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ORIGINAL RESEARCH

Information diffusion of upstream and downstream industry-wide earnings surprises and its implications

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Abstract This study presents new evidence that industry-wide earnings surprises diffuse gradually across the supply chain at both industry and individual-firm levels. This evidence provides fundamental support for studies in the literature of gradual information diffusion, commonly using lagged returns as a proxy for information. To allow for the possibility that firms react differently to the industry-wide earnings surprises, this study measures how a stock's returns respond to the part of its main customer or supplier industry's lagged returns that are associated with earnings surprises. A long/short equity strategy that combines the firm's response coefficient and the prior month's main customer/supplier industry return is shown to be profitable. The strategy tends to select medium-sized firms across industries. Firms in the winner portfolio are more likely to have a positive earning response coefficient and to be less capital intensive and financially constrained. Winners also experience positive responses to both positive and negative shocks while losers experience negative responses to both types of shocks.

Keywords Industry-wide earnings surprises · Information diffusion · Supply chain

JEL Classification G10 · G12 · G14

1 Introduction

In a dynamic model of a single asset in which information gradually diffuses across the investment public and investors are unable to rationally extract information from prices, Hong and Stein (1999) show that the asset's price underreacts to the information, leading to stock return predictability. Since then, a growing body of empirical research posits that

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gradual diffusion of information among investors explains the observed predictability of returns. Hou (2007) shows that the gradual diffusion of industry information is a leading cause of the lead-lag effect in stock returns. Hong et al. (2007) find that the stock market reacts with a delay to information about fundamentals contained in industry returns, and thus, the returns of industry portfolios are able to predict the movement of the stock market. Cohen and Dong (2012) document that easy-to-analyze standalone firms incorporate industry information first, and hence, their returns predict the subsequent returns of more complicated conglomerate firms.

Information flow is a complex and unobservable continuous process that is difficult to measure directly based on discrete news events. As a result, research testing the gradual diffusion of information hypothesis generally adopts an indirect approach where the past returns of a firm or its related firms are used as a measure of information flow. Menzly and Ozbas (2010) find that firm- and industry-level returns are cross-predictable based on lagged returns in supplier and customer industries. Cohen and Frazzini (2008) and Pandit et al. (2011) document that a company's stock prices do not promptly incorporate news implied by its principal customer returns, generating predictable subsequent price changes. The downside to this approach is that, while a firm's stock price assumingly incorporates all publicly available information about the firm's future prospects, it is subject to limits to arbitrage (Shleifer and Vishny (1997)) and is exposed to potential biases induced by investor behavior (Daniel et al. (1998) and Barberis et al. (1998)). In this paper, I examine a type of information that is directly observable and free of any trading friction to provide greater insight into how information diffuses across markets. Specifically, I focus attention on industry-wide earnings-related information across a supply chain. Earnings surprises represent a specific type of information that investors are reasonably expected to gather.[1] Firms along a supply chain interact with each other through their trading relationships and are likely exposed to similar technology and demand shocks. This implies that what happens to a company's customer- or supplier-industry is informative about what will happen to the company itself.[2] Unlike firm-specific information at which only few investors may be looking, industry-wide earnings surprise information is likely to affect a collection of firms, not only within the industry itself but also in its related industries along the supply chain.

However, investors' ability to extract information from upstream or downstream industry-wide earnings surprises may sometimes be limited. Although industries along a supply chain might face a similar shock, firms within an industry with different resources, business structures, and market positions might react differently to the same earnings shock. This masks the information content of related firms' earnings surprises. Firms also have different fiscal year-ends, and thus, earnings surprises typically arrive at different

[1] Since the late 1960s, the predictability of stock returns after earnings announcements has attracted substantial attention. Bernard and Thomas (1989; 1990) and Bartov (1992), among others, find evidence that the post-earnings-announcement drift represents the market's failure to fully reflect the attributes of the stochastic process underlying earnings. Bhushan (1994) concludes that transaction costs influence the trading and arbitrage activities of professionals in a way that preclude them from taking positions that would eliminate the drift. Mendenhall (2004) highlights that arbitrage risk impedes arbitragers who attempt to profit from the drift.

[2] The financial press identifies numerous such cases. For example, Hudson, Kris, 2006, "Wal-Mart Ripple Effect Strikes Again: Cutbacks Weigh on Supplier Earnings," *Wall Street Journal*, April 27, page C1. Chen, Stephanie, 2008, "Cargo Slump Bodes Ill for Supply Chain," *Wall Street Journal*, March 20, A13. Covel, Simona, 2008, "Banks' Pain Spreads to Their Suppliers," *Wall Street Journal*, October 7, B1. Stoll, John and Jeffrey McCracken, 2009, "Bankruptcy Fears Grip Auto-Parts Suppliers," *Wall Street Journal*, January 26, A1.

points in time, further challenging investors' ability to extract information about industry prospects from connecting upstream or downstream earnings surprises. In this study, I examine industry-wide earnings-related information of a firm's supply chain taking into account the fact that individual firms might react differently to a given news event. This sheds new light on the understanding of the gradual diffusion of information to literature.

To examine news with the greatest potential for informativeness, I focus on earnings surprises from an industry's main customer industry, to which the industry has the greatest sales, or main supplier industry, from which the industry has the greatest purchases. The Benchmark Input–Output Accounts of the Bureau of Economic Analysis (the BEA Benchmark I–O, hereafter) allows me to identify a firm's main customer/supplier industry and construct the industry earnings surprises. I ignore earnings surprises from all other related industries, which will guard against findings on information diffusion across a supply chain. However, I argue that studying earnings surprises only from the main supplier/customer industry—a single but important link—helps one in understanding how information diffuses.[3] I first document that industry-wide earnings surprises indeed diffuse gradually across the supply chain at both the industry and individual-firm levels. As a result, informative industry earnings signals with supply-chain content are only partially incorporated into prices, and individual stock returns exhibit predictability across the main upstream- and downstream-industry. This provides fundamental support for the cross-predictability of industry returns documented by Menzly and Ozbas (2010). This study also complements prior studies (e.g., Freeman and Tse (1992) and Ramnath (2002)) in the information transfer literature that has predominantly focused on documenting earnings expectations and stock price reactions of non-announcers around other *individual* earnings announcements in the *same* industry.

To capture the fact that firms even in the same industry might react to earnings signals from their main customer/supplier industry differently, I estimate the response coefficient of an individual firm as the firm's return in the current month relative to the return of its main customer/supplier industry in the prior month, if there was an earnings signal. I consider the earnings-related information of the main customer industry and the main supplier industry separately. This allows for the potential for the information diffusion across the customer-link to differ from the one across the supplier-link. Bartelsman et al. (1994) document that short run external effects are mostly related to the linkage with customer industries, while long run external effects are mostly related to the linkage with suppliers.

I develop an investment strategy based on gradual diffusion of earnings information by sorting the universe of stocks into quartile portfolios every month based on the stock's constructed expected return, which is the product of (1) the stock's response coefficient to the main customer/supplier industry's earnings-related information and (2) the main customer/supplier industry returns in the prior month, if there was an earnings surprise. A strategy of buying the top quartile and shorting the bottom quartile yields economically and statistically significant 4-factor (Fama–French 3-factor plus momentum) alphas of about 0.1–0.6% per month for up to 6 months. By examining characteristics of firms in the extreme portfolios in the strategy, I uncover several interesting findings which might

[3] Inter-industry trade network is another rich area to examine the transfer of information. Aobdia et al. (2014) study how centrality impacts transfers of information and find that the stock returns and accounting performance of central industries better predict the performance of industries linked to them. Although this study only focuses on the main customer/supplier industry, which is a subset of the trade network, the result based on the single but important link can provide not only a basic understanding on information diffusion but also a lower bound estimation of information diffusion effect.

explain why some firms react to supply-chain earnings shocks more efficiently than others. Medium-sized firms are more likely to be in the extreme portfolios. Most winners are pro-cyclical to their supply-chain prospects while losers show equal tendency to be pro-cyclical versus counter-cyclical. I further examine firms' financial leverage and capital intensity to better understand why some firms efficiently adjust to their supply chain's prospects.

Note that Menzly and Ozbas (2010) also analyze upstream and downstream industry links using the BEA Benchmark I–O accounts. This study is distinct from theirs in two important respects. First, I directly examine if industry-wide earnings surprises diffuse gradually across a supply chain at both the industry and individual-firm levels and study how a firm reacts to such surprises from its main customer/supplier industry separately, whereas Menzly and Ozbas (2010) aggregate all upstream and downstream industries to analyze how an entire supply chain's return predicts an industry's return. Unlike returns, earnings surprises are free of limits to arbitrage and investors' psychology biases. Second, I allow firms within an industry to have different resources, business structures, and market positions, which likely leads to different reactions to a specific earnings surprise emitted from their main customer/supplier industry. For example, a high commodity price in late 2007 is good news to Bunge Ltd but bad news to Hershey Corporation even though both firms are in the Food manufacturing industry (BEA 3110). It also allows one to differentiate firms that are pro-cyclical to their supply chain's prospects from firms that are counter-cyclical to their supply chain's prospects. More importantly, it helps one to understand why some firms efficiently adjust to their supply chain's prospects.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 tests information diffusion of industry-wide earnings surprises across the supply chain. Section 4 describes distributions of individual stocks' response coefficients to earnings surprises from their main customer and supplier industries. Section 5 examines investment strategies based on the gradual diffusion of industry-wide earnings-related information. Section 6 investigates how differences in firms' financial leverage and capital intensity affect the firms' reaction to supply-chain earnings news. Finally, Sect. 7 concludes.

2 Data

The Compustat database, CRSP return files, I/B/E/S Unadjusted Detail Historical Estimates and Unadjusted Actuals Database, and BEA Benchmark I–O constitute the main data sources in this study. I construct five quarterly standardized earnings surprises (SUE) for a firm with CRSP share code of 10 and 11. Following Livnat and Mendenhall (2006), I first construct SUEs using 3 methods.[4] The 1st method (SUE1), a rolling seasonal random walk model, is given by the following equation:

[4] I use "esurprises.sas" provided by Wharton Research Data Services (WRDS) to construct SUEs defined by Livnat and Mendenhall (2006). I adopt their data selection criteria which are described as follows: (1) The earnings announcement date is reported in Compustat for both quarter t and quarter $t + 1$. The earnings report dates in Compustat and in I/B/E/S (if available) differ by not more than one calendar day; (2) The price per share is available from Compustat as of the end of quarter t, and is greater than \$1; (3) The market (book) value of equity at the end of quarter $t - 1$ is available from Compustat and is larger than \$5 million (positive). Additionally, I use actual report dates (RDQ) in Compustat and forecast period end dates (FPEDATS) in I/B/E/S to remove any irregularity in the I/B/E/S dataset. I assume that quarterly forecasts for which RDQ does not fall within 6 months after FPEDATS are irregular. I find that over the entire sample period, more than 87% of actual quarterly earnings in I/B/E/S are reported within 2 months after FPEDATS. To make proper comparisons between I/B/E/S and Compustat data, I use the unadjusted (for splits and stock dividends) I/B/E/S forecasts and actual earnings. I thus avoid the potential rounding problems pointed out by

$$SUE_{j,t} = (X_{j,t} - X_{j,t-4}) / P_{j,t} \quad (1)$$

where $X_{j,t}$ is primary Earnings Per Share (EPS) before extraordinary items for firm j in quarter t (Compustat variable EPSFXQ or EPSPXQ), and $P_{j,t}$ is the price per share for firm j at the end of quarter t from Compustat. $X_{j,t}$ and $P_{j,t}$ are unadjusted for stock splits, but $X_{j,t-4}$ is adjusted for any stock splits and stock dividends during the period [t − 4, t]. Method 2 (SUE2) excludes "special items" from the Compustat Data. Specifically, to estimate *SUE* from the Compustat data after exclusion of special items (Compustat variable SPIQ), I subtract from the primary EPS the amount of special items times 65%, divided by the number of shares used to calculate primary (or diluted, if most analysts predict diluted EPS) earnings per share. Method 3 (SUE3) replaces the forecast ($X_{j,t-4}$) with a measure of analysts' expectations. Considering only the most recent forecast for each analyst, the measure of analysts' expectations is the median of forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement. SUE3 is based solely on IBES median estimates/actuals in Unadjusted Detail History Estimates and Actuals data and does not use Compustat data. Instead of deflating the earnings surprise by the stock price in SUE3, SUE4 deflates it by the dispersion of analysts' forecasts, a method used in Mendenhall (2004). SUE5 is the same as SUE4 but sets a zero standard deviation to \$0.01* $\sqrt{N-1}/N$, where N is the number of analyst forecasts.[5] Although I/B/E/S coverage begins in 1976, I follow Diether et al. (2002) in limiting the sample period to begin in January 1983. Until 1983, the I/B/E/S coverage is sparse and unreliable. The sample period ends in December 2015.

Table 1 provides summary statistics for all firm-quarters and firms per quarter. When a stock price is used as the deflator in SUEs, the median historical *SUE* is close to zero. When the dispersion of analysts' forecasts is used as the deflator in SUEs, the mean and median historical *SUE* are relatively away from zero. Note that the time-series *SUE* exhibits a wide distribution with extreme values. To address the outliers and differences in the earnings surprises across months and industries, I transform the *SUE* into percentile ranks. In a way similar to Mendenhall (2004), every month I assign a stock a percentile rank score between 0 (the lowest) and 1 (the highest) according to its *SUE* and then subtract 0.5 from the *SUE* rank score in order to assign a score of 0 to the median observation. Firms without a quarterly earnings announcement in a given month are excluded from the ranking for that month. I then construct scaled SUEs for each BEA industry monthly, using the market capitalization of a firm at the beginning of each month as a weight. Constructed industry-wide earnings surprises based on reports by a few firms in some months will be less informative. Such a construction guards against findings on information diffusion. However, monthly earnings surprise signals better represent *information flow*, from which street investors can gradually glean the industry prospect, than quarterly earnings surprise signals.

Footnote 4 continued
Payne and Thomas (2003). Further, I/B/E/S determines whether most forecasts are based on primary or diluted EPS. When matching I/B/E/S forecasts and Compustat actual earnings figures, I use the earnings definition (primary or diluted EPS) as indicated by I/B/E/S.

[5] Mendenhall (2004) sets the standard deviation to \$0.01 if it is zero. The correct lower bound for non-zero standard deviations in this context should be \$0.01* $\sqrt{N-1}/N$. This is derived when all analysts provide the same earnings estimates except one analyst who estimates the earnings one penny difference. In the 1st fiscal quarter in 1997, for example, Bed Bath & Beyond Inc. was given an identical earnings estimate by 11 analysts and thus the denominator of SUE5 is set to 0.003. Stocks with only one earnings estimate in a quarter are excluded from calculations in both SUE4 and SUE5 for the quarter.

Table 1 Summary statistics of earnings surprises

	# Obs.	Distribution of percentiles					AVG	STD
		10th	25th	50th	75th	90th		
SUE1								
All firm-quarters	564,918	− 0.032	− 0.007	0.001	0.008	0.029	0.011	3.228
Firms/quarter 1983–2015	4279	− 0.035	− 0.007	0.001	0.008	0.030	0.009	1.281
Firms/quarter 2000–2015	4805	− 0.039	− 0.008	0.001	0.009	0.036	0.016	1.907
Firms/quarter 1983–1999	3769	− 0.031	− 0.007	0.002	0.007	0.025	0.002	0.674
SUE2								
All firm-quarters	565,084	− 0.028	− 0.006	0.001	0.007	0.025	0.009	3.335
Firms/quarter 1983–2015	4280	− 0.030	− 0.007	0.001	0.007	0.026	0.007	1.332
Firms/quarter 2000–2015	4806	− 0.033	− 0.007	0.001	0.008	0.030	0.011	1.914
Firms/quarter 1983–1999	3770	− 0.028	− 0.006	0.002	0.007	0.022	0.003	0.766
SUE3								
All firm-quarters	332,251	− 0.007	− 0.001	0.000	0.002	0.006	− 0.003	0.096
Firms/quarter 1983–2015	2595	− 0.009	− 0.002	0.000	0.002	0.006	− 0.004	0.075
Firms/quarter 2000–2015	3185	− 0.007	− 0.001	0.000	0.002	0.007	− 0.002	0.067
Firms/quarter 1983–1999	1987	− 0.012	− 0.003	0.000	0.002	0.006	− 0.005	0.083
SUE4								
All firm-quarters	239,075	− 2.410	− 0.686	0.458	1.940	4.130	0.505	8.259
Firms/quarter 1983–2015	1867	− 2.772	− 0.771	0.359	1.740	3.885	0.281	8.040
Firms/quarter 2000–2015	2406	− 2.265	− 0.480	0.618	2.158	4.574	0.787	7.534
Firms/quarter 1983–1999	1312	− 3.295	− 1.071	0.092	1.308	3.175	− 0.241	8.562
SUE5								
All firm-quarters	255,106	− 2.510	− 0.662	0.470	2.010	4.460	0.552	10.141
Firms/quarter 1983–2015	1993	− 3.003	− 0.781	0.371	1.855	4.261	0.313	10.283
Firms/quarter 2000–2015	2537	− 2.335	− 0.468	0.627	2.242	4.850	0.830	8.204
Firms/quarter 1983–1999	1431	− 3.692	− 1.103	0.106	1.456	3.653	− 0.220	12.427

This table first calculates quarterly standardized earnings surprises (SUE) using 3 methods considered by Livnat and Mendenhall (2006). Method 1 (SUE1) assumes a rolling seasonal random walk model. Method 2 (SUE2) excludes "special items" from the Compustat Data. Method 3 (SUE3) is based solely on IBES median estimates/actuals in Unadjusted Detail History Estimates and Actuals data and does not use Compustat data. Instead of deflating the earnings surprise by the quarter-end stock price in SUE3, SUE4 deflates it by the dispersion of analysts' forecasts. SUE5 is the same as SUE4 but sets a zero standard deviation to \$0.01 × $\sqrt{N-1}/N$, where N is the number of analyst forecasts. The sample period is from January 1983 to December 2015. This table reports the distribution of SUEs for all firm-quarters as well as the distribution of average SUEs per quarter for the entire period and two sub-periods

To identify upstream and downstream industries, I begin with the BEA Benchmark Input–Output (I–O) Accounts, which assigns economic activity in the U.S. to an I–O industry account and reports the extent of inter-industry flows of goods and services. Because benchmark I–O accounts are based largely on 5-year economic census data from the Census Bureau, the benchmark I–O accounts lag the reference year by at least 5 years. To coincide with I/B/E/S quarterly earnings estimates data starting in 1983, this study uses the benchmark I–O accounts covered in the 1972, 1977, 1982, 1987, 1992, 1997, 2002, and

2007 surveys, which were released during 1979, 1984, 1991, 1994, 1997, 2002, 2007, and 2013, respectively. In this study I consistently delay using any data from a given census until the end of the year in which the census is publicly released. I access information at the same time as a street investor would, that is, I use data from the 1982 Census between January 1992 and December 1994, the 1987 Census between January 1995 and December 1997, and so on. This eliminates any look-ahead bias. The restriction on data use is different from Menzly and Ozbas (2010) in which they use data from a given census until a new snapshot is provided by the following census to test the cross-predictability of accounting performance.[6] However, the trade data, which is not observed by market participants until the census is released, simply reflects the underlying economic links represented by the connection of accounting performance across the supply chain.

The BEA I–O industry accounts are based on Standard Industrial Classification (SIC) codes prior to 1997 while they are based on North American Industry Classification System (NAICS) codes since then. In pre-1997 BEA I–O industry accounts, there is a small number of instances where a SIC code is associated with more than one industry account. I keep the first entry in the dictionary and drop the remaining entries to prevent mechanical cross-industry information diffusion. In post-1997 BEA I–O industry accounts, three separate industry accounts, namely, 2301 (new residential construction), 2302 (new non-residential construction), and 2303 (maintenance and repair construction) are in the same NAICS code and thus I merge these three industry accounts into a single account. Additionally, I drop miscellaneous industry accounts related to government, import, and inventory adjustments because they do not appear to correspond to any clear economic activity or industry. In total, I have 77 I–O industry accounts prior to 1997 and 125 I–O industry accounts in the post years.[7] They are described in the appendices.

Using SIC and NAICS code dictionaries provided as part of the BEA Benchmark I–O industry accounts, I assign firms to their respective industries based on their reported SIC and NAICS codes in CRSP. If this information is missing in CRSP, I use the reported code in COMPUSTAT. I define upstream (representative supplier) and downstream (representative customer) industries for each industry using the flow of goods and services reported

[6] For the second part of their analysis investigating various trading strategies based on cross-predictability effects, Menzly and Ozbas (2010) correctly delay using any data from a given survey until the end of the year in which the survey is publicly released. Aobdia, Caskey, and Ozel (2014), only using the BEA's 1997 Input–Output account, is also subject to the look-ahead bias.

[7] In post-1997 BEA I–O industry accounts, the NAICS coding structure changes periodically. However, the difference in I–O industry codes does not necessarily imply that the industry composition has changed. This creates a challenge for obtaining consistent I–O industry accounts over time. Using the Census Bridge between the 1997 and 2002 NAICS industries available at the web site, http://www.census.gov/econ/census02/data/bridge/, I am able to align the following different NAICS codes in the information sector across time. I–O industry account 5131 (Radio and television broadcasting), 5132 (Cable networks and program distribution), 5111 (Newspaper, book, and directory publishers), 5133 (Telecommunications), and 5142 (Data processing services) in 1997 NAICS code corresponds to their counterpart 5151 (Radio and television broadcasting), 5152 (Cable networks and program distribution), 5161 (Internet publishing and broadcasting), 5170 (Telecommunications), and 5182 (Data processing, hosting, and related services) in 2002 NAICS code, respectively. I–O industry code 5181 (Internet service providers and web search portals) and 5190 (Other information services) in 2002 NAICS code corresponds to 5141 (Information services) in 1997 NAICS code. The bridge between the 1997 and 2007 NAICS industries is more direct according to the file at https://www.bea.gov/scb/pdf/2013/06%20June/0613_preview_comprehensive_iea_revision.pdf. I–O industry account 5131 (Radio and television broadcasting), 5132 (Cable networks and program distribution), 5133 (Telecommunications), 5141 (Information services), and 5142 (Data processing services) in 1997 NAICS code corresponds to their counterpart 5151 (Radio and television broadcasting), 5152 (Cable networks and program distribution), 5170 (Telecommunications), 5190 (Other information services), and 5180 (Data processing, hosting, and related services) in 2007 NAICS code, respectively.

in the Use Table of the I–O accounts. For each industry-year, I first rank the flow of goods and services of upstream (downstream) industries into (out of) the industry. The flow of goods and services into (out of) the industry itself are excluded from the ranking. I then define the industry with the highest rank in the upstream (downstream) industries as the main supplier (customer).[8]

Using the monthly stock return file in CRSP, I calculate the market capitalization of a company at the beginning of every month from January 1983 to December 2015. I then calculate value-weighted scaled SUEs and returns monthly, using the market capitalization at the beginning of each month as a weight, for each BEA industry. The appendices present the number of publicly traded firms and the average market capitalization of firms for the industry itself, its main customer, and its main supplier for each BEA I–O industry account.

In the pre-1997 census surveys, Finance/Insurance (BEA 70) has the greatest number of firms but Petroleum Refining (BEA 31) and Household Appliances (BEA 54) have more large firms. Firms within an industry might not have the same fiscal end periods or the same earnings forecast release dates and thus the industry might not experience signals every month. On average, an I–O industry has at least one signal in more than 86% of the months for SUE1 and SUE2 and in more than 61% of the months for SUE4 and SUE5 during this period. The average number of signals per month is 15 for SUE1 and SUE2 while it is 7 for SUE4 and SUE5. In the post-1997 census surveys, Monetary Authorities, Credit Intermediation and Related Activities (BEA 52A0) has the greatest number of firms but Petroleum and Coal Products Manufacturing (BEA 3240) and Tobacco Manufacturing (BEA 3122) have larger average market capitalizations. On average, an I–O industry has at least one signal in more than 71% of the months for SUE1 and SUE2 and in more than 61% of the months for SUE4 and SUE5 during this period. The average number of signals per month is 12 for SUE1 and SUE2 while it is 7 for SUE4 and SUE5.

Signals based on only a few firms are less likely to be informative. Thus, I do not use BEA I–O industries with less than or equal to three publicly traded firms to identify an industry's main upstream- and downstream-industries. The excluded BEA industries are 1, 3, 10, 12, 21, and 33 in the pre-1997 period and 1120, 1130, 1140, 1150, 3315, 3321, 4850, 4910, 4930, 5414, 6240, 8111, 811A, 813A, 813B, and 8140 in the post-1997 period. These filters leave a total of 71 BEA I–O industry accounts in the pre-1997 census surveys and 109 BEA I–O industry accounts in the post-1997 census surveys for the main customer and supplier identification.

Table 2 provides the distribution of quarterly earnings announcement months for the BEA I–O industries. Although the majority of firms have fiscal quarter-ends in March, June, September, and December, about 15% of the firms in any given industry have quarter-ends in other months. About 60% of the firms announce actual EPS within one month after the fiscal quarter-end with the exception of December. This is shorter than the common perception would suggest. Still, earnings announcements are dispersed over all months. Additionally, an industry's main customer/supplier industry and the industry itself may not have earnings announcements coincide in the same months. (See, for example,

[8] Note that Industry A is Industry B's main supplier but Industry B may not be Industry A's main customer. In the 1987 BEA Benchmark I–O account, for example, BEA 38 Primary Nonferrous Metals Manufacturing is BEA 53 Electric Industrial Equipment/Apparatus' main supplier but BEA 38 Primary Nonferrous Metals Manufacturing's main customer is BEA 11 New Construction. In the 1992 BEA Benchmark I–O account, the supplier relationship between BEA 38 and BEA 53 still holds but BEA 38 Primary Nonferrous Metals Manufacturing's main customer changes to BEA 59 Motor vehicles/equipment.

Table 2 Distribution of quarterly earnings announcements

	% Firms in each month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Overall BEA industries												
Fiscal period end	2.1	1.6	22.2	2.1	1.6	22.4	2.0	1.6	21.3	2.0	1.5	19.7
Actual announcement	7.4	12.4	5.7	13.2	10.2	2.3	12.9	9.7	2.1	12.9	9.2	2.0
BEA 14: food/kindred products												
Fiscal period end	4.3	3.2	17.6	4.3	3.4	17.8	4.3	3.3	17.5	4.1	3.0	17.2
Actual announcement	8.4	10.6	5.8	12.9	7.1	4.3	13.6	7.6	5.1	11.8	8.6	4.1
The main customer in 1972, 1977, 1982, 1987, and 1992 (BEA 74: eating/drinking places)												
Fiscal period end	4.3	3.5	17.9	4.5	3.6	17.3	4.4	3.7	16.4	4.2	3.5	16.6
Actual announcement	8.0	9.1	7.6	11.8	8.8	5.2	10.8	9.9	4.3	11.4	8.0	5.1
The main supplier in 1972, 1977, 1982, 1987, and 1992 (BEA 2: Other agricultural products)												
Fiscal period end	0.0	5.5	20.2	0.0	5.6	19.1	0.0	5.7	19.4	0.0	4.9	19.6
Actual announcement	5.1	8.1	13.2	10.0	13.7	1.6	12.4	10.2	0.0	12.0	11.4	2.3
BEA 3254: pharmaceutical and medicine manufacturing												
Fiscal period end	0.4	0.4	25.9	0.4	0.4	25.9	0.4	0.4	24.2	0.3	0.4	20.8
Actual announcement	3.3	11.6	11.2	7.7	17.1	0.8	7.8	15.9	0.9	7.2	15.7	0.7
The main customer in 1997 and 2007 (BEA 6220: hospitals)												
Fiscal period end	0.0	0.7	25.1	0.0	0.4	26.5	0.0	0.3	24.9	0.0	0.3	21.8
Actual announcement	0.9	21.5	3.9	12.4	11.9	0.6	12.5	10.4	1.2	13.2	11.1	0.4
The main customer in 2002 (BEA 6210: ambulatory health care services)												
Fiscal period end	0.9	0.5	25.1	0.9	0.5	25.7	0.8	0.6	23.4	0.8	0.4	20.4
Actual announcement	2.1	15.3	8.4	9.8	14.9	1.2	9.8	13.4	1.1	9.8	13.1	1.1
The main supplier in 1997, 2002, and 2007 (BEA 5500: management of companies and enterprises)												
Fiscal period end	0.2	0.2	21.7	0.2	0.2	27.9	0.2	0.2	27.5	0.2	0.2	21.5
Actual announcement	15.4	5.0	1.9	16.3	4.3	0.6	23.1	5.4	0.4	21.7	5.6	0.2

This table records quarterly earnings announcement months and fiscal period-end months for each individual firm in I/B/E/S Detail History file, Actuals, to construct a calendar month distribution of earnings announcements. This table excludes BEA industries with less than three publicly traded firms from identifying the upstream- and downstream-industries of an industry. The BEA industry classification is updated in each of Benchmark Input–Output accounts of 1972, 1977, 1982, 1987, 1992, 1997, 2002, and 2007 according to SIC or NAICS codes at the *end* of its release year while individual company SIC or NAICS codes are updated continuously. This table calculates the percentage of firms in a BEA industry falling in each calendar month for the firm's announcement month and fiscal period-end month in a given year, and averages the time-series percentages of each BEA industry. The average of the percentages across all industries is reported first. Additionally, this table reports the distribution for BEA industry 14, Food/kindred products, and BEA industry 3254, Pharmaceutical and medicine manufacturing, as well as their associated main customer and supplier industries. For each industry in each release year, this table ranks the flow of goods and services of upstream (downstream) industries into (out of) the industry. The flow of goods and services into (out of) the industry itself are excluded from the ranking. The industry with the highest rank in the upstream (downstream) industry is defined as the main supplier (customer)

BEA 14, Food/kindred products, and BEA 3254, Pharmaceutical and medicine manufacturing.) Discordant earnings announcements across upstream and downstream industries make gradual diffusion of information more likely along the supply chain.

3 Information diffusion of earnings surprises across the supply chain

I first explore how earnings surprises at the industry level diffuse across the supply chain.

Using the framework of Fama and MacBeth (1973) cross-sectional regressions, I estimate the following specification:

$$SUE_{I,t} = \alpha + \beta_1 SUE_{I,t-1} + \beta_2 SUE_{I,t-2} + \beta_3 SUE_{C,t} + \beta_4 SUE_{C,t-1} + \beta_5 SUE_{C,t-2} + \beta_6 SUE_{S,t} + \beta_7 SUE_{S,t-1} + \beta_8 SUE_{S,t-2} + \varepsilon \quad (2)$$

where $SUE_{I,t}$ is the earnings surprise of a BEA industry I in month t, $SUE_{C,t}$ is the earnings surprise of I's main customer industry C in month t, and $SUE_{S,t}$ is the earnings surprise of I's main supplier industry S in month t. Terms in month $t-1$ and $t-2$ are defined analogously. This estimation completely covers a 3-month span in which firms within an industry could possibly disclose quarterly earnings. To investigate the existence of gradual information diffusion, it is crucial to control for contemporaneous surprises. When contemporaneous surprises, $SUE_{C,t}$ and $SUE_{S,t}$, are omitted from the regressors, potential serially-correlated surprises in either the customer or supplier industry might show false evidence of gradual information diffusion along the supply chain, even though the market might have reacted to the information instantaneously. Predictability of industries returns by Hong et al. (2007) and cross-predictability of industry returns by Menzly and Ozbas (2010) are subject to this criticism.

Table 3 provides new evidence to the literature that industry-wide earnings surprises gradually diffuse across the supply chain. An earnings surprise that originates from a BEA industry's main customer industry clearly reaches the BEA industry with a one-month lag regardless of which SUE is used. A ten percentile rank increase in the prior-month earnings surprise of an industry's main customer industry transforms into approximately a 0.6–1.3 percentile rank increase in the industry's current earnings surprise.[9] The earnings surprise link between an industry and its main supplier industry is less consistent across all SUE measures. For example, the coefficient on one-month lagged supplier industry SUE3 is negative and insignificant.

I next examine how a firm's own and industry-wide past earnings surprises diffuse into the firm's current earnings surprises. Following Fama and MacBeth (1973) cross-sectional methodology, at the end of every month I regress a stock's scaled SUE on its prior-quarter scaled SUE as well as other three industry-wide SUEs. Stocks which do not have the prior-quarter SUE available within the prior 5 months are excluded. Over the time interval between the stock's current SUE reported date and its prior-quarter SUE reported date, industry-wide earnings surprises do not have the same information quality across months.

[9] The coefficient on one-month lagged SUE from either customer or supplier industry is always stronger using analyst forecasts (for example, SUEs 4 and 5) than using lagged earnings (for example, SUEs 1 and 2). Contrastingly, the coefficient on one-month lagged own industry SUE is insignificant or weaker using analyst forecasts. It seems that financial analysts are more or less able to incorporate information content of the lagged earnings surprises from an industry itself, but cannot completely incorporate information content of the lagged earnings surprises from its customer/supplier industry. The availability of more accurate information in a firm's own industry, in turn, leads to a lesser degree of financial analysts' forecast dispersion. It is consistent with Kwon (2002) showing that increases in more accurate information available for high-tech firms lead to a higher level of financial analysts' earnings forecast accuracy. A further investigation on when and how analysts consider customer versus supplier industry information in their forecasts would provide greater insights into the diffusion of industry information. To effectively conduct this investigation, I have to collect analyst forecast revision data and leave this pursuit to future research. I thank an anonymous referee for making this point.

Table 3 Diffusion of industry earnings surprises across the supply chain

$SUE_{I,t} = \alpha + \beta_1 SUE_{I,t-1} + \beta_2 SUE_{I,t-2} + \beta_3 SUE_{C,t} + \beta_4 SUE_{C,t-1} + \beta_5 SUE_{C,t-2} + \beta_6 SUE_{S,t} + \beta_7 SUE_{S,t-1} + \beta_8 SUE_{S,t-2} + \varepsilon$

β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	Adj. R^2
SUE1								
0.079***	0.090***	− 0.011	0.058***	− 0.004	0.000	0.043***	− 0.002	7.70{156}
SUE2								
0.096***	0.109***	− 0.010	0.033**	0.002	0.003	0.042***	− 0.002	8.63{156}
SUE3								
0.021	0.086***	− 0.049*	0.060*	− 0.022	0.050**	− 0.007	0.019	10.0{131}
SUE4								
− 0.001	0.040	− 0.077*	0.133***	0.091**	0.104	0.111**	0.036	13.14{65}
SUE5								
− 0.008	0.055**	− 0.099***	0.111***	0.023	0.131	0.140**	− 0.019	13.18{73}

The construction of five SUEs for each firm is described in Table 1. To address the outliers and differences in the earnings surprises across months and industries, This table assigns a stock a rank score between 0 (the lowest) and 1 (the highest) according to its SUE every month and then subtracts 0.5 from the SUE rank score in order to assign a score of 0 to the median observation. The market capitalization of a stock at the beginning of each month is used to calculate the value-weighted average of monthly scaled SUEs for each of the 71 BEA industries prior to December 2002 and 109 BEA industries after then. Note that 1997 Benchmark Input–Output Account first using NAICS codes was released in 2002. At the end of every month, this table performs Fama and MacBeth (1973) cross-sectional regressions based on the scaled SUE of a BEA industry (I) and its main customer (C) industry as well as main supplier (S) industry. This table requires at least 15 observations in performing the regression, and reports the time-series average of the regression coefficients with Newey-West adjustment with two-month lags for potential heteroskedasticity and serially correlated errors. The asterisk of ***, **, and * indicates significance at the 1, 5 and 10% level, respectively. The curly bracket in "Adj. R^2" indicates the number of valid regressions over the sample period from January 1983 to December 2015

As a result, I further calculate the weighted average of scaled SUEs across this time interval for its BEA (I) industry, its main customer (C) industry, and its main supplier (S) industry, using the number of individual SUEs in a month as the weight. When I construct the past scaled SUEs for the stock's BEA industry, I exclude values of the specific firm under consideration.

Consistent with Freeman and Tse (1992) and Ramnath (2002) who document intra-industry information transfers, Table 4 clearly shows that a stock's current earnings

Table 4 Diffusion of supply-chain earnings surprises to individual firms

$SUE_{j,t} = \alpha + \beta_1 SUE_{j,t-1} + \beta_2 SUE_{I,[t-1,t)} + \beta_3 SUE_{C,[t-1,t)} + \beta_4 SUE_{S,[t-1,t)} + \varepsilon$

Sample period	β_1	β_2	β_3	β_4	Adj. R^2
SUE1					
1983–2015	0.366***	0.136***	0.039***	0.029***	14.61 [1012]
1999–2015	0.346***	0.140***	0.051***	0.022**	13.17 [1169]
1983–1998	0.388***	0.132***	0.025**	0.036***	16.11 [848]
SUE2					
1983–2015	0.402***	0.146***	0.033***	0.025***	17.43 [1012]
1999–2015	0.388***	0.151***	0.046***	0.019	16.37 [1169]
1983–1998	0.417***	0.141***	0.020	0.032***	18.53 [848]
SUE3					
1983–2015	0.211***	0.102***	0.025**	0.020**	5.34 [595]
1999–2015	0.195***	0.126***	0.021	0.014	4.67 [718]
1983–1998	0.230***	0.073***	0.030*	0.027*	6.16 [444]
SUE4					
1983–2015	0.239***	0.105***	0.023*	0.013	6.80 [473]
1999–2015	0.229***	0.119***	0.039**	− 0.002	6.34 [569]
1983–1998	0.252***	0.088***	0.002	0.032	7.42 [346]
SUE5					
1983–2015	0.243***	0.106***	0.024*	0.017*	7.03 [490]
1999–2015	0.228***	0.135***	0.028*	− 0.001	6.54 [588]
1983–1998	0.261***	0.069***	0.019	0.041**	7.68 [362]

The construction of five SUEs for each firm is described in Table 1 and the construction of monthly scaled SUEs for each of the 71 BEA industries prior to December 2002 and 109 BEA industries after then is described in Table 3. Following Fama and MacBeth (1973) cross-sectional methodology, at the end of every month a stock j's scaled SUE is regressed against its prior-quarter scaled SUE as well as its related three industry-wide SUEs. Stocks which do not have the prior-quarter SUE available within the prior 5 months are excluded. Over the time interval between the stock's current SUE reported date (excluding) and its prior-quarter SUE reported date (including), I further calculate the weighted average of scaled SUEs across this time interval for its BEA industry (I), its main customer (C) industry, and its main supplier (S) industry, using number of individual SUEs in a month as the weight. When the past scaled SUEs for the stock's BEA industry is calculated, values of the specific firm under consideration are excluded from the calculation. This table reports the time-series average of the regression coefficients with Newey-West adjustment with five-month lags for potential heteroskedasticity and serially correlated errors. The asterisk of ***, **, and * indicates significance at the 1, 5 and 10% level, respectively. The square bracket in "Adj. R^2" indicates the average number of firms in each regression over the entire sample period from January 1983 to December 2015 and over two sub-periods surprise is positively correlated with its own past earnings surprise and its intra-industry past earnings surprise. In addition to the prior literature, this study documents that past earnings surprises from the stock's main customer industry positively affect the stock's current earnings surprise and it is strong later in the sample period from 1999 to 2015. Increased complexities in the supply chain in the modern period make it tough to determine a broad market trend and make slow diffusion of information more likely. Also, the increased economy-wide competition documented in Irvine and Pontiff (2009) might increase the degree of interaction across the supply chain over time.

Overall, it seems that sophisticated analysts do not completely incorporate the information content of the earnings surprises and thus earnings surprises diffuse gradually. This could lead to a profitable investment strategy, a subject I examine in the next section.

4 Responses to earnings surprises from main customer/supplier industries

Although firms along a supply chain might face similar shocks, firms with different resources, business structures, and market positions might react to the same shocks differently. For instance, a high commodity price in late 2007 is good news to Bunge Ltd but bad news to Hershey Corporation even though both firms are in the Food manufacturing industry (BEA 3110). It follows, therefore, that firms in the same industry may react to earnings signals from their main customer/supplier industry heterogeneously. To consider this possibility, I measure reactions to industry-wide earnings news on an individual firm basis.

The post-earnings-announcement drift literature and the information transfer literature predominantly document *cross-sectional* stock price reactions or analyst reactions to past earnings information of firms themselves or other firms in the same industry. However, how markets impound *time-series* earnings surprise information into individual stock prices is still largely unknown. In addition, true economic earnings are likely to be imperfectly measured by reported accounting earnings and a firm's stock price might incorporate sources of earnings information other than reported accounting earnings. I therefore measure how a stock's returns respond to the part of its main customer or supplier industry's lagged returns that are associated with earnings surprises. To ensure the extracted information actually relates to earnings news, I only consider months when the firm's main customer/supplier industry has an earnings signal.

At the beginning of each month starting January 1986, I use the prior 36 months of data and regress an individual firm's month t stock returns on the returns of its main customer industry in month $t-1$ (in which the firm's main customer industry has an earnings signal). I measure the stock's response coefficient to the main supplier industry's earnings-related information analogously. I require at least 8 observations in performing the regression and retain only those stocks with *significant* response coefficients (i.e., the absolute value of the associated t-statistic is no less than 1.645). By imposing the significance criterion, I lose about half of the sample on average but am more likely to capture the firm's information-driven response to earnings signals across the supply chain. I record a stock's most recent response coefficient at the beginning of a given month and construct the quartile distribution of response coefficients every month. For brevity concern, I only report the results for SUE2.[10]

Table 5 reports the average breakpoints for each year. On average, individual stocks are more sensitive to the earnings-related signals of their main customer industry relative to their main supplier industry but such reaction is also more volatile. For example, whenever the main customer industry has an earnings surprise signal (SUE2) and its return is up 1%, the median response coefficient indicates that the median stock price increases 0.452% the next month. But the median stock price increases only 0.422% the next month when the main supplier industry has an earnings surprise signal and its return is up 1%. The overall spreads between the 25th percentile and the 75th percentile are also larger in terms of the stock's reaction to its main customer industry. Interestingly, not all stocks positively react to earnings-related returns of their main customer/supplier industry: at least 25% of the sample stocks react negatively to earnings-related returns on their main customer/supplier industry—these are firms counter-cyclical to their industry prospects.[11]

5 Self-financing investment strategies

5.1 The 4-factor Alphas

At the beginning of each month starting January 1986, I sort the universe of stocks into quartile portfolios based on the stock's constructed expected return, which is the product of (1) the stock's response coefficient to the main customer/supplier industry's earnings-related information and (2) the main customer/supplier industry returns in the prior month, if there was an earnings surprise. Stocks are excluded from the sorting if their main customer/supplier industry did not have an earnings signal in the prior month. I use the stock's most current response coefficient up to the portfolio formation date.

If the earnings-related information diffuses gradually across the supply chain, I can exploit the potential profit opportunity by taking a long position in stocks with the highest constructed expected returns and a short position in stocks with the lowest constructed expected returns. To increase the power of the tests, I construct overlapping portfolios by following the methodology used to form momentum strategies as proposed by Jegadeesh

[10] Livnat and Mendenhall (2006) conclude that the earnings surprise measured by the random walk model and analyst forecast represents somewhat different forms of mispricing. Bradshaw and Sloan (2002) point out that many of the expenses omitted from the analyst forecasts are captured by Compustat's special item variable. Analyses based on SUE1 and SUE2 result similarly while analyses based on SUE4 and SUE5 result similarly. Clement (1999) and Jacob, Lys, and Neale (1999) argue that the price-deflated forecast error is more vulnerable to intertemporal and cross-sectional differences in price-to-earnings ratios, thus the interpretation on results by SUE3 needs additional caution. All results, not reported here, are available upon the request.

[11] Petersen and Strongin (1996) measure the cyclicality of an industry as the sensitivity of the percentage change in real value added in the industry to the real growth rate in gross national product. This study simply defines that a pro-cyclical (countercyclical) firm relative to its supply chain's prospects is the firm whose stock returns positively (negatively) react to its main customer/supplier industry returns. A good example of counter-cyclical firms is identified in "In Tough Times, Auto-Parts Firms Receive a 'Countercyclical Boost'" by David Gaffen, *Wall Street Journal*, February 20, 2009, page C6. Poor sales of new cars mean more business for auto-parts stores such as AutoZone and O'Reily Automotive.

Table 5 Response of individual stock returns to supply chain's earnings surprises

Year	Num	Breakpoints of quartile distribution					Avg	STD
		Min	25%	50%	75%	Max		
X variable: returns on the main customer industry in month t − 1								
1986	788	− 4.634	− 0.026	0.530	0.830	4.629	0.424	0.863
1990	1920	− 4.982	0.120	0.444	0.643	4.191	0.307	0.678
1995	2993	− 5.670	− 0.388	0.542	0.934	6.533	0.389	1.098
2000	3396	− 10.544	− 0.372	0.530	0.887	8.474	0.385	1.081
2005	3198	− 5.221	− 0.312	0.457	0.823	6.882	0.361	0.977
2010	3064	− 6.489	0.204	0.512	0.832	9.132	0.427	0.848
2015	2555	− 7.099	− 0.576	− 0.182	0.573	12.006	− 0.024	0.959
Avg	2730	− 7.001	− 0.242	0.452	0.794	8.988	0.331	0.944
X variable: returns on the main supplier industry in month t − 1								
1986	709	− 7.299	0.087	0.546	0.869	4.303	0.419	0.942
1990	1827	− 4.934	− 0.290	0.409	0.651	6.285	0.276	0.751
1995	2979	− 7.666	− 0.437	0.463	0.896	7.122	0.325	1.087
2000	3465	− 14.454	− 0.284	0.467	0.852	7.481	0.378	1.008
2005	3011	− 10.738	− 0.143	0.417	0.812	7.243	0.403	1.021
2010	2995	− 9.751	0.224	0.486	0.795	12.011	0.416	0.882
2015	2553	− 15.552	− 0.578	− 0.144	0.515	8.651	− 0.056	1.019
Avg	2682	− 8.975	− 0.205	0.422	0.776	7.578	0.318	0.947

The market capitalization of a stock at the beginning of each month is used to calculate the value-weighted average of monthly returns and scaled SUEs for each BEA industry. The construction of scaled SUEs for each firm and industry in each month is described in Table 3. For brevity concern, this table only reports results for SUE2. At the beginning of each month since January 1986, using the prior 36 months of data a firm's stock return in month t is regressed against returns on its main customer (supplier) industry in month $t-1$ in which the customer (supplier) industry has an earnings announcement. This table require at least 8 observations in performing the regression and only retain stocks with *significant* response coefficients (i.e., the absolute value of the associated t-statistic is no less than 1.645). This table records a stock's most current response coefficient at the beginning of a given month and constructs the quartile distribution of response coefficients every month. The table reports the snapshot of average breakpoints for years in a rough 5-year interval as well as the time-series average across all years from 1986 to 2015. All statistics are expressed on a monthly basis. The numbers in column "Num" indicate the average number of firms per month for the distribution construction

and Titman (1993).[12] Each portfolio is held for up to 6 months following the ranking month and the out-of-sample performance is calculated.

Panel A of Table 6 reports the average monthly realized returns in excess of the one-month T-bill for the two extreme quartile portfolios as well as the long/short portfolio for each holding month. In general, both the extreme quartile portfolios and the long/short

[12] In any given month t, the strategies hold a series of portfolios that are selected in the current month as well as in the previous K-1 months, where K is the holding period. For instance, for a 6-month holding strategy, a December long portfolio comprises stocks with the highest constructed expected returns ranked at the end of the previous November, the previous October, and so on up to the previous June. Each monthly cohort is assigned an equal weight in this portfolio.

Table 6 Performance of investment strategies

	Num	Sorting variable	Holding periods					
			1-month	2-month	3-month	4-month	5-month	6-month
Panel A: Excess returns								
Sorting variable: expected returns formed by main customer industry								
Winner (W)	682	6.102	0.982***	0.912***	0.875***	0.837***	0.803**	0.767**
Loser (L)	682	− 5.387	0.403	0.468	0.533*	0.584*	0.628**	0.656**
W–L		11.489	0.579***	0.444***	0.343***	0.253***	0.175***	0.111***
Sorting variable: expected returns formed by main supplier industry								
Winner (W)	670	6.542	0.850***	0.822***	0.761**	0.736**	0.734**	0.716**
Loser (L)	670	− 5.806	0.496	0.557*	0.606*	0.655**	0.700**	0.715**
W–L		12.348	0.355***	0.265***	0.155*	0.081	0.034	0.001

	Holding periods					
	1-month	2-month	3-month	4-month	5-month	6-month
Panel B: 4-factor Alphas						
Sorting variable: expected returns formed by main customer industry						
Winner (W)	0.450***	0.325***	0.289***	0.268***	0.235**	0.199**
Loser (L)	− 0.194**	− 0.100	− 0.013	0.047	0.096	0.133
W–L	0.644***	0.424***	0.302***	0.221***	0.139***	0.066*
Sorting variable: expected returns formed by main supplier industry						
Winner (W)	0.258***	0.180*	0.124	0.113	0.129	0.125
Loser (L)	− 0.116	− 0.022	0.060	0.134	0.167*	0.191**
W–L	0.375***	0.201**	0.063	− 0.021	− 0.038	− 0.065

Table 6 continued

	Holding periods					
	1-month	2-month	3-month	4-month	5-month	6-month
Panel C. 4-factor Alphas after removing the supply-chain earnings related information						
Sorting variable: expected returns formed by main customer industry						
Winner (W)	0.197	0.073	0.209	0.142	0.067	0.027
Loser (L)	0.079	− 0.001	− 0.040	− 0.019	− 0.069	− 0.060
W–L	0.118	0.074	0.249	0.161	0.137	0.087
Sorting variable: expected returns formed by main supplier industry						
Winner (W)	0.165	0.062	− 0.002	− 0.008	0.036	− 0.018
Loser (L)	− 0.379**	− 0.130	− 0.051	− 0.077	− 0.080	− 0.029
W–L	0.544**	0.193	0.049	0.069	0.116	0.011

At the beginning of every month starting in January 1986, this table constructs the expected return on individual stocks, the sorting variable, for month t by multiplying the stock's most current response coefficient available at the beginning of the month t and the stock's main customer (supplier) industry return in the month $t - 1$ in which the customer (supplier) industry has an earnings surprise defined by SUEs. For brevity concern, this table only reports results for SUE2. The construction of response coefficients is described in Table 5. Stocks are sorted by its stock's expected returns into quartiles every month. Stocks are excluded from the sorting if their main customer/supplier industry did not have an earnings signal in the prior month. Stocks in the extreme top quartile are winners while stocks in the extreme bottom quartile are losers. To increase the power of the tests, this table constructs overlapping portfolios. Each portfolio is held for up to 6 months following the ranking month. Panel A reports number of firms, the average value of the expected returns (the sorting variable), and the average monthly realized returns excess of the risk free rates. In Panel B, for each holding period, the table regresses the portfolio's monthly returns on the 4-factor (Fama–French 3 factors plus a momentum) portfolios retrieved directly from French web site and reports the intercepts. Panel C has the empirical construction identical to Panel B, except that a stock's response coefficient is estimated based on monthly observations not used for Panel B in a 36-month window. In the portfolio of winner minus loser, the total returns are used for the dependent variable in the regression. Otherwise, the returns excess of the risk free rates are used for the dependent variable in the regression. The unit of excess returns and alphas is a percentage per month. The sample period is January 1986 to December 2015. The significance level of the excess return or the alpha equaling to zero is indicated by *** (1%), ** (5%), and * (10%)

portfolio experience significantly positive excess returns.[13] The effect is particularly strong when the expected return sorts are constructed based on the response coefficients to a stock's main customer industry.

To adjust for potential exposures to systematic risk factors, I report the intercepts from the regression of the 4-factor model (Fama–French 3-factor plus momentum) for each holding period in Panel B of Table 6. The factor returns are retrieved directly from Kenneth French's web site. The 4-factor alphas are highly significant for the long/short portfolio up to the 6-month holding period, particularly again when we consider main customer industry earnings signals.[14] For example, the long/short portfolio generates a 4-factor alpha of 0.644% for the 1st month, which is in line with Menzly and Ozbas (2010), who report a 4-factor alpha of 0.5% for the self-financing trading strategies formulated on the basis of returns in customer industries in the previous month. Note that Menzly and Ozbas (2010) analyze how an entire supply chain's return predicts an industry's return while this study utilizes an individual firm's response coefficient to the main customer/supplier industry's earnings-related information for the return predictability. In addition, the large positive alphas of the long/short portfolio documented in this study are mainly driven by the winner portfolio. This result is consistent with Moskowitz and Grinblatt (1999), who show that industry momentum generates as much or more of its profits from the buy side than the sell side.

To further highlight the importance of the supply-chain information in determination of stock prices, I run a contrast test by removing supply-chain earnings related information from the estimation of individual stock's response coefficients. After the removal, I anticipate that the self-financing investment strategies would not be profitable if industry earnings signals with the supply-chain content are indeed incorporated into stock prices gradually. To estimate a stock's response coefficient without the content of the supply-chain earnings surprises, at the beginning of each month I use the prior 36 months of data and regress an individual firm's month t stock returns on the returns of its main customer/supplier industry in month $t-1$, in which the firm's main customer/supplier industry has *no* earnings signal. Panel C of Table 6 confirms the conjecture and shows that almost all 4-factor alphas for the long/short portfolios in different holding periods are insignificant.

In unreported analyses, I estimate factor loadings for both the extreme portfolios and the long/short portfolio for each holding period. I fund that the extreme portfolios have stable factor loadings across holding periods. Most factor loadings, except for the loading on RMRF, are insignificant for the long/short portfolio particularly when I consider main customer industry earnings signals. Notably, the winner portfolio loads negatively on the momentum factor in every case and across every holding period. Thus, the investment strategy proposed in this study is not just a replication of the price momentum documented by Jegadeesh and Titman (1993). I also examine the investment strategies' 4-factors alphas over two sub-periods, January 2001 to December 2015 and January 1986 to December

[13] Over the sample period of January 1986 to December 2015, the average return is 0.20% (1.37%) per month for the bottom (top) portfolio of the 10 portfolios formed on momentum directly retrieved from Kenneth French's web site as of February 19, 2017. Although the portfolio construction is different here, it is not unusual that the past loser has positive returns over the considered sample period.

[14] When we consider main supplier industry signals, the 4-factor alphas are only significant for the long/short portfolio up to the 2-month holding period. It seems to contradict the argument made earlier that it takes longer for the supplier information to diffuse than the customer information. While this is a conflicting finding, the result is still consistent with the expectation that the strategies based on the gradual diffusion of industry-wide earnings surprises across the supplier industry link are weaker.

Table 7 Fama–MacBeth cross-sectional regressions

Explanatory variables	Benchmark	Model 1	Model 2	Model 3	Model 4
LN(Size)	− 0.019	− 0.041	− 0.022	− 0.016	− 0.008
	[− 0.16]	[− 0.37]	[− 0.20]	[− 0.14]	[− 0.07]
LN(B/M)	0.934	0.824	0.883	0.818	0.871
	[3.73]	[3.55]	[3.61]	[3.63]	[3.56]
		SUE2			
Exp_Customer		0.045			
		[3.44]			
Exp_Supplier			0.033		
			[2.49]		
				SUE4	
Exp_Customer				0.025	
				[1.94]	
Exp_Supplier					0.024
					[1.57]
Ret_{t-1}	− 0.029	− 0.027	− 0.032	− 0.025	− 0.035
	[− 3.89]	[− 3.41]	[− 3.96]	[− 3.08]	[− 4.44]
$Ret_{t-12,t-2}$	0.010	0.010	0.008	0.009	0.009
	[1.47]	[1.46]	[1.23]	[1.29]	[1.26]
Ind_Ret_{t-1}	0.184	0.181	0.169	0.177	0.169
	[10.08]	[9.62]	[8.78]	[9.22]	[7.66]
$Ind\_Ret_{t-12,t-2}$	0.042	0.036	0.039	0.039	0.039
	[3.95]	[3.49]	[3.84]	[3.69]	[3.83]
Adjusted R^2 (%)	3.88	3.96	4.11	4.00	4.28
Number of Firms	3715	2500	2456	2286	2165

This table reports Fama and MacBeth (1973) forecasting regressions of individual stock returns. The dependent variable is 3-month-ahead buy-and-hold stock return. The explanatory variables are the stock's expected returns constructed by the response coefficients to the earnings-related information in SUE2 or SUE4 of its main customer industry (Exp_Customer) or its main supplier industry (Exp_Supplier), the stock's own lagged return (Ret), the lagged return of the corresponding BEA industry portfolio (Ind_Ret), Size (market capitalization as of the end of the previous month), B/M (the book value of equity divided by the market value of equity). The construction of the stock's expected returns based on the earnings-related information from the supply chain is described in Table 6. The construction and timing of B/M follows Fama and French (1996) and is as of the previous December year-end. Cross-sectional regressions are run every calendar month from January 1986 to December 2015. This table requires at least 30 observations in performing the regression and reports the time-series average of the regression coefficients with Newey-West adjustment with 11-month lags for potential heteroskedastic and serially correlated errors. The parentheses report the associated *t*-statistics. The average adjusted R^2 and the number of firms per monthly regression are reported at the bottom

2000. The alphas of the long/short portfolio are still markedly strong in these sub-periods. The unreported results are available upon request.

5.2 Robustness tests

Since I am interested in testing return predictability of individual stocks generated by earnings-related information from the stocks' main customer/supplier industry, it is important to control for variables that would cause commonalities across asset returns. I use Fama and MacBeth (1973) forecasting regressions of individual stock returns on a series of controls. The dependent variable is the 3-month-ahead buy-and-hold stock return. The independent variables of interest are the stock's expected returns constructed at the beginning of the month based on the gradual diffusion of earnings-related information from the firm's main customer/supplier industry. I include as controls the firm's own 1-month lagged stock return and 1-year lagged stock return. These variables control for the reversal effect of Jegadeesh (1990) and for the price momentum effect of Jegadeesh and Titman (1993). I control for the industry momentum effect of Moskowitz and Grinblatt (1999) by using lagged returns of the firm's BEA industry portfolio.[15] I also include firms' size and book-to-market as additional controls and require at least 30 observations in performing the regression. Table 7 reports the time-series average of the regression coefficients with Newey and West (1987) adjustment using 11-month lags for potential heteroskedastic and serially correlated errors.

Consistent with the literature, the result in the benchmark model indicates that industry momentum, short-term price reversal, and book-to-market predict individual stock returns 3-month ahead cross-sectionally. Unambiguously, the slow diffusion of earnings surprises from a firm's main customer industry forecasts the firm's subsequent returns. It provides the returns predictability and is independent of price and industry momentum.[16] I obtain a similar result when one-month-ahead return is used as the dependent variable in the cross-sectional regressions.

6 Understanding firms in reacting to supply-chain earnings surprises

6.1 Winners versus losers

I have shown that it is possible to predict a firm's returns using industry-wide earnings surprise information from the firm's supply chain. By further examining characteristics of the winners and the losers, I might be able to identify types of firms more likely to successfully respond to supply-chain earnings surprises.

For each portfolio in every portfolio formation date, I begin by calculating the percentage of firms that have positive or negative response coefficients, which indicate whether a firm is pro-cyclical or counter-cyclical relative to its supply chain's prospects. Table 8 clearly indicates that most winners are pro-cyclical relative to their supply chain's prospects in an odds ratio of 70.2–29.8% while losers are equally likely to show a pro-cyclical versus counter-cyclical relation in an odds ratio of 50.1–49.9%, when the strategies are formed based on information related to SUE2 of the main customer industry. A

[15] I do not control for the intra-industry lead-lag effect of Hou (2007) for several reasons. First, I focus on the slow diffusion of earnings-related information across the supply chain, not on the diffusion of news on certain firms within an industry. Additionally, given there are 71 BEA industries prior to 1997, three size-sorted portfolios within an industry will yield 213 portfolios. Some portfolios might contain few firms and thus their returns will be noisy and may not be good as control variables. Furthermore, the extreme portfolios in this study are composed of medium-sized firms and are diversified across industries. The intra-industry lead-lag effect will thus be less of a concern.

[16] Using the same methodology that the investment strategies are formed, I only include firms in the regressions of Models 1–4 if they have significant response coefficients and their associated main customer/supplier industry had an earnings signal in the prior month. Thus, the average number of observations is about half of those in the benchmark model.

Table 8 Characteristics of winners and losers

Interest variables	Winner (W)	Loser (L)	W–L
Sorting variable: expected returns formed by main customer industry			
% of firms having + response coefficients	0.702	0.501	0.202***
% of firms having − response coefficients	0.298	0.499	− 0.202***
Ratio of idiosyncratic risk over total risk in the response regression	0.895	0.899	− 0.004***
Within-industry size percentile rank score	0.478	0.497	− 0.020***
Universe size percentile rank score	0.505	0.535	− 0.030***
Within-industry book-to-market percentile rank score	0.508	0.501	0.008***
Universe book-to-market percentile rank score	0.499	0.495	0.005*
% of BEA industries covered	0.663	0.704	− 0.041***
The highest concentration in a given BEA industry	0.198	0.184	0.014*
Sorting variable: expected returns formed by main supplier industry			
% of firms having + response coefficients	0.691	0.487	0.203***
% of firms having − response coefficients	0.309	0.513	− 0.203***
Ratio of idiosyncratic risk over total risk in the response regression	0.892	0.896	− 0.004***
Within-industry size percentile rank score	0.478	0.499	− 0.021***
Universe size percentile rank score	0.503	0.539	− 0.036***
Within-industry book-to-market percentile rank score	0.505	0.497	0.008***
Universe book-to-market percentile rank score	0.495	0.498	− 0.003
% of BEA industries covered	0.638	0.676	− 0.038***
The highest concentration in a given BEA industry	0.179	0.181	− 0.002

Two extreme quartile portfolios, Winner and Loser, are constructed every month as described in Table 6. For brevity concern, this table only reports results for an earnings surprise defined by SUE2. In the response regression in a given month as described in Table 5, This table record the ratio of the idiosyncratic risk over the total risk (i.e. 1 − adjusted R^2) for each firm. At the beginning of each month, to create the within-industry size rank score This table sort all firms in a BEA industry by the firm's total market capitalization and assign a firm in the industry a percentile rank score between zero (the smallest) and one (the largest). To create universe size percentile rank scores, all firms in the market are sorted by the firm's market capitalization at the beginning of each month. The construction and timing of book-to-market (B/M) follows Fama and French (1996) and is as of the previous December year-end. To create universe B/M percentile rank scores, This table sort all available firms by the firm's B/M at the beginning of each year and assign a firm a percentile rank score between zero (the lowest) and one (the highest). To create the within-industry B/M rank score, This table sort all firms in a BEA industry by the firm's B/M at the beginning of each year and assign a firm in the industry a percentile rank score between zero (the smallest) and one (the largest). For each portfolio in every portfolio formation date, This table calculate (1) the percentages of firms that have positive or negative response coefficients, (2) the average of the firms' ratio of the idiosyncratic risk over the total risk, and (3) the average of the firms' size and B/M percentile rank scores. Additionally, this table calculates the percentage of numbers of different BEA industries getting into the extreme portfolio. This table also constructs the proportion of firms in the extreme portfolio belonging to each BEA industry and report the proportion for the industry that has the most firms in the extreme portfolio. This table reports the average of interest variables over the sample period from January 1986 to December 2015. The significance level of the difference equaling to zero is indicated by *** (1%), ** (5%), and * (10%)

similar pattern also obtains when the investment strategies are formed based on earnings surprise information from the main supplier industry.

To gauge the proportion of a firm's return variation that does not respond to earnings-related information from its main customer/supplier industry, each month I record the ratio of the firm's idiosyncratic risk over total risk (i.e., 1 − adjusted R^2) for each firm in the response regression. The results indicate that earnings-related information from a stock's main customer/supplier industry generally explains about 10–11% of the stock's total return variation. However, the return variation of losers is explained less by earnings-related information of the main customer/supplier industry than is the return variation of winners.

The largest firms in an industry are more likely to be industry leaders, which are typically covered by more analysts and hence less likely to react slowly to information. Since the investment strategies are based on the gradual diffusion of earnings-related information from a stock's main customer/supplier industry to the stock in question, I do not expect the extreme portfolios to be systematically composed of large firms from each industry. To investigate this issue, at the beginning of each month I independently sort all firms in a BEA industry by the firm's total market capitalization at the end of the previous month and assign a firm in the industry a size percentile rank score between zero (the smallest) and one (the largest). For each portfolio at every portfolio formation date, I calculate the equally-weighted average of the firms' size percentile rank score. The result confirms that I am not selecting large firms from an industry. When the size rank score is constructed based on universe stocks, both extreme portfolios comprise about-medium-sized firms on average but the winners are relatively smaller than the losers. Next, book-to-market (B/M) percentile rank scores are created in a similar way. While both winners and losers are close to neutral in growth-value, the winners are slightly more value-oriented than the losers.

Since firms within an industry operate in the same regulatory environment and are exposed to similar supply and demand fluctuations, firms in the winner or loser portfolio could be from the same industry in a given portfolio. In this case, the investment strategies might still be confounded by the industry momentum strategies documented by Moskowitz and Grinblatt (1999). To investigate this issue, on every portfolio formation date I calculate the percentage of numbers of different BEA industries that are in the extreme portfolios. I also construct the proportion of firms in the extreme portfolios belonging to each BEA industry. The results indicate that more than 63% of the BEA industries are present in either winner or loser portfolios. The investment strategies do not concentrate in a particular industry. In addition, the highest concentration in any given BEA industry is 19.8% for the winner portfolio when the strategy is formed based on SUE2 from the main customer industry.

6.2 Constrained firms

Why can some firms effectively adjust to their supply chain's prospects and become more likely to be a winner? When full debt capacity is reached or a large scale of capital is in place, firms cannot adjust to the supply chain shocks without paying high costs. Facing greater uncertainty, a firm has an incentive to retain the capability to make adjustments and to avoid irreversible actions. I examine firms' financial leverage and capital intensity to better understand this important issue.

Debt-loaded firms have less flexibility in making a big change during the turn of business cycles. Using the survey sent to CFOs in the Fortune 500 list and Financial Executives Institute members, Graham and Harvey (2001) document that firms are very concerned about financial flexibility when issuing debt. Gamba and Triantis (2008) and Byoun (2008) argue the motives to attain financial flexibility are related to the future

Table 9 Firms structures and reactions to shocks

Interest variables	Winner (W)	Loser (L)	W–L
Sorting variable: expected returns formed by main customer industry			
Within-industry LEV percentile rank score	0.506	0.506	0.000
Universe LEV percentile rank score	0.502	0.509	− 0.007***
Within-industry CAP percentile rank score	0.497	0.504	− 0.007***
Universe CAP percentile rank score	0.515	0.532	− 0.016***
Sorting variable: expected returns formed by main supplier industry			
Within-industry LEV percentile rank score	0.504	0.505	− 0.001
Universe LEV percentile rank score	0.503	0.515	− 0.012***
Within-industry CAP percentile rank score	0.492	0.501	− 0.009***
Universe CAP percentile rank score	0.511	0.527	− 0.016***

Two extreme quartile portfolios, Winner and Loser, are constructed every month as described in Table 6. For brevity concern, this table only reports results for an earnings surprise defined by SUE2. The construction of measuring a firm's financial leverage (LEV) and capital intensity (CAP) is as of the previous December year-end. To create universal percentile rank scores for financial leverage, DLTT/CEQ, this table uses two annual Compustat variables: Total Long-Term Debt (DLTT) and Total Common Ordinary Equity (CEQ). To create universe capital intensity percentile rank scores, all available firms are sorted by the firm's CAP at the beginning of each year and assign a firm a percentile rank score between zero (the lowest) and one (the highest). This table uses two annual Compustat variables: Total Net Property Plant and Equipment (PPENT), Total Assets (AT), to construct PPENT/AT in measuring the firm's capital intensity. The same procedure described above is also used to create the within-industry rank score. All firms in a BEA industry are sorted by the firm's LEV or CAP or at the beginning of each year and assign a firm in the industry a percentile rank score between zero and one. For each portfolio in every portfolio formation date, this table calculates the average of the firms' LEV and CAP percentile rank scores. This table reports the average of interest variables over the sample period from January 1986 to December 2015. The significance level of the difference equaling to zero is indicated by *** (1%), ** (5%), and * (10%)

ability of firms to raise external funds and restructure their financing at low cost.[17] In reacting to a possible hit of demand or supply shocks, I argue that firms with less financial leverage have greater flexibility in deploying debt financing and are more likely to be in the winner portfolio.

To measure the firm's financial leverage, I construct the ratio, DLTT/CEQ, using two annual Compustat variables: Total Long-Term Debt (DLTT) and Total Common Ordinary Equity (CEQ). At the beginning of each year, I sort all available firms by the firm's financial leverage as of the previous December year-end and assign the firm a percentile rank score between zero (the lowest) and one (the highest). To have a consistent comparison over time, the percentile rank score is used to take time-varying leverage ratios into consideration. The sorting is done universally and within an industry to which the firm belongs. Table 9 shows that winner firms have significantly less financial leverage than the loser firms. When the sorting is done within the industry to which the firm belongs, the effect of financial flexibility is not significant.

Changes in technology, the demand for output, or factor prices can lead to the displacement of capital from its original use. The flexibility with which capital can be

[17] After taking into account endogeneity among leverage, debt maturity, and cash holding, Brick and Liao (2017) present evidence that firms facing financial constraints borrow long term debt to build up the firm's cash reserves in order to have the flexibility to fund future investments.

redeployed is an important determinant of a firm's speed of transition/adjustment after a shock. Bernanke (1983) argues that once an investment project is constructed, it cannot be "undone" or made into a radically different type of project without high costs. Ramey and

Table 10 Response coefficients to positive versus negative shocks

	Winner (W)	Loser (L)	W–L
Panel A: average of response coefficients			
Sorting variable: expected returns formed by main customer industry			
Response coefficients to positive shocks	1.118	− 1.049	2.167***
	[513]	[368]	
Response coefficients to negative shocks	− 1.303	1.068	− 2.371***
	[244]	[401]	
Difference	2.420***	− 2.118***	4.538***
Sorting variable: expected returns formed by main supplier industry			
Response coefficients to positive shocks	1.096	− 1.072	2.169***
	[498]	[374]	
Response coefficients to negative shocks	− 1.279	1.031	− 2.310***
	[249]	[385]	
Difference	2.376***	− 2.103***	4.479***
Panel B: fraction of positive and negative response coefficients			
Sorting variable: expected returns formed by main customer industry			
Firms having positive response coefficients to positive shocks	1.000	0.005	0.995***
Firms having negative response coefficients to positive shocks	0.000	0.995	− 0.995***
Firms having positive response coefficients to negative shocks	0.003	0.999	− 0.995***
Firms having negative response coefficients to negative shocks	0.997	0.001	0.995***
Sorting variable: expected returns formed by main supplier industry			
Firms having positive response coefficients to positive shocks	0.997	0.011	0.987***
Firms having negative response coefficients to positive shocks	0.003	0.989	− 0.987***
Firms having positive response coefficients to negative shocks	0.004	0.991	− 0.987***
Firms having negative response coefficients to negative shocks	0.996	0.009	0.987***

The detailed construction of response coefficients is described in Table 5. For brevity concern, this table only reports results for an earnings surprise defined by SUE2. At the beginning of every month, starting in January 1986, This table construct the expected return on individual stocks, the sorting variable, for month t by multiplying the stock's most current response coefficient available at the beginning of the month t and the stock's main customer (supplier) industry return in the month $t-1$ in which the customer (supplier) industry has an earnings surprise defined by SUE. Two extreme quartile portfolios, Winner and Loser, are constructed every month as described in Table 6. A stock's response coefficient is classified as response coefficients to positive (negative) shocks if the stock's main customer/supplier industry return in the month $t-1$ is positive (negative). Panel A reports the average of response coefficients over the sample period from January 1986 to December 2015. The average number of firms is indicated in the square bracket. Panel B presents the fraction of firms in each extreme quartile having positive or negative response coefficients to either positive or negative shocks. The significance level of the difference equaling to zero is indicated by *** (1%), ** (5%), and * (10%)

Shapiro (2001) empirically document costly capital reversibility in Aerospace plant closings. Given that new information relevant to assessing long-run project returns arrives continuously, a firm can improve its chances of making a correct decision by sequentially taking a conservative position in capital deployment. In the consideration of costly adjustment of capital, I argue that firms that are less capital intensive are more likely to be in the winner portfolio when facing industry-wide earnings surprises.

To measure the firm's capital intensity, I construct the ratio, PPENT/AT, using two annual Compustat variables: Total Net Property Plant and Equipment (PPENT) and Total Assets (AT). The sorting based on capital intensity is done in the same way as the financial leverage score construction. The results in Table 9 confirm the prediction. While firms in both the winner and loser portfolios are capital intensive relative to the universal median, the result shows that the winners are significantly less capital intensive than the losers regardless of whether the sorting is done universally or within an industry.

The findings support that the winners are less-constrained firms, and could be better to cope with industry shocks than others by riding on positive shocks and shielding themselves from negative ones. A natural prediction is that these firms will have a larger response coefficient to positive shocks than to negative shocks. Since every month I construct winners and losers based on a stock's constructed expected return, a stock's response coefficient is classified as response coefficients to positive (negative) shocks if the stock's main customer/supplier industry return in the prior month is positive (negative). Every month I average response coefficients in each category for each extreme portfolio and report the time-series average. Panel A of Table 10 shows that better performing firms respond to positive shocks positively and negative shocks negatively. Meanwhile, worse performing firms respond to shocks mistakenly. Winner firms also experience more positive shocks than negative shocks. For example, on average 513 winner firms experience positive shocks while 244 winner firms experience negative shocks when the shocks are defined by a firm's main customer industry returns. It is questioned whether the likelihood of a positive shock rather than the likelihood of a positive response coefficient drives a firm to become a winner. I address this issue in Panel B of Table 10, which reports the fraction of firms in each extreme quartile having positive or negative response coefficients to either type of shocks. The result clearly shows that the likelihood of a *correct* response drives a firm to become a winner. For example, in facing negative shocks defined by a firm's main customer industry returns, only 0.3% of 244 winner firms made a mistake to have a positive coefficient while 99.9% of 401 loser firms made the mistake. When firms face positive shocks, none of winners made a mistake to have a negative coefficient while 99.5% of losers made the mistake. When shocks are defined by a firm's main supplier industry returns, less than 0.4% of winners made a mistake in responding to shocks while more than 98.9% of losers made mistakes. Overall, Table 10 provides evidence that winners experience positive responses to both positive and negative shocks while losers experience negative responses to both types of shocks.

7 Conclusion

This study explores how industry-wide earnings surprises diffuse from a stock's main upstream- and downstream-industry to the stock itself. Earnings signals are issued routinely and thus represent salient information that investors are reasonably expected to analyze. By examining the diffusion of this specific form of information across the supply chain, I shed new light for the literature on the gradual diffusion of information hypothesis.

I begin by providing quantitative evidence suggesting that information of industry-wide earnings surprises diffuses gradually from an industry's main customer and supplier industry to the industry and an individual firm in question. In addition, individual stocks are more sensitive to the earnings-related information of their main customer industry than to those of their main supplier industry. This is not inconsistent with the finding by Bartelsman et al. (1994) that over shorter horizons the linkage between an industry and its customers is pivotal in the transmission of external effects. I also find that at least 25% of firms react negatively to earnings-related returns in their main customer/supplier industry, and thus are counter-cyclical relative to their supply chain's prospects.

Next, in cases where the earnings-related information diffuses gradually across the supply chain, I exploit the potential profit opportunity by taking a long position in stocks with the highest constructed expected returns and a short position in stocks with the lowest constructed expected returns. When I consider earnings surprises from a stock's main customer industry, the 4-factor alphas are highly significant for the long/short portfolio at least up to the 6-month holding period. Moreover, the alphas of the long/short portfolio are mainly driven by the winner portfolio. Further, once the supply-chain earnings related information is removed from the estimation of a stock's response coefficients, the long/short portfolio is no longer profitable.

Finally, I explore the characteristics of firms in the extreme portfolios to understand why some firms react to supply-chain earnings shocks more effectively than others. Most winners are pro-cyclically related to its supply chain's prospects while losers show an equal tendency to be pro-cyclical versus counter-cyclical. The earnings-related information from a stock's main customer or supplier industry generally explains about 10–11% of the total return variation of the stock. On average, medium firms within an industry are more likely to get into the extreme portfolios but both winners and losers are of above-medium size universally. Overall, each extreme portfolio consists of more than 670 firms, covers more than 63% of the BEA industries, and is dispersed across industries.

In considering the flexibility of deploying debt financing to react to demand shocks, winner firms typically have the financial leverage at the universal median and have significantly less financial leverage than the losers. Firms in the extreme portfolios are all relatively capital intensive universally but the winners are significantly less capital intensive than the losers. I also provide evidence that winners experience positive responses to both positive and negative shocks while losers experience negative responses to both types of shocks.

I note that although the supply chain provides a rich area for understanding the information diffusion process, reactions to demand/supply shocks are not homogeneous at the industry or the firm level. More work on how to measure and distinguish the impact of various impediments to the information diffusion process could lead to fruitful empirical predictions about asset prices. Another interesting area of research that would provide greater insights into the diffusion of industry information is when and how financial analysts consider customer versus supplier industry information in their forecasts. I leave these pursuits to future research.

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Appendix 1: BEA I–O industries before 1997

Using the flow of goods and services reported in the Use Table of the Benchmark Input–Output Accounts before 1997, this table defines upstream and downstream industries for each industry in the accounts of the Bureau of Economic Analysis (BEA). For each industry in each Economic Census survey of 1972, 1977, 1982, 1987, and 1992, this table ranks the flow of goods and services of upstream (downstream) industries into (out of) the industry. The flow of goods and services into (out of) the industry itself are excluded from the ranking. The industry with the highest rank among the upstream (downstream) industries is defined as the main supplier (customer). The BEA industry classification is updated according to SIC codes at the *end* of the release year while individual company SIC codes are updated continuously. Using CRSP data, this table calculates the market capitalization of a company at the beginning of every month from January 1983 to December 2002, the year 1997 Census survey was released. Only stocks with CRSP share code of 10 or 11 are included in the sample. Stocks with price below $1 at the beginning of a year are excluded for the year. This table reports monthly average number (Num) of publicly traded firms, and the average market capitalization of firms in an industry as well as its main customer/supplier industry.

	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
1	Livestock/livestock products	2.6	278.4	3247.7	370.2
2	Other agricultural products	4.1	370.2	2151.7	937.6
3	Forestry/fishery products	1.0	76.8	1178.1	140.7
4	Agricultural/forestry/fishery services	4.2	125.2	370.2	1394.2
5	Iron/ferroalloy ores mining	4.6	582.9	535.5	1562.2
6	Nonferrous metal ores mining	30.9	407.7	1084.8	1634.2
7	Coal mining	6.1	460.5	1620.0	898.9
8	Crude petroleum/natural gas	122.4	631.4	9479.1	185.8
9	Stone/clay mining/quarrying	5.1	463.0	300.1	1562.2
10	Chemical/fertilizer mineral mining	2.0	1375.3	2050.8	1562.2
11	New construction	98.7	272.2	414.3	777.8
12	Repair/maintenance construction	–	–	207.3	1085.2
13	Ordnance/accessories	6.0	1754.7	679.1	2896.8
14	Food/kindred products	78.4	3247.7	500.6	278.4
15	Tobacco manufactures	6.2	11,827.9	658.2	687.7
16	Broad/narrow fabrics/yarn/thread mills	19.3	238.4	356.2	2404.5
17	Miscellaneous textile goods/floor coverings	7.3	324.1	337.4	2407.9
18	Apparel	51.0	356.2	752.9	238.4
19	Miscellaneous fabricated textile products	3.1	106.3	3085.1	238.4
20	Lumber/wood products-except containers	11.5	1178.1	272.2	76.8

	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
21	Wood containers	–	–	370.2	1178.1
22	Household furniture	14.1	434.8	790.7	1178.1
23	Other furniture/fixtures	7.9	416.6	1830.5	805.6
24	Paper/allied products-except containers	32.1	2404.4	1067.4	1178.1
25	Paperboard containers/boxes	6.5	622.6	3247.7	2404.4
26	Printing/publishing	70.3	1067.4	416.3	2404.4
27	Chemicals/selected chemical products	45.5	2050.8	2458.3	1301.0
28	Plastics/synthetic materials	11.2	2458.3	427.4	2050.8
29	Drugs/cleaning/toilet preparations	202.5	2253.3	414.3	689.7
30	Paints/allied products	7.7	777.2	285.1	2050.8
31	Petroleum refining/related industries	25.7	9479.1	641.0	631.4
32	Rubber/miscellaneous plastics products	48.5	427.4	2972.4	2458.3
33	Leather tanning/finishing	1.8	96.7	336.5	3247.7
34	Footwear/other leather products	19.3	336.5	653.8	96.7
35	Glass/glass products	11.3	2147.7	3247.7	1576.4
36	Stone/clay products	21.9	395.1	272.2	604.0
37	Primary iron/steel manufacturing	38.0	535.5	1341.9	1083.0
38	Primary nonferrous metals manufacturing	21.2	1084.8	1183.1	881.8
39	Metal containers	3.7	1023.7	3247.7	940.4
40	Heating/plumbing/fabricated structural metals	25.8	676.7	272.2	535.5
41	Screw machine products/stampings	12.8	816.2	3085.1	535.5
42	Other fabricated metal products	32.2	1273.6	272.2	535.5
43	Engines/turbines	6.6	1339.1	3085.1	535.5
44	Farm/garden machinery	9.4	1156.3	370.2	535.5
45	Construction/mining machinery	15.0	1116.4	368.8	535.5
46	Materials handling machinery/equipment	7.3	942.7	272.2	535.5
47	Metalworking machinery/equipment	12.9	466.4	3035.5	535.5
48	Special industry machinery/equipment	10.2	141.5	1842.5	805.6
49	General industrial machinery equipment	31.2	497.6	390.1	535.5
50	Miscellaneous machinery-except electrical	5.3	528.8	3085.1	519.3
51	Office/computing/accounting machines	65.7	2388.0	746.6	1880.9
52	Service industry machines	13.4	416.1	272.2	816.8
53	Electric industrial equipment/apparatus	34.9	1247.4	264.2	908.9
54	Household appliances	8.6	16,404.3	284.0	533.0
55	Electric lighting/wiring equipment	12.5	6296.3	272.2	901.7
56	Radio/TV/communication equipment	77.4	790.7	2781.5	2134.2
57	Electronic components/accessories	69.9	2134.2	1963.1	780.9
58	Miscellaneous electrical machinery/supplies	11.1	399.2	3085.1	1998.3
59	Motor vehicles/equipment	32.9	3085.1	650.9	797.0
60	Aircraft/parts	16.2	3866.7	641.0	791.9
61	Other transportation equipment	23.2	564.0	641.0	553.6
62	Scientific/controlling instruments	87.6	1218.1	414.3	2115.1
63	Optical/ophthalmic/photographic equipment	26.7	1393.4	689.7	1468.0

	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
64	Miscellaneous manufacturing	35.6	334.9	457.1	794.2
65	Transportation/warehousing	106.7	641.0	2775.1	5295.4
66	Communications-except radio/TV	109.4	2833.3	814.4	1693.7
67	Radio/television broadcasting	32.7	1756.6	702.6	879.3
68	Private electric/gas/water/sanitary services	194.1	1620.0	816.1	631.4
69	Wholesale/retail trade	496.6	816.1	272.2	689.7
70	Finance/insurance	1070.7	1000.0	580.0	689.7
71	Real estate/rental	47.9	185.8	495.1	114.9
72	Hotels/personal/repair services-except auto	48.2	639.0	816.1	689.7
73	Business services	425.3	689.7	816.1	185.8
74	Eating/drinking places	86.4	500.6	575.9	3247.7
75	Automobile repair/services	11.7	332.2	661.2	3085.1
76	Amusements	56.7	879.3	1756.6	684.5
77	Health/educational/social services/nonprofits	132.8	414.3	706.2	543.4

Appendix 2: BEA I–O industries after 1997

Using the flow of goods and services reported in the Use Table of the 1997, 2002, and 2007 Benchmark Input–Output Accounts, this table defines upstream and downstream industries for each industry in the accounts of the Bureau of Economic Analysis (BEA). For each industry in each Economic Census survey period, this table ranks the flow of goods and services of upstream (downstream) industries into (out of) the industry. The flow of goods and services into (out of) the industry itself are excluded from the ranking. The industry with the highest rank among the upstream (downstream) industries is defined as the main supplier (customer). The BEA industry classification is updated according to NAICS codes at the *end* of the release year while individual company NAICS codes are updated continuously. Using CRSP data, this table calculates the market capitalization of a company at the beginning of every month from January 2003, the 1st year after 1997 Census survey was released, to December 2015. Only stocks with CRSP share code of 10 or 11 are included in the sample. Stocks with a price below $1 at the beginning of a year are excluded for the year. This table reports monthly average number (Num) of publicly traded firms, and the average market capitalization of firms in an industry as well as its main customer/supplier industry.

Code	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
1110	Crop production	4.6	355.7	4422.2	875.6
1120	Animal production	2.1	858.2	4422.2	1301.7
1130	Forestry and logging	1.1	9197.4	1205.2	316.0
1140	Fishing, hunting and trapping	–	–	3680.2	35,035.8
1150	Agriculture and forestry support activities	1.0	316.0	355.7	8210.5
2110	Oil and gas extraction	95.0	4026.5	40,261.0	427.9

Code	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
2121	Coal mining	8.3	2724.3	5634.7	7971.9
2122	Metal ores mining	17.8	4056.7	2746.7	12,067.3
2123	Nonmetallic minerals mining and quarrying	6.2	1804.7	1297.5	8818.1
2130	Support activities for mining	33.0	2808.0	4026.5	8587.1
2211	Power generation and supply	60.1	6840.8	1139.3	9837.0
2212	Natural gas distribution	28.0	4620.4	3088.8	4026.5
2213	Water, sewage and other systems	13.9	785.0	2507.5	1442.5
2300	Construction (2301 + 2302 + 2303)	47.8	1442.5	1139.3	1966.1
3110	Food manufacturing	56.2	4422.2	3113.8	858.2
3121	Beverage manufacturing	23.2	12,889.5	3113.8	4422.2
3122	Tobacco manufacturing	5.7	32,948.4	1146.1	763.4
3130	Textile mills	5.5	287.0	1920.6	6949.0
3140	Textile product mills	3.7	1901.8	7970.8	287.0
3150	Apparel manufacturing	23.9	1997.4	3553.4	287.0
3160	Leather and allied product manufacturing	17.0	2951.5	2042.9	4422.2
3210	Wood product manufacturing	11.3	1205.2	1442.5	9197.4
3221	Pulp, paper, and paperboard mills	18.3	2578.9	4659.4	10,841.1
3222	Converted paper products manufacturing	12.8	4659.4	4422.2	2578.9
3230	Printing and related support activities	16.0	879.4	3529.3	2578.9
3240	Petroleum and coal products manufacturing	17.0	40,261.0	1442.5	4026.5
3251	Basic chemical manufacturing	28.7	2723.3	6949.0	31,001.6
3252	Resin, rubber, artificial fibers manufacturing	13.8	6949.0	1431.8	2723.3
3253	Agricultural chemical manufacturing	7.5	8210.5	355.7	2723.3
3254	Pharmaceutical and medicine manufacturing	227.6	5077.9	2441.1	1314.4
3255	Paint, coating, and adhesive manufacturing	7.2	3203.2	1442.5	2723.3
3256	Soap/cleaning compound/toiletry manufacturing	20.3	10,307.7	1357.8	1481.4
3259	Other chemical products/preparation manufacturing	10.4	1654.4	879.4	2063.6
3260	Plastics and rubber products manufacturing	24.6	1431.8	1442.5	6949.0
3270	Nonmetallic mineral product manufacturing	11.5	1468.9	1442.5	1744.1
3315	Foundries	2.1	10,905.3	2042.9	2483.7
331A	Iron and steel mills and manufacturing from purchased steel	16.0	2007.7	1617.5	3305.4
331B	Nonferrous metal production/manufacturing	9.8	2483.7	2668.0	3305.4
3321	Forging and stamping	2.0	262.1	2042.9	2007.7
3322	Cutlery and handtool manufacturing	6.2	2609.8	2509.6	2007.7
3323	Architectural/structural metals manufacturing	10.8	867.7	1442.5	2007.7
3324	Boiler/tank/shipping container manufacturing	4.6	2720.8	6903.4	2483.7
332A	Ordnance and accessories manufacturing	6.1	1491.4	69.2	1807.6
332B	Other fabricated metal product manufacturing	22.8	1807.6	1442.5	2007.7
3331	Agriculture/construction/mining machinery	22.4	4998.2	1825.4	13,441.9
3332	Industrial machinery manufacturing	19.5	1966.8	2345.3	1807.6
3333	Commercial and service industry machinery	23.4	1256.1	1442.5	2783.7
3334	HVAC/commercial refrigeration equipment	13.4	2287.6	1442.5	2479.9

Code	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
3335	Metalworking machinery manufacturing	7.6	1276.5	1807.6	1598.7
3336	Turbine and power transmission equipment manufacturing	8.4	19,520.5	13,142.5	10,905.3
3339	Other general purpose machinery manufacturing	31.5	3605.5	1442.5	1707.7
3341	Computer and peripheral equipment manufacturing	51.6	14,516.5	1897.7	2768.6
3344	Semiconductor and electronic equipment manufacturing	164.0	2768.6	4884.6	1319.2
3345	Electronic equipment manufacturing	129.2	1945.0	10,506.3	2236.0
3346	Magnetic media manufacturing/reproducing	15.7	1790.3	5581.5	1431.8
334A	Audio/video/communications equipment manufacturing	86.4	2804.9	5594.2	2768.6
3351	Electric lighting equipment manufacturing	6.4	9432.8	1442.5	3305.4
3352	Household appliance manufacturing	5.0	2094.7	1442.5	1206.2
3353	Electrical equipment manufacturing	18.1	1136.0	1994.0	2479.9
3359	Other electrical equipment/component manufacturing	26.4	2977.3	1442.5	2483.7
3361	Motor vehicle manufacturing	6.1	13,142.5	2042.9	2042.9
3364	Aerospace product and parts manufacturing	21.7	10,506.3	2641.7	1235.4
336A	Motor vehicle body/trailer/parts manufacturing	45.3	2042.9	13,142.5	1517.1
336B	Other transportation equipment manufacturing	16.9	2743.9	15,101.3	1488.7
3370	Furniture and related products manufacturing	23.1	1285.4	1442.5	1205.2
3391	Medical equipment/supplies manufacturing	89.2	3215.0	1602.3	3665.3
3399	Other miscellaneous manufacturing	28.8	1521.3	969.7	2371.4
4200	Wholesale trade	92.6	3305.4	2294.7	1314.4
4810	Air transportation	19.9	2641.7	2419.1	30,865.2
4820	Rail transportation	7.4	15,101.3	5634.7	8208.6
4830	Water transportation	8.6	1235.5	4181.4	8626.6
4840	Truck transportation	22.9	1029.3	2182.3	27,662.7
4850	Transit and ground passenger transportation	1.6	3335.9	2315.8	8189.4
4860	Pipeline transportation	8.3	4873.2	4620.4	34,383.5
48A0	Scenic and sightseeing transportation and support activities for transportation	9.5	2398.5	2641.7	13,641.9
4910	Postal service	–	–	3121.3	2232.0
4920	Couriers and messengers	4.8	18,207.2	3305.4	40,261.0
4930	Warehousing and storage	1.5	3808.7	5529.2	1139.3
4A00	Retail trade	203.5	5529.2	1442.5	1350.2
5111	Newspaper, book, and directory publishers	28.9	3529.3	1229.3	879.4
5112	Software publishers	132.9	4666.9	10,498.1	1197.5
5120	Motion picture/sound recording industries	14.1	5581.5	4571.9	1980.0
5131	Radio and television broadcasting	24.7	2482.2	2140.7	4795.4
5132	Cable networks and program distribution	16.4	10,874.1	4368.0	5581.5
5133	Telecommunications	71.3	5594.2	1444.0	2096.1
5141	Information services	36.5	7365.1	3529.3	6354.6
5142	Data processing services	32.8	3151.4	3067.9	3745.5
5230	Securities, commodity contracts, investments	74.2	4362.8	833.8	2330.1
5240	Insurance carriers and related activities	126.4	6734.6	2256.1	2315.8
5250	Funds, trusts, and other financial vehicles	19.5	833.8	6734.6	4362.8

Code	BEA I–O industry	Num	Market capitalization ($million)		
				Customer	Supplier
52A0	Monetary authorities, credit intermediation and related activities	502.9	2950.1	2379.7	4362.8
5310	Real estate	25.8	1139.3	5529.2	1862.7
5321	Automotive equipment rental and leasing	3.7	3501.0	4895.1	2581.2
5324	Machinery and equipment rental and leasing	10.3	755.9	1442.5	3640.3
532A	Consumer goods and general rental centers	6.1	981.5	1446.6	1340.7
5330	Lessors of nonfinancial intangible assets	5.7	403.7	3218.1	2136.7
5411	Legal services	3.1	13,350.9	1576.3	1139.3
5412	Accounting and bookkeeping services	4.0	1227.6	2675.7	1139.3
5413	Architectural and engineering services	20.3	790.5	1442.5	1296.6
5414	Specialized design services	3.0	784.2	1022.2	1139.3
5415	Computer systems design and related services	102.9	1876.5	1210.7	907.9
5416	Management/technical consulting services	34.7	1078.4	1922.3	1952.7
5417	Scientific research and development services	57.1	1857.3	4310.0	1451.0
5418	Advertising and related services	15.8	2140.7	5529.2	3442.8
5419	Other professional and technical services	14.6	1882.1	5587.2	1139.3
5500	Management of companies and enterprises	97.0	1314.4	4442.5	2140.7
5613	Employment services	18.2	907.9	1459.8	1314.4
5615	Travel arrangement and reservation services	3.3	4295.0	2761.6	2140.7
561A	All other administrative and support services	47.1	1652.5	2501.4	22,347.3
5620	Waste management and remediation services	16.9	2489.0	1139.3	2502.3
6100	Educational services	18.6	1267.4	4392.0	1139.3
6210	Ambulatory health care services	43.8	1602.3	2521.8	1139.3
6220	Hospitals	12.6	2521.8	–	2446.4
6230	Nursing and residential care facilities	13.9	735.6	–	1139.3
6240	Social assistance	2.4	581.4	3402.9	1139.3
7130	Amusements, gambling and recreation	20.7	5002.2	1807.1	1139.3
71A0	Performing arts, spectator sports, museums, zoos, and parks	12.0	1195.0	3047.5	1139.3
7210	Accommodation	16.8	3158.6	2419.1	2431.3
7220	Food services and drinking places	50.6	3113.8	2429.6	4422.2
8111	Automotive repair and maintenance	1.7	738.3	4823.7	2042.9
811A	Electronic/commercial/household goods repair	1.0	69.2	2226.1	1637.9
8120	Personal and laundry services	11.9	969.7	4045.3	1139.3
813A	Religious, grant making and giving, and social advocacy organizations	1.0	256.6	673.3	2191.5
813B	Civic, social, professional and similar organizations	1.0	302.1	2950.1	1952.7
8140	Private households	–	–	302.1	302.1

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