocks into predictable and unpredictable components. The predicted and unpredicted components are uncorrelated so including them both in the regression should not bias estimates.

Firm-level characteristics

In addition to systematic risk factors and volatility, firm-level characteristics can influence stock returns (Ang, Liu, and Schwarz, 2008; Daniel and Titman, 1997). Therefore, to be sure that the estimated influence of linkages is not biased because of omitted firm characteristics, I include the following firm characteristics as control variables:

- Firm size (market capitalization at last fiscal year end)
- Book-to-market ratio (the ratio of book value of equity to market capitalization at last fiscal year end)
- Profitability (the ratio of sales to total assets at last fiscal year end)
- Book leverage (the ratio of total debt to the book value of equity)

[16] I also calculated the residuals from the standard CAPM (i.e. $R_i - \beta_i R_{Mt}$) over the past 24 months, however the variance of the residuals from the CAPM were highly correlated with the variance of the market return, so $\mathrm{Var}(R_i)$ is a better choice for use in the regressions.

- Trade credit ratio (the ratio of accounts payable to total cost of goods sold).

The first two variables are standard controls taken from the Fama French three factor model (Fama and French, 1992; Daniel and Titman, 1997). In addition I control for profitability, leverage and trade credit. Fama and French (2008) confirm a 'profitability' effect in pricing, showing that among profitable firms, higher profitability tends to be associated with abnormally high returns. In the context of production linkages, the profitability of a counterparty affects whether or not it can fulfil its obligations to supply or purchase goods and/or services, so the firm's own profitability is included as a control to ensure that any effects of counterparty risk on returns are not a results of excluding an important firm-specific factor that affect the counterparty relationship. Similarly, leverage and trade credit so are controlled for because they have been proposed as factors related to the propagation of shocks between counterparties (Raddatz, 2010).

Finally, an industry dummy variable was created using the 12 industry classification scheme from Fama and French (1997). This classification scheme was chosen as it is the lowest level of disaggregation which cleanly separates all Finance, Banking, Insurance, Real Estate, and Trading businesses (SIC codes 6000-6999) from other industries. Industry level summary statistics and regression results are not included due to the very low significance of the industry dummies and because they did not alter the results.

6.3.5 Summary statistics

Table 6.3 presents descriptive statistics for the firm-level control variables for the whole period of 1990 to 2010, and also broken into consecutive five year periods. The descriptive statistics illustrate that the accounting ratios vary over the sample period. In particular, leverage is noticeably higher, and more variable, in the years 2000 to 2005. The variance in profitability is lower, both across firms and over time. The mean firm size (or market value of equity) increases noticeable over the full sample period, however the measurements in the table are in nominal dollars so this trend is reasonable. The dispersion of firm size (large standard deviation, positive skewness and kurtosis, and the fact that the maximum firm

Table 6.3: Descriptive statistics for the firm-level covariates, for the Compustat/CRSP population of US listed firms, 1990 to 2010.

	Mean	S.D.	Skew	Kurt	Min	Max
Size ($m)	2,626.86	13,336.31	14.37	307.66	0.07	508,329.47
BTM	0.64	3.56	-201.17	48,950.67	-906.64	60.75
Leverage	3.49	289.46	298.87	90,575.56	-2,941.78	87,750.70
Trade Credit	0.35	7.39	104.37	13,860.12	-8.07	1,272.35
Profit	1.10	1.10	51.54	7,639.67	-0.93	183.86
1st-order CL	0.46	1.19	6.00	73.91	0.00	34.00
1st-order SL	0.49	3.79	27.01	1,132.47	0.00	247.00
Total CL	1.10	0.26	6.32	78.48	1.00	8.44
Total SL	1.11	0.85	26.74	1,101.40	1.00	57.97
Conc. CL	0.19	0.35	1.52	3.58	0.00	1.00
Conc. SL	0.09	0.26	2.81	9.32	0.00	1.00

size is significantly higher than the average firm size) indicates that there are a few very large firms in the sample, whereas the majority are much smaller. To minimize some of the extreme values in the explanatory variables, I winsorize all ratio variables at the first and 99th percentiles.

The dispersion of the linkage measures (1st-order CL, 1st-order SL, Total CL, Total SL) also indicates that there are a few very connected firms in the sample, whereas the majority are much less connected. The most striking feature of this data is that the supplier linkages (out-degree) are several times more heavy-tailed than the customer linkages (in-degree). These summary statistics are consistent with the evidence presented in Chapter 3 that the out-degree distribution of listed firms (or number of dependent suppliers that a customer firm has) is much more heavy-tailed than the in-degree distribution of listed firms (or the number of customers that account for over 10% of sales revenue).

Correlation between covariates

It is important to investigate whether any explanatory power attributed to the degree and/or structure of linkages is directly related to firm-level linkages, or whether it derives from the covariance of firm-level linkages with another factor that is driving returns. For robustness, to ensure that linkages are not merely a proxy for correlation with the market risk factor, I also calculated the correlation between the linkage measures and CAPM beta, estimated by fitting the following rolling regression over 24 month periods: $R_{it} = \beta_i R_{mt} + \varepsilon_{it}$.

Table 6.4: Correlation of firm-level model covariates: size, beta, degree of customer linkage, degree of supplier linkage, concentration of customer linkage and concentration of supplier linkage.

	Size	Beta	1st ord CL	1st ord SL	Total CL	Total SL	Conc. CL
Size	1.000						
Beta	-0.021	1.000					
1st ord CL	-0.018	0.047	1.000				
1st ord SL	0.454	-0.016	-0.009	1.000			
Total CL	-0.016	0.051	0.983	-0.010	1.000		
Total SL	0.443	-0.016	-0.010	0.993	-0.010	1.000	
Conc. CL	-0.041	0.053	0.555	-0.022	0.524	-0.022	1.000
Conc. SL	0.162	0.005	0.005	0.154	0.007	0.143	-0.017

Table 6.4 shows the correlation of the covariates measuring the degree and structure of linkage, with the firm-level covariates: beta and size. Other than a correlation between the measures of total supplier and customer linkage (Total CL and Total SL) and 1st order supplier and customer linkage there appears is little evidence of multi-collinearity among the firm-level predictors[17]. To address this issue I never include both measures of Total CL (Total SL) and 1st order linkage in the same regression.

6.4 Empirical results

6.4.1 Average returns for portfolios

Table 6.5 shows the mean excess return and standard deviation of the excess return for each portfolio, and the characteristics of the firms in each portfolio. There is an increasing trend in excess returns in all portfolios, as both the degree and concentration of a firm's supplier and customer linkages increase. The increasing trend in average excess returns is clearer in the portfolios sorted on forward (supplier) linkages than backward (customer) linkages. These trends suggest that returns are positively related to transmitted volatility over the period 1990 to 2010.

[17] The high correlation between the measures of total supplier and customer linkage and 1st order supplier and customer linkage indicates that second-order and higher-order connections are secondary effects.

Table 6.5: Average excess returns, linkage measures and characteristics for 4 sets of portfolios formed by sorting on 1 of the following measures of economic linkage: degree of linkage to customers (CL deg.), degree of linkage to suppliers (SL deg.), concentration of linkage to customers (CL conc.), concentration of linkage to suppliers (SL conc.).

Portfolio:		No. obs	ER	Beta	CL deg.	SL Deg.	CL conc.	SL conc.	Size	BTM	Leverage
CL Deg.	**1**	945,275	**0.4%**	**1.08**	**1.00**	**1.11**	**0.00**	**0.09**	**2,904**	**0.65**	**3.85**
			17.1%	1.03	0.00	0.92	0.00	0.26	14,288	2.01	330.69
	2	129,992	**0.6%**	**1.18**	**1.20**	**1.08**	**1.00**	**0.09**	**1,566**	**0.63**	**2.25**
			17.7%	1.11	0.00	0.42	0.00	0.26	8,654	0.87	44.60
	3	66,522	**0.6%**	**1.31**	**1.38**	**1.10**	**0.73**	**0.08**	**1,731**	**0.72**	**1.90**
			18.4%	1.13	0.08	0.79	0.09	0.25	10,305	1.27	27.84
	4	86,899	**0.5%**	**1.24**	**1.80**	**1.08**	**0.58**	**0.10**	**1,991**	**0.48**	**2.77**
			17.3%	1.14	0.55	0.51	0.14	0.28	10,366	11.39	41.51
SL Deg.	**1**	1,084,064	**0.4%**	**1.12**	**1.10**	**1.00**	**0.19**	**0.00**	**1,068**	**0.65**	**3.61**
			17.6%	1.08	0.26	0.00	0.36	0.00	4,791	3.79	308.87
	2	68,944	**0.8%**	**1.17**	**1.12**	**1.20**	**0.18**	**1.00**	**4,399**	**0.53**	**2.60**
			14.9%	0.96	0.34	0.00	0.35	0.00	9,976	1.30	20.19
	3	38,223	**0.9%**	**1.12**	**1.09**	**1.45**	**0.18**	**0.71**	**10,044**	**0.54**	**2.32**
			13.3%	0.87	0.27	0.11	0.35	0.12	21,674	0.56	35.25
	4	37,457	**0.8%**	**1.04**	**1.10**	**3.67**	**0.17**	**0.40**	**34,514**	**0.47**	**3.02**
			11.4%	0.76	0.31	4.06	0.35	0.15	55,753	0.45	17.86
CL Conc.	**1**	945,275	**0.4%**	**1.08**	**1.00**	**1.11**	**0.00**	**0.09**	**2,904**	**0.65**	**3.85**
			17.1%	1.03	0.00	0.92	0.00	0.26	14,288	2.01	330.69
	2	71,138	**0.5%**	**1.33**	**1.85**	**1.07**	**0.52**	**0.10**	**1,881**	**0.46**	**2.73**
			18.0%	1.15	0.55	0.36	0.08	0.29	9,222	12.59	45.63
	3	75,794	**0.5%**	**1.26**	**1.42**	**1.10**	**0.73**	**0.08**	**1,548**	**0.69**	**2.23**
			18.0%	1.14	0.24	0.80	0.06	0.25	9,532	1.02	19.13
	4	136,481	**0.6%**	**1.16**	**1.22**	**1.08**	**1.00**	**0.09**	**1,765**	**0.63**	**2.17**
			17.5%	1.10	0.09	0.46	0.00	0.26	9,846	1.01	45.62
SL Conc.	**1**	1,084,064	**0.4%**	**1.12**	**1.10**	**1.00**	**0.19**	**0.00**	**1,068**	**0.65**	**3.61**
			17.6%	1.08	0.26	0.00	0.36	0.00	4,791	3.79	308.87
	2	40,037	**0.7%**	**1.06**	**1.10**	**3.50**	**0.17**	**0.40**	**33,882**	**0.47**	**2.85**
			11.2%	0.76	0.31	3.97	0.35	0.13	54,936	0.42	16.85
	3	31,741	**0.9%**	**1.11**	**1.09**	**1.47**	**0.18**	**0.70**	**9,452**	**0.55**	**2.46**
			13.5%	0.88	0.24	0.21	0.35	0.07	20,008	0.60	38.49
	4	72,846	**0.9%**	**1.16**	**1.12**	**1.22**	**0.18**	**1.00**	**4,447**	**0.53**	**2.60**
			14.9%	0.95	0.35	0.08	0.35	0.00	10,088	1.27	19.98
Total Avg.		**1,228,688**	**0.5%**	**1.12**	**1.10**	**1.11**	**0.19**	**0.09**	**2,627**	**0.64**	**3.49**
Total S.d.			17.2%	1.05	0.26	0.85	0.35	0.26	13,336	3.56	289.47

In relation to the other characteristics, firms with a high degree of supplier linkage (more concentrated supplier-base) are larger than average and have higher beta. For example, the average size of firms in the top quartile of firms with one or more suppliers (SL DEG., Group 4) is \$34,514m, which is much greater than the sample mean of \$2,627m. To check whether the uneven distribution of size across the portfolios affects the results I run the regressions below using portfolios formed on exposure to transmitted risk and on size. The double sorted portfolios produced comparable results to single sorted portfolios, suggesting that the results are robust to size.

6.4.2 CAPM and APT tests

The standard approach for testing multi-factor explanations of returns is to first test whether the CAPM or Fama-French (1992) three factor model fully explains returns by testing whether the model has a zero intercept. Empirical findings that the model intercepts deviate from zero suggest that further factors should be included to explain the risk return relationship.

The CAPM and Fama-French three factor model were fit to the portfolio grouped data. The results are in Appendix 6.A. The key result is that α, the intercept, is significantly different from zero in almost all of these models. The positive alpha in the CAPM and APT regressions, for almost all of the portfolios, indicates that the three Fama French factors are not sufficient to explain the average level of asset prices in portfolios ranked on linkage measures. The R^2 in the FF three factor regressions ranges from 6% to 19%. In comparison, the R^2 in comparable regressions in Table 6 of Fama and French (1993) range from 83% to 97%. This difference may be explained by the method of portfolio sorting. In Fama and French (1993) portfolio sorting on size and BTM induces higher association between these variables and average returns (Lo and MacKinlay, 1999). When R^2 is higher the bias attributable to induced ordering interferes with the test that the intercept is significantly different from zero. Lo and MacKinlay (1999) criticize the Fama and French (1993) conclusions and method of portfolio sorting on the grounds that it induces significant 'data-snooping bias'.

6.4.3 Cross-sectional tests

I use FM cross-sectional regressions to test whether there is a significant risk premium associated with transmitted volatility (i.e. the impact on average expected returns). Specifically, I fit model (6.3)

$$E_{t-1}(R_{i,t}) = \alpha + \sum_{k=1}^{K} \beta_{i,k}\gamma_k + CONC_{i,t-1}\gamma_{CONC} + DEG_{i,t-1}\gamma_{DEG}$$

where β_k for $k = 1, \cdots, K$ are exposures to systematic risk factors estimated as described in Section 6.2.3[18], and $CONC_{i,t}$ is a measure of the concentration of firm i's total connectivity and $DEG_{i,t}$ is a measure of the degree of firm i's total connectivity. I include four measures of exposure to transmitted volatility, as developed in Section 6.3.4:

- degree of customer linkage
- degree of supplier linkage
- concentration of customer linkage
- concentration of supplier linkage.

When the intercept of this model (α) is not significantly different from zero, the gamma coefficients ($\hat{\gamma}$) can be interpreted as the compensation for exposure to that factor, after controlling for all other factors in the regression[19]. Table 6.26 presents the results of cross-sectional Fama Macbeth regressions of the excess returns on the FF factor betas (i.e. β_{MktRF}) estimated over the full sample period and on the exposures to transmitted volatility estimated from the previous years

[18] I.e. For each portfolio I regress portfolio returns on the market excess return (MktRF) to get the CAPM beta, and on the FF three factors (MktRF, SMB and HML) to estimate the factor exposures to the FF factors.

[19] I.e. The gamma coefficients from Fama Macbeth regressions are the sum of compensation for factor exposure and the historical rate of return on the factor itself (Welsh, 2008). If the intercept is different from zero then the FM coefficients are complex functions of exposure to all factors in the regression (Welsh 2008)

financial accounts.

In order to estimate the gamma coefficients, as in Fama and French (1992), in each calendar year I match account information from year $t-1$ with return information from July of year t to June of year $t+1$. This ensures there is a minimum gap of 6 months between account measures (including the exposures to transmitted volatility derived from key customer disclosures) and the returns they are used to explain.

Table 6.6 and 6.7 present the coefficient estimates and t-statistics from the cross-sectional regression of excess returns on Beta, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. The FM regression results show that there is a significant positive risk premium attached to the concentration of supplier linkages. Having a concentrated supplier base was related to higher cross-sectional average returns, suggesting investors demand a positive risk premium for this exposure. The coefficient for degree of customer linkage, however, was insignificant in most cases, indicating that a higher number or concentration of customers does not attract a risk premium. Together the results in Tables 6.5 to 6.7 show that there is a significant relationship between the average return on stocks and the degree and concentration of their supply chain exposure. The stock of firms with more concentrated supplier bases have higher expected returns, suggesting that investors demand a significant positive risk premium for bearing this risk.

The results in Table 6.6 and 6.7 show that the risk premium associated with concentration of supply-base is relatively constant across different portfolios formed on degree of customer linkage, degree of supplier linkage, concentration of customer linkage and concentration of supplier linkage. Connor and Korajczyk (1993) argue that a testable implication of the APT equality of the price of risk across different subsets of assets. Therefore these results provide support for the inclusion of supply chain concentration as a priced risk factor.

Table 6.6: Average slopes (t-statistics) from monthly regressions of log excess returns on Beta, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *Four sets of portfolio tests are formed. Each set is formed yearly by sorting on one of the following measures of exposure to transmitted volatility: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST DEG.				**SUPP DEG.**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta	-0.005	-0.004	-0.001	-0.004	-0.005	-0.007	-0.006	-0.003
	-1.43	-1.22	-0.37	-1.13	-1.38	-1.72	-1.47	-0.82
Size	0.000***	0.000*	0.000	0.000*	0.000***	0.000	0.000	0.000
	-4.51	-2.38	-1.06	-2.49	-5.41	-1.06	-0.33	-1.25
BTM	0.001	0.003*	0.006**	0.002	0.001*	0.003	0.000	-0.001
	-1.61	-2.31	-2.76	-1.30	-2.03	-1.84	-0.04	-0.38
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.34	-0.69	-0.63	-0.18	-0.66	-0.39	-0.10	-1.35
Profit	0.002***	0.001	0.002	0.001	0.002***	0.002*	0.000	0.000
	-4.19	-1.58	-0.98	-0.97	-3.96	-2.54	-0.37	-0.27
Cust Deg	-0.007*	0.001	-0.004	0.001	0.000	-0.006*	0.006	-0.003
	-2.00	-0.24	-0.79	-0.83	-0.30	-2.21	-1.22	-0.95
Supp Deg	0.000	-0.003	-0.005	0.002	0.013	0.005	-0.001	0.000
	-0.09	-1.47	-0.72	-0.81	-1.66	-0.98	-0.27	-0.90
Cust Conc	-0.002	0.002	0.004	0.004	0.000	0.004	-0.003	-0.001
	-1.61	-1.14	-1.23	-1.45	-0.59	-1.85	-1.12	-0.55
Supp Conc	0.007***	0.008***	0.005	0.004	0.000	0.000	-0.001	-0.001
	-5.86	-3.68	-1.12	-1.56	-0.07	-0.03	-0.61	-0.3
cons	0.001	-0.005	-0.003	-0.012*	-0.020*	0.002	0.003	0.009
	-0.28	-1.03	-0.31	-2.52	-2.38	-0.34	-0.47	-1.86
Rsq	3.9%	6.1%	10.3%	7.5%	3.7%	10.1%	15.1%	16.5%

Table 6.7: Average slopes (t-statistics) from monthly regressions of log excess returns on Beta, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *Four sets of portfolio tests are formed. Each set is formed yearly by sorting on one of the following measures of exposure to transmitted volatility: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta	-0.005	-0.004	-0.003	-0.004	-0.005	-0.004	-0.006	-0.007
	-1.43	-1.01	-0.86	-1.25	-1.38	-0.99	-1.48	-1.71
Size	0.000***	0.000*	0.000	0.000*	0.000***	0.000	0.000	0.000
	-4.51	-2.34	-1.86	-2.52	-5.41	-0.96	-0.25	-0.90
BTM	0.001	0.003*	0.003	0.004**	0.001*	-0.001	-0.001	0.003*
	-1.61	-1.99	-1.87	-2.66	-2.03	-0.5	-0.44	-2.02
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.34	-0.87	-0.44	-1.19	-0.66	-0.59	-0.52	-0.56
Profit	0.002***	0.001	0.001	0.001	0.002***	0.000	0.001	0.002*
	-4.19	-0.49	-1.08	-1.52	-3.96	-0.4	-0.62	-2.52
Cust Deg	-0.007*	0.003	0.000	0.002	0.000	-0.002	0.008	-0.005*
	-2.00	-1.95	-0.15	-0.72	-0.30	-0.75	-1.23	-2.05
Supp Deg	0.000	0.002	-0.004	-0.002	0.013	0.000	0.001	0.005
	-0.09	-0.69	-1.65	-1.22	-1.66	-0.57	-0.38	-1.23
Cust Conc	-0.002	0.002	0.001	0.002	0.000	0.000	-0.003	0.003
	-1.61	-0.52	-0.41	-1.21	-0.59	-0.15	-1.03	-1.57
Supp Conc	0.007***	0.003	0.008**	0.007***	0.000	0.000	-0.004	0.000
	-5.86	-1.02	-2.93	-3.58	-0.07	-0.10	-1.59	-0.05
cons	0.001	-0.015**	-0.004	-0.008	-0.020*	0.009	0.002	0.001
	-0.28	-3.07	-0.64	-1.67	-2.38	-1.80	-0.23	-0.19
Rsq	3.9%	7.9%	7.6%	6.1%	3.7%	16.2%	17.0%	9.8%

Robustness checks I tested whether the risk premia on the transmitted volatility measures was still significant after

- Using market beta estimated from past 24 months data only, rather than full sample period (i.e. this is an out-of-sample test)
- Using untransformed excess returns (ER) as the response, rather than taking logs of ER
- Controlling for the 3 Fama French factors and aggregate volatility and idiosyncratic volatility.

The full results from the robustness checks are shown in Appendix 6.B and are summarized below in Tables 6.8 and 6.9.

The results show that the significant positive risk premia associated with the concentration of a firm's supplier-base is robust to the method of estimating market risk exposure (beta), transformation of the response and to the inclusion of other systematic risk factors and controls for market volatility and idiosyncratic volatility. This suggests that investors require higher expected returns on firms that are more exposed to counterparty risk along the supply chain, which is significant over and above premia for aggregate volatility and purely idiosyncratic volatility.

6.4.4 Time-series tests

To complement the cross-sectional tests, I also test the significance of economic linkage factors in explaining average stock returns over time. As explained in Section 6.2.2, it is not possible to fit (6.2) because the shocks transmitted to a firm from its suppliers and customers are not directly observable. It is possible, however, to observe the structure of economic linkages and to include measures of the structure of linkages alongside other pervasive factors (e.g. the three Fama French factors, or macroeconomic factors) in a time series model. That is, I fit

Table 6.8: Robustness checks of the main results. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. T-statistics are shown under the coefficients.*

	CUST DEG				**SUPP DEG**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Standard:								
Cust Deg	-0.007*	0.001	-0.004	0.001	0.000	-0.006*	0.006	-0.003
Supp Deg	0.000	-0.003	-0.005	0.002	0.013	0.005	-0.001	0.000
Cust Conc	-0.002	0.002	0.004	0.004	0.000	0.004	-0.003	-0.001
Supp Conc	0.007***	0.008***	0.005	0.004	0.000	0.000	-0.001	-0.001
Rolling 2 year beta:								
Cust Deg	-0.004	0.001	-0.003	0.000	-0.001	-0.002	0.006	0.000
Supp Deg	0.000	-0.004	0.000	0.002	0.004	0.009*	-0.002	0.000
Cust Conc	-0.002	0.000	0.000	0.001	0.000	0.001	-0.003	-0.003
Supp Conc	0.005***	0.005*	0.001	0.002	0.000	-0.002	-0.002	0.001
Untransformed returns:								
Cust Deg	-0.001	0.002	-0.003	0.000	0.001	-0.005	0.006	-0.003
Supp Deg	0.000	-0.001	-0.006	0.001	0.013	0.003	-0.001	0.000
Cust Conc	0.000	0.000	0.002	0.002	0.001	0.004	-0.002	0.000
Supp Conc	0.003*	0.004	0.003	0.001	-0.003	0.000	0.000	0.001
Full incl FF factors and volatility:								
Cust Deg	-0.003	0.002	-0.002	-0.001	0.000	-0.001	0.007	-0.001
Supp Deg	0.000	-0.002	-0.004	0.001	-0.003	0.007	-0.002	0.000
Cust Conc	0.000	-0.001	-0.002	-0.001	0.001	0.001	-0.003	-0.003
Supp Conc	0.002*	0.002	0.002	-0.001	0.000	-0.001	-0.001	0.002

Table 6.9: Robustness checks of the main results. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. T-statistics are shown under the coefficients.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Standard:								
Cust Deg	-0.007*	0.003	0.000	0.002	0.000	-0.002	0.008	-0.005*
Supp Deg	0.000	0.002	-0.004	-0.002	0.013	0.000	0.001	0.005
Cust Conc	-0.002	0.002	0.001	0.002	0.000	0.000	-0.003	0.003
Supp Conc	0.007***	0.003	0.008**	0.007***	0.000	0.000	-0.004	0.000
Rolling 2 year beta:								
Cust Deg	-0.004	0.001	0.000	0.002	-0.001	-0.001	0.006	-0.002
Supp Deg	0.000	0.002	-0.001	-0.003	0.004	0.000	0.000	0.008*
Cust Conc	-0.002	-0.002	-0.001	0.000	0.000	-0.001	-0.003	0.000
Supp Conc	0.005***	0.000	0.005	0.004*	0.000	0.001	-0.005	-0.002
Untransformed returns:								
Cust Deg	-0.001	0.000	-0.001	0.001	0.001	-0.003	0.008	-0.005
Supp Deg	0.000	0.001	-0.004	0.000	0.013	0.000	0.001	0.005
Cust Conc	0.000	0.002	0.000	0.001	0.001	0.001	-0.003	0.004
Supp Conc	0.003*	-0.001	0.005	0.003	-0.003	0.000	-0.004	0.000
Full incl FF factors and volatility:								
Cust Deg	-0.003	0.001	-0.001	0.001	0.000	-0.002	0.008	0.000
Supp Deg	0.000	0.003	-0.002	-0.001	-0.003	0.000	0.000	0.006
Cust Conc	0.000	-0.001	-0.003	-0.001	0.001	-0.001	-0.003	0.000
Supp Conc	0.002*	-0.004	0.003	0.001	0.000	0.002	-0.003	-0.001

the following time-series regression for each portfolio:

$$R_{p,t} = \alpha_p + \sum_{k=1}^{K} \beta_{p,k} F_{k,t} + \sum_{m=1}^{M} \beta_{p,m} X^m_{p,t-1} + b_{p,CONC} CONC_{p,t-1} + b_{p,DEG} DEG_{p,t-1} + \varepsilon_{p,t} \tag{6.6}$$

where R_{pt} is the excess return in portfolio p at time t; α_p is the time-fixed non-systematic premium for portfolio p; $\beta_{p,k}$ is portfolio p's loading on systematic factor $F_k \in \mathbf{F}$; $\beta_{p,m}$ is portfolio p's loading on firm characteristic $X^m_{p,t-1}$ e.g. $b_{p,CONC}$ is portfolio p's loading on the concentration of economic linkages $CONC_{p,t-1}$ and $b_{p,DEG}$ is portfolio p's loading on the degree of economic linkages $DEG_{p,t-1}$.

In each calendar year I match returns from July of year t to June of year $t+1$ with account information from year $t-1$ to ensure there is a minimum gap of 6 months between account measures and the returns they are used to explain. The following covariates ($X^m_{p,t-1}$) are constructed from account information: the degree and concentration of a firm's supplier and customer linkages, firm size, BTM, leverage, trade credit and profit.

As financial time-series may exhibit heteroscedasticity, auto-correlation and firm and/or time effects which may bias the estimates of the coefficient standard errors, I use standard error estimates that are robust to these issues[20].

The underlying return generating process corresponding to model (6.6) is shown in full in equation (6.4); in this specification the degree and concentration of linkages are firm characteristics that are assumed to directly influence expected returns. The results from the estimation of equation (6.6) are shown in Table 6.10. As a cross-check, I also estimate equation (6.6) including both the first and second lags of the degree and concentration of exposure to customers and suppliers. Linkages may have contemporaneous effects on cash-flow (and hence asset prices) if shock transmission is fast. However, if shocks take several months to transmit along supply chains or stock prices take time to adjust (as found

[20] White (1982) proposed estimates of s.e.s robust to heteroscedasticity. The version of the White (1982) estimator implemented in STATA (the 'Huber White sandwich estimator') is also robust to autocorrelation and firm-effects.

in Cohen and Frazzini (2008)) then lagged linkage measure should be included in the regression. As the linkage measures are constructed from annual account figures, they are lagged 12 months in the regression. The results including both the first and second lags of supply chain exposure are shown in Appendix 6.C.

The main finding is that increasing the concentration of exposure to upstream or downstream counterparties reduces returns over the long term. That is, the significant negative coefficients on the proxies for concentration of supplier and/or customer linkages indicate that firms with highly concentrated supplier and/or customer linkages have lower long term returns than firms with less concentrated supplier and/or customer linkages. Secondly, unlike the CAPM and APT models fit in Section 6.4.2, the intercept of the time-series model (6.6) equals zero for most portfolios. This implies that the inclusion of linkages, volatility and/or firm characteristics is necessary to meet the requirements of APT.

Discussion of results and comparison to other studies The finding that increasing the concentration of exposure to upstream or downstream counterparties reduces returns over the long term is consistent with the positive contemporaneous risk premium found above[21] and also with the theory in Chapter 3 showing that returns may be influence by shocks transmitted via economic linkages.

In addition, the estimated coefficients for all parameters are consistent with published studies. The Fama French factor coefficients (β_{SMB} and β_{HML}) reveal a negative loading on SMB (small minus big) and HML (high BTM ratio minus low BTM ratio) for each year. This result implies that large growth companies heavily influenced the returns of these portfolio during the study period, consistent with evidence presented in Cai and Houge (2008). The results show a small negative size effect, consistent with many studies (see Crain (2011) for a review). As in Fama and French (1989), Schwert (1990) and Fraser (1995), the results show excess returns are positively related to the term spread. Regarding

[21] As increasing current period required return creates downward pressure on prices which lowers the long term return of an investor who purchased the stock before the risk premium (or supply chain concentration) increased.

Table 6.10: Time series regressions of excess returns on systematic factors, firm characteristics, linkage measures and volatility for portfolios sorted on the **degree** of exposure to customers and suppliers. **,**,*** indicate significance at the* $p < .05$, $p < .01$, $p < .001$ *levels. T-statistics are shown under the coefficients.*

	CUST DEG				SUPP DEG			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
MktRF	1.000***	1.062***	1.130***	1.130***	1.015***	1.131***	1.124***	1.075***
	-127.740	-53.990	-44.730	-43.360	-135.270	-44.360	-33.700	-31.740
SMB	0.006***	0.007***	0.007***	0.008***	0.007***	0.005***	0.003***	0.001
	-68.190	-30.050	-22.950	-27.030	-83.460	-15.580	-7.180	-1.490
HML	0.003***	0.003***	0.002***	0.002***	0.003***	0.002***	0.002***	0.001
	-30.840	-9.420	-5.670	-5.830	-32.300	-6.410	-4.900	-1.960
Size	-0.000***	-0.000*	-0.000**	-0.000**	-0.000***	-0.000***	-0.000***	-0.000**
	-5.570	-2.400	-2.850	-2.700	-7.440	-5.020	-3.820	-3.180
BTM	0.003	0.005	0.006**	0.000	0.000	0.000	0.009*	0.015***
	-1.470	-1.840	-3.040	-0.270	-0.850	-0.020	-2.030	-4.080
Bid Ask	0.003***	0.003	0.008*	0.014***	0.004***	0.001	0.009**	0.001
	-3.670	-1.020	-2.260	-4.400	-5.240	-1.480	-2.680	-0.760
Leverage	0.000***	0.000	0.000	0.000	0.000***	0.000	0.000	0.000
	-8.800	-1.270	-0.790	-1.630	-5.090	-0.190	-1.380	-1.430
Trade Cred	0.000	0.000	0.001	0.000	0.000	0.004*	-0.015	0.002
	-0.820	-1.000	-0.920	-0.190	-0.240	-2.320	-1.270	-0.520
Profit	0.007***	0.007**	0.005	0.011**	0.008***	0.002	0.005	0.008*
	-6.130	-2.800	-0.930	-3.290	-7.360	-0.610	-1.120	-2.040
Cust Deg	-0.005	0.003	-0.004	-0.002	-0.003*	-0.003	0.006	-0.001
	-1.350	-0.670	-0.860	-1.010	-2.360	-0.760	-1.200	-0.450
Supp Deg	-0.001	-0.008*	-0.006	0.001	0.000	0.005	-0.002	-0.001
	-0.960	-2.460	-1.550	-0.350	-0.060	-0.980	-0.510	-1.550
Cust Conc	0.006***	-0.008***	-0.006	0.005	0.001	-0.002	-0.002	-0.001
	-3.820	-4.380	-1.650	-1.290	-1.430	-0.720	-0.480	-0.380
Supp Conc	-0.002*	-0.008*	0.000	-0.008*	-0.003	-0.007***	-0.004	0.000
	-2.430	-2.570	-0.070	-2.260	-1.530	-3.460	-1.250	-0.060
D.Var(Rm)	-32.266***	-34.569***	-32.299***	-30.173***	-34.269***	-25.351***	-16.511***	-5.514
	-29.770	-11.830	-9.400	-7.530	-32.870	-6.840	-4.460	-1.460
L.Var(Rm)	-0.668***	-1.287*	-2.159***	-2.284**	-0.482**	-0.364	-2.425***	-2.269***
	-3.480	-2.370	-3.360	-3.250	-3.010	-0.600	-3.800	-4.710
D.Var(Ri)	5.907***	6.870***	6.414***	5.490***	6.125***	4.275***	3.631***	1.675
	-39.580	-21.550	-14.050	-13.090	-49.100	-6.060	-3.710	-0.850
L.Var(Ri)	0.040	0.136*	0.259***	0.092	0.050**	-0.024	0.263	0.271
	-1.780	-2.530	-3.320	-1.350	-2.760	-0.210	-1.840	-1.800
Cons	-0.016***	-0.014	-0.010	-0.028***	-0.019*	-0.003	-0.013	-0.012
	-4.120	-1.800	-1.130	-4.160	-2.480	-0.470	-1.110	-1.630
Rsq	12.8%	14.5%	17.3%	14.6%	13.1%	16.4%	17.6%	18.9%

Table 6.11: Time series regressions of excess returns on systematic factors, firm characteristics, linkage measures and volatility for portfolios sorted on the **concentration** of exposure to customers and suppliers. $^{*}, ^{**}, ^{***}$ *indicate significance at the* $p < .05$, $p < .01$, $p < .001$ *levels. T-statistics are shown under the coefficients.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
MktRF	1.000***	1.062***	1.130***	1.130***	1.015***	1.131***	1.124***	1.075***
	-127.740	-53.990	-44.730	-43.360	-135.270	-44.360	-33.700	-31.740
SMB	0.006***	0.007***	0.007***	0.008***	0.007***	0.005***	0.003***	0.001
	-68.190	-30.050	-22.950	-27.030	-83.460	-15.580	-7.180	-1.490
HML	0.003***	0.003***	0.002***	0.002***	0.003***	0.002***	0.002***	0.001
	-30.840	-9.420	-5.670	-5.830	-32.300	-6.410	-4.900	-1.960
Size	-0.000***	-0.000*	-0.000**	-0.000**	-0.000***	-0.000***	-0.000***	-0.000**
	-5.570	-2.400	-2.850	-2.700	-7.440	-5.020	-3.820	-3.180
BTM	0.003	0.005	0.006**	0.000	0.000	0.000	0.009*	0.015***
	-1.470	-1.840	-3.040	-0.270	-0.850	-0.020	-2.030	-4.080
Bid Ask	0.003***	0.003	0.008*	0.014***	0.004***	0.001	0.009**	0.001
	-3.670	-1.020	-2.260	-4.400	-5.240	-1.480	-2.680	-0.760
Leverage	0.000***	0.000	0.000	0.000	0.000***	0.000	0.000	0.000
	-8.800	-1.270	-0.790	-1.630	-5.090	-0.190	-1.380	-1.430
Trade Cred	0.000	0.000	0.001	0.000	0.000	0.004*	-0.015	0.002
	-0.820	-1.000	-0.920	-0.190	-0.240	-2.320	-1.270	-0.520
Profit	0.007***	0.007**	0.005	0.011**	0.008***	0.002	0.005	0.008*
	-6.130	-2.800	-0.930	-3.290	-7.360	-0.610	-1.120	-2.040
Cust Deg	-0.005	0.003	-0.004	-0.002	-0.003*	-0.003	0.006	-0.001
	-1.350	-0.670	-0.860	-1.010	-2.360	-0.760	-1.200	-0.450
Supp Deg	-0.001	-0.008*	-0.006	0.001	0.000	0.005	-0.002	-0.001
	-0.960	-2.460	-1.550	-0.350	-0.060	-0.980	-0.510	-1.550
Cust Conc	0.006***	-0.008***	-0.006	0.005	0.001	-0.002	-0.002	-0.001
	-3.820	-4.380	-1.650	-1.290	-1.430	-0.720	-0.480	-0.380
Supp Conc	-0.002*	-0.008*	0.000	-0.008*	-0.003	-0.007***	-0.004	0.000
	-2.430	-2.570	-0.070	-2.260	-1.530	-3.460	-1.250	-0.060
D.Var(Rm)	-32.266***	-34.569***	-32.299***	-30.173***	-34.269***	-25.351***	-16.511***	-5.514
	-29.770	-11.830	-9.400	-7.530	-32.870	-6.840	-4.460	-1.460
L.Var(Rm)	-0.668***	-1.287*	-2.159***	-2.284**	-0.482**	-0.364	-2.425***	-2.269***
	-3.480	-2.370	-3.360	-3.250	-3.010	-0.600	-3.800	-4.710
D.Var(Ri)	5.907***	6.870***	6.414***	5.490***	6.125***	4.275***	3.631***	1.675
	-39.580	-21.550	-14.050	-13.090	-49.100	-6.060	-3.710	-0.850
L.Var(Ri)	0.040	0.136*	0.259***	0.092	0.050**	-0.024	0.263	0.271
	-1.780	-2.530	-3.320	-1.350	-2.760	-0.210	-1.840	-1.800
Cons	-0.016***	-0.014	-0.010	-0.028***	-0.019*	-0.003	-0.013	-0.012
	-4.120	-1.800	-1.130	-4.160	-2.480	-0.470	-1.110	-1.630
Rsq	12.8%	14.5%	17.3%	14.6%	13.1%	16.4%	17.6%	18.9%

the relationship between market volatility and returns, and firm-level volatility and returns: Campbell and Hentschel (1992); Bekaert and Wu (2000) also find a negative relationship between market volatility and realized returns, while Duffee (1995) also finds a negative relationship between firm-level volatility and realized returns.

Returns data are very noisy and the predictive R^2 values tend to be low (Timmermann and Granger, 2004). The R^2 of the models is in the order of 10% to 15%. This is reasonable predictive power in comparison to other firm-level studies such as Ang, Liu, and Schwarz (2008) and Pavlov, Bauer, and Schotman (2004)[22].

Recession periods

Theory suggests that the relationship between linkages and returns is likely to shift across economic regimes. Bekaert and Wu (2000) note that volatility feedback at the firm-level is stronger if covariances respond asymmetrically to shocks. Many empirical studies of financial contagion have noted that covariance between asset returns tend to increase in crisis periods (see Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005) for a review). Although models of financial contagion focus on unobservable linkages between assets and/or markets, the covariance created by observable supply links should also to increase in crisis periods because supply linkages to be more influential in a recessions(Lang and Stulz, 1992). That is, suppliers and customers are harder to replace when the economy is in recession[23].

To empirically test whether the relationship between customer and supplier link-

[22] The R^2 should be compared to firm-level studies because R^2 is usually higher in portfolio based studies of returns because aggregation usually averages out some variation which cannot be explained by the model, resulting in higher R^2 values than comparable firm-level studies. As portfolio studies generally have a higher level of R^2 than firm-level studies(Reisinger, 1997), the R^2 of model (6.6) should be compared to similar firm-level studies.

[23] Similarly in studies of default contagion, it has been shown that shocks are more likely to spread between suppliers and customers when the respective counterparty cannot be replaced, for example, because the market as a whole is depressed (Lang and Stulz, 1992; Jorion and Zhang, 2009). Both Lang and Stulz (1992); Jorion and Zhang (2009) find empirical evidence that default contagion is stronger in recessions or when an entire industry is in distress.

ages and returns is different in recession periods to expansion periods, I estimate (6.6) over NBER recession periods. The results indicate that her the risk premia attached to transmitted volatility is only present in certain stages of the business cycle.

To test this hypothesis I run the same regressions above over pooled data from all of the NBER recession periods between 1990 and 2010, and the test whether the coefficients for the supply chain factors are significantly different in the recession regimes versus the full period. The NBER contraction and expansion periods are listed in Table 6.12 In the period 1990 to 2010 there were three recession periods

Table 6.12: NBER US Business Cycle, Expansion and Contraction dates. *Contractions are peak to trough, expansions are trough to following peak. Available at: www.nber.org/cycles.html*

Peak	Trough	Contraction (months)	Expansion (months)
July 1981	November 1982	16	12
July 1990	March 1991	8	92
March 2001	November 2001	8	120
December 2007	June 2009	18	73

noted by NBER. The first two of these were only 8 months long, the third was 18 months long. The results from estimation of model (6.6) over these recession periods are shown in Tables 6.13 and 6.14.

The results of the regressions in recession periods versus the full sample period (mainly comprised of expansions) illustrate that economic linkages (i.e. Supp Deg and Conc, Cust Deg and Conc) have a different affect on returns in contraction versus expansion periods. The main results can be seen by comparing the magnitude of the coefficients for the Supplier and Customer degree and concentration measures in Tables 6.13 and 6.14 to the corresponding results in Tables 6.10 and 6.11. On average, the coefficients on the degree and concentration of supplier linkages are more negative in the recession periods (Tables 6.13 and 6.14) than in the full period regressions (Tables 6.10 and 6.11); however the magnitude of this

Table 6.13: Time series regressions of excess returns on systematic factors, firm characteristics, linkage measures and volatility for portfolios sorted on the **degree** of exposure to customers and suppliers in **recession periods**. *,**,*** *indicate significance at the* $p < .05$, $p < .01$, $p < .001$ *levels. T-statistics are shown under the coefficients.*

	CUST DEG				SUPP DEG			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
MktRF	1.086***	1.187***	1.205***	1.214***	1.104***	1.196***	1.163***	1.120***
	-69.23	-25.17	-24.34	-21.71	-73.59	-22.12	-17.11	-20.90
SMB	0.005***	0.006***	0.006***	0.007***	0.005***	0.005***	0.005***	0.002
	-18.42	-7.31	-6.51	-7.69	-21.03	-5.60	-4.29	-1.82
HML	0.002***	0.000	0.001	0.001	0.002***	0.001	0.000	0.000
	-7.59	-0.49	-1.43	-0.84	-7.70	-1.51	-0.47	-0.19
Size	-0.000**	-0.000*	0.000	0.000	-0.000***	0.000	0.000	0.000
	-2.62	-2.16	-1.02	-1.22	-4.70	-1.96	-0.23	-1.45
BTM	0.002	0.005	0.009	0.000***	0.000***	-0.010	-0.022	0.022
	-0.91	-0.35	-1.71	-9.67	-3.73	-0.87	-1.21	-1.48
BidAsk	0.001	-0.001	0.006	0.021*	0.001	0.000	0.016*	0.000
	-1.57	-0.72	-0.78	-2.42	-0.87	-0.53	-2.42	-0.28
Leverage	0.000	0.000	-0.000**	0.001	0.000	-0.001	-0.001*	0.000
	-0.95	-0.05	-3.21	-1.43	-0.89	-1.70	-2.02	-0.18
Trade Cred	0.000	-0.017	0.016	-0.000**	0.000	-0.020	0.002	-0.031
	-1.58	-1.53	-1.14	-2.83	-0.53	-1.54	-0.04	-0.48
Profit	0.005*	0.028*	0.009	0.028	0.009**	-0.001	0.036	0.003
	-2.08	-2.52	-0.55	-1.90	-3.17	-0.55	-1.16	-0.22
Cust Deg	-0.025	0.010	-0.029	-0.006	-0.008	0.008	-0.004	-0.015**
	-1.89	-0.48	-1.17	-0.68	-1.43	-0.39	-0.10	-2.78
Supp Deg	-0.001	-0.015	-0.015	0.009	-0.016	0.022	-0.050*	-0.002
	-0.33	-0.97	-0.68	-0.84	-0.38	-0.64	-2.04	-1.20
Cust Conc	0.020**	-0.007	-0.032	0.015	0.007	-0.032	-0.005	-0.008
	-2.75	-0.63	-1.77	-0.71	-1.61	-1.81	-0.14	-0.49
Supp Conc	-0.002	-0.030*	0.005	-0.017	0.005	-0.018	0.033	-0.040
	-0.47	-2.14	-0.27	-0.69	-0.42	-1.49	-1.94	-1.39
D.Var(Rm)	-59.589***	-52.239***	-43.963***	-51.531***	-61.185***	-61.527***	-24.234*	-15.874
	-16.11	-5.37	-4.13	-3.87	-17.56	-4.45	-1.98	-1.70
L.Var(Rm)	3.124***	-4.183	-2.186	-6.353*	3.722***	-3.370	-7.925*	-4.957*
	-4.29	-1.84	-0.81	-2.18	-5.36	-0.80	-2.31	-2.17
D.Var(Ri)	4.211***	4.808***	4.119**	5.575***	4.580***	3.672	-1.659	0.742
	-8.10	-3.94	-2.74	-3.94	-10.13	-1.71	-0.44	-0.21
L.Var(Ri)	0.291**	0.786**	0.491	0.480	0.246***	0.591	1.375	1.082*
	-3.11	-3.16	-1.48	-1.48	-3.50	-0.78	-1.61	-2.08
cons	-0.005	-0.034	0.034	-0.048	-0.010	-0.004	0.015	0.034
	-0.35	-1.07	-0.73	-1.56	-0.23	-0.09	-0.24	-1.08
Rsq	20.7%	22.7%	23.0%	23.1%	20.7%	26.4%	27.0%	30.3%

Table 6.14: Time series regressions of excess returns on systematic factors, firm characteristics, linkage measures and volatility for portfolios sorted on the **degree** of exposure to customers and suppliers in **recession periods**. *,**,*** *indicate significance at the* $p < .05$, $p < .01$, $p < .001$ *levels. T-statistics are shown under the coefficients.*

	CUST CONC				SUPP CONC			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
MktRF	1.086***	1.247***	1.229***	1.155***	1.104***	1.162***	1.107***	1.200***
	-69.23	-21.73	-23.12	-25.84	-73.59	-22.52	-15.13	-22.91
SMB	0.005***	0.007***	0.006***	0.006***	0.005***	0.001	0.004***	0.005***
	-18.42	-7.39	-6.73	-7.41	-21.03	-1.62	-4.07	-5.95
HML	0.002***	0.000	0.002	0.001	0.002***	-0.001	0.001	0.001
	-7.59	-0.51	-1.90	-1.19	-7.70	-0.81	-1.01	-1.55
Size	-0.000**	-0.000**	0.000	-0.000**	-0.000***	0.000	0.000	0.000
	-2.62	-2.70	-0.17	-2.85	-4.70	-1.45	-0.47	-1.89
BTM	0.002	0.000***	0.009	0.007	0.000***	0.005	-0.025	-0.005
	-0.91	-10.27	-1.62	-0.60	-3.73	-0.32	-1.58	-0.39
BidAsk	0.001	0.019*	0.006	-0.001	0.001	0.000	0.017*	0.000
	-1.57	-2.31	-0.72	-0.55	-0.87	-0.44	-2.27	-0.57
Leverage	0.000	0.001	-0.000***	0.000	0.000	0.000	0.000	-0.001
	-0.95	-1.46	-3.49	-0.08	-0.89	-0.33	-0.54	-1.45
Trade Cred	0.000	-0.000*	0.016	-0.017	0.000	-0.049	0.066	-0.021
	-1.58	-2.37	-1.09	-1.49	-0.53	-0.87	-0.90	-1.57
Profit	0.005*	0.015	0.026	0.023*	0.009**	0.009	0.046	-0.001
	-2.08	-1.04	-1.30	-2.20	-3.17	-0.65	-1.06	-0.31
Cust Deg	-0.025	-0.003	-0.018	0.015	-0.008	-0.010**	-0.029	0.004
	-1.89	-0.31	-0.85	-0.80	-1.43	-2.87	-0.79	-0.17
Supp Deg	-0.001	0.021	-0.019	-0.018	-0.016	-0.001	-0.023	-0.003
	-0.33	-1.71	-1.12	-1.54	-0.38	-0.61	-1.03	-0.1
Cust Conc	0.020**	-0.002	-0.021	-0.009	0.007	-0.002	0.028	-0.047
	-2.75	-0.09	-1.10	-0.78	-1.61	-0.16	-1.36	-1.83
Supp Conc	-0.002	-0.004	-0.022	-0.026	0.005	0.010	0.022	-0.011
	-0.47	-0.23	-0.70	-1.87	-0.42	-0.34	-1.19	-0.97
D.Var(Rm)	-59.589***	-57.227***	-38.278***	-51.028***	-61.185***	-10.887	-32.203*	-58.582***
	-16.11	-4.42	-3.32	-5.47	-17.56	-1.26	-2.29	-4.45
L.Var(Rm)	3.124***	-8.034**	-2.358	-3.506	3.722***	-6.030**	-6.809	-4.231
	-4.29	-2.65	-0.84	-1.66	-5.36	-2.94	-1.68	-1.07
D.Var(Ri)	4.211***	6.695***	3.009	4.615***	4.580***	-0.333	-0.949	3.396
	-8.10	-5.02	-1.86	-3.78	-10.13	-0.09	-0.24	-1.57
L.Var(Ri)	0.291**	0.512	0.550	0.763**	0.246***	1.494***	0.820	0.567
	-3.11	-1.45	-1.73	-3.10	-3.50	-4.15	-0.76	-0.80
cons	-0.005	-0.041	0.001	-0.032	-0.010	0.006	-0.014	0.025
	-0.35	-1.29	-0.03	-1.08	-0.23	-0.19	-0.18	-0.61
Rsq	20.7%	23.4%	23.5%	22.2%	20.7%	32.3%	25.3%	26.2%

difference is small and far less noticeable than the increased sensitivity of returns to the volatility of the market (Var(Rm)) in recession periods.

Wald tests are used to check whether the coefficients for the degree and concentration of supplier and customer linkages (Supp deg, Supp conc, Cust deg and Cust conc) are equal in recession periods and in the full period regressions. That is, I test the following hypothesis:

$$H_0 : \beta^- = \beta^+$$

vs.

$$H_A : \beta^- \neq \beta^+.$$

The results are summarized in Table 6.15. In about one quarter of cases the

Table 6.15: The p-values from Wald tests comparing the coefficients from a regression of excess returns on Supplier degree, Customer degree, Supplier concentration and Customer concentration.

	P1,1	**P1,2**	**P1,3**	**P1,4**
Supp deg	0.731	0.608	0.572	0.617
Cust deg	0.000	0.032	0.291	0.371
Cust conc	0.063	0.449	0.601	0.879
Supp conc	0.549	0.822	0.722	0.631
	P2,1	**P2,2**	**P2,3**	**P2,4**
Supp deg	0.000	0.888	0.117	0.735
Cust deg	0.948	0.548	0.059	0.926
Cust conc	0.261	0.229	0.339	0.065
Supp conc	0.110	0.145	0.766	0.229
	P3,1	**P3,2**	**P3,3**	**P3,4**
Supp deg	0.731	0.110	0.996	0.596
Cust deg	0.000	0.479	0.053	0.067
Cust conc	0.063	0.288	0.458	0.511
Supp conc	0.549	0.676	0.827	0.857
	P4,1	**P4,2**	**P4,3**	**P4,4**
Supp deg	0.000	0.957	0.189	0.855
Cust deg	0.948	0.387	0.002	0.587
Cust conc	0.261	0.253	0.459	0.031
Supp conc	0.110	0.974	0.084	0.123

coefficients on the economic linkage factors in recession periods are significantly greater than the corresponding coefficients in the full period. This provides weak support for the hypothesis that the transmission of idiosyncratic risk through economic linkages is stronger in recessions.

6.4.5 Macroeconomic factor models

As a final set of cross-checks on the results, I fit a macroeconomic specification of model (6.6) in which the systematic risk factors (MktRF, SMB and HML) are replaced with macroeconomic risk factors. This model is fit to firm-level data and the response is the excess return on individual securities rather than portfolio excess returns. Consistent with findings in Bekaert and Hodrick (1992) and Aretz, Bartram, and Pope (2010), the macroeconomic factors that have been shown to explain returns are:

- Excess return on the S&P 500 index (from Kenneth French's website)
- The average market dividend yield on the S&P 500 index (from Robert Schiller's website)
- The term spread, defined as the difference between the 10-year, constant maturity, Treasury bond rate (series GS10 from the Federal Reserve Board website) and the 1-month Treasury bill rate (from Ibbotson Associates).)

I replace the three Fama French factors with these macroeconomic factors and estimate model (6.6) at the firm-level. I use estimators that are robust to firm and time effects, as well as to endogeneity (described in detail in Appendix 6.D). The Hausman test (p=0.000) showed that the firm effect was a fixed effect, rather than a random effect. Industry effects were not significant in any specification, so although they were controlled for, they have been left out of the table above, and left out of future regressions.

In addition to the covariates included in the time series regressions in Table 6.11, I include lagged systematic factors and interactions between the market return (MktRF) and the linkage measures. The interaction terms can be interpreted as the effects of transmitted systematic shocks separate from transmitted idiosyncratic shocks. That is, in specifications where the interaction of l and f_k is included, the co-efficient of l is the effect of l when $f_k = 0$, the coefficient of f_k represents the effect of f_k when $l = 0$ and the coefficient of $l * f_k$ is the effect of l for a one unit increase in f_k. When f_k is the market return, the co-efficient of $l * f_k$ can be interpreted as the extent to which linkages amplify (or dampen) macroeconomic risk.

The results provide strong support for two findings. First, measures of the degree and the concentration of economic linkages interact with market returns and amplify market shocks. For example, the market beta, β_{MktRF}, is 0.89, the coefficient on $Mkt * CLdeg.$ is 0.14 so when the underlying firm adds an additional key customer, exposure of its stock returns to market risk ($\beta_{MktRF} + \beta_{Mkt*CLdeg.}$) increases 15% from 0.89 to 1.03. The interaction of forward and customer linkages (supplier and customer linkages) and market risk is highly significant in all models, implying that linkages transmit market shocks. The positive coefficients suggest that customer linkages are a procyclical force i.e. a firm with more 'key customers' will be affected more strongly by market movements[24] as linkages amplify the effects of market shocks on returns. Second, the observable (last account figure) concentration of supplier linkage (L.SL conc) is negatively related to excess returns. This implies that as the concentration of a firm's supplier linkages (supplier-base) increases, its stock returns decrease. Over the long-run, the returns for firms with concentrated supplier-bases are lower on average than stocks issued by firms with less concentrated supplier bases.

The consistency of the time-series results across all three estimates is evidence that the results are robust to clustering through time and across firms. Thompson (2011) shows that in panels where N is larger than T, clustering by time is sufficient and the increase in bias from failing to cluster also by firm is small. For this reason, the second column above shows the results of the panel fixed effects model with the robust standard error correction proposed by Driscoll and Kraay

[24] This is potentially because suppliers are unable to pass on price rises (as in theories of cost-push inflation (Seelig, 1974)) when their customers dominate the buyers market for their goods and services.

Table 6.16: Log excess returns, macroeconomic factors and supply linkages. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

		Panel: Huber White (1982)	Panel: Driscoll and Kraay (1998)	Panel GMM: Schaffer (2010)
Macro factors	MktRF	0.886***	0.886***	0.886***
		(27.57)	(11.61)	(44.97)
	DivYield	-2.135***	-2.135	-2.135***
		(-10.45)	(-1.04)	(-10.73)
	spread	2.778***	2.778	2.778***
		(13.33)	(1.00)	(13.75)
Linkage factors	CL deg	0.00	0.00	0.00
		(-0.98)	(-0.99)	(-1.11)
	SL deg	0.00	0.00	0.00
		(1.10)	(1.08)	(1.34)
	CL conc	0.00	0.00	0.00
		(-1.10)	(-1.05)	(-1.20)
	SL conc	0.00	0.00	0.00
		(-0.22)	(-0.23)	(-0.24)
Interactions	Mkt*CLdeg	0.137***	0.137***	0.137***
		(4.67)	(6.28)	(7.53)
	Mkt*SLdeg	-0.013**	-0.013*	-0.013***
		(-2.83)	(-2.18)	(-4.93)
	Mkt*CLconc	0.102***	0.102***	0.102***
		(4.71)	(5.30)	(7.05)
	Mkt*SLconc	0.073**	0.073*	0.073***
		(2.89)	(2.57)	(4.88)
Firm controls	Size	-0.000***	-0.000*	-0.000***
		(-4.32)	(-2.23)	(-7.51)
	BTM	0.00	0.00	0.000*
		(0.75)	(1.39)	(1.98)
	Leverage	0.000***	0.000*	0.00
		(5.13)	(2.33)	(1.72)
	Trade Credit	0.00	0.00	0.00
		(-0.22)	(-0.21)	(-0.16)
	Profit	0.006***	0.006***	0.006***
		(7.03)	(7.48)	(10.47)
Lagged macro	L.MktRF	0.00	0.00	0.00
		(-0.74)	(-0.07)	(-0.73)
	L.DivYield	1.779***	1.779	1.779***
		(8.91)	(0.86)	(8.81)
	L.spread	1.559***	1.559	1.559***
		(8.77)	(0.78)	(8.83)
Lagged linkage	L.CL deg	0.00	0.00	0.00
		(-0.54)	(-0.68)	(-0.59)
	L.SL deg	-0.002	-0.002*	-0.002*
		(-1.75)	(-1.98)	(-2.40)
	L.CL conc	0.00	0.00	0.00
		(0.31)	(0.36)	(0.33)
	L.SL conc	-0.003**	-0.003***	-0.003**
		(-2.84)	(-3.35)	(-3.17)
Volatility	D.σ_M^2	-35.175***	-35.175**	-35.175***
		(-36.37)	(-2.89)	(-36.32)
	L.σ_M^2	-1.823***	-1.823	-1.823***
		(-7.84)	(-0.79)	(-8.04)
	D.σ_i^2	6.087***	6.087***	6.087***
		(50.27)	(4.94)	(48.45)
	L.σ_i^2	0.092***	0.092	0.092***
		(5.36)	(1.23)	(5.69)
	R^2	11.1%	12.0%	12.0%

(1998), which controls for heteroscedasticity, autocorrelation and time effects in the errors. The results from this estimator are very close to the Panel fixed effects model with Huber White (1982) adjusted standard errors (which only control for heteroscedasticity and autocorrelation). This implies that the time effects in the error term are not strong. Finally the results from the instrumental variable regression estimated by GMM are also consistent with the other models, suggesting that endogeneity is not a significant problem.

Volatility decomposition

A useful way of examining the estimation results from model (6.6) is to consider the contribution that each factor makes to total volatility of returns. Under the assumption that the factors in the model are independent, it is possible to decompose the variance of excess returns as follows

$$Var(y_i) = \sum_{k=1}^{K} \beta_{i,k}^2 Var(F_k) + Var(\varepsilon_i). \tag{6.7}$$

This is one way to quantify the relative importance of macroeconomic factors, firm-level characteristics, transmitted volatility (linkages) and other volatility. The full time-series model (6.6) was fit over all firms, in order to approximate the proportion of the total return volatility explained by each group of covariates. The results of the volatility decomposition are shown below.

This table illustrates that linkage factors primarily influence returns via their

Table 6.17: Volatility decomposition of time-series model shown in Table 6.16.

Volatility decomposition	
Macro factors	7.89%
Macro volatility	0.30%
Linkage factors: direct	0.02%
Linkage factors: interactions	0.25%
Firm characteristics	0.15%
Firm volatility	2.21%
Model SS (R^2)	**10.84%**
Residual SS	**89.16%**

interaction with market returns. In this respect, the proportion of variation in returns explained by market risk passed through linkages (0.25%) is almost as important as volatility in the macroeconomic factors (0.30%), and is explains more variability in returns that the firm characteristics (0.15%).

6.4.6 Model specification and robustness checks

Tests for endogeneity

Given the evidence that the linkage betas may be non-normally distributed, it is important to check the regression residuals. Furthermore, it is possible that the linkage factors are simply acting as a proxy for a firm-specific covariate that is not included, e.g. size, as it is reasonable to hypothesize that the largest firms have the most suppliers. Omitted variables or simultaneity bias can create endogeneity which can might cause the regression results to be inconsistent. While including firm-specific covariates: size, profitability and leverage did not affect the findings, it is possible that latent factors (e.g. management strategy) simultaneously affect a firm's stock return and the firm's characteristics (size, profitability and leverage) included in (6.6) and (6.6). Therefore, as a precaution I perform two sets of tests for endogeneity.

First I plot the residuals of (6.6) and (6.6) versus predicted values. The residual plot for the 'macroeconomic' specification of (6.6) shown in Table 6.16 is shown in Figure 6.2. The graph suggests that the model residuals are distributed randomly about zero and are not correlated with the model covariates. The residual plot in figure 6.2 shows no trend between the residuals and the fitted values. The residuals are distributed randomly about zero. I also formally test whether the residuals are normally distributed, mean zero using the Jacque Bera test. Both the graph and the statistical tests suggest that the fixed effects model is correctly specified in the sense that $E(\varepsilon|\mathbf{f}, \mathbf{x}) = 0$.

As a second check that the results were robust to potential endogeneity I estimated model (6.6) with GMM estimation using one-year and two-year lagged terms as instrumental variables for the firm characteristics that are potentially

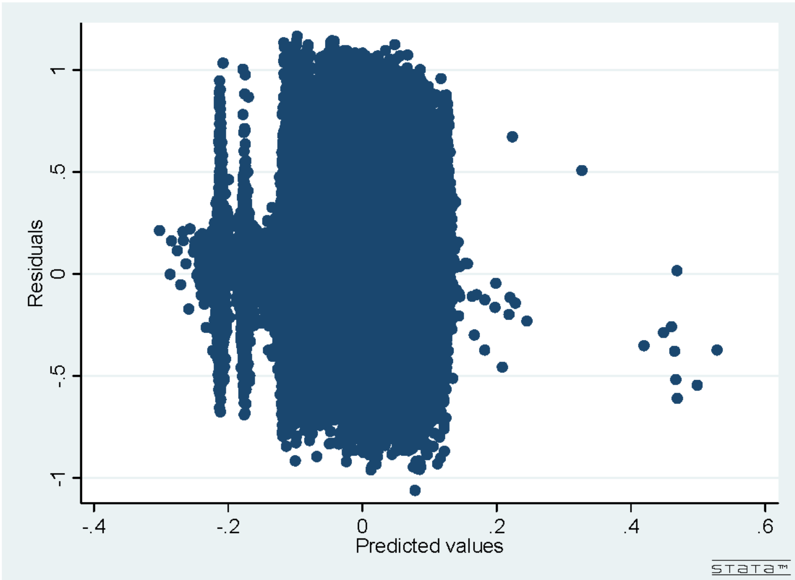

Figure 6.2: Residual plots from the time series regressions of excess returns on macroeconomic factors, firm characteristics, degree and concentration of exposure to customers and suppliers, and volatility.

endogenous (size, profitability and leverage). The use of lagged terms as instrumental variables is common practice in econometrics, and is correct so long as the lagged terms are not correlated with the response (Baum, Schaffer, and Stillman, 2003). The results of the GMM IV estimations (included in Appendix 6.D) show that the results in the original model are robust to potential endogeneity problems.

Dependent customer subsample

Regulation FAS No. 131 requires firms to report key customers (contributing at least 10% of total sales) but not major suppliers. This provides a direct measure of backward linkages, but not a direct measure of forward (supplier) linkages. In this work, I calculate the degree and concentration of forward (supplier) linkages by inverting the FAS No. 131 disclosures (or equivalently by taking the columns sums of the adjacency and Leontief matrices, **A** and **CS**, rather than the row sums). This method however, generates an incomplete sample of suppliers. As noted in Section 4.4, it is not necessarily the case that key customers are, conversely, reliant on the supplier. In addition, it is not necessarily the case that if a customer is reliant on a particular supplier, that the customer is a 'key customer' of the supplier (contributing at least 10% of the supplier's total sales).

I address this issue by using the ratio of supplier sales to a given customer to the customer's cost of goods sold, to identify 'dependent customers'. Customer firms in which the supplier sales received are a large proportion of total cost of goods sold should, all other things being equal, have cash flows more affected by shocks to these 'major' suppliers. I check the robustness of the return results on the sub-sample of co-dependent suppliers and customers, to ensure that the asymmetry in the supplier-customer dependence did not mean that the results above could not be generalized to the wider population of supplier and customer firms.

Table 6.18 contains the results of time-series regressions using a sub-sample of firms where customers depend upon suppliers for at least 5% of their total cost of goods sold (and suppliers depend on customers for at least 10% of their sales revenue). These results are consistent with the results for similar regressions using the full sample of firms. That is, the concentration of supplier linkages (SL conc and L.SL conc) is significant and is negative, while the concentration of customer linkages is not significant on its own. This implies that stock issued by firms with a more concentrated supplier-base have lower long term returns than stock issued by firms with less concentrated supplier bases. Furthermore, the interaction of supplier and customer linkages and market risk is highly significant in all models, implying that linkages transmit market shocks. These results confirm that the significance of forward linkage is not just an artifact of the data generating process.

Table 6.18: Regression results for the subsample of dependent customers. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

	(1)	(2)	(3)
	b/t	b/t	b/t
MktRF	0.011***	0.011***	0.011***
	(27.42)	(27.42)	(27.43)
DividendYield	-0.004***	-0.004***	-0.005***
	(-12.39)	(-11.13)	(-11.22)
spread	0.003***	0.002***	0.002***
	(11.43)	(6.42)	(6.52)
CL deg	-0.002	-0.002	-0.002
	(-1.74)	(-1.93)	(-1.46)
SL deg	-0.001**	-0.001	-0.001
	(-3.08)	(-1.85)	(-0.99)
CL conc	0.000	-0.001	-0.001
	(0.01)	(-1.16)	(-0.61)
SL conc	-0.002**	-0.003**	-0.001
	(-2.59)	(-2.72)	(-1.28)
Mkt* CL deg	0.001***	0.001**	0.001**
	(3.46)	(2.74)	(2.73)
Mkt* SL deg	-0.000***	-0.000***	-0.000***
	(-4.72)	(-4.64)	(-4.64)
Mkt*CL conc	0.001*	0.001*	0.001*
	(2.22)	(2.51)	(2.52)
Mkt*SL conc	-0.001	-0.001	-0.001
	(-1.88)	(-1.91)	(-1.91)
L.MktRF		-0.000**	-0.000**
		(-3.27)	(-3.27)
L.DividendYield	0.002***	0.002***	
		(4.54)	(4.50)
L.spread		-0.000	-0.000
		(-0.85)	(-0.81)
Leverage		-0.000	-0.000
		(-0.93)	(-0.93)
SaleTA		0.008***	0.008***
		(5.41)	(5.42)
Size		-0.000***	-0.000***
		(-5.25)	(-5.26)
L.CL deg			0.000
			(0.16)
L.SL deg			-0.000
			(-0.25)
L.CL conc			-0.001
			(-0.86)
L.SL conc			-0.003**
			(-2.82)
cons	0.039***	0.022***	0.023***
	(13.86)	(6.45)	(6.58)
R^2	0.118	0.121	0.121

Robust estimates and standard errors

If linkages are a source of non-diversifiable risk that are not included in (6.1), then market beta will be time varying. As (6.6) includes observable linkages, however, as the estimators used are robust to the effects of unobservable linkages, it is reasonable to assume constant betas in the FF time-series regressions. However, the Fama Macbeth tests provide a cross-check on this assumptions as coefficients may change over time in FM cross-sectional regressions. In addition I use three different fixed effects panel estimators for the FF time-series regressions to ensure that the results are robust to heteroscedasticity, autocorrelation, time and firm clustering and possible endogeneity between firm-level returns and firm-level characteristics (see Appendix 6.D for a review of the robust time-series estimators used).

Errors-in-variables bias

There are error-in-variables issues that are associated with the Fama Macbeth method due to the inputs in the cross sectional steps being estimates from the first step (Welsh, 2008). The original motivation for using portfolios was to reduce the errors in variables problem, however (Ang, Liu, and Schwarz, 2008) show that smaller standard errors of beta estimates from creating portfolios do not lead to smaller standard errors of cross-sectional coefficient estimates. (Ang, Liu, and Schwarz, 2008) advocate the use of firm-level tests wherever possible. Therefore, the time-series results and firm-level macroeconomic models are cross-checks of the FM results that transmitted volatility affects stock returns.

6.5 Discussion

I previous chapters I have shown that the network of supplier-customer linkages among firms can affect their stock prices, because firm-specific shocks transmitted via these inter-linkages (transmitted volatility) may be non-diversifiable. In this chapter, I investigate the implications of the model of returns in Chapter 3 for expected returns, cross-sectionally and over time.

The results show that the concentration of linkages is more influential on returns than the degree of linkage. Shocks spread via economic linkages significantly influence average stock returns, however the economic significance of transmitted volatility on stock returns is small compared to the influence of systematic risk factors. The influence of transmitted volatility does, however, increase in recessions, and is much larger in the presence of feedback (for example, 'volatility feedback' on asset prices as proposed by French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992)). Thus the empirical evidence suggests that shocks spread along supply chains affect stock returns, with firms that have concentrated supplier or customer bases having lower returns on average over time than firms with balanced supplier or customer bases. These results were robust to the inclusion of a range of common systematic factors (including the three Fama French factors and macroeconomic factors), firm-level controls and controls for market volatility and idiosyncratic volatility in the models.

Specifically, the Fama Macbeth regressions showed that there is a significant, positive risk premium attached to the concentration of supplier linkages. Consistent with this result, the time series results showed that an increase in the concentration of supplier linkages in period t lowered returns in period $t + 1$ (as the regression coefficients on the lagged concentration of supplier linkages were significant and negative). That is, if investors demand a positive risk premium (higher expected return) in the current period for concentration of supplier linkages, this places downward pressure on the stock prices of firms with concentrated supplier bases. If an investor buys a stock at the start of period t, and the firm that issued the stock subsequently increases the concentration of its supplier base, the resulting downward pressure on the firm's stock price will decrease the realized return in period $t + 1$ (i.e. it will lower holding period returns).

These results imply that multi-factor models of stock returns should be extended to include a factor allowing for shocks transmitted via economic linkages. This factor should reflect the concentration of a firm's supplier-base, including indirect linkages to suppliers (e.g. firm's suppliers' suppliers and so on). Both the theoretical and empirical results in this thesis suggest that the concentration of economic linkages influences whether or not shocks to linked 'counterparty' firms are diversified away, more so than the degree of linkage. Shocks transmitted between counterparties have already been incorporated into credit risk models. For example, Jarrow and Yu (2001) show that credit counterparty relationship among firms influence default probabilities and the term structure of credit spreads; and they develop a model for pricing credit securities allowing for counterparty relations. The results in this chapter support the conclusion that factor models of stock returns should be extended in a similar manner because shocks transmitted via economic linkages can influence stock prices. Future work could therefore look at allowing for multiple types of linkages (e.g. credit linkages and/or unobservable informational linkages) within a multi-factor model of stock returns.

6.A CAPM and APT tests

Table 6.19: The CAPM model fit to the four sets of portfolios (based on degree and concentration of customer and supplier linkages). **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

Cust Deg	**P1**	**P2**	**P3**	**P4**
MktRF	1.139***	1.256***	1.351***	1.318***
	-147.45	-68.35	-55.41	-51.66
cons	**-0.017*****	**-0.017*****	**-0.017*****	**-0.018*****
	(-385.09)	(-161.97)	(-169.88)	(-126.57)
R^2	0.087	0.098	0.122	0.103
Supp Deg	**P1**	**P2**	**P3**	**P4**
MktRF	1.180***	1.237***	1.168***	1.071***
	-157.01	-49.26	-36.00	-30.72
cons	**-0.018*****	**-0.009*****	**-0.006*****	**-0.005*****
	(-432.80)	(-72.88)	(-33.62)	(-25.26)
R^2	0.087	0.132	0.150	0.173
Cust Conc	**P1**	**P2**	**P3**	**P4**
MktRF	1.139***	1.387***	1.337***	1.232***
	-147.45	-50.63	-53.65	-68.98
cons	**-0.017*****	**-0.018*****	**-0.017*****	**-0.017*****
	(-385.09)	(-138.04)	(-145.17)	(-161.75)
R^2	0.087	0.117	0.112	0.097
Supp Conc	**P1**	**P2**	**P3**	**P4**
MktRF	1.180***	1.099***	1.167***	1.220***
	-157.01	-32.77	-31.32	-49.95
cons	**-0.018*****	**-0.005*****	**-0.006*****	**-0.009*****
	(-432.80)	(-27.50)	(-30.03)	(-71.62)
R^2	0.087	0.180	0.150	0.130
Double sorted on linkages and size				
	CL deg. P1 / S1	**SL deg. P1 / S1**	**CL conc. P1 / S1**	**SL conc. P1 / S1**
MktRF	1.220***	0.972***	0.938***	0.972***
	-49.95	-79.65	-68.11	-79.65
cons	**-0.009*****	**-0.024*****	**-0.025*****	**-0.024*****
	(-71.62)	(-358.92)	(-329.38)	(-358.92)
R^2	0.130	0.044	0.040	0.044
	CL deg. P4 / S4	**SL deg. P4 / S4**	**CL conc. P4 / S4**	**SL conc. P4 / S4**
MktRF	1.220***	1.048***	1.212***	1.134***
	-49.95	-29.73	-36.57	-41.12
cons	**-0.009*****	**-0.004*****	**-0.013*****	**-0.006*****
	(-71.62)	(-20.58)	(-71.73)	(-43.70)
R^2	0.130	0.186	0.136	0.160

Table 6.20: The Fama French model fit to portfolios based on degree/concentration of customer/supplier linkages and portfolios double-sorted on size. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

Cust Deg	**P1**	**P2**	**P3**	**P4**
MktRF	1.066***	1.138***	1.200***	1.182***
	-153.51	-66.56	-52.05	-49.87
SMB	0.007***	0.008***	0.008***	0.009***
	-85.08	-38.51	-28.1	-32.57
HML	0.002***	0.001***	0.001	0
	-17.26	-4.13	-1.53	-1.35
cons	**-0.018*** **	**-0.018*** **	**-0.019*** **	**-0.018*** **
	-347.77	-132.33	-129.85	-90.43
R^2	0.103	0.120	0.143	0.130

Supp Deg	**P1**	**P2**	**P3**	**P4**
MktRF	1.088***	1.174***	1.146***	1.077***
	-163.42	-49.69	-37.15	-34.66
SMB	0.007***	0.005***	0.003***	0.001*
	-103.29	-19.63	-9.65	-2.51
HML	0.002***	0.002***	0.002***	0.001*
	-15.63	-4.85	-5.07	-2.48
cons	**-0.019*** **	**-0.011*** **	**-0.007*** **	**-0.005*** **
	-399.78	-56.21	-29.79	-21.89
R^2	0.106	0.144	0.157	0.174

Cust Conc	**P1**	**P2**	**P3**	**P4**
MktRF	1.066***	1.230***	1.189***	1.120***
	-153.51	-48.7	-50.51	-67.68
SMB	0.007***	0.009***	0.009***	0.008***
	-85.08	-28.51	-31.35	-39.11
HML	0.002***	0	0.001	0.001***
	-17.26	-0.02	-1.66	-5.02
cons	**-0.018*** **	**-0.019*** **	**-0.019*** **	**-0.017*** **
	-347.77	-103.57	-107.79	-134.47
R^2	0.103	0.140	0.136	0.118

Supp Conc	**P1**	**P2**	**P3**	**P4**
MktRF	1.088***	1.101***	1.145***	1.162***
	-163.42	-37.52	-32.00	-50.79
SMB	0.007***	0.001*	0.003***	0.005***
	-103.29	-2.47	-8.86	-19.70
HML	0.002***	0.001	0.002***	0.002***
	-15.63	-1.93	-4.64	-5.56
cons	-0.019***	-0.005***	-0.007***	-0.011***
	-399.78	-24.73	-25.22	-57.74
R^2	0.106	0.181	0.157	0.142

Table 6.21: The Fama French model fit to portfolios based on degree/concentration of customer/supplier linkages and portfolios double-sorted on size. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown under the coefficients.*

Double sorted	**C.Deg1 / S1**	**S.Deg1 / S1**	**C.Conc1 / S1**	**S.Conc1 / S1**
MktRF	1.162***	0.869***	0.836***	0.869***
	-50.79	-73.89	-62.73	-73.89
SMB	0.005***	0.008***	0.008***	0.008***
	-19.7	-55.22	-47.94	-55.22
HML	0.002***	0.002***	0.002***	0.002***
	-5.56	-10.96	-8.97	-10.96
cons	**-0.011*** **	**-0.025*** **	**-0.026*** **	**-0.025*** **
	-57.74	-269.29	-244.79	-269.29
R^2	0.142	0.059	0.055	0.059
	C.Deg4 / S4	**S.Deg4 / S4**	**C.Conc4 / S4**	**S.Conc4 / S4**
MktRF	1.162***	1.056***	1.125***	1.103***
	-50.79	-34.51	-38.48	-44.58
SMB	0.005***	0	0.005***	0.003***
	-19.7	-0.97	-13.02	-9.41
HML	0.002***	0.001	0	0.001**
	-5.56	-1.49	-0.69	-2.63
cons	**-0.011*** **	**-0.004*** **	**-0.013*** **	**-0.007*** **
	-57.74	-18.51	-63.82	-39.34
R^2	0.142	0.187	0.149	0.165

6.B Cross-sectional robustness checks

Table 6.22: Average slopes (t-statistics) from monthly regressions of log excess returns on **Rolling 2 year Beta**, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *Four portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST DEGREE				SUPP DEGREE			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta (2yr)	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.003	0.001
	-0.74	-0.53	-0.3	-0.57	-0.71	-0.51	-0.89	-0.22
Size	0.000***	0.000*	0.000	0.000	0.000***	0.000	0.000	0.000
	-3.49	-2.06	-0.96	-1.62	-4.24	-0.41	-0.14	-1.33
BTM	0.001	0.002	0.004	0.002	0.001	0.001	0.000	-0.003
	-0.84	-1.55	-1.87	-1.16	-1.01	-0.68	-0.16	-1.08
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.17	-0.25	-1.19	0.00	-1.79	-0.19	-0.28	-0.67
Profit	0.002***	0.002*	0.002	0.001	0.002***	0.002	0.000	0.000
	-3.46	-2.38	-0.97	-0.48	-3.55	-1.88	-0.18	-0.35
Cust Deg	-0.004	0.001	-0.003	0.000	-0.001	-0.002	0.006	0.000
	-1.20	-0.29	-0.60	-0.25	-0.62	-0.87	-1.23	-0.02
Supp Deg	0.000	-0.004	0.000	0.002	0.004	0.009*	-0.002	0.000
	-0.94	-1.96	-0.04	-0.75	-0.47	-2.04	-0.78	-0.78
Cust Conc	-0.002	0.000	0.000	0.001	0.000	0.001	-0.003	-0.003
	-1.07	-0.12	-0.1	-0.28	-0.59	-0.24	-1.26	-1.23
Supp Conc	0.005***	0.005*	0.001	0.002	0.000	-0.002	-0.002	0.001
	-4.19	-2.37	-0.3	-0.96	-0.03	-1.1	-0.69	-0.42
cons	0.000	-0.003	-0.003	-0.007	-0.008	-0.006	0.003	0.001
	-0.04	-0.64	-0.27	-1.25	-1.01	-1.09	-0.41	-0.29
R^2	7.5%	9.9%	14.9%	11.4%	7.3%	13.9%	18.3%	20.2%

Table 6.23: Average slopes (t-statistics) from monthly regressions of log excess returns on **Rolling 2 year Beta**, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *Four portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta (2yr)	-0.002	-0.002	-0.001	-0.002	-0.002	0	-0.003	-0.002
	-0.74	-0.56	-0.3	-0.56	-0.71	-0.03	-0.86	-0.59
Size	0.000***	0.000	0.000	0.000*	0.000***	0.000	0.000	0.000
	-3.49	-1.39	-1.29	-2.16	-4.24	-1.35	-0.17	-0.31
BTM	0.001	0.002	0.003*	0.002	0.001	-0.003	-0.001	0.001
	-0.84	-1.21	-2.02	-1.51	-1.01	-1.12	-0.58	-0.74
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.17	-0.88	-0.4	-0.71	-1.79	-0.22	-0.32	-0.31
Profit	0.002***	0.000	0.001	0.002*	0.002***	0.000	0.000	0.002
	-3.46	-0.15	-0.93	-2.51	-3.55	-0.48	-0.02	-1.79
Cust Deg	-0.004	0.001	0.000	0.002	-0.001	-0.001	0.006	-0.002
	-1.20	-0.77	0.00	-0.54	-0.62	-0.32	-0.99	-0.76
Supp Deg	0.000	0.002	-0.001	-0.003	0.004	0.000	0.000	0.008*
	-0.94	-0.58	-0.5	-1.89	-0.47	-0.73	0	-2.1
Cust Conc	-0.002	-0.002	-0.001	0.000	0.000	-0.001	-0.003	0.000
	-1.07	-0.57	-0.53	-0.19	-0.59	-0.39	-1.08	-0.02
Supp Conc	0.005***	0.000	0.005	0.004*	0.000	0.001	-0.005	-0.002
	-4.19	-0.08	-1.78	-2.22	-0.03	-0.20	-1.72	-1.02
cons	0.000	-0.007	-0.006	-0.004	-0.008	0.003	0.003	-0.006
	-0.04	-1.40	-0.88	-1.00	-1.01	-0.62	-0.35	-1.08
R^2	7.5%	11.8%	12.0%	9.9%	7.3%	19.7%	20.6%	13.7%

Table 6.25: Average slopes (t-statistics) from monthly regressions of **excess returns** on Beta, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *For set of portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta	0.002	0.004	0.004	0.003	0.002	0.002	0.002	0.002
	-0.66	-1.1	-1.22	-0.98	-0.77	-0.41	-0.39	-0.48
Size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-0.86	-0.28	-0.06	-0.59	-0.82	-0.33	-1.34	-1.43
BTM	0.001*	0.004*	0.003*	0.003**	0.001*	0	0	0.003*
	-2.38	-2.4	-2.01	-2.94	-2.59	-0.17	-0.08	-2.29
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.15	-0.98	-0.52	-1.03	-0.58	-0.9	-0.24	-0.42
Profit	0.002***	0.001	0.002	0.001	0.002**	0.000	0.001	0.003**
&	-3.46	-0.82	-1.43	-1.5	-3.21	-0.48	-1.06	-2.87
Cust Deg	-0.001	0.000	-0.001	0.001	0.001	-0.003	0.008	-0.005
	-0.42	-0.28	-0.39	-0.37	-0.64	-0.89	-1.27	-1.88
Supp Deg	0.000	0.001	-0.004	0.000	0.013	0.000	0.001	0.005
	-0.39	-0.44	-1.67	-0.02	-1.61	-0.48	-0.41	-1.24
Cust Conc	0.000	0.002	0.000	0.001	0.001	0.001	-0.003	0.004
	-0.27	-0.49	-0.15	-0.33	-1.23	-0.4	-1.07	-1.86
Supp Conc	0.003*	-0.001	0.005	0.003	-0.003	0.000	-0.004	0.000
	-2.05	-0.43	-1.71	-1.41	-1.21	-0.02	-1.44	-0.30
cons	0.003	-0.005	0.004	-0.001	-0.013	0.009	0.000	0.002
	-0.72	-0.92	-0.76	-0.25	-1.49	-1.68	-0.01	-0.38
R^2	3.9%	7.9%	7.6%	6.1%	3.8%	16.3%	17.2%	9.9%

Table 6.24: Average slopes (t-statistics) from monthly regressions of **excess returns** on Beta, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage. *For set of portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST DEGREE				**SUPP DEGREE**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Beta	0.002	0.003	0.005	0.004	0.002	0.002	0.001	0.002
	-0.66	-0.98	-1.49	-1.01	-0.77	-0.5	-0.38	-0.5
Size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-0.86	-0.75	-0.07	-0.22	-0.82	-1.29	-1.81	-0.03
BTM	0.001*	0.003**	0.006**	0.002	0.001*	0.003*	0.000	0.001
	-2.38	-2.60	-2.87	-1.53	-2.59	-2.18	-0.22	-0.27
Leverage	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.15	-0.49	-0.31	-0.11	-0.58	-0.32	-0.38	-1.57
Profit	0.002***	0.001	0.002	0.002	0.002**	0.003**	0.001	0.001
&	-3.46	-1.51	-1.35	-1.23	-3.21	-2.87	-0.77	-0.68
Cust Deg	-0.001	0.002	-0.003	0.000	0.001	-0.005	0.006	-0.003
	-0.42	-0.46	-0.53	-0.28	-0.64	-1.93	-1.30	-0.98
Supp Deg	0.000	-0.001	-0.006	0.001	0.013	0.003	-0.001	0.000
	-0.39	-0.63	-0.87	-0.30	-1.61	-0.75	-0.57	-0.60
Cust Conc	0.000	0.000	0.002	0.002	0.001	0.004	-0.002	0.000
	-0.27	-0.19	-0.49	-0.8	-1.23	-1.93	-0.91	0
Supp Conc	0.003*	0.004	0.003	0.001	-0.003	0.000	0.000	0.001
	-2.05	-1.69	-0.7	-0.4	-1.21	-0.13	-0.19	-0.31
cons	0.003	0.000	0.005	-0.002	-0.013	0.004	0.003	0.007
	-0.72	-0.03	-0.41	-0.36	-1.49	-0.62	-0.44	-1.51
R^2	3.9%	6.1%	10.3%	7.6%	3.8%	10.2%	15.2%	16.6%

Table 6.27: Average slopes (t-statistics) from monthly regressions of log excess returns on **Fama French three factor betas**, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage and **idiosyncratic volatility**. *For set of portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST CONC				**SUPP CONC**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
BetaMkt	0.001	0.001	0.002	0.002	0.001	-0.001	-0.003	0.001
	-0.39	-0.32	-0.66	-0.52	-0.41	(-0.19)	(-0.79)	-0.23
BetaSMB	-0.090	-0.151	-0.196	-0.162	-0.074	-0.456	-0.313	-0.514
	(-0.39)	(-0.54)	(-0.73)	(-0.67)	(-0.32)	(-1.41)	(-1.05)	(-1.90)
BetaHML	-0.024	-0.098	-0.119	0.194	0.009	-0.368	-0.316	-0.165
	(-0.10)	(-0.36)	(-0.45)	-0.81	-0.04	(-1.19)	(-1.09)	(-0.62)
Size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000*
	-0.24	(-0.56)	(-0.43)	(-0.39)	-0.79	(-0.82)	(-1.74)	(-2.49)
BTM	0.001*	0.002	0.004*	0.002	0.001*	0.003	0.003	0.004*
	-2.25	-1.06	-2.25	-1.36	-2.08	-1.18	-1.45	-2.14
Leverage	-0.000*	0.001	0.000	0.000	-0.000*	0.000	0.000	0.000
	(-2.29)	-1.82	-0.06	(-1.08)	(-2.05)	-0.35	(-0.08)	-0.55
Profit	0.002***	0.001	0.001	0.002*	0.002***	0.001	0.001	0.002**
	-3.64	-0.47	-0.77	-2.1	-3.37	-1.07	-0.96	-2.66
Cust Deg	-0.003	0.001	-0.001	0.001	0.000	-0.002	0.008	0.000
	(-0.79)	-0.39	(-0.24)	-0.25	-0.04	(-0.70)	-1.33	(-0.17)
Supp Deg	0.000	0.003	-0.002	-0.001	-0.003	0.000	0.000	0.006
	(-0.32)	-1.04	(-0.97)	(-0.34)	(-0.35)	(-0.65)	-0.01	-1.55
Cust Conc	0.000	-0.001	-0.003	-0.001	0.001	-0.001	-0.003	0.000
	(-0.03)	(-0.28)	(-1.04)	(-0.61)	-1.50	(-0.59)	(-1.08)	-0.20
Supp Conc	0.002*	-0.004	0.003	0.001	0.000	0.002	-0.003	-0.001
	-2.38	(-1.78)	-1.22	-0.69	(-0.03)	-0.61	(-1.23)	(-0.64)
Var(Ri)	-0.457***	-0.352***	-0.318***	-0.273***	-0.423***	-0.110	-0.091	-0.328***
	(-11.99)	(-6.19)	(-5.33)	(-5.11)	(-11.40)	(-0.76)	(-0.70)	(-4.58)
cons	0.006	-0.002	0.005	0.000	0.005	0.005	0.002	-0.001
	-1.58	(-0.34)	-0.85	(-0.00)	-0.61	-1.04	-0.26	(-0.22)
R^2	7.8%	13.4%	13.0%	10.4%	7.3%	24.0%	24.8%	15.8%

[H]

Table 6.26: Average slopes (t-statistics) from monthly regressions of log excess returns on **Fama French three factor betas**, Size, Book-to-market ratio (BTM), Leverage, Profit, degree of customer linkage, degree of supplier linkage, concentration of customer linkage, concentration of supplier linkage and **idiosyncratic volatility**. *For set of portfolios are formed. Each set is formed yearly by sorting on a measure of exposure to transmitted volatility (one of: degree of total linkage to customers, degree of total linkage to suppliers, concentration of total linkage to customers, concentration of total linkage to suppliers. Firms with no customer (supplier) linkages are in Group 1 (P1), and the remaining firms are divided into three groups (P1, P2, P3) containing firms with one exposure and then those above and below the 50'th percentile of firms with more than one exposure. The average slope is the time series average of the monthly regression slopes from Jan 1990 to Dec 2010.*

	CUST DEGREE				**SUPP DEGREE**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
BetaMkt	0.001	0.002	0.002	0.002	0.001	0.001	-0.004	0.000
	-0.39	-0.59	-0.48	-0.47	-0.41	-0.18	(-0.95)	(-0.07)
BetaSMB	-0.090	-0.141	-0.151	-0.207	-0.074	-0.509	-0.383	-0.318
	(-0.39)	(-0.58)	(-0.52)	(-0.76)	(-0.32)	(-1.86)	(-1.28)	(-1.00)
BetaHML	-0.024	0.194	-0.255	-0.076	0.009	-0.156	-0.43	-0.438
	(-0.10)	-0.82	(-0.92)	(-0.28)	-0.04	(-0.58)	(-1.49)	(-1.42)
Size	0.000	0.000	0.000	0.000	0.000	-0.000*	0.000	0.000
	-0.24	(-0.18)	(-0.11)	-0.08	-0.79	(-2.48)	(-1.96)	(-0.32)
BTM	0.001*	0.002	0.004	0.002	0.001*	0.003	0.003	0.005
	-2.25	-1.34	-1.64	-1.00	-2.08	-1.87	-1.41	-1.77
Leverage	-0.000*	0.000	0.000	0.000	-0.000*	0.000	0.000	0.000
	(-2.29)	(-0.34)	(-0.38)	-0.35	(-2.05)	-0.32	-0.79	-1.27
Profit	0.002***	0.002	0.002	0.001	0.002***	0.002**	0.001	0.001
	-3.64	-1.91	-0.93	-1.01	-3.37	-2.61	-0.49	-1.11
Cust Deg	-0.003	0.002	-0.002	-0.001	0.000	-0.001	0.007	-0.001
	(-0.79)	-0.41	(-0.42)	(-0.62)	-0.04	(-0.45)	-1.44	(-0.31)
Supp Deg	0.000	-0.002	-0.004	0.001	-0.003	0.007	-0.002	0.000
	(-0.32)	(-0.92)	(-0.50)	-0.47	(-0.35)	-1.74	(-0.64)	(-0.91)
Cust Conc	0.000	-0.001	-0.002	-0.001	0.001	0.001	-0.003	-0.003
	(-0.03)	(-0.73)	(-0.44)	(-0.51)	-1.50	-0.58	(-1.16)	(-1.15)
Supp Conc	0.002*	0.002	0.002	-0.001	0.000	-0.001	-0.001	0.002
	-2.38	-0.86	-0.48	(-0.60)	(-0.03)	(-0.72)	(-0.46)	-0.72
Var(Ri)	-0.457***	-0.277***	-0.325***	-0.363***	-0.423***	-0.321***	-0.037	-0.300*
	(-11.99)	(-5.19)	(-5.00)	(-6.46)	(-11.40)	(-4.44)	(-0.36)	(-2.04)
cons	0.006	0.000	0.009	0.003	0.005	-0.002	0.004	0.004
	-1.58	-0.03	-0.87	-0.59	-0.61	(-0.32)	-0.60	-0.90
R^2	7.8%	10.5%	17.4%	12.6%	7.3%	16.1%	22.2%	24.5%

6.C Times series model with lagged linkages

Table 6.28: Time series model for portfolios sorted on the degree of exposure to transmitted shocks from customers. *,**,*** *indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown under the coefficients.*

	CUST DEG P1	P2	P3	P4
MktRF	1.000*** -127.74	1.062*** -53.99	1.130*** -44.73	1.131*** -43.29
SMB	0.006*** -68.19	0.007*** -30.05	0.007*** -22.92	0.008*** -27.05
HML	0.003*** -30.84	0.003*** -9.42	0.002*** -5.64	0.002*** -5.83
Size	-0.000*** -5.58	-0.000* -2.42	-0.000** -2.80	-0.000** -2.62
BTM	0.003 -1.47	0.005 -1.84	0.006** -3.04	0.000 -0.26
BidAsk	0.003*** -3.67	0.003 -1.02	0.008* -2.27	0.014*** -4.43
Leverage	0.000*** -8.81	0.000 -1.29	0.000 -0.79	0.000 -1.63
Trade Credit	0.000 -0.82	0.000 -0.98	0.001 -0.91	0.000 -0.46
Profit	0.007*** -6.13	0.007** -2.81	0.005 -0.95	0.011*** -3.33
Cust Deg	0.000 0.00	0.000 0.00	-0.032 -1.40	0.001 -0.43
Supp Deg	0.001 -0.81	0.000 -0.08	0.002 -0.27	-0.007 -1.31
Cust Conc	0.000 0.00	0.000 0.00	-0.050* -2.30	-0.011 -0.94
Supp Conc	0.001 -1.14	-0.002 -0.65	0.002 -0.36	0.001 -0.2
L.Cust Deg	-0.005 -1.35	0.003 -0.67	-0.004 -0.93	-0.003 -1.32
L.Supp Deg	-0.001 -1.23	-0.008 -1.75	-0.008 -1.11	0.004 -1.09
L.Cust Conc	0.006*** -3.81	-0.008*** -4.4	-0.005 -1.42	0.006 -1.56
L.Supp Conc	-0.003** -2.61	-0.007* -2.41	0.000 -0.03	-0.008* -2.28
D.Var(MktRF)	-32.266*** -29.77	-34.569*** -11.83	-32.206*** -9.37	-30.191*** -7.52
L.Var(MktRF)	-0.669*** -3.48	-1.289* -2.37	-1.961** -2.91	-2.418*** -3.38
D.Var(Ri)	5.907*** -39.58	6.870*** -21.55	6.410*** -14.04	5.489*** -13.09
L.Var(Ri)	0.041 -1.78	0.136* -2.53	0.258*** -3.32	0.093 -1.37
Cons	-0.016*** -4.18	-0.014 -1.71	0.069 -1.56	-0.018 -1.6
R^2	12.80%	14.50%	17.30%	14.60%

Table 6.29: Time series model for portfolios sorted on the degree of exposure to transmitted shocks from suppliers. **,**,*** indicate significance with * for p < .05, ** for p < .01, and *** for p < .001. The t-statistics are shown under the coefficients.*

	SUPP DEG P1	P2	P3	P4
MktRF	1.015***	1.131***	1.125***	1.074***
	-135.27	-44.40	-33.72	-31.72
SMB	0.007***	0.005***	0.003***	0.001
	-83.46	-15.57	-7.17	-1.50
HML	0.003***	0.002***	0.002***	0.001*
	-32.30	-6.41	-4.88	-1.99
Size	-0.000***	-0.000***	-0.000***	-0.000**
	-7.43	-5.05	-3.87	-3.24
BTM	0.000	0.000	0.009*	0.015***
	-0.84	-0.02	-2.03	-4.07
BidAsk	0.004***	0.001	0.009**	0.001
	-5.24	-1.48	-2.69	-0.76
Leverage	0.000***	0.000	0.000	0.000
	-5.09	-0.19	-1.44	-1.38
Trade Credit	0.000	0.004*	-0.015	0.002
	-0.25	-2.26	-1.24	-0.42
Profit	0.008***	0.002	0.005	0.007*
	-7.36	-0.57	-1.12	-2.01
Cust Deg	-0.001	-0.009	-0.001	-0.007*
	-0.85	-1.60	-0.10	-2.58
Supp Deg	0.000	0.000	-0.016	0.002*
	0.00	0.00	-1.15	-2.29
Cust Conc	0.001	-0.006	-0.003	-0.004
	-0.86	-1.36	-0.53	-0.88
Supp Conc	0.000	0.000	-0.016	0.015
	0	0	-1.08	-1.14
L.Cust Deg	-0.002	0.004	0.006	0.005
	-1.36	-0.75	-0.98	-1.23
L.Supp Deg	0	0.005	-0.002	-0.003**
	-0.06	-1.01	-0.42	-2.68
L.Cust Conc	0.001	-0.001	-0.001	0
	-0.94	-0.32	-0.26	-0.03
L.Supp Conc	-0.003	-0.007***	-0.004	-0.006
	-1.54	-3.45	-1.19	-0.72
D.Var(MktRF)	-34.265***	-25.303***	-16.372***	-5.65
	-32.87	-6.82	-4.42	-1.5
L.Var(MktRF)	-0.476**	-0.323	-2.304***	-2.326***
	-2.97	-0.53	-3.59	-4.83
D.Var(Ri)	6.125***	4.268***	3.624***	1.686
	-49.11	-6.06	-3.7	-0.85
L.Var(Ri)	0.049**	-0.025	0.252	0.276
	-2.76	-0.22	-1.75	-1.85
Cons	-0.018*	0	0.022	-0.016
	-2.39	-0.05	-0.73	-1.88
R^2	13.10%	16.40%	17.60%	19.00%
AIC	-651,543	-65,986	-44,068	-52,620
BIC	-651,325	-65,818	-43,894	-52,446

Table 6.30: Time series model for portfolios sorted on the concentration of exposure to transmitted shocks from customers. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown under the coefficients.*

	CUST CONC			
	P1	P2	P3	P4
MktRF	1.000***	1.185***	1.125***	1.040***
	-127.74	-43.06	-43.43	-55.1
SMB	0.006***	0.008***	0.008***	0.007***
	-68.19	-23.27	-25.65	-30.61
HML	0.003***	0.002***	0.002***	0.003***
	-30.84	-4.39	-5.72	-10.32
Size	-0.000***	-0.000**	-0.000**	-0.000**
	-5.58	-2.87	-2.74	-2.78
BTM	0.003	0.000	0.009***	0.004*
	-1.47	-0.48	-4.27	-2.51
BidAsk	0.003***	0.016**	0.008*	0.003
	-3.67	-3.26	-2.51	-1.03
Leverage	0.000***	0.000	0.000	0.000
	-8.81	-1.37	-0.79	-1.41
Trade Credit	0.000	0.000	0.001	0.000
	-0.82	-0.03	-0.96	-0.99
Profit	0.007***	0.010**	0.005	0.007**
	-6.13	-2.9	-1.01	-2.9
Cust Deg	0.000	-0.002	0.003	0.001
	0.00	-0.69	-0.69	-0.21
Supp Deg	0.001	-0.005	0.000	0.000
	-0.81	-0.91	-0.01	-0.13
Cust Conc	0.000	-0.025	-0.008	0.000
	0.00	-1.32	-0.39	0.00
Supp Conc	0.001	-0.002	0.000	-0.002
	-1.14	-0.54	-0.03	-0.57
L.Cust Deg	-0.005	-0.002	-0.006	0.003
	-1.35	-0.69	-1.54	-0.66
L.Supp Deg	-0.001	0.008*	-0.008	-0.008
	-1.23	-2.15	-1.29	-1.95
L.Cust Conc	0.006***	0.007	-0.003	-0.008***
	-3.81	-1.35	-0.74	-4.33
L.Supp Conc	-0.003**	-0.011**	0.004	-0.007*
	-2.61	-2.88	-0.81	-2.46
D.Var(MktRF)	-32.266***	-28.112***	-34.430***	-34.094***
	-29.77	-6.85	-9.61	-12.24
L.Var(MktRF)	-0.669***	-2.556***	-1.664*	-1.297**
	-3.48	-3.64	-2.55	-2.69
D.Var(Ri)	5.907***	5.706***	6.044***	6.867***
	-39.58	-12.81	-13.77	-21.96
L.Var(Ri)	0.041	0.092	0.178*	0.138**
	-1.78	-1.29	-2.41	-2.67
Cons	-0.016***	-0.01	-0.008	-0.015
	-4.18	-0.65	-0.46	-1.92
R^2	12.80%	15.90%	16.30%	14.40%
AIC	-622,813	-42,612	-50,657	-91,026
BIC	-622,597	-42,428	-50,471	-90,837

Table 6.31: Time series model for portfolios sorted on the concentration of exposure to transmitted shocks from supplies. *,**,*** *indicate significance with * for p < .05, ** for p < .01, and *** for p < .001. The t-statistics are shown under the coefficients.*

	SUPP CONC P1	P2	P3	P4
MktRF	1.015***	1.099***	1.116***	1.122***
	-135.27	-33.74	-29.36	-45.28
SMB	0.007***	0	0.002***	0.005***
	-83.46	-1.13	-6.36	-15.91
HML	0.003***	0.001	0.002***	0.003***
	-32.3	-1.46	-4.39	-7.21
Size	-0.000***	-0.000***	-0.000***	-0.000***
	-7.43	-3.36	-4.12	-5.22
BTM	0.000	0.013***	0.007	0.000
	-0.84	-3.34	-1.58	-0.08
BidAsk	0.004***	0.001	0.010**	0.001
	-5.24	-0.81	-3.25	-1.45
Leverage	0.000***	0.000	-0.000*	0.000
	-5.09	-1.06	-2.06	-0.14
Trade Credit	0.000	0.001	-0.018	0.004*
	-0.25	-0.3	-1.28	-2.19
Profit	0.008***	0.007*	0.004	0.002
	-7.36	-2.09	-0.81	-0.59
Cust Deg	-0.001	-0.007**	0.005	-0.010
	-0.85	-2.99	-0.70	-1.84
Supp Deg	0.000	0.002*	-0.001	-0.005
	0	-2.4	-0.14	-0.57
Cust Conc	0.001	-0.003	-0.005	-0.005
	-0.86	-0.78	-0.86	-1.18
Supp Conc	0.000	0.014	-0.004	0.000
	0	-1.15	-0.21	0
L.Cust Deg	-0.002	0.006	0.003	0.007
	-1.36	-1.52	-0.52	-1.18
L.Supp Deg	0	-0.003**	0.002	0.004
	-0.06	-2.74	-0.64	-0.83
L.Cust Conc	0.001	0.002	-0.003	-0.002
	-0.94	-0.43	-0.61	-0.54
L.Supp Conc	-0.003	-0.003	-0.004	-0.006**
	-1.54	-0.48	-1.05	-3.26
D.Var(MktRF)	-34.265***	-4.894	-14.382***	-25.262***
	-32.87	-1.27	-3.53	-7.21
L.Var(MktRF)	-0.476**	-2.198***	-3.036***	-0.329
	-2.97	-4.37	-4.06	-0.58
D.Var(Ri)	6.125***	0.272	4.058***	4.337***
	-49.11	-0.13	-4.06	-6.28
L.Var(Ri)	0.049**	0.264	0.277	-0.039
	-2.76	-1.85	-1.71	-0.35
Cons	-0.018*	-0.016*	-0.012	0.006
	-2.39	-2.21	-0.5	-0.5
R^2	13.10%	19.80%	17.10%	16.40%
AIC	-651,543	-56,392	-36,935	-69,794
BIC	-651,325	-56,217	-36,764	-69,616

6.D Robust estimation

In addition, financial time-series may exhibit heteroscedasticity, auto-correlation and firm and/or time effects which may bias the estimates of the coefficient standard errors(Petersen, 2009). This can lead to incorrect inference. Therefore, I estimate the time-series models, for single and double sorted portfolios using estimators that are robust to heteroscedasticity and auto-correlation. In order to estimate the parameters of (6.6) I use panel least squares and GMM estimation. Panel regression models allowing for both the cross-sectional and the time-series structure of the data. They produce more efficient estimates of the parameters in (6.6) than cross-sectional techniques because the variance of the parameter estimates decreases as the length of the data sample increases (Ang, Liu, and Schwarz, 2008). Furthermore, cross-sectional techniques (such as the three-step approach devised by Fama and MacBeth (1973)) can produce biased coefficient estimates in the presence of firm fixed effects (Thompson, 2011; Petersen, 2009). In contrast, the coefficient estimates from panel OLS will be consistent (but not always efficient) so long as the error terms are uncorrelated with the explanatory variables. Correlation within the error terms can lead to bias in the estimates of the standard error of coefficients, but several robust estimates of standard errors within panels control for both firm fixed effects and time effects in the residuals (i.e. correlation in the residuals across time and across firms) (Thompson, 2011; Petersen, 2009). Therefore, these models provide better estimates of coefficients and standard errors than cross-sectional techniques.

As in Thompson (2011), correlation between the error terms can take three general forms: firm effects ($corr(\varepsilon_{it}\varepsilon_{is}) \neq 0$), time effects ($corr(\varepsilon_{it}\varepsilon_{jt}) \neq 0$) and/or persistent common shocks ($corr(\varepsilon_{is}\varepsilon_{jt}) \neq 0$). To understand these effects it helps to consider the general data generating process for the errors:

$$\varepsilon_{it} = \theta_i' g_t + \eta_{it} + \mu_{it} \tag{6.8}$$

$$\eta_{it} = \phi \eta_{i,t-1} + \epsilon_{it} \tag{6.9}$$

where $\mathbf{g_t}$ is a vector of random factors common to all firms, $\theta_\mathbf{i}$ is a vector of factor loadings specific to firm i, μ_{it} and ϵ_{it} are random shocks, uncorrelated across firms and across time, and η_{it} generates firm effects.

Common factors, if unmodelled, produce clustering of the error term across linked firms. That is, linkages between firms cause their outcomes to be correlated due to mutual exposure to each others (macro and idiosyncratic) shocks. Many studies do not allow for this source of correlation at all. If linkages are ignored in the set of common factors $\mathbf{f}$, it is likely that errors are cross-sectionally correlated (across linked firms) in a given time period. Furthermore if there is a lag in the transmission of shocks through linkages, the errors may be correlated across firms and across time periods. Failing to account for these effects will lead to incorrect estimates of standard errors and may lead to incorrect statistical inference about the statistical significance of factors explaining returns (Thompson, 2011). Therefore, as discussed below I ensure the tests are robust to all three sources of bias in standard errors[25].

Petersen (2009) shows that if residuals are independent across time but correlated across firms and if the factors are correlated across time or across firms, then the OLS standard errors of estimates of factor loadings will understate the true standard error, and the covariates and errors may exhibit both serial correlation (a firm effect) and cross-sectional dependence (a time effect). In (6.6) inter-firm linkages would create cross-sectional dependence in the residual returns. In addition, residual returns may also exhibit serial correlation. The estimated standard errors of parameters may be significantly biased when both the covariates and errors are dependent across firms and/or time. To address this problem I compare the robustness of different estimators of the standard errors in 6.5. None of the estimators reviewed is robust to persistent time effects[26], the bias associated with persistent time effects disappears as T increases (Thompson, 2011).

[25] Using time dummies will not address this bias as time dummies are likely to be correlated with macro covariates (which will cause s.e. to increase), and is unlikely to correctly model factor structure of cross-sectional dependence.

[26] Although Thompson (2011) contains an extension of the 2-way robust estimator that is robust to persistent time effects

Table 6.32: Summary of the properties of different panel estimators of the standard errors. *From left to right, the estimators included were standard LS panel model, with robust estimates of s.e.s from White (1982), LS panel estimators with s.e.s adjusted for spatial and time dependence as in Driscoll and Kraay (1998) and OLS 2-way robust estimators proposed in Thompson (2011).*

Robust to:	Panel: Huber White (1982)	Panel: Driscoll Kraay (1998)	OLS 2-way robust: Thompson (2011)
Autocorrelation	✓	✓	✓
Heteroscedasticity	✓	✓	✓
Firm effect: time fixed	✓	✓	✓
Firm effect: time varying	✓	x	✓
Time effect: contemporaneous	x	✓	✓
Time effect: persistent	x	x	x

Given I have 240 monthly observations, this bias is assumed to be small so it was not a necessary criteria for the estimator. All fixed effect panel models are robust to time fixed firm effects. In addition several panel least-squares estimators are also robust to heteroscedasticity, autocorrelation (HAC) and time varying firm effects and/or time effects. White (1982) proposed estimates of s.e.s robust to heteroscedasticity. The version of the White (1982) estimator implemented in STATA (the 'Huber White sandwich estimator') is also robust to autocorrelation and firm-effects. LS panel estimators with s.e.s adjusted for spatial and time dependence are outlined in Driscoll and Kraay (1998). Finally, the OLS 2-way robust estimators proposed in Thompson (2011) are only estimators available that control for both firm and time effects in addition to HAC.[27]

[27] In addition GMM estimators of the fixed-effects panel data models produce s.e.s that are robust to heteroscedasticity, autocorrelation and firm effects (Wooldridge 2002), these estimators are used in the additional regressions run to test for endogeneity. GMM results are included in Appendix 6.A. The Fama Macbeth estimator is not included above because, as noted in Petersen (2009), the standard errors of Fama Macbeth procedure are unbiased in the presence of a time effect but significantly downward bias in the presence of a firm effect. Petersen (2009) notes that while many authors have proposed simple adjustments to the Fama Macbeth procedure to allow for autocorrelation in the betas, the adjusted Fama Macbeth standard errors are still biased downward when there is an auto-regressive component in the residuals. Given firm effects are often present in financial time-series Pavlov, Bauer, and Schotman (2004); Ang, Liu, and Schwarz (2008) panel estimators that can control for both firm and time effects are more efficient and less biased than the Fama Macbeth procedure.

6.E First differenced macro variables and GMM IV regressions

Instrumental variables regressions control for possibly endogenous regressors by using 'instrument' variables that are correlated with the suspect endogenous regressors, but not correlated with the regression errors. Lagged terms are often used as instruments if it is reasonable to assume that the lagged covariates are not correlated with current period errors. In financial processes, a frequent assumption is that returns follow a stochastic process with little persistent correlation in returns over time (McNeil, Frey, and Embrechts, 2005), therefore the use of lagged terms as IVs is reasonable.

The GMM estimator was selected because while both the conventional IV estimator and the GMM estimator are consistent in the presence of heteroscedasticity, only the GMM estimator is efficient[28]. Therefore, the usual approach when facing heteroscedasticity of unknown form is to use the Generalized Method of Moments (GMM), introduced by L. Hansen (1982).

I test the robustness of the main results to a) the inclusion of the macro terms as first differenced variables rather than as levels and b) possible endogeneity of the firm characteristics size, leverage and profitability (measured by the ratio of Sales to Total Assets). That is, to check the results are robust to endogeneity, I estimated the full model three different ways: using a GMM estimate without IV, and using two separate IV estimations with one-year and then two-year lagged covariates as IVs. These three regressions are compared to the first-differenced Panel fixed effects model (FE model) in Table 6.33.

[28] GMM makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroscedasticity of unknown form(Baum, Schaffer, and Stillman, 2003).

Table 6.33: First-difference models, estimated with Instrumental Variables via GMM. **,**,*** indicate significance with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The t-statistics are shown in brackets under the coefficients.*

	GMM - no IV	GMM - 1yr lags IV	GMM - 2yr lags IV	GMM - 2yr lags and FD[1]
	b/t	b/t	b/t	b/t
MktRF	0.886***	0.896***	0.887***	-0.177***
	(44.97)	(28.46)	(27.29)	(-24.44)
DivYield	-2.135***	-2.177***	-2.555***	-6.157***
	(-10.73)	(-10.59)	(-12.10)	(-3.48)
spread	2.778***	2.738***	2.720***	12.915***
	(13.75)	(13.17)	(12.88)	(-29.03
CL deg.	0.00	0.00	0.00	-0.008***
	(-1.11)	(-1.05)	(-0.82)	(-4.73)
SL deg.	0.00	0.00	0.00	0.00
	(1.34)	(1.09)	(1.07)	(-0.11)
CL conc.	0.00	0.00	0.00	0.00
	(-1.20)	(-1.22)	(-1.24)	(1.25)
SL conc.	0.00	0.00	0.00	0.00
	(-0.24)	(-0.17)	(0.07)	(0.04)
Mkt*CLdeg	0.137***	0.126***	0.133***	1.019***
	(7.53)	(4.36)	(4.48)	(33.10)
Mkt*SLdeg	-0.013***	-0.013**	-0.013**	0.04
	(-4.93)	(-2.95)	(-2.86)	(1.65)
Mkt*CLconc	0.102***	0.105***	0.108***	-0.173***
	(7.05)	(4.86)	(4.77)	(-6.87)
Mkt*SLconc	0.073***	0.073**	0.070**	0.094**
	(4.88)	(2.87)	(2.69)	(3.03)
Size	-0.000***	-0.000***	-0.000***	-0.000***
	(-7.51)	(-4.46)	(-4.43)	(-4.39)
Leverage	0.00	-0.000***	-0.000*	-0.000*
	(1.72)	(-8.77)	(-2.25)	(-2.10)
Profit	0.006***	0.007***	0.005*	0.005*
	(10.47)	(4.76)	(2.40)	(2.45)
L.MktRF	0.00	0.00	0.00	-0.01
	(-0.73)	(-0.14)	(-0.40)	(-1.22)
L.DivYield	1.779***	1.866***	2.231***	-0.354***
	(8.81)	(9.30)	(10.80)	(-5.22)
L.spread	1.559***	1.681***	1.633***	3.036***
	(8.83)	(9.39)	(8.73)	(17.36)
L.CL deg	0.00	0.00	0.00	0.00
	(-0.59)	(-0.54)	(-0.22)	(0.67)
L.SL deg	-0.002*	0.00	0.00	0.00
	(-2.40)	(-1.57)	(-1.48)	(-0.97)
L.CL conc	0.00	0.00	0.00	0.00
	(0.33)	(-0.00)	(-0.01)	(-0.38)
L.SL conc	-0.003**	-0.003**	-0.003**	-0.003**
	(-3.17)	(-2.82)	(-2.84)	(-2.67)
D.σ_M^2	-35.175***	-35.307***	-32.822***	-32.579***
	(-36.32)	(-36.60)	(-33.23)	(-28.83)
L.σ_M^2	-1.823***	-1.893***	-2.461***	-0.07
	(-8.04)	(-8.04)	(-10.00)	(-0.39)
D.σ_i^2	6.087***	5.985***	5.814***	5.834***
	(48.45)	(49.37)	(45.77)	(45.95)
L.σ_i^2	0.092***	0.096***	0.107***	0.112***
R^2	(5.69)	(5.58)	(5.98)	(6.24)

Chapter 7

Conclusion

Motivated by financial crises where the downfall of a small number of firms had an economy-wide impact, this thesis focusses on how shocks spread via linkages between suppliers and customers (economic linkages) affect stock returns. This is a significant problem because if shocks spread via economic linkages are a significant source of risk, then models ignoring counterparty linkages between firms may incorrectly price stocks, or underestimate their risk. The main objective of this thesis, therefore, is to increase knowledge of how economic linkages between firms influence stock returns.

Literature review and research questions There is a large body of research on financial contagion that shows how shocks spread between financial markets and asset classes influence stock prices. However, this research is almost exclusively conducted at the level of an entire market or asset class and mainly focuses on shock transmission via financial linkages (including credit linkages and investor behavior). The literature reviewed in Chapter 2 shows that there is limited understanding of how shocks spread via economic linkages influence firm-level stock returns. Studies find that significant movements in a firm's stock returns forecast subsequent movements in the stock price of its major suppliers. Several questions remain open, however, regarding how shocks spread via economic linkages influence stock returns. For instance how do shocks spread via economic linkages influence return volatility and correlation? What characteristics of economic linkages (e.g. the degree or the concentration of linkage) are most important in the process of contagion? And does the spread of shocks via economic linkages increase during recessions?

My approach is to examine how a firm's economic linkages influence three dimensions of its stock returns: volatility, pairwise correlation between linked firms' returns and the cross-sectional distribution of average returns. Specifically, I address the following research questions:

1. How does the structure of economic linkages influence the volatility of stock returns?
2. How do shocks transmitted via economic linkages increase correlation between linked firms' returns?
3. How do shocks transmitted via economic linkages affect average returns, cross-sectionally and/or over time?

For each dimension of stock returns (volatility, pairwise correlation and average returns) I examine what characteristics of economic linkages are most influential, and whether the influence of economic linkages increases in recessions.

Theoretical framework To address the research questions I develop a theoretical model explaining how the spread of cash-flow shocks via economic linkages between firms influences the volatility, pairwise correlation and mean of stock returns. The model augments a factor model of returns based on the Arbitrage Pricing Theory of Ross (1976) with an additional factor to allow for shocks transmitted via economic linkages. I prove that when the distribution a firm's economic linkages is heavy-tailed (such that it has an extremely high degree of economic linkage to a few firms and a far lower degree of economic linkage to all others), shocks to the firm's suppliers and/or customers can significantly influence its return volatility because they are non-diversifiable. Intuitively, shocks to the most connected suppliers and/or customers are not offset by shocks to less connected suppliers and/or customers, so they can significantly influence a firm's cash-flow and therefore stock returns.

The theoretical model is used to answer research question 1, as I show that the aggregate affect of shocks transmitted to a firm via its economic linkages does not only depend on the number of linkages the firm has, but also on the distribution of its linkages to other firms. If a firm's linkages are balanced, shocks to suppliers and customers are likely to average out and are less likely to influence the firm's cash-flow or stock price. However, if a firm's linkages are highly concentrated, so that it is highly exposed to a single firm, shocks to its suppliers and customers are unlikely to average out and may significantly affect its stock price. In contrast to Allen and Gale (2000) who argue that financial contagion depends on the *degree* of exposure to other firms, I show that contagion via economic linkages also depends on the *distribution* a firm's linkages to its suppliers and customers.

The finding that firm-level shocks spread via economic linkages can have a significant influence on aggregate volatility even in large portfolios has important implications for asset pricing theory. This is because the assumption that diversification occurs at rate $\frac{1}{\sqrt{N}}$ underpins the Arbitrage Pricing Theory (APT) of Ross (1976). APT states that if asset returns follow a strict factor structure then the expected return of a financial asset is a linear function of various systematic (or macroeconomic) factors (Ross, 1976). However, this result only holds if there is negligible correlation between residual returns after allowing for systematic factors. In Section 3.3, however, I prove that in heavy-tailed network structures the portion of the variance of returns explained by transmitted shocks (which are not systematic factors) is non-zero even in large portfolios. That is, in heavy-tailed network structures there may be significant correlation between residual returns even after allowing for systematic risk factors. These results imply that factor models of stock returns should be extended to include an additional factor to allow for non-diversifiable risk created by economic linkages (especially, in heavy tailed network structures).

Research methodology, data and results The testable hypotheses arising from the theory (i.e. Equation (3.4), and Proposition 1 and Proposition 2 in Chapter 3) are that the structure of linkages significantly affect return volatility, return correlation and the average level of returns. In particular, equation (3.4) suggests that the concentration of total connectivity (or heavy-tailedness of the degree distribution) affects return volatility, the linkage 'distance' affects return correlation and the degree of linkages affects mean returns. In addition, equations (4.6) and (4.7) suggest that the concentration of linkages also affects mean returns.

To empirically test whether shocks transmitted via inter-firm linkages (transmitted volatility) influence stock returns, therefore, I augment a multi-factor model of returns with a proxy for exposure to transmitted volatility. The methodology consists of two main components: i) specifying a factor model of average returns allowing for shocks transmitted via economic linkages, and ii) developing measures of the exposure to transmitted volatility to be included in the factor model. The methodology is described in detail in Chapter 4, and the main methods are summarised below.

To address research questions 2 and 3 (how shocks transmitted via economic linkages affect correlation between linked firms' returns and the level of average returns), I extracted data on the significant supplier-customer links between listed US firms is extracted from the annual Compustat/CRSP files from 1990 to 2010. This data shows that the structure of supplier-customer links between US listed firms is highly heterogeneous. A few firms have a large number of supplier-customer links while most firms have only a few links. In addition I show that there was an increasing trend in the degree of economic linkage between firms on the Compustat/CRSP database from 1990 to 2010, implying that listed firms have become more connected to their suppliers and customers over the past twenty years. These findings support the assumptions of the theoretical model, and suggest that shocks spread via the economic linkages between US listed firms may significantly influence their stock prices in many cases. Therefore, analyzing the influence of inter-firm connectivity on asset prices is of increasing importance.

To investigate how shocks transmitted via economic linkages influence correlation between linked firms' returns, I test the hypothesis that an increase in the degree of linkage between two firms increases the pairwise correlation between their stock returns. First, I adapt standard correlation-based tests of contagion (reviewed in Dungey, Fry, Gonzlez-Hermosillo, and Martin (2005)) to test whether the correlation between US listed firms' returns is higher in years in which they are linked than in years in which they are not linked. Second, I develop measures of the strength of linkage between firms (using principles from network theory and economic input-output modeling). I then estimate regressions of the correlation of linked firms' returns against the strength of their linkage and a number of controls (such as industry-pair fixed-effects and credit usage along the supply chain). The results in Chapter 5 show that an increase in the economic linkage between two firms is associated with increased correlation between their stock returns. This relationship is stronger when credit is involved in the supplier-customer relationship and in recessions, implying that it is harder to replace a supplier or customer in these situations. These results imply that economic linkages may be a source of volatility in stock portfolio returns, as small increases in pairwise return correlation between stocks in a portfolio can significantly increase the volatility of the portfolio's return.

In Chapter 6 I test whether shocks spread via economic linkages influence average stock returns over and above systematic risk factors that have been shown to explain stock returns. The reduced form of the theoretical model corresponds to a simple extension of factor models of stock returns based on Arbitrage Pricing Theory, where an additional factor is added to allow for non-diversifiable risk created by economic linkages. Accordingly, I develop factors that capture the degree and concentration of a firm's supplier and customer linkages. These factors (or statistical measures of economic linkage) are based on the theory developed in Chapter 3. I include these linkage factors in a factor model of stock returns alongside a number of other factors that have been shown to explain stock returns.

Cross-sectional regressions show that, in a given time-period, firms with more concentrated supplier bases have higher average returns than firms with less concentrated supplier bases. Second, time-series regressions showed that an increase in the concentration of a firm's supplier-base lowered realized returns in the following period. These results suggest that investors demand a positive risk premium (higher expected return) in the cross-section for holding the stock of firms whose supplier-base is concentrated. This places downward pressure on prices, which results in lower returns following an increase in supplier-base concentration. While concentration of a firm's supplier and customer linkages has a significant influence on stock returns, the magnitude of the impact of economic linkages on stock returns is small compared to the influence of systematic risk factors. The influence of economic linkages on stock returns, however, increases in recessions.

Limitations of the results The source of the data on economic linkages limits the interpretability of the results in Chapter 6 relating to average returns. The data on the significant supplier-customer links between listed US firms is extracted from the FAS 131 account disclosures recorded on the Compustat/CRSP files. Under FAS 131 firms are required to disclose information on significant customers to which sales represent more than 10% of total sales revenue or profits, however there is no information on a firm's significant supplier linkages. Supplier linkages were estimated by inverting the key customer disclosures. Robust results have been obtained for US listed firms using this data[1]. Comprehensive firm-level data on economic linkages is not widely available, however, so cross-testing the results in other markets will be limited by the availability of data on linkages between suppliers and customers.

Recommendations and practical implications of the results The theoretical results in Chapter 3, showing that independent shocks to a firm's suppliers and/or customers may not average out, imply that an additional factor should be added to factor models of stock returns to allow for non-diversifiable risk created by economic linkages. That is, economic linkages create common exposures to firm-level shocks which may create clustering or cross-sectional dependence in the

[1] Since FAS 131 require firms to report major customers but not major suppliers inverting the links generates an incomplete sample of 'key suppliers', as it is not necessarily the case that key customers are, conversely, reliant on the supplier. I test whether the results are robust to this issue by using the ratio of supplier sales to a given customer to the customer's cost of goods sold, to identify a sub-sample of 'dependent customers' and checking that the main results are the same for this sample. As discussed in Chapter 6, the main results of this thesis are the same regardless of whether the full dataset or a sub-sample of 'dependent customers' are used; so the results are not an artefact of the data generating process.

residual returns of asset pricing models, even after allowing for common factors[2]. Most studies do not allow for this source of correlation. Failing to account for these effects will lead to incorrect estimates of standard errors and may lead to incorrect statistical inference about the statistical significance of factors explaining returns (Thompson, 2011). Therefore the results present a strong case to allow for linkages in asset pricing studies. If data is not available on linkages, standard error estimates for the model coefficient should be robust to correlation across time and across firm effects. Petersen (2009) and Thompson (2011) provide a comparison of robust standard error estimates.

With respect to the practice of risk management within firms and also with regard to stock portfolio risk management, the findings should spur managers to analyze their supplier portfolios with respect to direct and indirect customer and supplier exposures. In-house risk managers at firms should avoid concentrated (direct and indirect) exposures when making sourcing decisions. Investment risk managers should avoid concentrated (direct and indirect) exposures when making portfolio restructuring and buy/sell decisions.

Another implication of these findings is that concentrated risk exposures in real economic activities have implications for financial stability. Both monopoly and monopsony market forms are likely to increase volatility in the price of the stock of (direct and indirect) customer and supplier firms respectively. Therefore financial regulators should be aware of which firms act as 'hub' firms along supply chains (e.g. General Motors), because shocks to these firms are more likely to create financial instability than shocks to unconnected firms. In other words, hub firms may be 'too connected to fail'.

Further research Further empirical research is required to establish the influence of different types of inter-firm linkages (such as credit linkages or unobservable behavioral linkages) on stock returns, and how this influence changes over different economic regimes. The theoretical framework in Chapter 3 and

[2] Furthermore if there is a lag in the transmission of shocks through linkages, the errors may be correlated across firms and across time periods.

the empirical methodology (outline in Chapter 4 and developed in Chapters 5 and 6) can be applied to test for the significance shock transmission or for the influence of different types of inter-firm linkages on asset prices in any situation in which inter-firm linkages are observable or may be inferred (e.g. from expert knowledge or accounting data). Empirical work to date has been limited as data on inter-linkages is generally unavailable. However, recently developed methods for extracting assessments of connections from accounting and market data (e.g. Diebold and Yilmaz (2011)) could pave the way for future empirical work.

The return model allowing for economic linkages developed in this thesis can also be extended in several ways to offer further insight into how transmitted shocks affect financial asset prices. First, the model can be extended to include other forms of linkage and also to include dynamic feedback effects. For example, this framework can be extended to model the effect of unobservable linkages on returns by including a latent factor in the model. Second, if (3.1) is used to define firm value in a structural default model (originally developed by Merton (1974)), the framework can be used to examine how inter-linkages affect default correlation.

Given the trend for increased integration within and between firms' economic activities, international financial systems and stock markets, and the huge loss of wealth that contagion in these markets can cause, extending economic and financial models to allow for the transmission of shocks between linked firms is extremely important. This thesis provides a useful theoretical and empirical framework for modeling the consequences of inter-firm contagion in a range of contexts.

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