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ESSAYS ON INVESTOR ATTENTION

Bilkent University 2022

ESSAYS ON INVESTOR ATTENTION

A Ph.D. Dissertation
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January 2022

To My Family



ESSAYS ON INVESTOR ATTENTION

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

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In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN BUSINESS ADMINISTRATION

DEPARTMENT OF MANAGEMENT
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
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January 2022

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ABSTRACT

ESSAYS ON INVESTOR ATTENTION

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Ph.D. in Department of Management

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January 2022

This thesis investigates the impact of firm centrality and macroeconomic uncertainty on attention allocation decisions of investors. First, we examine whether investor attention towards stocks is related to firm centrality in the input-output network. Using a data set of US firms' principal customers, we find that stock prices do not promptly incorporate news about principal customers, generating return predictability which diminishes with the customer firm centrality levels. We show that this result is driven by limited investor attention. The evidence reveals that customer firms occupying more central positions in the network receive more investor attention. The results indicate that centrality effect is distinct from size effect. Our findings suggest that more central firms are associated with greater financial analyst coverage and greater institutional investor equity holdings. Second, we examine two competing theoretical models regarding the impact of macroeconomic uncertainty on investor attention to firm specific news. Kacperczyk et al. (2016) show that attention to firm-specific news decreases with the macroeconomic uncertainty, while Andrei et al. (2020) document that investor attention to firm-level news increases with the economic uncertainty. In line with the former hypothesis, we demonstrate that institutional investors raise their attention to customer news as economic uncertainty

declines. However, there is no evidence of a meaningful association between retail attention to customer news and market-level uncertainty. We also find that stock prices incorporate customer news more quickly in times of low uncertainty, which is attributable to high institutional attention. During times of high uncertainty, stock prices underreact to customer news, generating return predictability which declines with an increase either in institutional attention or retail attention.

Keywords: Investor Attention, Stock Return Predictability, Network Centrality, Macroeconomic Uncertainty

ÖZET

YATIRIMCI İLGİSİ ÜZERİNE MAKALELER

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Ocak 2022

Bu tez, firma merkeziliği ve makroekonomik belirsizliğin yatırımcıların ilgi tahsisi kararları üzerindeki etkisini incelemektedir. İlk olarak, hisse senetlerine yönelik yatırımcı ilgisinin girdi-çıktı ağındaki firma merkeziliği ile ilgili olup olmadığını incelemekteyiz. ABD firmalarının büyük/ana/önemli müşterilerinin veri setini kullanarak, hisse senedi fiyatlarının, ana müşteriler hakkındaki haberleri hızlı bir şekilde yansıtmadığını, bu durumun getiri tahmin edilebilirliğine sebebiyet verdiğini, tahmin edilebilirliğin ise müşteri firmanın merkezilik seviyeleri ile azaldığını buluyoruz. Bu sonucun sınırlı yatırımcı ilgisi kaynaklı olduğunu gösteriyoruz. Bulgular, girdi-çıktı ağında daha merkezi konumlarda bulunan müşterilerin yatırımcı ilgisini daha fazla çektiğini ortaya koymaktadır. Sonuçlar, merkezilik etkisinin firma büyüklüğü etkisinden farklı olduğunu göstermektedir. Bulgularımız daha merkezi firmaların daha fazla finansal analist kapsamı ve daha fazla kurumsal yatırımcı hisse senedi sahipliği ile ilişkili olduğunu ortaya koymaktadır. İkinci olarak, makroekonomik belirsizliğin yatırımcıların firmaya özel haberlere yönelik ilgisi üzerindeki etkisine ilişkin iki rakip teorik modeli incelemekteyiz. Kacperczyk vd. (2016), makroekonomik belirsizlikle birlikte yatırımcıların firmaya özgü haberlere olan ilgisinin azaldığını gösterirken, Andrei vd. (2020) ise firmaya özgü haberlere

olan yatırımcı ilgisinin, ekonomik belirsizlik ile birlikte arttığını göstermektedir. İlk hipotezle uyumlu olarak, belirsizlik azaldıkça kurumsal yatırımcıların müşteri haberlerine karşı ilgilerinin arttığını buluyoruz. Öte yandan, müşteri haberlerine yönelik bireysel yatırımcı ilgisi ile piyasa düzeyindeki belirsizlik arasında anlamlı bir ilişki olduğuna dair bir kanıt bulunmamaktadır. Ayrıca, belirsizliğin düşük olduğu zamanlarda hisse senedi fiyatlarının müşteri haberlerini daha hızlı yansıttığını buluyoruz ki bu sonuç yüksek kurumsal yatırımcı ilgisine atfedilebilmektedir. Belirsizliğin yüksek olduğu dönemlerde ise hisse senedi fiyatları müşteri haberlerine yetersiz tepki vermesi getiri tahmin edilebilirliğine neden olmakta, gerek kurumsal yatırımcının ilgisindeki gerekse perakende yatırımcının ilgisindeki artış getiri tahmin edilebilirliğinin azalmasına yol açmaktadır.

Anahtar Kelimeler: Yatırımcı İlgisi, Hisse Senedi Getirisi Tahmin Edilebilirliği, Ağ Merkeziliği, Makroekonomik Belirsizlik

ACKNOWLEDGEMENTS

First and foremost, I would like to express my sincere gratitude to my advisor, Assoc. Prof. Dr. Süheyla Özyıldırım for her invaluable support and patience throughout my Ph.D. process. I would not have been able to complete my thesis without her help and encouragement.

Second, I would also like to thank Assoc. Prof. Dr. Zeynep Önder and Prof. Dr. Jülide Yıldırım Öcal who provide valuable comments and suggestions to the progress of the thesis. It was a great pleasure for me to work with them.

My special appreciation is reserved for Assoc. Prof. Ahmet Ekici for his endless support. I am grateful to him for his help in overcoming difficult times.

I am grateful to Ms & PhD Programs Coordinator of the Faculty of Business Administration, Remin Tantoğlu, for her interest and concern. I express thanks to my colleagues and other people whose names not mentioned here.

I acknowledge the financial support of The Scientific and Technological Research Council of Turkey (TÜBİTAK).

I would like to express my deepest gratitude to my mother and father; to my whole family and my wife's family for their support, sacrifice, love and belief in me.

A very special thanks to my wife and daughter. Words cannot express how grateful I am to my wife who gives me the inner strength, invaluable support and motivation in the toughest moments. My little daughter, Melis Yağmur, who has filled my life with happiness and joy has always been my shining light and inspiration.

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CHAPTER I

INTRODUCTION

1.1 Overview

Standard asset pricing models suggest that stock prices instantly reflect all publicly available information. The theory relies on the assumption that investors have infinite cognitive resources to collect and process all value-relevant information instantaneously and properly. However, Kahneman (1973) states that attention is a scarce cognitive resource and therefore it is limited. Voluminous studies show that investors' attention is limited which results in stock price underreaction to relevant news, generating return predictability (Cohen and Frazzini, 2008; Da et al., 2014; Della Vigna and Pollet, 2009; Hirshleifer and Teoh, 2003). Investors facing a large number of choices pay attention to only a subset of publicly available information (Hirshleifer and Teoh, 2003; Li and Yu, 2012; Peng and Xiong, 2006). Increased investor attention leads to a more immediate incorporation of information into stock prices and thus improves market efficiency. The literature has attempted to understand the determinants of investors' attention allocation decisions and the stock price implications of investor attention. Despite the advances in the literature, there remain significant gaps to be addressed. This thesis aims to broaden and deepen the scope of the field by providing new insights about the investor attention allocation and its implications on stock price movements.

In the next chapter of this thesis, we examine whether investor attention towards stocks is related to firm centrality in the input-output network.¹ US government bailed out General Motors and Chrysler in the midst of the recent financial crisis with the

¹ This chapter is accepted for publication in the *International Review of Finance and Economics*, forthcoming.

justification that they were “too interconnected to fail”. It was presumed that if these companies had been allowed to fail, the crisis would have been more devastating. The firms’ interconnectedness with other firms might be very large and strong through which they have the systemic effect for the whole economy. A recent event also reveals the significance of critical nodes in the economy. Boeing company, one of the most interconnected firms with 680 supplier companies, slowed the production of Max 737 airplane in April 2019 after two fatal crashes and it completely stopped the production in January 2020. Financial Times made a detailed analysis about the impact of the cease of production both on its supplier firms and on the overall economy. These examples show that regulators and the press pay great attention to the “critical firms” of the economy. We expect that investors pay high attention to these firms as well due to their systemic importance. Therefore, we pose a hypothesis that more central (“critical” or “too interconnected”) firms attract greater investor attention. Ours is the first study investigating the relationship between investor attention and firm centrality in the production network.

We use a data set of firms’ principal customers to identify the centrality of firms which can be described as the relative importance of a firm within the network of domestic trade between firms. Since our sample is more informative about customer firms, to test our prediction, we examine the supplier stock price response to information about customer firms with varying degree of centrality. Both portfolio formation tests and Fama-MacBeth cross-sectional regression results indicate that stocks underreact to news about principal customer firms, generating cross-return predictability which diminishes with the customer firm centrality levels. In order to show that these results are driven by investor attention, we inquire whether cross-return predictability decreases with the well-known investor attention measures. We find that either higher attention to supplier stocks or higher attention to customer stocks reduces the stock return predictability. This implies that firm centrality exhibits the same pattern as the other attention measures, supporting that the centrality effect on return predictability is driven by investor attention. One may raise the point that large firms acquire higher centrality scores and thus the centrality effect is simply a rediscovery of the size effect. We adjust firm centrality scores for firm

size and we re-examine the centrality effect by using residual centrality values. We show that the centrality effect on return predictability remains strong even when we use size-adjusted centrality scores. Lastly, we examine how firm centrality influences the investor attention. We find that more central firms are followed by a greater number of financial analysts and owned by more institutional investors; that is, informed investors pay greater attention to more central firms. Our findings contribute to the literature by revealing that investor attention is associated with firm centrality. Specifically, firms occupying more central positions in the production network receive greater investor attention. In addition, we contribute to the literature on investor attention by explicating that the source of information has also an important role in drawing investor attention.

In the third chapter of the thesis, we examine the impact of macroeconomic uncertainty on investor attention to firm-level news. In the literature, two theoretical models investigate the relationship between economy-wide uncertainty and investor attention to firm-specific news. These models provide conflicting predictions. On the one hand, Kacperczyk et al. (2016) show that investors allocate more attention to firm-specific news in low uncertainty periods. On the other hand, Andrei et al. (2020) show that investor attention to firm-level announcements diminishes with the amount of macroeconomic uncertainty. Empirical studies overlook the role of uncertainty on investor attention to firm news. In this study, we fill this gap in the literature by investigating the association between these two variables and by showing which theoretical model is supported by the empirical data. We use principal customer firm news, a novel indicator in this strand of the literature, as firm specific news and VIX as a proxy for macroeconomic uncertainty. Based on the direct investor attention measures, we find that extreme customer firm stock returns receive more institutional investor attention. In addition, the evidence show that institutional investors raise their attention to customer news as VIX declines. Our findings support the predictions of Kacperczyk et al.'s (2016) theoretical model. We also find that retail investors neglect relevant information about customer firms and there is no meaningful relationship between retail investor attention to customers news and VIX.

Besides, we explore the stock price implications of investor attention in times of low and high market-level uncertainty. The results show that supplier stock returns are not predictable from customer stock returns during low VIX periods which is more likely attributable to high institutional attention to customer news which increases with a decline in uncertainty. During high VIX periods, investors underreact to customer news, generating cross-return predictability. We find that cross-return predictability diminishes with an increase either in institutional investor attention or in retail investor attention. We contribute to the literature on investor attention by examining the impact of macroeconomic uncertainty on investor attention to firm-level news. To the best of our knowledge, the only papers that empirically investigate the association between uncertainty and investor attention to firm-specific news are those of Kacperczyk et al. (2016) and Andrei et al. (2020). In their theoretical paper, they also examine their conflicting predictions with empirical data. We provide a new insight to this research area. We also contribute to the literature on the role of institutional attention vis-à-vis retail attention in price discovery. We highlight the differences in institutional and retail investors' attention allocation decisions and reveal the role of institutional and retail investor attention in the price diffusion of an information.

CHAPTER II

FIRM CENTRALITY AND LIMITED ATTENTION

2.1. Introduction

Traditional asset pricing theory assumes that investors sufficiently allocate their attention and thus any news is efficiently incorporated into the prices. However, numerous studies show that investors' attention is limited, which results in return predictability (Cohen and Frazzini, 2008; Da et al., 2014; Della Vigna and Pollet, 2009; Hirshleifer and Teoh, 2003). Within the limited attention framework, empirical works reveal that increasing investor attention gives rise to a decline in return predictability and in turn increases market efficiency. This line of research uses various attention-grabbing factors. For example, firm size, stock trading volume, media coverage, analyst coverage, institutional ownership are, among others, important measures of investor attention (Drake et al., 2014; Grullon et al., 2004; Hong et al., 2000; Lee et al., 2019; Lou, 2014; Menzly and Ozbas, 2010; Twedt, 2016). These studies do not consider the role of firm centrality in drawing investor attention. In this article, we explore the effect of firm centrality in attracting investor attention.

After the Global Financial crisis of 2007/2008, regulators and academics emphasize the significance of the firms having extensive interconnections with other firms in the economy. The US government bailed out General Motors and Chrysler in the midst of this crisis with the justification that they were "too interconnected to fail". The assumption was that if these companies had been allowed to fail, the crisis would have been devastating because the firms' excessive interconnectedness with other firms meant

they had the systemic effect for the whole economy. One recent event highlights the importance of critical nodes further. Boeing, one of the most interconnected firms with 680 supplier companies, slowed the production of Max 737 airplane in April 2019 after two fatal crashes and halted the production in January 2020. As the Financial Times reported on the aftermath of the cease of production:

“Small manufacturers across the US are hurting from the silencing of the 737 Max assembly line (...) US industrial output declined 30 basis points in January from the previous month, partly because of the shutdown, and economists predict the crisis will shave half a percentage point of gross domestic product in 2020. (...) Spirit AeroSystems, the Wichita, Kansas company that makes the Max’s fuselage, laid off 2,800 in January. Component maker Precision Castparts laid off 150 this month in Oregon. (...) The threat for Boeing is that the longer it idles its own machines and workers, the greater the risk of long-term damage to the supply chain.” (Financial Times, February 19, 2020)

These events reveal that regulators, academics, and even the press pay great attention to the critical firms of the economy. We expect that heavily interconnected firms receive more attention from investors as well due to their systemic importance. In this paper, we use the production network to identify the central (critical or “too interconnected”) firms and explore whether which stocks investors are aware of and which stocks they ignore can be attributed to firm centrality in the production network. Ours is the first study investigating the relationship between investor attention and firm centrality.

US firms under the regulation Statement of Financial Accounting Standards (SFAS) No. 131 have to report their major customers, that is, those which account for more than 10% of their annual sales. We focus on these well defined customer-supplier links between firms which enable us to establish inter-firm input-output relationships. Since customer firms account for a significant part of their supplier firms’ sales, they are substantive

stakeholders in the supplier firms (Cohen and Frazzini, 2008).² Thus, the studies in the literature generally focus on the information flow from customer firms to supplier firms. For instance, any value-relevant information about customers is informative for suppliers' stock price (Gosman and Kohlbeck, 2009; Pandit et al., 2011; Patatoukas, 2012). Similarly, to test our prediction, we investigate the supplier stock price response to information about customer firms with varying degree of centrality.

Supplier firms attract more investor attention when they establish trading relationships with high attention-grabbing customer firms (Cen et al., 2021). If central customers receive high investor attention, it is then expected that their dependent suppliers attract high investor attention, as well. In other words, investors are anticipated to pay higher attention to supply chain links between central customers and their suppliers. The relation between trading partners is publicly available and often delineated in long-standing contractual arrangements (Katz, 1989; Pandit et al., 2011).³ Due to the explicit and strong economic links, a high level of attention on customer firms which is more likely paid by supplier firms' investors facilitates the transmission of customer news to supplier firms which reduces the supplier stock return predictability generated by customer news (Madsen, 2016; Zhou, 2021). By similar reasoning, we argue that investors of focal (supplier) stocks are attentive to central trading partners and take immediate action when the news about central customers is released into the market. Accordingly, we pose a hypothesis that the stock return predictability from the news about the customer decreases with customer firm centrality.

This paper seeks to contribute to several strands of existing literature. First, we contribute to investor attention literature by showing that investor attention is associated with firm centrality. Prior studies show that investors pay more attention to salient firms while overlook less salient ones (e.g., Barber and Odean, 2008; Fang and Peress, 2009; Lou, 2014). Firm size, stock return volatility, stock liquidity, firm profitability are found to be

² In the sample, the average customer accounts for 20 percent of the sales of the supplier firm.

³ The average duration of the supplier-customer links in our sample is more than 3 years.

salient indicators of firms which affect investor attention (Barber and Odean, 2008; Barinov, 2014; Peng, 2005; Zang, 2006). However, these studies do not consider the firm centrality as salient factor in drawing investor attention.

Second, our paper contributes to the literature which shows that the source of information has an important function in drawing investor attention. The studies show that recommendations of analysts from larger brokerages, New York Times article compared to Nature article, reports released by high-reputation brokers, Twitter news about smaller securities opposed to larger securities, and Wall Street Journal "Category Kings" ranking list attract more attention (Gurun et al., 2016; Huberman and Regev, 2001; Jegadeesh and Kim, 2010; Kaniel and Parham, 2017; Rakowski et al., 2019). Our study complements this literature by focusing on the information releases by major customer firms and investigating which customer firms' news is more attractive.

Lastly, we extend the studies on the asset pricing implications of customer-supplier network characteristics by relating firm centrality to the stock return predictability. The prior studies show that the input-output trade flow network characteristics matter for asset pricing. For example, Ahern (2013) documents that industries having a more central position in the network earn higher returns than the industries occupying a less central position. Aobdia et al. (2014) find that central industries' returns depend more on aggregate risks when compared to non-central industries. Herskovic (2018) shows that network concentration and network sparsity are sources of systematic risks that are reflected in equilibrium asset prices. Our work is distinct from this literature as we focus specifically on the investor attention by investigating the return predictability effect of firm centrality.

To show return predictability decreases with customer firm centrality we double sort the stocks into portfolios. First, we rank stocks into quintiles on their customers' centrality scores measured in prior fiscal year. Then, within each of the centrality quintiles we rank stocks into further quintiles based on their customers' stock returns earned in previous month. For each centrality quintile, we form the hedge portfolios by buying stocks whose

customers performed best in the prior month and selling stocks short whose customers performed worst in the prior month. We calculate abnormal returns using a variety of factor models.

We find that stock returns are predictable by using the customer firm returns and cross-return predictability declines with the customer firm centrality value. Specifically, the results indicate that abnormal returns on hedge portfolios monotonically decline across the customer centrality quintiles. The hedge portfolios formed on the lower centrality quintiles earn monthly returns of 0.487% to 1.807% per month, whereas the hedge portfolio formed on the highest centrality quintile do not earn any significant abnormal returns.

We demonstrate that the centrality effect on return predictability is driven by limited investor attention. To this end, we show that customer return is related to limited investor attention. We use analyst coverage, number of institutional owners and firm size as proxies for investor attention. We find that smaller firms, firms with lower analyst coverage and firms with lower number of institutional owners react more sluggishly to customer returns. We also examine the effect of investor attention towards customer firms on return predictability. Similar to the attention towards firm itself, investor attention towards customer firms reduces return predictability. We find that stock price reaction to news about smaller customers, customers with lower analyst coverage, and customers with less institutional owners is more sluggish. These findings also contribute to the line of research showing that the source of news has an important role in attracting investor attention.

One may raise the point that the centrality effect is simply a rediscovery of the size effect. We first calculate Pearson correlation between each firm centrality measure and firm size. The highest correlation is obtained between Degree centrality and firm size, but it is only 0.303. Second, we adjust firm centrality for firm size and we re-examine the centrality effect by using residual centrality values. We show that the centrality effect on return predictability remains strong even we use size-adjusted centrality scores. These

findings support that the centrality effect is distinct from the size effect.

We examine that how firm centrality influences the investor attention. We propose that the interests of informed investors increase with firm centrality. We use the number of analysts covering the stock and the number of institutional owners holding the stock as proxies for informed investors. We find that more central firms are likely to be followed by more financial analysts and to be owned by more institutional investors; that is, informed investors pay greater attention to more central firms.

This paper is organized as follows. In Section 2.2, we describe the theoretical background and testable hypothesis of this study. Section 2.3 provides a detailed analysis of network centrality and describes the data. Section 2.4 presents the methodology and main results. Section 2.5 discusses the distinct effect of firm centrality from firm size. Section 2.6 examines the strength of customer-supplier relationships on return predictability. The paper concludes with final remarks in Section 2.7.

2.2. Theoretical Background and Testable Hypothesis

Attention is a scarce cognitive resource and therefore it is limited (Kahneman, 1973). Limited investor attention suggests that investors may overlook the relevant information when it is released to the market. This leads to the slow diffusion of information in stock prices inducing price underreaction and thus return predictability. A number of studies show that attention is limited, whereby investors pay attention to only a subset of publicly available information (see, for example, Hirshleifer and Teoh, 2003; Li and Yu, 2012; Peng and Xiong, 2006). Grossman and Stiglitz (1980) theoretically and Menzly and Ozbas (2010), Drake et al. (2014), Vozlyublennaia (2014), Lou (2014), Twedt (2016) and Lee et al. (2019) empirically show that increased investor attention reduces return predictability and, therefore, improves market efficiency.

The literature provides evidence that firm characteristics have an impact on grabbing investor attention. For example, large firms, firms having high trading volume, and firms

having high turnover ratio among others, attract more investor attention because they are followed by more financial analysts, covered by more financial news media, and are found to be less informationally uncertain (Barber and Odean, 2008; Barinov, 2014; Li et al., 2019; Zang, 2006; Zhu et al., 2020). In a similar vein, we argue that central firms are followed by more financial analysts and news about more central firms grab more investor attention.

Hypothesis: Investors are more attentive to news about customer firms occupying in more central position in the input-output network. Hence, stock price underreaction to news about less central customer firms is more severe causing higher subsequent price drifts.

Input-output networks are a powerful means of representing patterns of economic connections or links between the firms. Firm centrality shows the importance of a firm in a network. We focus on the influence measures of centrality, where firms are more central (also known as key or critical) in the network if they are well-connected with other firms. Due to this connectedness, the central firms are systemically more important because shocks to central firms have the potential to generate nontrivial aggregate shocks that affect total output (Acemoglu et al., 2012; Carvalho and Gabaix, 2013).

Barrot and Sauvagnat (2016) and Boehm et al. (2019) provide evidence that shocks to a firm propagate to its direct supplier firms. Ozdagli and Weber (2017) show that shocks to a firm affect not only its direct suppliers but also transmit to indirect suppliers. For example, a negative shock to a car manufacturer leads to decrease in tire demand which in turn causes a decline in demand for rubber and ultimately oil. Through the direct and indirect effects of the shocks, the central nodes in the input-output network of the economy are important entities having potential to generate aggregate fluctuations from idiosyncratic shocks (Acemoglu et al., 2012; Gabaix, 2011). Therefore, central firms are considered to be followed by more financial analysts and thus attract investor attention.

2.3. Data

2.3.1. Network Centrality

The centrality values of firms can be computed from the inter-firm input-output network. According to regulation SFAS No. 131, firms have to report the identity of customer firms which account for more than 10% of their sales in a fiscal year. Compustat customer segment file provides the name of the principal customers and the sales amounts to those particular customers. We use the database of Cohen and Frazzini (2008) who merge Compustat customer segment file with CRSP database and uniquely identify principal customers' CRSP permno numbers.⁴ Their data set covers the fiscal years between 1979 and 2009. By using their methodology, we extend the sample up to the end of fiscal year 2017. The final sample ranging from 1979 to 2017 fiscal years includes 69,470 firm-year observations, representing a total of 21,276 unique supplier-customer relationships. We estimate centrality scores of firms in every fiscal year, separately.

The financial regulation requires firms to report major customers and not-major suppliers. Given the presence of the 10% cutoff, the sample is more informative about customer firms, and not the reverse. Therefore, we construct a customer-based network in each fiscal year which enables us to investigate the effect of customer firm centrality on supplier firm's return predictability, and not the opposite. To this end, we explore the relative importance of each customer firm in terms of its contribution to the networked economy. In its simplest form, if a customer firm has many suppliers (if a customer firm is the buyer of many suppliers), it might have strong market power in the product market, which may induce the investors of supplier firms pay greater attention to the information about this customer firm. Therefore, it is more reasonable to compute customer firm's centrality by using the links from suppliers to customers.

⁴ We thank Lauren Cohen for sharing with us a broader and revised version of the sample used in the seminal paper of Cohen and Frazzini (2008). The data set covers the period between 1979 and 2009.

Since we argue that more central firms grab more investor attention due their systemic importance, we use centrality measures that are widely used in the systemic risk literature to characterize the relative position of customer firms in the network, namely Degree, Katz-Bonacich and Closeness. These measures capture different aspects of economic networks. While Degree centrality considers only direct connections, Katz-Bonacich and Closeness centrality account for not only direct connections but also indirect connections. Atalay et al. (2011) show that Degree centrality is a more proper indicator to compute firm centrality using the truncated customer-supplier links. Additionally, due to its simplicity and intuitiveness, investors can easily figure out firm centrality without making any complex calculations. Therefore, we use Degree centrality measure as a baseline indicator in our estimations. We employ other two measures for robustness purposes.

To compute the centrality measures, we first construct an N by N adjacency matrix in which N is the number of firms in the network. It is a directed matrix in the sense that the links point from supplier firms to customer firms. The adjacency matrix A is specified as

$$A = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{pmatrix}$$

where entries of matrix, x_{ij} , are equal to one if firm i has sales to firm j , and equal to zero otherwise in an unweighted network.⁵ In a weighted network, x_{ij} is equal to the fraction of firm i 's sales accounted for by firm j .⁶ Degree centrality is the simplest and the most intuitive measure. Degree centrality of a given node is simply the number of

⁵ Due to the nature of the data, we focus on the incoming links to customer firms. Therefore, we compute in-Degree, in-Closeness and in-Katz-Bonacich centralities. For brevity, we call them as Degree, Closeness and Katz-Bonacich.

⁶ In the data set, we observe that some suppliers do not report the sales amount committed to their customers and the missing sales values account for around 19.7% of all samples. In the weighted network, we lose these observations. Therefore, our main tests are based on the directed but unweighted network. For robustness, we use weighted network.

links that come to it. Given the adjacency matrix A , Degree (d_j) for a firm j is calculated as

$$d_j = \sum_{i(\neq j)} x_{ij}$$

which is the sum of the column of the adjacency matrix. In an unweighted network, a customer firm gets a higher Degree centrality score if the number of its supplier firms is larger.

Katz-Bonacich centrality also known as PageRank algorithm is an extended version of the Degree centrality and the Katz-Bonacich (k_j) for a firm j is

$$k_j = \lambda \sum_{i(\neq j)} x_{ij} k_i + \beta$$

where λ is a constant standing for the biggest eigenvalue of the adjacency matrix and k_i is the centrality value of firm i (Bonacich, 1987). This indicator assigns each node a small amount of centrality value (β), regardless of the its position in the network.⁷ Katz-Bonacich centrality of a customer firm is proportional to the sum of centralities of its supplier firms plus a constant β . Accordingly, this measure accounts for not only the number of neighbors but also the importance of the neighbors in the network. Closeness centrality is entirely different from both Degree centrality and Katz-Bonacich centrality and assesses the mean distance from a node to other nodes. Closeness centrality (c_j) for firm j is defined as

$$c_j = \frac{1}{\frac{1}{N-1} \sum_{i(\neq j)} d_{ij}}$$

⁷ The only difference between Eigenvector and Katz-Bonacich centrality is the constant term β . We have truncated network due to the 10% cutoff which results in zero incoming edges for some firms that lead to zero centrality scores for them. If we had used Eigenvector centrality, we would have had zero centrality scores for the customer firms whose supplier firms has no incoming links. Therefore, Katz-Bonancich is a more appropriate measure for our data set.

where D_{ij} is the shortest path through a network between firm i and firm j , and N is the total number of firms. Closeness centrality assigns a higher centrality score to a firm if it is close to other firms in the network.

The Degree and Katz-Bonacich centrality measures can be affected by the size of the network. Bigger networks may yield larger centrality scores for the nodes due to more connection possibilities. Given that network sizes vary over time, we normalize both measures by the maximum possible number of connections $N-1$, where N is the total number of firms in a given fiscal year.

In most of the regressions, as we use centrality values to sort firms, our primary interest is to find the relative rankings of firm centralities rather than their exact values. Two conditions need to be satisfied for the accuracy of the relative ranking of firm centrality values: (i) The Compustat customer-supplier sample needs to be a good representation of population and (ii) the 10% threshold level for reporting customers should not influence the shape of the customers' centrality distribution.

Firstly, Herskovic (2018), on the sector level, compares the network factors obtained from the Compustat customer-supplier data set with the network factors acquired from the Bureau of Economic Analysis database which represents the whole US economy. Although the former is a smaller sample of the latter due to the 10% threshold, Herskovic (2018) demonstrates that factors from the two databases are highly correlated. This shows that the Compustat data set is a good representation of the input-output table of the US economy.

Secondly, the Compustat customer data set for firms that account for more than 10% of their sales leads to a truncation in the number of edges. Atalay et al. (2011) show that this truncation does not influence the shape of centrality distribution for customers if the Degree centrality measure is used. They report that the likelihood of observing an edge is similar for both a large and a small customer firm. Thus, for customer firms in the CRSP/Compustat data set, the fraction of edges that is missing due to the 10% threshold

is similar for low and high centrality firms and the relative ranking of these firms is not affected because of missing links.

In addition, we check the reliability of the data and the centrality measures. If the Compustat customer data are reliable, the rank of firm centrality should not change sharply, at least in two successive years. Figure 2.1 represents the Spearman rank correlation of firm centrality scores between two consecutive years for each centrality measure. For example, the year 1981 indicates the rank correlation between 1980 and 1981. The correlation coefficients are very high, almost close to 1, for each centrality measure. This means that a firm has a very similar rank order of centrality scores in a given year when compared to the previous year. Furthermore, the coefficients range within a small interval, hovering around 0.8 throughout the years. It can be inferred that both the data set and our centrality measures are reliable.

Table 2.1 exhibits the summary statistics of the sample used in input-output network. The sample covers Compustat customer-supplier firms which are listed in CRSP. The data are on a fiscal year basis covering the period between 1979 and 2017. In Panel A, we represent the sample coverage statistics. Our sample has 1453 firms on average, which covers 59% of the total market capitalization of CRSP universe and 21% of the total number of firms in CRSP universe. Panel B investigates the correlation coefficients between the three centrality metrics. The table also includes their correlation with firm size. The correlations between the Degree centrality scores and Katz-Bonacich centrality scores are high as expected because the latter is the extension of the former. Additionally, Closeness centrality has a high correlation with the other two centrality measures.

2.3.2. Stock-Return Sample

The seminal papers of Hou (2007), Cohen and Frazzini (2008) and Lee et al. (2019) use linked firm's stock return as firm news.⁸ Following them, we use monthly customer

⁸ Cohen and Frazzini (2008) use customer firm stock return as a customer news for the supplier firm. We use customer returns as a news for the supplier firm in the same context.

returns as proxy for customer news. We extract the stock returns from CRSP and the sample includes common stocks only. We impose a standard six-month interval between fiscal year-end and portfolio formation, to ensure that investors are aware of the customer-supplier links and centrality of the firms. Following Fama and French (1992), we match the accounting data of fiscal year $t-1$ with monthly stock returns from July of year t to June of $t+1$.⁹ In case a firm reports more than one principal customer in year $t-1$, we use equal weighted customer returns and centrality scores from July of year t to June of $t+1$. Our supplier-customer sample spans the fiscal years between 1979 and 2017, and the estimation sample covers the period between July 1980 and June 2019. Following Cohen and Frazzini (2008), we exclude stocks with a closing price below five dollars at the end of the previous month to ensure that results are not driven by illiquid and thinly-traded stocks.¹⁰ The sample includes all firms listed in the CRSP-Compustat universe. We do not include stocks with missing book equity and market equity values at the fiscal year-end to identify the customer as another traded CRSP-Compustat firm.

2.4. Methodology and Results

2.4.1. Portfolio Formation

In this section, we first examine return predictability from news embedded in customer returns and then we investigate the extent of return predictability across customer centrality levels. We adopt the Cohen and Frazzini (2008) approach and use monthly customer returns as proxy for customer news. To show that returns are predictable from customer news, we sort the stocks into five portfolios based on customer firm stock return. At the beginning of each calendar month t , we first sort stocks into quintiles based on customer stock returns earned in the previous month. These portfolios are then

⁹ Stock returns spanning from July of year t to June of year $t+1$ are based on the customer-supplier links reported in year $t-1$ only, not the prior years.

¹⁰ Lo and MacKinlay (1990) documents that large stocks lead small stocks. Similarly, Hou (2007) and Menzly and Ozbas (2010) find that large firms in an industry lead same industry small firms. We exclude small and thinly traded stocks so that return predictability is not driven by the small stocks.

rebalanced at the beginning of each month to maintain either equal weights or value weights. At the end of month t , both equal- and value-weighted portfolio returns are estimated.¹¹

We compute abnormal returns from a regression of portfolio excess returns on common risk factors by using the CAPM and a variety of factor models. The factor models include the three-factor model of Fama and French (1993), a four-factor model consisting of Fama-French's three factors and Carhart's (1997) momentum factor, the five-factor model of Fama and French (2015), and a six-factor model consisting of Fama-French's five factors and the momentum factor. Abnormal returns are measured as the intercept term of the regression. Positive (negative) abnormal returns following good (bad) news on customer firms indicate that returns are predictable.

Table 2.2 shows the portfolio abnormal returns from the CAPM and the factor models. Table values exhibit average monthly risk-adjusted returns (alphas) to each quintile of customer returns. We construct a zero-investment trading strategy that buys stocks whose customer returns are in the highest quintile and sell short the stocks whose customer returns are in the lowest quintile (L/S). The table also reports abnormal returns to these zero investment portfolios. The results show evidence that customer returns predict supplier stock returns. Low (high) customer returns in month $t-1$ are followed by low (high) supplier returns in month t . Equal weighted long-short strategy adjusted for CAPM yields average monthly returns of 0.821%, or roughly 9.85% per year. The value-weighted L/S portfolio generates CAPM abnormal returns of 0.881% per month. Fama and French (1993) risk factors adjusted equal- (value-) weighted L/S portfolio yields average monthly returns of 0.811% (0.849%). Augmenting the three-factor model with Carhart's (1997) momentum factor has a negligible effect on the abnormal returns of the hedged strategy. We have a four-factor alpha of 0.703% (0.805%) per month in equal- (value-) weighted portfolios. We also adjust returns using the Fama and French (2015)

¹¹ Cohen and Frazzini (2008) use customer-supplier data to examine whether the news about customer firms can predict the supplier firm stock returns whose sample ends in 2004. By using same methodology but an extended sample which covers the period until 2019, we find similar results.

five-factor model, and a model using the five-factor model plus the momentum factor (sixth factor). The five- and six-factor alphas yield 0.778% (0.675%) and 0.701% (0.66%) per month in equal- (value-) weighted portfolios, respectively.

In order to test return predictability across customer centrality levels, we use a conditional double sort methodology following Rouwenhorst (1998). We double sort the stocks into 25 portfolios based on the customer firm centrality value and customer firm stock return. At the beginning of each calendar month t , we first sort stocks into quintiles based on the customer centrality scores measured in the prior fiscal year. Subsequently, within each of these centrality quintiles we rank stocks into further quintiles based on the customer stock returns earned in the previous month. At the beginning of each month t , portfolios are rebalanced to keep either equal weights or value weights. For each centrality quintile, the zero investment (hedge portfolios) are constructed by buying stocks whose customers performed best in the prior month and selling stocks short whose customers performed worst in the prior month.

Panel A of Table 2.3 documents the equal-weighted portfolio abnormal returns across customer centrality quintiles. The hedge portfolios exhibit striking evidence.¹² The abnormal returns of the hedge portfolios monotonically decrease with the customer centrality quintiles. We find that the hedge portfolios based on the first four quintiles yield positive and statistically significant abnormal returns, but the L/S portfolio based on the highest centrality quintile does not yield significant abnormal returns.¹³ Furthermore, the hedge portfolio based on the lowest customer centrality quintile earns a monthly abnormal return of 1.177%, whereas the hedge portfolio based on the fourth customer centrality quintile earns less than half of it (0.487%). Panel B reports the value-weighted portfolio abnormal returns across customer centrality quintiles. The results are very

¹² The full table, including 25 double sorted quintile portfolios, consists of 1500 entries which takes many pages. For brevity, we present the abnormal returns of L/S portfolios which contain information about the extreme customer returns.

¹³ There seems to be an anomaly on the results of fourth quintile in Table 2.3 because they diverge from the monotonically declining abnormal returns across increasing quintiles. When we control for recession periods with a dummy variable in abnormal return estimations, the anomaly disappears.

similar to those obtained in Panel A. Additionally, there is a large spread between the abnormal returns of the hedge portfolio based on the lowest customer centrality quintile and that based on the highest customer centrality quintile. These results provide evidence that return predictability from news about economically linked firms declines with the customer firm centrality quintiles.

Price diffusion of news about customer firms might be slow and thus might take longer periods for incorporation into stock prices. In Table 2.4, we explore the magnitude of price adjustments of both customer and supplier stocks in the medium-term (six-month) across customer firm centrality quintiles as in Cohen and Frazzini (2008) and Fabozzi et al. (2013). The price drifts of the supplier firm stock after the initial news continues for roughly six months and thus, we examine the underreaction during the six-month horizon.¹⁴ We construct calendar time equal and value weighted customer portfolios in Panel A and Panel B, respectively. To be comparable with the supplier portfolio returns, customer returns are scaled by the total fraction of the firm's sales to their customers. In the upper parts of both panels, we exhibit the hedge portfolios' returns in month t ($SRET$) when news on customers arrives and the subsequent six-month cumulative returns from month $t+1$ to month $t+6$ ($SCAR$). Similarly, $CRET$ shows the customer portfolio return in month t and $CCAR$ shows the customer portfolio cumulative return from month $t+1$ to month $t+6$.

The lower part of both Panel A and Panel B show the underreaction coefficients for both customers (URC_{cust}) and suppliers (URC_{sup}). The underreaction coefficient is defined as the ratio of initial price response to a shock in month t to the six-month cumulative returns from month t to month $t+6$. This metric measures the degree of underreaction of a stock. In an efficient market this ratio should be equal to one. Ratios less than one indicate that price reaction to news about customers is sluggish. On the other hand, ratios greater than one indicate that prices are overreacting to news about customers. Values

¹⁴ Similarly, Cohen and Frazzini (2008) show that the price reaction of firms to customer news roughly stabilizes after six months.

under the coefficients exhibit t-statistics which measure the distance of the coefficients from one.

The results in Panel A indicate that customer portfolios do not have a significant cumulative return over the subsequent periods after the initial price jump. None of the URC_{cust} coefficients is significantly different from one. That is to say, news that leads to a price jump for the customer is promptly incorporated into the customer's stock price. However, these news releases generate positive cumulative returns over the six-month period for the supplier firms with less central customers. Conversely, firms with the most central customers do not exhibit a significant cumulative return after the initial shock to the customer.

The URC_{sup} is below one for the suppliers whose customers are from the lowest four quintiles, whereas the URC_{sup} is not different from one for the suppliers whose customers are lying on the highest central position. More specifically, firms with customers in the lowest 80% centrality group underreact to customer information. The initial reaction of suppliers to large customer return movements accounts for 62% to 72% of their total responses and thus suppliers underreact to news content embedded in customer return in the range of 28% to 38%. On the other hand, we do not find underreaction or overreaction for stocks of firms with the customer in the highest centrality quintile. Accordingly, it can be inferred that firms with the most central customers incorporate customer news into prices more promptly and more efficiently.

In Panel B, value-weighted portfolios yield similar results to that of equal-weighted portfolios. None of the URC_{cust} coefficients is significantly different from one. News causing a price jump for the customer is promptly incorporated into the customer's stock price. As for the supplier firm price reaction, while URC_{sup} is below one for the supplier firms whose customers are from the lowest four quintiles, the URC_{sup} is not different from one for the supplier firms whose customers are belonging to the highest centrality quintile. In other words, supplier firms with customers in the lowest 80% centrality group underreact to customer news, whereas supplier firms with customers in the highest 20%

centrality group do not underreact to customer news.

Tables 2.3 and 2.4 together suggest that return predictability decreases with the centrality of customer firms. The results imply that investors are more attentive to news of customer firms occupying the highest degree of centrality in the network than those having a lower central position.

2.4.2. Cross-Sectional Regressions

In this section, we test our hypothesis in a regression framework by using Fama and Machbeth (1973) forecasting regressions of individual stock returns while controlling for a number of variables. The form of the cross-section regression is as follows:

$$\begin{aligned}
 RET_{i,t} = & \alpha_0 + \beta_1 CRET_{i,t-1} + \delta_1 RET_{i,t-1} + \delta_2 MOM_{i,t-2,t-12} + \delta_3 INDRET_{i,t-1} \\
 & + \delta_4 CINDRET_{i,t-1} + \theta_1 \ln(SIZE_{i,t-1}) + \theta_2 MB_{i,t-1} + \theta_3 TURNOVER_{i,t-1} \\
 & + \epsilon_{i,t}
 \end{aligned}$$

where $RET_{i,t}$ is the supplier firm i 's raw return in month t . The independent variable of the interest is the lagged return of firm i 's principal customer in month $t-1$, $CRET_{i,t-1}$. In the equation, customer return is one-month lagged from the supplier firm stock return, enabling us to test whether customer stock returns in month $t-1$ can predict the future price movement of supplier in month t . To control for the short-term reversals of Jagadeesh (1990) and for the price momentum effect of Jagadeesh and Titman (1993), we add the stock's own lagged return in month $t-1$, ($RET_{i,t-1}$) and the stock's own lagged return from $t-2$ to $t-12$ ($MOM_{i,t-2,t-12}$), respectively. We include the lagged return of firm i 's industry portfolio, $INDRET_{i,t-1}$, to capture the intra-industry lead-lag effect of Hou (2007). We also include the lagged return of customer firm's industry portfolio, $CINDRET_{i,t-1}$ to control for the cross-industry momentum of Menzly and Ozbas (2005). Finally, we control for firm characteristics such as the log of firm size ($\ln(SIZE_{i,t-1})$), the market to book ratio ($MB_{i,t-1}$), and share turnover ratio ($TURNOVER_{i,t-1}$) measured

in month $t-1$. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation.

Table 2.5 shows the estimated coefficients of time series averages of the cross-sectional regressions. Columns 1-5 report the basic results with different control variables. The results indicate that the lagged customer return is a strong predictor of next month's supplier firm return in all specifications. Before controlling for any variables in Column 1, the coefficient on lagged customer returns is 0.039 with a t-statistic 6.049. The magnitude of the coefficient is economically significant. When we multiply the coefficient with the median returns of customer portfolio on which hedge portfolios are based (18.4%), we get 0.72% monthly return which is consistent with the abnormal returns obtained by portfolio formations. Augmenting the equation with the firm's own reversal factor and firm's own momentum factor has a negligible effect on the $CRET$ as seen in Column 2. As expected, the firm's own lagged return is negatively associated with future returns and the firm's own momentum factor is positively correlated with future returns. In Column 3 and Column 4 we include lagged firm's own industry portfolio return and customer firm industry portfolio return as control variables, respectively. The coefficients on these control variables are consistent with the prior literature. The lagged customer return, $CRET_{i,t-1}$, remains significant but the coefficient decreases slightly. In Column 5, we further include firm characteristics, i.e. firm size, market to book ratio and share turnover ratio. Although firm specific characteristics are negatively related with the future return, only the market to book ratio is statistically significant. The lagged customer return is still significant in this specification. In all specifications, stock returns are predictable from its principal customer returns.

In order to test the hypothesis of this study that return predictability declines with customer firm centrality, we rank customers by their centrality values. Firms in the bottom 30 percentiles are classified as the lowest centrality firms, firms in the top 30 percentile are classified as the highest centrality firms and all remaining firms are classified as medium centrality firms. Additionally, to show that the results are not driven by the centrality measure, we use three different measures, namely Degree, Katz-

Bonacich and Closeness centrality.

Table 2.6 reports return predictability across customer firm centrality values. Through Column 1 to Column 3, customer firms are ranked by Degree, Katz-Bonacich and Closeness centrality, respectively. Regardless of the centrality measure, we find that customer stocks with low centrality scores exhibit more predictive ability than customer firms with high centrality scores. The coefficients on customer returns decrease monotonically across the customer centrality groups. In addition, there are large spreads across the centrality groups: customer stocks in the lowest 30 percentile of centrality represent significant predictive ability whereas customer firm stocks in the highest 30 percentile of centrality exhibit no predictive ability at conventional levels. These regression results provide strong evidence of declining predictability with the centrality of customer firm even if we control for firm characteristics, own industry return and customer industry return.

Overall, the magnitude of stock return predictability decreases with customer firm centrality. The results are driven by limited investor attention to the extent that firm centrality can be considered a good proxy for investor attention.

2.4.3. The Test of Limited Attention

To ensure that firm centrality is a good proxy for investor attention, first we inquire whether customer return is related to limited investor attention. If it is associated with limited investor attention, we expect to observe that the extent of predictability should be lower for the firms that receive higher attention. As frequently used in the literature, we employ analyst coverage, the number of institutional owners and firm size as proxies for investor attention (Bajo et al., 2016; Hou, 2007; Menzly and Ozbas, 2010). We hypothesize that smaller firms, firms with lower analyst coverage and firms with lower institutional owners receive less attention from investors. Therefore, price reaction of these firms to news about customers will be more sluggish. To test this prediction, we rank stocks into three clusters with respect to analyst coverage, the number of

institutional owners and firm size: the bottom 30 percentile, the medium 40 percentile (30 to 70) and the top 30 percentile.

The first column of Table 2.7 provides the results of analyst coverage. The analyst coverage shows the number of different analysts making one-year ahead earning per share forecast at the end of the previous month. The Institutional Brokers' Estimate System (I/B/E/S) history file is used to extract the number of analysts covering a unique stock. We find that stocks with low analyst coverage have more predictability than stocks with high analyst coverage. Additionally, the spread across the bottom and top 30 percentile of analyst coverage is large. The coefficients on customer return decrease monotonically across the analyst coverage clusters.

Column 2 of Table 2.7 shows the results on the number of institutional investors. The institutional owner represents the number of different institutional investors holding a unique stock. The data is collected from the Thomson Financial's 13F Holdings database, which contains the stock-level holdings of institutional money managers. Since the institutional ownership data is quarterly but our cross-sectional estimations are monthly, we use the most recent quarterly ownership data. We find that predictability declines with the number of institutional owners, and stocks with low institutional owners have more predictability than stocks with high institutional owners.

The results in Column 3 are based on customer return ranked on firm size. We calculate firm size by multiplying the stock price by the total amount of outstanding shares at the end of the previous month. Firm size has the same effect as analyst coverage and institutional owners. The coefficients on customer return decrease monotonically across firm size clusters. Stocks in the bottom 30 percentile of size indicate significant predictability whereas stocks in the top 30 percentile of analyst coverage do not indicate statistically significant predictability. The results suggest that as the size of a firm increases, return predictability from customer returns decreases.

Up to this point, we have investigated to what extent stock return predictability varies

with attention towards the firm itself. The literature provides evidence that source of news as well as content of news are related to investor attention. Huberman and Regev (2001) document that investors pay little attention to a Nature article but significant attention to a New York Times article although the latter is published five months later with the same information. Gurun et al. (2016) show that reports released by high-reputation brokers give rise to a quicker trading response. Similarly, we expect that news about more central customers draws more attention when compared to the similar news about less central customers because of two reasons. First, as more central firms have larger numbers of suppliers, information about more central customers concerns a higher number of supplier firms. Second news about more central firms convey more information to the market if they have systemic importance.

In our sample, customer firms account for approximately 20 percent of their supplier firms' sales. The relation between partners is often characterized by relationship-specific investments, repeated transactions, and frequent interactions (Cen et al., 2017). Due to the strong economic links, a high level of attention to customer firm attributable to supplier's investors facilitates the transmission of customer news to supplier firm stock price (Madsen, 2016; Zhou, 2021). Moreover, supplier firms attract higher investor attention when they establish trading relationships with attention grabbing customer firms (Cen et al., 2021). If central customer firms receive more attention, then it is expected that their supplier firms also acquire higher attention. Therefore, higher investor attention to links between central customers and their supplier accelerates the diffusion of customer news, which in turn reduces the supplier stock return predictability. In order to test that our results in section 2.4.2 are driven by the mechanism described above, we examine information flow from attention grabbing customer firms to supplier firms using well known attention indicators such as firm size, analyst coverage and institutional owners.

We posit that news about customer firms with higher analyst coverage, more institutional owners, and larger size receives higher attention from investors. Therefore, information about these customers will be impounded quicker into supplier prices. The last three

columns of Table 2.7 provides the results based on attention towards customer firms. We find that return predictability from customer returns becomes weaker with the increase in investor attention in all equations. The coefficient on customer returns declines along with an increase in analyst coverage, number of institutional owners and customer firm size. Specifically, the coefficient on customer return is high and significant if the customer firms are in the lowest 30 percentile of analyst coverage, institutional owners and firm size. Conversely, the coefficient on customer returns is low and insignificant if the customer firms are in the highest 30 percentile of analyst coverage, institutional owners and firm size. The extent of predictive effect between the customer firms in the highest and lowest 30 percentile of attention proxies is large. The results show that there is no lag in price response to news about high attention-grabbing customers. Moreover, the evidence is consistent with the mechanism suggested by Madsen (2016), Cen et al. (2021) and Zhou (2021).

Overall, smaller firms, and firms with lower analyst coverage and firms with lower institutional owners exhibit a more sluggish price reaction to publicly available customer news. Furthermore, firm price reaction to news about smaller customers, and customers with lower analyst coverage and lower institutional owners is more sluggish. These findings show that not only attention to the firm itself but also attention to the source of the news is important in the diffusion of information about customers into prices. We can conclude that customer return is related to limited investor attention and thus firm centrality exhibits the same pattern as the other attention proxies. Therefore, the results support that the centrality effect on return predictability is driven by the limited attention.¹⁵

In order to study the effect of the centrality of the firm itself on its stock return

¹⁵ We made several robustness tests. Firstly, we winsorized the variables at 1% and 99% levels. The regression results in Table 5 to Table 7 did not change qualitatively which shows the results are not driven by the outliers. Secondly, we repeat the estimations by including stocks with closing price below five US dollars, we got similar results. That is to say, the results are robust to the inclusion of small and thinly traded stocks. Lastly, we used weighted network centrality values of firms and obtained consistent results. Hence, the results are not sensitive to weighting schemes of the network.

predictability, we invert the relationship where customer stock return is the dependent variable and lagged supplier stock return is the independent variable. In other words, we investigate the customers' stock price response to lagged suppliers' stock price. In this setup, we analyze whether customer stock return predictability vary with its own centrality. We find that customer firm's stock return predictability decreases with its own centrality value.¹⁶ That is to say, the results remain strong even after re-estimated by inverting the relationship.

2.4.4. Informed Investors and Firm Centrality

In this section, we study how firm centrality affects investor attention, and thus we investigate the relationship between firm centrality and the number of informed investors. If firm centrality is related to informed investors, we will observe that participation of financial market players increases with firm centrality value. Following Bajo et al. (2016), we use the number of analysts and the number of institutional investors as proxies for the number of informed investors. As firm centralities are measured on a fiscal year basis, we run the following regression using annual data:

$$\begin{aligned}
 I_INVESTORS_{i,t} &= \alpha_0 + \beta_1 CENTRALITY_{i,t-1} + \beta_2 RET_{i,t-1} + \beta_3 \ln(SIZE_{i,t-1}) \\
 &+ \beta_4 MB_{i,t-1} + \beta_5 TURNOVER_{i,t-1} + \beta_6 IOR_{i,t-1} + \epsilon_{i,t}
 \end{aligned}$$

where the dependent variables are the number of analysts covering firm i at the beginning of fiscal year t , and the number of institutional investors holding the firm i 's shares at the beginning of fiscal year t . The independent variables are based on the fiscal year-end in year $t-1$. The variable of the interest is the centrality score of firm i in fiscal year $t-1$. Centrality measures include Degree, Katz-Bonacich and Closeness centrality and they are standardized by their standard deviation. Hong et al. (2000) argues that lagged stock

¹⁶ This result must be interpreted cautiously because inverting the links generates only an incomplete sample of suppliers (Cohen and Frazzini, 2006). The results are available in Appendix Table A1.

returns are negatively associated with the number of informed investors. Thus, we include the past performance of the stock i , measured as the lagged return in $t-1$. Bhushan (1989) argues that large firms generate more transactions and shows that the number of informed investors is very strongly correlated with firm size. Hence, we control for the log of firm size ($\ln(SIZE)$). Hong et al. (2000) discuss that book-to-market is known to forecast returns. Hence, informed investors are expected to follow stocks with higher book-to-market ratio. They find that book-to-market ratio is positively correlated with analyst coverage. Thus, we include the market to book ratio (MB) in our regressions. Hayes (1996) finds that informed investors are more inclined to follow high-turnover stocks because this strategy makes it easier to generate brokerage commissions for their employers. We include share turnover ratios ($TURNOVER$). Bhushan (1989) also argues that the ownership structure of a firm is likely to affect both the demand and supply of analyst services. To control this effect we add institutional ownership ratios (IOR). Lastly, regressions include firm fixed effects.

Both analyst coverage and the number of institutional owners are count variables which are bounded at zero. Rock et al. (2000) show that the true data generating process of analyst coverage is closer to negative binomial distribution rather than normal distribution. Moreover, Bajo et al. (2016) report that negative binomial estimation is a more appropriate technique to model the number of institutional owners. Hence, we use the negative binomial estimation technique instead of ordinary least square (OLS).

In Table 2.8, we document the results on the number of analysts covering firm stock. We find that all three firm centrality measures have positive and significant coefficient estimates, indicating that more central firms are followed by larger numbers of financial analysts. Furthermore, firms with higher market to book ratio, firms with lower turnover ratio and firms with higher institutional ownership ratio are covered by greater numbers of financial analysts. Similarly, Table 2.9 shows that more central firms are owned by larger numbers of institutional investors. These findings are broadly consistent with those of Bajo et al. (2016) who show that more central lead IPO underwriters attract more attention from institutional investors.

2.5. Firm Centrality and Firm Size

To ensure that the centrality effect is not a rediscovery of the firm size effect, we exhibit the correlation between customer firms' centrality scores and their firm size (Panel B of Table 2.1). The correlation coefficients of centrality indicators with firm size are close to each other and range from 0.279 to 0.303. These coefficients suggest that centrality measures are positively correlated with firm size, but the correlations are not high enough that centrality can be deemed as the reformation of firm size.

In addition, to show that the centrality effect is distinct from the size effect, we calculate the size-adjusted centrality scores. The literature on analyst coverage frequently adjusts analyst coverage for firm size by using Griffin and Lemmon's (2002) method. We adapt their methodology to our context. Accordingly, residual centrality values are computed by subtracting the average centrality score of the CRSP size quintile of the firm from its centrality score. Then, we re-examine the impact of centrality on return predictability by ranking customer returns with respect to residual centrality scores. Table 2.10 reports the regression results which are based on the residual centrality values. The results from Column 1 to Column 3 are based on the residual Degree, residual Katz-Bonacich and residual Closeness centrality values, respectively. We get similar results across three equations. Low and medium centrality customer firm stocks can still predict future supplier firm stock returns. The most central customer stock returns do not have significant predictive impact on future supplier firm stock returns. The coefficients on customer return decrease monotonically across the size-adjusted customer centrality groups. These findings also confirm our proposition that stock return predictability decreases with customer firm centrality. Thus, we conclude that the centrality effect is not driven by firm size.¹⁷

¹⁷ We also examine whether firm centrality is distinct from the institutional ownership and analyst coverage. To this aim, we adjust centrality values for institutional ownership and analyst coverage by means of a OLS regression and obtain residual centrality values. Then, we use residual centrality values in the stock return predictability regression. The results show that stock return predictability still decreases with the residual centrality values. Additionally, we obtain similar results when we adjust firm centrality

We can explain why it is reasonable that firm centrality differs from firm size. First, a firm might be large, but the number of its domestic supplier firms can be limited if the supplier firm dominates the market or the competition is not intense. Second, firm centrality might be independent of firm size if the firm imports its inputs. A hypothetical large firm which does not use any domestic input will have a zero centrality score irrespective of whatever measure we use. Last, centrality of a firm can be also related to the goods that are produced. Consider the production of cars and furniture. A variety of inputs might be required to produce a car, whereas relatively limited number of inputs might be needed to produce furniture. Hence, a car producer may have higher centrality than a furniture producer of the same size.

2.6. The Effect of Link Duration and Percentage of Sales on Predictability

In this section, we examine the effect of the strength of customer-supplier relationships on return predictability. Banerjee et al. (2008) show that if a supplier firm is highly dependent on a customer in the sense that the customer accounts for a major part of its sales, then news about the customer is a relevant consideration for the supplier. Accordingly, we employ the percentage of sales to the customer as a proxy for the strength of connections. Furthermore, we use the duration of the supplier-customer link. We posit that if these indicators are related to investor attention, we have to observe that firms with longer duration of link and firms with a higher percentage of sales to customer have lower stock return predictability from lagged customer returns.

To test this assumption, we rank the stocks into three groups on the basis of the firm's percentage of sales to customer and firm's duration of link with customer. We classify groups as low, medium and high percent of sales and duration of links, respectively,

for firm size, analyst coverage and institutional ownership at the same time. These results suggest that our attention measure is distinct from the attention proxies used in this paper. The regression results are available in Appendix Table A2.

based on the breakpoints for the lowest 30 percentile, middle 40 percentile, and highest 30 percentile of the observations. Column 1 of Table 2.11 provides the results on the percentage of supplier's sales to its principal customer. Firms in the low sales group have higher predictability than firms in the medium sales group. However, firms in the medium sales category have lower predictability than firms in the high sales category. The spread across the low and high sales is very small. These results show that there is no meaningful relationship between stock return predictability and percentage of sales to the customer. Column 2 of Table 2.11 reports the results based on the duration of customer-supplier relationships. Similar to percentage of sales results, there is no increasing or decreasing patterns across the duration of firm linkages. Firms in the low duration group have higher predictability than firms in the medium duration group. However, firms in the medium duration cluster have lower predictability than firms in the high duration cluster. The resulting spread between the low and high duration is almost zero. This means that there is no meaningful association between cross-return predictability and duration of links. Therefore, we can conclude that neither percentage of sales to the customer nor duration of relationship is related to investor attention.

2.7. Concluding Remarks

In this paper, we study the asset pricing implications of firm centrality in the input-output trade flow network, which have been overlooked in the literature. We make use of the production network to identify the centrality of firms and explore whether which stocks investors are aware of can be explained by the centrality of firms. To test our hypothesis, we use information flow from customer firm stock returns to supplier firm stock returns by employing customer-supplier links between US firms. We propose that if more central firms attract more investor attention, then stock return predictability decreases with the customer firm's centrality value.

Our empirical findings can be summarized as follows. First, we find that stock returns are predictable from news about customer firms. However, return predictability declines with customer firm centrality values. Second, consistent with limited attention, we find that

firms which attract less attention react more sluggishly to news about their customer firms. We also examine the effect of investor attention towards customer firms on return predictability from news about customers. Similar to attention towards the firm itself, stocks of customer firms that receive higher attention have lower predictive ability, as well. These findings demonstrate that the effect of customer firm centrality on return predictability is driven by investor attention. We show that these results remain strong even if we use different centrality measures or network weights. Third, we document that more central firms are likely to be followed by more financial analysts and to be owned by more institutional investors, indicating that more central firms draw the attention of institutional investors. Fourth, we show that the centrality effect on return predictability remains similar even when we use size-adjusted centrality scores. This ensures that the centrality effect is not driven by firm size. Finally, we investigate the strength of customer-supplier relationship on the stock return predictability. We find that the strength of the customer-supplier relationship has no meaningful effect on stock return predictability.

This paper reveals the role of firm centrality in the domestic trade network in attracting investor attention. Further research can be conducted using global trade network. The recent pandemic of the new coronavirus has highlighted the importance of the global trade network. The COVID-19 outbreak has induced a break not only in domestic supply chains but also in many global supply chains. The spread of the coronavirus in March 2020 led to sharp declines in stock prices and increases in stock-price volatility. The recovery of asset prices is slow even in countries that have brought the spread of the virus under control, due to the cut in global demand. A worthwhile future extension would be to test whether central industries in the global trade network receive greater attention from investors. The COVID-19 pandemic is both a demand and supply shock. To such a huge unexpected shock, investors might overreact to news about central industries which have a systemic effect for the global economy. Hence, it would be interesting to investigate the stock price reaction to a shock to a central linked industry.

Figure 2. 1: Spearman Rank Correlations between Two Consecutive Years

This figure plots the Spearman rank correlations of firm centrality scores between two consecutive years. For a given year, the coefficient indicates the rank correlation of firms' centrality scores between the given and the previous year. The firm centrality measures include Degree, Katz-Bonacich and Closeness centrality.

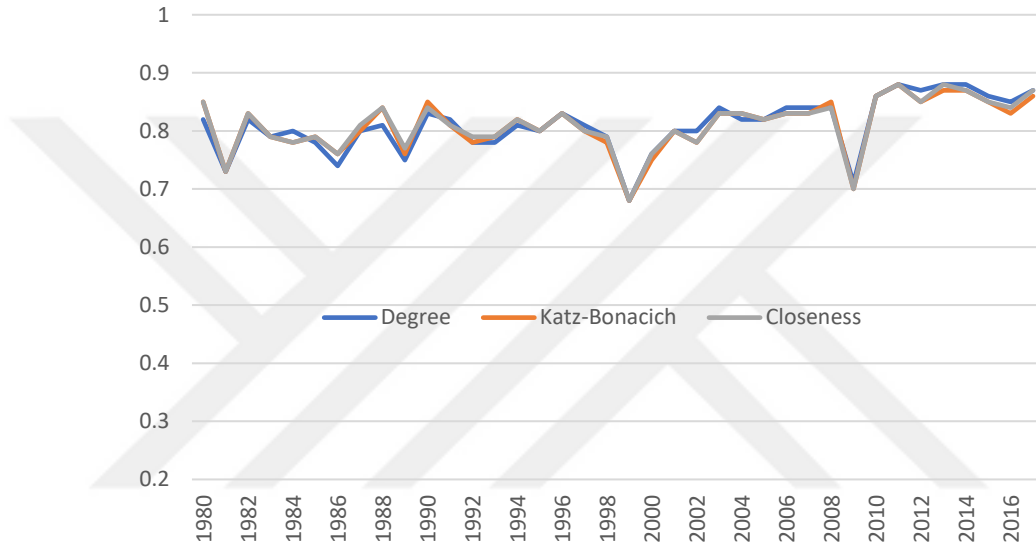


Table 2.1: Summary Statistics

This table represents summary statistics for the key variables used in the input-output network. The sample includes Compustat customer-supplier firms that are listed in CRSP. Panel A shows the sample coverage statistics. % Value of CRSP stands for the total market value of our sample firms as a percentage of the total market value of the CRSP universe. % Number of Stocks in CRSP is the total number of firms in our sample as a percentage of the total number of firms in the CRSP universe. $\ln(SIZE)$ is the logarithm of the market value of equity. Panel B exhibits the Pearson correlation coefficients between firm size and centrality values of different measures. Centrality measures include Degree centrality, Katz-Bonacich centrality and Closeness centrality. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Descriptive Statistics	Mean	Std Dev	Min	Median	Max
# of Firms	1453	274	807	1415	1967
% Value of CRSP	0.59	0.05	0.45	0.60	0.68
% Number of Stocks in CRSP	0.21	0.02	0.17	0.21	0.25
$\ln(SIZE)$	5.75	2.52	-1.90	5.72	13.67
Panel B. Pearson Correlation Coefficients	Degree	Katz-Bonacich	Closeness		
Katz-Bonacich	0.847***				
Closeness	0.884***	0.979***			
$\ln(SIZE)$	0.303***	0.279***	0.288***		

Table 2.2: Abnormal Returns of the Portfolios

This table shows the abnormal returns for the portfolios. At the beginning of the month t , stocks are ranked in ascending order according to customers' returns computed in month $t-1$ and assigned to one of five quintile portfolios. These portfolios are rebalanced at the beginning of each month to maintain either equal weights or value weights. We compute abnormal returns from a regression of the portfolio excess returns (portfolio return minus risk free rate) on common risk factors by using a variety of factor models. The factor models include the three factor model of Fama and French (1993), a four factor model consisting of Fama-French's three factors and Carhart's (1997) momentum factor, the five factor model of Fama and French (2015) and a six factor model consisting of Fama-French's five factors and the momentum factor. Abnormal returns are measured as the intercept term of the regression. L/S is the zero-cost portfolio by holding the stocks whose customers had the highest 20% return and selling short the stocks whose customers had the lowest 20% return in the previous month. All available stocks with stock price greater than five dollars at portfolio formation are included. *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

	Panel A. Equal-Weighted					
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
Excess returns	0.118	0.465	0.544**	0.727***	0.917***	0.796***
	[0.392]	[1.714]	[2.035]	[2.584]	[3.155]	[5.150]
CAPM	-0.714***	-0.310**	-0.229*	-0.080	0.107	0.821***
	[-4.225]	[-2.258]	[-1.748]	[-0.570]	[0.678]	[5.250]
3-factor	-0.664***	-0.299***	-0.239***	-0.082	0.147	0.811***
	[-5.844]	[-3.696]	[-2.946]	[-0.952]	[1.408]	[5.144]
4-factor	-0.521***	-0.244***	-0.182**	-0.043	0.181*	0.703***
	[-4.723]	[-2.995]	[-2.229]	[-0.490]	[1.705]	[4.431]
5-factor	-0.504***	-0.228***	-0.184**	-0.014	0.274**	0.778***
	[-4.374]	[-2.735]	[-2.192]	[-0.153]	[2.571]	[4.733]
6-factor	-0.413***	-0.194**	-0.147*	0.009	0.287***	0.701***
	[-3.694]	[-2.326]	[-1.758]	[0.101]	[2.674]	[4.280]
	Panel B. Value-Weighted					
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
Excess returns	-0.013	0.467*	0.307	0.353	0.865***	0.874***
	[-0.044]	[1.89]	[1.30]	[1.29]	[3.117]	[4.070]
CAPM	-0.769***	-0.226*	-0.322**	-0.374**	0.112	0.881***
	[-4.608]	[-1.715]	[-2.278]	[-2.264]	[0.700]	[4.050]
3-factor	-0.644***	-0.172	-0.278**	-0.297*	0.205	0.849***
	[-4.115]	[-1.347]	[-1.998]	[-1.811]	[1.319]	[3.875]
4-factor	-0.553***	-0.150	-0.282**	-0.320*	0.252	0.805***
	[-3.500]	[-1.153]	[-1.985]	[-1.915]	[1.593]	[3.608]
5-factor	-0.399**	-0.127	-0.208	-0.106	0.276*	0.675***
	[-2.535]	[-0.960]	[-1.447]	[-0.638]	[1.715]	[2.983]
6-factor	-0.355**	-0.115	-0.216	-0.139	0.305*	0.660***
	[-2.243]	[-0.858]	[-1.491]	[-0.837]	[1.878]	[2.886]

Table 2.3: Abnormal Returns of the Hedged Portfolios Across Centrality Quintiles

This table shows the abnormal returns for the hedge portfolios across centrality quintiles. At the beginning of the month t of year k , stocks are double sorted. First, stocks are sorted in ascending order based on customers' centrality scores measured in fiscal year $k-1$ and assigned to one of five quintile portfolios. Then, within each customer centrality quintile, stocks are ranked in ascending order according to customers' returns computed in month $t-1$ and assigned to one of five quintile portfolios. These portfolios are rebalanced at the beginning of each month to maintain either equal weights or value weights. For each centrality quintile, hedge portfolios are constructed by buying stocks whose customers performed best in the prior month and selling stocks short whose customers performed worst in the prior month. We compute abnormal returns from a regression of the portfolio excess returns (portfolio return minus risk free rate) on common risk factors by using a variety of factor models. The factor models include the three factor model of Fama and French (1993), a four factor model consisting of Fama-French's three factors and Carhart's (1997) momentum factor, the five factor model of Fama and French (2015) and a six factor model consisting of Fama-French's five factors and the momentum factor. Abnormal returns are measured as the intercept term of the regression. Centrality quintiles are based on the Degree centrality measure. All available stocks with stock price greater than five dollars at portfolio formation are included. t-statistics are shown in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Equal-Weighted	CAPM	3-factor	4-factor	5-factor	6-factor
Q1(Low Centrality)	1.191*** [4.469]	1.205*** [4.481]	1.127*** [4.122]	1.238*** [4.418]	1.177*** [4.172]
Q2	0.895*** [3.002]	0.943*** [3.140]	0.857*** [2.805]	1.022*** [3.273]	0.952*** [3.027]
Q3	0.503* [1.752]	0.525* [1.814]	0.515* [1.746]	0.649** [2.161]	0.631** [2.080]
Q4	0.880*** [3.171]	0.811*** [2.913]	0.547** [1.978]	0.668** [2.310]	0.487* [1.706]
Q5(High Centrality)	0.198 [0.936]	0.250 [1.176]	0.330 [1.529]	0.291 [1.316]	0.346 [1.553]
Panel B. Value-Weighted	CAPM	3-factor	4-factor	5-factor	6-factor
Q1(Low Centrality)	1.142*** [3.193]	1.167*** [3.234]	1.060*** [2.889]	1.103*** [2.934]	1.031*** [2.721]
Q2	1.481*** [3.542]	1.490*** [3.559]	1.672*** [3.938]	1.694*** [3.895]	1.807*** [4.132]
Q3	0.252 [0.686]	0.278 [0.749]	0.225 [0.595]	0.252 [0.653]	0.216 [0.553]
Q4	0.881** [2.369]	0.893** [2.388]	0.669* [1.773]	0.749* [1.928]	0.599 [1.540]
Q5(High Centrality)	0.308 [1.044]	0.327 [1.097]	0.471 [1.563]	0.331 [1.064]	0.437 [1.402]

Table 2.4: Underreaction Coefficients

The table exhibits returns on hedge portfolios and corresponding customer portfolios. At the beginning of the month t of year k , stocks are double sorted. First, stocks are sorted in ascending order based on customers' centrality scores measured in fiscal year $k-1$ and assigned to one of five quintile portfolios. Then, within each customer centrality quintile, stocks are ranked in ascending order according to customers' returns computed in month $t-1$ and assigned to one of five quintile portfolios. These portfolios are rebalanced at the beginning of each month. For each centrality quintile, hedge portfolios are constructed by buying stocks whose customers performed best in the prior month and selling stocks short whose customers performed worst in the prior month. Centrality quintiles are based on Degree centrality measure. Customer portfolios are formed by using equal-weights in Panel A and value-weights in Panel B. To be comparable with the hedge portfolio supplier returns, customer portfolio returns are multiplied by the total fraction of the firm's sales accounted for by the principal customers. All available stocks with stock price greater than five dollars at portfolio formation are included. In Panel A, $SRET$ and $CRET$ stands for supplier and corresponding customer portfolio returns in month t , respectively. $SCAR$ and $CCAR$ are the cumulative returns over the following six months $[t+1, t+6]$ of supplier portfolios and corresponding customer portfolios, respectively. The numbers in brackets are t-statistics. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. In Panel B, URC_{cust} and URC_{sup} are underreaction coefficients for customers and suppliers, respectively. The underreaction coefficient is the ratio of initial price response to a shock in month t to the total returns from month t to month $t+6$, $URC = RET / (RET + CAR)$. t-statistics in Panel B are the test results for the difference of the coefficients from one.

	Panel A: Equal-Weighted					Panel B: Value-Weighted				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Supplier and Customer Returns										
$CRET$	4.364*** [32.51]	5.228*** [13.09]	4.408*** [40.81]	4.014*** [40.81]	3.708*** [44.67]	4.335*** [32.80]	4.190*** [35.56]	4.441*** [36.53]	3.654*** [36.53]	3.389*** [40.23]
$SRET$	4.210*** [14.14]	5.103*** [14.52]	4.486*** [14.72]	4.064*** [14.72]	2.812*** [11.77]	5.226*** [13.16]	5.081*** [11.38]	4.454*** [9.51]	3.781*** [9.51]	3.197*** [10.30]
$CCAR_{t+1,t+6}$	0.308 [1.30]	-0.433 [-1.21]	-0.06 [-0.30]	-0.0162 [-0.08]	-0.082 [-0.43]	0.262 [1.12]	-0.047 [-0.21]	-0.092 [-0.43]	-0.037 [-0.20]	-0.076 [-0.34]
$SCAR_{t+1,t+6}$	2.086*** [2.80]	2.006** [2.26]	1.891** [2.51]	2.468*** [3.49]	0.588 [0.95]	1.836* [1.91]	1.452 [1.42]	2.187** [2.46]	1.351 [1.41]	0.753 [0.92]
Underreaction Coefficients										
URC_{cust}	0.934 [1.40]	1.09 [1.15]	1.013 [0.30]	1.004 [0.10]	1.022 [0.42]	0.943 [1.196]	1.011 [0.20]	1.021 [0.424]	1.010 [0.20]	1.023 [0.332]
URC_{sup}	0.668*** [4.21]	0.717*** [3.13]	0.703*** [3.44]	0.622*** [5.64]	0.827 [1.15]	0.74*** [2.596]	0.778* [1.792]	0.671*** [3.557]	0.737* [1.889]	0.809 [1.131]

Table 2.5: Fama-MacBeth Cross Sectional Regression Results

This table reports the Fama-MacBeth forecasting regressions of stock returns with different control variables. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm ($CRET$). The explanatory variables include the firm's own lagged monthly return (RET), medium-term price momentum (MOM), firm's own value-weighted industry return ($INDRET$), customer firm's value-weighted industry return ($CINDRET$), the logarithm of firm size ($\ln(SIZE)$), stock turnover ratio ($TURNOVER$) and market to book ratio (MB). All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
$CRET_{i,t-1}$	0.039*** [6.049]	0.039*** [7.204]	0.030*** [7.008]	0.024*** [5.229]	0.023*** [4.956]
$RET_{i,t-1}$		-0.018*** [-3.551]	-0.022*** [-4.626]	-0.023*** [-4.825]	-0.022*** [-4.564]
$MOM_{i,t-2,t-12}$		0.006*** [2.775]	0.006*** [2.703]	0.005*** [2.633]	0.005*** [2.846]
$INDRET_{i,t-1}$			0.105*** [5.796]	0.096*** [5.743]	0.082*** [5.566]
$CINDRET_{i,t-1}$				0.040*** [2.698]	0.038*** [2.660]
$LN(SIZE_{i,t-1})$					-0.0003 [-1.052]
$TURNOVER_{i,t-1}$					-0.001 [-0.840]
$MB_{i,t-1}$					-0.0005** [-2.397]
Constant	0.009*** [3.422]	0.008*** [3.037]	0.007*** [3.041]	0.007*** [2.772]	0.011*** [2.857]
Observations	235,153	232,542	232,531	232,485	227,775
R-squared	0.006	0.032	0.040	0.044	0.072
Number of groups	468	468	468	468	468

Table 2.6: Firm Centrality and Return Predictability

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged customer returns interacted with the dummy variable of lagged customer centrality values. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm (*CRET*). Customer centrality values are ranked into three categories: lowest 30 percentile (*P1*), between 30 and 70 percentiles (*P2*) and highest 30 percentile (*P3*). *P1_CENTRALITY*, *P2_CENTRALITY* and *P3_CENTRALITY* are dummy variables equal to one if the centrality value of the customer firm is in the corresponding category, and zero otherwise. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. All regressions also include the dummy variables for *P2_CENTRALITY* and *P3_CENTRALITY* themselves, with *MOM* and one-month lagged *RET*, *INDRET*, *CINDRET*, *SIZE*, *TURNOVER*, *MB* as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Degree	Katz-Bonacich	Closeness
	(1)	(2)	(3)
$CRET_{i,t-1} \times P1_CENTRALITY_{t-1}$	0.030*** [4.562]	0.030*** [4.403]	0.029*** [4.261]
$CRET_{i,t-1} \times P2_CENTRALITY_{t-1}$	0.024** [2.342]	0.019* [1.844]	0.021** [2.086]
$CRET_{i,t-1} \times P3_CENTRALITY_{t-1}$	0.010 [0.787]	0.017 [1.263]	0.016 [1.201]
Constant	0.011*** [2.677]	0.010*** [2.680]	0.010*** [2.696]
Controls	Yes	Yes	Yes
Observations	227,775	227,775	227,775
R-squared	0.085	0.085	0.085
Number of groups	468	468	468

Table 2.7: Investor Attention and Return Predictability

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged customer returns interacted with lagged investor attention proxies. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm (*CRET*). The investor attention proxies include analyst coverage, firm size and number of institutional owners. Attention proxies are ranked into three categories: lowest 30 percentile (*P1*), between 30 and 70 percentiles (*P2*) and highest 30 percentile (*P3*). *P1*, *P2* and *P3* are dummy variables equal to one if the value of the proxy variable is in the corresponding category, and zero otherwise. The results in the first three columns are based on the proxies for attention towards supplier firms, whereas the results in the last three columns are based on the proxies for attention towards customer firms. Degree, Katz-Bonacich and Closeness centrality scores are employed in Column 1 (4) to Column 3 (6), respectively. All regressions also include the dummy variables for *P2* and *P3* themselves, with *MOM* and one month lagged *RET*, *INDRET*, *CINDRET*, *SIZE*, *TURNOVER*, *BM* as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Attention Towards Supplier Firms			Attention Towards Customer Firms		
	<u>Analyst Coverage</u>	<u>Institutional Owners</u>	<u>Firm Size</u>	<u>Analyst Coverage</u>	<u>Institutional Owners</u>	<u>Firm Size</u>
	(1)	(2)	(3)	(4)	(5)	(6)
$CRET_{i,t-1} \times P1_{t-1}$	0.040*** [4.365]	0.027*** [2.945]	0.028*** [2.814]	0.029*** [4.291]	0.027*** [4.119]	0.031*** [4.587]
$CRET_{i,t-1} \times P2_{t-1}$	0.017** [1.988]	0.024*** [3.170]	0.025*** [3.345]	0.026** [2.306]	0.040*** [4.348]	0.029*** [3.120]
$CRET_{i,t-1} \times P3_{t-1}$	0.014* [1.843]	0.017** [2.249]	0.009 [1.265]	0.006 [0.571]	-0.018 [-1.339]	-0.016 [-1.155]
Constant	0.017*** [4.297]	0.014*** [3.679]	0.015*** [3.702]	0.011*** [3.127]	0.011*** [3.089]	0.012*** [3.238]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220,628	226,278	227,775	227,681	227,722	227,775
R-squared	0.086	0.085	0.084	0.084	0.083	0.083
Number of groups	468	468	468	468	468	468

Table 2.8: Analyst Coverage and Firm Centrality

This table exhibits Negative Binomial coefficient estimates from annual data regressions of the number of analyst coverage on lagged centrality values of firms. The dependent variable is the number of analysts covering the stock in the beginning of fiscal year t . *CENTRALITY* is the firm's centrality value measured at the end of fiscal year $t-1$. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. Centrality values are standardized by their standard deviation. All regressions also include the past return of the stock ($RET_{i,t-1}$), market value of equity ($\ln(SIZE_{i,t-1})$), share turnover ratio ($TURNOVER_{i,t-1}$), market to book ratio ($MB_{i,t-1}$) and institutional ownership ratio ($IOR_{i,t-1}$) as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Degree	Katz-Bonacich	Closeness
	(1)	(2)	(3)
$CENTRALITY_{i,t-1}$	0.029*** [5.426]	0.022*** [4.916]	0.021*** [4.342]
$RET_{i,t-1}$	0.001 [0.170]	0.002 [0.172]	0.002 [0.175]
$\ln(SIZE_{i,t-1})$	0.006 [1.523]	0.007 [1.603]	0.007* [1.691]
$TURNOVER_{i,t-1}$	-0.033*** [-10.753]	-0.034*** [-10.899]	-0.034*** [-10.871]
$MB_{i,t-1}$	0.003** [2.246]	0.003** [2.176]	0.003** [2.157]
$IOR_{i,t-1}$	0.066** [2.561]	0.062** [2.434]	0.061** [2.365]
Constant	3.836*** [53.017]	3.835*** [53.035]	3.829*** [53.040]
Firm Fixed Effect	Yes	Yes	Yes
Number of Years	39	39	39

Table 2.9: Number of Institutional Owners and Firm Centrality

This table exhibits Negative Binomial coefficient estimates from annual data regressions of the number of institutional owners on lagged centrality values of firms. The dependent variable is the number of institutional owners holding the stock in the beginning of fiscal year t . *CENTRALITY* is the firm's centrality value measured at the end of fiscal year $t-1$. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. Centrality values are standardized by their standard deviation. All regressions also include the past return of the stock ($RET_{i,t-1}$), market value of equity ($\ln(SIZE_{i,t-1})$), share turnover ratio ($TURNOVER_{i,t-1}$), market to book ratio ($MB_{i,t-1}$) and institutional ownership ratio ($IOR_{i,t-1}$) as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Degree	Katz-Bonacich	Closeness
	(1)	(2)	(3)
$CENTRALITY_{i,t-1}$	0.020*** [4.762]	0.022*** [6.941]	0.022*** [6.264]
$RET_{i,t-1}$	-0.012* [-1.657]	-0.012* [-1.650]	-0.012 [-1.643]
$\ln(SIZE_{i,t-1})$	0.385*** [104.049]	0.383*** [103.384]	0.383*** [102.951]
$TURNOVER_{i,t-1}$	-0.005** [-2.119]	-0.005** [-2.328]	-0.005** [-2.268]
$MB_{i,t-1}$	-0.005*** [-5.756]	-0.005*** [-5.499]	-0.005*** [-5.406]
$IOR_{i,t-1}$	1.525*** [72.984]	1.531*** [73.328]	1.530*** [73.186]
Constant	-1.348*** [-41.196]	-1.335*** [-40.690]	-1.336*** [-40.646]
Firm Fixed Effect	Yes	Yes	Yes
Number of Years	39	39	39

Table 2.10: Size-Adjusted Centrality Values and Return Predictability

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged customer returns interacted with lagged customer centrality values. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm ($CRET$). Residual centrality values are acquired by subtracting the centrality score from the average centrality score of the CRSP size quintile of the firm. Size-adjusted customer centrality values are ranked into three categories: lowest 30 percentile ($P1$), between 30 and 70 percentiles ($P2$) and highest 30 percentile ($P3$). $P1_CENTRALITY$, $P2_CENTRALITY$ and $P3_CENTRALITY$ are dummy variables equal to one if the centrality value of the customer firm is in the corresponding category, and zero otherwise. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. All regressions also include the dummy variables for $P2$ and $P3$ themselves, with MOM and one-month lagged RET , MOM , $INDRET$, $CINDRET$, $\ln(SIZE)$, $TURNOVER$, BM as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Degree (1)	Katz-Bonacich (2)	Closeness (3)
$CRET_{i,t-1} \times P1_CENTRALITY_{t-1}$	0.029*** [4.394]	0.028*** [3.964]	0.026*** [3.767]
$CRET_{i,t-1} \times P2_CENTRALITY_{t-1}$	0.024** [2.278]	0.023** [2.218]	0.026** [2.573]
$CRET_{i,t-1} \times P3_CENTRALITY_{t-1}$	0.011 [0.793]	0.019 [1.348]	0.017 [1.235]
Constant	0.013*** [2.660]	0.014*** [2.953]	0.013*** [2.869]
Controls	Yes	Yes	Yes
Observations	227,775	227,775	227,775
R-squared	0.088	0.088	0.088
Number of groups	468	468	468

Table 2.11: Percentage of Sales to Customer, Duration of Customer-Supplier Relationship and Predictability Effects

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged customer returns interacted with the strength of customer-supplier relationship proxies. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm ($CRET$). The strength of customer-supplier relationship proxies include percentage of sales to customer and the duration of customer-supplier relationship. The relationship indicators are ranked into three categories: lowest 30 percentile ($P1$), between 30 and 70 percentiles ($P2$) and highest 30 percentile ($P3$). $P1$, $P2$ and $P3$ are dummy variables equal to one if the indicator value of a firm is in the corresponding category, and zero otherwise. All regressions also include the dummy variables for $P2$ and $P3$ themselves, with MOM and one month-lagged RET , $INDRET$, $CINDRET$, $\ln(SIZE)$, $TURNOVER$, MB as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Percentage of Sales	Duration
	(1)	(2)
$CRET_{i,t-1} \times P1_{t-1}$	0.026*** [3.919]	0.023*** [3.662]
$CRET_{i,t-1} \times P2_{t-1}$	0.018** [2.402]	0.017** [1.976]
$CRET_{i,t-1} \times P3_{t-1}$	0.030*** [3.244]	0.024*** [2.815]
Constant	0.011*** [2.830]	0.010*** [2.800]
Controls	Yes	Yes
Observations	203,381	227,775
R-squared	0.085	0.082
Number of groups	468	468

CHAPTER III

MACROECONOMIC UNCERTAINTY AND INVESTOR ATTENTION

3.1. Introduction

There are two competing theories in the literature regarding the relationship between investor attention and macroeconomic uncertainty. On the one hand, Kacperczyk et al. (2016) investigates the institutional investors' priority of information choice in different states of the economy-wide uncertainty. Using states of business cycle as macroeconomic uncertainty and assuming investors have limited attention, they theoretically show that investors allocate more attention to firm-specific news in low uncertainty periods. On the other hand, a recent study by Andrei et al. (2020) model the impact of macroeconomic uncertainty on investor attention to firm level announcements. They postulate that investor attention is not limited and it increases with the economy-wide uncertainty. Using VIX as economy-wide uncertainty, they show that investors are more attentive to firm-specific news in high-VIX periods.

In this study, our aim is to show which theoretical model is supported by empirical data. We use major customer firm news, a novel indicator in this strand of the literature, as a firm specific news. The regulation Statement of Financial Accounting Standards (SFAS) No. 131 requires US firms to report their major customers (or, alternatively, principal customers) which account for more than 10 percent of their annual sales. In the sample, customer firms account for approximately 20 percent of a dependent supplier's total sales. Therefore, customers are substantive stakeholders in the supplier firms (Cohen and Frazzini, 2008) and the switching cost for a supplier firm to find an alternative customer firm is very high (Lian, 2017). Accordingly,

value-relevant information about the customer firms has an impact on their dependent suppliers (Gosman and Kohlbeck, 2009; Hertz et al., 2008; Patatoukas, 2012). We focus on the well-defined customer-supplier relationships between firms enabling us to test the impact of macroeconomic uncertainty on investor attention to firm-level news.

We use customer news for several reasons. First, empirical studies examining the relationship between macroeconomic uncertainty and investor attention generally make use of earnings announcements (Andrei et al., 2020; Liu et al., 2019). Earnings announcement includes only accounting information, whereas customer firm news may include speculative and intangible information, as well. Therefore, customer news may convey more information than earnings announcements. Second, in a survey study by Edmans et al. (2021) show that institutional investors perceive the need to avoid controversy with customers, implying that investors are focusing on the firm's customer reputation. Third, Ma et al. (2020) argues that any shock to the customer firm is exogenous to its supplier firm because the shock is less likely to affect the supplier firm through channels except for the supply chain link. Therefore, idiosyncratic shocks to customer firms can be regarded as exogenous to the dependent supplier firms.

Using direct investor attention proxies, we examine the impact of uncertainty on investor attention to supplier firms driven by customer news in the distinction of retail and institutional investor attention. We use abnormal Google search volume as a direct measure of retail investor attention and SEC EDGAR company filing downloads as a direct measure of institutional investor attention. Following Cohen and Frazzini (2008), customer news is proxied by customer firm stock returns. Incorporating the VIX as a time-varying measure of economic uncertainty, we find that institutional investors pay more attention to extreme customer firm stock returns. In addition, the evidence show that they raise their attention to customer news as VIX declines. Our findings compatible with the predictions of Kacperczyk et al.'s (2016) theoretical model. We also find that retail investors ignore the relevant information about customer firms and there is no meaningful relationship between retail investor attention to customers news and VIX.

We also investigate the price implications of investor attention during low and high economic uncertainty periods. To this end, we split the sample into high and low VIX periods. The regression results show that supplier stock returns are not predictable from customer stock returns during low VIX periods which is attributable to high institutional attention to customer news which increases with a decline in uncertainty. On the other hand, investors underreact to customer news in high VIX periods generating cross-return predictability. The return predictability decreases with an increase either in institutional investor attention or in retail investor attention when uncertainty is high.

We do not directly test both theoretical papers' controversial assumption regarding the investors' total attention allocation, but our findings have implications on the assumption. According to limited investor attention theory, investors may overlook the relevant information when it is announced to the market, generating subsequent price drifts and thus return predictability (DellaVigna and Pollet, 2009; Hirshleifer and Teoh, 2003). Increased investor attention leads to more immediate stock price incorporation of value-relevant information, which diminishes return predictability and, in turn, improves market efficiency (Drake et al., 2014; Lee et al., 2019; Menzly and Ozbas, 2010). Our findings regarding the stock return predictability are compatible with the limited investor attention. Therefore, our results also support the assumption of Kacperczyk et al. (2016) stating that attention is limited. Furthermore, we show that investors pay less attention to individual stocks as the total number of earnings releases by other firms in the same month increases. This result is also compatible with the limited attention because as more firm-specific information for other firms is released to the market, investor attention to a firm-level news declines. Our results support both the assumption and the predictions of the Kacperczyk et al.'s (2016) model.

Our paper contributes to the literature on the determinants of investor attention. Prior literature, in general, examines the role of investor attention in price diffusion of an information release (Barber and Odean, 2008; Ben-Rapheal et al., 2017; DellaVigna and Pollet, 2009; Hirshleifer and Teoh, 2003). Some other studies investigate the determinants of investor attention to firm-level information including earnings announcement, analyst recommendation change, merger announcements (Andrei et

al., 2020; Ben-Raphael et al., 2017; Liu and Krystyniak, 2021). In contrast to these studies, we focus on major customer firm news that attracts investor attention. Furthermore, these studies neglect the role of macroeconomic uncertainty on investor attention to firm specific news. The only papers that investigate the association between uncertainty and investor attention to firm-specific news is those of Kacperczyk et al. (2016) and Andrei et al. (2020). In their theoretical papers, they also examine their models' predictions with the empirical data and document contradictory results. While our study is similar to their empirical works, but our findings are consistent with the predictions of Kacperczyk et al. (2016). Moreover, while they only focus on the institutional investors, we also analyze the retail attention response to macroeconomic uncertainty.

Our paper also contributes to the literature on the role of institutional attention vis-à-vis retail attention in price discovery. High institutional investor attention facilitates information incorporation and reduces future price drifts, which, in turn, increases market efficiency (Ben-Rephael et al., 2017; Li et al., 2019). However, the role of the retail investor attention in price discovery is inconclusive. Some researchers find that price efficiency increases with retail investor attention (Han et al., 2017; Israeli et al., 2017; Kelley and Tetlock, 2013), whereas Ben-Rephael et al. (2017) find that retail attention does not alleviate the post earnings announcement price drift. Our analysis contributes this literature by demonstrating the differences in institutional and retail investors' attention allocation decisions and revealing the role of institutional and retail investor attention in the price diffusion of an information.

The remainder of the paper is organized as follows. Section 3.2 discusses our contribution to the literature. Section 3.3 describes the data used in the regression analysis. Section 3.4 introduces the methodology. Section 3.5 presents the results from empirical analyses. Section 3.6 provides robustness tests. Section 3.7 concludes.

3.2. Literature Review

Our study is related to several strand of the literature. Firstly, this study is related to investor attention and market-wide uncertainty. There are two competing theoretical

models in this research area. On the one hand, Kacperczyk et al. (2016) explore the investors' priority of information choice in different states of the economic uncertainty such as business cycle. They show that information about aggregate shocks receives higher attention in recessions and news about idiosyncratic shocks attracts greater attention in booms. They argue that in recessions volatility is high and macroeconomic shocks lead to more uncertain outcomes. Since macroeconomic shocks influence a large fraction of the portfolio's value, allocating more attention to macroeconomic shocks alleviates more portfolio risk than learning about firm specific risks. In addition, the price of risk increases in times of recession, which, in turn, augments this allocation process because risk minimizing attention choices are more profitable when the price of risk is high.

On the other hand, Andrei et al. (2020) show that investors' attention to firm-specific news increases with the amount of economic uncertainty. In their model, they assume that the total amount of attention defined as the fraction of informed investors in the economy increases with economic uncertainty. They find that the benefits of paying attention to firm-level announcement increases with the level of economic uncertainty. They also investigate the price implication of earning announcement. They reveal that increase in attention triggered by higher uncertainty amplifies the response coefficients to firm specific news. We contribute to this strand of the literature by empirically examining the predictions of both theoretical models.

There are only a few empirical studies considering the association of investor attention with economic uncertainty. Kacperczyk et al. (2016) empirically test their model for the mutual fund managers. They show that during expansionary periods covariance of each fund's portfolio holdings with the firm-level earnings innovation which represents fund managers' skill to choose stocks that subsequently experience unexpected increases in earnings. This finding implies that fund managers are more attentive to firm-specific shocks in times of booms. Andrei et al. (2020) also empirically test their theoretical predictions. Using firm-level news, i.e., earnings announcement, and firm-level institutional attention measures, they show that higher economic uncertainty increases institutional attention to firm-level earning news. Moreover, they find that earning response coefficients are higher on days with higher VIX, which is attributed to increase in investors' attention caused by higher

uncertainty magnifying the price reaction to earnings announcement. Our study differs from both studies in that we use a novel firm specific news, i.e., customer news which may contain both speculative and intangible information. Furthermore, we investigate the role of both institutional and retail investor attention in price diffusion of customer news during the different states of the economic uncertainty. Additionally, Liu et al. (2019) investigates the impact of market-wide uncertainty on investors' attention decision. However, their main goal is to explore whether investors' attention allocation follows a pecking order rather than directly testing the predictions of theoretical models. Therefore, their analysis is based on the crowding out effect of macroeconomic news on attention to firm-specific news during high and low macroeconomic uncertainty periods.

We investigate the response of investor attention to firm-specific news under economic uncertainty in the distinction of retail investor and institutional investors. Therefore, this study also contributes to the literature investigating the reaction of retail investor vis-à-vis institutional investors. Ben Rapheal et al. (2017) show that both retail and institutional investors' attention rises in days when firm specific news such as quarterly earnings announcement and analyst recommendation changes are released. The majority of the studies in this research area focus on the role of investors in price diffusion of an information release. For example, retail investors are net buyers of attention-grabbing stocks (Barber and Odean, 2008), retail investor attention and trading volume is positively associated (Da et al., 2011), institutional investor attention reduces the price drift after news announcement (Ben-Rapheal et al., 2017), stock return on announcement day is lower for the stocks which grab more pre-announcement institutional attention (Li et al., 2019). These studies do not consider the role of macroeconomic uncertainty in investors' attention allocation decisions.

3.3. Data

3.3.1. Direct Investor Attention Measures

We use EDGAR downloads of company filings as a direct institutional investor attention measure like Ben-Raphael et al. (2017) and Focke et al. (2020). SEC's EDGAR website provides the download logs from February 14, 2003 to June 30, 2017 on a daily basis. Automated software programs can download large volumes of filings for later analysis. In order to extract the investors' use of financial information in SEC's EDGAR, downloads requested by the robots should be excluded. To filter the data from mass automated or robot downloads and errors, we follow the approach described by Ryans (2017).¹⁸ Specifically, the downloads from IP addresses that access more than 25 items in a single minute or 3 different companies' items in a single minute or 500 items in a single day are excluded. For the robustness, we also use alternative filtering methodologies suggested by Drake et al. (2015) and Loughran and McDonald (2017). Since Google provides search volume indices at a monthly frequency for the periods exceeding 5 years, for compatibility purposes, we convert the daily data for each firm to monthly data by taking averages EDGAR download statistics in a given month. In our tests, we exploit abnormal requests (AEDGAR) for firm filings on the SEC EDGAR website as a proxy for institutional investor attention. We calculate the AEDGAR as the natural log of the ratio of EDGAR to the EDGAR in the previous month. We merge the EDGAR data with CRSP stock returns by using the CIK-CUSIP links provided by the WRDS.

We use Google Search Volume Index (GSVI) as a direct retail investor attention measure following Drake et al. (2012), Da et al. (2011). Google Trends provides search volume data from January 2004. Following Da et al. (2011), by using stock tickers as search terms we download Search Volume Index for every stock from January 2004 to June 2017. Google Trends provides data at a monthly frequency when the search period exceeds 5 years. Hence, we use monthly GSVI data. Some stock tickers may have generic meaning such as ALL, DNA, GPS etc. GSVI of these tickers do not truly reflect the search activity of retail investors. We obtain the lists of noisy tickers from Da et al. (2011) and exclude these tickers from our sample.¹⁹ We calculate abnormal search volume (AGSVI) for stocks in the same way as

¹⁸ We thank James Ryans for generously sharing the data. The data is available at <http://www.jamesryans.com>

¹⁹ We thank Zhi Da for generously sharing the too noisy stock tickers data with us.

AEDGAR.²⁰ We calculate the AGSVI as the natural log of the ratio of current month GSVI to the GSVI in the previous month. While EDGAR data ranges from February 2003 to June 2017, GSVI can range from January 2004 to current month. To be consistent in empirical analysis, our sample spans the period from January 2004 to June 2017.

3.3.2. Customer-Supplier Links

According to the regulation Statement of Financial Accounting Standards (SFAS) No. 131, US firms have to disclose the name of the principal customer firm which account for more than 10% of annual sales. Compustat customer segment file reports the identity of the major customers and the sales amounts to those customers on annual basis. To uniquely identify the principal customers by their CRSP permno numbers, we match customer firm names with the company names in CRSP database. For the period between 2004 and 2009, we use the customer-supplier links provided by Cohen and Frazzini (2008). From 2009 onwards, we extract the customer supplier links by using their methodology. We extract the customer-supplier links from Compustat customer segment file until the 2017 fiscal year-end. We merge Compustat segment data with CRSP to uniquely identify the firms in both data set.

3.3.3. Stock Returns

We retrieve stock returns from CRSP database. We exclude stocks with missing book and market values at the fiscal year-end to identify the customer firm as another traded CRSP-Compustat firm. The sample includes all common stocks listed in the CRSP-Compustat universe. Lo and MacKinlay (1990) show that large stocks lead small stocks. Additionally, Hou (2007) and Menzly and Ozbas (2010) document that large firms in an industry lead same industry small firms. Therefore, we do not include small stocks whose closing price below five dollars at the end of the previous month to make sure that results are not driven by the small and illiquid stocks.

²⁰ There is no consensus in the literature in identifying the abnormal requests for Edgar company filings and Google search volume. While some researchers use abnormal requests as a proxy for abnormal attention (Focke et al., 2020; Liu et al., 2019), others define it as a proxy for just attention (Da et al., 2011; Drake et al., 2012; Gamm, 2020). In this study, we follow the latter approach.

In order to ensure that investors are aware of the customer-supplier links, we allow a six-month gap between the disclosure of major customers by supplier firms and the formation of test assets. More specifically, we match the accounting data of a firm in month t of year k with monthly stock returns starting from month $t+6$ of year k to month $t+5$ of year $k+1$. Customer-supplier links are used for one year period only and links are updated with the new accounting information is released. In some years, firms may have multiple customer firms. When a firm has multiple customers, we use equal weighted customer returns as customer news.

3.4. Methodology

In this section, we first examine the impact of economic uncertainty on both institutional and retail investor attention to customer news. To this end, we use a panel data regression model. The form of the regression is as follows:

$$AEDGAR_{i,t}(AGSVI_{i,t}) = \alpha + \gamma|CustRet_{i,t}|_{Decile} + \delta|CustRet_{i,t}|_{Decile} * VIX_t + \beta VIX_t + \sum_k \theta_k Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t}$$

where $AEDGAR$ ($AGSVI$) represents abnormal request for company filings (Google search volume) for firm i in month t . As a proxy for customer news, we use firm i 's major customer firm stock return decile ($|CustRet_{i,t}|_{Decile}$). We include VIX as a macroeconomic uncertainty indicator. In order to control whether investor attention to customer news is affected by the economic uncertainty, we interacted customer returns with VIX .

We also include control variables that have been suggested by Liu et al. (2019) and Andrei et al. (2020). The control variables include dummy variable for earnings announcement, stock returns, firm size, book-to-market ratio, share turnover ratio, institutional ownership ratio, number of analysts covering the stock and the total number of earnings announcements by other firms. We include the dummy variable $EarnAnn$ for the quarterly earnings announcement which takes the value of 1 in months when the firm i 's earnings are announced. We measure firm size ($SIZE$) as the

market value of equity, calculated by multiplying the stock price by the total amount of outstanding shares. Book-to-market ratio (*BM*) represents the ratio of the book value to the market value of equity in calendar year $t-1$. To obtain share turnover ratio (*TURNOVER*), we divide the number of shares traded by the number of outstanding shares in month t . Institutional ownership ratio (*IOR*) is expressed as a fraction of the outstanding shares held by institutional investors. The analyst coverage (*ANALYST*) indicates the number of analysts making one-year ahead earning per share forecast for stock i in month t . Number of announcement (*# of Announcement*) represents the total number of earnings announcements by other firms in concurrent month. We also include year fixed effects as in Liu et al. (2019) and Andrei et al. (2020). Additionally, Liu and Peng (2015) show that Google search volume displays strong seasonal pattern. In order to capture seasonal effects and the effect of macro-news releases we also include month of year fixed effects as in Liu and Peng (2015). Finally, we also control for time-invariant firm specific characteristics by including firm fixed effects.

Table 3.1 represents the Pearson correlation coefficients between the variables used in the regressions. The correlation between *AEDGAR* and $|CustRet_{i,t}|_{Decile}$ is positive and significant at conventional level, providing raw evidence that customer news attracts institutional attention. However, the correlation between *AGSVI* and $|CustRet_{i,t}|_{Decile}$ is not statistically significant, implying that retail investors neglect the customer news. Furthermore, correlation coefficient between *ANALYST* and $\ln(SIZE)$ is very high. In order to avoid collinearity problem, we adjust this problem by regressing analyst coverage on logarithm of firm size. We then use the residuals of the regression as our measure of analyst coverage net of firm size.

We also investigate the stock price implications of investor attention during high and low economic uncertainty periods. Cohen and Frazzini (2008) document that investors underreact to relevant information about customer firms which, in turn, generates stock return predictability from customer stock returns. We follow and extend their methodology to gauge the impact of increased attention on stock return predictability and then to examine the effect during high and low VIX periods. We split our sample into low and high VIX periods with respect to median value of the

VIX. The periods in which VIX is greater than the median VIX is classified as high VIX periods and less than the median VIX values are classified as low VIX periods. Using Fama-MacBeth cross-sectional forecasting regression, we estimate the following regression for both periods separately:

$$\begin{aligned} SupRet_{i,t} = & \alpha_0 + \beta_1 CustRet_{i,t-1} + \beta_2 CustRet_{i,t-1} * AttentionDum \\ & + \delta_1 SupRet_{i,t-1} + \delta_2 MOM_{i,t-2,t-12} + \delta_3 Indret_{i,t-1} \\ & + \delta_4 Cindret_{i,t-1} + \theta_1 \ln(Size_{i,t-1}) + \theta_2 MB_{i,t-1} + \theta_3 Turnover_{i,t-1} \\ & + \varepsilon_{i,t} \end{aligned}$$

where $SupRet_{i,t}$ is the raw return of supplier firm i in month t . The main independent variable is the lagged return of supplier firm i 's major customer in month $t-1$, $CustRet_{i,t-1}$. In order to examine whether customer news in month $t-1$ can forecast the supplier stock returns in month t , we use customer firm stock return which is one-month lagged from the supplier stock return. We add an interaction term to explore the impact of investor attention on return predictability. We multiply lagged customer return with dummy variable for investor attention ($AttentionDum$) which takes the value of 1 if the AEDGAR (alternatively, AGSVI) of the supplier firm is in the highest quartile in a month and zero otherwise. This interaction term measures whether stocks that extensively attract investor attention react to customer news different from those that attract less investor attention. The regression also includes lagged control variables that have been used by Cohen and Frazzini (2008). We control for the short-term reversal effect of Jagadeesh (1990) by adding the supplier stock's own lagged return in month $t-1$ ($SupRet_{i,t-1}$). In addition, we control for the price momentum effect of Jagadeesh and Titman (1993) using the supplier firm stock's cumulative return from $t-2$ to $t-12$ ($MOM_{i,t-2,t-12}$), respectively. The regression contains the lagged return of firm i 's industry portfolio ($Indret_{i,t-1}$) to control for the intra-industry lead-lag effect of Hou (2007). The equation also includes the lagged return of customer firm's industry portfolio ($Cindret_{i,t-1}$) to capture the cross-industry momentum of Menzly and Ozbas (2005). Finally, the regression includes control variables about firm characteristics which are logarithm of firm size ($\ln(Size)$), market to book ratio (MB) and equity turnover ratio ($Turnover$) measured in month $t-1$.

3.5. Results

3.5.1. Attention to Customer News

We first analyze the impact of economic uncertainty on institutional investor attention. Table 3.2 presents the results with varying control variables. In column (1), the equation includes only VIX as an explanatory variable. The coefficient on VIX is positive and statistically significant at 1 percent significance level. That is to say, we find significant evidence for active searching for firm level information on months with higher VIX. When we multiply the coefficient with the median VIX value (16.05), we get 3.02 percentage point change in EDGAR search/download activity. Hence, the coefficient is not only statistically significant but also economically significant. Before controlling for any variables in Column 2, the coefficient on absolute value of customer returns decile ($|CustRet|_{decile}$) is 0.015 with a t-statistic 2.01. The rise in the absolute value of customer returns attracts more institutional attention to supplier firm. In other words, investors pay high attention to extreme customer news. The magnitude of the coefficient is economically significant, as well. When we multiply the coefficient with the median value of absolute customer return decile (5.4), we get 8.1 percentage point change in firm filing download activity for supplier firm. In column (3), the equation includes both customer news and VIX as independent variables. Augmenting the equation with VIX in column 2 has negligible effect on the significance of ($|CustRet|_{decile}$). In order to control for the effect of quarterly earnings announcements on attention, the equation includes the dummy variable for the earnings announcement months in column 4. The coefficients on customer news retain significant. Furthermore, institutional investors allocate greater attention to firms on months when their earnings reports are announced.

Column (5) includes additional control variables. Stocks with higher analyst coverage, larger book-to-market ratio, more negative returns and greater turnover ratio attracts higher institutional attention. Fama and French (1992, 1998) show that stocks with high book-to-market ratio (value stocks) earn higher average returns than the stocks with low book-to market ratio (growth stocks). This suggests that institutional investors focus more on the stocks whose expected returns are higher. The negative

sign of the stocks' own returns seems contrary to expectations, but it can be explained by that institutional investors might pay greater attention to negative return (bad news) than positive returns (good news).²¹ Additionally, this result indicates that institutional investors might follow a contrarian investment strategy which requires buying loser stocks. Hence, they might pay greater attention to stocks with negative returns. The positive coefficient on turnover ratio means that institutional investors allocate more attention to stocks with higher liquidity. On the other hand, total number of reports announced in the concurrent month and institutional ownership ratio have negative impacts on institutional attention. The negative sign on total number of earnings announcements is consistent with the limited investor attention theory. Since investors have limited time and cognitive resources according to this theory, search activity for firm filings decreases on months when the number of earnings announcements released by other firms increased. The sign of the coefficient on institutional ownership ratio is opposite to expectations. The reason might be that institutions closely monitor the stocks that they already hold and thus this can reduce the need for additional searching activity about the firm. Lastly, the firm size has no meaningful effect on institutional attention. This result might be due to the sample of stocks. Since we do not include stocks with a price less than five dollars, the sample relatively consists of large stocks. In the last column, we investigate the effect of VIX on institutional attention to customer news. To this end, we use an interaction term which multiplies customer news by VIX. The coefficient on this interaction term is negative and statistically significant at conventional levels. This means that investors allocate less attention to customer news in high VIX periods compared to low VIX periods.²² This result is compatible with the theoretical prediction of Kacperczyk et al. (2016).

Next, we examine the impact of economic uncertainty on retail investor attention. Table 3.3 represents the reaction of retail attention to principal customer firm returns. Column (1) includes only VIX as an explanatory variable. The coefficient on VIX is

²¹ There might be concerns about using the same-month observations of attention indicators and stock's own return which may create endogeneity problem. For the robustness check, we re-run the regressions with one month lagged stock's own return. The results remain qualitatively same. They are available in Appendix Table A3.

²² The marginal effect of $|CustRet|_{decile}$ on search activity for firm filings is $0.043 - 0.001 * VIX$. Marginal impact is positive if VIX is lower than 43. In our sample, 6 out of 162 monthly VIX observations exceeds 43. Hence, the marginal impact rarely turns to negative.

negative but statistically insignificant which means that uncertainty does not have a meaningful impact on retail attention. The reason might be that existing retail investors (intensive margin) can increase their Google search activity with the amount of uncertainty, but potential retail investors (extensive margin) may delay their investment decisions in high VIX periods due to high uncertainty, which in turn reduces Google search activity. Consequently, the total effect is not significant. In Column 2, we have only customer returns decile as independent variable. The coefficient on $|CustRet|_{decile}$ is -0.006 with a t-statistic 0.40. The coefficient on customer news is statistically insignificant implying that retail investors neglect the relevant information about the customer firm. In column (3), customer news and VIX are included together as explanatory variables. Still, both variables are statistically insignificant. In column (4), we augment the equation with dummy variable for quarterly earnings announcement (*EarnAnn*). The coefficient on *EarnAnn* is statistically significant with a coefficient estimate of 0.099 and a t-statistic of 7.96. This finding suggests that retail investors pay greater attention to firms on months when their earnings are announced.

The coefficient estimates on the control variables in column (5) of Table 3.3 shed light on the other determinants of retail investor attention. We find that the coefficients on stocks returns, analyst coverage, and turnover ratio are positive and significant, implying that firms with higher stock returns, greater number of analyst coverage and higher turnover ratio attract higher retail investor attention. On the other hand, retail investors are less attentive to stocks with higher institutional ownership ratio. The positive coefficient on stock's own return suggest that retail investors might be following a momentum strategy by following winner stocks. Retail investors' ownership ratio is higher in small stocks compared to that in big stocks. The reverse is true for institutional investors. Therefore, it is reasonable that retail investor attention is negatively related with stocks with higher institutional ownership ratio. Firm size, book-to-market ratio and number of earnings announcements have no meaningful effect on retail attention. In column (6), to examine the impact of economic uncertainty on retail attention to customer news, we interact customer news with VIX. The coefficient on the interaction term is positive but statistically insignificant. Specifically, the evidence shows that there is no meaningful relationship between retail attention to firm specific news and economic uncertainty.

3.5.2. Stock Price Implications of Economic Uncertainty

In this part, we investigate the impact of investor attention on stock price formation during high- and low-VIX periods. Cohen and Frazzini (2008) show that investors underreact to news about principal customer firms when it is released to the market which generates predictable subsequent price moves. We extend their methodology to analyze the impact of macroeconomic uncertainty on incorporation of relevant information into stock prices.

First, we estimate the predictive ability of customer news during high and low economic uncertainty periods. Table 3.4 represents the estimated coefficients of Fama-MacBeth forecasting regressions. Column (1) indicates the cross-stock return predictability for all sample. The coefficient on lagged customer returns is 0.025 with a t-statistic of 2.60. Consistent with the Cohen and Frazzini's result, our findings show that investors underreact to customer firm news, generating cross predictability of stock returns. As for control variables, lagged turnover ratio is negatively associated with the stock return and lagged industry return is positively associated with the stock return. We also find that lagged stock return, customer firm industry return, firm size, book to market ratio and momentum factor do not have meaningful relationship with the stock return.

Column 2 represent the coefficient estimates during low-VIX periods. The coefficient on the variable of the interest, lagged customer return, is positive but statistically insignificant. Specifically, the customer news can not predict the supplier stock returns in low-VIX periods which is more likely attributable to high institutional attention to customer firm news during low uncertainty periods. This finding is compatible with our previous results. As VIX decreases, institutional attention to customer news increases and retail attention to customer news remains unchanged. Since the share of institutional investors in the stock market in US exceeds 70 percent, the increase in institutional investor attention to supplier firm is expected to reduce underreaction to customer news, which in turn lowers the stock return predictability.²³

²³ Iselin et al. (2020) demonstrate that the average percentage of institutional ownership is around 77 percent during the period between 2005 and 2014.

In high-VIX periods, the coefficient on lagged customer returns is positive and statistically significant with a coefficient estimate of 0.036 and t-statistic of 2.63 (column (3)). The evidence suggest that customer returns can predict the supplier stock returns which can be attributable to low institutional investor attention to customer news when uncertainty is high. In other words, when VIX increases, institutional investor attention to customer news decreases which results in stock return predictability from customer return.

Next, we investigate the impact of high investor attention on stock return predictability during low and high VIX periods for both institutional and retail investors. Table 3.5 examines the impact of institutional investor attention on stock return predictability. To this end, in addition to variables used in Table 3.4, we interact customer stock returns with the institutional attention dummy, where the dummy variable (*AEDGAR_DUM*) takes the value of one if abnormal request for company filings is in the highest quartile and zero otherwise. Column (1) shows that neither the coefficient on customer stock returns nor the coefficient on the interaction term is statistically significant in low-VIX periods. That is to say, supplier stocks attracting the highest institutional attention do not underreact or overreact to customer news. Since in low-VIX periods institutional attention to customer news is already high and thus supplier stock returns are not predictable from customer news, stocks with highest institutional investor attention does not underreact or overreact to customer news, as well.

Column (2) of Table 3.5 indicates that the coefficient on customer returns is positive, but the interaction term is negative and statistically significant in high-VIX periods. This indicates that stock returns are predictable from customer news, but the stock return predictability decreases with increased institutional attention to customer news. The summation of the coefficient on customer returns and the coefficient on the interaction term is not statistically different from zero (with a coefficient of 0.002 and p-value of 0.80). This means that while stock prices underreact to customer news in high uncertainty periods, prices of stocks attracting high institutional investor attention respond to customer firm news more immediately. Our finding is consistent with the limited investor attention theory, stating that increased attention reduces the stock return predictability.

Table 3.6 investigates the impact of retail investor attention on supplier stock price response to customer news. We control this effect with an interaction term which multiplies customer news by the retail attention dummy variable (*AGSVI_DUM*) taking the value of one if a firm's retail investor attention is in the highest quartile and zero otherwise. Column (1) reports the regression results in low-VIX periods. Both the coefficient on customer stock returns and the coefficient on the interaction term is not statistically significant in low-VIX periods. During low-VIX periods customer news can not predict the supplier stock returns due to the high institutional investor attention and the amount of retail attention to supplier firms do not have meaningful impact on return predictability. Column (2) represents the regression results in high-VIX periods. While the coefficient on customer stock returns is positive and statistically significant, the coefficient on interaction term is negative and statistically significant only at 10% significance level. This indicates that stock returns are predictable from customer news, but the stock return predictability decreases as retail attention increases. The summation of the coefficient on customer returns and the coefficient on interaction term is not statistically different from zero (with a coefficient estimate of 0.001 and p-value of 0.98). This means that while stock prices underreact to customer news in high uncertainty periods, stocks attracting high retail investor attention incorporates customer news more quickly.

Overall, institutional investor attention to firms driven by customer news is higher during low-VIX periods which results in predictable stock return generated by customer news in months with high VIX. The stock return predictability decreases with the increase either in institutional investor attention or in retail investor attention. These findings suggest that consistent with the theoretical analysis of Kacperczyk et al. (2016) investor attention is limited.

3.6. Robustness Tests

In the previous section, we follow Ryans' (2017) filtering methodology to reveal the human users of SEC's EDGAR and remove company filing downloads by computer programs. For robustness, we use Drake et al. (2015) and Loughran and McDonald (2017) filtering methodology to exclude robot downloads of SEC's EDGAR filings.

Drake et al. (2015, hereinafter DRT) make two assumptions: i) humans can not download more than 1000 items in a day ii) humans can not download more than 5 items per minute. They classify the downloads satisfying both assumptions from the same IP as robot downloads. On the other hand, Loughran and McDonald (2017, hereinafter LM) postulates that humans can not download more than 50 items in a day. Therefore, we remove the robot downloads based on the measures of DRT and LM, respectively.

Table 3.7 represents the impact of economic uncertainty on institutional investor attention to individual firms driven by the customer news. Institutional attention indicators are based on DRT and LM measures in Column (1) and Column (2), respectively. In both regressions, we obtain qualitatively same results. The evidence reveals that institutional investors allocate less attention to customer news as VIX increases. These findings show that results are not sensitive to filtering methodology of robot downloads of company filings.

In Table 3.8, using DRT and LM measures we investigate the impact of high institutional investor attention on stock return predictability during low and high VIX periods. In column (1) and (2), AEDGAR is measured by DRT methodology, in column (3) and (4) AEDGAR is based on LM methodology. We find very similar results with both measures. During low VIX periods, customer returns can not predict the supplier stock returns due to high institutional investor attention and supplier stocks attracting the highest institutional attention do not underreact or overreact to customer news (Column (1) and (3)). On the other hand, customer returns can predict the supplier stock returns in high VIX periods, but return predictability decreases with the increase in institutional investor attention to supplier firms (Column (2) and (4)). Irrespective of the filtering methodology, the evidence is consistent with the limited investor attention theory.

3.7. Conclusion

In this study, we examine the relationship between market-level uncertainty and investor attention to firm-level news. Two conflicting theories exist regarding the

impact of macroeconomic uncertainty on investor attention to firm-specific news. Kacperczyk et al. (2016) show that investors allocate more attention to firm-specific news in times of low uncertainty, whereas Andrei et al.'s (2020) model predicts the reverse. We empirically examine the predictions of these theoretical models using major customer firm news as an indicator of firm specific news in the period between January 2004 and June 2017. The empirical works overlook the role of macroeconomic uncertainty in investors' attention allocation to firm news. In this study, we fill this gap by investigating the relationship between these two variables and by empirically testing the predictions of both theoretical models.

The regression results show that institutional investors are attentive to customer news and raise their attention as VIX declines. The retail investors, on the other hand, neglect the value-relevant information about major customer firms and their inattention to customer news is not associated with VIX. Our findings suggest that the attention allocation decision of institutional investors is consistent with the predictions of Kacperczyk et al.'s (2016) theoretical model, but that of retail investors is consistent with neither hypothesis. Furthermore, we explore the stock price impact of investor attention during low and high macroeconomic uncertainty periods. We find that supplier stock prices incorporate customer news faster during low VIX periods which is attributable to high institutional attention to customer news in times of low uncertainty. On the other hand, during high VIX periods, investors underreact to customer news, generating cross-return predictability from customer news. We reveal that cross-return predictability diminishes with an increase either in institutional attention or in retail attention.

This study provides some insights for the future research implementation, since the gap in the literature still exists. It would be interesting to inquire whether the impact of macroeconomic uncertainty on investor attention is news dependent. To this end, this research can be extended by including different types of firm-specific news such as firms' and customer firms' credit rating changes, their analysts' recommendation changes, etc.

Table 3.1: Pearson Correlation Coefficients

This table exhibits the Pearson correlation coefficients between the variables used in the regressions. The variables are the first difference of the logarithm of Google search volume (AGSVI), the first difference of the logarithm of company filings downloads (AEDGAR), the stock market volatility index (VIX), decile rank of absolute value of firm *i*'s principal customer stock returns ($|CustRet|_{decile}$), firm's own returns (RET), number of analysts covering the stock (ANALYST), institutional ownership ratio (IOR), the logarithm of firm size ($\ln(SIZE)$), book to market ratio (BM), stock turnover ratio (Turnover) and logarithm of the total number of earnings reports announced in month *t* ($\ln(\# \text{ of Report})$). The numbers in bold represent statistically significant coefficients at 5% significance level.

Variables		1	2	3	4	5	6	7	8	9	10	11
AGSVI	1	1										
AEDGAR	2	0.023	1									
VIX	3	-0.006	0.011	1								
$ CRET _{decile}$	4	-0.003	0.012	-0.032	1							
RET	5	0.029	-0.007	-0.098	0.002	1						
ANALYST	6	-0.003	0.003	0.014	-0.003	-0.031	1					
IOR	7	-0.003	0.008	0.051	-0.012	-0.05	0.36	1				
$\ln(SIZE)$	8	-0.003	0.002	-0.021	-0.034	0.001	0.755	0.426	1			
Book-to-Market	9	0.001	0.005	0.009	0.025	0.052	-0.233	-0.094	-0.272	1		
TURNOVER	10	0.024	0.048	0.048	0.023	0.127	0.164	0.11	0.084	-0.032	1	
$\ln(\# \text{ of Report})$	11	0.004	0.063	-0.022	0.016	-0.004	-0.005	-0.006	-0.012	0.004	0.008	1

Table 3.2: Macroeconomic Uncertainty and Institutional Investor Attention

This table exhibits time-series panel data regression analyses of institutional investor attention to individual stocks with different control variables. The dependent variable is the first difference of the logarithm of company filings downloads of firm i in month t . VIX is the stock market volatility index. The independent variable of the interest is the decile rank of absolute value of firm i 's principal customer stock returns ($|CustRet|_{decile}$). We also include following control variables: dummy variable for the earnings announcement (EarnAnn), firm's own return (Ret), number of analysts covering the stock (Analyst), institutional ownership ratio (IOR), the logarithm of firm size ($\ln(SIZE)$), book to market ratio (Book-to-Market), stock turnover ratio (Turnover) and logarithm of the total number of earnings reports announced in month t ($\ln(\# \text{ of Report})$). All regression also includes month of the year fixed effects, year fixed effects and firm fixed effects. The regressions cover all common stocks with stock price greater than five dollars. T-statistics are reported in brackets. *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

VARIABLES	AEDGAR	AEDGAR	AEDGAR	AEDGAR	AEDGAR	AEDGAR
VIX	0.002*** [8.785]		0.002*** [8.823]	0.002*** [8.636]	0.001*** [4.782]	0.002*** [4.816]
$ CustRet _{decile}$		0.015** [2.010]	0.015** [2.055]	0.016** [2.214]	0.016** [2.104]	0.043*** [2.634]
$ CustRet _{decile} \times VIX$						-0.001** [-2.289]
EarnAnn				0.191*** [25.398]	0.189*** [23.848]	0.189*** [23.838]
Ret					-0.058*** [-2.972]	-0.058*** [-2.997]
Analyst					0.002*** [2.749]	0.002*** [2.725]
IOR					-0.039*** [-3.689]	-0.039*** [-3.680]
$\ln(Size)$					-0.001 [-0.210]	-0.001 [-0.271]
Book-to-Market					0.013** [2.345]	0.013** [2.322]
Turnover					0.013*** [3.606]	0.013*** [3.606]
$\ln(\# \text{ of Report})$					-0.122*** [-4.864]	-0.122*** [-4.872]
Constant	0.177*** [18.710]	0.194*** [20.410]	0.170*** [16.640]	0.118*** [11.641]	1.033*** [5.486]	1.024*** [5.442]
Month of the Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,362	78,362	78,362	78,362	74,904	74,904
R-squared	0.059	0.059	0.059	0.076	0.079	0.079

Table 3.3: Macroeconomic Uncertainty and Retail Investor Attention

This table exhibits time-series panel data regression analyses of institutional investor attention to individual stocks with different control variables. The dependent variable is the first difference of the logarithm of Google search volume index of firm i in month t . VIX is the stock market volatility index. The independent variable of the interest is the decile rank of absolute value of firm i 's principal customer stock returns ($|CustRet|_{decile}$). We also include following control variables: dummy variable for the earnings announcement (EarnAnn), firm's own return (Ret), number of analysts covering the stock (Analyst), institutional ownership ratio (IOR), the logarithm of firm size ($\ln(SIZE)$), stock turnover ratio (TURNOVER), book to market ratio (Book-to-Market) and logarithm of the total number of earnings reports announced in month t ($\ln(\# \text{ of Report})$). All regression also includes month of the year fixed effects, year fixed effects and firm fixed effects. The regressions cover all common stocks with stock price greater than five dollars. T-statistics are reported in brackets. *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

VARIABLES	AGSVI	AGSVI	AGSVI	AGSVI	AGSVI	AGSVI
VIX	-0.0001 [-0.810]		-0.0001 [-0.819]	-0.0001 [-0.895]	-0.0001 [-0.129]	-0.0001 [-0.210]
$ CustRet _{decile}$		-0.006 [-0.40]	-0.006 [-0.400]	-0.005 [-0.361]	-0.008 [-0.513]	-0.013 [-0.372]
$ CustRet _{decile} \times VIX$						0.0001 [0.166]
EarnAnn				0.099*** [7.960]	0.095*** [7.440]	0.095*** [7.443]
Ret					0.184*** [4.762]	0.184*** [4.757]
$\ln(Size)$					-0.006 [-1.162]	-0.006 [-1.157]
Analyst					0.001* [1.672]	0.001* [1.677]
IOR					-0.041*** [-2.823]	-0.041*** [-2.823]
Book-to-Market					-0.009 [-1.150]	-0.009 [-1.148]
Turnover					0.010*** [2.702]	0.010*** [2.702]
$\ln(\# \text{ of Report})$					0.077 [1.027]	0.077 [1.027]
Constant	0.087*** [4.646]	0.085*** [4.51]	0.090*** [4.422]	0.065*** [3.222]	-0.479 [-0.849]	-0.477 [-0.846]
Month of the Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,597	71,597	71,597	71,597	68,945	68,945
R-squared	0.001	0.001	0.001	0.002	0.004	0.004

Table 3.4: Cross Stock Return Predictability During High and Low VIX Periods

This table exhibits the Fama-MacBeth cross-sectional forecasting regressions of supplier firm stock returns. The dependent variable is the monthly supplier firm I stock return in month t . The HIGH (LOW) VIX period corresponds to months on which VIX is higher than (lower than) its median value for the period between 2004m2 and 2017m6. The independent variable of the interest is the one-month lagged stock return of principal customer (CustRet) of firm i . The explanatory variables include the firm's own lagged monthly return (SupRet), medium-term price momentum (MOM), firm's own value-weighted industry return (IndRet), customer firm's value-weighted industry return (CindRet), the logarithm of firm size (ln(Size)), stock turnover ratio (Turnover) and market to book ratio (Market-to-Book). The regression includes all common stocks with stock price greater than five dollars. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

VARIABLES	<u>ALL SAMPLE</u> SupRet _{<i>i,t</i>}	<u>LOW VIX</u> SupRet _{<i>i,t</i>}	<u>HIGH VIX</u> SupRet _{<i>i,t</i>}
CustRet _{<i>i,t-1</i>}	0.025*** [2.599]	0.014 [1.049]	0.036*** [2.634]
SupRet _{<i>i,t-1</i>}	-0.006 [-0.782]	-0.008 [-0.850]	-0.004 [-0.324]
IndRet _{<i>i,t-1</i>}	0.045* [1.796]	0.068** [1.993]	0.022 [0.597]
CindRet _{<i>i,t-1</i>}	0.020 [0.700]	0.034 [0.797]	0.006 [0.161]
MOM _{<i>i,t-2,t-12</i>}	-0.000 [-0.138]	0.004 [1.225]	-0.004 [-0.896]
ln (Size _{<i>i,t-1</i>})	0.000 [0.162]	-0.001 [-1.041]	0.001 [1.024]
Turnover _{<i>i,t-1</i>}	-0.001** [-2.145]	-0.00 [-0.350]	-0.002** [-2.553]
Market-to-Book _{<i>i,t-1</i>}	-0.00 [-0.102]	0.00 [0.398]	-0.00 [-0.468]
Constant	0.005 [0.872]	0.017** [2.479]	-0.007 [-0.731]
Observations	77,621	39,906	37,715
R-squared	0.066	0.064	0.069
Number of Groups	162	81	81

Table 3.5: Cross Stock Return Predictability, Macroeconomic Uncertainty and Institutional Investor Attention

This table exhibits the Fama-MacBeth cross-sectional forecasting regressions of supplier firm stock returns. The dependent variable is the monthly supplier firm *I* stock return in month *t*. The dependent variable is the monthly supplier firm *I* stock return in month *t*. The HIGH (LOW) VIX period corresponds to months on which VIX is higher than (lower than) its median value for the period between 2004m1 and 2017m6. The independent variable of the interest is the one-month lagged stock return of principal customer (CustRet) of firm *i*. AEDGAR_DUM is a dummy variable which takes the value of 1 if abnormal request for company filings is in the highest quartile and zero otherwise. The explanatory variables include the firm's own lagged monthly return (SupRet), medium-term price momentum (MOM), firm's own value-weighted industry return (IndRet), customer firm's value-weighted industry return (CindRet), the logarithm of firm size (ln(Size)), stock turnover ratio (Turnover) and market to book ratio (Market-to-Book). The regression includes all common stocks with stock price greater than five dollars. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

VARIABLES	LOW VIX	HIGH VIX
	SupRet _{i,t}	SupRet _{i,t}
CustRet _{i,t-1}	0.011 [0.643]	0.046*** [3.161]
CustRet _{i,t-1} x AEDGAR_DUM	-0.034 [-1.465]	-0.044** [-2.243]
AEDGAR_DUM	0.004** [2.610]	0.004** [2.458]
SupRet _{i,t-1}	-0.007 [-0.786]	-0.004 [-0.349]
IndRet _{i,t-1}	0.078** [2.274]	0.022 [0.613]
CindRet _{i,t-1}	0.028 [0.665]	0.007 [0.186]
MOM _{i,t-2,t-12}	0.004 [1.376]	-0.004 [-0.881]
ln (Size _{i,t-1})	-0.000 [-0.794]	0.001 [1.195]
Turnover _{i,t-1}	-0.000 [-0.518]	-0.002*** [-2.718]
Market-to Book _{i,t-1}	0.000 [0.360]	-0.000 [-0.208]
Constant	0.015** [2.143]	-0.009 [-0.913]
Observations	38,549	36,537
R-squared	0.069	0.072

Table 3.6: Cross Stock Return Predictability, Macroeconomic Uncertainty and Retail Investor Attention

This table exhibits the Fama-MacBeth cross-sectional forecasting regressions of supplier stock returns. The dependent variable is the monthly supplier firm *I* stock return in month *t*. The dependent variable is the monthly supplier firm *I* stock return in month *t*. The HIGH (LOW) VIX period corresponds to months on which VIX is higher than (lower than) its median value for the period between 2004m1 and 2017m6. The independent variable of the interest is the one-month lagged stock return of principal customer (CustRet) of firm *i*. AGSVI_DUM is a dummy variable which takes the value of 1 if abnormal Google search volume is in the highest quartile and zero otherwise. The explanatory variables include the firm's own lagged monthly return (SupRet), medium-term price momentum (MOM), firm's own value-weighted industry return (IndRet), customer firm's value-weighted industry return (CindRet), the logarithm of firm size (Ln(Size)), stock turnover ratio (Turnover) and market to book ratio (Market-to-Book). The regression includes all common stocks with stock price greater than five dollars. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

VARIABLES	LOW VIX SupRet _{i,t}	HIGH VIX SupRet _{i,t}
CustRet _{i,t-1}	0.019 [1.108]	0.052*** [3.489]
CustRet _{i,t-1} x AGSVI_DUM	0.000 [0.014]	-0.051* [-1.890]
AGSVI_DUM	-0.001 [-0.645]	0.001 [0.556]
SupRet _{i,t-1}	-0.007 [-0.765]	-0.006 [-0.471]
IndRet _{i,t-1}	0.060* [1.759]	0.042 [1.104]
CindRet _{i,t-1}	0.023 [0.536]	0.003 [0.083]
MOM _{i,t-2,t-12}	0.004 [1.216]	-0.004 [-0.896]
Ln (Size _{i,t-1})	-0.001 [-1.083]	0.001 [1.236]
Turnover _{i,t-1}	-0.000 [-0.127]	-0.002** [-2.341]
Market-to-Book _{i,t-1}	0.000 [0.554]	-0.000 [-0.736]
Constant	0.017** [2.575]	-0.009 [-0.910]
Observations	35,848	33,237
R-squared	0.068	0.076
Number of groups	81	80

Table 3.7: Macroeconomic Uncertainty and Alternative Institutional Investor Attention

This table exhibits time-series panel data regression analyses of institutional investor attention to individual stocks. The dependent variable is the first difference of the logarithm of company filings downloads of firm i in month t . In column 1, Edgar downloads of company filings (AEDGAR(DRT)) is filtered by the methodology of Drake et al. (2015) and in column 2, Edgar downloads (AEDGAR(LM)) is filtered by the methodology of Loughran and McDonald (2017). VIX is the stock market volatility index. The independent variable of the interest is the decile rank of absolute value of firm i 's principal customer stock returns ($|CustRet|_{decile}$). We also include following control variables: dummy variable for the earnings announcement (EarnAnn), firm's own return (Ret), number of analysts covering the stock (Analyst), institutional ownership ratio (IOR), the logarithm of firm size ($\ln(SIZE)$), stock turnover ratio (TURNOVER), book to market ratio (Book-to-Market) and logarithm of the total number of earnings reports announced in month t ($\ln(\# \text{ of Report})$). All regression also includes month of the year fixed effects, year fixed effects and firm fixed effects. The regressions cover all common stocks with stock price greater than five dollars. T-statistics are reported in brackets. *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

VARIABLES	AEDGAR(DRT)	AEDGAR(LM)
$ CustRet _{decile}$	0.045*** [2.689]	0.044*** [2.683]
$ CustRet _{decile} \times VIX$	-0.002** [-2.439]	-0.002** [-2.561]
VIX	0.001*** [3.735]	0.002*** [4.608]
EarnAnn	0.176*** [15.603]	0.149*** [13.847]
$\ln(Size)$	-0.001 [-0.209]	-0.003 [-0.821]
Analyst	0.002*** [2.650]	0.001** [2.252]
IOR	-0.031*** [-2.842]	-0.033*** [-3.044]
Ret	-0.043** [-2.168]	-0.027 [-1.288]
Book-to-Market	0.012** [2.223]	0.009* [1.831]
Turnover	0.013*** [3.556]	0.014*** [3.565]
$\ln(\# \text{ of Report})$	-0.165*** [-6.246]	-0.128*** [-4.590]
Constant	1.311*** [6.613]	1.040*** [4.959]
Month of the Year Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Observations	74,904	74,904
R-squared	0.076	0.075

Table 3.8: Cross Stock Return Predictability, Macroeconomic Uncertainty and Alternative Institutional Investor Attention Measures

This table exhibits the Fama-MacBeth cross-sectional forecasting regressions of stock returns with different control variables. The dependent variable is the monthly supplier firm I stock return in month t . The HIGH (LOW) VIX period corresponds to months on which VIX is higher than (lower than) its median value for the period between 2004m1 and 2017m6. In Column 1 and 2 Edgar downloads of company filings is filtered by the methodology of Drake et al. (2015) and in column 3 and 4 it is filtered by the methodology of Loughran and McDonald (2017). The independent variable of the interest is the one-month lagged stock return of principal customer (CustRet) of firm i . AEDGAR_LM (AEDGAR_DRT) is a dummy variable which takes the value of 1 if abnormal request for company filings is in the highest quartile and zero otherwise. The control variables include the firm's own lagged monthly return (SupRet), medium-term price momentum (MOM), firm's own value-weighted industry return (IndRet), customer firm's value-weighted industry return (CindRet), the logarithm of firm size (ln(Size)), stock turnover ratio (Turnover) and market to book ratio (Market-to-Book). The regression includes all common stocks with stock price greater than five dollars. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

VARIABLES	LOW VIX SupRet _{i,t}	HIGH VIX SupRet _{i,t}	LOW VIX SupRet _{i,t}	HIGH VIX SupRet _{i,t}
CustRet _{i,t-1}	0.008 [0.510]	0.047*** [3.142]	0.027 [1.375]	0.047*** [2.924]
CustRet _{i,t-1} x AEDGAR_DRT	-0.01 [-0.415]	-0.052** [-2.348]		
AEDGAR_DRT	0.003** [2.138]	0.004** [2.074]		
CusRet _{i,t-1} x AEDGAR_LM			-0.026 [-1.005]	-0.041* [-1.800]
AEDGAR_LM			0.003** [2.294]	0.002 [1.158]
SupRet _{i,t-1}	-0.007 [-0.746]	-0.004 [-0.387]	-0.007 [-0.748]	-0.004 [-0.341]
IndRet _{i,t-1}	0.073** [2.140]	0.022 [0.606]	0.074** [2.175]	0.024 [0.659]
CindRet _{i,t-1}	0.028 [0.665]	0.006 [0.146]	0.025 [0.595]	0.002 [0.041]
MOM _{i,t-2,t-12}	0.004 [1.394]	-0.004 [-0.875]	0.004 [1.413]	-0.004 [-0.872]
ln (Size _{i,t-1})	0.000 [-0.806]	0.001 [1.066]	-0.001 [-0.860]	0.001 [1.117]
Turnover _{i,t-1}	0.000 [-0.511]	-0.002*** [-2.744]	0.000 [-0.525]	-0.002** [-2.622]
Market-to-Book _{i,t-1}	0.000 [0.329]	0.000 [-0.247]	0.000 [0.306]	0.000 [-0.326]
Constant	0.016** [2.222]	-0.008 [-0.829]	0.016** [2.262]	-0.008 [-0.818]
Observations	38,549	36,537	38,549	36,537
R-squared	0.069	0.073	0.07	0.073

CONCLUSION

There is a growing finance literature documenting that investor attention has a significant role to play in the efficiency of stock prices. Since attentive investors gather and process publicly available information, the efficiency of the asset prices improves with the investor attention. Although a voluminous study reveals the firm characteristics, events and other factors that affect investor attention, the determinants of investor attention are not completely understood. In this study, we contribute to the literature by studying a novel attention-grabbing firm characteristic, firm centrality in the trade network, and the role of macroeconomic uncertainty in investor attention allocation to firm-specific news.

In the second chapter, we study the role of firm centrality in the input-output network in investor attention allocation, which have been overlooked in the literature. We explore whether which stocks investors are aware of can be explained by the centrality of firms. To test our hypothesis, we use a principal customer data of US firms for the period between 1979 and 2017. Because of the nature of the data, we examine the information flow from principal customer firms to supplier firms. The main results of our analyses can be summarized as follows. First, we find that stock returns are predictable from news about principal customer firms. However, cross-return predictability declines with customer firm centrality values. Second, consistent with limited attention, we find that firms attracting more investor attention react more immediately to news about their customer firms. We also investigate the impact of investor attention to customer firms on cross-return predictability. Similar to attention towards the firm itself, customer firm stocks receiving more attention have lower predictive ability. These results show that the effect of customer firm centrality on cross-return predictability is driven by investor attention. We exhibit that the results remain strong even if we use different centrality measures. Third, we document that more central firms are followed by more financial analysts and owned by more

institutional investors, indicating that more central firms attract the attention of institutional investors. Fourth, we represent that the centrality effect on return predictability remains unchanged even when we use size-adjusted centrality scores. This ensures that the centrality effect is distinct from the firm size effect. The recent pandemic of the new coronavirus has further highlighted the significance of the trade network. The COVID-19 outbreak has led to a break not only in domestic supply chains but also in many global supply chains. The spread of the coronavirus in March 2020 induced sharp declines in stock prices and dramatic increases in stock-price volatility. A worthwhile future extension for future research would be to test whether central industries in the global trade network receive greater attention from investors.

In the third chapter, we examine the relationship between macroeconomic uncertainty and investor attention to firm-level news. Two conflicting theories exist concerning the impact of economy-wide uncertainty on investor attention to firm-specific news. While Kacperczyk et al. (2016) show that investors allocate more attention to firm-specific news during low uncertainty periods, Andrei et al.'s (2020) model predicts the reverse. We empirically test the predictions of these theoretical models using principal customer firm news as a proxy for firm specific news in the period between January 2004 and June 2017. The results show that institutional investors are attentive to customer news and raise their attention as VIX declines. The retail investors, on the other hand, overlook the relevant information about customer firms and their inattention to customer news is not sensitive to VIX. Our results suggest that the behavior of institutional investors is consistent with the predictions of Kacperczyk et al.'s (2016) theoretical model, but that of retail investors is consistent with neither hypothesis. In addition, we investigate the stock price impact of investor attention in times of low and high market-level uncertainty. We find that supplier stock prices incorporate customer news more immediately during low VIX periods which is attributable to high institutional attention to customer news in times of low uncertainty. During high VIX periods, investors underreact to customer news, generating stock return predictability from customer news. We show that cross-return predictability decreases with an increase either in institutional investor attention or in retail investor attention. This research can be extended by including different types of firm-specific news such as firms' and customer firms' credit rating changes and their

analysts' recommendation changes. It would be interesting to inquire whether the impact of macroeconomic uncertainty on investor attention is news dependent.



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APPENDIX

Table A.1: Firm Centrality and Customer Stock Return Predictability

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of customer stock returns on lagged supplier stock returns interacted with the dummy variable of lagged customer centrality values. The dependent variable is the monthly supplier stock returns. The independent variable of the interest is the one-month lagged stock return of supplier firm (*CRET*). Customer centrality values are ranked into three categories: lowest 30 percentile (*P1*), between 30 and 70 percentiles (*P2*) and highest 30 percentile (*P3*). *P1_CENTRALITY*, *P2_CENTRALITY* and *P3_CENTRALITY* are dummy variables equal to one if the centrality value of the customer firm is in the corresponding category, and zero otherwise. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. All regressions also include the dummy variables for *P2_CENTRALITY* and *P3_CENTRALITY* themselves, with *RET_{t-1}*, *MOM*, *INDRET*, *CINDRET*, *SIZE*, *TURNOVER* and *MB* as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Dependent Variable: <i>CUSTRET_{i,t}</i>	Degree	Katz	Closeness
<i>SUPRET_{i,t-1} x P1_CENTRALITY_{t-1}</i>	0.016*** [3.940]	0.017*** [4.023]	0.017*** [3.963]
<i>SUPRET_{i,t-1} x P2_CENTRALITY_{t-1}</i>	0.016*** [3.013]	0.012** [2.437]	0.012** [2.515]
<i>SUPRET_{i,t-1} x P3_CENTRALITY_{t-1}</i>	0.010 [1.559]	0.009 [1.309]	0.011 [1.608]
Constant	0.017*** [3.957]	0.017*** [3.849]	0.017*** [3.866]
Controls	Yes	Yes	Yes
Observations	121,459	121,459	121,459
R-squared	0.145	0.146	0.146
Number of groups	468	468	468

Table A.2: Stock Return Predictability with Institutional Ownership and Analyst Coverage Adjusted Centrality Values

This table exhibits time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged customer returns interacted with lagged customer centrality values. The dependent variable is the monthly stock return. The independent variable of the interest is the one-month lagged stock return of principal customer firm (*CRET*). The centrality values are adjusted for both institutional ownership and analyst coverage by using a regression. Institutional ownership and analyst coverage-adjusted customer centrality values are ranked into three categories: lowest 30 percentile (*P1*), between 30 and 70 percentiles (*P2*) and highest 30 percentile (*P3*). *P1_CENTRALITY*, *P2_CENTRALITY* and *P3_CENTRALITY* are dummy variables equal to one if the centrality value of the customer firm is in the corresponding category, and zero otherwise. The results in Column 1 to Column 3 are based on Degree centrality, Katz-Bonacich centrality and Closeness centrality, respectively. All regressions also include the dummy variables for *P2* and *P3* themselves, with one month lagged *RET* and *MOM*, *INDRET*, *CINDRET*, $\ln(\text{SIZE})$, *TURNOVER*, *BM* as controls. All available stocks with stock price greater than five dollars at portfolio formation are included. Cross sectional regressions are run every calendar month. The standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

VARIABLES	Degree	Katz	Closeness
$CRET_{i,t-1} \times P1_CENTRALITY_{t-1}$	0.025*** [2.852]	0.027*** [2.856]	0.026*** [2.800]
$CRET_{i,t-1} \times P2_CENTRALITY_{t-1}$	0.024*** [3.086]	0.023*** [3.031]	0.026*** [3.413]
$CRET_{i,t-1} \times P3_CENTRALITY_{t-1}$	0.024 [1.613]	0.022 [1.556]	0.015 [1.028]
Constant	0.009*** [2.631]	0.010*** [2.704]	0.010*** [2.739]
Controls	Yes	Yes	Yes
Observations	225,423	225,423	225,423
R-squared	0.086	0.086	0.086
Number of groups	468	468	468

Table A. 3: Macroeconomic Uncertainty and Investor Attention

This table exhibits the robustness regression results with one month lagged stock's own return. The dependent variable is the first difference of the logarithm of Google search volume (AGSVI) and company filings downloads (AEDGAR). VIX is the stock market volatility index. The independent variable of the interest is the decile rank of absolute value of firm i 's principal customer stock returns ($|CustRet|_{decile}$). We also include following control variables: dummy variable for the earnings announcement (EarnAnn), firm's own return (Ret), number of analysts covering the stock (Analyst), institutional ownership ratio (IOR), the logarithm of firm size ($\ln(SIZE)$), book to market ratio (Book-to-Market), stock turnover ratio (Turnover) and logarithm of the total number of earnings reports announced in month t ($\ln(\# \text{ of Report})$). All regression also includes month of the year fixed effects, year fixed effects and firm fixed effects. The regressions cover all common stocks with stock price greater than five dollars. t-statistics are reported in brackets. *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

VARIABLES	AGSVI	AEDGAR
VIX	-0.001 [-0.682]	0.001*** [4.224]
$ CRET _{decile}$	-0.009 [-0.262]	0.041** [2.558]
$ CRET _{decile} \times VIX$	0.000 [0.046]	-0.001** [-2.209]
EarnAnn	0.097*** [7.531]	0.188*** [23.763]
Ret	0.013 [0.358]	-0.104*** [-5.964]
$\ln(Size)$	0.001 [0.122]	0.001** [2.455]
Analyst	0.000 [0.632]	-0.041*** [-3.970]
IOR	-0.056*** [-3.800]	0.001 [0.213]
Book-to-Market	-0.003 [-0.373]	0.015** [2.570]
Turnover	0.012*** [2.889]	0.012*** [3.694]
$\ln(\# \text{ of Report})$	0.072 [0.955]	-0.123*** [-4.935]
Constant	-0.469 [-0.832]	1.032*** [5.487]
Month of the Year Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Observations	68,943	74900
R-squared	0.003	0.079