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RESEARCH PAPER

Supply Chain and Predictability of Return

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Abstract

Customer and supplier companies (which form a supply chain) have long-term economic relationships and affect each other. In this study, we answer the question that "whether past returns of the customer (supplier) company can predict the future return of the supplier (customer) company". To answer this question, we have investigated the predictability of return (or lead-lag relationship) at the industry-level in 10 supply chains of the Tehran Stock Exchange from March 2015 to March 2020 using the vector autoregression model. We found that considerable numbers of supply chains, specifically, 6 out of 10 supply chains in our sample show the lead-lag relationship. In 3 supply chains, customer industry returns lead (or predict) supplier industry returns. Whereas, in the other 3 supply chains, supplier industry returns lead customer industry returns. These observed lead-lag relationships (or predictable returns) across industries provide some evidence of inefficiency in the Tehran Stock Exchange. In addition, we can use these predictable returns to construct profitable trading strategies.

Keywords:
Predictability of Return;
Supply Chain;
Vector Autoregression;
Market Efficiency;
Trading Strategy

Introduction

Companies are not independent entities and relate to each other in different ways. Customer-supplier relationships (or supply chains) are examples of long-term economic relationships between companies. If stock market investors ignore customer-supplier relationships, the supplier (customer) firm stock price will react with a lag to new information about the customer (supplier) firm. Thus, investors' inattention[†] to customer-supplier relationships causes that price changes (or returns) across firms in a supply chain to be predictable. In summary, we want to examine whether past returns of the customer (supplier) company can predict the future return of the supplier (customer) company.

Cohen and Frazzini [1] using company-level relationships, found that customer's lagged returns are positively correlated with the supplier's current return, so that customer's past returns can predict the supplier's future return. Afterwards, Menzly and Ozbas [2] using industry-level relationships found that customer and supplier industries cross-predict each other's returns. In other words, there is a bi-directional relationship between customer and supplier industries, so

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† We have used the term "investors' inattention" because information about customer-supplier relationships is publicly available. IFRS No. 8 states that an entity shall provide information about the extent of its reliance on its major customers. If revenues from transactions with a single external customer amount to 10 percent or more of an entity's revenues, the entity shall disclose that fact, the total amount of revenues from each such customer.

that customer's past returns can predict the supplier's future return, as well as supplier's past returns, can predict the customer's future return.

Our study similar to Menzly and Ozbas [2] research, investigates customer-supplier relationships at the industry-level in the Tehran Stock Exchange and provides non-US evidence on return predictability along the supply chain. As mentioned above, this study uses industry-level data (instead of company-level data), for the following reasons:

1. The results of Cohen and Frazzini [1] research show that on average 78% of customer-supplier relationships are between companies from different industries. Thus, the predictability of return is often related to stocks in different industries as opposed to stocks within the same industry.

2. Moskowitz and Grinblatt [3] found a strong and persistent momentum effect in industry-level returns, even after controlling for individual stock momentum. They showed that industry momentum strategies‡ are more profitable than individual stock momentum strategies. Therefore, if there is a predictable return between stocks within the same industry, then part of its risk premium is attributable to the non-diversifiable risk.

This study has two major objectives. First, this study investigates the efficiency of the Tehran Stock Exchange at the industry-level. Based on the efficient market hypothesis (EMH), the current stock price should reflect all available information and the stock price changes should be random and unpredictable. But the predictability of return in the supply chain provides some evidence of market inefficiency. The second objective is to provide investors with useful trading strategies. Investors who are informed of the customer-supplier relationships can use the predictable returns in the supply chains to buy or sell industry portfolios.

The rest of the article is organized as follows. Section 2 reviews the existing literature on the predictability of return in stock markets (especially in supply chains). Section 3 describes the data and methodology used in our study, while our results are provided in Section 4. Finally, in Section 5, we provide concluding remarks.

Literature review

Reasons for predictability of return in stock markets

In this section, we focus on reasons that have been suggested as to why returns may be predictable. Prior research has suggested four major reasons for the predictability of return (or lead-lag relationship§):

1. Non-synchronous trading: Boudoukh et al. [4] found that non-synchronous trading in some stocks plays an important role in creating the lead-lag relationship. For example, consider two stocks (A and B) that the stock B is not traded today. If important news comes out during the trading day, the price of stock A will reflect the news and is adjusted. In contrast, the price of the stock B will not reflect the news because it is not traded today. The price of the stock B will be adjusted when it trades the following trading day. Therefore, the return on stock A seems to lead (or predict) the return on stock B.

2. Firm size (or market capitalization): Lo and MacKinlay [5] showed that returns of larger stocks lead to returns of smaller stocks. This means that past returns of large stocks can predict the future return of small stocks. But they did not answer the question that what is the reason for the positive cross-autocorrelations between large and small stocks? To answer this

‡ Momentum strategy is a trading strategy in which investors buying winner stocks (or stocks that have had high returns over the past period and are rising) and selling loser stocks (or stocks that have had poor returns over the past period and are dropping).

§ Lead-lag relationship is a form of return predictability in stock markets whereby past returns of a stock (known as leader) can predict future returns on other stock (or follower stock) but not vice versa.

question, Brennan et al. [6] showed that returns on stocks that are followed by many analysts lead to returns on stocks that are followed by fewer analysts. Afterwards, Badrinath et al. [7] found that returns on stocks with the highest level of institutional ownership lead to returns on stocks with lower levels of institutional ownership. Finally, Chordia and Swaminathan [8] showed that returns of high trading volume stocks lead to returns of low trading volume stocks. These results show that analyst coverage, institutional ownership, and trading volume are all positively correlated with firm size.

3. Industry factor: Hou [9] found that there is a persistent and significant lead-lag effect between stocks intra-industry. Large stocks lead to small stocks within the same industry and this effect is stronger than the effect across industries. He argues that firms within an industry have a lot of commonalities. They compete in the same product market and have similar supply and demand conditions. In addition, they are in the same regulatory environment and have similar investment and financing opportunities. These commonalities show that new information about a given firm is likely to affect firms within (not outside) their own industry.

4. Supply Chain: The fourth and one of the most important reasons for the predictability of return is investors' inattention to customer-supplier relationships (or supply chains). We discuss prior research on the supply chain in detail in the next section.

Predictable returns in supply chains

Using monthly returns of common stocks traded on the NYSE[**], AMEX[††], and NASDAQ[‡‡] between 1980 and 2004, Cohen and Frazzini [1] showed that past returns of the customer stock forecast subsequent returns of the supplier stock. They refer to this return predictability as "customer momentum". To ensure that the firm size does not affect the magnitude or significance of the predictability of return, they excluded all supply chains in which the customer stock is larger than the supplier stock from their sample. Results show that the predictability of return is not affected after controlling the firm size, but its persistence is negatively correlated with the firm size so that for smaller stocks, predictable returns persist even more than a year.

Menzly and Ozbas [2] examined the predictability of industry-level returns at the NYSE, AMEX, and NASDAQ from July 1963 to June 2005 using Fama-MacBeth [10] regressions. They found that customer and supplier industries cross-predict each other's returns. In addition, they found that the magnitude of cross-predictability is negatively correlated with the number of informed investors (proxied by the level of analyst coverage and institutional ownership) in the market. They also introduced some self-financing trading strategies based on the predictable returns documented in their study.

Shahrur et al. [11] extended the work of Menzly and Ozbas [2] to international stock markets. Using monthly returns of stocks listed on exchanges of 22 developed countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom) from January 1995 to July 2007, they found that customer industries returns predict supplier industries returns. In addition, they found that the predictability of return is stronger for smaller suppliers industries and suppliers industries with dispersed sales to their customers.

Using 1083 supply chains for the period 1983-2011, Zhu [12] found that supplier cumulative returns (surrounding and following its customer's earnings announcements) are positively correlated with its customers' unexpected earnings. This confirms that information diffuses

[**] New York Stock Exchange
[††] American Exchange
[‡‡] National Association of Securities Dealers Automated Quotations

from customers to suppliers through customers' earnings announcements. In fact, customer's earnings announcements lead to customer returns and then customer returns generate supplier returns. He argues that investors' inattention is more likely when a large number of earnings announcements are made by customer firms and this limited attention makes suppliers' returns predictable.

Long Chen et al. [13] investigated the predictability of return along supply chains in the corporate bond market for the 1974 to 2011 period. They found that lagged returns of customer bond predict the future return of supplier bond, while lagged returns of supplier bond only predict the future return of customer bond with less bargaining power (proxied by profitability, book-to-market, credit ratings, and relative industry Herfindahl index). In addition, they found that the bond market diffuses new information slower than the stock market. They argue that the bond market is less active than the stock market because bond investors often use the position trading strategy and also many institutional investors (such as pension funds, banks, and insurance companies) are prohibited from investing in bonds with poor credit rating levels.

Li et al. [14] investigated the predictability of industry-level returns in the Chinese stock market from January 2001 to December 2017 using the conditional Fama-MacBeth [10] regression model. Their results are consistent with the findings of Menzly and Ozbas [2], who found significant predictability of returns at industry-level supply chains in the US stock market. But, they found that the customer momentum is stronger than the supplier momentum in the short term in the Chinese stock market. They attribute this asymmetry to the fact that compared with the US market, there is a high proportion of retail investors in the Chinese market and retail investors often focus on the customer side (which affects the firm revenue), rather than the supplier side (which affects firm costs).

Rui Chen et al. [15] extended the work of Cohen and Frazzini [1] to inter-country supply chains. Using a sample of US suppliers and their principal Chinese customers from 2009 to 2015, they indicated that lagged stock returns of Chinese customers predict future stock returns of the US suppliers. They also showed that the strategy of buying suppliers stocks whose customers had positive returns in the previous month and selling suppliers stocks whose customers had negative returns in the previous month (or the long–short portfolio strategy) yields abnormal returns of 2.18% per month.

Li et al. [16] examined the predictability of return between commodity futures and its customer and supplier stocks in China's market from 2005 to 2019. They found that in a considerable number of commodities, daily lagged returns of commodity futures predict the future return of its customer and supplier stocks, especially for supplier- side stock returns. They introduced the macroeconomic risk premium, which is captured by all commodity futures prices, as an important source of this predictability. They also found that this return predictability is stronger during recessionary periods, or when there are economic constraints.

The effect of investors' inattention

The theoretical model of investor inattention was initially proposed by Merton [17]. He developed a simple model of capital market equilibrium in which an investor has information only about a small number of available securities and these securities vary across investors. He then explored the impact of incomplete information on equilibrium expected returns and securities prices. He found that investors will not hold mean-variance efficient portfolios in the incomplete information model. He argues that investors must pay a significant receiver or set-up cost to information processing. Paying this fixed cost will cause each investor to follow only a small number of securities.

Hong and Stein [18] developed a unified behavioral model with two types of investors (news-watchers and momentum traders). The news watchers trade securities based on signals that they receive, while momentum traders trade securities based on past price changes. Therefore, each type of investor can only process some part of the available information. They showed that when only news watchers are active, their demand (or supply) for securities slowly adjusts prices. Momentum traders then accelerate the speed of prices adjustment and arbitrage away any underreaction by the news watchers. As a result, if information diffuses gradually across markets, then prices underreact and this provides the predictability of return.

Hirshleifer and Teoh [19] examined the consequences of different presentations of firm information in accounting reports (i.e. levels of discretion in pro forma earnings disclosure, methods of accounting for employee option compensation, and degrees of aggregation in reporting) on investor perceptions and market prices when investors have limited attention and processing power. Their model shows that investors' inattention affects the price of securities because limited attention influences the allocation of investors' resources. In addition, the effects of investors' inattention on prices are likely stronger when fundamentals, reporting behavior, or accounting rules have recently changed.

Menzly and Ozbas [2] tested the effect of informed investors on the cross-predictability of returns. They used the amount of analyst coverage and institutional ownership as proxies for the number of informed investors. They found that the magnitude of cross-predictability of returns is stronger for stocks with low levels of analyst coverage and institutional ownership. They argue that in two segmented markets (or industries) with correlated fundamentals, new information about one market is received only by investors who specialize in that market. Therefore, due to the specialization of informed investors, new information diffuses slowly from one market to another, making returns predictable.

Data and methodology

Input-output accounts

Menzly and Ozbas [2] have used input-output accounts published by the Bureau of Economic Analysis[§§] (BEA) to identify customer and supplier industries for a given industry. Input-output accounts are series of tables showing flows of goods and services across industries of the U.S. economy and are published once every 5 years. Similar to the method used by Menzly and Ozbas [2], we have identified customer-supplier relationships by using input-output accounts for the Iran economy (which has reported by the Central Bank of Iran in 2016).

Table 1 is a part of input-output accounts for the Iran economy that has put the supplier industries in the first row from the top and customer industries in the first column from the left. The numbers in the table show the percentage of the output of the jth supplier industry that is sold to the ith customer industry. For example, 22.19% of the output of the chemical industry is sold to the pharmaceutical industry. These two industries form a supply chain because the sales percentage is more than 10% of the total sales of the chemical industry. As you can see in the table, we identified 10 supply chains at the industry-level from the input-output accounts for the Iran economy. Thus, our sample includes the weekly returns of industries within these 10 supply chains of the Tehran Stock Exchange from March 2015 to March 2020.

Shahrur et al. [11] used an alternative approach to identify supply chains at the industry-level. They identified industry-level supply chains using the benchmark input-output accounts for the U.S. economy. This approach is based on evidence that the pattern of inter-industry flows in developed countries is very similar (see Chenery and Watanabe [20]). In addition, the United States is a large trading partner for many countries and has the world's largest equity

[§§] The Bureau of Economic Analysis (BEA) is a U.S. government agency that provides official macroeconomic and industry statistics.

market. The disadvantage of using U.S. input-output accounts to identify industry-level supply chains in other developed markets is that the actual customer-supplier relationships may not be identified.

Table 1. Input-Output Accounts for the Iran Economy

Supplier / Customer	Chemical	Electrical Devices	Basic Metals	Paper	Wood	Metal Ores	Extraction of Petroleum
Computer		15.80%					
Chemical							19.70%
Pharmaceutical	22.19%						
Basic Metals						12.20%	
Metal Products			22.21%				
Rubber and Plastic	36.26%						
Petroleum products							25.85%
Printing				16.24%			
Paper					18.13%		
Textiles	19.37%						

The weekly closing values of the industries index have been collected from the website of the Tehran Stock Exchange Technology Management Company (TSETMC). Then weekly closing values of industries index have been converted to continuously compounded weekly returns using Eq. 1.

$$R_{i,t} = Ln\left(\frac{I_{i,t}}{I_{i,t-1}}\right) \tag{1}$$

Where $R_{i,t}$ is the return of industry i in week t, $I_{i,t}$ is the index closing value of industry i in week t, and $I_{i,t-1}$ is the index closing value of industry i in week t-1.

Vector autoregression (VAR) model

As introduced by Christopher Sims [21] in the "Macroeconomics and Reality" article, vector autoregressions try to model interdependencies between economic variables. The theory of general equilibrium analyzes the economy as a whole and states that everything in the economy is related to other things. Thus it is impossible to say that some variables are exogenous in the model. VAR model allows all variables to be endogenous and does not impose arbitrary assumptions on the data.

The results of the Augmented Dickey-Fuller (ADF) test show that all variables of the research are stationary. As said before, Menzly and Ozbas [2] research shows that the current return of the supplier industry depends on the past returns of its customer industry and vice versa. Therefore, we estimate the following VAR model which has two variables (R_S and R_C) and eight lags (i = 8):

$$R_{S,t} = \alpha_1 + \sum_{i=1}^{8} A_i\, R_{S,t-i} + \sum_{i=1}^{8} B_i\, R_{C,t-i} + \varepsilon_{S,t} \tag{2}$$

$$R_{C,t} = \alpha_2 + \sum_{i=1}^{8} C_i\, R_{S,t-i} + \sum_{i=1}^{8} D_i\, R_{C,t-i} + \varepsilon_{C,t} \tag{3}$$

Where, $R_{S,t}$ is the return of supplier industry in week t, $R_{S,t-i}$ is the return of supplier industry in week t-i, $R_{C,t}$ is the return of customer industry in week t, and $R_{C,t-i}$ is the return of customer industry in week t-i.

The standard approach to selecting the appropriate VAR lag length is to use an information criterion including Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and Hannan and Quinn information criterion (HQIC). But a common problem is that different information criteria may suggest different lag lengths and there is no accepted answer to this problem. We estimate Eqs. 2 and 3 with eight lags because it seems reasonable to assume that the supplier (customer) industry will react to new information about the customer (supplier) industry within two months (or eight weeks). In addition, the selected lag length (i = 8) is longer than the lag lengths used in prior studies.

Now we run the Granger causality test to see whether customer and supplier industries Granger-cause[***] each other. We would say that R_C Granger-causes (or leads) R_S if lagged values of R_C in Eq. 2 are jointly significantly different from zero (i.e. Eq. 4 should be met). In addition, the sum of coefficients on $R_{C,t-i}$ in Eq. 2 should be greater than the sum of coefficients on $R_{S,t-i}$ in Eq. 3 (i.e. Eq. 5 should be met):

$$\sum_{i=1}^{8} B_i > 0 \tag{4}$$

$$\sum_{i=1}^{8} B_i > \sum_{i=1}^{8} C_i \tag{5}$$

And, we say that R_S Granger-causes (or leads) R_C if Eqs. 6 and 7 are both satisfied:

$$\sum_{i=1}^{8} C_i > 0 \tag{6}$$

$$\sum_{i=1}^{8} C_i > \sum_{i=1}^{8} B_i \tag{7}$$

Results

Granger causality

Table 2 has put the sum of $R_{C,t-i}$ coefficients in Eq. 2 (ΣB_i) and the sum of $R_{S,t-i}$ coefficients in Eq. 3 (ΣC_i) in the first row from the top and industry-level supply chains in the first column from the left. As you can see in the table, 6 out of 10 supply chains [(computer, electrical devices), (chemical, extraction of petroleum), (basic metals, metal ores), (petroleum products, extraction of petroleum), (paper, wood), and (textiles, chemical)] in our sample show the lead-lag relationship. These observed lead-lag relationships (or predictable returns) across industries provide some evidence of inefficiency in the Tehran Stock Exchange.

In 3 supply chains [(computer, electrical devices), (chemical, extraction of petroleum), and (basic metals, metal ores)], Eqs. 4 and 5 have been met. In other words, in these supply chains, the weekly returns of the customer industry lead (or predict) the weekly returns of the supplier

[***] Granger-causality shows only the correlation between the current value of one variable and the past values of other variables and does not show the real causality.

industry. While, in other 3 supply chains [(petroleum products, extraction of petroleum), (paper, wood), and (textiles, chemical)], Eqs. 6 and 7 have been met. In other words, in these supply chains, the weekly returns of the supplier industry lead the weekly returns of the customer industry. These results are consistent with prior research (Menzly and Ozbas [2], Shahrur et al. [11], and Li et al. [14]) and confirm the predictability of return at industry-level supply chains in the Tehran Stock Exchange. But our results show that there is often a positive uni-directional (not bi-directional) causality between the customer and supplier industries. We also found that the direction of this positive uni-directional causality varies in different supply chains. In other words, in 3 supply chains, there is customer momentum while in the other 3 supply chains, there is supplier momentum.

Table 2. Cross-predictability of Returns between Customer and Supplier Industries

Sum of Coefficients / (Customer Industry , Supplier Industry)	$\sum_{i=1}^{8} B_i$	$\sum_{i=1}^{8} C_i$
(Computer , Electrical Devices)	2.27 $(27.39)^{***}$	0.24 $(19.94)^{***}$
(Chemical , Extraction of Petroleum)	0.99 $(38.12)^{***}$	0.10 (13.40)
(Pharmaceutical , Chemical)	-0.13 $(25.99)^{***}$	0.31 (9.38)
(Basic Metals , Metal Ores)	1.23 $(27.45)^{***}$	-0.56 (10.10)
(Metal Products , Basic Metals)	0.08 (12.88)	0.07 (3.95)
(Rubber and Plastic , Chemical)	0.19 (13.28)	0.41 (11.57)
(Petroleum Products , Extraction of Petroleum)	0 (9.23)	0.38 $(20.52)^{***}$
(Printing , Paper)	0.32 (10.91)	0.16 (7.07)
(Paper , Wood)	-0.07 (4.92)	0.19 $(14.75)^{*}$
(Textiles , Chemical)	-0.04 (3.58)	0.40 $(19.82)^{***}$

***, **, and * denote significance at the 1, 5, and 10% levels, respectively.
Chi-square (χ^2) statistics are presented in parentheses ().

Impulse Response Functions (IRFs)

Granger causality test results do not indicate the sign of the relationship between customer and supplier industries or how long these relationships persist. Impulse response functions will give us such information about the relationship. It would be much easier to explain the relationship when we can see visually how changes in one variable affect other variables over time. Impulse response graphs for 6 supply chains (in which there is a lead-lag relationship) are plotted in Fig. 1 and interpreted as follows:

1. In 3 supply chains [(computer, electrical devices), (chemical, extraction of petroleum), and (basic metals, metal ores)] that the customer industry leads the supplier industry, impulse response graph shows the effect of a 1% shock to the weekly returns of the customer industry (which is plotted in red) on the weekly returns of the supplier industry (which is plotted in green) for the 9 weeks following that shock.

2. In the other 3 supply chains [(petroleum products, extraction of petroleum), (paper, wood), and (textiles, chemical)] that the supplier industry leads the customer industry, impulse

response graph shows the effect of a 1% shock to the weekly returns of the supplier industry on the weekly returns of the customer industry for the 9 weeks following that shock.

On the whole, these results provide a useful trading strategy for individual and institutional investors to manage their portfolios. This trading strategy consists of buying the follower industry with a apositive return on its leader industry (which are in the same supply chain) in the previous week and simultaneously selling the follower industry with a negative return on its leader industry in the previous week. In addition, as you can see in Fig. 1, the effect of a shock to leader industries on follower industries persists only 8 weeks and then converges to zero. This confirms that the selected lag length (i = 8) is optimal for the estimated VAR model. To see what happens to R_S and R_C when there is a one-unit shock to the R_S, for example, suppose we estimate the following VAR model which has two variables (RS and RC) and one lag (i = 1):

$R_{S,t} = 0.10R_{S,t-1} + 0.25R_{C,t-1} + \varepsilon_{S,t}$
$R_{C,t} = 0.50R_{S,t-1} + 0.10R_{C,t-1} + \varepsilon_{C,t}$

In week 1:

$R_{S,1} = 0.10(0) + 0.25(0) + 1 = 1$
$R_{C,1} = 0.50(0) + 0.10(0) + 0 = 0$

In week 2:

$R_{S,2} = 0.10R_{S,1} + 0.25R_{C,1} + \varepsilon_{S,2} = 0.10(1) + 0.25(0) + 0 = 0.10$
$R_{C,2} = 0.50R_{S,1} + 0.10R_{C,1} + \varepsilon_{C,2} = 0.50(1) + 0.10(0) + 0 = 0.50$

In week 3:

$R_{S,3} = 0.10R_{S,2} + 0.25R_{C,2} + \varepsilon_{S,3} = 0.10(0.10) + 0.25(0.50) + 0 = 0.135$
$R_{C,3} = 0.50R_{S,2} + 0.10R_{C,2} + \varepsilon_{C,3} = 0.50(0.10) + 0.10(0.50) + 0 = 0.10$

The process does not stop there and persists until the shock effect reaches zero.

Conclusion

Customer-supplier relationships (or supply chains) are long-term economic relationships between companies that are publicly available to stock market investors. Investors' inattention to these relationships causes that the stock price of the supplier (customer) company react with a lag to new information about the customer (supplier) company. This can lead to return predictability across customer and supplier firms within a supply chain. We identified 10 supply chains at the industry-level using input-output accounts for the Iran economy that are published once every 5 years by the Central Bank of Iran.

In this article, we find some support for the predictability of return at industry-level supply chains (or lead-lag relationship) that was documented by prior research (Menzly and Ozbas [2], Shahrur et al. [11], and Li et al. [14]). But our results show that there is often a positive uni-directional (not bi-directional) causality between the customer and supplier industries. We also found that the direction of this positive uni-directional causality varies in different supply chains. In-sample results show that in 6 out of 10 identified supply chains, there is a lead-lag relationship. In 3 supply chains [(computer,electrical devices), (chemical,extraction of petroleum), and (basic metals,metal ores)], the customer industry leads the supplier industry. Whereas, in other 3 supply chains [(petroleum products,extraction of petroleum), (paper,wood), and (textiles,chemical)], the supplier industry leads the customer industry.

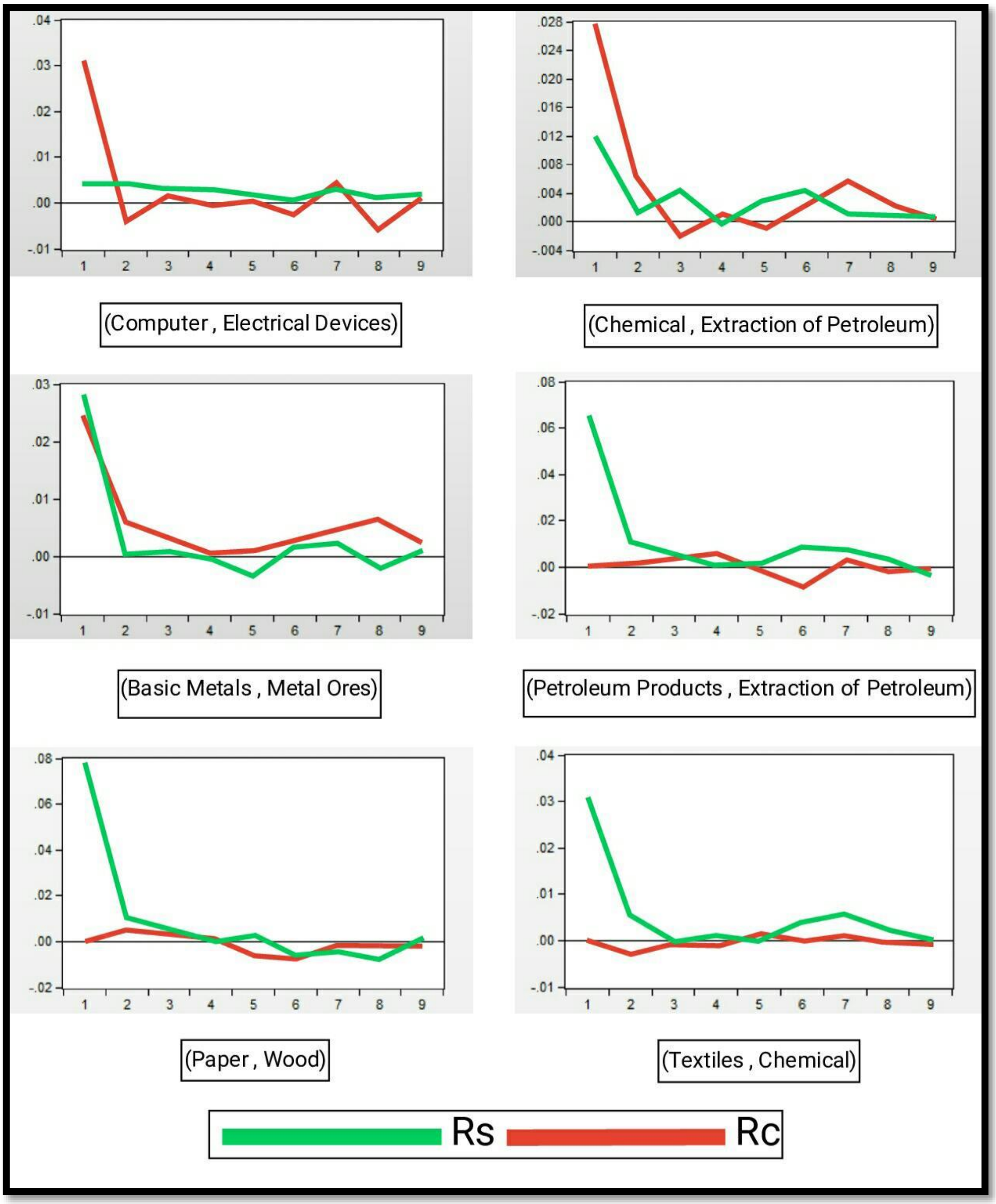

Fig 1. Combined Impulse Response Graphs

This study has two main results. First, the observed lead-lag relationships across customer and supplier industries reject the informational efficiency of prices at the industry-level in the Tehran Stock Exchange, because based on the efficient market hypothesis (EMH), the current stock price should reflect all available information and stock price changes should be random and unpredictable. Second, there are profitable trading strategies in some supply chains of the Tehran Stock Exchange at the industry-level. This trading strategy consists of buying the follower industry whose leader industry had a positive return in the previous week and selling the follower industry whose leader industry had a negative return in the previous week.

In general, like intra-industry lead-lag effects between big firms and small firms documented by Hou [9], customer-supplier relationships at the inter-industry level confirm the gradual diffusion of information across industries. This channel of industry-level information diffusion still cannot be explained by the current asset pricing models. Thus, the supply chain factor plays an important role in constructing and managing investors portfolios.

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