Trade Linkage and Cross-country Stock Return Predictability

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Abstract

Little is known about the role of trade linkages in predicting future equity return despite growing importance of international trade. In this paper, I test whether cross-predictability exists among trade-linked industries across international borders, and explore possible explanations. I find strong evidence of cross-border stock return predictability among trade-linked industries. A trading strategy of buying industry portfolios whose trade-linked industry had high returns, and shorting industry portfolios whose trade-linked industry had low returns, yields an annualized return of 12%. Such returns cannot be explained by known risk factors and are different from industry momentum. I find some evidence against the leading explanation, which posits information segmentation as the only reason for cross-predictability, and find support for illiquidity as a new channel of explanation.

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1 Introduction

International trade volume and shares of exports in the GDP of many countries have been growing steadily over the past few decades[1]. This increase in trade activity has served to strengthen economic linkages between industries and countries. In this environment, it is possible that information originating with trade partners within an industry can predict future returns of that industry. In this paper, I test whether future returns of industry portfolios can be predicted using past information from trading partners. Moreover, I characterize cross-predictability and explore possible explanations for it utilizing trading partner relationships between industries.

Researchers have documented some evidence of cross-industry predictability in the United States. Menzly and Ozbas (2010) show that stock returns of economically related industries can cross-predict each other's returns in US stock markets. Similarly, Cohen and Frazzini (2008) investigate whether firm level public information on customer and supplier relationships can be used to obtain abnormal returns. So far, such evidence has focused almost exclusively on the domestic US market. However, as inter-industry relationships extend beyond national borders, international interdependence of industries warrants further investigation of this issue in a more global setting.[2] In this paper, I will bring in a new data source, the GTAP (Global Trade Analysis Project), to address this issue.

[1] The World Bank (http://data.worldbank.org/): Export volume index, Exports of goods and services(% of GDP)
[2] A recent paper by Rizova (2011) examines the interdependence of country-level trade relationships and country-level equity market performance.

The GTAP provides data on cost spent on imported and exported goods by industries around the world. This data, widely used in international trade literature but never in finance literature, enables us to look not only at the breakdown of exported and imported goods and services, but also dependences of industries on particular imported goods. For example, the data describes quantities of iron and steel products imported from Japan to Korea. Moreover, the data reports amounts of this iron and steel consumed by Korean industries. The rich structure of the data helps us understand relationships among industries across countries. More importantly, such a broad cross section of economically linked industries enables us to relate sources of cross-predictability to their customers and suppliers.

To quantify degrees of international linkages between industries, I consider international trade flows and imported goods usage by industries. Based on such linkages, I can quantify how an industry in a country is related to other industries around the world. I construct related industry portfolios and examine whether industry portfolio returns can be predicted by past returns of internationally related industries. Also, bilateral relationships between related industries allow for new possibilities for testing existing theories. In particular, we have access to a cross section of related industries with varying levels of international trade relationships, which can be used along with other relationships between two industries, such as institutional co-ownership and analyst co-coverage. This data structure enables us to break down the predictor variable into several pieces and analyze whether there is varying level of predictability along certain criteria, such as co-ownership or co-coverage, on top of the international trade link.

Overall, I find strong evidence for cross-border stock return predictability among trade-linked industries. A trading strategy of buying industry portfolios whose trade-linked industries had high returns, and shorting industry portfolios whose trade-linked industries had low returns, yields annualized returns of 12%. Such returns cannot be explained by known risk factors, and are different from industry momentum. I find some evidence against the leading explanation that posits information segmentation as the only reason for this cross-predictability, and find support for illiquidity as a new channel of explanation.

My paper makes the following three contributions to the literature. First, I uncover effects on returns of industry-level trade linkages across the world. Second, I test whether relative information is efficiently priced across countries and industries and decouple effects of within-country predictability and across-country predictability. Third, by selecting an international setting in which there is natural information segmentation across countries and great variability of liquidity, I obtain a better testing ground for these theories.

I find the following four empirical results. First, as noted above, I find that self-financing trading strategies based on past information from economically related industries yield significant premiums.

Second, I analyze the characteristics of past returns that are most powerful in predicting an industry's return. If information segmentation is the main explanation of cross-predictability, then returns from obscure or ignored stocks are more likely to carry more weight in predicting related industry returns in foreign countries. In contrast, I find that the strongest predictive power comes from past returns of economically linked industries that (1) share greater degrees of institutional ownership, and that (2) share more analyst coverage. Such industries are likely more well-known and familiar among investors. This suggests that information segmentation does not fully explain cross-predictability.

Third, I test whether liquidity can explain the observed cross-predictability and compare this with the information explanation. If equities of certain industries are highly illiquid, this will result in slow price adjustments. Utilizing double-sort results, I find evidence in favor of the illiquidity explanation, which, unlike information segmentation, can explain cross-predictability among economically linked industries.

Finally, I find that institutional investors increase their holdings quickly in response to positive news, but do not decrease their holdings quickly after negative return news. This is in line with the fact that most excess return gains from cross-predictability come from the long side of the long-short portfolio. Moreover, the responsiveness of portfolio rebalancing in light of positive news increases as liquidity of stocks increases, while responsiveness to negative return news is about the same across different liquidity levels.

The rest of the paper proceeds as follows: Section 2 describes data used, Section 3 present empirical findings, and Section 4 concludes.

2 Data

Data used in this paper comes from a number of sources. Bilateral trade data of disaggregated commodities and services and use of imported goods and services by disaggregated industries comes from the GTAP. This data provides bilateral trade of various goods and services and cost structures of industries for each country as snapshots of the world economy. In this paper, GTAP versions 5 and 6 were used, representing 1997 and 2001, respectively. Only with disaggregated trade data and interdependence of industries within countries may we establish industry relationships between countries. Description of reorganized GTAP industries can be found in the Appendix, Table A1.

I merge these GTAP industries with corresponding industry classifications provided by Professor Ken French. [3] Correspondences between the GTAP and French's industrial classifications are also described in the Appendix, Table A1.

Menzly and Ozbas (2010) identify customer and supplier relationships of US industries using Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA).[4] The BEA surveys document amounts of goods from an industry used across all industries. One potential downside of GTAP data, compared to the BEA Use table, is that it comprises only 56 industries, whereas the BEA tables include more than 400 industries, though exact numbers vary depending on publication year. Moreover, many GTAP industries are related to agriculture; thus, if we group them into one industry, the total number of industries is reduced further to 23. Since customer-supplier relationships may weaken following aggregation, this higher level of aggregation likely biases against finding any cross-sectional predictability, given such a small

[3] Industry classification is obtained from Ken French's data library, at his web site http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] Cohen and Frazzini (2008) utilize public information of major customers, which firms are required to report under Regulation SFAS No. 131, as obtained from Compustat. But this approach means that results are mostly driven by relatively small stocks whose customers are concentrated and not diversified. In contrast, input-output relationships across industries are relatively free of small stock problems. In the input-output table, supplier and customer industries are well identified and there is no asymmetry of identifying suppliers, as is seen in the Compustat data.

number of industries. Despite such limitations, I still find a strong level of cross-sectional predictability across countries.

Returns of international stocks are from Datastream. I use the same data filter as Griffin, Kelly, and Nadari (2009), which involves screening non-common equity. The data error screening of Ince and Porter (2006) is also applied to the returns data. Numbers of firms and average market capitalization of firms in each country-industry group are reported in Table A2 and Table A3, respectively. The sample period for the returns data is from 1990 to 2009. I only include countries in the Morgan Stanley Capital Index (MSCI) World Index or MSCI Emerging Markets Index as of 2010, and countries available in the GTAP database. [5]

Institutional ownership data for international stocks is from the Lionshares database. The sample period for the ownership data is from March 1999 to March 2009. The ownership data is, at most, quarterly and contains holdings reports of institutions comparable to those of 13F in the US. Detailed data description of Lionshares can be found in Ferreira and Matos (2008) and Bartram, Griffin, Lim, and Ng (2014).

3 Empirical results

In order to test the hypothesis of slow diffusion of information or slow reaction of prices from economically linked industries, I construct a portfolio of economically linked industries for each industry in question. Economic links considered in this study are customer and supplier relationships across countries and industries. Under the null hypothesis of immediate information

[5] I drop Russia due to low data coverage in Datastream.

diffusion of economically relevant information and price adjustments, the portfolio returns of linked industries should not lead returns of the industry. In contrast, when there is slow diffusion of information or sluggish price adjustments, we should be able to predict an industry's returns from returns of economically linked industries, where the returns are used as proxies for news from linked industries. The next section describes the construction of the customer and supplier industry portfolios.

Portfolio return of international customer and supplier industries

I follow procedure similar to that of Menzly and Ozbas (2010) and Cohen and Frazzini (2008), in that I use lagged returns of economically related industries to predict a particular industry's returns. What is different from their approach is that I am focusing on international linkages of industries across the world, rather than industry interdependence within one country. For this purpose, I construct two portfolios for each country-industry, namely international customer and supplier portfolios. These portfolios consist of foreign industries that are customers or suppliers of the industry in the country.

The customer portfolio is first weighted by trade flows between countries and, secondly, by intra-country dependences of industries. In particular, return of customer portfolio of industry i in country c is constructed as

$$R_{ic,t}^{customer} = \sum_{d \in C} w_{ic,d} \sum_{j \in J_d} v_{ijd} R_{jd} \tag{1}$$

where $w_{ic,d}$ is proportion of exported good i to country d from country c to all of exported good i from country c, and v_{ijd} is proportion of cost spent by industry j in country d on imported good i to cost spent on imported good i by all industries in country d, and R_{jd} is value-weighted portfolio return of stocks industry j in country d. For example, Chinese electronic equipment is exported to multiple countries; 35% of these exports go to the US, 15% to Japan, 50% to other countries across the world. Imported electronic equipment is used in many industries in each country. In the US, for instance, 50% of imported electronic equipment is used in the electronic equipment industry, 14% in the fabricated products and machinery industry, 12% in the service industry, and 24% in other industries. Weight $w_{ic,d}$ describes how important country d is to industry i of country c as a customer country, and v_{ijd} describes how important industry j of country d is as a customer industry of imported goods produced by industry i.

The supplier portfolio for industry i of country c is constructed similarly as

$$R_{ic,t}^{supplier} = \sum_{j \in J_d} v'_{jic} \sum_{d \in C} w'_{jd,c} R_{jd,t} \tag{2}$$

where v'_{jic} is proportion of cost spent on imported good j by industry i of country c to costs spent on all imported goods by industry i of country c, and $w'_{ic,d}$ is proportion of imported good j from country d to country c. In the electronic equipment industry in the US, for example, out of all costs of imported goods used in the industry, 86% was spent on imported electronic equipment, 5% on imported fabricated products and machinery, and the rest on imported goods and services. There are many imported goods used in the electronic equipment industry in the US and these come from different countries: 22% from Japan, 10% from Singapore, 10% from Taiwan, and 58% from the rest of the world. Weight v'_{jic} describes how important imported good j is to industry i in country c, and $w'_{jd,c}$ describes how important country d is as a supplier country of good j in country c.

Abnormal returns of portfolios sorting on lagged customer and supplier industry returns

For a first piece of evidence for cross-predictability of returns, I investigate whether abnormal returns could be obtained from a trading strategy utilizing available information of economically linked industries. At the beginning of every month, value-weighted industry portfolios are sorted on the basis of the returns of a portfolio of its international customers and suppliers at the end of the previous month. These sorted industry portfolios are assigned to one of five quintile portfolios. These quintile portfolios are equal-weighted. Reported in Table 1 are quintile portfolio returns sorted according to previous month customer and supplier industry returns. Portfolio returns of long top quintile and short bottom quintile sorting on customer and supplier returns are also considered. See Figures 1A and 1B for long-short portfolio return sorting on customer and supplier industry returns. Excess returns of portfolios are calculated by subtracting risk free rates for the US, value-weighted returns for our sample firms are used as world market returns in calculating world CAPM alphas, and global size, value, momentum factors used in Fama and French (2012) are used to obtain global Fama-French 4 factor alpha.

The long-short portfolio gives monthly excess returns of 1.09% when sorted on customer industry returns, and 1.06% when sorted on supplier industry returns. The fact that the excess returns of the top quintile portfolio turn out to be the most significant suggests two interesting points. First, profit from the trading strategy doesn't depend crucially on short positions. Hence, the trading strategy may have less difficulty in real world applications due to restrictions on short sales. Second, it suggests that good news tends to travel more slowly or is priced more slowly than bad news.

To test and to further investigate whether industry-level returns are cross-predictable based on past returns of supplier and customer industries, I conduct the following regression using Fama-MacBeth (1973) methodology:

$$r_{ci,t} = \alpha_t + \lambda_{1,t}^{related} r_{ci,t-1}^{related} + \lambda_{2,t}^{related} r_{ci,t-2:t-12}^{related} + \Lambda_t Z_{ci,t-1} + e_{ci,t} \tag{3}$$

where $r_{ci,t}$ is the return of the value-weighted portfolio of stocks in industry i of country c in month t and $Z_{ci,t-1}$ is a vector of lagged control variables known to predict country-industry portfolio return. $r_{ci,t-1}^{related}$ is either customer or supplier country-industry portfolio return as described above. Table 2 reports regression results. Coefficients on lagged customer industry portfolio returns are significant and robust across different subsamples. The magnitude of the coefficients is many times greater than the coefficient on lagged industry portfolio returns, which are known factors to predict industry returns, as in Moskowitz and Grinblatt (1999).

To check whether cross-predictability is not driven by the smallest and most neglected stocks, I conduct the same regression for different subsamples. I get robust results in the following samples: excluding industries in the bottom 20 percentile in market capitalization, industries from emerging economies, and industries from advanced economies.

Since the economic relationships used in this paper are coming from two snapshots of the world economy, one taken in 1997 and the other in 2001, it would be interesting to see the performance of the predictor using samples after the snapshots. Panel B of Tables 1 and 2 report excess returns from the long-short portfolio, and regression results from samples after 1997. We find greater predictability both in terms of magnitude of excess returns and Fama-MacBeth coefficient size. Using later data samples, the long-short portfolio yields an even greater excess return. The excess return is close to a monthly return of 1.5% or annualized return of 18%. Coefficients of Fama-MacBeth regressions also show increased magnitude when the later sample is used. It is interesting to see that the predictability of past supplier industry returns improved when we used the later sample.

In an unreported table, where only one GTAP snapshot is used to determine customers and suppliers, the excess return and the coefficients were smaller compared to results where we utilize two snapshots. From the results we have seen so far, we can deduce that a more accurate description of the world economy relationship would allow us to predict future industry returns with greater precision.

Can cross-predictability better explained by liquidity than information coverage?

Information segmentation and investor inattentiveness are the dominant explanations of the cross-predictability of economically linked stocks [Cohen and Frazzini (2008); Menzly and Ozbas (2010)]. In the literature, information coverage and institutional ownership are generally used as proxies for information coverage and the level of investor attention stocks receive. However, the same variable could be a proxy for liquidity, because illiquid stocks generally get less analyst coverage and are owned less by institutional investors. Because of this close correlation, it is often difficult to discern the two effects from the proxies.

Analyst coverage and institutional ownerships were used as proxies for information coverage in previous literature. However, in this exercise, I am going to use only analyst coverage as a proxy for information coverage because it is direct measure of the information coverage an industry gets, and indirect measures, such as institutional ownership levels, can contain mixed information about preferences of institutional investors. For each month, I counted the number of analyst forecasts for each firm in an industry during past 6 months and took value weighted average of this number to proxy information coverage. Since I am aggregating all firms in an industry to get this measure, there sporadic analyst coverage is less of an issue.

As for the liquidity measure, I use the percentage of observed zero daily returns in the previous month and aggregate this number for all firms in each industry. The liquidity measure was first proposed in Lesmond, Ogden, and Trzcinka (1999) and is widely used in international finance [Lesmond (2005), Bekaert, Harvey, and Lundblad (2007), and Bartram, Griffin, Lim, and Ng (2014)].

In this section, I try to compare the information and liquidity explanations of cross-predictability among economically linked stocks. First, I try to characterize excess returns from long-short portfolios. If level of predictability has anything to do with information coverage or liquidity, we should see meaningful differences in excess returns along different levels of information coverage or liquidity. I investigate returns of long-short portfolios formed from subsets of the industry portfolio pool where subsets are divided according to liquidity and information coverage measures. First, I separately analyze the effects of liquidity and information coverage on cross-predictability. Industries are sorted according to information coverage or liquidity measures and grouped into three subgroups. Within each subgroup, I form a long-short portfolio and report average returns from each. Second, I do a double sort as a preliminary comparison between the information and liquidity explanations.

Returns from each subgroup and each double sort group are reported in Table 3. Panel A divides industries according to the information coverage measure, and finds very little difference between returns of portfolios formed from the least coverage group and the most analyst coverage group. If information coverage mostly explains cross-predictability, we should see greater returns from a portfolio formed from industries with less analyst coverage. However, the results in Panel A provides only very weak evidence. Panel B reports analogous results where industries are sorted according to liquidity levels. The difference is significant at the conventional 5% significant level and the magnitude of the difference is larger than we saw in Panel A.

Further dissecting the industries using finer subgroups, we see more interesting results. Panel C reports average returns from long-short portfolios in each double-sort industry group and differences in returns between top and bottom tertiles. Among the industries with least analyst coverage, we see significant differences between returns from most liquid and most illiquid industries. On the other hand, return differences among the analyst coverage portfolios are either non-existent or show signs that are the opposite of the difference expected from the information theory.

In support of the double sort analysis, I conducted additional regression analysis controlling for known factors of cross-predictability. Results are reported in Table 4. The additional regression analysis confirms what we found in the double sort analysis. The least liquid industries show predictability in all groups while most liquid industries show little predictability. It is interesting to see that Fama-MacBeth regression results in Panel A are in line with the results in existing literature. However, I interpret this result a little differently that analyst coverage alone could be picking up variations in liquidity levels of industries. Once we considered liquidity as well as analyst coverage, I see in Panel C that most of the variation in predictability can be explained with the different levels of liquidity.

What type of information is most useful in cross-predictability?

Previous literature focused on characteristics of industries whose returns were to be predicted. Such characteristics are useful in exploring the underlying reason for the cross-predictability, but only shed lights on one side of a two sided problem. If one industry’s returns can be predicted, analysis of the information that enables the cross-prediction would complete the picture. Up to this point, I have established that economically linked industries’ past returns cross-predict an industry’s returns, and that certain industries are more predictable than others, but haven’t said anything about which economically linked industry provides the most valuable information on future returns.

To answer this question, I dissect the customer industry returns into several parts in a meaningful way. As a first step, I separate the economically linked industries into five groups according to their economic dependence. Since the customer returns are basically an economic link weighted average of customer industry returns and a successful predictor of future return, it is expected and confirmed that we see the most useful information from industries with greater linkages.

Now, we take the analysis a step further, in a more meaningful way, by looking at characteristics within the group of industries with the most significant economic linkages. In this analysis, we look at two aspects, namely analyst co-coverage and institutional co-ownership. This type of analysis is not possible with the major customer data of Cohen and Frazzini (2008) because there is not large enough number of customers to conduct such analysis. BEA's Use table used in Menzly and Ozbas (2010) was more suitable for this type of analysis, but such was never carried out in their paper. The advantage of this data is that there are large numbers of linked industries across different countries with varying levels of interesting characteristics.

By dissecting and sorting the past information, we should be able to answer more questions about how and why we see cross-predictability, because we will be able to distinguish information that is useful from that which is not if there is meaningful variation among the measures used.

Table 5 reports Fama-MacBeth regression results where analyst co-coverage is used to group economically linked industries. In the first column of Table 5, we see that most of the predictions are coming from industries with high trade links, whether the industries are co-covered by analyst houses or not. Interestingly, the magnitude of the coefficient to the past return of industries that are commonly covered by at least one analyst house is greater than that of the coefficient to industries that are not covered. The second and third columns demonstrate again that high trade link industries are the most important predictor. The fourth and fifth columns use a group of industry returns sorted according to the co-coverage measure, which is the number of analyst houses covering both the predicted industry and the linked industries. In line with what we find in the first column, we see monotone increasing importance of past returns of linked industries as levels of co-coverage increase. This result, however, is not in line with the existing information explanation of cross-predictability, because information for the connected industries is likely to be known by investors since it is covered by the same analyst houses.

I do a similar analysis on the level of institutional co-ownership and report results in Table 6. For pairs of industries, institutional co-ownership is measured as the sum of the product of portfolio weights of the first industry and second industries in an institution's equity portfolio. The sum is taken for all of the institutions that hold both industries. This measure is designed to reflect connectedness via institutional ownership and is greater as more institutions hold both industries in their portfolios, and as the industries' weights are larger in their portfolio. Varying levels of predictability across the co-ownership measure may also serve as a proxy for the level of informational barriers between industries. Institutional investors pay attention to and act upon what is happening in parts of their portfolios; hence there would be much less of an informational barrier between industries in their portfolios.

The results in Table 6 are in line with what we found using co-coverage of industries by analysts. Past return information for industries with the largest economic linkages, and that are commonly owned by institutional investors, is the most relevant information in predicting future returns of industries. These results lend themselves to the following interpretations. First, the most useful predictors are known by investors. Second, institutional investors are slow to react to useful information at hand.

Under the slow diffusion of information theory, the most useful predictor would be information from industries that are most economically dependent, yet not likely followed by investors. However, regression results in Table 5 and 6 suggest otherwise. These results open a new possible explanation involving institutional investors, which we are going to explore in the sections that follow.

Institutional investor trading, illiquidity, and cross-predictability

In previous sections I have established that the most useful information is likely to be already known by institutional investors and that liquidity of an industry may play a more important role than the level of attention an industry receives or level of segmentation. In this section, I am going to present evidence of slow reactions by the most sophisticated investor group, namely institutional investors trading illiquid industry portfolios.

It is generally accepted that institutional investors are sophisticated investors and that, most of the time, they make informed decisions. In previous literature on cross-predictability of economically linked stocks/industries, institutional investors were considered to make informed decisions. I find a similar result: that institutional investors in international settings react to useful information. Moreover, I add to the existing finding that there are some industries that do not act as intelligently in trading as others, which could possibly explain the cross-predictability we see in certain type of industries.

An informed trader would acknowledge cross-linkages between international industries and trade based on positive signals observed in linked industries. Moreover, investors will trade the relevant industries simultaneously in order to fully utilize the information. We test these two implications and further explore the cases where institutional investors do not behave as informed traders.

In order to test the simultaneous trading of related industries by institutional investors, I estimate panel regression of the following form:

$$\Delta IO_{i,t} = \alpha_i + \gamma_t + \beta^{customer} \Delta IO_{i,t}^{customer} + \delta\, \Delta IO_{i,t-1} + e_{i,t}$$

where $\Delta IO_{i,t}$ is change of institutional ownership of industry i and $\Delta IO_{i,t}^{customer}$ is changes in institutional ownership in customer industries. The change of institutional ownership of customer industry is calculated in a way that is analogous to customer and supplier industry returns. To test whether institutional investors trade the same way across industries with different liquidity levels, I interact the liquidity dummy variables with the changes of institutional ownership in the customer industry. I include industry-level fixed effects α_i and quarter fixed effects γ_t to control for unobserved heterogeneity across different industries and systematic fund inflows over time. A lag of change of institutional ownership is included to control for persistence in change of ownership by institutional investors.

Results are reported in Table 7. In line with results found in previous literature, I also find evidence of simultaneous trading of related industries, as seen in the first and second columns of Table 7. Interestingly, however, institutional investors do not behave the same way with illiquid industries. The third and fourth columns of the table report estimation results of the above regression using interactions of change of customer industries institutional ownership with liquidity level dummies. The results indicate that moderately to highly liquid industries are traded simultaneously with customer industries, but do not behave the same way as illiquid industry groups.

I do an additional analysis replacing changes of ownership of customer industries with returns. This analysis is designed to measure the responsiveness of institutional investors to useful information. If institutional investors are behaving as informed traders, they will react positively to the current period customer returns because these returns are known to predict future returns of an industry portfolio. I also include the previous quarter's customer returns to assess responsiveness to past information, as well as to current information. Responding to past information would indicate that investors are not reacting to a signal to the full extent. In the following analysis, I separate customer returns into positive and negative customer returns to see if institutional investors react differently to positive and negative signals from economically linked industries.

Estimation results analyzing institutional investor reaction to customer industry returns are reported in Tables 8 and 9. Results in the first column of Table 8 indicate that institutional investors indeed react to current signals from customer industries. Moreover, we see evidence of lagged response to past signals. Results from separating positive and negative signals are reported in the second and third columns of the table, and we see that there is no evidence of lagged response to negative signals from customer industries, yet there are some lagged responses to positive signals. So, we could deduce that lagged responses are likely to come from positive signals. Lagged responses to positive signals are in line with what I find in the section on portfolio formation. We saw that most predictability or profit came from the long leg of the long-short portfolio, and that the selection of industries in the long leg portfolio was in the top quintile, sorted by customer industries.

The fourth column of Table 8 also reports results similar to the change of institutional ownership according to liquidity levels. In line with what I found in Table 7, we see institutional investors do not react to customer industry signals when trading the least liquid industries.

One may argue the non-existence of reaction in the most illiquid stocks may be in the nature of how institutional investors trade illiquid industries, and not related to lack of informed trading or slow reaction. To address this issue, I provide two additional results that shed light on institutional investor behavior and illiquid industries. In Table 8 we see that institutional investors react to negative customer returns in the way that an informed trader would, and lagged reaction to positive customer returns. If it is simply that institutional investors do not adjust their holdings of the most illiquid stocks for whatever reason, then these investors should not react to negative customer industry returns, either, and moreover should not show lagged reaction to positive customer industry returns. On the other hand, if institutional investors show immediate reaction to some signals and lagged reaction to other signals in trading illiquid industries, we would have more support to our explanation.

To test this prediction, I estimate institutional investors' change of holdings of industry portfolios in reaction to positive and negative customer industry returns for different levels of illiquidity. Estimated results are reported in Table 9. In this regression analysis we see evidence of immediate responses to negative signals from customer industries, even for the most illiquid industries (see column 3 and 4) and lagged responses to the positive signals concentrated in illiquid industries. These results are in line with our initial conjecture that cross-predictability is caused by lagged response in illiquid industry portfolios.

4 Conclusion

This paper demonstrates that industry stock returns can be predicted from internationally linked industries, and finds that slow reaction to known information is more likely to be an explanation for cross-predictability, rather than slow information diffusion or investor inattention.

Trading strategies utilizing this cross-predictability result in monthly returns as high as 1.57%, with a significant part of these returns coming from the long leg of the long-short portfolio. We see greater returns from trading strategies in the latter sample where snapshots of the economic linkage are more accurate and trade volume is greater.

The international testing ground in my paper is suitable for testing existing theories of cross-predictability because the conditions upon which these theories rely, such as informational segmentation, illiquidity, and other market friction, are more natural in international settings. I explore possible explanations for cross-predictability, including slow information diffusion and slow price reaction due to liquidity. Among these possible explanations, I see liquidity explanation as most in line with my findings. According to my findings, the existing theory of investor inattention doesn't fully explain the predictability because the most relevant information for the prediction was likely to be known by investors, either by analyst co-coverage or institutional co-ownership. Moreover, I find evidence that institutional investors do not promptly react to signals obtained from linked industries when trading illiquid industries, while they quickly react to news, hence behaving more like informed traders, when trading liquid industries. Lagged reactions were most prominent in most illiquid industries in response to positive signal from their linked industries, but not so much for negative signals. Such lagged reactions to positive signals by investors are in line with the fact that most of the cross-predictability is coming from the long leg of the long-short portfolio.

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Table 1 Portfolio returns sorted based on lagged customer or supplier industry return

This table reports excess returns and abnormal returns of five portfolios and a long-short portfolio of the top and bottom portfolios. At the beginning of every month, each country-industry portfolio is sorted into five quintile groups based on its customer/supplier industry portfolio returns at the end of the previous month. Quintile portfolios are formed by putting equal weight on country-industry portfolios within the quintile group, and these are rebalanced every month. Average excess returns of portfolios are reported in the first column. World CAPM alpha is the intercept on a regression on world market returns constructed from value-weighted returns in our sample. Third column reports estimated intercept using world market returns, and global size, value, momentum factors used in Fama and French (2012). All returns are monthly returns in percentage. Numbers in parentheses are t-statistics. Statistically significant estimates at the 5% significance level are bold faced.

Panel A: sample period from 1990 to 2009

	Sorting on customer return			Sorting on supplier industry return		
	Excess return	World CAPM alpha	Global FF4 factor alpha	Excess return	World CAPM alpha	Global FF4 factor alpha
Low 1	0.004	-0.147	-0.189	-0.069	-0.219	-0.225
	(0.01)	(-0.69)	(-0.92)	(-0.20)	(-0.99)	(-1.05)
2	0.288	0.147	0.055	0.338	0.208	0.125
	(0.95)	(0.85)	(0.35)	(1.10)	(1.15)	(0.76)
3	**0.573**	**0.438**	**0.322**	**0.581**	**0.446**	**0.329**
	(1.88)	(2.60)	(2.10)	(1.94)	(2.65)	(2.15)
4	**0.628**	**0.489**	**0.407**	**0.748**	**0.608**	**0.481**
	(2.03)	(2.83)	(2.45)	(2.41)	(3.44)	(2.87)
High 5	**1.099**	**0.950**	**0.780**	**0.993**	**0.834**	**0.662**
	(3.41)	(4.96)	(4.25)	(2.95)	(4.20)	(3.39)
High-Low	**1.095**	**1.097**	**0.969**	**1.062**	**1.054**	**0.887**
	(6.03)	(6.04)	(5.03)	(4.84)	(4.79)	(3.79)

Panel B: sample period from 1997 to 2009

Low 1	-0.174	-0.216	-0.269	-0.305	-0.346	-0.382
	(-0.36)	(-0.79)	(-1.03)	(-0.63)	(-1.21)	(-1.39)
2	0.227	**0.188**	0.086	0.238	**0.198**	0.100
	(0.54)	(0.87)	(0.46)	(0.55)	(0.88)	(0.49)
3	0.583	**0.544**	**0.375**	0.668	**0.629**	**0.486**
	(1.37)	(2.64)	(2.13)	(1.61)	(3.18)	(2.90)
4	0.737	**0.696**	**0.567**	0.813	**0.774**	**0.598**
	(1.72)	(3.45)	(3.07)	(1.90)	(3.63)	(3.10)
High 5	**1.316**	**1.274**	**1.103**	**1.273**	**1.230**	**1.057**
	(2.90)	(5.41)	(5.04)	(2.68)	(4.96)	(4.48)
High-Low	**1.489**	**1.490**	**1.372**	**1.578**	**1.576**	**1.439**
	(6.16)	(6.14)	(5.39)	(5.38)	(5.36)	(4.64)

Table 2 Fama-MacBeth regressions (Robustness checks and different markets)

Dependent variables are industry returns. Explanatory variables are past returns of own industry returns, customer industry returns, and supplier industry returns. Regressions are run using all samples (ALL), excluding the bottom 20% in market cap size (EX20), emerging markets (EMR), and advanced economies (ADV). Explanatory variables are lagged returns of customer (CR) and supplier (SR) portfolio returns and lagged returns of own industry returns (RI). Sample periods are from Jan 1990 to Mar 2009 for results in Panel A, and from Jan 1997 to Mar 2009 for Panel B. Statistically significant estimates at the 5% significance level are bold faced.

Panel A: sample period from 1990 to 2009

Variable	ALL	ALL	EX20	EMR	ADV	ALL	ALL	EX20	EMR	ADV
Intercept	**0.008**	0.005	0.004	**0.007**	0.003	**0.008**	0.004	0.003	0.006	0.003
	(2.80)	(1.88)	(1.50)	(2.04)	(1.08)	(2.68)	(1.58)	(1.01)	(1.57)	(0.99)
CR (t-1)	**0.160**	**0.132**	**0.117**	**0.121**	**0.139**					
	(6.26)	(5.89)	(5.18)	(3.25)	(5.29)					
CR (t-2:t-12)		**0.149**	**0.159**	0.051	0.136					
		(2.48)	(2.57)	(0.52)	(1.95)					
SR (t-1)						**0.141**	**0.101**	**0.107**	0.107	**0.107**
						(4.57)	(3.70)	(3.99)	(1.73)	(3.98)
SR (t-2:t-12)							**0.149**	**0.162**	0.108	0.065
							(2.13)	(2.40)	(0.85)	(0.84)
IR (t-1)		**0.028**	**0.026**	**0.031**	**0.031**		**0.026**	**0.025**	**0.032**	**0.031**
		(2.68)	(2.27)	(2.19)	(2.74)		(2.58)	(2.14)	(2.26)	(2.74)
IR (t-2:t-12)		**0.084**	**0.080**	0.039	**0.156**		**0.087**	**0.082**	0.038	**0.160**
		(3.31)	(2.69)	(1.06)	(5.84)		(3.50)	(2.78)	(1.07)	(6.04)
Adjusted R squared	0.0063	0.0474	0.0624	0.0682	0.0646	0.0086	0.0502	0.0664	0.0733	0.0675
NOB	168776	164090	132682	64426	99664	168776	164090	132682	64426	99664
Avg NOB	730.6	710.3	574.4	278.9	431.4	730.6	710.3	574.4	278.9	431.4

Panel B: sample period from 1997 to 2009

Variable	ALL	ALL	EX20	EMR	ADV	ALL	ALL	EX20	EMR	ADV
Intercept	0.008	0.004	0.003	0.004	0.003	0.007	0.003	0.001	0.002	0.003
	(1.86)	(1.18)	(0.77)	(1.01)	(0.75)	(1.78)	(0.86)	(0.35)	(0.51)	(0.72)
CR (t-1)	**0.225**	**0.182**	**0.155**	**0.181**	**0.174**					
	(7.11)	(7.25)	(5.84)	(5.10)	(5.35)					
CR (t-2:t-12)		**0.152**	**0.165**	0.164	0.067					
		(2.09)	(2.07)	(1.76)	(0.73)					
SR (t-1)						**0.218**	**0.160**	**0.155**	**0.199**	**0.125**
						(6.10)	(5.52)	(5.21)	(4.99)	(3.72)
SR (t-2:t-12)							**0.201**	**0.195**	**0.276**	0.067
							(2.30)	(2.36)	(2.22)	(0.69)
IR (t-1)		**0.035**	**0.035**	**0.031**	**0.041**		**0.034**	**0.033**	0.030	**0.042**
		(2.90)	(2.67)	(2.03)	(3.16)		(2.82)	(2.54)	(1.95)	(3.26)
IR (t-2:t-12)		**0.098**	**0.096**	0.029	**0.165**		**0.102**	**0.099**	0.031	**0.164**
		(2.96)	(2.35)	(0.61)	(4.50)		(3.14)	(2.44)	(0.68)	(4.51)
Adjusted R squared	0.0080	0.0506	0.0681	0.0626	0.0729	0.0104	0.0535	0.0711	0.0658	0.0770
NOB	116273	115049	92611	49954	65095	116273	115049	92611	49954	65095
Avg NOB	791.0	782.6	630.0	339.8	442.8	791.0	782.6	630.0	339.8	442.8

Table 3 Long-short portfolio returns from subgroups of industries

Reported in this table are average returns of the long-short portfolio formed from subgroups of industries. Long short portfolios are formed using industry portfolios in each subgroup. In Panel A, subgroups are divided by analyst coverage level measured by the number of analysts covering an industry. In Panel B, the liquidity of an industry is used to form subgroups. Liquidity of an industry is measured using a value-weighted average of the number of non-zero return days in the previous month. In Panel C, pools of industries are sorted independently according to analyst coverage and liquidity. Reported returns are in monthly percentage. t-statistics are shown in parentheses. Estimates with 5% statistical significance are in bold face.

Panel A:	Least coverage	Moderate coverage	Most coverage	Difference
	0.012	**0.009**	**0.012**	0.000
	(4.81)	(4.09)	(5.41)	(0.06)
Panel B:	**Least liquid**	**Moderately liquid**	**Most liquid**	**Difference**
	0.015	**0.011**	**0.009**	**0.006**
	(6.57)	(4.40)	(3.99)	(2.32)
Panel C:	**Least liquid**	**Moderately liquid**	**Most liquid**	**Difference**
Least analyst coverage	**0.018**	0.005	0.002	**0.015**
	(5.73)	(1.25)	(0.47)	(2.95)
moderate analyst coverage	**0.011**	**0.008**	**0.007**	0.004
	(3.82)	(2.94)	(2.24)	(1.21)
Most analyst coverage	**0.014**	**0.014**	**0.010**	0.003
	(4.06)	(4.79)	(4.25)	(0.98)
Difference	0.004	**-0.009**	-0.008	
	(0.89)	(-2.04)	(-1.79)	

Table 4

Fama-MacBeth regression coefficients on corresponding interaction terms are reported in this table. The dependent variable is industry returns. The product of two dummy variables and customer industry portfolio returns are used to form interaction terms. The interaction terms and industry returns of previous months are included in the regression; however only coefficients to the interaction terms are reported. In Panel A and B, the following Fama-MacBeth regression was estimated:

$$r_{i,t} = \alpha_t + \sum_{k=1}^{3} \lambda_t^k A_{i,t-1}^k r_{i,t-1}^{customer} + \Lambda_t Z_{i,t-1} + e_{i,t}$$

where $r_{i,t}$ is industry return, $A_{i,t-1}^k$ is dummy variable for analyst coverage in Panel A and for liquidity in Panel B, and $Z_{i,t-1}$ is a vector of industry's own past return. Only averages of λ_t^k are reported

In Panel C, the following Fama-MacBeth regression was estimated, and only averages of λ_t^{jk} are reported:

$$r_{i,t} = \alpha_t + \sum_{k=1}^{3} \sum_{j=1}^{3} \lambda_t^{jk} A_{i,t-1}^j A_{i,t-1}^k r_{i,t-1}^{customer} + \Lambda_t Z_{i,t-1} + e_{i,t}$$

where $A_{i,t-1}^j$ and $A_{i,t-1}^k$ are respectively dummy variables for liquidity and analyst coverage. t-statistics are shown in parentheses. Estimates with 5% statistical significance are in bold face.

Panel A:	Least coverage	Moderate coverage	Most coverage
	0.154	**0.112**	**0.096**
	(4.79)	(3.94)	(3.13)
Panel B:	Least liquid	Moderately liquid	Most liquid
	0.180	**0.115**	**0.079**
	(5.73)	(4.07)	(2.62)
Panel C:	Least liquid	Moderately liquid	Most liquid
Least analyst coverage	**0.200**	0.088	0.107
	(5.14)	(1.76)	(1.73)
Moderate analyst coverage	**0.152**	**0.090**	0.074
	(3.90)	(2.54)	(1.67)
Most analyst coverage	**0.144**	**0.159**	0.051
	(2.58)	(4.31)	(1.50)

Table 5 Source of cross-predictability and analyst co-coverage

Dependent variables are industry returns. Explanatory variables are decomposed international customer portfolio returns in the previous month. Explanatory variables are constructed using past month stock returns of trade-linked industries similar to the construction of the customer return, however the linked industries are now decomposed into several groups and explanatory variables are created for each group of linked industries. In regression specifications (1), (2), and (3), international customers are divided into ten groups: five groups by trade links, with each trade link group divided into two groups, one with common analyst house coverage and the other without. In specification (4), I further divide the high trade linked customer industry group into five sub groups according to number of co-covering analyst houses. Previous month industry stock returns of each subgroup of customer industries are averaged and are used as explanatory variables.

	(1)	(2)	(3)	(4)
Constant	**0.024**	**0.020**	**0.011**	**0.039**
	(3.89)	(3.39)	(2.73)	(3.54)
CR Q1 Low trade link, w/o common coverage	**-0.271**	**-0.489**		**-0.310**
	(-2.97)	(-4.41)		(-2.94)
CR Q2 trade link, w/o common coverage	-0.015	-0.012		-0.027
	(-1.11)	(-0.77)		(-1.68)
CR Q3 trade link, w/o common coverage	0.004	-0.009		0.005
	(0.28)	(-0.64)		(0.33)
CR Q4 trade link, w/o common coverage	-0.004	-0.002		-0.011
	(-0.32)	(-0.17)		(-0.75)
CR Q5 High trade link, w/o common coverage	**0.027**	**0.041**		
	(2.08)	(2.91)		
CR Q1 Low trade link, w/ common coverage	-0.029		-0.028	**-0.161**
	(-0.92)		(-0.92)	(-2.07)
CR Q2 trade link, w/ common coverage	0.022		0.030	0.011
	(1.33)		(1.71)	(0.38)
CR Q3 trade link, w/ common coverage	-0.025		-0.020	-0.014
	(-1.48)		(-1.19)	(-0.45)
CR Q4 trade link, w/ common coverage	0.015		0.027	0.047
	(0.89)		(1.51)	(1.53)
CR Q5 High trade link, w/ common coverage	**0.113**		**0.135**	
	(4.55)		(5.07)	
CR Q5 High trade link, Low common coverage				0.019
				(1.12)
CR Q5 High trade link, 2 common coverage				**0.028**
				(2.48)
CR Q5 High trade link, 3 common coverage				0.031
				(1.87)
CR Q5 High trade link, 4 common coverage				**0.045**
				(2.16)
CR Q5 High trade link, High common coverage				**0.048**
				(2.06)
Avg adj R2	0.0333	0.0143	0.0201	0.0525
Number of obs	115826	168230	115900	70090

Table 6 Source of cross-predictability and co-ownership

Dependent variables are industry returns. Explanatory variables are decomposed international customer portfolio returns in the previous month. Explanatory variables are constructed using past month stock returns of trade-linked industries similar to the construction of the customer return, however the linked industries are now decomposed into several groups and explanatory variables are created for each group of linked industries. In regression specifications (1), (2), and (3), international customers are divided into ten groups: five groups by trade links, with each trade link group divided into two groups, one with common institutional ownership and the other without. In specification (4), I further divide the high trade linked customer industry group into five sub groups according to number of common institutional ownership measures. Previous month industry stock returns of each subgroup of customer industries are averaged and are used as explanatory variables.

	(1)	(2)	(3)	(4)
Constant	**0.040**	**0.023**	**0.030**	**0.048**
	(3.52)	(3.26)	(3.25)	(2.92)
CR Q1 Low trade link, w/o common ownership	-0.136	**-0.296**		-0.135
	(-1.54)	(-2.48)		(-1.46)
CR Q2 trade link, w/o common ownership	-0.014	-0.014		-0.020
	(-1.02)	(-0.87)		(-1.25)
CR Q3 trade link, w/o common ownership	-0.012	-0.027		0.003
	(-0.84)	(-1.83)		(0.21)
CR Q4 trade link, w/o common ownership	-0.019	0.002		-0.013
	(-1.39)	(0.13)		(-0.99)
CR Q5 High trade link, w/o common ownership	0.001	**0.038**		
	(0.04)	(2.07)		
CR Q1 Low trade link, w/ common ownership	-0.093		-0.143	-0.196
	(-0.70)		(-1.10)	(-1.00)
CR Q2 trade link, w/ common ownership	0.055		0.045	0.044
	(1.65)		(1.39)	(1.12)
CR Q3 trade link, w/ common ownership	0.034		0.025	0.011
	(0.94)		(0.74)	(0.25)
CR Q4 trade link, w/ common ownership	0.008		0.017	0.037
	(0.24)		(0.52)	(0.93)
CR Q5 High trade link, w/ common ownership	**0.195**		**0.195**	
	(4.67)		(4.51)	
CR Q5 High trade link, Low common ownership				-0.007
				(-0.36)
CR Q5 High trade link, 2 common ownership				0.015
				(1.02)
CR Q5 High trade link, 3 common ownership				**0.055**
				(2.85)
CR Q5 High trade link, 4 common ownership				**0.051**
				(2.14)
CR Q5 High trade link, High common ownership				**0.086**
				(2.82)
Avg adj R2	0.0249	0.0100	0.0172	0.0350
Number of obs	73315	95616	74901	67340
Avg NOB	632.0	783.7	645.7	580.5

Table 7 Institutional investors and informed trading

This table reports estimates from panel regressions. The dependent variables are quarterly changes of institutional ownership in the country-industry portfolio. The explanatory variables are previous quarter's change of institutional ownership in the country-industry portfolio, quarterly change of institutional ownership in the customer industry, and its interaction terms with dummies representing liquidity levels. Country-industry fixed effects and time fixed effects are controlled for in all regressions.

		(1)	(2)	(3)	(4)
d_IO_customer(t)		**0.079**	**0.080**		
		(3.37)	(3.39)		
d_IO_customer(t)	× Q1 least liquid			**-0.246**	**-0.227**
				(-6.18)	(-5.50)
	Q2			0.001	0.004
				(0.01)	(0.08)
	Q3			**0.206**	**0.186**
				(5.56)	(4.77)
	Q4			**0.157**	**0.131**
				(4.08)	(3.28)
	Q5 most liquid			**0.178**	**0.196**
				(5.19)	(5.53)
d_IO_customer(t-1)	× Q1 least liquid				0.006
					(0.14)
	Q2				0.061
					(1.26)
	Q3				**0.130**
					(3.12)
	Q4				**0.158**
					(3.89)
	Q5 most liquid				0.009
					(0.23)
d_IO(t-1)			**0.048**	**0.047**	**0.046**
			(8.28)	(8.19)	(8.02)
R squared		0.0688	0.0709	0.0746	0.0753
Number of observations		30949	30947	30947	30947

Table 8

This table reports estimates from panel regressions. The dependent variables are quarterly changes of institutional ownership in the country-industry portfolio. The explanatory variables are previous quarter's change of institutional ownership in the country-industry portfolio, customer industry portfolio returns, their interaction terms with dummies representing liquidity levels, and positive and negative customer industry returns. Country-industry fixed effects and time fixed effects are controlled for in all regressions.

		(1)	(2)	(3)	(4)
CR(t)		**0.016**			
		(5.37)			
CR_pos(t)			**0.013**		
			(3.16)		
CR_neg(t)				**0.029**	
				(5.28)	
CR(t)	× Q1 least liquid				0.004
					(0.92)
	Q2				**0.012**
					(3.04)
	Q3				**0.023**
					(5.86)
	Q4				**0.017**
					(4.30)
	Q5 most liquid				**0.025**
					(6.52)
CR(t-1)		**0.006**			
		(2.14)			
CR_pos(t-1)			**0.009**		
			(2.38)		
CR_neg(t-1)				0.001	
				(0.26)	
CR(t-2)		0.001			
		(0.36)			
CR_pos(t-2)			0.001		
			(0.24)		
CR_neg(t-2)				0.001	
				(0.14)	
d_IO(t-1)		**0.047**	**0.048**	**0.048**	**0.048**
		(8.19)	(8.23)	(8.25)	(8.31)
R squared		0.0716	0.0711	0.0714	0.0727
Number of observations		30947	30947	30947	30947

Table 9

This table reports estimates from panel regressions. The dependent variables are quarterly change of institutional ownership in the country-industry portfolio. The explanatory variables are the previous quarter's changes of institutional ownership in the country-industry portfolio, positive and negative customer industry portfolio returns, and their interaction terms with dummies representing liquidity levels. Country-industry fixed effects and time fixed effects are controlled for in all regressions.

		(1)	(2)	(3)	(4)
CR_pos(t) ×	Q1 least liquid	-0.001 (-0.10)	-0.001 (-0.25)		
	Q2	0.010 (1.84)	0.009 (1.50)		
	Q3	**0.021** (3.91)	**0.019** (3.51)		
	Q4	**0.017** (3.17)	**0.017** (3.08)		
	Q5 most liquid	**0.020** (3.66)	**0.020** (3.67)		
CR_neg(t) ×	Q1 least liquid			0.010 (1.50)	**0.016** (2.31)
	Q2			**0.021** (3.14)	**0.020** (2.84)
	Q3			**0.035** (5.31)	**0.032** (4.56)
	Q4			**0.027** (4.16)	**0.023** (3.38)
	Q5 most liquid			**0.043** (6.68)	**0.045** (6.65)
CR_pos(t-1) ×	Q1 least liquid		**0.011** (2.01)		
	Q2		**0.012** (2.37)		
	Q3		**0.010** (2.14)		
	Q4		0.006 (1.16)		
	Q5 most liquid		0.004 (0.82)		
CR_neg(t-1) ×	Q1 least liquid				**-0.015** (-2.16)
	Q2				0.003 (0.37)
	Q3				0.008 (1.16)
	Q4				0.010 (1.44)
	Q5 most liquid				-0.003 (-0.47)
d_IO(t-1)		**0.048** (8.25)	**0.048** (8.22)	**0.043** (6.68)	**0.048** (8.25)
R squared		0.0714	0.0717	0.0724	0.0730
Number of observations		30947	30947	30947	30947

Table A1

Industry classification

Industries	Description	French SIC30	GTAP industries
1	Food Products	1	pdr,wht,gro,v_f,osd,c_b,pfb,ocr,ctl,oap, rmk,wol,fsh,cmt,omt,vol,mil,pcr,sgr,ofd
2	Beer & Liquor, Tobacco Products	2,3	b_t
3	Recreation	4	ros
4	Printing and Publishing	5	ppp
5	Apparel	7	wap, lea
6	Chemicals	9	crp
7	Textiles	10	tex
8	Construction and Construction Materials	11	for,lum,nmm,cns
9	Steel Works Etc	12	i_s,nfm
10	Fabricated Products and Machinery	13	fmp,ome,omf
11	Electrical Equipment, Business equipment	14, 23	ele
12	Automobiles and Trucks	15	mvh
13	Aircraft, ships, and railroad equipment	16	otn
14	Precious Metals, Non-Metallic, and Industrial Metal Mining	17	omn
15	Coal	18	col
16	Petroleum and Natural Gas	19	oil,gas,p_c
17	Utilities	20	ely,gdt,wtr
18	Communication	21	cmn
19	Personal and Business Services	22	obs,dwe
20	Transportation	25	otp,wtp,atp
21	Wholesale, Retail	26, 27	trd
22	Banking, Insurance, Real Estate, Trading	29	ofi,isr
23	Everything Else	6, 8, 24, 28, 30	osg

Table A2

Time-series averages of market capitalization for all firms in the country-industry portfolio in billions USD. Sample period is from January 1980 to March 2009

Country	Food	Beer & Tobacco	Recreation	Printing and publishing	Apparel	Chemicals	Textile	Construction	Steel works	Machinery	Electrical & Business equip	Auto	Air craft, ships, railroad	Precious Metals	Coal	Petroleum & Natural gas	Uitilities	Communication	Personal & Bus Srv	Transportation	Wholesale, retail	Finance	Everything else	Num industries in a country
Argentina	1.32	0.41		0.02	0.16	0.39		0.54	3.61	0.10		0.29				15.29	1.28	8.90	0.06	0.01	0.27	4.11	0.09	17
Australia	7.21	6.48	4.61	3.99	0.36	4.02	0.07	6.27	7.54	0.58	0.94	0.88	0.26	58.31	3.92	13.51	6.15	26.65	13.36	8.26	23.82	76.51	15.41	23
Austria	0.63	0.37	0.80			0.50	0.07	2.56	2.25	0.83	0.41	0.50				5.39	4.60	6.75	1.07	1.35	0.65	15.11	1.77	18
Belgium	0.68	7.18	0.23	0.35	0.38	5.30	0.23	2.48	1.61	0.19	1.68		0.08	0.06	0.01	6.13	14.41	4.14	0.65	0.98	7.49	40.26	5.11	22
Brazil	1.96	9.26	0.07	0.16	0.83	42.54	2.98	18.30	14.60	1.03	1.82	25.93	2.10	24.68		31.64	29.08	17.65	0.93	2.75	10.69	34.41	3.94	22
Canada	7.55	9.75	0.40	16.09	0.14	4.33	0.62	5.00	3.91	2.43	35.66	4.53	1.71	62.31	0.34	91.83	15.71	28.20	11.42	9.95	17.20	116.69	13.61	23
Chile	2.57	2.93	0.32	0.06		1.11	0.12	2.77	2.72		0.02			0.65	0.07	8.88	21.03	5.81	0.37	2.53	8.33	11.33	4.19	19
China	11.77	14.26	8.75	1.03	3.13	27.93	6.21	15.43	41.98	15.92	32.88	17.14	3.84	8.52	8.44	35.37	34.01	7.86	6.22	36.51	24.55	75.94	36.42	23
Colombia	1.20	2.09	0.05				0.09	3.04	0.10	0.02				0.08			1.44	0.37	0.04	0.02	0.69	6.60	0.28	15
Czech Republic	0.03	0.68	0.01			0.06	1.17	0.07								0.85	10.74	5.77	0.01		0.24	2.96	0.69	13
Denmark	0.64	1.90	0.77	0.20	0.31	3.57	0.08	1.96	0.60	3.77	1.25	0.05	0.09	0.06			0.48	6.64	1.44	11.56	1.48	18.49	14.82	21
Finland	0.71	0.48	0.81	1.70	0.10	1.56	0.30	1.49	3.96	6.79	57.93	1.82		1.86		2.66	10.35	8.58	2.31	1.52	1.81	7.65	14.00	21
France	19.16	7.64	8.32	2.29	24.03	12.61	0.40	28.67	12.01	13.19	44.24	17.51	16.56	4.03		86.33	39.43	42.31	16.36	10.31	67.61	106.84	127.62	22
Germany	4.41	2.42	1.45	2.55	6.16	27.27	0.43	16.47	9.99	11.49	50.09	70.42	0.87	2.22	0.82	2.38	65.39	86.63	27.49	17.43	26.11	148.02	55.55	23
Greece	5.26	0.45	3.00	1.00	0.20	0.34	0.51	4.99	2.91	0.34	0.67		0.30	0.98		4.26	5.91	10.35	1.56	1.41	3.43	25.20	3.26	21
Hong Kong	4.67	1.44	2.18	1.91	3.62	2.72	1.49	6.61	5.62	2.64	9.70	1.91	0.78	0.73	0.78	12.41	24.01	87.68	3.17	38.00	12.12	113.13	10.67	23
Hungary	0.04	0.08			0.00	0.52	0.01	0.05		0.06		0.09				5.26	0.92	4.85	0.05		0.01	3.91	2.67	15
India	4.44	9.65	0.67	0.57	0.42	8.90	3.07	21.61	25.17	15.10	7.98	11.44	0.23	3.80	0.27	64.18	17.27	27.71	39.18	3.64	1.68	41.52	36.11	23
Indonesia	3.81	5.47	0.15	0.04	0.23	1.20	0.64	3.85	0.25	0.08	0.01	1.67		1.80	1.64	0.94	2.82	10.17	0.27	0.73	4.23	11.72	5.41	22
Ireland	2.92	2.44	0.73	0.86		0.04		6.10			0.13			0.24		0.66		0.44	0.83	2.07	1.60	16.24	5.88	15
Italy	2.58	1.00	1.90	6.04	2.70	0.99	0.77	4.66	2.20	4.05	2.46	10.78	3.21	1.50		77.32	31.19	32.93	5.52	7.56	3.71	119.33	8.74	22
Japan	62.56	32.78	159.67	15.58	12.95	107.38	20.64	132.96	108.96	135.93	254.56	247.06	4.79	4.45	0.25	32.16	131.78	191.53	77.61	141.97	222.93	488.57	279.52	23
Korea	4.70	3.08	33.99	0.32	0.92	6.62	1.70	14.93	15.32	4.71	18.59	11.40	7.36	0.65		3.46	17.91	18.23	5.56	4.48	9.70	28.89	9.00	22
Malaysia	13.07	2.89	5.46	0.93	0.18	1.45	0.35	9.05	2.23	1.33	1.74	3.54	0.34	0.36		1.77	13.89	12.13	3.12	8.45	3.77	23.03	5.62	22
Mexico	8.70	4.37	0.13	0.01	0.04	0.64	0.07	5.03	0.96	0.01		0.09		2.20		2.30		13.71		0.63	18.57	13.37	3.44	18
Morocco	3.08	0.40				0.11		2.65	0.58		0.06	0.02		0.43		0.84	0.34	14.44	0.01		0.27	6.36	0.12	15
Netherlands	4.10	9.21	20.49	10.85	0.05	10.76		3.63	8.68	5.17	3.73	0.34	0.02			70.05		23.30	7.04	6.22	22.02	49.07	3.97	19
New Zealand	0.48	0.08	0.03	0.06	0.05	0.18	0.11	2.82	0.16	0.11	0.15			0.07		0.45	2.89	6.99	0.35	2.08	2.37	0.05	1.55	20
Peru	0.57	0.98		0.03		0.05	0.08	0.74	0.23	0.00	0.00	0.00		3.76		0.35	1.66	2.07		0.03	0.27	3.41	0.01	18
Philippines	0.64	2.10	0.16	0.08		0.06	0.01	0.77	0.12		0.13		0.05	0.40	0.01	0.89	1.79	5.31	0.26	0.64	1.15	7.78	0.68	20
Poland	0.57	1.25	0.16	0.86	0.29	1.09	0.09	1.99	0.77	0.79	1.01	0.42		2.79		8.10	0.55	9.85	0.83	0.17	1.20	17.17	2.02	21
Portugal	0.15	0.18	0.14	0.17		0.14	0.03	5.78		0.01	0.09	0.17	0.12			11.50	11.68	10.01	0.64	0.07	4.70	8.31	2.06	19
Singapore	4.43	1.41	0.40	4.27	0.40	0.34	0.28	3.54	1.04	1.33	4.52	1.31	8.48		1.43	1.65	0.24	28.51	3.00	17.75	2.42	26.44	6.13	22
Spain	3.33	0.42	0.11	1.88	0.30	1.53	0.12	39.25	3.17	4.62	0.42	0.67	0.30	0.28	0.04	19.25	55.37	61.28	4.45	7.96	19.70	96.42	5.27	23
Sweden	0.68	1.77	0.49	1.11	11.26	1.84	0.02	7.56	2.87	12.19	30.85	8.99	1.43	1.35		1.34	1.54	15.04	5.73	1.91	4.16	33.65	21.08	22
Switzerland	2.61	0.08	0.17	0.50	0.06	2.04		1.53	0.40	6.49	3.38	0.40				0.07	6.05	0.11	2.52	1.39	2.70	22.67	26.96	19
Taiwan	5.10	0.03	4.53	0.08	2.84	29.21	8.88	11.22	15.59	2.54	159.41	5.83		0.10		18.83	0.56	22.86	3.42	9.33	7.26	19.34	8.18	21
Thailand	2.22		0.40	0.41	0.50	5.49	0.34	3.33	0.90	0.19	1.84	0.37	0.01	0.19	0.85	11.66	1.44	9.55	0.87	2.52	2.17	17.14	3.39	22
Turkey	1.19	1.32	0.71	1.43	0.07	1.89	0.50	5.40	2.10	0.16	1.06	3.14		0.07		2.73	1.71	8.20	0.04	1.35	3.74	15.00	3.79	21
United Kingdom	58.61	97.36	18.75	42.79	3.04	24.32	2.87	43.89	9.28	18.16	37.04	11.29	19.15	102.99	0.56	240.96	73.47	184.15	70.87	36.65	133.66	319.44	243.10	23
United States	253.03	109.24	122.93	77.29	28.17	140.51	7.95	100.06	64.26	308.46	832.25	107.96	87.68	30.15	8.65	486.08	300.82	471.15	533.08	118.97	523.45	1323.91	1170.78	23
Number of countries with the industry	41	40	37	36	32	40	36	41	37	36	36	33	24	33	16	39	38	41	39	38	41	41	41	

Table A3

Number of firms that ever existed in each country-industry portfolio. Sample period is from January 1980 to March 2009.

Country	Food	Beer & Tobacco	Recreation	Printing and publishing	Apparel	Chemicals	Textile	Construction	Steel works	Machinery	Elecrical & Business equip	Auto	Air craft, ships, railroad	Precious Metals	Coal	Petroleum & Natural gas	Utilities	Communication	Personal & Bus Srv	Transportation	Wholesale, retail	Finance	Everything else	Total number of firms
Argentina	12	3		1	2	8		10	4	4		4				7	9	3	1	1	4	9	5	87
Australia	48	18	36	12	6	16	2	51	19	26	56	17	2	526	44	132	21	49	212	29	102	94	146	1664
Austria	7	4	3			3	4	16	5	10	6	5				2	7	3	10	4	7	18	15	129
Belgium	7	4	3	4	1	7	5	9	7	4	12		2	2	1	1	7	7	21	6	18	25	19	172
Brazil	21	3	5	3	4	18	10	23	22	12	9	11	1	3		5	39	29	8	7	23	43	25	324
Canada	24	10	25	19	2	27	3	54	19	37	115	19	9	967	20	478	31	52	237	26	85	99	172	2530
Chile	19	7	7	1		6	2	13	9		1			2	2	2	23	7	3	9	16	22	15	166
China	57	26	20	4	12	115	47	82	92	71	139	60	10	16	20	12	59	5	32	67	114	83	198	1341
Colombia	4	2	1				3	10	2	1				1			3	1	3	1	3	12	7	54
Czech Republic	1	1	1			2	2	1								2	9	2	1		1	3	5	31
Denmark	8	5	13	5	3	8	3	21	2	12	16	3	1	1			3	2	19	14	23	67	22	251
Finland	6	2	5	10	1	3	3	8	4	16	22	3		1		3	3	6	22	8	15	14	21	176
France	50	20	46	20	22	19	12	59	24	57	115	21	15	6		14	13	30	255	30	151	96	178	1253
Germany	19	23	47	15	12	26	14	56	14	77	133	25	8	7	1	4	33	24	191	26	87	130	117	1089
Greece	31	6	6	10	5	6	18	42	19	3	10		2	6		3	3	13	18	12	72	30	36	351
Hong Kong	28	7	49	15	30	24	24	44	18	24	105	10	3	10	7	8	19	30	97	34	115	80	125	906
Hungary	4	1			1	1	1	1		2		1				1	3	3	2		4	5	9	39
India	50	13	22	9	8	93	53	83	68	67	56	44	5	6	1	27	25	23	90	21	20	80	163	1027
Indonesia	39	5	1	3	11	13	13	16	13	5	2	12		8	5	7	2	9	13	17	29	55	40	318
Ireland	8	1	1	1		1		8						6		9		2	10	4	10	11	13	86
Italy	12	2	10	10	11	11	11	31	8	22	20	9	1	3		4	26	12	23	25	18	82	45	396
Japan	174	9	126	49	39	186	50	421	103	321	487	137	12	10	1	18	27	44	520	158	747	222	460	4321
Korea	64	9	63	9	37	78	44	145	90	108	304	80	9	4		7	12	21	128	30	98	56	216	1612
Malaysia	92	3	19	13	15	26	12	151	41	41	60	27	3	2		20	18	18	99	43	73	91	111	978
Mexico	10	1	2	1	1	3	2	9	4	2		1		2		1		8		4	12	16	12	91
Morocco	7	2				4		4	2		1	1		3		2	1	1	1		5	12	3	49
Netherlands	5	2	4	8	3	7		22	5	6	26	3	1			2		6	33	6	36	16	27	218
New Zealand	17	3	3	2	1	3	4	7	2	4	3			2		2	9	5	13	13	29	7	13	142
Peru	19	3		1		2	4	3	3	1	1	1		12		1	8	3		1	4	24	4	95
Philippines	13	2	6	1		4	1	13	3		6		1	14	1	10	8	9	9	6	10	41	10	168
Poland	16	3	1	4	6	8	4	40	10	7	16	5		1		4	5	13	22	2	31	24	25	247
Portugal	8	2	6	5		2	4	14		1	3	1	1			1	1	8	8	4	12	17	17	115
Singapore	40	2	20	14	6	17	6	49	24	44	104	5	11		1	19	4	7	51	34	75	43	91	667
Spain	10	5	1	4	3	4	1	23	5	7	2	3	1	2	1	3	17	7	7	7	16	28	19	176
Sweden	5	2	17	9	5	8	2	24	7	37	82	11	2	13		9	5	15	108	26	42	27	71	527
Switzerland	10	1	4	2	1	5		15	2	32	24	1				2	10	1	19	12	28	50	46	265
Taiwan	32	1	30	4	15	56	57	58	53	59	548	22		1		2	8	7	57	25	68	58	94	1255
Thailand	54		14	13	12	19	14	44	25	10	25	9	1	2	4	11	6	15	24	13	48	48	82	493
Turkey	26	3	5	7	7	14	25	34	12	4	12	14		2		1	9	1	2	3	23	28	40	272
United Kingdom	83	33	165	88	30	52	31	166	24	100	218	26	16	152	14	125	60	90	676	88	341	170	397	3145
United States	355	74	523	211	198	252	139	571	208	546	2176	193	98	190	29	871	302	660	2649	408	1755	3935	3263	19606
Total number of firms	1495	323	1310	587	510	1157	630	2451	972	1780	4916	784	215	1983	152	1832	848	1251	5694	1224	4370	5971	6377	

Figure 1A

Time series of the monthly long-short portfolio sorted based on lagged customer industry returns. For each month, the long-short portfolio is formed from a long top quintile portfolio of equal-weighted industry portfolios and a short bottom quintile portfolio. The portfolio is rebalanced each month.

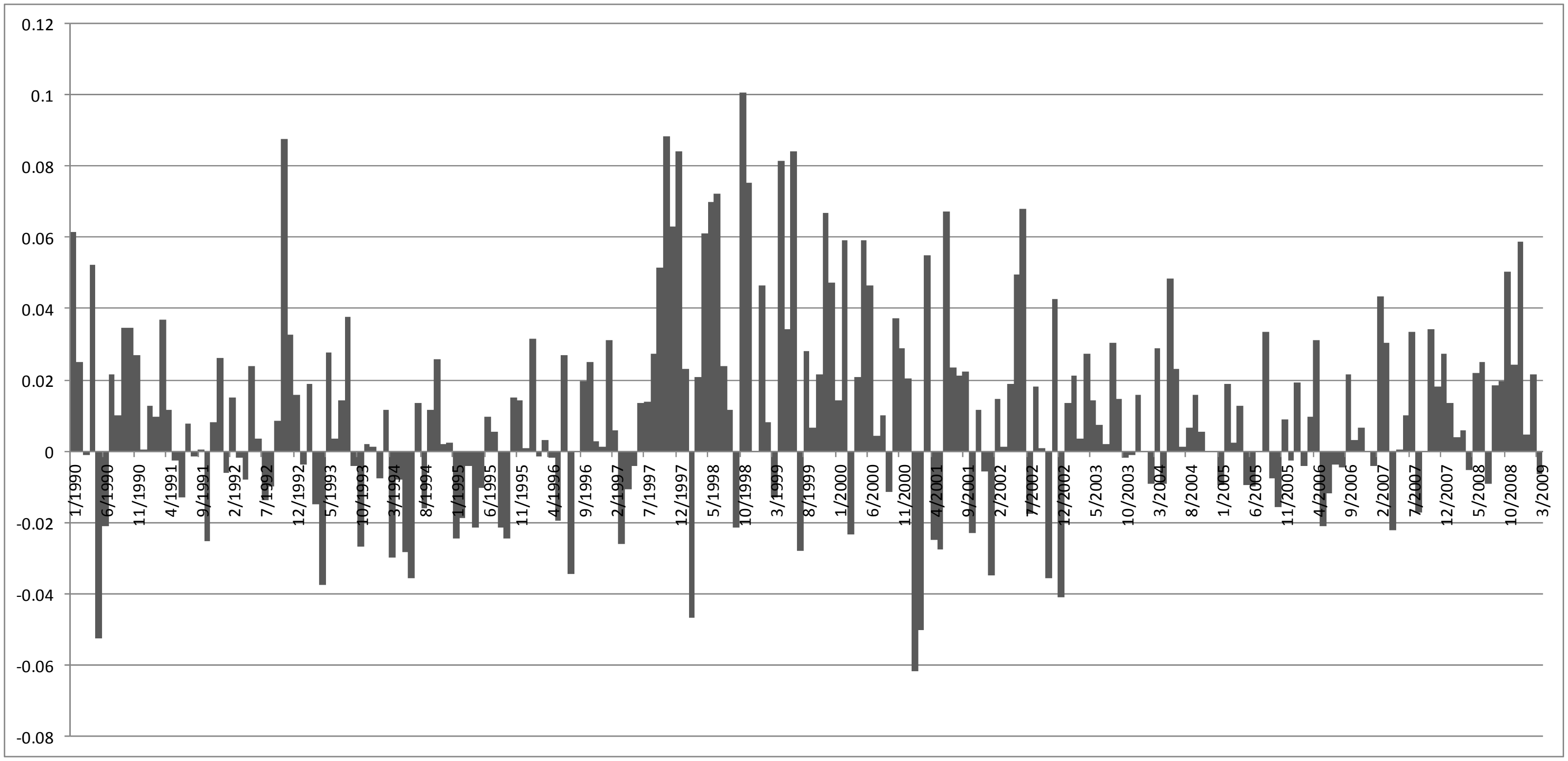

Figure 1B

Time series of the monthly long-short portfolio sorted based on lagged supplier industry returns. For each month, the long-short portfolio is formed from a long top quintile portfolio of equal-weighted industry portfolios and a short bottom quintile portfolio. The portfolio is rebalanced each month.

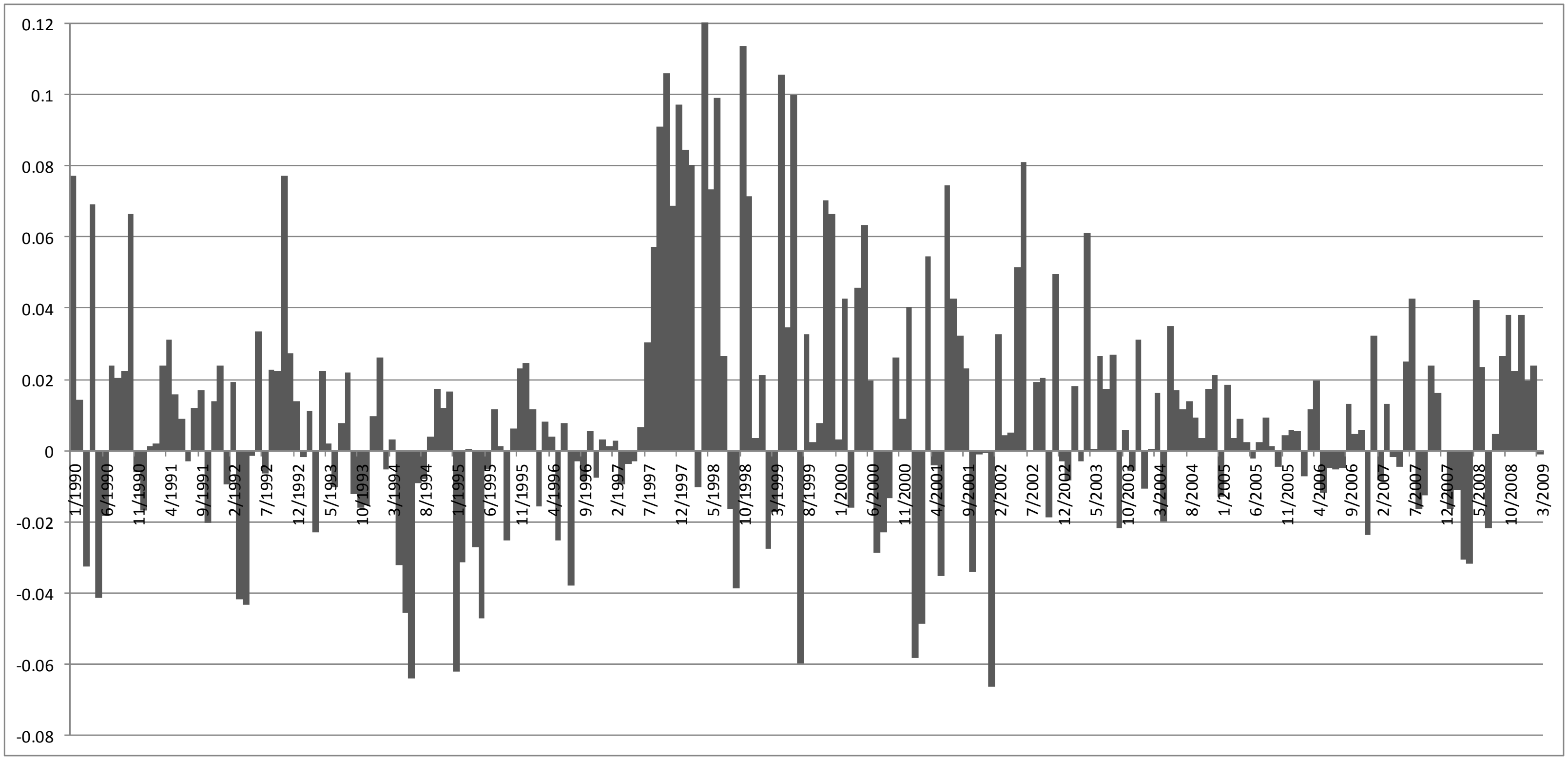

Figure 2A

Cumulative returns of the momentum portfolio from its formation up to 36 months. Top quintile minus bottom quintile sorted according to previous month's industry/customer/supplier returns.

Figure 2B

Cumulative returns of the momentum portfolio from its formation up to 36 months. Top quintile minus bottom quintile sorted according to previous month's industry/customer/supplier returns. When I form the customer/supplier momentum portfolio, I avoid top and bottom quintile industries in past industry returns so that reversal of the industry momentum portfolio is avoided. Cumulative returns of the industry momentum portfolio are depicted for purposes of comparison.