THREE ESSAYS ON FINANCIAL MARKETS

Three Essays on Financial Markets

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Abstract

This thesis studies anomalies and information dissemination in financial markets. The first essay examines seasonality and momentum jointly across national equity markets at the index level. We find that seasonality and momentum are almost uncorrelated and appear to arise from different global or local risk factors, rather than from different loadings on the same risk factor. We confirm our conclusion with a combination trading strategy: while the pure seasonality and momentum strategies individually generate sizable and significant returns, the combination strategy significantly outperforms the pure strategies in a way that is quantitatively consistent with their lack of correlation.

The second essay predicts corporate earnings with composite peer return information. We find that explicitly utilizing interim focal firm returns and an optimal aggregate of peer firm returns improves the earnings forecast for the focal firm. A combination forecast with aggregate peer returns is significantly better than without. With aggregate peer returns the forecast moreover improves significantly on a pure consensus analyst forecast. A trading strategy of holding (shorting) stocks of firms for which combination forecasts of earnings exceed (fall short of) consensus analyst forecasts during the days leading up to and including the earnings announcement produce annualized abnormal returns of 11.5%.

The third essay examines the insider's role as an active information producer during major corporate events. Using the distinctive setting of trading suspension during mergers and acquisitions (M&As) in China, we show that insiders actively engage in private effort during trading suspensions to facilitate successful deal closure for higher equity trading profits. When regulatory tightening inhibits such efforts, insider profits fall by 0.39% over a 3-day window and the probability of successful deal closure drops by 1.88% for each one percentage point increase in insider trading. However, insider private effort in information production does not predict firm long-term performance, suggesting that information produced by insiders is non-fundamental and transitory.

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Declaration of Authorship

I, Jian Song, declare that this thesis, entitled, "Three Essays on Financial Markets", and the work presented in it, are my own or to which I have made significant contribution. I confirm that the thesis comprises the following chapters:

- Seasonality and Momentum across National Equity Markets
- Predicting Corporate Earnings with Composite Peer Return Information
- Insider Information Production: Evidence from Insider Trading around M&As

The first two chapters are prepared under the close supervision of my Ph.D. supervisor, Dr. Ronald Balvers, and the third chapter is a collaboration with Ya Gao (University of Manitoba), Jun Wen (Xi'an Jiaotong University) and Xiaozhou Zhou (University of Quebec at Montreal).

This thesis is entirely my own or me and my coauthors' original work unless otherwise indicated. Any use of the work of other authors is acknowledged at their point of use.

Introduction

In financial markets, the existence of either the seasonality effect or the momentum effect has important implications for asset pricing and the perspective on market efficiency. Both effects have received much attention from finance scholars and practitioners (e.g., Jegadeesh and Titman, 1993, Carhart, 1997, Heston and Sadka, 2008, Keloharju, Linnainmaa, and Nyberg, 2016). However, previous studies usually consider these effects separately and only provide a cursory discussion of their relationship.

In the first chapter “Seasonality and Momentum across National Equity Markets”, we examine the seasonality effect and the momentum effect jointly at the national equity index level with 18 developed markets, aiming to uncover their relationship and their relative strengths for national equity index returns. We find that seasonality and momentum are almost uncorrelated and appear to arise from different global or local risk factors, rather than from different loadings on the same risk factor. Employing a trading strategy that integrates seasonality and momentum parametrically, we confirm our conclusion about the relationship between seasonality and momentum: while the pure seasonality and momentum strategies individually generate sizable and significant returns, the combination strategy significantly outperforms the pure strategies in a way that is quantitatively consistent with their lack of correlation.

Considering the existence of such significant effects in financial markets, it is interesting and important to explore the possible sources of them. One potential determinant is the fundamentals (e.g., earnings, cash flows) of a company, as highlighted in Huang, Zhang, and Zhou (2019). This perspective aligns with the idea put forth by Cochrane (2011) that “asset prices should equal expected discounted cash flows," which is widely accepted in academia and featured in various textbooks (e.g., Ross et al., 2019). In fact, earlier studies have shown that momentum and seasonality in stock returns are strong around earnings announcements (Chordia and Shivakumar, 2006 and Chari, Jagannathan, and Ofer, 1988). In addition, Han, Hong, and Warachka (2009) demonstrate that stock price momentum can result from uncertainty surrounding the accuracy of analyst forecasts. Therefore, the more accurate the earnings forecasts, the better we may establish a link between stock returns and future cash flows.[1]

In the second chapter "Predicting Corporate Earnings with Composite Peer Return Information", we aim to enhance the accuracy of analyst earnings forecasts by incorporating return information from the financial markets. While the first chapter examines 18 developed markets, we focus specifically on the U.S. market in the second chapter due to its wealth of available information, which offers greater potential to explore for better earnings forecasts. We find that explicitly utilizing interim focal firm returns and an optimal aggregate of peer firm returns improves the earnings forecast for the focal firm. A combination forecast with aggregate peer returns is significantly better than without. With aggregate peer returns the forecast moreover improves significantly on a pure consensus analyst forecast. To explore the economic implications of our findings, we design a trading strategy. Holding (shorting) stocks of firms for which combination forecasts of earnings exceed (fall short of) consensus analyst forecasts during the days leading up to and including the earnings announcement can generate annualized abnormal returns of 11.5%. We find that financial analysts may not adequately account for the complex peer firm signals affecting followed firms.

Given the fact that analyst forecasts may not fully capture certain information that could impact stock returns, it is worth exploring what other types of information could be at play, apart from the information derived from peer companies,

[1] Future earnings are often used as a proxy for future cash flows (e.g., as in Han, Hong, and Warachka, 2009).

as discussed in the second chapter. One potential factor is the presence of insider information/trading. It is reported that there is insider trading in financial markets (e.g., Jaffe, 1974, Meulbroek, 1992, Bhattacharya and Daouk, 2002, Bris, 2005, among others). However, previous studies mostly look at the information *acquisition* (insiders use their privileged access to such information to gain abnormal returns) issue. Whether there is information *production* (insiders insert some private effort to generate some new information to enhance their trading returns) usually is not answered. This is partly due to endogeneity concerns, as insiders usually make their trading (mainly from information acquisition) and private effort (mainly about information production) decisions concurrently. Hence, it is empirically challenging for researchers and regulators to distinguish the portion of transactions motivated by existing private information from those motivated by insider endogenous rent-seeking efforts. As a result, researchers usually cannot separate them in most financial markets.

In the third chapter "Insiders Information Production: Evidence from Insider Trading around M&As", we address this endogeneity issue with the distinctive setting of trading suspension around mergers and acquisitions (M&As) in Chinese stock markets. We examine the insider's role as an active information producer during major corporate events and show that insiders actively engage in private effort during trading suspensions to facilitate successful deal closure for higher equity trading profits. When regulatory tightening inhibits such efforts, insider profits fall by 0.39% over a 3-day window and the probability of successful deal closure drops by 1.88% for each one percentage point increase in insider trading. However, insider private effort in information production does not predict firm long-term performance, suggesting that information produced by insiders is non-fundamental and transitory.

Chapter 1

Seasonality and Momentum across National Equity Markets

1.1 Introduction

The existence of either the seasonality effect or the momentum effect has important implications for asset pricing and the perspective on market efficiency. Both receive much attention from finance scholars and practitioners. However, previous studies usually consider them separately and only provide a cursory discussion of their relationship. In this paper, we examine the seasonality effect and the momentum effect jointly at the national equity index level, aiming to uncover their relationship and their relative strengths for national equity index returns. Considering these historical return effects jointly facilitates investigating their interaction. For instance, momentum effects based on the typical six-month or nine-month recent history may be affected by the seasonal spacing of high- and low-return months as well as by changes in their strengths over time.

Our results strongly confirm the existence of both seasonality and momentum at the index level. Although the correlation between seasonality and momentum is small, it is quantitatively important for explaining index returns. The results further indicate that the momentum effect has a quantitatively larger influence than the seasonality effect. Using the MSCI indexes from 18 developed markets covering the regions of North America, Europe and Asia-Pacific, a parametric combination trading strategy based on both seasonality and momentum generates mean returns that are both statistically and economically significant and potentially can be exploited in an international equity allocation strategy.

The objective of this paper is to distinguish anomalies that are purely dependent on historical returns. These require no other information than past pricing, and thus avoid such issues as measurement error in accounting ratios. The parametric approach is essential here, in comparison to a more standard approach of double sorting, because it accounts explicitly for differences in the numerical strength of each effect. Seasonality and momentum are both persistent phenomena, which may indicate they are manifestations of the same risk factor. Seasonality and momentum also mutually interact. For instance, Keloharju, Linnainmaa, and Nyberg (2016) and Bhootra (2019) find that momentum portfolios display seasonality. It is worthwhile to examine if one is more primary than the other or if they are essentially independent. Ideally, in linking these anomalies we add in the impact of mean reversion, another historical return-based anomaly, to the seasonality and momentum effects. However, because of the slow reversion process and a limited time series, the reversion effect becomes difficult to separate from seasonality and momentum.[1]

Heston and Sadka (2008) document a significant seasonality effect in the cross-section of stock returns in the U.S. They define seasonality as "stocks tend to have relatively high (or low) returns every year in the same calendar month." Although finance scholars had previously acknowledged a seasonality effect,[2] these papers did

[1]As a practical matter, the parameter estimates needed for implementing the parametric approach appear to become quite unstable when the mean reversion effect is added to the momentum and seasonality effects. This suggests an identification issue that is likely to interfere with generating representative trading strategy results.

[2]For example, see Rozeff and Kinney (1976), Keim (1983), Gultekin and Gultekin (1983), Ariel (1987), Chang, Pinegar, and Ravichandran (1998), Bouman and Jacobsen (2002), Kamstra, Kramer, and Levi (2003), Ogden (2003), Garrett, Kamstra, and Kramer (2005), and Lynch, Puckett, and Yan (2014).

not consider seasonality for cross-sectional differences of stock returns. Heston and Sadka (2010) subsequently document seasonality with international evidence from 14 non-U.S. markets, and Heston, Korajczyk, and Sadka (2010) document a seasonality pattern at the intraday level. Keloharju, Linnainmaa, and Nyberg (2016) uncover similar seasonality effects in anomalies, commodities, and international stock market indexes. Li, Zhang, and Zheng (2018) extend Heston and Sadka (2008) and Heston and Sadka (2010) to a comprehensive example of 42 international markets and identify a difference between developed and emerging markets.

At the same time, momentum, another historical return effect, has been more widely investigated. Jegadeesh and Titman (1993) document momentum strategies as "strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past". Subsequently, many scholars have researched momentum: Carhart (1997) builds a momentum factor and adds it to the Fama-French 3-factor model (Fama and French, 1993) to obtain a 4-factor model; Fama and French (2012) find that "except for Japan, there is return momentum everywhere" in the 23 countries they examine; Asness, Moskowitz, and Pedersen (2013) even conclude that value and momentum are everywhere; in addition, Hou, Xue, and Zhang (2020) document that by replicating 6 categories of a total of 452 anomalies in the finance literature, "momentum" and "investment" are the only two categories with acceptable replication rates.[3] In fact, the origin of Heston and Sadka (2008) is their study of momentum, attempting to identify the crossover point when winner stocks stop outperforming loser stocks and begin to underperform.

Seasonality and momentum both imply continuation in asset returns, but the seasonality effect mainly considers the pattern for same-calendar-months or annual intervals, while momentum usually focuses on the autocorrelation within 12

[3]The replication rate is about 56%-84% for momentum, depending on different methods, while some other categories only have a 12%-40% replication rate.

months. Although the two effects exist simultaneously, the current literature examines them separately. When the momentum effect (usually within 12 months) is encountered, existing studies choose to avoid interaction with seasonality. For example, in Keloharju, Linnainmaa, and Nyberg (2016), when checking other-month returns, portfolios are sorted based on average other-calendar-month returns over the same period as the same-calendar-month, skipping months t-11 through t-1 (the typical momentum months). Further, while Keloharju, Linnainmaa, and Nyberg (2016) consider both seasonality and momentum, they mainly work with seasonality of momentum-sorted portfolios or momentum anomalies, rather than joint seasonality and momentum of underlying asset returns. In addition, their empirical work predominantly involves individual stocks in the U.S., rather than indexes at the global market level.[4]

Considering previous studies about seasonality or momentum, several questions can be raised: What is the relationship between seasonality and momentum? Are they totally independent from each other or correlated to some extent? What would happen if we considered them jointly? In this paper, we try to answer these questions. We contribute to the literature in several respects.

First, we confirm the existence of both the seasonality effect and the momentum effect across national equity market indexes. Our findings are not based on raw asset returns but on global-market-risk-adjusted returns, which implies that the sources of both effects do not stem from different loadings on the global market risk factor among countries.

[4]Hofmann and Keiber (2021) examine both seasonal and momentum-type strategies for the German stock market but do not consider the interactions.

Second, a weak or even negligible negative correlation is observed between seasonality and momentum. Such a weak correlation implies that seasonality and momentum may emanate from different global risk factors or from dissimilar market-specific local risk factors, such as tax-loss harvesting related to different tax seasons (Gultekin and Gultekin, 1983), the difference in holidays (Cadsby and Ratner, 1992; Kim and Park, 1994), inflation risks (Chaieb and Errunza, 2007), earnings-to-price ratio (Bali and Cakici, 2010) and risks associated with consumption (Li and Zhong, 2005).

Third, applying the parametric procedure in Balvers, Wu, and Gilliland (2000) and Balvers and Wu (2006), we find that the combination trading strategy, which combines seasonality and momentum jointly and potentially rebalances the weights of each effect dynamically through time, yields returns of 10.34% per year and outperforms the returns from pure seasonality and pure momentum strategies, which are 6.16% and 8.28%, respectively. This confirms that the correlation between momentum and seasonality cannot be very high. Otherwise, the effect of one phenomenon would be fully absorbed by the other, making it hard or even impossible for the combination trading strategy to generate significantly higher returns.

Fourth, we find that momentum by itself displays more strength than seasonality in explaining asset returns, which is apparent in both the regression estimates and the correlation among trading strategy returns. If we take trading costs into consideration, momentum strategy gains, all else equal, are larger since momentum strategies naturally have a lower turnover rate than seasonality strategies. Unlike momentum strategies, trading strategies based on seasonality typically require monthly turnover.

Fifth, we show that the combined momentum and seasonality effect decreases in strength to about half its prior value, though remaining significant, in the second half of the sample period. This observation accords with increasing return correlation across country indexes as noted by Goetzmann, Li, and Rouwenhorst (2005) and Umutlu and Bengitoz (2021), linked to increasing market integration (Kearney and Lucey, 2004, and Quinn and Voth, 2008) over time. Our finding therefore suggests that the predictability of returns has not changed but that the occasions to exploit it have diminished.

We further contribute to the current literature on seasonality. Although the seasonality effect at the individual stock level within a specific market is evidenced by Heston and Sadka (2008), Heston and Sadka (2010), Li, Zhang, and Zheng (2018), and Hofmann and Keiber (2021), this does not necessarily imply a similar effect at the index level across different markets, as the high and low returns of individual stocks in a specific market may offset each other, thus failing to show any significant seasonal variation in that market compared to other markets. Previous studies of the seasonality effect at the index level mainly focus on a single market, only capturing the time series effect.[5] In this study, like Heston and Sadka (2008) and Heston and Sadka (2010), we focus on the *cross-sectional differences* in the seasonality effect, but unlike Heston and Sadka (2008) and Heston and Sadka (2010), who consider individual stocks within one market, we study different markets at the index level.

In addition, Lewellen (2002) argues that momentum should not be attributed to firm-specific risk because well-diversified portfolios show similarly strong momentum. Similarly, for seasonality we find that the seasonality effect shows up strongly at the index level, suggesting that seasonality may arise from global or market-specific local risk factors rather than from firm-specific risks.

An advantage of working at the index level is that the index returns should be less influenced by the size effect (Keim, 1983). Keloharju, Linnainmaa, and Nyberg

[5]For example, see Rozeff and Kinney (1976); Gultekin and Gultekin (1983); Bouman and Jacobsen (2002); Kamstra, Kramer, and Levi (2003); and Garrett, Kamstra, and Kramer (2005).

(2016) show that size is associated with seasonality. They find that most of the seasonality in individual stock returns can be traced to characteristics such as size and industry. When we work at the index level, because MSCI indexes consist of large companies and cover most of the industries in a country, this potentially provides us with more information about the origin of seasonality while excluding a substantial part of the possibly confounding influence from size and industry.

Although Keloharju, Linnainmaa, and Nyberg (2016) document a similar seasonality effect to capture cross-sectional differences across national markets, their findings are based on same-calendar-month returns up to 5 years. Similarly, except for the U.S.,[6] most previous findings of seasonality at the individual stock level are for up to 5 years in international markets (Heston and Sadka, 2010; Li, Zhang, and Zheng, 2018). Our findings show that at the index level the seasonality effect extends to 10 years, longer than in previous findings.

The remainder of chapter is organized as follows: In Section 1.2, we describe our data and methodology. In Section 1.3, we provide some illustrative parameter estimates. Section 1.4 presents trading results for the base case. Section 1.5 furnishes robustness checks, and Section 1.6 concludes.

1.2 Data and Methodology

1.2.1 Data

The data consist of the monthly gross MSCI indexes in US dollar terms for 18 developed markets starting from December 1969. The return data, accordingly, cover the 1970-2020 period with the monthly return of index i for month t defined as $r_t^i = log(P_t^i) - log(P_{t-1}^i)$, where P_t^i is the closing gross price of index i at the end

[6]Heston and Sadka (2008) and Keloharju, Linnainmaa, and Nyberg (2016) show the seasonality effect for up to 20 years at the individual stock level in the U.S.

of month t. The construction of the MSCI indexes includes reinvested dividends. Therefore, our return definition that uses the log difference in the index, accounts for dividends as well as capital gains. The 18 developed markets included are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States. They cover the regions of North America, Europe, and the Asia-Pacific. We use the monthly returns from the MSCI gross World index as the benchmark market return.[7]

[Table 1.1 about here]

This set of data provides a relatively long period of data in the international equity markets. The 18 markets are those considered also in Balvers, Wu, and Gilliland (2000) and are closely comparable to the 15 markets in Heston and Sadka (2008), Heston and Sadka (2010) and Keloharju, Linnainmaa, and Nyberg (2016): while not including Finland,[8] we include four additional markets – Australia, Denmark, Hong Kong and Singapore. Table 1.1 presents the summary statistics for our data.

1.2.2 Model and Methodology

Currently, the trading strategies to verify the seasonality effect are all non-parametric in nature. These strategies typically hold the past same-calendar-month winners and short the past same-calendar-month losers. It is difficult for a non-parametric trading strategy to combine the seasonality effect with the momentum effect, as the relative strength of each effect cannot be determined.

[7]Although called World index by MSCI, in fact it is an index for the developed markets. The true world index including both developed and emerging markets in MSCI is the ACWI index – the All-Country World Index.

[8]In the MSCI data, Finland's monthly return data starts in January 1982, which is 12 years later than for the 18 markets in our sample.

To consider seasonality and momentum jointly, we follow the parametric procedure in Balvers, Wu, and Gilliland (2000), and also combine the strengths of two attributes as in Balvers and Wu (2006). These papers focus, respectively, on mean reversion and on mean reversion combined with momentum. We exclude the mean reversion attribute and thus omit the error-correction component that ties return to price deviations from fundamentals. In the parametric procedure, we generate parameter estimates to measure the relative strength of seasonality and momentum. Using these parameters, we obtain the expected returns for each market relative to the fundamentals based on market risk and then employ a combination investment strategy, considering seasonality and momentum jointly, to confirm whether this generates significant returns and outperforms corresponding pure seasonality and pure momentum strategies.

We mainly work with the following pooled regression to capture the parametric nature of the combination trading strategy to join both seasonality and momentum effects:

$$RET_t^i = \mu + \rho SEA_t^i + \gamma MOM_t^i + \eta_t^i \tag{1.1}$$

where t denotes time and i denotes a specific developed market. $RET_t^i = r_t^i - \beta^i r_t^w$ is the world market risk adjusted return for market i at time t, with w denoting the World index and r_t^i the monthly log return for market i at time t, β^i is the world market beta of national market i corresponding to the MSCI World index. SEA_t^i and MOM_t^i are the seasonality and momentum effects, respectively, defined as follows.

The seasonality effect SEA_t^i is defined as $SEA_t^i = \frac{\sum_{k=2}^{10} RET_{t-12k}^i}{9}$. We use the long-term seasonality effect up to 10 years. To avoid the direct interaction with momentum, we skip the first year in seasonality and start in year 2. Thus, the seasonality effect for market i is the average of the same-calendar-month returns for market i from 2 to 10 years prior.

The momentum effect MOM_t^i is defined as $MOM_t^i = \frac{TMOM_t^i}{\sqrt{\sum_{j=2}^{12}(RET_{t-j}^i - TMOM_t^i)^2/10}}$, where $TMOM_t^i = \frac{\sum_{j=2}^{12} RET_{t-j}^i}{11}$ is the traditional momentum effect. The momentum effect defined here equals traditional momentum, based on the monthly global market risk adjusted return RET_t^i, divided by the standard deviation. The standardization is intended to improve the performance of traditional momentum as used in previous studies (Blitz, Huij, and Martens, 2011; Blitz, Hanauer, and Vidojevic, 2020; Gutierrez Jr. and Prinsky, 2007; Zaremba, Umutlu, and Karathanasopoulos, 2019). Following previous studies, we exclude the first month for momentum in the estimation stage to separate the momentum effect from the short-term mean reversal effect documented by Jegadeesh (1990) and Lehmann (1990). Thus, the momentum months are the preceding 2 to 12 months.

The specification generates the expected return forecast from the time-series returns of the individual country indexes and the world index. Assuming that the fundamental returns adjusted for market risk are identical across countries on average (as implied by a zero-beta CAPM), the time-series return estimation may be combined cross-sectionally to generate the long strategy choices as the indexes with the highest potential relative to their fundamental returns, and the short strategy choices as the indexes with the lowest potential relative to their fundamental returns.

To check whether this combination trading strategy based on equation (1.1) truly generates an improvement, we compare it with a pure seasonality strategy and a pure momentum strategy using the following models, respectively:

$$RET_t^i = \mu + \rho SEA_t^i + \eta_t^i \tag{1.2}$$

$$RET_t^i = \mu + \gamma MOM_t^i + \eta_t^i \tag{1.3}$$

We update the parameter estimates of the three models on a rolling month-by-month basis. Then we obtain the expected return in each market for the following month based on these estimates. Finally, we trade based on the expected returns.

1.3 Illustrative Parameter Estimates and Expected Trading Returns

To illustrate the implications of considering seasonality and momentum simultaneously, we examine the parameters of the three models in the base case, which uses the full-sample data for all 18 markets from Jan 1970 to Dec 2020. Table 1.2 provides the key parameter estimates.

[Table 1.2 about here]

The coefficient for the seasonality (SEA) variable under the combination (COM) trading strategy is 0.0843, somewhat larger than that for the pure SEA strategy, which is 0.0813. Similarly, the coefficient for the momentum (MOM) variable under COM is 0.00645, somewhat larger than that in the pure MOM strategy, which is 0.00637. The t-stats for the coefficients of SEA and MOM under COM are also larger than that for the pure SEA and pure MOM strategies, respectively.[9] Although the SEA variable and the MOM variable display quite low correlation, which is as small as -0.02 or -0.03, the small interaction between them is nevertheless important and the COM strategy captures it, producing larger coefficients and corresponding t-stats for both. The minor, or even negligible, negative correlation implies that the seasonality and the momentum effects arise from different risk factors,[10] rather

[9] To adjust for the fact that the returns data are autocorrelated and may be heteroskedastic we present in the tables the adjusted t-statistics (Newey and West, 1987).

[10] Some factors that potentially could affect those effects are such as tax-loss harvesting related to different tax seasons (Gultekin and Gultekin, 1983), the difference in holidays (Cadsby and Ratner, 1992; Kim and Park, 1994), inflation risks (Chaieb and Errunza, 2007), earnings-to-price ratio (Bali and Cakici, 2010), risks associated with consumption (Li and Zhong, 2005), etc.

than from different loadings on the same factor(s). COM then captures both latent factors jointly. The R^2 under COM (0.36%) is (somewhat) larger than the sum of 0.09% (pure SEA) and 0.26% (pure MOM). This information implies that when we consider the effects one at a time, the estimates are probably biased by omission of the other variable.

If we look more closely at R^2, it provides further information about the relative strength of each effect. Comparing the R^2 of COM (0.36%) with those of pure SEA (0.09%) and pure MOM (0.26%), we see that the momentum effect contributes a little more than the seasonality effect to the cross-sectional return differences at the index level. While the relative strengths are different, either effect makes a significant contribution.

Although a regression R^2 of 0.36% seems small, Cochrane (2005) p.447 notes that, at the individual stock level, even a tiny R^2 of 0.25% for forecasting monthly returns is more than adequate to generate quite strong momentum results. To compute the expected trading returns in our base case, we closely follow the methodology in Cochrane (2005) p.447:

First, we look for

$$E(r|r \geq x) = \int_x^\infty r \cdot \left(\frac{f(r)}{\int_x^\infty f(r)dr} \right) \cdot dr = \frac{\int_x^\infty r f(r)dr}{\int_x^\infty f(r)dr} \tag{1.4}$$

where x is defined as the top 1/6 (top 3 out of all 18 markets, anticipating the empirical approach we take in the following) cutoff, such that

$$\int_x^\infty f(r)dr = \frac{1}{6} \tag{1.5}$$

if we assume a normal distribution for r, we have $x = 0.9674\sigma$. Then we obtain

$$E(r|r \geq x) = 1.4991\sigma \tag{1.6}$$

Second, the standard deviation of the predictable part of monthly excess returns (take COM as an example) is $\sigma = \sqrt{R^2 \times Var(RET)} = \sqrt{0.36\% \times 0.00208} = 0.2725\%$.

It follows that $E(r|r \geq x) = 1.4991\sigma = 1.4991 \times 0.2725\% \approx 0.41\%$.

Thus, for the COM strategy in the base case, the top 3 out of all 18 markets predicted to perform best will have an average monthly excess return of 0.41%. Similarly, the bottom 3 out of the 18 markets predicted to perform worst will have an average monthly excess return of -0.41%. The long-short trading strategy for COM in the base case, accordingly, is expected to have a monthly return of about 0.82% or an annualized return of 9.80%. Similarly, the expected annual returns for the pure SEA and pure MOM strategies would be 4.91% and 8.38%, respectively. In fact, in our base case the realized mean annual returns for COM, pure SEA and pure MOM turn out to be 10.34%, 6.16% and 8.28% respectively, which are quite close to the expected returns. We provide the details for the base-case trading strategy returns in the next part.

With the parameter estimates shown in Table 1.2, which imply the little correlation between the SEA and MOM variables, one may ask the following: since COM successfully captures both effects, is it possible that COM may generate mean returns that are close to the sum of the mean returns from pure SEA and pure MOM? The answer to the question is no.

With the assumption that the correlation between SEA and MOM is almost 0 (close enough as shown in our data), we have the following:

$$\text{Pure SEA:} \quad RET_t^i = \mu_{SEA} + \rho SEA_t^i + \eta_t^i \tag{1.7}$$

$$\text{Pure MOM:} \quad RET_t^i = \mu_{MOM} + \gamma MOM_t^i + \epsilon_t^i \tag{1.8}$$

$$\text{COM:} \quad RET_t^i = \mu_{COM} + \rho SEA_t^i + \gamma MOM_t^i + \varepsilon_t^i \tag{1.9}$$

The coefficients for the SEA variable and the MOM variable in COM are assumed to be the same as those in pure SEA and pure MOM (which also approximately holds in our parameter estimates). Then we have:

$$\text{Pure SEA:} \quad Var(RET) = \rho^2 Var(SEA) + Var(\eta) \tag{1.10}$$

$$\text{Pure MOM:} \quad Var(RET) = \gamma^2 Var(MOM) + Var(\epsilon) \tag{1.11}$$

$$\text{COM:} \quad Var(RET) = \rho^2 Var(SEA) + \gamma^2 Var(MOM) + Var(\varepsilon) \tag{1.12}$$

Since we assume zero correlation between SEA and MOM, there is no covariance term in the COM specification. Based on these, we obtain the following R^2:

$$\text{Pure SEA:} \quad R^2_{SEA} = \frac{\rho^2 Var(SEA)}{Var(RET)} \tag{1.13}$$

$$\text{Pure MOM:} \quad R^2_{MOM} = \frac{\gamma^2 Var(MOM)}{Var(RET)} \tag{1.14}$$

$$\text{COM:} \quad R^2_{COM} = \frac{\rho^2 Var(SEA) + \gamma^2 Var(MOM)}{Var(RET)} \tag{1.15}$$

Thus, we have $R^2_{COM} = R^2_{SEA} + R^2_{MOM}$, which also holds approximately in our parameter estimates. Then we follow the approach in Cochrane (2005) p.447 again to find expected trading returns based on the explained part of the regressions:

$$E(r) = 2 \times 1.4991 \times Std(RET) \times \sqrt{R^2} \tag{1.16}$$

As $R^2_{COM} = R^2_{SEA} + R^2_{MOM}$, we easily infer that:

$$\max[E(r_{SEA}), E(r_{MOM})] < E(r_{COM}) < E(r_{SEA}) + E(r_{MOM}) \tag{1.17}$$

1.4 Trading Strategy Returns in the Base Case

Before back-testing the above parametric trading strategies to confirm the existence of seasonality and momentum across national equity markets at the index level and examining the advantage of COM over pure SEA and pure MOM, we need to decide on three settings.

The first decision concerns the starting point for trading. As we are considering the long-term seasonality effect up to 10 years and we need enough data points from the 11th year to start estimation, we choose to start the forecasts and trading in the 12th year after the first data point in January 1970 and then update parameter estimates each month as we roll the sample forward until December 2020. For the market beta estimation, we use all data available at the forecast point.

The second decision concerns the holding period for our trading strategies. As we need to capture the seasonality effect and compare across all three trading strategies, the holding period in our trading is constrained to be one month. Otherwise, it would not capture the same-calendar-month characteristic in the seasonality effect.

The third decision involves the number of markets in each portfolio. To maintain a balance between the total number of portfolios and the number of markets in each portfolio, we choose to divide the 18 markets into six portfolios based on their expected returns and then trade following the Max3-Min3 strategy, as used by Balvers, Wu, and Gilliland (2000), Balvers and Wu (2006), and Keloharju, Linnainmaa, and

Nyberg (2016). We also keep these settings for the other cases discussed in later parts.

With these settings, the strategy implementation requires that we first generate self-financed portfolios without world market risk for each national market (by shorting β^i times the world market portfolio), with returns $RET_t^i = r_t^i - \beta^i r_t^w$. The β^i in each period are estimated from past data so that the risk-adjusted returns can be locked in in advance. In each period, the estimated excess return in equation (1.1) for the next period is obtained given parameters and betas obtained from past data only. We hold the three national market index portfolios with the highest expected returns and short the three index portfolios with the lowest expected returns. We record the return on this position and, subsequently, keep rolling forward one month at a time, updating the various parameters and betas with the additional month's data.

1.4.1 Overall portfolio performance in the base case

In the base case, the trading involves all 18 markets with a full test sample period from January 1981 to December 2020. Table 1.3 shows the performance of the trading strategies of pure SEA, pure MOM, and COM in the base case. Overall, the portfolios show increasing mean returns from the bottom (Min3) to the top (Max3) in all three trading strategies. Such returns confirm the existence of the seasonality effect and the momentum effect in the national equity market indexes. Further, the results for COM reveal advantages compared to pure SEA and pure MOM. If we inspect the mean returns for portfolios 1-3, COM tends to be smaller than pure SEA and pure MOM, while, for portfolios 4-6, COM tends to be larger than pure SEA and pure MOM. The long-short strategy of top minus bottom (Max3-Min3) in COM performs substantially better than the others. Similar results apply for the comparison of t-stats and Sharpe ratios. On the whole, COM displays a better risk-return tradeoff than pure SEA or pure MOM, which makes it potentially more appealing as an investment strategy.

[Table 1.3 about here]

In our sample data, the Max3-Min3 seasonality effect shows up with an annualized return of 6.16%. As a brief comparison, the top10%-bottom10% annualized returns from Heston and Sadka (2008) and Heston and Sadka (2010) at the individual stock level are around 5% - 8% for seasonality years of 2 and above. Their sample data consist of hundreds or even thousands of individual stocks in each market and trades the top10% - bottom10% while we only work with 18 indexes and trade top 1/6 - bottom 1/6, which gives us fewer opportunities and less cross-sectional difference to exploit. Thus, intuitively our trading returns from pure SEA would tend to be lower. In fact, our trading returns are quite comparable, although 6.16% does not seem abnormal at first glance. In addition, the return is quite comparable with the results from Keloharju, Linnainmaa, and Nyberg (2016), which is 5.76% per year.

In the parameter estimation section, we indicated that the momentum effect seems to have more influence on the COM than the seasonality effect. To check this with our trading returns, we compute the correlations among the top minus bottom (Max3-Min3) trading returns from all trading strategies in the base case. Table 1.4 presents the results.

[Table 1.4 about here]

Overall, the results from the trading strategies are closely aligned with the results from the parameter estimation. For example, the correlation between trading returns from COM and pure SEA is around 0.4 while it is around 0.7 for COM and pure MOM, showing a relatively stronger influence from the momentum effect on COM.

Further, the correlation between trading returns from pure SEA and pure MOM is about -0.05 or -0.08, which is a minor negative correlation. This is similar to the correlation between the SEA variable and MOM variable, which is about -0.02 or -0.03 as shown in Table 1.2. Thus, we confirm that the seasonality effect and the momentum effect are almost uncorrelated, at least at the index level for developed markets.

1.4.2 Cumulative returns and returns in subperiods

Figure 1.1 shows the cumulative returns in the base case. COM improves the trading returns significantly when compared to pure SEA and pure MOM. Note also that COM seems to capture the better of both SEA and MOM. For example, MOM does not work quite as well in the second half of the sample period, but COM seems to be affected little by the poor performance of MOM in that period. Rather, it seems COM captures the strong performance of SEA for that period.

[Figure 1.1 about here]

It is common for a trading strategy to perform relatively well in one subperiod and relatively poorly in another subperiod. One advantage of our parametric approach applied to the COM trading strategy is that it potentially rebalances the weights of each effect dynamically through time. To check this in detail, Table 1.5 presents the long-short portfolio performance in subperiods for the three trading strategies. We observe that COM performs better than SEA and MOM in each subperiod. The Sharpe ratios convey a similar message.

[Table 1.5 about here]

The reason that COM performs better than either pure SEA or pure MOM can be explained intuitively. There may be some subperiods when only one of SEA or

MOM works well. In the COM strategy, as we update the regression parameters each month through time, the effect that works better in most recent months is assigned a larger coefficient while the one that works less well is assigned a smaller coefficient. This mechanism potentially rebalances the weights of SEA and MOM dynamically, thus capturing the better effect in each period. The trading results of one are potentially enhanced by the other in bad periods in comparison to their pure counterparts.

Comparison of the strategy performances relative to the strategy of borrowing and investing to hold the world market portfolio illustrates that all three of the strategies (SEA, MOM, and COM) outperform the market in each of the sub-periods (except for SEA in 1991-2000), apart from the last period 2011-2020 for which the market strategy performs better.

Note that using the market excess return as a benchmark here is only for considering relative magnitudes. The market excess returns have substantial market risk (beta equals one by design), whereas the COM strategy returns are market neutral (beta equals zero by design). The reason that the COM strategy returns fall during the sample period may be random chance or could be a manifestation of the post-publication reversion documented by Mclean and Pontiff (2016). A more fitting explanation, however, is that return correlations have increased across country indexes as noted by Goetzmann, Li, and Rouwenhorst (2005) and Umutlu and Yargi (2021). In turn, the higher correlations are linked to increasing market integration (Kearney and Lucey, 2004, and Quinn and Voth, 2008) over time. From this perspective there is no post-publication reversion. The lower strategy returns occur because there are simply fewer opportunities to exploit differences among country indexes.

1.4.3 The time trend in returns

From checking the trading strategy performance in the 4 subperiods of 10 years, we note a major difference before and after 2000. To examine whether it is a structural change in the efficiencies of our trading strategies or just evolution of the markets themselves, we plot Figure 1.2. In the top panel of Figure 1.2, each data point represents the 60-month moving average of the cross-sectional standard deviations for the 18 markets monthly returns over time. In the bottom panel of Figure 1.2, we show the 60-month moving averages of the trading returns from our three trading strategies through time.

[Figure 1.2 about here]

We observe that the cross-sectional differences among the 18 markets are reduced over time. Meanwhile, most long-short trading strategies in the literature, including our three trading strategies, attempt to exploit cross-sectional differences among stocks or indexes. Thus, the returns from such trading strategies based on current sample data tend to fall over time. Zaremba, Umutlu, and Maydybura (2020) document that the profitability of 53 anomalies in country and industry indexes from 64 markets has significantly decreased and that the phenomenon is strongest in large developed markets, identifying an overall improvement in international equity market efficiency as the cause. In addition, Mclean and Pontiff (2016) argue that investors learn about mispricing in the market from academic publications, which contributes to narrowing the cross-sectional differences among stocks or indexes. Such mechanisms may explain the decline in the returns of our three trading strategies through time.

1.4.4 Trading returns across calendar months

As we consider seasonality in this research, it is necessary to check the mean returns across calendar months, to check whether the effect arises merely from specific calendar months such as the well-known January effect (Rozeff and Kinney, 1976). Table 1.6 presents results for the base case. It shows that 8 out of the 12 calendar months perform well in the pure SEA strategy, while 7 out of 12 perform well in the pure MOM strategy. At the same time, COM shows its advantage over both pure SEA and pure MOM with 10 out of 12 calendar months performing well. Especially for April, when neither pure SEA nor pure MOM works, COM still achieves a relatively good trading return. Table 1.6 also shows the standard deviation for the mean returns across calendar months for each trading strategy. COM demonstrates its advantage with smaller variation across calendar months in comparison to pure SEA and pure MOM.

[Table 1.6 about here]

Interestingly, the trading returns from pure MOM illustrate a pattern quite like the Halloween indicator "sell in May and go away", which claims that stock returns are lower during the May-October period than during the remainder of the year (Bouman and Jacobsen, 2002). Although the literature generally treats the Halloween indicator as a sign of the existence of the seasonality effect and Bouman and Jacobsen (2002) test the Halloween indicator also with MSCI indexes, our trading returns from pure SEA do not display a Halloween indicator pattern. In fact, there is a methodological difference between Bouman and Jacobsen (2002) and our study. Bouman and Jacobsen (2002) mainly focus on the time series of each market, while we are interested in the cross-sectional differences among markets. Our trading returns from pure SEA imply that the Halloween indicator is more significant in some markets than in others. Thus, cross-sectional differences exist among the indexes, which enables our pure SEA trading strategy to perform well even during the May-October period. Affected by both pure SEA and pure MOM, therefore, the trading returns from COM do not show a pattern that is similar to the Halloween indicator.

1.4.5 Returns after risk adjustment with the Fama-French risk factors for developed markets

Although the current parametric procedure embeds the basic risk adjustment from the global market factor, it is interesting to check whether the trading returns arise from exposure to other common risk factors. Fama and French (1993) and Fama and French (2015) introduce 3-factor and 5-factor models to explain asset returns in the U.S. market. They have modified these factors for use in developed international markets. The data are available in Kenneth R. French's online data library. We control here for these international Fama-French factors to investigate the risk adjusted returns for the three trading strategies. As the international Fama-French factor data start from July 1990, we perform these risk adjustments for our trading returns in the base case from July 1990 to December 2020 with a total of 366 months. Table 1.7 shows the results.

[Table 1.7 about here]

We note that the alphas (risk-adjusted returns) are quite like, and in fact tend to be larger than, the raw trading returns. Although sometimes the coefficients for the international Fama-French factors are statistically significant, which could explain the trading returns, the coefficients are quantitatively quite small, which makes them economically insignificant. Thus, a large part of the trading returns remains unexplained by the international Fama-French factors. If we were to stick with a risk explanation of the trading returns, this would require some unknown or latent risk factors to contribute to the two effects and the associated returns for the three trading strategies.[11]

1.4.6 Controlling for trading costs

Heston and Sadka (2008) point out an important distinction between seasonality strategies and other trading strategies such as momentum, that the seasonality strategy potentially requires rebalancing the entire portfolio every month, while momentum requires rebalancing only part of the portfolio every few months. Thus, it is necessary to check the turnover rate inherent in our three trading strategies to control for the transaction costs. In the base case, the turnover rates for the pure SEA, pure MOM and COM trading strategies are 82.64%, 27.70% and 54.49%, respectively. These turnover rates are as expected. Considering that the mean returns for the three trading strategies are 6.16%, 8.28% and 10.34%, respectively, the advantage of COM over pure SEA is easy to spot. When comparing COM with pure MOM, it is a little difficult to obtain an unambiguous conclusion without quantitatively specifying the trading costs.

Considering the current situation in which many online brokers provide commission-free service to investors,[12] the main difference in the trading costs of the three strategies is contained in the bid-ask spread. Taking the average bid-ask spread for the series of iShares ETFs tracking various MSCI developed markets to be 11 bps,[13] the annualized trading cost for the pure SEA, pure MOM, and COM strategies would be

[11]Explanations for the trading returns may be found among the country-specific characteristics discussed in Bali and Cakici (2010), Kim (2012), Zaremba (2019), Umutlu and Bengitoz (2021), and others. Many of these characteristics are captured by the five Fama-French global risk factors. We consider these in a Fama-MacBeth framework and find that the factor betas are all insignificant for the cross-sectional index return differences when added to our COM measure (results are available from the authors). The Fama-MacBeth methodology may also be used to examine the explanatory power of alternative characteristics addressed in the above literature such as political risk, economic freedom, idiosyncratic volatility, and credit risk, but we leave an exhaustive study of these for future research.

[12]For example, Robinhood, InteractiveBrokers, Fidelity, TD Ameritrade and E*TRADE in the U.S. and WealthSimple Trade and National Bank Direct Brokerage in Canada.

[13]iShares has ETFs in U.S. dollars tracking the MSCI developed markets indexes in our sample (all 18 except the U.S.) The average bid-ask spread for each ETF can be found at

1.09%, 0.37%, and 0.72%, respectively. These do not differ enough to compensate for the difference in expected returns. Moreover, if we could choose to trade only in selected calendar months rather than all year, COM provides a better perspective as 10 months works well for COM while only 7 months works well for pure MOM. Overall, the results are strong enough to demonstrate the advantage of COM over pure SEA and pure MOM. COM could be a desirable option for active trading in the practice of global asset allocation.

1.4.7 Trading returns sensitivity to sextiles

To check the robustness of our trading returns to variation in the current Max3-Min3 strategy for the base case, Table 1.8 reports the trading returns for different numbers of markets in each of the Max and Min portfolios for the three trading strategies. The more markets are included in the Max and Min portfolios, the smaller the mean trading returns, which is as expected. Even when we trade with Max6-Min6 using two thirds of all 18 markets, while the mean returns are smaller than for the Max3-Min3 strategies, they are still comparable with returns from previous studies. Furthermore, the trading returns from different numbers of markets in the Max and Min portfolios remain statistically significant. Thus, the positive trading returns are not confined to a small subset of markets.

[Table 1.8 about here]

1.5 Trading Strategies Returns for Other Cases

To confirm whether the seasonality effect and the momentum effect exist in national equity markets and the combination trading strategy truly performs better

iShares.com. The average of 11 bps here is based on the data reported on the website for March 2021.

than both the pure seasonality strategy and pure momentum strategy, we check whether the results are to some extent due to some individual markets with particularly high or low average returns.

To execute the task above, we randomly choose 9 out of the 18 markets and then trade along the previous strategies. We estimate the parameters and compute the expected returns for the 9 markets chosen, then we long the Max3 and short the Min3. We choose 9 markets because it represents exactly half of the 18 markets, thus giving us the most different possible combinations of markets. As we trade with Max3-Min3 we are trading two thirds of the 9 markets chosen, which is a quite strict standard in long-short trading strategies of this type. With a total of 48,620 different combinations of 9 markets,[14] we generate the trading results shown in Table 1.9. Each mean return in the data is the average of all 48,620 possible mean returns for that specific trading strategy.

[Table 1.9 about here]

The mean returns for pure SEA, pure MOM, and COM are 3.76%, 5.95%, and 6.43%, respectively. These results confirm that the seasonality effect and the momentum effect truly exist in national equity market indexes. The results are comparable to the Max6-Min6 trading returns when we also trade two thirds of all included markets. From Table 1.8, these mean returns are 4.37%, 6.20% and 6.68%, respectively. This "choosing 9 markets" methodology has the advantage that it generates distributions for the mean returns of the three trading strategies, making it possible to conduct a formal t-test to check whether COM genuinely outperforms pure SEA and pure MOM, as a robustness check relative to the Newey-West (Newey and West, 1987) t-statistics which are robust but generated alternatively. The results in

[14] We also use an analogous approach for randomly choosing 10, 11 and 12 markets and generate similar results. The more markets in our sample, the stronger the results, which is as expected because more markets mean more opportunities for trading strategies to exploit.

Table 1.9 show that the superior performance of COM is statistically significant in all cases.

To further examine the distributions of the mean returns from the 48,620 combinations of "choosing 9 markets", we plot Figure 1.3. We also add a pure random trading strategy with 48,620 simulations for the sake of comparison. In each simulation with the 9 markets already chosen, we randomly choose 3 markets to hold and another 3 markets to short each month. This pure random strategy is used as a benchmark to help us identify the significance of both effects.

[Figure 1.3 about here]

Comparing the distributions in Figure 1.3, the existence of both seasonality and momentum is confirmed. The improved performance of COM is confirmed as well. Furthermore, for the pure SEA, there is a probability of 3.52% of obtaining negative mean returns, out of all 48,620 combinations, while such probability for pure MOM or COM is 0.

A further advantage of the "choosing 9 markets" robustness check is that it provides the frequency with which certain markets are selected in Max3 or Min3. With this information, we can take a closer look at whether the seasonality effect and the momentum effect are driven by several specific markets or whether these phenomena exist across all developed markets. Table 1.10 shows the frequency table of markets which are selected in Max3 and Min3 based on the 48,620 combinations of Choosing 9 markets.

[Table 1.10 about here]

The overall picture presented by Table 1.10 is that the returns from our three trading strategies are not just driven by several specific markets. As there are a total of 18 markets, the probability for each market to be selected in the Max3 or Min3 should be about 1/18=5.56% if realizations are fully random and seasonality and momentum are absent. Viewing the top 3 markets in each category, their frequencies in Max3 or Min3 are mostly around 7%-8% (roughly 1/14 - 1/12), which is not a significant deviation from the mean of 5.56% under randomness. The difference in the frequencies is not substantial. We confirm that neither the seasonality effect nor the momentum effect is driven by a few specific markets.

When we compare the mean monthly return of a specific market with its probability to be selected in Max3 or Min3, a weak correlation pops up. For example, the three markets with the lowest mean returns are Austria, Singapore and Italy, and their ranks in the frequencies to be selected in the SEA Min3 are 6, 3, and 1, respectively, their ranks in the MOM Min3 are 6, 5, and 3, respectively; and their ranks in the COM Min3 are 9, 3, and 4, respectively. Singapore and Italy tend to be selected in the Min3, while Austria is not, although it has the lowest mean returns. Something similar happens with the top 3 highest mean returns markets: Sweden, Denmark, and the Netherlands. Their ranks in the frequencies to be selected in the SEA Max3 are 3, 1, and 12, respectively; their ranks in the MOM Max3 are 5, 1, and 4, respectively; and their ranks in the COM Max3 are 3, 1, and 6.

The weak correlation between a market's mean returns and its frequency to be selected in Max3 or Min3 may raise a question: what would happen if investors just chose to hold the 3 markets with historical high mean returns and short the 3 markets with historical low mean returns? Conrad and Kaul (1998) raise a similar question. We perform such a trading test. With the same period of 480 months from January 1981 to December 2020, the mean annualized trading return for the strategy is -0.94%.

Additionally, to examine the issue of choosing markets with higher returns more frequently in the long portfolio and less frequently in the short portfolio, we simply calculate the selection-frequency-weighted average returns shown in the bottom row of Table 1.10. The first column of the bottom row lists the equal-weighted monthly return of 0.78%. The subsequent entries are the sums of the country market mean monthly returns times the frequencies these markets are picked in the specific strategies. The weighted max3 returns are indeed higher than the weighted min3 returns for all three of the strategies. It is 4bps for SEA, and 7bps for MOM and COM. However, annualized these amounts are less than one percent in each case, insufficient to explain our trading returns.

These findings illustrate that although a weak correlation exists between historical mean returns and the likelihood of showing up in Max3 or Min3, it is not the driver for the seasonality effect or the momentum effect. It is the timing of when to select a country market rather than the frequency of the selection of the country market that is responsible for the seasonality and momentum results.

1.6 Conclusion

This paper examines seasonality and momentum jointly across national equity markets. We confirm their existence at the index level and find that seasonality and momentum have little or no correlation and may emanate from separate global or local risk factors, rather than from different loadings on the same risk factor(s). Employing a parametric trading strategy that enables combining seasonality and momentum, we confirm the conclusion about the relationship between seasonality and momentum. In addition, the combination trading strategy shows statistically and economically significant trading returns and outperforms the corresponding pure seasonality and pure momentum strategies, and potentially could be useful in practice as part of a global asset allocation strategy.

As global markets are becoming more integrated over time, especially among developed economies, it may be expected that cross-sectional return discrepancies are reduced over time, and that therefore the trading strategies based on our set of developed economies are becoming less profitable. We find, in fact, that cross-sectional return volatility has decreased over our sample period and that, concomitantly, the strategy returns have decreased, as illustrated in both panels of Figure 2. Comparing the 20 years before 2000 to the 20 years after, the cross-sectional standard deviation of returns fell from around 5.0% to 3.0%, and trading returns of the combination strategy fell from around 13.5% to 5.5%. If the reason for the reduced profitability is indeed the increased market integration, it is likely that no such reduction in profitability is observed for emerging economies, for which the level of market integration is lower. Investigation of the momentum and seasonality returns in emerging economies relative to developed economies would be an interesting issue for future research.

FIGURE 1.1: Cumulative returns in the base case

This figure shows the cumulative returns for the three trading strategies in the base case employing the full sample of data for all 18 markets from January 1981 to December 2020. SEA stands for seasonality; MOM stands for momentum and COM stands for the combination trading strategy which considers seasonality and momentum jointly. The seasonality years are 2:10 and the momentum months are 2:12.

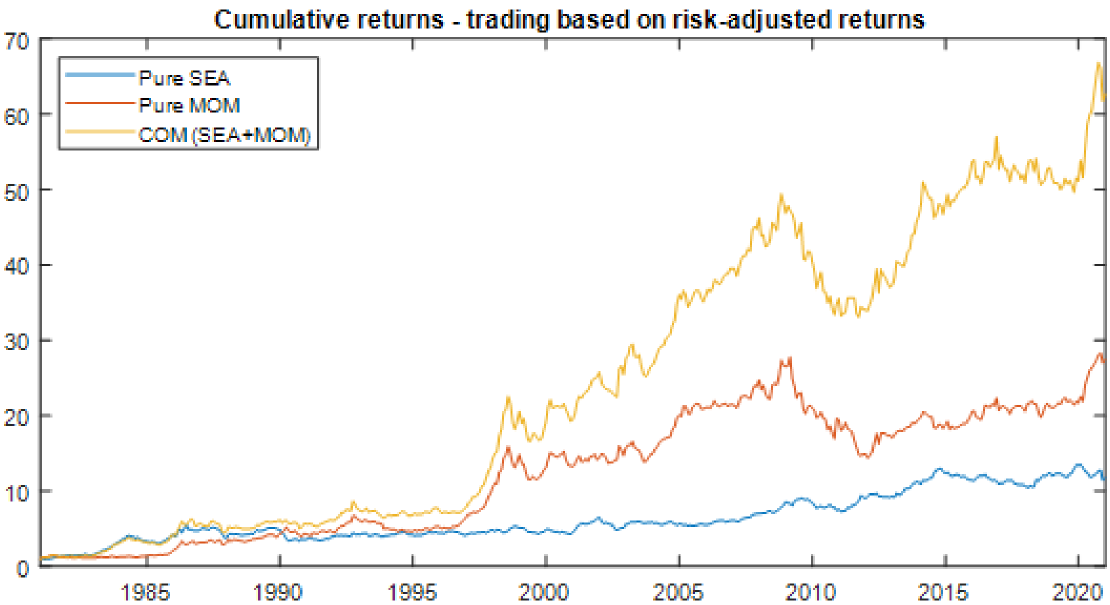


Figure 1.2: Time trend in returns

This figure uses a 60-month moving average to display the time trend in returns for both the cross-sectional standard deviation among the 18 markets (top panel) and for our three trading strategies returns (bottom panel). SEA stands for seasonality; MOM stands for momentum and COM stands for the combination trading strategy. The seasonality years are 2:10 and momentum months are 2:12.

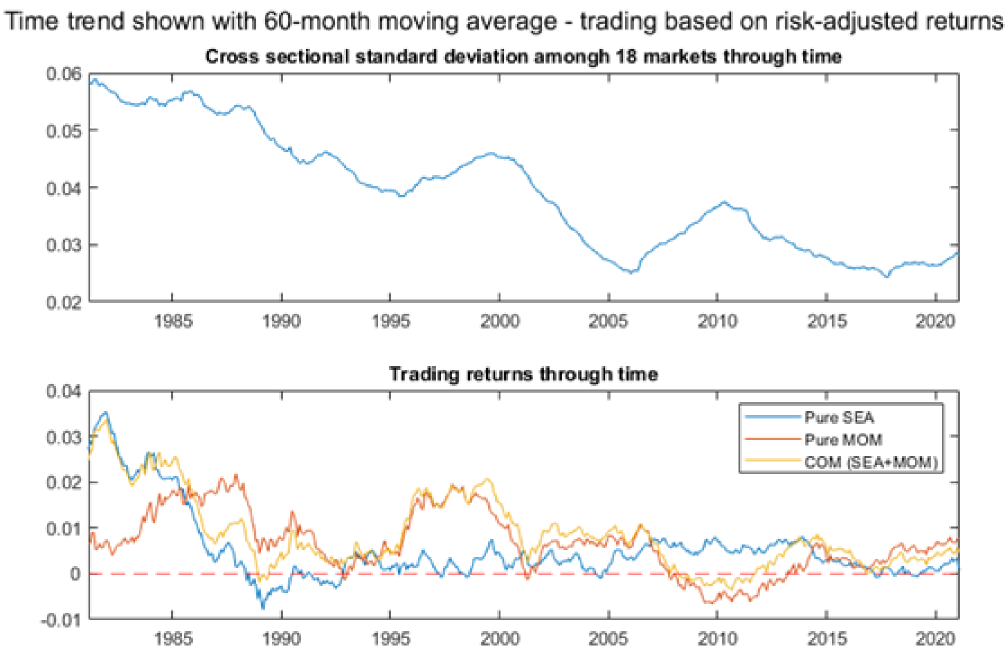


Figure 1.3: Distributions of mean returns from choosing 9 markets

This figure shows the distributions of mean returns for the pure random and the three parametric trading strategies from randomly choosing 9 markets out of the 18 markets. For pure random, in each simulation with the 9 markets chosen, we randomly choose 3 markets to hold and another 3 markets to short in each month. SEA stands for seasonality; MOM stands for momentum; and COM stands for the combination trading strategy which considers seasonality and momentum jointly. The seasonality years are 2:10 and momentum months are 2:12. The mean returns are annualized.

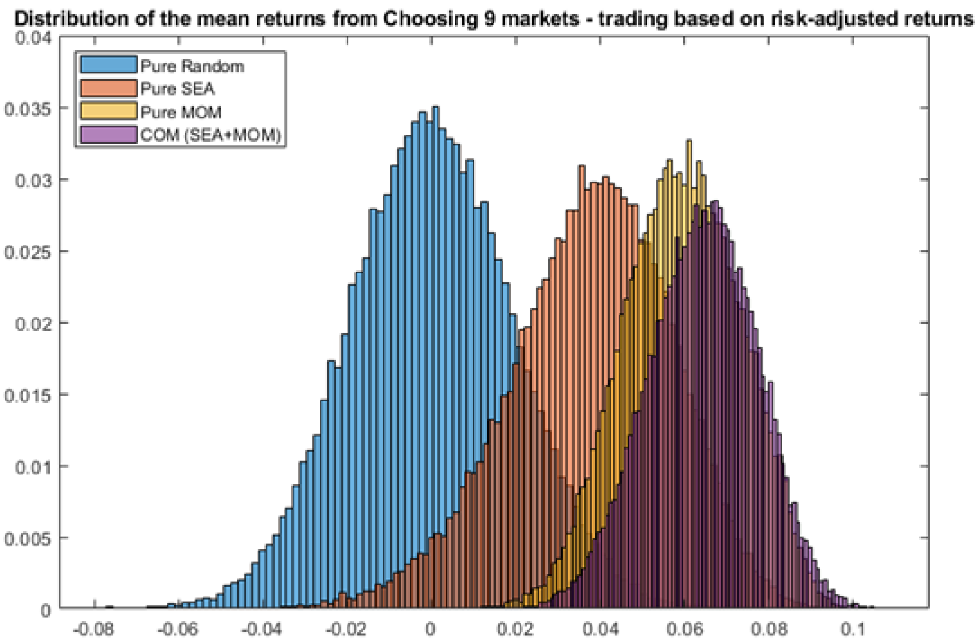


Table 1.1: Summary statistics of sample data

This table reports summary statistics for the monthly returns of 18 MSCI developed market indexes and the MSCI World index for the period from January 1970 to December 2020.

Market	Mean Ret.(% per month)	Std. Dev. (% per month)	β with the World index
Australia	0.71	7.09	1.11
Austria	0.61	7.09	0.95
Belgium	0.82	6.03	1.01
Canada	0.73	5.71	1.04
Denmark	1.05	5.54	0.81
France	0.78	6.41	1.11
Germany	0.75	6.34	1.09
Hong Kong	1.09	9.44	1.13
Italy	0.43	7.33	1.02
Japan	0.73	5.85	0.93
Netherlands	0.96	5.52	1.05
Norway	0.79	7.83	1.19
Singapore	0.80	7.93	1.16
Spain	0.64	6.81	1.03
Sweden	1.01	6.78	1.13
Switzerland	0.90	5.10	0.87
United Kingdom	0.72	6.02	1.06
United States	0.83	4.44	0.92
World	0.78	4.31	1.00

Table 1.2: Model parameters in the base case

This table reports key parameter estimates for the full sample data with all 18 markets from January 1970 to December 2020. The dependent variable in the three models in Panel A is RET - the World market risk adjusted return defined in Section 1.2. Panel B reports the correlation between SEA and MOM. SEA represents seasonality (the variable as well as the trading strategy); MOM represents momentum (the variable as well as the trading strategy) and COM indicates the combination trading strategy which considers seasonality and momentum jointly. The seasonality years are 2:10 and the momentum months are 2:12. Numbers in parentheses are adjusted t-stats (Newey and West, 1987).

Panel A: Key parameter estimates for three regression models			
Moment	Pure SEA	Pure MOM	COM (SEA+MOM)
Intercept	-0.00071	-0.00068	-0.00070
	(-1.35)	(-1.38)	(-1.41)
Coefficient for SEA variable	0.0813		0.0843
	(2.11)		(2.19)
Coefficient for MOM variable		0.00637	0.00645
		(4.54)	(4.59)
Var (RET)	0.00208	0.00208	0.00208
Var (Residual)	0.00208	0.00208	0.00208
Var (Residual) / Var (RET) (%)	99.91%	99.74%	99.64%
R^2 (%)	0.09%	0.26%	0.36%
Panel B: Correlation between SEA and MOM			
Correlation based on full sample		-0.0210	
Mean correlation based on rolling 10-year data		-0.0273	
		(-7.56)	

TABLE 1.3: Portfolio performance in the base case

This table reports portfolio performance for the full sample data with all 18 markets from January 1981 to December 2020. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and the momentum months are 2:12. Numbers in parentheses are adjusted t-stats (Newey and West, 1987). The mean returns, alphas (from the CAPM) and Sharpe ratios are annualized. Each portfolio consists of three markets based on the sextiles of the expected returns across all 18 markets. Panel A considers strategy results for unadjusted (raw) returns; Panel B considers strategy results for returns adjusted for world market risk.

Panel A: Portfolio performance based on raw returns								
		Bottom	2	3	4	5	Top	Top-Bottom
	Mean Return	5.26%	8.47%	10.26%	9.39%	11.16%	11.18%	5.92%
Pure SEA		(1.60)	(2.32)	(3.18)	(3.03)	(3.53)	(3.32)	(2.39)
	Alpha	-0.38%	2.04%	4.28%	3.27%	5.34%	4.95%	5.32%
		(-0.18)	(1.05)	(2.51)	(2.10)	(3.00)	(2.52)	(2.06)
	Sharpe Ratio	0.07	0.23	0.34	0.30	0.39	0.37	0.44
	Mean Return	4.84%	7.78%	9.80%	10.34%	11.09%	11.87%	7.03%
Pure MOM		(1.45)	(2.14)	(3.07)	(3.41)	(3.07)	(3.58)	(2.74)
	Alpha	-1.41%	1.41%	3.90%	4.63%	4.92%	6.06%	7.48%
		(-0.71)	(0.65)	(2.06)	(2.70)	(2.30)	(3.31)	(2.94)
	Sharpe Ratio	0.05	0.19	0.32	0.36	0.36	0.43	0.45
	Mean Return	3.77%	7.66%	9.96%	11.31%	9.65%	13.37%	9.60%
COM (SEA+ MOM)		(1.13)	(2.23)	(3.07)	(3.50)	(2.73)	(4.06)	(3.59)
	Alpha	-1.97%	1.14%	3.91%	5.48%	3.38%	7.55%	9.51%
		(-0.94)	(0.56)	(2.09)	(3.29)	(1.79)	(3.93)	(3.40)
	Sharpe Ratio	-0.01	0.18	0.32	0.41	0.29	0.51	0.67
Panel B: Portfolio performance based on risk-adjusted returns								
		Bottom	2	3	4	5	Top	Top-Bottom
	Mean Return	-3.96%	-0.49%	0.85%	0.41%	2.10%	2.19%	6.16%
Pure SEA		(-2.00)	(-0.25)	(0.53)	(0.27)	(1.26)	(1.18)	(2.39)
	Alpha	-4.07%	-1.45%	0.21%	-0.36%	1.55%	1.42%	5.49%
		(-1.99)	(-0.75)	(0.13)	(-0.24)	(0.89)	(0.76)	(2.06)
	Sharpe Ratio	-0.68	-0.42	-0.32	-0.38	-0.17	-0.16	0.45
	Mean Return	-4.71%	-1.96%	0.42%	1.62%	2.16%	3.57%	8.28%
Pure MOM		(-2.36)	(-0.95)	(0.23)	(1.00)	(1.08)	(2.00)	(2.96)
	Alpha	-5.46%	-2.87%	-0.02%	1.36%	1.36%	2.92%	8.37%
		(-2.70)	(-1.35)	(-0.01)	(0.83)	(0.67)	(1.59)	(2.94)
	Sharpe Ratio	-0.73	-0.49	-0.34	-0.23	-0.15	-0.03	0.52
	Mean Return	-5.61%	-1.88%	0.53%	2.20%	1.13%	4.73%	10.34%
COM (SEA+ MOM)		(-2.60)	(-0.98)	(0.31)	(1.37)	(0.61)	(2.61)	(3.58)
	Alpha	-5.76%	-2.95%	-0.07%	1.70%	0.23%	4.15%	9.90%
		(-2.66)	(-1.47)	(-0.04)	(1.08)	(0.13)	(2.21)	(3.40)
	Sharpe Ratio	-0.82	-0.51	-0.33	-0.17	-0.26	0.08	0.68

Table 1.4: Correlations among the trading returns

This table reports the correlations among the top minus bottom (Max3-Min3) trading returns in the base case with portfolios consisting of three indexes, using the full sample of data for all 18 markets from January 1981 to December 2020. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and the momentum months are 2:12. Panel A considers results for strategy returns for unadjusted (raw) returns; Panel B considers results for strategy returns adjusted for world market risk.

Panel A: Trading based on raw returns			
	Pure SEA	Pure MOM	COM (SEA+MOM)
Pure SEA	1.0000	-0.0834	0.3964
Pure MOM	-0.0834	1.0000	0.6808
COM (SEA+MOM)	0.3964	0.6808	1.0000
Panel B: Trading based on risk-adjusted returns			
	Pure SEA	Pure MOM	COM (SEA+MOM)
Pure SEA	1.0000	-0.0491	0.4141
Pure MOM	-0.0491	1.0000	0.6884
COM (SEA+MOM)	0.4141	0.6884	1.0000

Table 1.5: Trading returns in subperiods in the base case

This table reports the trading returns of the three strategies for four 10-year subperiods in the base case using the full sample of data for all 18 markets from January 1981 to December 2020. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and momentum months are 2:12. “World" is the return from the MSCI World index and “Rf" is the U.S. risk free rate. The mean returns and Sharpe ratios are annualized. Numbers in parentheses are adjusted t-stats (Newey and West, 1987). Panels A and B consider results for strategy returns for unadjusted (raw) returns; Panels C and D consider results for strategy returns adjusted for world market risk.

	1981-1990	1991-2000	2001-2010	2011-2020
Panel A: Mean returns – trading based on raw returns				
Pure SEA	12.75%	1.64%	4.12%	5.19%
	(1.69)	(0.49)	(1.11)	(1.60)
Pure MOM	11.41%	10.92%	2.86%	2.92%
	(1.89)	(1.78)	(0.76)	(0.82)
COM (SEA+MOM)	15.54%	12.00%	5.42%	5.45%
	(2.26)	(2.01)	(1.43)	(1.87)
World - Rf	5.68%	7.09%	0.62%	9.42%
	(1.05)	(2.09)	(0.09)	(2.55)
Panel B: Sharpe ratios – trading based on raw returns				
Pure SEA	0.65	0.13	0.40	0.53
Pure MOM	0.56	0.68	0.23	0.26
COM (SEA+MOM)	0.83	0.77	0.50	0.52
World - Rf	0.36	0.55	0.04	0.67
	1981-1990	1991-2000	2001-2010	2011-2020
Panel C: Mean returns – trading based on risk-adjusted returns				
Pure SEA	12.85%	2.23%	5.18%	4.36%
	(1.63)	(0.66)	(1.33)	(1.36)
Pure MOM	14.39%	11.44%	3.84%	3.43%
	(2.10)	(1.82)	(0.93)	(0.95)
COM (SEA+MOM)	17.28%	12.40%	6.03%	5.67%
	(2.25)	(2.00)	(1.51)	(1.95)
World - Rf	5.68%	7.09%	0.62%	9.42%
	(1.05)	(2.09)	(0.09)	(2.55)
Panel D: Sharpe ratios – trading based on risk-adjusted returns				
Pure SEA	0.64	0.18	0.48	0.45
Pure MOM	0.68	0.70	0.28	0.31
COM (SEA+MOM)	0.85	0.78	0.51	0.54
World - Rf	0.36	0.55	0.04	0.67

Table 1.6: Trading returns across calendar months

This table reports the trading returns across calendar months for the three strategies in the base case using the full sample of data for all 18 markets from January 1981 to December 2020. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and momentum months are 2:12. The mean returns are annualized. Numbers inside parentheses are adjusted t-stats (Newey and West, 1987). Panel A considers results for strategy returns for unadjusted (raw) returns; Panel B considers results for strategy returns adjusted for world market risk.

Panel A: Trading based on raw returns							
	Jan	Feb	Mar	Apr	May	Jun	
Pure SEA	9.25%	12.70%	-5.07%	-2.26%	14.44%	9.60%	
	(1.13)	(2.02)	(-0.58)	(-0.25)	(2.67)	(1.78)	
Pure MOM	15.06%	14.89%	19.47%	-0.94%	0.30%	14.04%	
	(1.67)	(2.27)	(2.03)	(-0.09)	(0.05)	(1.82)	
COM (SEA+MOM)	16.44%	18.40%	11.34%	6.23%	8.13%	14.45%	
	(1.91)	(2.23)	(2.08)	(0.77)	(1.07)	(2.47)	
	Jul	Aug	Sep	Oct	Nov	Dec	Std.
Pure SEA	6.10%	14.37%	-0.72%	8.62%	-4.56%	8.60%	7.20%
	(0.96)	(3.01)	(-0.12)	(1.11)	(-0.65)	(1.10)	
Pure MOM	-6.89%	-3.32%	11.83%	-4.62%	9.12%	15.39%	9.40%
	(-1.21)	(-0.46)	(1.59)	(-0.40)	(1.00)	(1.60)	
COM (SEA+MOM)	9.84%	0.89%	11.55%	-4.73%	9.38%	13.28%	6.49%
	(1.65)	(0.13)	(1.50)	(-0.53)	(1.60)	(1.71)	
Panel B: Trading based on global market risk adjusted returns							
	Jan	Feb	Mar	Apr	May	Jun	
Pure SEA	4.71%	15.26%	-2.71%	-1.39%	13.83%	9.64%	
	(0.68)	(2.22)	(-0.27)	(-0.15)	(2.31)	(2.01)	
Pure MOM	17.36%	15.02%	19.90%	1.06%	-0.35%	15.85%	
	(1.82)	(2.18)	(2.13)	(0.10)	(-0.05)	(2.06)	
COM (SEA+MOM)	14.89%	19.60%	12.72%	7.95%	8.50%	15.17%	
	(1.75)	(2.18)	(2.10)	(0.94)	(1.06)	(2.72)	
	Jul	Aug	Sep	Oct	Nov	Dec	Std.
Pure SEA	4.46%	13.97%	0.34%	7.59%	-4.65%	12.82%	7.09%
	(0.68)	(2.69)	(0.55)	(1.01)	(-0.71)	(1.66)	
Pure MOM	-5.52%	-3.71%	13.92%	-4.78%	13.13%	17.45%	9.96%
	(-0.91)	(-0.42)	(1.82)	(-0.43)	(1.40)	(1.72)	
COM (SEA+MOM)	10.25%	-1.75%	11.92%	-4.60%	13.18%	16.30%	7.13%
	(1.80)	(-0.22)	(1.43)	(-0.52)	(1.97)	(2.03)	

TABLE 1.7: Returns after adjustment for risk factors

Trading returns after adjustment with the international Fama-French factors for the base case using the full sample of data for all 18 markets from July 1990 to December 2020. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and the momentum months are 2:12. Raw returns are the mean returns from our three trading strategies for the period starting from July 1990, which is the available starting point for the international Fama-French three or five factors. Alphas are the risk-adjusted returns based on the CAPM, Fama-French three-factor, and Fama-French five-factor models. World-Rf is the world market risk premium. SMB is the size factor. HML is the value factor. RMW is the profitability factor and CMA is the investment factor. Raw returns and alphas are annualized based on monthly returns. The numbers shown for World-Rf, SMB and HML are coefficients. Numbers in parentheses are adjusted t-stats (Newey and West, 1987). Panel A considers results for strategy returns for unadjusted (raw) returns; Panel B considers results for strategy returns based on returns first adjusted for world market risk.

Panel A: Trading based on raw returns							
	Raw Returns	Alphas	World - Rf				
Pure SEA	3.68% (1.88)	3.60% (1.81)	0.0137 (0.27)				
Pure MOM	5.30% (1.95)	6.46% (2.28)	-0.1857 (-3.19)				
COM (SEA+MOM)	7.61% (2.97)	8.14% (3.12)	-0.0859 (-1.71)				
	Raw Returns	Alphas	World - Rf	SMB	HML		
Pure SEA	3.68% (1.88)	3.73% (1.92)	0.0111 (0.21)	-0.1319 (-1.37)	-0.0563 (-0.62)		
Pure MOM	5.30% (1.95)	7.02% (2.47)	-0.2042 (-3.54)	0.1112 (1.08)	-0.2448 (-2.35)		
COM (SEA+MOM)	7.61% (2.97)	8.63% (3.32)	-0.1007 (-2.00)	-0.0114 (-0.11)	-0.2101 (-1.87)		
	Raw Returns	Alphas	World - Rf	SMB	HML	RMW	CMA
Pure SEA	3.68% (1.88)	3.10% (1.52)	0.0203 (0.34)	-0.1020 (-1.02)	0.0031 (0.02)	0.1652 (1.11)	-0.0870 (-0.45)
Pure MOM	5.30% (1.95)	4.94% (1.63)	-0.1656 (-2.59)	0.2047 (1.81)	-0.1926 (-1.18)	0.4489 (2.62)	-0.1708 (-0.74)
COM (SEA+MOM)	7.61% (2.97)	6.72% (2.41)	-0.0719 (-1.27)	0.0746 (0.67)	-0.0998 (-0.61)	0.4530 (2.52)	-0.2449 (-1.23)
Panel B: Trading based on risk-adjusted returns							
	Raw Returns	Alphas	World - Rf				
Pure SEA	3.91% (1.95)	3.75% (1.79)	0.0265 (0.46)				
Pure MOM	5.86% (2.05)	6.84% (2.32)	-0.1577 (-2.30)				
COM (SEA+MOM)	7.79% (2.90)	7.98% (2.90)	-0.0307 (-0.49)				
	Raw Returns	Alphas	World - Rf	SMB	HML		
Pure SEA	3.91% (1.95)	3.87% (1.89)	0.0246 (0.43)	-0.1512 (-1.44)	-0.0489 (-0.50)		
Pure MOM	5.86% (2.05)	7.33% (2.46)	-0.1742 (-2.55)	0.1485 (1.35)	-0.2128 (-2.18)		
COM (SEA+MOM)	7.79% (2.90)	8.43% (3.07)	-0.0442 (-0.70)	0.0069 (0.06)	-0.1911 (-1.82)		
	Raw Returns	Alphas	World - Rf	SMB	HML	RMW	CMA
Pure SEA	3.91% (1.95)	2.73% (1.27)	0.0545 (0.79)	-0.0953 (-0.90)	-0.0438 (-0.31)	0.2299 (1.44)	0.0177 (0.08)
Pure MOM	5.86% (2.05)	5.01% (1.59)	-0.1287 (-1.79)	0.2547 (2.12)	-0.1769 (-0.98)	0.4836 (2.78)	-0.1540 (-0.59)
COM (SEA+MOM)	7.79% (2.90)	6.20% (2.06)	-0.0049 (-0.07)	0.1105 (0.90)	-0.1051 (-0.59)	0.4984 (2.57)	-0.2079 (-0.89)

Table 1.8: Trading returns' sensitivity to sextiles

This table reports the trading returns for different numbers of markets in each of the Max and Min portfolios for the three trading strategies in the base case using the full sample of data for all 18 markets from January 1981 to December 2020. The number listed after Max and Min is the number of markets in each of the Max and Min portfolios. For example, Max3-Min3 means trading returns from buying the top 3 markets and shorting the bottom 3 markets. SEA represents seasonality; MOM represents momentum and COM indicates the combination trading strategy which integrates seasonality and momentum. The seasonality years are 2:10 and the momentum months are 2:12. The mean returns are annualized. Numbers inside parentheses are adjusted t-stats (Newey and West, 1987). Panel A considers results for strategy returns for unadjusted (raw) returns; Panel B considers results for strategy returns based on returns first adjusted for world market risk.

Panel A: Trading based on raw returns			
	Pure SEA	Pure MOM	COM (SEA+MOM)
Max1-Min1	5.14% (1.20)	7.74% (1.73)	9.35% (2.29)
Max2-Min2	4.89% (1.65)	7.63% (2.42)	9.60% (2.98)
Max3-Min3	5.92% (2.39)	7.03% (2.74)	9.60% (3.59)
Max4-Min4	5.33% (2.49)	6.19% (2.56)	6.97% (2.79)
Max5-Min5	4.51% (2.44)	5.95% (2.59)	6.75% (3.09)
Max6-Min6	4.31% (2.75)	5.17% (2.45)	5.79% (2.91)
Panel B: Trading based on risk-adjusted returns			
	Pure SEA	Pure MOM	COM (SEA+MOM)
Max1-Min1	5.76% (1.32)	9.08% (1.92)	11.16% (2.61)
Max2-Min2	5.09% (1.64)	9.15% (2.68)	10.77% (3.13)
Max3-Min3	6.16% (2.39)	8.28% (2.96)	10.34% (3.58)
Max4-Min4	5.44% (2.43)	6.99% (2.73)	7.78% (2.89)
Max5-Min5	4.62% (2.38)	6.84% (2.83)	7.66% (3.21)
Max6-Min6	4.37% (2.61)	6.20% (2.77)	6.68% (3.10)

Table 1.9: Robustness checks

This table reports results of a robustness check. "Choosing 9 markets" means randomly choosing 9 markets out of the 18 markets and then carrying out the trading strategies. SEA stands for seasonality; MOM stands for momentum; and COM stands for the combination trading strategy which joins seasonality and momentum. The seasonality years are 2:10 and momentum months are 2:12. The mean returns are annualized. Numbers inside parentheses are adjusted t-stats (Newey and West, 1987). Panel A considers results for strategy returns for unadjusted (raw) returns; Panel B considers results for strategy returns based on returns first adjusted for world market risk.

Panel A: Trading based on raw returns					
	Pure SEA	Pure MOM	COM	COM vs SEA	COM vs MOM
Choosing 9 markets	3.65%	5.00%	5.64%	1.99%	0.64%
	(138.27)	(240.36)	(363.95)	(76.41)	(36.63)
Panel B: Trading based on risk-adjusted returns					
	Pure SEA	Pure MOM	COM	COM vs SEA	COM vs MOM
Choosing 9 markets	3.76%	5.95%	6.43%	2.68%	0.49%
	(133.12)	(283.02)	(371.26)	(94.32)	(29.39)

Table 1.10: Frequency table based on choosing 9 markets

This table reports the mean monthly returns and the frequency for a national market to be selected in Max3 (the long leg) or Min3 (the short leg) in the three trading strategies based on 48,620 combinations of 9 out of all 18 markets. The period is from January 1981 to December 2020. SEA stands for seasonality; MOM stands for momentum; and COM stands for the combination trading strategy which considers seasonality and momentum jointly. The seasonality years are 2:10 and momentum months are 2:12.

	Mean Return	SEA Max3	SEA Min3	MOM Max3	MOM Min3	COM Max3	COM Min3
Australia	0.73%	6.15%	6.16%	4.97%	5.66%	5.51%	5.65%
Austria	0.52%	5.94%	6.22%	4.92%	6.26%	5.60%	5.57%
Belgium	0.83%	6.32%	4.94%	6.87%	4.99%	6.28%	4.81%
Canada	0.67%	4.26%	6.24%	4.65%	6.51%	4.60%	6.81%
Denmark	1.08%	7.34%	4.31%	8.68%	2.96%	8.92%	2.79%
France	0.79%	3.87%	5.25%	4.14%	5.31%	3.62%	5.46%
Germany	0.78%	6.18%	5.18%	4.65%	5.09%	5.11%	5.20%
Hong Kong	0.81%	6.88%	6.50%	5.38%	5.63%	5.98%	6.03%
Italy	0.54%	4.60%	6.96%	4.20%	6.80%	4.23%	6.95%
Japan	0.55%	5.27%	6.88%	5.35%	7.48%	4.91%	7.63%
Netherlands	0.98%	5.23%	3.73%	6.44%	3.85%	6.09%	3.54%
Norway	0.70%	5.80%	5.71%	5.20%	5.59%	5.22%	5.87%
Singapore	0.53%	5.19%	6.83%	4.89%	6.27%	4.51%	7.20%
Spain	0.82%	5.79%	5.54%	5.82%	5.48%	5.57%	5.35%
Sweden	1.11%	6.76%	4.61%	6.38%	4.63%	6.75%	4.09%
Switzerland	0.91%	5.71%	4.37%	6.32%	4.49%	6.58%	4.24%
United Kingdom	0.68%	3.78%	5.63%	2.79%	7.76%	2.70%	7.82%
United States	0.92%	4.93%	4.94%	8.37%	5.23%	7.82%	4.99%
(Weighted) Average Return	0.78%	0.79%	0.75%	0.81%	0.74%	0.81%	0.74%

Chapter 2

Predicting Corporate Earnings with Composite Peer Return Information

2.1 Introduction

Corporate earnings information provides an essential indication of a company's market value. Forecasting the earnings accurately and in a timely manner is one of the main purposes of financial analysis. Stock market prices incorporate investor forecasts about nearby earnings, as well as earnings further into the future. They incorporate the information of investors as a heterogeneous group, which usually includes insiders, institutional investors, and retail investors. Meanwhile, analyst forecasts represent firm-specific information filtered through the analyst's skills and experience. Consensus analyst forecasts may diversify idiosyncratic views and biases to produce a reliable signal of earnings. With both stock prices and consensus analyst forecasts publicly available for some time before earnings are announced, it is not clear which provides the best information about earnings. Nor is it clear how best to extract the information from stock prices to generate the best earnings signal.

Ball and Ghysels (2018) are the first to attempt to improve earnings predictions by combining analyst forecasts with regression model forecasts. The model they use may be viewed as a way of extracting the component relevant for nearby earnings from financial market information. By using higher-frequency (essentially monthly) macroeconomic and financial market data they neutralize the timing advantage that analysts traditionally have had relative to time-series models. They conclude that a combination model, with weights of around 50% placed on both the consensus analyst forecasts and the predictions from MIDAS (mixed data sampling) models, outperforms the consensus analyst forecast alone by roughly 11% (in terms of MABER, the median absolute error ratio) when the forecasts are made around the earnings announcement, although this number does not necessarily tell us much about the economic importance.

We combine consensus analyst forecasts and regression model forecasts as in Ball and Ghysels (2018), but with some important differences. We use fewer predictor variables but incorporate daily (as opposed to monthly in Ball and Ghysels, 2018) financial market and macroeconomic data. In addition, to produce the regression model forecasts we apply all variables jointly (as opposed to Ball and Ghysels, 2018, who combine individual variable forecasts at the model level in their MIDAS approach). The key difference, however, lies in how we include financial market information in the model. In addition to firm-level stock returns, we account for the important information stemming from complex correlations between earnings of peer firms within the same industry.[1] We construct an index from the returns

[1]Peer is about similarities. To define peer firms, there are many ways, such as by industry (most commonly used, e.g, Bhojraj, Lee, and Oler, 2003, Hoberg and Phillips, 2016), by size (Albuquerque, 2009), by region (Fang et al., 2021), by valuation multiples (Bhojraj and Lee, 2002), by business complexity (Albuquerque, De Franco, and Verdi, 2013), etc. Even by industry, there are many methods to classify industries. The most commonly used are Standard Industrial Classification (SIC) codes, North American Industry Classification System (NAICS) codes, Global Industry Classifications Standard (GICS) and Fama-French industry classifications. In this paper, we follow the Fama-French industry classifications, which are widely used in finance academia, to define peer firms as those in the same industry. More details about the industry classification in this paper can be found at Appendix A1.

of firms in the industry that optimally summarizes what we learn about the firm's earnings from peer returns. The index generator is a characteristic mimicking portfolio (CMP) applied here so that the characteristic is corporate earnings. The index has the property that the sensitivity of each firm's return to it is proportional to the firm's earnings. Incorporating it enables the regression model to reflect how the contemporaneous stock returns of peer firms inform us about the focal firm's earnings.

Our results indicate that the combination forecast of analysts and regression model improves on the consensus analyst forecast alone, although the weight in the combination forecast on the regression model is lower than that in Ball and Ghysels (2018). The information from the peers (proxied by firms in the same industry in this paper), which is condensed by the earnings CMP, considerably enhances the model's earnings prediction for an average firm. Moreover, the deviation between the combination model forecasts and the individual analyst forecasts is substantial in economic terms. Specifically, investing in (shorting) the firms where the model forecast exceeds (falls short of) the consensus analyst forecast results in a statistically significant annualized return of 11.5% over the earnings announcement day and the day preceding.

In the next section, we will present a literature review. Section 2.3 presents our regression model and the combination model. The data, variable construction, timeline, and descriptive statistics are presented in Section 2.4. The empirical results are in Section 2.5. Section 2.6 provides trading strategy results to demonstrate the economic importance of the forecast differences. Section 2.7 concludes.

2.2 Literature Review

2.2.1 Earnings Expectations

The fact that earnings announcements are an important source of stock price fluctuations was recognized as far back as Ball and Brown (1968). In more recent times, Basu et al. (2013) argue that surprises in earnings announcements in fact represent a dominant source of stock price fluctuations. Earnings surprises are typically calculated as the difference between announced earnings and expected earnings, which are commonly represented by consensus analyst forecasts mainly due to their widespread availability (e.g., Brown et al., 1987, O'Brien, 1988, Bradshaw et al., 2012, Kothari and Wasley, 2019).

In fact, analyst forecasts of earnings are a natural benchmark for earnings expectations (O'Brien, 1988). They are timilier when compared to earnings from time series models (e.g., Brown et al., 1987), provide a better indication of the persistence of earnings components (e.g., Baber, Kim, and Kumar, 1999), and are more responsive to idiosyncratic firm-specific events such as lawsuits. However, analyst forecasts are not perfect. They may be *biased* as well as *imprecise* for a variety of reasons. For example, analyst forecast biases may arise from ties to the management of followed firms or from various career concerns (see Keskek and Tse, 2021, for a discussion).[2] Imprecision in analyst forecasts occurs because of limited resources (Clement, 1999), especially in combination with career concerns (Choi and Gupta-Mukherjee, 2022, Chan, Wang, and Wang, 2021, Harford et al., 2019, Hilary and Hsu, 2013) or because of cognitive limits, such as model uncertainty in Linnainmaa, Torous, and Yae

[2] Analysts may bias their earnings forecasts to increase access to managers' private information (e.g., Lim, 2001), improve investment banking ties (e.g., Scherbina, 2008), or enhance their career prospects (e.g., Hong and Kubik, 2003). In addition, Raedy, Shane, and Yang (2006) explain that analysts may rationally underreact to available information in issuing forecasts to prevent loss of reputation when subsequent opposite revisions may be required. Furthermore, such bias may be also related to the herding behavior of analysts (e.g., Durand, Limkriangkrai, and Fung, 2014, Lee and Lee, 2015, Frijns and Huynh, 2018).

(2016) whereby analysts can learn about some features of the earning process but not others.[3]

An alternative benchmark for earnings expectations is traditionally derived from a time-series model. The initial earnings presentation of a seasonal random walk with drift, as proposed by Ball and Brown (1968), was later expanded by Foster (1977) and Morton (1998) to include lagged earnings. Recently, Byun and Roland (2022) argue that, in the case of quarterly earnings, both the earnings of the previous quarter and the earnings from the same calendar quarter in the previous year should be included in the analysis.

In addition to the most recent annual earnings announcement, Shores (1990) and Lev and Thiagarajan (1993) include additional accounting ratios to aid in predicting earnings. Wahlen and Wieland (2011) find that six accounting ratios, which are primarily derived from the income statement, can be used to predict the direction of earnings announcement changes even after taking into account both analyst consensus forecasts and stock prices. However, the accounting ratios used are selected based on their previous predictive performance, indicating the presence of look-ahead bias, and the predictability is limited to the direction of earnings changes only. Li and Mohanram (2014) show that adding book value of equity and accruals, in addition to past earnings, can improve forecast accuracy when compared to the random walk formulation. In general, the time-series models have not been effective as a benchmark for earnings expectations when compared to consensus analyst forecasts, as noted in Kothari and Wasley (2019).

[3] Analyst forecast accuracy is the summation of precision and bias. It depends on many factors such as timeliness (Clement and Tse, 2003), experience and number of firms followed (Hilary and Shen, 2013, Clement, 1999), number of industries followed (Mikhail, Walther, and Willis, 1997, Clement, 1999, Jacob, Lys, and Neale, 1999, Sinha, Brown, and Das, 1997, Dunn and Nathan, 2005), and the size of the brokerage house (Jacob, Lys, and Neale, 1999, Huang, Lin, and Zang, 2022, Hwang, Liberti, and Sturgess, 2019, Gibbons, Iliev, and Kalodimos, 2021).

2.2.2 Financial Market Information

There is empirical evidence to support the idea that stock prices provide insight into future earnings, as demonstrated by studies such as Beaver, Lambert, and Morse (1980). This raises the question of whether utilizing stock prices and returns observed after previous earnings announcements but prior to analyst forecasts of future earnings could enhance time-series models and lead to improved earnings forecasts.

Collins, Kothari, and Rayburn (1987) find that cumulative abnormal returns predict earnings substantially better than the time-series model of earnings. In addition, Morton (1998) shows that cumulative returns prior to the earnings announcement as well as lags of this measure could explain earnings announcements incrementally, given an expanded time-series model of earnings. These findings suggest that supplementing traditional time-series information and interim accounting data with higher-frequency (e.g., daily) financial market observations, which can reflect the information available to investors, may enable the creation of more robust earnings forecasting models. However, Kothari (2001) concludes that including stock price information in addition to time-series information has made only an economically marginal improvement in earnings forecast precision. The reason suggested by Kothari (2001) is that stock returns are a noisy indicator of nearby earnings because they reflect anticipated earnings improvements for future periods as well.

Given that the information sets of analysts and investors overlap only *partially*, the ability to extract investors' information about a followed firm from the firm's stock price fluctuations is considered an important aspect of the analyst's job (see Lys and Sohn, 1990, Abarbanell, 1991, Clement, Hales, and Xue, 2011, Kumar, Rantala, and Xu, 2022, and Choi and Gupta-Mukherjee, 2022). Studies investigating how analysts incorporate stock return information into their earnings forecasts have shown that while analysts do make use of this information to some extent, their use of it is not all-encompassing. Lys and Sohn (1990), for example, estimate that analysts incorporate around two thirds of the relevant earnings information contained in stock prices into their forecasts, leaving approximately the other one third of the relevant information unaccounted for.

Starkweather (2019) reports that 96% of analysts claim they do not consider stock returns. However, using FOMC announcements as an instrument, he finds that analysts in practice do respond to stock returns in forming their earnings forecasts, even when these returns are clearly uninformative. Analysts seem to overreact to stock returns in this case. Other research supports the conclusion that analysts use returns in their earnings forecasts but tend to underreact to this information (Brown et al., 1987, Abarbanell, 1991, Cooper, Day, and Lewis, 2001, Clement, Hales, and Xue, 2011, Dong et al., 2016, Miller and Sedor, 2014 (experimentally), and Kang, 2019). While analysts may underreact on average, some appear to do consistently better than others, and the ability to react judiciously to stock return changes is viewed as an important source of analyst expertise. Gibbons, Iliev, and Kalodimos (2021) document, for instance, that analysts using EDGAR produce more accurate forecasts, presumably because this allows them to identify how much of the returns result from insiders (with superior information, relative to both the analysts and the investors at large).

In addition, mispricing in financial markets likely makes it more difficult for analysts to extract earnings-relevant information from prices. Bagnoli et al. (2009) find that analysts' recommendations are correlated with a proxy for security mispricing (i.e., investor sentiment). This suggests that analysts, as a group, are ineffective at extracting true information components from stock prices. Changes in and deviations from consensus forecasts are more important determinants of analysts' forecast revisions than lagged stock prices (e.g., Stickel, 1990). Consequently, prices are unlikely to be the sole source of analyst information when analysts revise their earnings forecasts.

In fact, analysts face limitations in terms of their resources (Clement, 1999, Luo and Nagarajan, 2015, Drake, Hales, and Rees, 2019), as they must allocate finite attention to a portfolio of firms they follow and may have only limited access to the internal operations of each firm. While analysts can leverage the resources of their brokerage houses, insiders and institutional investors likely possess superior information that is extracted more efficiently from stock returns. This suggests that firm-specific stock price information, particularly at a daily frequency, could be incorporated into models to enhance the accuracy of analyst earnings forecasts.

Wiedman (1996) combines analyst and time-series forecasts. More recently, Ball and Ghysels (2018) integrate higher frequency financial market data into an earnings forecast model. They find that, by combining model (including returns) and analyst information, the result is more accurate than that of analyst (or model) information by itself, out of sample. Once higher frequency financial market information is incorporated in a forecast model for earnings, the analyst advantage of more timely information compared to lagged earnings disappears and the analyst information is, in fact, relatively stale, as daily stock returns provide a signal of current investor information. Moreover, analysts appear not to fully exploit model information, and maybe in particular the financial information of the model.

2.2.3 Industry Information

The literature does not present a consensus on whether analysts efficiently incorporate all public *firm-specific* information in their earnings forecasts, particularly that from the firm's stock returns. In addition, it is not clear whether analysts efficiently exploit *industry-specific* information to enhance their earnings forecasts for individual firms. Here it is important to differentiate between industry-wide information, which is typically available to analysts through their brokerage houses, and the knowledge and expertise pertaining to how specific firms within an industry are impacted by industry developments or the actions of other firms in the same industry.

Discussion on the transfer of earnings-related information can be traced back to Firth (1976) and Foster (1981). More recent literature has placed greater emphasis on the complex interactions between firms in a particular industry.[4] This issue has become increasingly important as firms have become more connected over time (see, for instance, Holstead, Kalay, and Sadka, 2012). The earnings announcements of related firms, such as industry peers or rivals, can have various implications: they can offer insight into industry-wide profitability conditions that would impact a followed firm, as well as reveal the competitive positions within the industry. Peers may share opportunities and threats, highlighting the potential for both cooperation and rivalry.

The earnings of one firm are connected to other firms that may experience similar demand determinants, cost components, or regulatory constraints. As a result, positive earnings correlation can occur in this perspective. However, competition among similar businesses means that factors that benefit one firm's earnings may harm a competitor's earnings, resulting in negative earnings correlation. This implies that when one firm announces its earnings, it provides relevant information about other firms in the industry that have yet to announce their earnings. Therefore, both investors and analysts should take into account the impact of information concerning related firms on their focal firms when making their earnings forecasts.

Using historical earnings correlations for specific pairs of firms, Baber, Kim,

[4]In addition to connections within industry classifications, there are also other economically linked firms outside of these classifications: i) customers predicting suppliers (Cohen and Frazzini, 2008); ii) stand-alone pure players predicting conglomerates (Cohen and Lou, 2012); and iii) strategic-alliance–linked firms predicting another firm in the alliance (Cao, Chordia, and Lin, 2016). Also, Burt and Hrdlicka (2021) discuss why linked firms returns are predictable. Chen et al. (2021) find cross-firm return predictability, in which good accounting-quality firm returns can be used to predict returns of bad accounting-quality firms.

and Kumar (1999) find that the announcements of the earlier-announcing firm help explain the earnings announcements of the later-announcing firm, incrementally to a time-series model. This additional explantion is significant in the direction of the correlation sign when the historical correlation is statistically significant. This confirms earlier similar findings of Lees (1981) and is supported by Ramnath (2002) and Thomas and Zhang (2008). Additionally, Lim (2001) and Ramnath (2002) demonstrate that analysts revise their earnings forecasts in response to the earnings announcements of other firms within the same industry. Hope and Zhao (2018) and Easton et al. (2021) find that stock prices of focal firms react to analyst earnings forecast revisions of their closest peers. Specifically, Hope and Zhao (2018) show that the focal firm stocks generate cumulative abnormal returns of around 0.5% following positive earnings forecast revisions of close peers. Stock prices are less sensitive to the earnings information of other, less close peers. In addition, Hameed et al. (2015) reveal that the forecast revisions for "bellwether firms" (those with very heavy analyst coverage) are more important in influencing earnings forecasts of other firms.

To better infer the industry impact on a specific firm, one must have a comprehensive understanding of both industry-wide developments and how such developments affect the particular firm. Hilary and Shen (2013) find that analysts are well-situated to apply information from one firm to a related firm. In a related study, Bradley, Gokkaya, and Liu (2017) show that analysts who have prior work experience in the same industry tend to provide more accurate earnings forecasts. Underlining the importance of the intra-industry connections, Merkley, Michaely, and Pacelli (2017) find that having more analysts in an industry results in positive spillovers for forecast accuracy. Furthermore, Choi and Gupta-Mukherjee (2022) assert that analyst expertise is derived from their ability to extract relevant information from market sources which they can interpret and use in earnings forecasts.

Further emphasizing the importance of firm interactions for analysts, Piotroski and Roulstone (2004) suggest that analysts enhance the transfer of price-relevant information across peer firms and that an analyst's comparative advantage lies in interpreting specific industry or market sector trends and improving intra-industry information transfers. On the other hand, investors may not fully understand the interactions between firms within an industry, resulting in inefficient incorporation of this information into stock prices. For more recent research on this topic, refer to Giles and Chen (2013), Einhorn, Langberg, and Versano (2018), and Huang et al. (2021), in addition to Ramnath (2002) and Thomas and Zhang (2008).

The industry-related proficiency may vary across analysts. Balashov and DeVides (2020) report that 60% of analysts cover multiple industries, which leads to reduced forecast accuracy. Choi and Gupta-Mukherjee (2022) indicate that analysts may use industry-wide information from their brokerage house to obtain forecasts for a larger group of firms in an industry at a lower cost, but this approach may lead to less accurate earnings forecasts for those analysts who rely more on in-house industry information. Additionally, Choi and Gupta-Mukherjee (2022) argue that analyst diversification across industries is driven not only by efficiency, but also by the desire to enhance their employment security (becoming a more likely match with current or other future employers), regardless of forecast accuracy. While some analysts fully specialize in specific industries, the consensus forecasts include all analysts following a particular firm, even those who cover multiple industries or rely mostly on in-house industry forecasts.

In general, there seems to be inefficiency in incorporating intra-industry links between firms in both stock market prices and analyst forecasts. Mueller (2019) observes only gradual information diffusion across linked firms at the industry level. Kadan et al. (2012) finds that industry information is essentially orthogonal to firm information. Keskek and Tse (2021), building on the work of Hui and Yeung (2013), report that forecast revisions are less complete for industry-wide information, and that investors tend to underreact to news in analyst forecasts about the industry. In addition, the value of analyst forecasts is enhanced when industry-specific information is added separately, indicating that individual firm earnings forecasts may not accurately reflect industry information in a timely manner.

2.2.4 Macro Issues

The impact of macroeconomic information on firm-level earnings cannot be overstated, as noted by Ball and Brown (1968). Using principal components analysis (PCA), Ball, Sadka, and Sadka (2009) extract three latent common factors that account for 60% of the variability in firm earnings, underscoring the importance of macroeconomic news for both investors and analysts. It comes as no surprise that macroeconomic disclosures are widely found in 10-K filings, and that analyst forecasts tend to be more accurate for firms with higher levels of macroeconomic disclosure, as found by Holstead, Kalay, and Sadka (2012). In addition, Sinha (2021) discovers that more disagreement among macro forecasters leads to reduced accuracy in analyst earnings forecasts.

Carabias (2018) reports that real-time macroeconomic indicators can predict quarterly earnings at the firm-level, and that this information is not fully incorporated in investor expectations.[5] Hence, predictable abnormal stock returns can be expected around earnings announcements. Hutton, Lee, and Shu (2012) find that analysts who put more weight on macroeconomic information such as commodity prices and business cycles, tend to have higher forecast accuracy, particularly for focal firms in more cyclical industries. This may explain why analysts appear to herd. Macro shocks at a monthly frequency represent common earnings shocks, which can

[5] In the paper, the author considers a total of 160 macroeconomic indicators that are released on a monthly basis. These indicators encompass a wide range of variables, including but not limited to PMI, monetary base, unemployment rate, industrial production, sales, PPI, CPI, federal funds rate, etc.

be more informative for long-term forecasts. Hann, Ogneva, and Sapriza (2012) find that a series of macro variables, including aggregate earnings, can be useful for forecasting individual earnings. Hugon, Kumar, and Lin (2016) conclude that analysts tend to underreact to negative macroeconomic news, but this underreaction can be mitigated when the analyst's brokerage employs an active in-house economist.

Analysts may be viewed as industry specialists (e.g., Ramnath, 2002, Boni and Womack, 2006, Hutton, Lee, and Shu, 2012, and Hui and Yeung, 2013). Thus, their industry-wide information is likely to incorporate insights about macroeconomic events that are not available elsewhere. On the other hand, Sadka and Sadka (2009) find that current stock returns contain more information at the aggregate level, which is not fully considered by analysts. It may be beneficial to include higher frequency macroeconomic indicators in earnings forecasts to further improve the accuracy of forecasts from analysts and financial market information incorporated in stock returns.

2.3 Interim Inference of Earnings

2.3.1 Earnings Mimicking Portfolios

The analyst's job of tracking firms with strong connections to the industry (e.g., a high R-squared of forecast revisions regressed on industry returns) may be made easier by the potentially lower cost of obtaining industry-wide or macroeconomic knowledge. To achievie this automatically, a Characteristics Mimicking Portfolio (CMP, see Balduzzi and Robotti, 2008, and Balvers and Luo, 2018) that focuses on earnings as a time-varying characteristic may be used. By drawing on earnings information available from industry peers, this approach provides a more comprehensive perspective that takes into account the complex interactions between firms within a specific industry, with a focus on nearby earnings. Specifically, the CMP considers the historical ties in earnings among all industry peers and takes into account the relevant information about earnings captured by cumulative abnormal post-earnings-announcement returns of all peers.

Overall, the financial market information about firm earnings from peer sources can be captured with the application of CMPs, which are portfolios specifically constructed to represent the industry-wide market information about a particular characteristic.[6] They have the property that the loadings of each asset return on the CMP return equal the asset's characteristic. In this particular application, earnings per share (EPS) are considered to be the time-varying firm characteristic. The sensitivity of the firm to the CMP return represents a sufficient statistic for the aggregate impact of interim information about the earnings of all relevant competing firms (i.e., those in the firm's industry) on the firm's earnings estimates (and stock returns). When generated, the CMP takes into account the covariances among all peer stock returns in a specific industry, thus incorporating more information than individual returns only, or even other accounting variables.

To maximize the information that firm return sensitivities to the CMP brings to bear on the characteristic under consideration (EPS, in this case), the CMP is calculated using varying weights on the stock returns of all related firms. This approach aggregates the information in return observations of all firms within a particular industry and takes into account the importance and strength of competing firm returns, which vary over time and across firms. The resulting measure, which is the CMP, is optimally set to be as informative as possible regarding each firm's earnings.

CMPs may be utilized to provide estimates of firm-level characteristics that cannot be directly observed in real-time. Since earnings qualify as a characteristic of a stock, they can be inferred from the CMP returns whenever the return is available.

[6]Details about how CMPs are constructed can be found in section 2.4.

This is particularly advantageous because actual earnings observations occur only once per quarter, whereas financial data are often available at a daily (or even much higher) frequency. Using daily returns data, estimates for the latent real-time earnings data can be generated on a daily basis through the use of CMPs. This allows for a more frequent and up-to-date estimation of earnings, which can be useful for investors who need to make informed decisions in a timely manner.

2.3.2 Methodology

In recent years, Ball and Ghysels (2018) and Azevedo, Bielstein, and Gerhart (2021) combine analyst forecasts with earnings predictions from a regression model to improve upon the analyst forecasts alone. In this study, we apply their approach to investigate whether financial market-based information about the industry environment, which is relevant for a firm's earnings, is fully internalized by analysts, and if not, whether it can be utilized to enhance the pure analyst forecasts. To arrive at the best forecast, it will always be necessary to put some weight on the pure analyst forecasts because they incorporate idiosyncratic, firm-specific value considerations that are impossible to be captured with a stylized model designed to apply to any firm. On the other hand, analysts, in theory, may be able to incorporate any relevant publicly available information in their forecasts. However, they may not necessarily be experts on value components stemming from outside of the firms that they specialize in. Thus, it is an empirical question whether analysts underweight or miss relevant information concerning a firm's competitive environment, and this study aims to address that question.

Our model to forecast the next statement of quarterly earnings consists of four groups of variables: past firm earnings (E), interim financial market information (F), macro variables (M), and consensus analyst forecasts (A).

The basic forecast equation for firm i is:[7]

$$E_{i,t} = \hat{b}_{0,i,t} + \hat{b}_{1,i,t}E_{i,t-1} + \hat{b}_{2,i,t}F_{i,t} + \hat{b}_{3,i,t}M_{i,t} + \varepsilon_{i,t} \tag{2.1}$$

The coefficients $\hat{b}_{n,i,t}$ are estimated by linear regression using only information up to time t. The values assigned to the vectors of variables E, F, and M at time t should be interpreted as being available during the interim period between time t and before time $t+1$. For E, this represents the most recent quarterly earnings level available, while for M, this would be the latest available macro information which may be updated on a monthly or daily basis. As for F, this represents the most current daily financial market information.

It is important to treat the analyst forecast variable as a separate variable from the other forecast variables because the analyst forecast (A) incorporates and overlaps with the information from the other groups of variables (E, F, and M) to a considerable extent. Similar to the method employed by Ball and Ghysels (2018), we combine the forecast from equation (2.1) with the analyst forecast (A), determining the weights on each based on the forecast combination that worked best in past data:

$$\hat{C}_{i,t} = \hat{a}_{1,i,t}\hat{E}_{i,t} + \hat{a}_{2,i,t}A_{i,t}, \qquad \hat{E}_{i,t} = \hat{b}_{0,i,t} + \hat{b}_{1,i,t}E_{i,t-1} + \hat{b}_{2,i,t}F_t + \hat{b}_{3,i,t}M_{i,t} \tag{2.2}$$

In this equation, $\hat{C}_{i,t}$ is the "combination" forecast for the next announced quarterly earnings $E_{i,t}$ for firm i, with $\hat{a}_{1,i,t}$, $\hat{a}_{2,i,t}$ the weights on the equation (2.1) forecast ($\hat{E}_{i,t}$) and the consensus analyst forecast ($A_{i,t}$), respectively, obtained from regression using past forecasts and outcomes.

[7]We are making forecasts after the end of quarter t but before $EPS_{i,t}$ is announced. Usually, this period is about 1-1.5 months. Although both the dependent variable and some independent variables are denoted with time t, there is still some difference. For the independent variables denoted with time t, they are *observable* during the period we are making forecasts. While for the dependent variable $EPS_{i,t}$, it is *realized but not yet observable*. A brief timeline is shown in Figure 2.1.

The variables selected in each category, with the intent of using a parsimonious model that avoids overfitting, are as follows:

Earnings information (E). Our earnings measure in this study is earnings per share (*EPS*), adjusted by shares outstanding and the most recent *CPI*, to make *EPS* data for the same company comparable through time. As it is standard to account for seasonal fluctuation in quarterly earnings, we use the earnings from the most recent quarter ($t-1$) as well as the earnings from the corresponding quarter one year ago ($t-4$). Thus, $E_{t-1} = \{EPS_{t-1},\ EPS_{t-4}\}$.

Financial Market information (F). The financial market information is available at daily frequency and we mainly focus on three variables. Firstly, we examine the individual firm's cumulative daily stock returns in the calendar quarter with which we are going to predict earnings, which is denoted as *RET*. Secondly, we introduce the industry-wide return variable that captures the relevance of all returns in the firm's industry for earnings forecast purposes, denoted as *CMP*. Finally, to account for the reliability of return information used in earnings forecasts, we employ a measure of return volatility called the quarterly realized variance (QRV), which is computed by squaring the daily returns over the most recent quarter. Thus, $F_t = \{RET_t,\ CMP_t,\ QRV_t\}$.

Macroeconomic information (M). Although our set of financial market information captures industry-specific information, it does not account for macroeconomic information that may impact earnings. To address this, we use an aggregate measure based on the S&P 500 firms: their aggregate earnings divided by the S&P 500 stock price index, earnings-to-price ratio (E/P ratio), denoted as MEY (macro earnings yield). In addition, we add a measure of commodity prices (energy, metal and agricultural products), the *CRB* index return. Both data are available on a daily basis from Bloomberg. Thus, $M_t = \{MEY_t,\ CRB_t\}$.

Analyst information (A). For each firm in each quarter, we use the average earnings forecast of all analysts covering a firm as our consensus analyst forecast (analyst earnings estimate, AEE). To normalize and to be consistent with our other variable choices, we adjust it with shares outstanding and the most recent available CPI data. Thus, $A_t = \{AEE_t\}$.

With the variables mentioned above, we then have the following as our first-stage forecast equation for firm i in industry j:

$$\begin{aligned} E\hat{P}S_{i,t} = \hat{c}_{0,i,t} &+ \hat{c}_{1,i,t}EPS_{i,t-1} + \hat{c}_{2,i,t}EPS_{i,t-4} + \hat{c}_{3,i,t}RET_{i,t} \\ &+ \hat{c}_{4,i,t}CMP_{j,t} + \hat{c}_{5,i,t}QRV_{i,t} + \hat{c}_{6,i,t}MEY_t + \hat{c}_{7,i,t}CRB_t \end{aligned} \tag{2.3}$$

Then the second-stage, combination forecast equation for firm i is:

$$C\hat{O}M_{i,t} = \hat{a}_{1,i,t}E\hat{P}S_{i,t} + \hat{a}_{2,i,t}AEE_{i,t} \tag{2.4}$$

With such forecasting results, we will analyze the performance of the combination forecast (COM) relative to the realized value for earnings (EPS), and compare it to the performance of AEE relative to EPS. In addition, we want to investigate whether any advantage of the combination forecast over the analyst consensus forecast is significantly dependent on the CMP variable that we are contributing.

2.4 Data and Variable Construction

2.4.1 Earnings

The EPS data used in this study are obtained from I/B/E/S (Institutional Brokers' Estimate System) and cover the period from January 1985 to December 2021. The data are at the quarterly frequency with quarter end in March, June, September and December, and matched with common stocks from CRSP (Center for Research in Security Prices). To ensure comparability across time periods, the data are adjusted for inflation using the most recent available CPI data from FRED (Federal Reserve Economic Data), maintained by the Federal Reserve Bank of St. Louis.

[Table 2.1 about here]

The firms in this study are assigned to an industry based on the 12-industry grouping of Fama and French.[8] with 3 industries (Utilities, Finance, and Other) excluded for standard reasons. Detailed information about the remaining 9 industries is shown in Appendix A1. To perform regression analysis, a minimum of 41 quarters of data are required for each firm (20 quarters for each of the two stage regressions, and at least 1 quarter for forecasting). As a result, we are left with 1,064 firms until 2021 and a total of 76,733 firm quarters in the data sample. Finally, we have 34,173 firm quarters as predictions. Table 2.1 shows the details of the data sample selection process. The number of firm-quarter observations left in the sample is comparable with other similar studies attempting to predict quarterly earnings, such as Ball and Ghysels (2018) and Carabias (2018).

2.4.2 Financial Market Information

This study considers common stocks traded on U.S. markets with a share price of at least $5 and market value at least $1 million as of the quarter end. The returns data (RET) are from CRSP at a daily frequency. To measure return volatility, the realized variance (QRV) is obtained by squaring daily returns and summing them up to a quarterly measure on a rolling basis.

[8] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

We follow the approach of Balvers and Luo (2018) and Balduzzi and Robotti (2008) to generate CMPs, which maximize the exposure to earnings (as a characteristic) for given variance in this case. The key components in CMPs are the covariance matrix among stock returns of all firms within the relevant market.[9]

The *CMP* measure for industry j is generated as follows, in matrix notation:

$$CMP_t = \mathbf{RET'_t} \left(\frac{\mathbf{\Sigma_t^{-1}} \cdot \mathbf{EPS_t}}{\mathbf{EPS'_t} \cdot \mathbf{\Sigma_t^{-1}} \cdot \mathbf{EPS_t}} \right) \tag{2.5}$$

Here the covariance matrix of the returns of all firms in the industry is denoted by $\mathbf{\Sigma_t}$ and estimated with daily returns data following Ledoit and Wolf (2003). $\mathbf{EPS_t}$ is the vector of characteristics – here the preceding quarter's realized EPS for each firm in the industry. To provide a timelier measure, the EPS is replaced by the *AEE* which leads to similar but more up-to-date weights.

The portfolio weights for all stocks in the industry are reflected in the term in parentheses, which is then multiplied by the vector of most recent cumulative daily returns of each firm during the quarter to determine the resulting CMP at time t. The CMP is the same for each firm in the industry, but each firm in the industry may have a different loading on this portfolio. Theoretically, the loading reflects a measure of the firm's characteristic, which is the expected EPS in this case.

The CMP is designed to have maximum exposure to expected earnings information (as a characteristic) for a given variance of CMP returns. The return of the CMP provides an optimal aggregate of information about the firm's earnings, inferred from the stock returns of all peer/competing firms in its industry. Therefore, accounting information is used, but it is filtered by how the stock market interprets

[9]Light, Maslov, and Rytchkov (2017) propose an alternative approach for aggregating characteristic information of peer/competing firms through the use of the partial least squares method. However, for the purpose of this study, it is less useful for several reasons. It uses time information in a different way, focuses on just one characteristic and possibly only a small subset of firms. It also requires one to select a number of factors in advance.

it on a day-to-day basis for each of the industry peers/competitors. Please refer to Appendix A2 for further details on the derivation of the CMP return as the optimal aggregate of intra-industry information affecting a focal firm's earnings.

2.4.3 Macroeconomic Indicators

The aggregate *MEY* measure is derived by taking the inverse of the price-to-earnings (P/E) ratio of the S&P 500 index, which is obtained from Bloomberg. The *CRB* index return is the price change of a basket of commodities, which includes energy, metals and agricultural products, and is also available from Bloomberg on a daily basis.

2.4.4 Analyst Earnings Forecasts

The consensus analysts forecast (*AEE*) for each firm in each quarter is obtained from I/B/E/S, and the data used in this study covers the period from January 1985 to December 2021. The consensus analyst forecast is the average of the latest available forecast of each analyst covering the firm for the quarter. To make the data comparable through time, the measure is adjusted by shares outstanding and most recent available CPI in this study.

2.4.5 Timeline

Please see Figure 2.1 for a brief timeline about when a firm's quarterly EPS is realized, forecasted by financial analysts and our models, and finally announced by the firm. Variable definitions are given in section 2.3.

[Figure 2.1 about here]

2.4.6 Descriptive Statistics

Table 2.2 presents the industry-wise average values of the model variables used in this study. The sample consists of firms from the 12-industry classification of Fama and French, with Utilities, Finance, and Other excluded. The total number of sample firms is 1,064. The average number of analysts covering each firm varies by industry, ranging from approximately 7 for Durables to 14 for Energy. To clarify, the variables used in the model do include EPS, although not directly presented in the table. To allow for comparability across firms and industries, it is scaled by share price to generate the earnings-to-price (E/P) ratio, which ranges from a low of 1.71% in the Healthcare sector to a high of 30.12% in the Energy sector.

[Table 2.2 about here]

The financial market variables: Average stock returns (RET) vary between 14.66% for Nondurable Goods, to 20.63% for Business Equipment; The average Characteristic Mimicking Portfolio (CMP) return for the earnings characteristic varies greatly from -34.77% for Durables, to 548.83% for the Telecom industry; The average annualized realized volatility of stock returns (ARV) ranges from 0.71 for Telecom and Nondurables, to 0.94 for Business Equipment.

The macro indicators used in the study, which do not vary by industry, include the average annualized Macro Earnings Yield (MEY) for the S&P 500 firms, which is 5.33%, and the average commodity index return (CRB) available daily from Bloomberg, equal to 3.67% per quarter.

2.5 Empirical Results

We start by using rolling regressions to estimate the model using all available data by industry, with a minimum of 20 quarters for each firm before time t. The first stage model for firm i in industry j is shown in equation (2.3).

In Table 2.3, the estimated coefficient values for the model variables are provided, along with the average t-statistics. The analysis suggests that lagged EPS values at one and four quarters are significant predictors. Additionally, the financial variables and macro variables have similar average t-statistics, which indicates that they have similar importance in the model forecast, with the exception that financial market variables are more volatile and therefore explain a larger fraction of forecast changes. Overall, the model fit is similar across industries, with an R-squared ranging from 62% in Telecom to 74% in Shops.

[Table 2.3 about here]

The second-stage regression involves combining the first-stage model forecast with the consensus analyst forecast for each firm and quarter, as shown in equation (2.4). The average weight of the first-stage model forecast $E\hat{P}S_{i,t}$ when added to $AEE_{i,t}$ in the combined forecast $COM_{i,t}$ is shown in Table 2.3 for each industry. Overall, the weight for the first-stage model forecast is around 10%-15%, leaving the remaining 85%-90% from analyst forecasts. To generate a reasonable forecast, we ignore the cases that suggest negative weight for the first-stage model forecast. For those firms in the case of forecasting, the model is not relevant and is not usefully contributing to the earnings forecast. The fraction of the cases (*Fraction* in Table 2.3) for which the model is used is around 52% overall and is presented in the table by industry.

The first-stage model forecast (*MF*), consensus analyst forecast (*AF*), and the second-stage combination forecast (*CF*), for all firm-quarters, are each compared to the realized (announced) EPS numbers (*RE*). Panel A of Table 2.4 presents the forecast-to-forecast correlations, which are highest for CF vs AF at 0.88, lower for CF vs MF at 0.54, and lowest for AF vs MF at 0.20, suggesting that analyst and first-stage model forecasts provide mostly different information. Furthermore, Panel A of Table 2.4 also shows the correlations between the earnings forecasts and the announced earnings. These are highest for the combination model at 0.80, not much lower for the analyst forecast at 0.79, and lower for the first-stage model forecast, at 0.53. This reflects the fact that the combination model has lower weights on the first-stage model forecasts than on the analyst forecasts.

[Table 2.4 about here]

In this study, we use the mean squared prediction error (*MSPE*) as our measure to compare forecasting results. It is computed for each forecast by squaring the prediction error (the difference between the forecasted earnings and the announced earnings) and then scaling it by the share price at the end of the quarter. These values are then averaged across all firm-quarters to obtain the MSPE for each forecast model. An additional forecast model is included in the analysis for reference purposes. This model is similar to the one previously presented, but it does not include the industry peer information variable (*CMP*), which is the main focus of the study.

In Panel B of Table 2.4, the t-statistics of the difference in the log MSPE of any two of the forecasts are presented . For the combination model, comparing the results with (*CF*) and without (*CF0*) the industry peer information variable, we find a t-statistic of -2.20, indicating that the forecast errors are significantly reduced when we include the industry peer information. Comparing the MSPE's for the combination model forecast (CF) with the consensus analyst forecast (AF), we obtain a t-statistic of -2.00, which reveals that the combination model provides a significantly better forecast than the consensus analyst forecast. In addition, comparing the combination forecast (CF) to the first-stage model forecast (MF), we find a t-statistic of -1.08. While the combination forecast is also better than the first-stage model forecast, the difference is not significant.

In addition, Table 2.5 presents a detailed comparison of MSPE ratios of the combination forecast (CF) over the consensus analyst forecast (AF). The "All" result, which is 0.815 in the table, indicates that the difference in forecast accuracy is economically relevant, and this means that the CF is, on average, 18.5% more accurate than the AF.

[Table 2.5 about here]

In Panel A of Table 2.5, we first divide the firm-quarters into deciles for both the combination and analyst forecast based on the squared prediction errors, sorted from highest to lowest. Then we calculate the ratio of the MSPE of the combination forecast (CF) to the MSPE of the consensus analyst forecast (AF) by decile. The results in Panel A show that for 9 out of the 10 deciles, the CF forecast outperforms the AF forecast. However, for the first decile, the AF forecast clearly outperforms the CF forecast. This suggests that in the case of the worst outcomes, where the prediction errors are the highest, the "automated" CF forecasts perform worse than the "managed" AF outcomes. One possible reason is that analysts are able to make common-sense adjustments and respond to salient information, which prevents them from making the most serious misjudgments.

Panel B of Table 2.5 shows the comparison of the MSPE ratios of the combination forecast (CF) to the consensus analyst forecast (AF) by industry. Out of the 9 industries analyzed in this study, the CF forecast performs better than the AF forecast in 8 industries. The only exception is the Telecom industry, where the AF forecast outperforms the CF forecast.

2.6 Trading Strategy Results

To provide an idea of the economic significance of the more accurate earnings forecasts generated by the combination model, we present the results of a particular trading strategy that focuses on the difference between using the model forecasts of earnings and using the consensus analyst forecasts of earnings to make investment decisions. If the financial market is already pricing the earnings information obtainable from the analysts, and if the more accurate earnings forecasts from the model offer incremental value, then there should be a market reaction at the time of the quarterly earnings announcement. Specifically, if the model prediction exceeds the analyst prediction, then the event return should be positive; if the model prediction falls short of the analyst prediction, the event return should be negative.

2.6.1 Main Trading Results

The trading strategy involves analyzing the difference between the model forecast and the analyst forecast for each firm in the data sample. If the model forecast is higher than the analyst forecast, the strategy involves buying the firm's stock and holding it during the time interval surrounding the firm's earnings announcement. Conversely, if the model forecast is lower than the analyst forecast, the strategy involves shorting the firm's stock during the same time interval. The returns generated by this strategy are then compared to the market returns over the same period.

[Table 2.6 about here]

The results of the trading strategy are presented in Panel A of Table 2.6 and they are dependent on the event window used. If investment/shorting happens only on the day of earnings announcement, denoted by time interval [0] in the table, the annualized strategy return is 13.20% but not statistically significant (t-statistic equal to 1.37). If days before the announcement are included to account for information leakage, then, the time interval [-1, 0] produces an annualized return of 11.49%, which is statistically significant (t-statistic equals 2.30). If the time interval is further extended to include two days before the announcement (time inverval [-2, 0]), the annualized return is 8.67% with a t-statistic of 2.52. However, including additional days after the announcement dilutes the results. For instance, when we add one or two additional days after the announcement, taking the event interval as [-1, 1] or [-2, 2], the annualized return becomes 5.99% or 4.58% with a marginally significant t-statistic of 1.63 or 1.94. Also, it is worth noting the Sharpe ratios from this long-short trading strategy are relatively low, which implies that the trading returns are in fact quite volatile.

Overall, it is feasible to take advantage of a mechanized model forecast that outperforms the consensus analyst forecast, which is commonly viewed as the market expectation of earnings. It is worth noting that the trading strategy yields equivalent results whether the comparison is made between the second-stage combination forecast and the analyst forecast or between the first-stage model forecast and the analyst forecast, since the combination forecast is superior to the analyst forecast only when the first-stage model forecast is also superior.

2.6.2 Trading Results by Groups

Upon examining the trading results in detail for the event interval of [-1, 0], some interesting findings emerge. Panel A of Table 2.7 shows the trading returns by various groups. The table indicates that the trading strategy tends to underperform when the realized variance is low or the stock return is close to zero. One possible explanation is that the financial market provides little information regarding future earnings in this case. For example, when the realized variance is low, such as in an extreme case when it is close to zero, the covariance of the stock with peer firms also tends to be zero. This independence essentially makes it challenging for the CMP variable to contribute to earnings forecasts. In addition, the table shows the trading strategy performs quite well when the quarterly stock returns are low, especially when there are large negative returns. This may be related to the analyst forecast bias, which is well documented in the literature and briefly discussed in section 2.2. That is, when the market signals some bad news in the firm, the forecast model can capture it and incorporate it into the model forecasts. However, analysts tend to underreact to such bad news, which finally makes the trading strategy work well in such circumstances.

[Table 2.7 about here]

It is also noteworthy to check the trading returns by forecast distance (the absolute value of the EPS forecasts from the combination model minus the consensus analyst forecasts) and analyst dispersion (the standard deviation in analyst earnings forecasts, scaled by the quarter end share price). When the forecast distance is small, indicating that the combination model and analysts are giving similar earnings forecasts, the trading return is close to zero, which is expected. Conversely, when the distance is large, the trading returns are low, which confirms the previous findings on forecast accuracy: the combination model sometimes may make extreme forecasts while analysts can adjust by common sense. Additionally, when there is a large analyst dispersion, the trading returns are also poor. This may be because when there is major disagreement among analysts, the uncertainty in the information environment of the stock is high. Thus, there might be more noise in the information sets of both analysts and investors.

2.6.3 Trading the Long-legs Only

Considering there would be frequently trading in this strategy, the return may not be profitable after accounting for the transaction costs that are necessarily incurred and will be particularly high when stocks are shorted. To investigate this further, we separate the long and short legs of the strategy. Surprisingly, when the strategy is applied without shorting, and trades only occur when the model forecast exceeds the analyst forecast, the trading strategy returns (the long legs only) increase substantially with much higher Sharpe ratios (as shown in Panel B of Table 2.6), making the strategy more feasible to be implemented in real-life. For instance, for event interval [0], the annualized return becomes 38.54% with t-statistic of 3.58 and a Sharpe ratio of 0.44. For event interval [-1, 0], the return is 25.34% with t-statistic equal to 4.55 and a Sharpe ratio of 0.44. For event interval [-2, 0], the return is 18.60% with t-statistic of 4.86 and a Sharpe ratio of 0.32. If extending the event interval with additional days after earnings announcement (i.e., [-1, 1] and [-2, 2]), the results convey similar information. Overall, the trading results imply that the returns from the short legs are in fact negative.[10]

We can also check the trading returns for the long-only strategy by various groups as previously and the results are shown in Panel B of Table 2.7. Essentially, the results convey similar information as the long-short strategy. However, the information is clearer in the long-only case.

[10]One possible explanation may be related to Savor and Wilson (2016): risk-premia are large during an information period such as when earnings are announced because the stock's betas are large in those intervals. As a result, the average firm-level returns over the earnings announcement interval are higher than the market returns over the same interval. To adjust for this effect, the best approach may be to use matching firms that announce at the same time as a benchmark instead of the market return.

2.7 Conclusion

Security analysts may have industry-specific expertise, especially if they specialize by following firms in the same industry. In addition, they may benefit from industry expertise in their brokerage house. On the other hand, many analysts are not specialized in industries. To effectively evaluate the impact of specific events on a company, security analysts need to have knowledge not only of general industry information available from the brokerage house but also of how that company relates to its specific industry peers. Further, industry links among peers are complex and difficult to summarize. While some analysts may be able to handle this complexity well, it is not easy to identify them. When we consider consolidated analyst forecasts, less-informed or less-skilled analysts receive equal weight with the best analysts, which can result in less accurate consensus forecasts.

It is an open question, therefore, if consensus analyst forecasts properly consider the intra-industry information transfers available from peer firm stock returns, peer firm earnings announcements, and analyst forecasts for peer firms. In this study, we find empirically that incorporating intra-industry peer information by employing earnings mimicking portfolio returns can generate model forecasts that are significantly better than without use of the earnings mimicking portfolio returns. In addition, the forecasts when combined with consensus analyst forecasts are more accurate than the consensus analyst forecasts by themselves. The difference in forecast accuracy is economically important as we can exploit it with a simple trading strategy that generates significant annual returns of 11.5%, although it is difficult to implement due to high trading costs.

Security analysts may not fully integrate and incorporate interim industry-wide financial market information into their earnings forecasts. However, it is also possible that their information is relatively stale. The parsimoniously summarized market information regarding industry peers of a firm may be updated on a daily basis, which is more frequent than the updates made by analysts to their earnings forecasts. As a result, either of these factors may imply that the simple augmented time-series model used for the "automated" forecast contributes significant economic and statistical value to the analyst consensus forecast.

Figure 2.1: A brief timeline around earnings announcement

This figure shows the brief time line when a firm's quarterly EPS is realized, forecasted by financial analysts and our models and finally announced by the firm. Variable definitions are given in section 2.3.

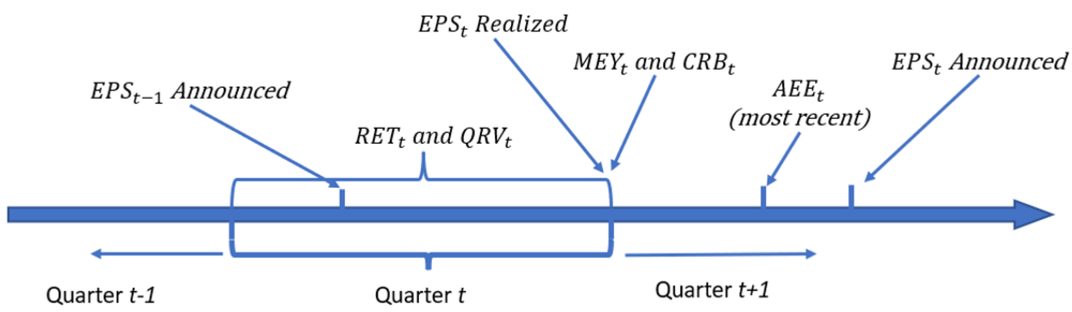


Table 2.1: Data sample selection process

This table provides information on the selection of the data sample used in this study. The data covers the period from January 1985 to December 2021 with data from I/B/E/S and CRSP. The table outlines several key filters used to select the data and provides detailed information on the number of observations. After applying the selection criteria, the final data sample consists of 1,064 firms and 76,733 firm-quarters.

Sample Selection (1985-2021)	**Firms**	**Firm-Quarters**
All I/B/E/S U.S. firms with actual quarterly EPS (Jan 1985 - Dec 2021)	16,430	1,493,998
Only keep the most recent analysts forecasts for each quarter	16,430	517,994
Keep quarter end in March/June/September/December	14,927	456,873
Merge with CRSP data, EXCD in (1,2,3,4) and SHRCD in (10,11)	11,085	319,876
Drop industries of Utilities, Finance and Other	6,057	189,119
Price > \$5 and market cap > \$1 million	5,711	157,060
At least 41 quarters	1,311	97,149
Other minor filters (e.g., daily returns, both t-1 and t-4, etc.)	1,064	76,733

Table 2.2: Descriptive statistics

This table presents the averages of key variables by industry. *NumFi* is the number of firms in the sample for each industry. *NumAn* is the average number of analysts per firm. *E/P* is the average ratio of annualized earnings to market equity in percent. *RET* is the average annualized stock return in percent. *CMP* is the annualized characteristic mimicking portfolio in percent. *ARV* is the average annualized realized volatility of stock returns. *MEY* is the average macro earnings yield annualized for the S&P 500 firms. *CRB* is the commodity index return average. *All* represents the total number of firms in the sample and for the other variables the industry weighted average value. The industries are from the Fama-French 12-industry classification, excluding Utilities, Finance, and Other. The remaining industries are: Consumer Nondurables (*NoDur*), Consumer Durables (*Durbl*), Manufacturing (*Manuf*), Oil, Gas, and Coal Extraction and Products (*Enrgy*), Chemicals and Allied Products (*Chems*), Business Equipment (*BusEq*), Telephone and Television Transmission (*Telcm*), Wholesale, Retail, and Some Services (*Shops*), Healthcare, Medical Equipment, and Drugs (*Hlth*). Detailed industry definitions are shown in Appendix A1.

	NumFi	NumAn	E/P (%)	RET (%)	CMP (%)	ARV (%)	MEY (%)	CRB (%)
NoDur	75	7.70	6.84	14.66	5.04	0.71	5.33	3.67
Durbl	40	7.07	5.44	15.68	-34.77	0.80	5.33	3.67
Manuf	201	7.80	5.14	16.63	4.74	0.79	5.33	3.67
Enrgy	66	14.25	30.12	17.59	15.29	0.86	5.33	3.67
Chems	47	9.22	7.59	16.70	-1.21	0.67	5.33	3.67
BusEq	287	9.46	14.83	20.63	-47.04	0.94	5.33	3.67
Telcm	41	10.63	4.44	15.26	548.83	0.71	5.33	3.67
Shops	142	8.41	5.41	16.80	5.52	0.80	5.33	3.67
Hlth	165	9.38	1.71	19.75	2.95	0.87	5.33	3.67
All	1,064	9.11	9.02	18.05	10.49	0.83	5.33	3.67

Table 2.3: First and second-stage model coefficients

This table presents the results for equation (2.3), first-stage regression, and equation (2.4), second-stage regression. *EPS*, earnings per share, is the left-hand side variable. For lagged right-hand side variables, -1 representing one-quarter lag and -4 representing four-quarter lag. The financial market variables are cumulative returns of individual stock (*RET*), cumulative earnings-mimicking portfolio returns (*CMP*), and quarterly realized volatility (*QRV*). The macro index variables are macro earnings yield for the S&P 500 (*MEY*) and the commodity index return (*CRB*). *R-square* indicates the time-series fit for the first-stage model averaged over all firms in the industry. *Model Share* is the weight on the first-stage model forecasts in the combination with the analyst forecasts. *Fraction* is the share of firms that is used when the weight on the first-stage model forecasts is positive. The industry categories are defined in Appendix A1.

	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Shops	Hlth	All
				Average First-Stage Coefficients						
Constant	0.40	0.35	0.12	16.30	0.06	1.67	0.70	0.26	0.02	2.21
EPS-1	0.33	0.46	0.56	0.72	0.54	0.59	0.43	0.44	0.54	0.51
EPS-4	0.54	0.35	0.27	0.09	0.31	0.22	0.29	0.43	0.32	0.31
RET	-0.28	-0.03	0.01	2.89	0.03	0.36	0.29	0.10	0.06	0.38
CMP	0.07	-0.01	-0.01	1.32	0.00	-0.04	0.05	0.05	0.11	0.17
QRV	-1.32	-1.64	-1.19	-57.31	-1.32	-4.34	-3.80	-0.99	-0.38	-8.03
MEY	0.29	0.78	0.41	65.11	0.72	2.14	0.65	0.45	0.14	7.86
CRB	-4.95	-3.27	0.10	-183.35	2.59	-24.71	-7.97	-2.77	1.44	-24.77
				Average Absolute t-Statistics						
Constant	1.56	1.77	1.26	1.24	1.13	1.28	1.21	1.33	1.09	1.32
EPS-1	3.62	5.42	6.81	9.15	6.31	6.90	4.65	4.91	5.72	5.94
EPS-4	7.72	3.92	3.74	1.65	3.84	3.02	3.28	5.65	3.19	4.00
RET	1.21	0.90	1.03	1.00	0.98	1.11	0.80	1.25	0.94	1.02
CMP	0.70	0.73	0.88	1.31	0.67	0.61	0.75	0.86	0.93	0.83
QRV	1.28	1.82	1.77	1.60	1.51	1.21	1.07	1.51	1.06	1.43
MEY	0.98	1.38	1.16	1.23	1.05	0.90	0.78	1.16	1.00	1.07
CRB	1.29	1.27	1.09	1.21	0.96	1.21	1.08	1.22	1.07	1.16
				Average Regression Fit						
R-square	0.72	0.68	0.73	0.73	0.71	0.72	0.62	0.74	0.72	0.71
				Second-Stage Results						
Model Share	0.14	0.10	0.12	0.08	0.09	0.11	0.13	0.14	0.15	0.12
Fraction	0.60	0.45	0.59	0.44	0.48	0.56	0.46	0.58	0.55	0.52

Table 2.4: Forecast result comparisons

This table presents various comparisons between different forecast results. Panel A provides the correlations between the Model Forecasts (*MF*), the Combination Forecasts (*CF*), and the Analyst Forecasts (*AF*), with all three being correlated with the Realized Earnings (*RE*). Panel B provides the t-statistics for the Mean Squared Prediction Error (*MSPE*) of forecast to announced earnings for different pairs of forecasts: first-stage model forecast without CMP (*MF0*), first-stage model forecast with CMP (*MF*), analyst consensus forecast (*AF*), second-stage combination forecast without CMP (*CF0*) and second-stage combination forecast with CMP (*CF*). The t-statistic is based on differences in the MSPEs between two of these forecasts.

Panel A: Prediction Results Correlations							
	Forecast-Forecast Correlations				Forecast-Realized Correlations		
Pairs	CF vs MF	CF vs AF	AF vs MF		MF vs RE	AF vs RE	CF vs RE
Correlation	0.535	0.878	0.199		0.532	0.788	0.802
Panel B: Prediction Error Relative t-Statistics							
Relative MSPE	CF-CF0	CF-AF	CF-MF	CF0-AF	MF-AF	CF0-MF0	MF-MF0
T-Statistic	-2.20	-2.00	-1.08	-1.91	0.95	-0.42	1.01

TABLE 2.5: Forecast comparisons by decile and industry

This table presents different detailed comparisons of forecasting errors. Panel A displays the ratio of the MSPE of the second-stage combination forecast with CMP (CF) to the MSPE of the analyst consensus forecast (AF) for each decile of the MSPE (ranging from highest to lowest). Panel B displays a similar comparison but broken down by industry. Detailed industry definitions are shown in Appendix A1.

Panel A: Prediction Error Ratios by Ranking Decile										
Decile	1	2	3	4	5	6	7	8	9	
MSPE Ratio	2.051	0.919	0.812	0.814	0.815	0.882	0.919	0.972	0.991	
Panel B: Prediction Error Ratios by Industry										
Industry	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Shops	Hlth	All
MSPE Ratio	0.937	0.893	0.807	0.884	0.690	0.722	1.254	0.903	0.837	0.815

Table 2.6: Trading results based on earnings forecasts from the model

This table presents the trading results based on earnings forecasts from the model. When the model forecast is larger (less) than consensus analysts forecast, then buy (short) the stock. Day [0] is the day when actual earnings are announced. Days [-1, 0] are one day before and on the day of earnings announcement. Days [-2, 0] are two days before and on the day of actual earnings announcement. Days [-1, 1] are one day before, on the day of and one day after actual earnings announcement. Days [-2, 2] are two days before, on the day of and two days after actual earnings announcement. Trading returns are annualized and in excess of market returns. Sharpe ratios are annualized.

	Day [0]	Days [-1, 0]	Days [-2, 0]	Days [-1, 1]	Days [-2, 2]
Panel A: Long-Short Strategy					
Return	13.20%	11.49%	8.67%	5.99%	4.58%
t-stat	1.37	2.30	2.52	1.63	1.94
Sharpe ratio	0.12	0.14	0.13	0.08	0.07
Panel B: Long-Only Strategy					
Return	38.54%	25.34%	18.60%	15.94%	11.76%
t-stat	3.58	4.55	4.86	3.90	4.52
Sharpe ratio	0.44	0.44	0.32	0.36	0.42

TABLE 2.7: Trading returns by various groups

This table presents the trading returns of event interval [-1, 0] by various groups. Each quarter, the stocks are grouped into 5-subgroups by different characteristics from 1 (lowest) to 5 (highest). *Realized variance* is the sum of squared daily returns. *Stock returns* is the cumulative daily returns. *Forecast distance* is the absolute value of the EPS forecasts from combination model minus the consensus analyst forecasts. *Analyst dispersion* is the standard deviation in analyst earnings forecasts, scaled by the quarter end share price. *Firm size* the quarter end market capitalization of a stock. Trading returns are annualized and in excess of market returns.

Groups by		1(%)	2(%)	3(%)	4(%)	5(%)
Panel A: Long-short returns						
Realized variance	Return	-9.65	9.84	26.56	13.13	17.11
	t-stat	-1.37	1.12	2.58	1.08	1.12
Stock return	Return	45.56	13.26	-7.32	3.52	1.95
	t-stat	3.36	1.30	-0.76	0.36	0.17
Forecast distance	Return	-0.05	28.36	9.53	20.38	-1.19
	t-stat	-0.00	2.82	0.92	1.82	-0.09
Analyst dispersion	Return	14.74	31.39	6.86	3.19	1.01
	t-stat	1.47	3.31	0.64	0.28	0.08
Panel B: Long-only returns						
Realized variance	Return	-4.26	10.80	60.08	24.59	34.45
	t-stat	-0.54	1.12	5.21	1.85	1.99
Stock return	Return	55.07	23.46	6.09	23.73	17.31
	t-stat	3.67	2.06	0.57	2.15	1.32
Forecast distance	Return	21.62	44.71	30.47	19.17	9.65
	t-stat	1.93	4.05	2.60	1.55	0.64
Analyst dispersion	Return	38.88	28.94	39.46	26.48	-8.26
	t-stat	3.55	2.68	3.29	2.11	-0.55

Chapter 3

Insider Information Production: Evidence from Insider Trading around M&As

3.1 Introduction

Insider trading has been, for a long time, an important issue in both the legal and financial economics literature (Bhattacharya, 2014).[1] Nevertheless, do insiders trade based solely on their *endowed* superior information, or do they also actively engage in private efforts in major corporate events, such as mergers and acquisitions (M&As), to *produce* information in favor of their position? While prior studies suggest that insiders profit from information asymmetry (e.g. Banerjee, 2011; Cespa and Vives, 2015) and abnormal insider trading carries valuable price-related information (e.g., Akbulut, 2013; Agrawal and Nasser, 2012), the role of insiders in the process of information production remains vague. Most existing literature in the

[1] In this paper, we employ a broad definition of insiders, including not only individuals with *direct* privileged access to private information, such as managers and board members of a firm, but also those who have *indirect* access to undisclosed material information, such as relatives and friends of direct insiders. Remarkably, China Securities Regulatory Committee, 2017 reveals that 70% of insider trading in China is conducted by these indirect insiders. Consequently, the insiders discussed in this paper represent a group of individuals, and potentially even entities (such as another firm or trust under the control of these individuals) who share private information and possess aligned interests.

information asymmetry area assumes, explicitly or implicitly, that insiders are information acquirers, defined as people who acquire and trade on *existing* privileged information.[2] Accordingly, the resulting debate on regulation also assumes that insiders are information acquirers (Finnerty, 1976; DeMarzo, Fishman, and Hagerty, 1998; White, 2020).

This study aims to investigate whether insiders, to some extent, also engage in information production. To be broadly defined, as long as any new information is generated, it can be called as an information production. For instance, subjective ratings of borrower firms by bank loan officers (Qian, Strahan, and Yang, 2015) or voluntary disclosure of information by firms (Wang and Xie, 2022) are considered examples of information production. In financial markets, financial analysts, who frequently publish reports and forecasts, are commonly recognized as information producers (Corwin and Schultz, 2005; Keshk and Wang, 2018; Gao and Huang, 2019; Cornaggia, Cornaggia, and Israelsen, 2020; Driskill, Kirk, and Tucker, 2020; Zhu et al., 2021; Chen et al., 2022; Choi and Gupta-Mukherjee, 2022). The objective of this study is to examine whether insiders actively insert their private efforts and engage in information production. This includes their actions of actively seeking, exaggerating, and promoting positive information while intentionally disregarding negative information. The purpose of these activities is to make the deal more appealing to others, leading them to believe that the deal is favorable and likely to be successfully completed. Ultimately, insiders engage in these practices can enhance their trading profits. To address this, we leverage the distinctive setting of trading suspension during M&As in China. Our findings provide insight into insider roles as information producers during major corporate events, as well as empirical evidence

[2]The classic rational expectations equilibrium (REE) model of Grossman and Stiglitz (1980) and Hellwig (1980) assumes that traders use their private information as given to maximize their expected utility. Although the recent studies of Goldstein and Yang (2015) and Goldstein (2023) extend the model by allowing traders to be endowed with different types of information from various sources, the information set by assumption is still exogenously given rather than produced by traders.

of insider "rent-seeking" behaviors[3] during corporate acquisitions.

Insider actions within a firm have been more thoroughly discussed in the corporate governance literature,[4] but have been less of a focus in the information asymmetry and insider trading literature. This is partly due to endogeneity concerns, as insiders usually make their trading and private effort decisions concurrently. Hence, it is empirically challenging for researchers and regulators to distinguish the portion of transactions motivated by existing private information from those motivated by insider endogenous rent-seeking efforts. As a result, researchers usually model private information as exogenous to insiders and focus on insider trading activities in the financial markets (e.g. Biggerstaff, Cicero, and Wintoki, 2020; Augustin, Brenner, and Subrahmanyam, 2019; Cline and Houston, 2022). For regulators like the U.S. Securities and Exchange Commission (SEC), insider trading policies are therefore constructed around indirect trades derived from insider private information (Goldie et al., 2022), regardless of insider roles in information production. We address this issue with the trading suspension mechanism in M&A.

The trading suspension mechanism at M&A announcements is not unique to the Chinese stock market. Similar mechanisms like the trading halt have been established in the U.S. market since 1987 and have received considerable attention in the literature (e.g., Lee, Ready, and Seguin, 1994; Corwin and Lipson, 2000; Christie, Corwin, and Harris, 2002; Chakrabarty, Corwin, and Panayides, 2011; Menkveld and Zhou, 2018). Nonetheless, the prolonged trading suspension mechanism[5] provides a natural setting in which insiders can make their private effort decisions after

[3]In this paper, we use the term "rent-seeking" loosely to refer to an insider's private effort solely to influence a deal's outcome in order to elicit higher insider trading profits without improvements in firm long-term performance.

[4]For example, Bebchuk and Fershtman (1994); Augustin, Brenner, and Subrahmanyam (2019); McNally, Shkilko, and Smith (2015); Ali and Hirshleifer (2017); Dai et al. (2016); Cziraki, De Goeij, and Renneboog (2013); Hu and Noe (2001); Betzer and Theissen (2009) and Jagolinzer, Larcker, and Taylor (2011).

[5]Trading suspension in the Chinese stock market usually lasts from days to months, while U.S. market trading halts typically last for five minutes to an hour, and up to a maximum of ten days.

trading positions have been established. Meanwhile, non-insiders receive updated information on the deal twice[6]: once at deal announcement when trading suspension begins, and again at the mandatory progress disclosure immediately before trading resumes. With this mechanism in place, regulators are able to highlight deals with potential insider trading by comparing signals at two information releases. While insiders are motivated to disguise or even improve deals during the suspension to elicit more positive market reactions, they also attract potential regulator attention when doing so. Thus, we take an event study approach when a 2011 regulatory change significantly increases the legal risk of conviction for insiders who insert private efforts during deals. The expectation underlying our empirical approach is therefore fairly straightforward: as insiders withdraw private efforts in fear of heightened legal risk, outcomes of the deal (i.e. insider's abnormal return, probability of deal completion, etc.) also change, if private efforts indeed exist in deals prior to the regulatory shock.

Following this argument, we report that, after controlling for various deal-specific and market-wide factors, predictability of deal completion was reduced by 1.88% and insider profitability was reduced by 0.39% per percentage point increase in insider trading over a 3-day window around regulatory tightening. For robustness, we also include a more general regulation change immediately after the proposed event in 2013 and the results remain the same. Our results suggest that insiders are not only information acquirers utilizing existing information to "cherry-pick" deals that are more likely to succeed, as documented in the literature, but also information producers who engage in operational efforts to promote higher trading profits at deal completion. Our findings that insiders engage in private efforts during acquisitions in China also has strong implications for the U.S. market, as Chinese rent-seekers face a greater risk of exposure with the dual-update requirements under the trading suspension mechanism. For U.S. insiders, violations are usually identified

[6] In the Chinese stock market, most M&A procedures occur during the trading suspension period after the merger announcement. For a detailed discussion of this unique mechanism, please see Section 3.2.

from transactions in the securities market.

Our study also sheds light on the real effects of insider private efforts. An insider's private effort could improve shareholder welfare if it enhances the fundamentals of the deal and improves the firm's long-term performance. Meanwhile, efforts that misrepresent the fundamental value of the firm to elicit higher insider trading return could be value destructive to shareholders in the long term. We test the long-term impact of insider private efforts on a firm's operating income. Our results suggest that such rent-seeking behaviors have no significant predictive power relative to acquirer long-term performance, implying that insider private efforts improve the fundamentals of neither the acquirer nor the target.

We begin by characterizing insider trading activities around M&As in China. Consistent with the existing literature, univariate evidence suggests that insider trading is positively associated with deal completion (e.g., Fidrmuc and Xia, 2022) and acquirer cumulative abnormal returns (CARs) for various windows of observation (Shams, Duong, and Singh, 2016). Further, we show that after the 2011 regulatory shock, insider impacts on both the probability of deal completion and CARs were significantly reduced. We confirmed our findings with both dummies of convicted illegal insider trading cases and the probability of informed trading (*PIN*, Easley et al., 1996).[7] To control for the investor's expectation of further regulatory changes, we also include the effects of a major subsequent regulatory tightening in 2013. Our results remain robust, demonstrating that our findings are not driven by alternative major regulations. Finally, we conduct a placebo test with randomized

[7]The PIN initially is a measure designed to capture informed trading, which can be either legal or illegal. However, it is highly unlikely that legal informed trading is affected by the 2011 regulation tightening, which targets illegal insider trading. More details about this will be discussed in Section 3.2.2. Consequently, the change in PIN related to the 2011 regulatory shock (i.e., regressing PIN on the 2011 regulatory shock dummy, results are significant with control variables and available from the authors) is more likely attributable to illegal insider trading. This presents us an opportunity to use the PIN measure as a proxy for illegal insider trading in the event study analysis in this paper. Furthermore, to validate the PIN measure, more details are presented in Section 3.3.

regulation dates to establish the causal relationship between the 2011 regulation and the reduction in the private-effort type insider trading.

Our paper contributes to several strands of the literature. With respect to the literature on insider trading, our results demonstrate the insider role as a non-fundamental information producer, which has not been explicitly discussed in previous literature given its endogenous nature in the U.S. market. While extant literature acknowledged the importance of informed activist insiders (Collin-Dufresne and Fos, 2015; Collin-Dufresne and Fos, 2016; Albuquerque, Fos, and Schroth, 2022), these insiders tend to focus on long-term fundamental information production (i.e. value creation) as suggested in Albuquerque, Fos, and Schroth (2022). The corporate insiders in our study are short-term profit-driven market participants, without significant impact on firm long-term fundamentals. Similar to our work, Chen and Jorgensen (2021) document corporate insider accounting manipulation activities. In respect to the M&A literature, our paper expands on Biggerstaff, Cicero, and Wintoki (2020), who also studied the information content of corporate insiders. However, we contend that profit-seeking insiders not only increase their information advantage through trading, but also via operational efforts. Our paper is also related to Suk and Wang (2021), who studied the implications of insider legal long-term trading activities on M&A outcomes. While the findings in Suk and Wang (2021) suggest that insiders cherry-pick deals with superior quality through disclosed trading activities, our paper emphasizes insider undisclosed operational efforts in tandem with insider transactions.

The findings of our study are also relevant to other markets where trading suspensions are brief or absent. In these markets, investors receive information on the deal only once before trading begins at deal announcement. Consequently, insiders in such markets, like the U.S., would opt to carry out their private efforts *prior* to the announcement of the deal and conceal insider-generated information within information related to fundamentals. Therefore, insiders are more prone to be information producers in these markets, and our findings that insiders do produce information in the Chinese market lends strong support to similar insider behaviors in other markets. Our results also motivate further exploration into theories of insider trading behavior, in which the information set of insiders could be both exogenously endowed and endogeneouly generated by the insider. Our study further provides nuanced insights into the legal literature, suggesting that insider acquisition and production of information may be viewed differently legally. Exchanges could improve existing mechanisms such that insider operational efforts could be less vague to investors in the scheme.

This paper is organized as follows. In Section 3.2, we describe the institutional setting of the trading suspension mechanism in China and conduct a systematic review of previous literature. In Section 3.3, we discuss the data sample. Results and discussions are presented in Section 3.4. Additional robustness tests are presented in Section 3.5. Section 3.6 concludes the paper.

3.2 Institutional Background and Literature

3.2.1 Institutional Background in Chinese M&As

During an M&A deal, listed companies in China voluntarily suspend their trading for a relatively long period of time immediately after the M&A announcement (Tian, 2019; Chen, Li, and Wei, 2017; He et al., 2019). While most trading halts in the U.S. last for five minutes, and up to a maximum of ten days, trading suspension in China typically lasts from days to months. The existence of this prolonged trading suspension mechanism leads to a few systematic differences for acquirers in China. To better illustrate the differences, we provide a timeline of M&As in each market in Figure 3.1.

[Figure 3.1 about here]

We have divided the M&A process in China into three phases[8]: preparation (Phase I), trading suspension (Phase II), and deal closure (Phase III). In Phase I, the acquiring company establishes the choice of target, hires investment banks for preliminary consultation with a signed confidentiality agreement, and drafts the letter of intent. This period is usually short in duration with limited discussion of deal details.[9] Insiders may choose to engage in private effort during this phase. However, uncertainties associated with the deal could be very high at this time. Acquiring firms have up to 10 days to confirm their acquisition intention to the public or the deal may be dismissed. In fact, in our collected sample, only 31.12% of deals had declared M&A events at the suspension announcement, with the remaining 68.88% of deals confirming M&A within the 10 days following the announcement.

It is notable that for firms in the U.S. (presented in the bottom panel of Figure 3.1), the majority of the preparation, valuation, and negotiations are concentrated in Phase I, prior to the announcement. When U.S. insiders engage in private efforts during this phase, the public will receive a "decorated" signal regarding potential synergies of the deal at the announcement. This noisy signal is expected to elicit higher trading profit for acquirer insiders who hold net buy positions, and to avoid potential public and regulatory monitoring after the fact.

Phase II of the M&A process for Chinese firms begins with the deal announcement on Day 0. At Day 0, a trading suspension announcement is made to the public regarding the potential M&A. From Day 0 to Day T, independent advisors, financial consultants, lawyers, and accountants are hired to provide professional opinions on the deal, including asset valuation and earnings forecast. Audited results will be

[8]Description of the Chinese M&A process is based on Chen, Li, and Wei (2017), regulations for reorganization of Chinese listed companies, and interviews with M&A advisors.

[9]While this paper describes the usual scenario, there are deals that are mostly or even fully prepared during this phase. We discuss our treatment for such deals later in this section.

presented at the first board of directors meeting, during which a plan for the upcoming M&A deal will be voted on. At this stage, uncertainties around the deal have reduced significantly. Insiders may choose to engage in private effort to facilitate the deal, such that when the plan for the deal is released to the public on Day $T-1$ and trading resumes on Day T, higher insider returns can be achieved.[10] However, insiders must be careful about their level of private effort, as greater discrepancies between Day 0 and Day $T-1$ signals may not only elicit superior returns but also unsolicited regulatory attention. For most U.S. firms, Phase II is either non-existent or as short as five minutes, depending on the exchange where the firms are traded. For Phase III, X days after trading is resumed, the deal will be closed, either as a successfully completed deal or as a failed deal.

We now consider the possibility that corporate insiders have more certainty regarding the deal and choose to engage in private efforts early solely in Phase I. For example, in the deal in which BTG Hotels acquired 70% of Nanyuan Group's common equity, BTG Hotels was suspended for 2 days on June 23rd and 24th, 2014, and trading resumed on June 25th. It is unlikely that all negotiations and valuations were prepared within only a few days, nor could any insiders engage in private effort to impact the deal in a material manner. In such cases, Chinese regulators face the same challenge as their U.S. peers, as barely any significant information was produced during suspension. Hence, for deals in which insiders engage in private effort solely in Phase I, the deal outcome should not be affected by the 2011 regulation, which is most effective against Phase II insider efforts. By including these deals in our sample while observing significant results, we demonstrate the robustness of our findings. In fact, the exclusion of deals with short suspension periods (the bottom 25%) generates stronger results than our full sample.

Another advantage of using Chinese stock market data is the limited variety of

[10]Here we assume insiders tend to take the net long position, considering there are a limited number of insider trading channels in Chinese markets. More about this is discussed sooner.

insider trading channels. In developed markets, insider trading strategies can be employed with a variety of financial instruments and positions, such as combinations of long and short positions to achieve an effective net buy position (Agrawal and Nasser, 2012), options (Cao, Chen, and Griffin, 2005; Augustin, Brenner, and Subrahmanyam, 2019), and corporate bonds (Kedia and Zhou, 2014; Li and Galvani, 2021). In contrast, insiders in China have a limited choice of financial instruments.[11] Access to short sales was not granted until 2010 (Chang, Luo, and Ren, 2014), with subsequent regulated access, up until a tightening of regulations following the 2015 market crash, which was heavily criticized by the public as being a result of short selling (Riley and Chang, 2015). The concentration of insider trading in the equity market, dominated by the net long position, allows our research to capture a significant portion of insider trading activities in the market.

However, we are also aware of the limitations of using Chinese data for our study: in addition to variations in stock market structures, our sample is dominated by deals with publicly traded acquirers and private targets. As a result, we focus our study solely on acquirer insiders, setting aside the equally interesting question of target insider operational efforts.

3.2.2 The 2011 Regulatory Shock

Insider trading laws were established in China in 1993, and the level of enforcement has varied over time (Peng, Xiao, and Zhao, 2017; Bhattacharya and Daouk, 2002). In response to growing demand for a more efficient financial market, the China Securities Regulatory Commission (CSRC) initiated a series of regulatory changes between 2011 and 2014. In 2011, the CSRC, along with the Supreme People's Court

[11] The Chinese market currently does not allow option trading for individual corporate stocks on exchanges. The OTC market for options on corporate stocks was not available until 2016. The corporate bond market is represented by commercial bank counter sales, which lack the essential liquidity for corporate insiders (Zhang, Huang, and Wang, 2019; Asian Development Bank, 2019).

of the People's Republic of China, published a report identifying new legal liabilities of corporate insiders. The major impact of this regulation is an inverted presumption of innocence. That is, unless a corporate insider can provide evidence that they fulfilled their corporate responsibility without involvement in insider trading activities, they will be considered guilty. This memorandum has significantly increased legal risk for insiders, especially those who choose to engage in private operational efforts.

As mentioned in the previous section, deals with more private efforts generate greater discrepancies between signals released on the announcement day (Day 0) and the progress report day (Day $T-1$), which in turn attracts more regulatory attention. With the 2011 regulatory change, it became increasingly difficult for insiders to show that their operational efforts were motivated by responsibility rather than trading profitability. As a result, for the insiders, the probability that they are caught involved in insider trading activities is getting higher if private effort is inserted. As an illustration, a sample case provided by CSRC is presented in Appendix B2. In practice, the number of convictions in cases of insider trading increased considerably, by 21.4% in 2011 alone (Peng, Xiao, and Zhao, 2017).

In our study, we use the aforementioned 2011 regulatory change as an external shock. This was the first of several regulatory tightening actions during the period of 2011 to 2014. While substantial literature documents the effectiveness of insider trading laws (e.g., Agrawal and Jaffe, 1995; Maug, Halteren, and Ackerman, 2008; Pham and Ausloos, 2020; Christensen, Hail, and Leuz, 2016; White, 2020), a valid concern arises if insiders change their behaviors in expectation that more regulatory tightening will follow. In other words, our findings may be explained by insiders' reduced trading activities due to fear of future tightening in general, rather than, specifically, the increased legal risk of engaging in private effort.

To show that our results are robust to future regulations, we also include a 2013 major regulatory change in our analysis. In 2013, an interpretation of the law was published by the Chinese Supreme Court, providing a unified extended definition of corporate insiders similar to that in SEC rule 10b-5 (Li, 2015). This regulatory shock should negatively affect the ability of all insiders to trade based on private information (Peng and Xiao, 2018; Huang and Zhang, 2019). We compare the effects of the two regulations to show that our findings in 2011 are not likely to be driven by subsequent regulatory tightening.

3.2.3 Literature Review

Insider Trading

It is well documented that insider trading occurs in many financial markets (Bhattacharya and Daouk, 2002; Bris, 2005). Earlier researchers like Jaffe (1974), among others, document the existence of insiders who possess superior information, based on which they make trades. Meulbroek (1992) reports an average abnormal return of 3% per day for insiders while Fishe and Robe (2004) find significant increases in stock price and trading volume after informed trades. Recent research using U.S. data has also revealed insider trading activities outside of the traditional stock market channel, in derivatives markets (Cao, Chen, and Griffin, 2005; Augustin, Brenner, and Subrahmanyam, 2019; Acharya and Johnson, 2007), corporate bonds (Kedia and Zhou, 2014; Li and Galvani, 2021), and in combinations of equity and options (Dai et al., 2017). In the Chinese market, however, insider trading is still most prevalent in the equity market.

In addition to studies on market reactions to insider trading, some scholars debate the influence of insider trading on social welfare. Bhattacharya and Daouk (2002) find that illegal insider trading increases the cost of equity. Meulbroek and Hart (1997) report that takeover premiums for deals with detected illegal insider trading are approximately 10% higher. Aleksanyan et al. (2022) show that media articles about insider trading temporarily heighten the perception of litigation and reputation risk for target firms. Some scholars have studied the confounding motivations behind insider trading. For example, Kallunki et al. (2018) find that less wealthy insiders are more likely to time their insider selling, while Bhattacharya and Marshall (2012) claim that illegal insider trading may not be solely motivated by profits, leaving open the possibility of other motives.

In extension of the literature on insider trading market reactions, researchers have further studied the informativeness of insider trades. For example, Cohen, Malloy, and Pomorski (2012) show that opportunistic insider trades carry more information than routine trades. By examining insiders' disclosed trades, Kelly (2018) uncover that the sale of stock at a loss is a much more negative signal about future returns than the sale of stock at a gain. Similarly, Purnanandam and Seyhun (2018) find that short-selling activities are quite informative about future stock returns when the likelihood of insider trading is high. DeVault, Cederburg, and Wang (2022) find that insider "not-sold" stocks provide more information than "not-bought" stocks. Suk and Wang (2021) find that acquirers' abnormal returns increase with target firm insider net purchase ratios. Collin-Dufresne, Fos, and Muravyev (2021) provide evidence consistent with a theoretical model in which informed trading occurs mainly in the stock market and market makers update options prices based on stock-price and order-flow dynamics. Goldstein (2023) documents that corporate insiders actively incorporate information feedback from financial markets in their production and investment decisions. Biggerstaff, Cicero, and Wintoki (2020) provide evidence on insider efforts to elicit higher trading profits by intentionally disclosing their trades after market close.

Inspired by Biggerstaff, Cicero, and Wintoki (2020), our paper studies insider operational efforts within the firm. Most of the aforementioned studies either implicitly or explicitly assume that insiders are merely information acquirers. In other words, insiders take advantage of the information asymmetry around M&As and use the acquired information to trade in various channels for profit. The issue with such behaviors is mainly adverse selection (similar to the underpricing in IPO, see Rock, 1986 and Balvers et al., 1993). Recent papers such as Greenwood and Schor (2009) and Bebchuk et al. (2020) have suggested that activist insiders could cast their influence on M&As for higher insider trading profits and hence become information producers. Our paper extends this theory to shed light on the role of those corporate insiders who have contractual obligations to the firm and the ability to impact a deal (i.e., corporate managers). The research question we seek to answer is whether these corporate insiders are also information producers who engage in private efforts to achieve better insider trading profits during M&As. Thus, the issue with such behaviors is mainly moral hazard. We contribute to this stream of literature by providing empirical evidence on the insider's role as an information producer during M&As.

Corporate insiders may profit from either legal or illegal insider trading. Extant literature discusses insider trading in the context of legal insider trading, with corporate insiders disclosing their trading plans to the SEC on a regular basis. With a developed financial system in the U.S., the literature on illegal insider trading is relatively slim (e.g., Meulbroek, 1992; Meulbroek and Hart, 1997; Bhattacharya and Daouk, 2002; Bhattacharya and Marshall, 2012; Akey, Gregoire, and Martineau, 2022). In this paper, we focus on illegal insider trading for two reasons. First, as corporate insider private efforts are usually unobservable, these actions themselves are neither legal nor illegal. Only through the trading suspension mechanism and the 2011 regulatory tightening in China, when insider private efforts were tied to convictions for illegal insider trading, were we able to empirically test the existence of such information production behaviors. Second, Cline and Posylnaya (2019) report that

52.63% of event-driven illegal insider trading occurs around M&As.[12] As M&As are not regular corporate events, in the presence of the "short-swing" rule,[13] a significant portion of insider trading around M&As is opportunistic in nature and illegal. While Suk and Wang (2021) capture the effects of legal insider trading activities around M&As, our paper fills the gap on illegal insider trading around M&As.

Mergers & Acquisitions

A rich body of literature examines insider trading behaviors around M&As. Regardless of the various regulatory efforts around the globe, researchers like Jagolinzer, Larcker, and Taylor (2011) and Lee et al. (2014) have documented significant insider trading profits around M&As. Various insider trading patterns and channels are characterized in the literature (e.g., Augustin, Brenner, and Subrahmanyam, 2019; Schwert, 1996; Akbulut, 2013; Biggerstaff, Cicero, and Wintoki, 2020).

Numerous papers characterize insider trading activities around target firms. For example, Tang and Xu (2016) report that undisclosed insider trading activities explain much of target firm price run-ups prior to merger announcements. Fidrmuc and Xia (2022) demonstrate that insiders increase their net purchases in deals with a higher probability of completion. Augustin, Brenner, and Subrahmanyam (2019) document the extent, source and implications of insider trading in non-U.S. markets, while also providing evidence on the pervasiveness of insider trading activities using equity options. Agrawal and Nasser (2012) present a comprehensive examination of insider trading activities in target firms and demonstrate that insiders engage in "passive" trading prior to M&A announcements. Suk and Wang (2021), examining insider trades that took place up to one year prior to the public announcement of

[12] Besides those around M&As, 19.84% is around quarterly earnings announcements, 17.81% is around news announcements, 5.67% is around FDA announcements and clinical trials and 4.05% is around fraud-related events.

[13] The "short-swing" rule, enforced by the SEC, discourages most short-term profit-generating transactions in the U.S market. In the absence of rigorous enforcement of the short-swing rule in China, short-term insider trading is still a prominent phenomenon in China's A-share market.

acquisitions, suggest that target insiders trade based on their privileged information on deal fundamentals and that target insider trading serves as a reliable predictor of deal outcomes.

While most literature focuses on insider trading activities around target firms, our paper studies acquirer firms for two reasons. First, M&As in the Chinese market are dominated by deals with publicly traded acquirers and private targets whose fair market value is ambiguous. Managers at these private target firms are not obligated to disclose their transactions to regulators like their peers. Second, aside from empirical motivations, manager potential operational efforts can be better captured for acquiring firms, as acquirers are usually deal initiators and private efforts can begin as early as the preparation phase, before any communication with the target firm. For example, Billett and Qian (2008) use frequent acquirer CEOs' net purchases before acquisitions to quantify self-attribution bias. Akbulut (2013) uses managers' insider trades as a proxy for overvaluations and reports that overvaluation-driven stock acquisitions are value destructive to acquirer shareholders. Similarly to our study, Shams, Duong, and Singh (2016) and Gordon (2021) use samples of acquirer director transactions to discuss potential information asymmetry and agency problems during M&As. Hence, our study focuses on the potential interventions and transactions of acquirer insiders.

3.3 Data

Our data on Chinese M&A deals,[14] insider trading, stock performance, and firm- and market-level data are collected from a number of sources. We first collected information on M&A deals from Wind Financial, with hand-collected high-frequency trading data bookending the M&A suspension announcement dates for the period of

[14]We also include acquisition of materially significant major assets.

2006 to 2018.[15] Since our study focuses on the stock performance of the acquirer, we obtain firm stock returns and fundamentals, industry-level data, and corresponding market data from the China Stock Market & Accounting Research Database (CSMAR). The merged dataset contains 1,768 M&A deals dating from March 2006 to June 2018, with high frequency data up to 50 days prior to the M&A suspension announcement date. For this study, we retain 1,295 acquirers with necessary dependent and independent variables.

On average, acquirers experienced a positive abnormal return of 10.1% over the three-day period around trading resumption, which is consistent with papers based on U.S. data (e.g. Louis and Sun, 2010; Jarrell and Poulsen, 1989; Nguyen and Phan, 2017). Moreover, approximately 70% of deals were successfully completed. On average, the long-term abnormal return of the acquiring company one year after the acquisition was close to 0 after adjusting for risk factors. Summary statistics on the collected M&A deals are presented in Table 3.1.

[Table 3.1 about here]

We then retrieved confirmed cases of illegal insider trading from the announcements of the China Securities Regulatory Commission (CSRC).[16] Eighty deals announced by the CSRC involved illegal insider trading while the remaining 1,215 events could possibly be a mix of incidents of insider trading not yet confirmed or announced by the CSRC and deals without any insider trading.

Given the possibility of unconfirmed cases of insider trading, we needed to find a measure that could capture such information asymmetry carried out by insiders. Previous studies have proposed several measures to identify information asymmetry in financial markets, including the probability of informed trading (PIN, as in

[15] Our data ends in 2018 as the result of a regulatory change on the trading suspension mechanism, which limits firm access to trading suspensions.

[16] http://www.csrc.gov.cn/csrc_en/index.shtml

Easley et al., 1996), the Kyle model (Kyle, 1985), the conditional probabilities of an informed event (CPIE, as in Back, Crotty, and Li, 2018) and the Hasbrouck measure (Hasbrouck, 1991a; Hasbrouck, 1991b).

We first tested the CPIE measure, which is recently developed by Back, Crotty, and Li (2018). This measure is developed from combining a PIN model that captures order flow and Kyle model that strongly emphasizes price impact. However, unlike studies with U.S. data, our study finds that the predictive power of the CPIE measure is weakened by the daily price limits in Chinese stock markets.[17] To validate PIN, Figure 3.2 shows that the PIN measure can successfully distinguish between identified and unidentified insider trades, while the CPIE measure cannot. Given the presence of daily price limits in Chinese stock markets, the effectiveness of measures explicitly using price information (e.g., Back, Crotty, and Li, 2018; Hasbrouck, 1991a; Hasbrouck, 1991b; Kyle, 1985) are distorted. Hence, in the present study we use the PIN measure, as proposed by Easley et al. (1996).

[Figure 3.2 about here]

In addition, the PIN measure is initially designed to capture informed trading, which can be either legal or illegal. However, here we use it as a proxy for illegal insider trading. Our argument is that it is highly unlikely that legal informed trading is affected by the 2011 regulation tightening, which targets illegal insider trading, as discussed in Section 3.2.2. Consequently, the change in PIN related to the 2011 regulatory shock (i.e., regressing the PIN measure on the 2011 regulatory shock dummy with control variables)[18] is more likely attributable to illegal insider trading.

[17]In most cases, the daily price limits in Chinese stock markets are 10% of the previous closing price. For stocks with special treatment (ST) warning, such limits are 5%. There are several rules applied to give a stock the ST warning. A common case is that the net income of the listed company was negative in the last two consecutive fiscal years.

[18]The results are significant. To save space, the regression results are not presented but available from the authors.

This presents us an opportunity to use the PIN measure as a proxy for illegal insider trading in the event study analysis in this paper.

To further illustrate the efficacy of the PIN measure to be used, we show an extended window of PIN values up to 50 trading days prior to trading suspension in Figure 3.3. Approximately 10 trading days preceding deal announcement and trading suspension, abnormal trading activities are captured by our proxy for insider trading, the PIN measure.

[Figure 3.3 about here]

To control for other firm-level, deal-specific characteristics, we also extract information on the relatedness of the acquirer and target and the dates of decision and meeting related to M&A deals from company announcements listed on the websites of the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). For targets which are usually not listed companies, industry codes are prepared based on deal information from Wind Financial Terminal and then classified according to the CSRC Guidelines for the Industry Classification of Listed Companies (China Securities Regulatory Committee, 2012).

As noted in Li, Wang, and Wang (2017), Chen, Li, and Wei (2017) and Peng and Xiao (2018), a distinguishing feature of the Chinese corporate landscape is the state-owned enterprise (SOE). We define the SOE status of a company based on the controlling owner data from HiThink Data Service. We identified 371 companies that are SOEs. A complete list of all variables can be found in Appendix B1.

3.4 Empirical Results

3.4.1 Univariate Evidence

We begin with a brief examination of univariate evidence for variables documented to be associated with deal success. The set of variables includes short-term stock-price reaction to merger announcement after trading resumption (*Market Reaction*, such as *CAR(0,+1)*, *CAR(0,+2)* and *CAR(0,+3)*), short-term abnormal return before and after trading suspension (*Short-term Performance*, such as *CAR(-1,+1)*, *CAR(-2,+2)* and *CAR(-3,+3)*), and long-term performance of the firm (*Long-term Performance*, such as *1-Y abnormal*, *2-Y abnormal* and *3-Y abnormal*). The results are summarized in Panel A of Table 3.2. Consistent with existing literature with U.S. data (e.g., Meulbroek, 1992; Fishe and Robe, 2004), univariate evidence suggests a positive association between insider trading and market reaction as well as short-term abnormal returns. We also do not find a persistent relationship between insider trading activities and firm post-merger long-term performance, as in Agraval and Jaffe (2000), among others.

[Table 3.2 about here]

Panels B, C and D of Table 3.2 reports cross-sectional means for the set of measures before and after the 2011 regulation. Significant decreases are observed in post-resumption market reactions and short-term abnormal returns across different windows both in the full sample and within the group of deals in which the probability of insider trades is high. This is consistent with our expectation that insiders are selective on deals in which they trade. Within the group with a high level of insider trading, abnormal returns decreased from 11.3% to 6.6% on average over a 3-day period after the 2011 regulation. Similar significant decreases in CARs are observed in deals that are not successfully closed. This is also consistent with our expectation: for those deals with a lower probability to be completed successfully, insiders need to produce more information to generate positive abnormal returns, and thus, tend to be impacted heavily by the 2011 regulation. Meanwhile, in all the panels, we do not observe consistent change in firm long-term performance post event.

3.4.2 Insider Trading and Deal Success

Next, we formally test the effects of insider private efforts on deal outcomes. Specifically, we focus on two measures closely associated with insider efforts: insider cumulative abnormal returns on acquirer stocks and the probability of deal completion. As an extension of our discussion, we also test for changes in the long-term effects of insider private efforts.

Insider Cumulative Abnormal Returns

In this section, we consider the effect of insider private efforts on insider short-term abnormal returns, measured by CARs of acquirer stocks. For this purpose, our estimation model is:

$$CAR_i = \delta_0 + \delta_1 \cdot PIN_i + \delta_2 \cdot (PIN_i * Reg_{2011}) + \delta_3 \cdot Reg_{2011} + \Pi' \cdot M_i + \eta_i \quad (3.1)$$

where CAR_i is the 3-day cumulative abnormal return on acquirer stock (*CAR(-1,+1)*), PIN_i (as proxy for insider trading) is the average 10-day PIN before suspension, Reg_{2011} is a dummy variable for the 2011 regulatory shock, and M_i is the vector of other independent variables for event i.

Following Cohen, Malloy, and Pomorski (2012), we control for firm size (*TotalAsset*), market-to-book ratio (*RatioMB*), and leverage of the acquiring company (*Leverage*). Since the Chinese stock market is different from the U.S. market, we include control variables unique to Chinese stock market studies such as State Owned

Shares Percentage (*SOSPctg*) and whether the deal is with another company within the same business group (*ConnectedTrade*).

We also control for variables that may affect firm stock performance at trading resumption after an extended period of suspension, including stock market return during the trading suspension period (*MktRetDurSusp*)[19] and the prevalent business lending rate in the economy during the period of trading suspension (*BusiLendingRate*). We use the regulatory tightening in 2011, Reg_{2011}, as an exogenous shock to the established relationship between insiders and their ability to engage in private effort. The results are presented in Table 3.3.

[Table 3.3 about here]

In column (1) of Table 3.3, we present the base regression results for informed trading and abnormal returns. The coefficient estimation of Insider Trading is positive and significant. This finding is in line with the long standing literature documenting the positive relationship between insider trading activities and CARs (e.g., Meulbroek, 1992; Alldredge and Cicero, 2015; Aktas, Bodt, and Oppens, 2008). With a one-percentage-point increase in insider trading, the 3-day CAR increases by 0.32%.

In column (2), we introduce the regulatory tightening event into our model, with the dummy variable Reg_{2011}. The coefficient estimate on the interaction term $Insider \times Reg_{2011}$ is negative and significant, indicating reduced abnormal returns for insider trading activities after regulation tightening on insider private efforts. The negative and significant coefficient confirms our findings with univariate evidence, supporting the argument that some insider trading profits are driven by insider private efforts. The positive coefficient of the Reg_{2011} variable could be explained

[19] *MktRetDurSusp* captures the long-term market movements absent from the *CAR* calculation.

by insiders cherry-picking better deals. With increased legal risk after regulatory tightening, informed traders tend to trade only when they know that trading is more likely to be successful and profitable, which is consistent with the notion that in M&A deals, some informed traders (either individuals or financial institutions) take advantage of private information and engage in trading based on such information (Dai et al., 2017). Overall, after the regulatory shock, the 3-day CAR drops by 0.39% for each one percentage point increase in the PIN measure.

In columns (3) and (4), we repeat the same exercise but use convicted cases (*Convicted*, 1 for convicted insider trading cases and 0 otherwise) instead of the PIN measure as the proxy of insider trading. The results are similar to our base model but a little weaker in magnitude and significance.

Numerous studies also suggest that the cumulative abnormal return of bidders in all-equity deals differs from all-cash and mixed payment deals in a significant way (e.g., Betton, Eckbo, and Thorburn, 2008; Bradley and Sundaram, 2009; Agrawal and Nasser, 2012). In our subsample tests, we repeat the same exercise with subsamples of cash-only deals and stock-only deals, and report our results in columns (5) to (8) of Table 3.3. However, we find no significant difference in abnormal returns around the regulatory tightening event. The absence of explanatory power could potentially be the result of a significant reduction in the number of observations in the subsample given the rich variety of payment types in the Chinese market.[20] Only 18% of our sample, or 231 deals, are cash-only while 30%, or 389 deals, are stock-only. Among cash-only deals, prior performance before suspenstion (*PriorPerf*), which is the acquirer 30-day CAR before suspension, positively predicts abnormal returns, demonstrating the momentum of stock returns. The cost of debt financing (*BusiLendingRate*) negatively predicts abnormal returns, which is consistent with our expectation. Among stock-only deals, the acquirer level of leverage negatively

[20]A total of 12 types of payments are reported in our data sample.

predicts abnormal returns. Across two sub-types of deals, the coefficients of *MktRetDurSusp* remain positive and significant. At the same time, many contributing factors in the base model, such as *ConnectedTrade* and *ROA*, lose their explanatory power in subsample tests for abnormal returns.

Probability of Deal Completion

While acquiring and target firm financial conditions are determinants of deal completion, research has shown that a number of other factors also contribute to M&A deal completion. For example, Ishii and Xuan (2014) report significant impacts of social ties between acquirers and targets on merger outcomes. Aktas et al. (2016) find that acquiring CEO behavioral biases negatively affect the probability of deal completion. Among others, factors such as payment type (Netter, Stegemoller, and Wintoki, 2011; Huang, Officer, and Powell, 2016), policy uncertainties (Nguyen and Phan, 2017), institutional ownership (Harford, Jenter, and Li, 2011; Brooks, Chen, and Zeng, 2018), and corporate social responsibility (Arouri, Gomes, and Pukthuanthong, 2019) may also affect deal outcome. In addition, Schweizer, Walker, and Zhang (2019) and Erel, Liao, and Weisbach (2012) study the factors affecting completion of cross-border mergers. Built on prior research, we estimate the following model for the probability of deal completion:

$$f(IsCompleted_i = 1) = \frac{exp(\theta_i)}{1 + exp(\theta_i)} \tag{3.2}$$

$$\theta_i = \delta_0 + \delta_1 \cdot PIN_i + \delta_2 \cdot (PIN_i * Reg_{2011}) + \delta_3 \cdot Reg_{2011} + \Pi' \cdot M_i + \eta_i \tag{3.3}$$

where *IsCompleted* is a bivariate variable that takes the value of 1 or 0 to indicate whether the deal is completed or not, respectively. In Table 3.4, we present the regression results with the successful completion of the deal (1 for completed deals and 0 for failed deals) as the dependent variable.

[Table 3.4 about here]

Column (1) reports the baseline regression results without controlling for regulatory tightening in 2011. Consistent with the existing literature on insiders cherry-picking deals with better fundamentals, more intensive insider trading activities (proxied by *PIN*) predict a higher likelihood of deal completion. Our baseline results with controls for regulatory tightening in 2011 are presented in column (2). While the coefficient of insider trading remains positive, the coefficient on the interaction term $Insider \times Reg_{2011}$ is negative and significant, suggesting that the predictive power of insider trading on deal completion is reduced after regulatory tightening on insider private efforts. After the regulatory shock, the probability of completion drops by 1.88% for each one percentage point increase in the *PIN*. This result is robust after controlling for a set of related variables in the M&A literature, as well as controls unique to the Chinese M&A market. These findings suggest that insiders are not only cherry-picking deals that are more likely to be completed, but also engage in private effort to facilitate successful deal outcomes.

In column (3) and (4), we replace *PIN* with the convicted insider trading dummy (*Convicted*), which equals one if any participant in the deal is convicted of insider trading by CSRC. The coefficient estimate for our key variable of interest, $Insider \times Reg_{2011}$, remains significant as in our base model.

For our subsample tests, we repeat the same exercise with subsamples of cash-only deals and stock-only deals and report the results in columns (5) to (8) of Table 3.4. Similarly, we find no significant difference in most models given the loss in number of observations. Consistent with the literature on the connectiveness of Chinese firms (e.g., Chi, Sun, and Young, 2011; Lee, Qu, and Shen, 2019; Zhou et al., 2015), deals with cash-only and stock-only payments are, respectively, about 20.83% and 26.43% more likely to succeed when the acquirer and target firms are connected

(ConnectedTrade). For cash-only acquirers, however, deals that are announced to be acquisitions at the time of the suspension announcement are 8.73% less likely to succeed.

Overall, our results on deal completion and abnormal returns are in accordance. The regulatory tightening on insider private effort caused significant disturbance in the predicting power of insider trading relative to deal completion, and also showed a strong but reduced impact on the predictive power of abnormal returns. These results suggest that corporate insiders do engage in private efforts to improve the likelihood of deal completion, which enhances the CARs they receive from insider activities. In the following section, we discuss and control for insider expectations of subsequent regulatory tightening events.

Expectation of Regulation Tightening

As the 2011 regulation was the beginning of a series of regulatory tightenings on insider trading over the period 2011 to 2014, our findings could be explained by reduced insider trading activities due to fear of future regulatory tightening rather than in response to the 2011 regulatory change itself. To address these concerns, we conducted two tests. First, we use the actual general regulatory tightening in 2013 as a proxy for insider's expectation of future regulatory change. As one of the most important components of the regulatory tightening, the Supreme Court of China published an interpretation of the law in 2013, which provided a unified extended definition of corporate insiders (Li, 2015). This interpretation empowers law enforcers with access to information on a broader base of potential insiders and should negatively affect insider ability to trade based on private information in general (Peng and Xiao, 2018). If our previous findings are driven by insider expectations of future regulations, we would expect the explanatory power of the 2011 regulatory change to be overtaken by the 2013 regulatory shock. Our results about such tests are presented in Table 3.5.

[Table 3.5 about here]

In columns (1) to (3) of Table 3.5, we present the results for deal completion, and in columns (4) to (6), the results for abnormal returns. While the coefficient estimates associated with the 2013 regulatory change are significant as expected, the coefficients for the 2011 regulatory shock remain robust in both sign and significance. Notably, as in column (6), the coefficient estimate for Reg_{2013} is negative and significant, consistent with the expectation that after major regulatory changes limiting insider access to the capital market, insider cherry-picking activities would significantly subside. With increased legal risk after regulatory tightening, informed traders tend to trade only when they know that trading is more likely to be successful and profitable, which is consistent with the notion that in M&A deals, some informed traders take advantage of private information and engage in trading based on such information (Dai et al., 2017).

To address the possibility that our findings are driven by other events, we conduct placebo tests with pseudo regulation tightening dates prior to the actual event in 2011. A sample result of one random date on March 20th, 2010 is presented in Table 3.8 columns (10) and (11). The coefficients for *Insider* (proxied by *PIN*) remain positive and significant, consistent with the predictive power of insider trading activities on deal outcomes. However, with a placebo event date, the estimates for the interaction term $Insider \times Reg_{2011}$ are not significant with either dependent variable, while remaining qualitatively consistent with the results in our base model. For a 12-month rolling window around the pseudo-event date, 84.09% in abnormal return and 93.27% in deal completion of the coefficient estimates for the interaction term are insignificant and identical to those presented in Table 3.8 columns (10) and (11), respectively. Our results suggest no significant difference in the predictability of insider trading for deal outcomes around pseudo event dates.

Overall, our results in this section indicate that our findings are not likely to be driven by insider expectations of future regulatory tightening.

Deal Success and Financial Constraints

An alternative explanation to our findings would be financial constraints. Notably, for cash deals, the coefficient estimates of suspension duration (*SuspDuration*) - the number of days that a stock is suspended - are negative and significant for deal completion. Since prolonged suspension periods would limit a firm's access to the public equity market,[21] a reduction in the probability of deal completion seems to be natural in this case (due to potential financing issues to close the deal), as firms may experience financial constraints during suspension. Thus, we follow Whited and Wu (2006) and Huang et al. (2016) to construct the Whited-Wu index (*WW Index*) to proxy for firm-level financial constraints during the suspension period. Our second approach to capture the effect of financial constraints follows Hadlock and Pierce (2010). Specifically, we construct the Hadlock and Pierce Index (*H-P Index*) which is based solely on firm characteristics. Lastly, we also include the Kaplan-Zingales Index (*KZ index*), following Kaplan and Zingales (1997).

[Table 3.6 about here]

We report estimation results in Table 3.6. While financial constraints do demonstrate consistent impacts on the probability of a deal's successful closure, they fail to explain the short-term abnormal returns. The coefficients of *Insider* (proxied by *PIN*) and its interaction term with Reg_{2011} remain unchanged in sign and significance. The results thus rule out the alternative explanation that the change in deal outcome is the result of financial constraints.

[21] Companies in suspension can only raise equity with the SEO in private placement, however, private equity is more costly than public equity (Brav, 2009).

3.4.3 Long-term Performance

Building on our findings, researchers may be interested in whether insider private efforts could be beneficial to acquirer shareholders, especially when such efforts could enhance deal synergies. If this is the case, insiders are no longer rent-seekers with agency problems. To shed light on this question, we examine acquiring firm long-term performance. The results are displayed in Table 3.7 below.

[Table 3.7 about here]

In columns (1) to (6), we present the results for models with various windows of long-term abnormal return as the dependent variable. Consistent with our previous finding, insider trading does positively predict a firm's long-term performance up to one year after deal closure. However, after including dummy variables for regulatory shocks, we find no significant effects for firm performance up to two years after closure of the deal, after controlling for a set of variables for firm performance.

In columns (7) to (12), we follow Suk and Wang (2021) and use proxies of operating performance as our dependent variable. We find no significance across most proxies for operating performance at various time horizons. The absence of predictability in long-term performance in our data is consistent with the notion that insiders in our study have a short investment horizon and are driven by a transitory information advantage over the public. Our findings indicate that a reduction in the insider's level of private effort does not exert significant influence on acquirer long-term firm values, which in return implies that insiders are more likely to make private efforts to misrepresent existing deal quality than to improve it.

3.5 Robustness Tests

To further examine our results, we conducted robustness tests, the results of which are presented in Table 3.8 below.

[Table 3.8 about here]

In column (1) to (4), we present two robustness tests with the probability of successful deal closure as the dependent variable. In columns (1) and (2), a probit model is used in place of a logit model, while in columns (3) and (4), a linear regression model (OLS) is employed for interpretation purposes. Both signs and significance are identical to our base model. In columns (5) to (9), we present robustness test results with cumulative abnormal return as the dependent variable. In columns (5) and (6), we present our base model with an extended 5-day and 7-day event window. The sign and significance of our model remains the same, even with the presence of a proxy for future regulatory tightening. In columns (7) to (9), we replace the CARs adjusted by the Fama-French three-factor model with CARs measured in excess of the Fama-French five-factor model. All coefficient estimates remain similar, except that in column (9), the coefficient estimate of *Insider* (proxied by *PIN*) has the same sign but is marginally insignificant. The loss of significance is expected, as the influence of insider trading decays with the passage of time. In columns (10) and (11), we present results of a placebo test with a pseudo-event date on March 20th of 2010. Consistent with our findings, no significance is documented around the pseudo date.

3.6 Conclusion

Our study provides new insights on informed trading activities by corporate insiders. Following the intuition that corporate insiders would maintain and increase their information advantage to achieve higher insider trading profits, we exploit the unique setting of trading suspension in China to identify separate windows of insider private operational efforts and insider trading activities. Our results reveal that corporate insiders not only choose to trade on deals that are more profitable based on their fundamentals, but also insert private effort to increase the probability of deal closure and achieve higher abnormal returns. Meanwhile, insider private effort fails to improve acquirer long-term operational performance. These results imply that acquirer insider efforts are misdirecting in nature and do not significantly improve acquirer shareholder welfare by enhancing deal fundamentals.

Our findings have implications for regulators. The trading suspension boom of M&As was ended in 2018 by the Chinese government due to firms' excessive use of suspensions. While the mechanism itself introduces undesired market illiquidity, it also enables regulators to observe signals for insider private efforts. For future study, transaction-level data of identified corporate insiders with the direction of trading will afford a more accurate interpretation of the information content of insider trading activities.

Figure 3.1: Timeline for M&As in China and the United States

This figure presents the differences in M&A timelines between the Chinese and the U.S. stock markets.

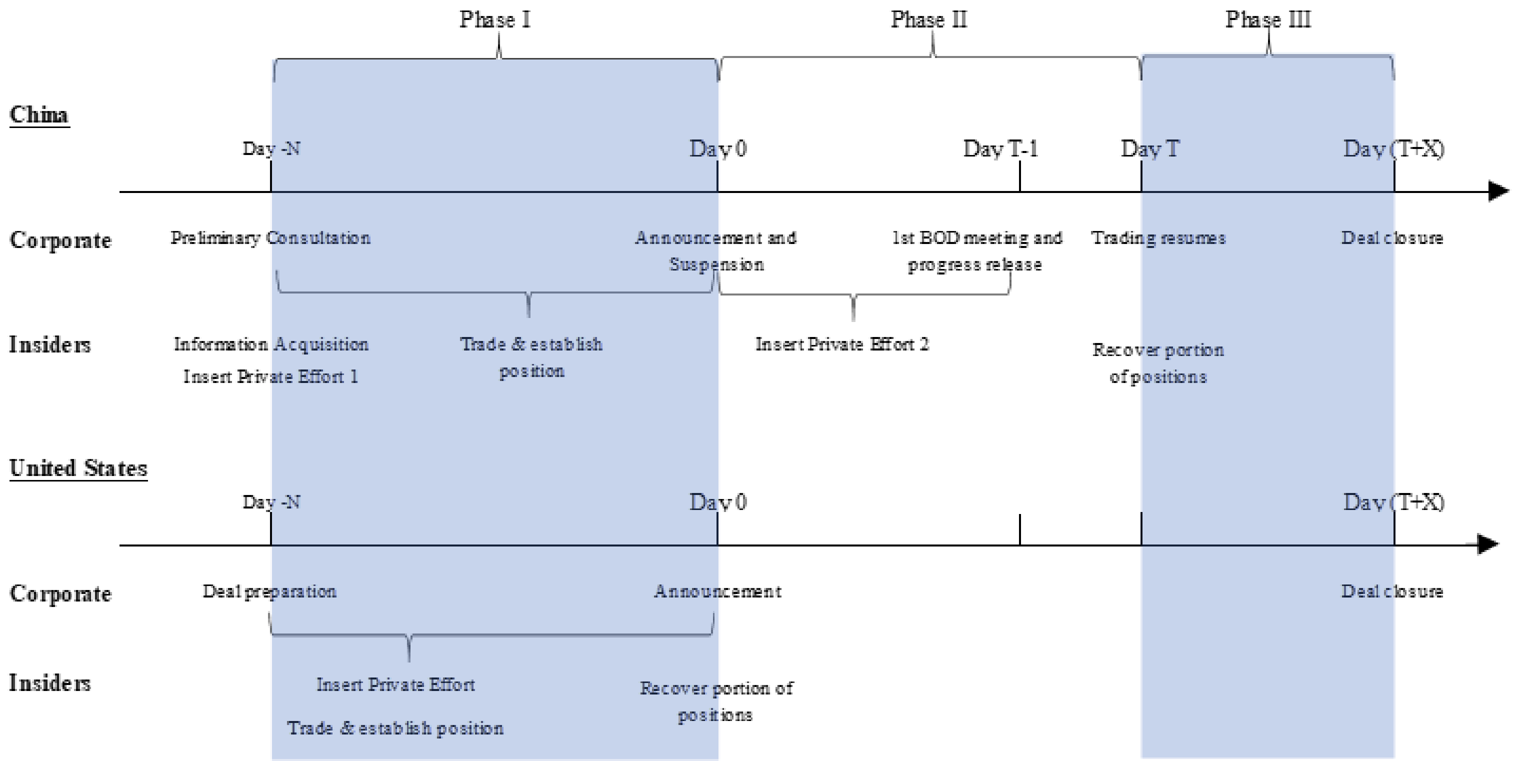


FIGURE 3.2: PIN validation (v.s. CPIE)

This figure presents the differences of PIN/CPIE 10 days before trading suspension in identified and unidentified insider M&A deals in Chinese stock markets. Time t is the day when trading is suspended.

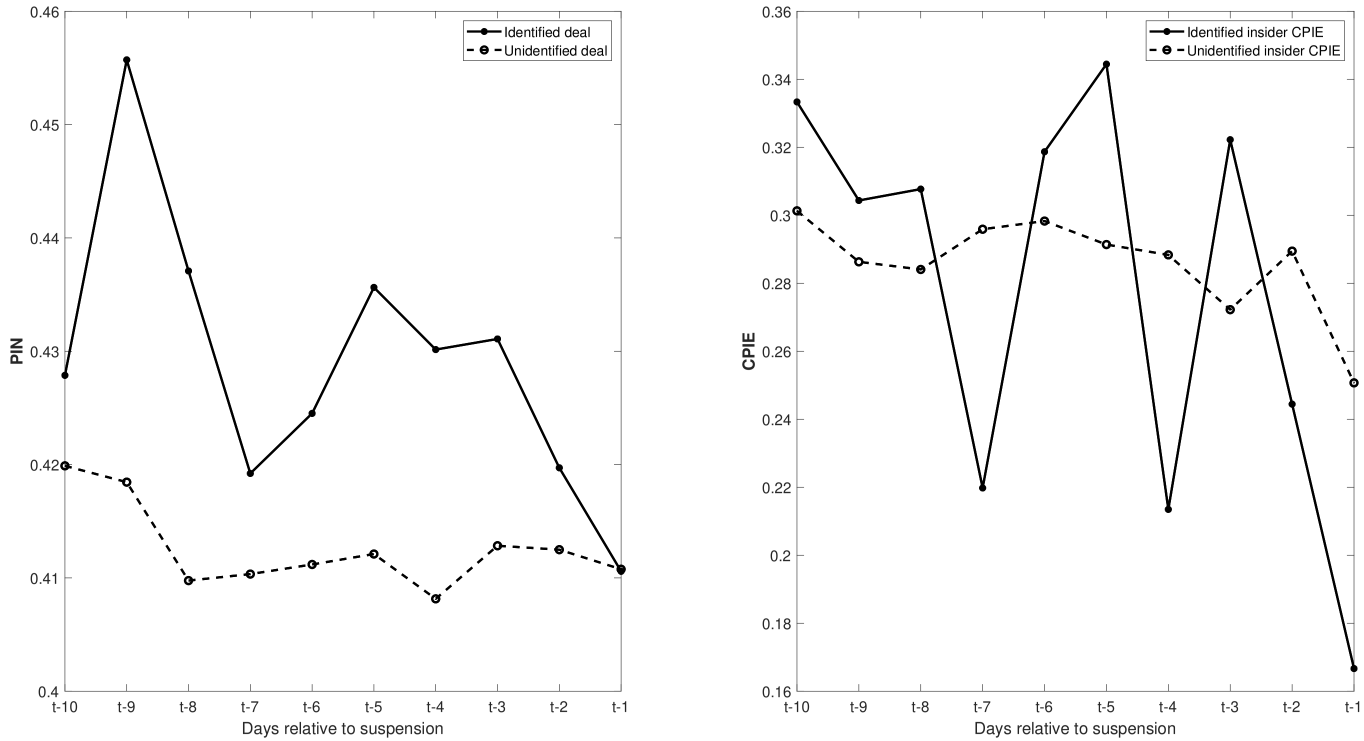
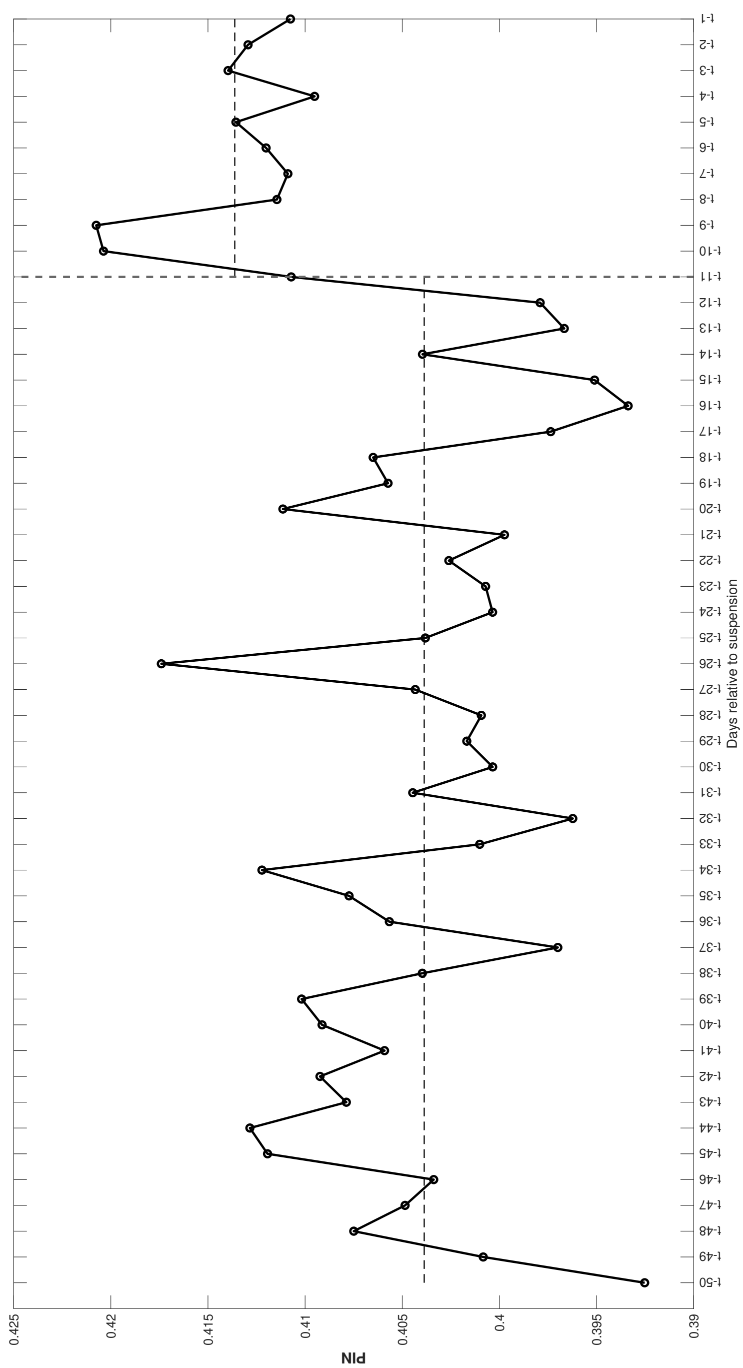


Figure 3.3: PIN values in time series



This figure presents the PIN values in time series.

Table 3.1: Summary statistics

This table presents the descriptive statistics of all variables used in this paper. Panel A contains statistics of continuous variables and Panel B shows statistics of dummy variables. The sample consists of 1,295 suspensions in China from March 2006 to June 2018. 25%, 50%, and 75% relate to the first, the second, and the third quartile, respectively. All variable definitions are given in Appendix B1.

Panel A

	N_{obs}	Mean	Std	25%	50%	75%
PIN	1295	0.414	0.095	0.347	0.404	0.469
TotalAsset	1295	12.301	1.211	11.495	12.150	12.963
Leverage	1295	0.244	0.381	0.061	0.186	0.361
BusiLendingRate	1295	3.199	0.904	2.405	3.276	3.921
RatioMB	1295	3.834	29.764	1.558	2.132	3.153
PriorPerf	1295	0.026	0.171	-0.057	0.028	0.114
SOSPctg	1295	3.579	11.616	0.000	0.000	0.000
HHI	1284	0.166	0.201	0.045	0.084	0.204
ROA	1295	0.006	0.032	0.000	0.006	0.014
SuspDuration	1295	86	87	54	73	105
RetBeforeSusp	1295	0.033	0.114	-0.020	0.032	0.091
MktRetDuSusp	1295	0.071	0.288	-0.044	0.029	0.126
PctgAcquired	945	0.911	0.188	0.965	1.000	1.000
Short-term Performance [-1,+1]	1295	0.101	0.822	-0.007	0.074	0.116
Short-term Performance [-2,+2]	1295	0.130	0.832	-0.028	0.120	0.195
Short-term Performance [-3,+3]	1295	0.153	0.840	-0.040	0.134	0.268
Long-term Performance: 1Y FF3	1295	0.001	0.098	-0.028	0.000	0.031
Long-term Performance: 2Y FF3	1295	0.002	0.029	-0.014	-0.001	0.016
Long-term Performance: 3Y FF3	1295	0.000	0.021	-0.012	-0.001	0.011

Panel B

	Dummy=1	Dummy=0	Total
Convicted	80	1215	1295
SOEDummy	371	923	1294
ConnectedTrade	608	687	1295
MentionDummy	403	892	1295
SuccessDummy	906	389	1295

TABLE 3.2: Univariate analysis

This table reports results of univariate tests. In Panel A of the table, we report univariate relations of insider trading (proxied by *PIN*) with market reaction, short-term performance and long-term performance, respectively. Panel B of the table reports cross-sectional means for the full sample before and after the 2011 regulation. Panel C shows cross-sectional means in sub samples based on insider trading levels (high and low correspond to PIN values in the top and bottom tercile). Panel D present cross-sectional means in sub samples based whether the deal is successfully closed or not. Test statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate Regressions									
	Market Reaction			Short-term Performance			Long-term Performance		
	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Coefficient	0.285***	0.353***	0.407***	0.295***	0.369***	0.427***	0.007	0.005**	0.001
t-stat	(3.707)	(4.578)	(5.270)	(3.830)	(4.767)	(5.522)	(1.187)	(2.406)	(0.348)
R2_adjusted	0.008	0.011	0.013	0.008	0.011	0.013	0.001	0.002	0.000
Nb_obs	1295	1295	1295	1295	1295	1295	1295	1295	1295
Panel B: Full Sample Means									
All samples									
2011 Regulation	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Before	0.079	0.114	0.147	0.084	0.126	0.163	-0.007	-0.004	-0.001
After	0.050	0.077	0.098	0.055	0.084	0.108	0.002	0.002	-0.000
Difference	-0.029***	-0.038**	-0.048**	-0.029***	-0.042**	-0.055**	0.009	0.006**	0.000
t-stat	(-3.061)	(-2.385)	(-2.301)	(-2.934)	(-2.553)	(-2.530)	(0.839)	(2.043)	(0.220)
Panel C: Subsample means by PIN values									
High PIN									
2011 Regulation	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Before	0.113	0.161	0.193	0.119	0.175	0.206	-0.006	-0.003	-0.001
After	0.066	0.106	0.135	0.068	0.111	0.143	0.008	0.003	0.001
Difference	-0.047***	-0.055**	-0.058*	-0.051***	-0.064**	-0.063*	0.013	0.006	0.002
t-stat	(-3.147)	(-2.309)	(-1.791)	(-3.251)	(-2.522)	(-1.847)	(1.164)	(1.267)	(0.622)
Low PIN									
2011 Regulation	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Before	0.066	0.095	0.121	0.067	0.107	0.134	-0.008	-0.005	0.000
After	0.035	0.044	0.053	0.042	0.053	0.063	-0.004	0.001	-0.001
Difference	-0.030	-0.051	-0.068	-0.026	-0.054	-0.071	0.004	0.006	-0.001
t-stat	(-1.559)	(-1.583)	(-1.599)	(-1.270)	(-1.623)	(-1.607)	(0.238)	(1.574)	(-0.360)
Panel D: Subsample means by deal closure									
Deal successfully closed									
2011 Regulation	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Before	0.076	0.113	0.147	0.082	0.124	0.161	-0.004	-0.003	0.000
After	0.054	0.087	0.113	0.058	0.093	0.120	0.008	0.005	0.001
Difference	-0.022**	-0.026	-0.0033	-0.024**	-0.031	-0.041	0.013	0.008**	0.000
t-stat	(-1.963)	(-1.370)	(-1.343)	(-2.054)	(-1.565)	(-1.577)	(1.347)	(2.107)	(0.158)
Deal not successfully closed									
2011 Regulation	CAR(0,+1)	CAR(0,+2)	CAR(0,+3)	CAR(-1,+1)	CAR(-2,+2)	CAR(-3,+3)	1-Y abnormal	2-Y abnormal	3-Y abnormal
Before	0.084	0.118	0.146	0.087	0.131	0.166	-0.011	-0.007	-0.004
After	0.039	0.052	0.062	0.046	0.063	0.076	-0.014	-0.004	-0.003
Difference	-0.045**	-0.066**	-0.085**	-0.041**	-0.069**	-0.089**	-0.003	0.003	0.001
t-stat	(-2.575)	(-2.301)	(-2.228)	(-2.198)	(-2.299)	(-2.257)	(-0.099)	(0.559)	(0.293)

Table 3.3: Abnormal return

The table presents the regression results of short-term performance (proxied by *CAR(-1,+1)*) as dependent variable, insider trading (*Insider*) and the 2011 regulation shock (Reg_{2011}) as independent variables, along with control variables, for the 2011 regulation. All variable definitions are given in Appendix B1. Models (1) and (2) present results using continuous variable *PIN* as proxy for insider trading while models (3) and (4) using dummy variable *Convicted* as such proxy. Models (5) and (6) present results for subsample with cash-only deals while models (7) and (8) present the results for subsample with stock-only deals. t-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	PIN		**Convicted**		**Cash-only**		**Stock-only**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.249	-1.482**	0.176***	-0.775*	0.211**	0.218	-0.774	-1.947**
	(-0.912)	(-2.251)	(5.494)	(-1.823)	(2.243)	(1.476)	(-1.282)	(-2.245)
Insider	0.316**	3.560**	0.013*	0.313**	0.091	0.047	1.185**	4.100*
	(2.160)	(2.056)	(1.901)	(2.101)	(1.623)	(0.187)	(2.405)	(1.653)
Insider*Reg_{2011}		-3.642*		-0.229*		0.050		-3.711
		(-1.937)		(-1.747)		(0.194)		(-1.179)
Reg_{2011}		1.113*		-0.079		0.015		0.887
		(1.709)		(-0.921)		(0.132)		(0.768)
SuspDuration	0.003**	0.003**	-0.000	0.005**	-0.000**	-0.000**	0.005*	0.006*
	(2.171)	(2.104)	(-1.630)	(2.351)	(-2.019)	(-2.092)	(1.764)	(1.825)
MentionDummy	0.060*	0.036	-0.001	0.049	-0.016	-0.016	0.0962	0.0267
	(1.901)	(1.390)	(-0.202)	(1.250)	(-1.249)	(-1.248)	(1.388)	(0.434)
RetBeforeSusp	0.170	0.096	0.080***	-0.134	0.019	0.024	-0.255	-0.361
	(1.382)	(0.857)	(3.435)	(-0.822)	(0.465)	(0.615)	(-0.434)	(-0.648)
SOSPctg	0.137*	-0.045	0.031	0.084	0.033	0.062	0.034	-0.252
	(1.772)	(-0.479)	(1.462)	(0.942)	(0.600)	(1.194)	(0.186)	(-1.231)
ConnectedTrade	-0.073**	-0.068**	-0.011*	0.008	-0.001	-0.002	-0.084	-0.071
	(-2.170)	(-2.196)	(-1.961)	(0.225)	(-0.104)	(-0.164)	(-0.971)	(-0.933)
TotalAsset	0.005	0.018	-0.008***	0.044*	-0.008	-0.009	0.011	0.028
	(0.350)	(1.182)	(-3.069)	(1.792)	(-1.195)	(-1.374)	(0.283)	(0.767)
Leverage	0.018	-0.027	-0.000	-0.063	0.037	0.040	-0.037	-0.112*
	(0.271)	(-0.480)	(-0.015)	(-1.321)	(1.102)	(1.186)	(-0.495)	(-1.731)
RatioMB	0.000	0.000	-0.000***	0.000	-0.002	-0.002	0.000	0.001
	(0.192)	(0.793)	(-3.152)	(1.115)	(-1.393)	(-1.519)	(0.692)	(1.058)
PriorPerf	0.053	0.060	0.101***	-0.043	0.075**	0.076**	-0.073	-0.020
	(0.763)	(0.885)	(4.836)	(-0.471)	(2.113)	(2.139)	(-0.284)	(-0.081)
ROA	-1.426*	-1.199	-0.255***	-0.738	0.053	0.052	-0.783	-0.444
	(-1.704)	(-1.539)	(-3.787)	(-1.026)	(0.317)	(0.310)	(-0.294)	(-0.173)
BusiLendingRate	-0.049***	-0.013	-0.008**	-0.046*	-0.034***	-0.036***	-0.061	0.029
	(-3.027)	(-0.571)	(-2.536)	(-1.823)	(-5.299)	(-5.157)	(-1.183)	(0.411)
MktRetDurSusp	1.521***	1.411***	0.165***	1.870**	0.253***	0.252***	1.982***	1.815***
	(3.666)	(3.858)	(11.500)	(2.537)	(6.181)	(6.142)	(3.949)	(4.111)
Adjusted R^2	0.347	0.367	0.194	0.191	0.224	0.220	0.447	0.465
N_{obs}	1295	1295	1295	1295	231	231	389	389

Table 3.4: Deal completion

The table presents the logit regression results of M&A completion, along with control variables for 2011 regulation. All variable definitions are given in Appendix B1. Models (1) and (2) present results using continuous variable *PIN* as proxy for insider trading while models (3) and (4) using dummy variable *Convicted* as such proxy. Models (5) and (6) present results for subsample with cash-only deals while models (7) and (8) present the results for subsample with stock-only deals. Estrella R-squared are presented for logit models. t-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	PIN		**Convicted**		**Cash-only**		**Stock-only**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.274	-3.796*	1.156	-1.289	3.906	-14.025	-3.378	-6.649*
	(0.240)	(-1.739)	(1.150)	(-1.087)	(1.199)	(-0.532)	(-1.401)	(-1.831)
Insider	1.433*	12.760**	-0.891***	0.857	0.143	49.113	3.193*	10.917
	(1.680)	(2.499)	(-2.983)	(1.221)	(0.064)	(0.633)	(1.751)	(1.507)
Insider*Reg_{2011}		-11.776**		-1.918***		-49.305		-7.958
		(-2.268)		(-2.582)		(-0.635)		(-1.060)
Reg_{2011}		4.098**		0.828**		18.008		2.321
		(2.116)		(2.275)		(0.680)		(0.824)
SuspDuration	-0.002**	-0.004***	-0.002**	-0.010***	-0.008	-0.008	0.001	-0.001
	(-2.173)	(-3.212)	(-2.149)	(-5.112)	(-1.532)	(-1.588)	(0.745)	(-0.344)
MentionDummy	-0.408**	-0.440***	-0.414**	-0.436***	-1.229***	-1.297***	-0.401	-0.519
	(-2.501)	(-2.676)	(-2.540)	(-2.596)	(-2.768)	(-2.865)	(-1.256)	(-1.572)
SOSPctg	-0.468	-0.733	-0.426	-0.187	-3.354	-2.791	-0.058	-0.450
	(-0.520)	(-0.793)	(-0.475)	(-0.204)	(-1.275)	(-0.954)	(-0.037)	(-0.278)
ConnectedTrade	1.088***	1.109***	1.070***	0.952***	1.573***	1.623***	1.535***	1.578***
	(6.714)	(6.805)	(6.579)	(5.829)	(2.649)	(2.672)	(4.890)	(4.982)
PctgAcquired	-0.006	-0.005	-0.006	-0.005	-0.014	-0.014	0.013*	0.014*
	(-1.395)	(-1.225)	(-1.441)	(-1.259)	(-1.640)	(-1.547)	(1.698)	(1.841)
TotalAsset	0.041	0.061	0.020	0.244***	-0.071	-0.066	0.107	0.193
	(0.534)	(0.785)	(0.272)	(2.706)	(-0.297)	(-0.271)	(0.680)	(1.119)
Leverage	-0.109	-0.135	-0.031	-1.510***	0.683	0.697	-0.706	-0.961
	(-0.326)	(-0.399)	(-0.092)	(-3.068)	(0.488)	(0.493)	(-1.006)	(-1.297)
RatioMB	0.003	0.003	0.002	-0.004	-0.039	-0.037	0.050	0.069
	(0.624)	(0.633)	(0.544)	(-0.275)	(-0.881)	(-0.836)	(1.242)	(1.592)
PriorPerf	-0.746*	-0.713	-0.710	-1.458***	-0.568	-0.522	-1.666*	-1.636*
	(-1.694)	(-1.595)	(-1.591)	(-2.957)	(-0.469)	(-0.422)	(-1.776)	(-1.694)
ROA	-0.261	-0.110	-0.586	-4.597	-0.545	-0.543	1.262	1.561
	(-0.117)	(-0.051)	(-0.265)	(-1.493)	(-0.113)	(-0.111)	(0.273)	(0.324)
HHI	0.346	0.402	0.329	0.072	1.308	1.241	-0.286	-0.312
	(0.914)	(1.053)	(0.863)	(0.166)	(1.154)	(1.099)	(-0.393)	(-0.426)
LR-ratio	67.37	74.64	73.13	52.75	22.42	23.93	39.84	42.60
Estrella R^2	0.059	0.065	0.064	0.045	0.133	0.142	0.124	0.133
Adjusted R^2	0.071	0.078	0.077	0.055	0.134	0.143	0.148	0.158
Liklihood	-536.19	-532.56	-533.32	-558.38	-73.18	-72.43	-140.67	-139.29
N_{obs}	945	945	945	945	167	167	265	265

Table 3.5: 2013 regulation

The table presents regression results of M&A deal completion and short-term abnormal return for 2011 and 2013 regulations. Models (1) - (3) present the results of logit models with M&A deal completion as dependent variable and models (4) - (6) present results of OLS models with CAR(-1,+1) as dependent variable. Insider trading (*Insider*) is proxied by *PIN*. All variable definitions are given in Appendix B1. *Deal Completion controls* and *Abnormal Return Controls* are a set of additional control variables for deal completion and abnormal returns, respectively. Adjusted R-squared are reported for OLS regressions and Estrella R-squared are presented for logit models. t-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Deal Completion			**Abnormal Return**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-3.796*	-1.896	-3.837*	-1.482**	-0.514*	-1.385**
	(-1.739)	(-1.266)	(-1.778)	(-2.251)	(-1.816)	(-2.146)
Insider	12.760**	6.658***	12.036**	3.560**	1.096**	3.312*
	(2.499)	(2.687)	(2.402)	(2.056)	(1.975)	(1.945)
Insider*Reg_{2011}	-11.776**		-9.479*	-3.642*		-3.464**
	(-2.268)		(-1.785)	(-1.937)		(-2.057)
Reg_{2011}	4.098**		3.450*	1.113*		1.331**
	(2.116)		(1.707)	(1.709)		(2.383)
Insider*Reg_{2013}		-6.126**	-2.495		-1.370*	-0.099
		(-2.327)	(-1.118)		(-1.827)	(-0.333)
Reg_{2013}		2.506**	0.650		0.204	-0.294**
		(2.258)	(0.675)		(0.711)	(-2.005)
SuspDuration	-0.004***	-0.003***	-0.004***	0.003**	0.003**	0.003**
	(-3.212)	(-2.936)	(-3.003)	(2.104)	(2.413)	(2.287)
MentionDummy	-0.440***	-0.427***	-0.441***	0.036	0.049*	0.040
	(-2.676)	(-2.600)	(-2.672)	(1.390)	(1.733)	(1.501)
SOSPctg	-0.733	-0.369	-0.851	-0.045	-0.093	-0.111
	(-0.793)	(-0.399)	(-0.909)	(-0.479)	(-1.029)	(-1.149)
ConnectedTrade	1.109***	1.112***	1.154***	-0.068**	-0.056**	-0.056*
	(6.805)	(6.832)	(7.012)	(-2.196)	(-1.963)	(-1.916)
TotalAsset	0.061	0.044	0.085	0.018	0.024	0.026
	(0.785)	(0.567)	(1.066)	(1.182)	(1.425)	(1.618)
Leverage	-0.135	-0.092	-0.180	-0.027	-0.034	-0.041
	(-0.399)	(-0.275)	(-0.525)	(-0.480)	(-0.739)	(-0.915)
RatioMB	0.003	0.003	0.004	0.000	0.000	0.000
	(0.633)	(0.614)	(0.643)	(0.793)	(1.119)	(1.188)
PriorPerf	-0.713	-0.737*	-0.752*	0.060	0.010	0.013
	(-1.595)	(-1.663)	(-1.676)	(0.885)	(0.133)	(0.173)
ROA	-0.110	-0.124	0.339	-1.199	-1.187	-1.147
	(-0.051)	(-0.057)	(0.149)	(-1.539)	(-1.549)	(-1.579)
Deal Completion Controls	Yes	Yes	Yes			
Abnormal Return Controls				Yes	Yes	Yes
LR-ratio	74.64	73.49	79.35			
Estrella R^2	0.065	0.064	0.070			
Adjusted R^2	0.078	0.077	0.083	0.367	0.376	0.383
Liklihood	-532.56	-533.14	-530.21			
N_{obs}	945	945	945	1295	1295	1295

Table 3.6: Financial constraints

The table presents the regression results of M&A completion and short-term performance when financial constraints are controlled. Models (1) - (3) present the results of logit models with M&A deal completion as dependent variable and models (4) - (6) present results of OLS models with CAR(-1,+1) as dependent variable. Insider trading (*Insider*) is proxied by *PIN*. All variable definitions are given in Appendix B1. *Deal Completion controls* and *Abnormal Return Controls* are a set of additional control variables for deal completion and abnormal returns, respectively. Adjusted R-squared are reported for OLS regressions and Estrella R-squared are presented for logit models. *t*-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Deal Completion			**Abnormal Return**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-3.705*	-4.026*	1.131	-1.350**	-1.325**	-1.311**
	(-1.704)	(-1.841)	(0.358)	(-2.208)	(-2.152)	(-1.969)
Insider	10.132**	10.889**	11.104**	3.020*	3.118*	3.311*
	(2.206)	(2.222)	(2.250)	(1.896)	(1.930)	(1.946)
Insider*Reg_{2011}	-7.417	-7.566	-8.382	-3.187**	-3.281**	-3.459**
	(-1.497)	(-1.443)	(-1.597)	(-2.031)	(-2.056)	(-2.062)
Reg_{2011}	-2.459	-3.051	-2.623	1.226**	1.264**	1.330**
	(-1.047)	(-1.286)	(-1.183)	(2.373)	(2.401)	(2.388)
Insider*Reg_{2013}	2.717	2.670	3.059	-0.132	-0.131	-0.100
	(1.417)	(1.327)	(1.526)	(-0.414)	(-0.425)	(-0.336)
Reg_{2013}	0.622	0.839	0.746	-0.305*	-0.299**	-0.293**
	(0.615)	(0.824)	(0.779)	(-1.943)	(-1.967)	(-1.968)
SuspDuration	-0.003***	-0.003***	-0.004***	0.004**	0.003**	0.003**
	(-2.714)	(-2.769)	(-2.829)	(2.278)	(2.259)	(2.302)
MentionDummy	-0.508***	-0.514***	-0.434***	0.035	0.033	0.040
	(-2.840)	(-2.913)	(-2.618)	(1.252)	(1.235)	(1.522)
SOSPctg	-0.764	-0.849	-0.801	-0.119	-0.111	-0.111
	(-0.806)	(-0.902)	(-0.858)	(-1.136)	(-1.082)	(-1.155)
ConnectedTrade	1.092***	1.138***	1.183***	-0.063*	-0.061*	-0.056*
	(6.269)	(6.633)	(7.136)	(-1.888)	(-1.898)	(-1.921)
TotalAsset	0.113	0.122	-0.211	0.032*	0.029	0.021
	(1.185)	(1.421)	(-1.318)	(1.739)	(1.636)	(0.697)
Leverage	-0.177	-0.146	-0.139	-0.052	-0.041	-0.040
	(-0.452)	(-0.408)	(-0.403)	(-1.103)	(-0.891)	(-0.909)
RatioMB	0.015	0.005	0.003	0.002	0.000	0.000
	(0.866)	(0.558)	(0.513)	(1.074)	(1.209)	(1.072)
PriorPerf	-0.597	-0.674	-0.747*	-0.012	-0.000	0.013
	(-1.252)	(-1.450)	(-1.667)	(-0.133)	(-0.003)	(0.174)
ROA	0.489	1.081	0.253	-1.053	-1.116	-1.150
	(0.193)	(0.470)	(0.111)	(-1.279)	(-1.448)	(-1.583)
KZ Index	0.03			-0.001***		
	(1.642)			(-2.739)		
WW Index		0.036*			0.184	
		(1.660)			(0.396)	
H-P Index			0.595**			0.009
			(2.129)			(0.254)
Deal Completion Controls	Yes	Yes	Yes			
Abnormal Return Controls				Yes	Yes	Yes
LR-ratio	69.19	77.69	83.86			
Estrella R^2	0.069	0.075	0.074			
Adjusted R^2	0.083	0.090	0.088	0.391	0.386	0.383
Liklihood	-467.93	-479.92	-527.95			
N_{obs}	832	856	945	1154	1186	1295

Table 3.7: Long-term performance

The table presents the regression results of long-term performance. Long-term abnormal returns are dependent variables in models (1) - (6) while proxies for long-term operating performance are dependent variables in models (7) - (12). Insider trading (*Insider*) is proxied by *PIN*. All variable definitions are given in Appendix B1. *LTRet* stands for long-term abnormal return, *OI* stands for operating income, and *NI* stands for net income. *Abnormal Ret Controls* are a set of additional control variables for abnormal returns. *t*-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Abnormal Return						**Operating Performance**					
	$LTRet_{1yr}$	$LTRet_{2yr}$	$LTRet_{1yr}$	$LTRet_{2yr}$	$LTRet_{1yr}$	$LTRet_{2yr}$	$Sales_{1yr}$	$Sales_{2yr}$	OI_{1yr}	OI_{2yr}	NI_{1yr}	NI_{2yr}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.022	0.023*	0.002	0.020	-0.002	0.020	0.891*	0.749	-0.024	-0.156	-0.002	-0.196
	(-0.644)	(1.937)	(0.053)	(1.055)	(-0.039)	(1.046)	(1.807)	(1.534)	(-0.308)	(-0.882)	(-0.026)	(-0.958)
Insider	0.070**	0.012	0.000	0.015	0.011	0.015	-0.383	-0.425	0.241*	0.296	0.177	0.316
	(2.111)	(1.396)	(0.001)	(0.414)	(0.135)	(0.419)	(-0.418)	(-0.519)	(1.939)	(1.317)	(1.569)	(1.215)
Insider*Reg_{2011}			0.081	-0.001	0.074	-0.000	0.026	0.287	-0.186	-0.281	-0.157	-0.351
			(0.969)	(-0.032)	(0.834)	(-0.010)	(0.027)	(0.336)	(-1.486)	(-1.180)	(-1.358)	(-1.343)
Reg_{2011}			-0.018	0.008	-0.028	0.007	-0.208	-0.245	0.055	0.065	0.047	0.084
			(-0.593)	(0.580)	(-0.773)	(0.460)	(-0.541)	(-0.699)	(0.976)	(0.676)	(0.867)	(0.818)
Insider*Reg_{2013}					0.003	-0.001						
					(0.050)	(-0.043)						
Reg_{2013}					0.013	0.001						
					(0.416)	(0.059)						
SuspDuration	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.001	-0.000	-0.000	-0.001	-0.000	-0.001
	(-0.451)	(-2.026)	(-0.597)	(-2.369)	(-0.882)	(-2.327)	(1.051)	(-0.133)	(-0.219)	(-1.196)	(-0.666)	(-1.231)
MentionDummy	-0.004	-0.004**	-0.004	-0.004**	-0.004	-0.004**	0.121*	0.023	-0.023*	0.009	-0.021	0.015
	(-0.982)	(-2.316)	(-0.805)	(-2.121)	(-0.841)	(-2.117)	(1.661)	(0.464)	(-1.699)	(0.686)	(-1.434)	(1.066)
RetBeforeSusp	0.022	0.005	0.024	0.006	0.026	0.006	-0.068	-0.020	0.025	0.047	0.054	0.078
	(0.914)	(0.822)	(1.007)	(0.956)	(1.063)	(0.946)	(-0.399)	(-0.108)	(0.887)	(0.774)	(1.208)	(0.859)
SOSPctg	0.001	-0.004	0.009	0.001	0.012	0.001	-0.086	-0.170	0.016	0.016	0.028	0.030
	(0.086)	(-0.572)	(0.622)	(0.108)	(0.829)	(0.113)	(-0.432)	(-0.860)	(0.920)	(0.368)	(1.503)	(0.604)
TotalAsset	0.000	-0.002**	-0.000	-0.002***	-0.000	-0.002***	0.001	0.024	-0.003	0.007	-0.005	0.006
	(0.185)	(-2.445)	(-0.033)	(-2.673)	(-0.194)	(-2.698)	(0.059)	(1.010)	(-1.118)	(0.808)	(-1.378)	(0.670)
Leverage	-0.006	-0.002*	-0.004	-0.001	-0.004	-0.001	0.002	-0.005	0.002	0.001	0.004	0.001
	(-1.105)	(-1.775)	(-0.782)	(-0.952)	(-0.702)	(-0.939)	(0.065)	(-0.209)	(0.358)	(0.064)	(0.975)	(0.092)
RatioMB	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000	0.000***	0.000***	0.000**	0.000**
	(-2.193)	(-5.824)	(-2.480)	(-5.655)	(-2.774)	(-5.663)	(-1.041)	(-1.175)	(3.233)	(2.799)	(2.260)	(2.406)
PriorPerf	-0.004	0.004	-0.004	0.004	-0.002	0.004	-0.386	-0.489	-0.007	0.056	0.006	0.055
	(-0.300)	(0.963)	(-0.309)	(0.989)	(-0.177)	(1.002)	(-1.069)	(-1.324)	(-0.279)	(1.135)	(0.284)	(1.049)
ROA	-0.034	0.006	-0.040	0.006	-0.042	0.006	-0.485	-0.883	0.259***	0.292**	0.237***	0.345**
	(-0.488)	(0.250)	(-0.568)	(0.231)	(-0.592)	(0.235)	(-0.954)	(-1.428)	(3.138)	(2.039)	(3.365)	(2.261)
Abnormal Ret Controls	Yes	Yes	Yes	Yes	Yes	Yes						
Adjusted R^2	-0.004	0.018	-0.005	0.020	-0.004	0.019	0.011	0.032	0.011	0.016	0.008	0.019
N_{obs}	1295	1295	1295	1295	1295	1295	784	651	784	651	784	651

TABLE 3.8: Robustness

The table presents results of various robustness tests. Models (1) - (4) are about deal completion, models (5) - (9) are about abnormal returns, and models (10) - (11) are about the placebo test. Insider trading (*Insider*) is proxied by *PIN*. All variable definitions are given in Appendix B1. *Deal Completion Controls* and *Abnormal Ret Controls* are a set of additional control variables for deal completion and abnormal returns, respectively. Adjusted R-squared are reported for OLS regressions and Estrella R-squared are presented for probit and logit models. *t*-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Probit		**OLS**		**CAR(FF3)**		**CAR(FF5)**			**Placebo test**	
					CAR(-2,2)	CAR(-3,3)	CAR(-1,1)	CAR(-2,2)	CAR(-3,3)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	0.155	-1.568	0.587***	0.019	-1.325*	-0.854	-1.378**	-1.318*	-0.854	-2.886	0.042
	(0.229)	(-1.427)	(2.600)	(0.044)	(-1.816)	(-1.485)	(-2.129)	(-1.803)	(-1.489)	(-1.237)	(0.083)
Insider	0.863*	5.575**	0.263*	1.799*	3.488*	2.607	3.298*	3.473*	2.582	9.636*	3.733*
	(1.713)	(2.479)	(1.780)	(1.838)	(1.845)	(1.645)	(1.931)	(1.835)	(1.635)	(1.904)	(1.684)
Insider*Reg_{2011}		-4.966**		-1.616*	-3.605*	-2.665*	-3.462**	-3.602*	-2.653*	-6.507	-3.636
		(-2.154)		(-1.647)	(-1.945)	(-1.714)	(-2.049)	(-1.940)	(-1.711)	(-1.222)	(-1.641)
Reg_{2011}		1.735*		0.573	1.414**	1.034**	1.327**	1.411**	1.030**	2.252	-0.120
		(1.904)		(1.467)	(2.249)	(2.011)	(2.368)	(2.241)	(2.009)	(1.015)	(-0.194)
Insider*Reg_{2013}					0.051	0.053	-0.084	0.070	0.073	-3.060	-0.074
					(0.166)	(0.168)	(-0.283)	(0.226)	(0.234)	(-1.418)	(-0.338)
Reg_{2013}					-0.362**	-0.362**	-0.300**	-0.370**	-0.371**	0.897	-0.275***
					(-2.255)	(-2.195)	(-2.050)	(-2.310)	(-2.257)	(0.986)	(-2.656)
SuspDuration	-0.001**	-0.002***	-0.000*	-0.001**	0.003**	0.003**	0.003**	0.003**	0.003**	-0.003***	0.003**
	(-2.402)	(-3.332)	(-1.783)	(-2.576)	(2.143)	(2.085)	(2.286)	(2.142)	(2.083)	(-2.771)	(2.216)
MentionDummy	-0.241**	-0.263***	-0.080**	-0.088**	0.023	0.016	0.040	0.024	0.016	-0.442***	0.018
	(-2.457)	(-2.654)	(-2.122)	(-2.293)	(0.914)	(0.611)	(1.527)	(0.946)	(0.643)	(-2.686)	(0.689)
SOSPctg	-0.265	-0.447	-0.084	-0.137	-0.064	-0.060	-0.109	-0.063	-0.074	-0.862	-0.146
	(-0.502)	(-0.818)	(-0.559)	(-0.854)	(-0.693)	(-0.655)	(-1.129)	(-0.685)	(-0.801)	(-0.925)	(-1.354)
TotalAsset	0.025	0.037	0.007	0.011	0.020	0.013	0.026	0.020	0.014	0.083	0.021
	(0.556)	(0.797)	(0.474)	(0.688)	(1.267)	(0.823)	(1.612)	(1.264)	(0.857)	(1.045)	(1.234)
Leverage	-0.084	-0.091	-0.024	-0.026	-0.049	-0.036	-0.041	-0.048	-0.035	-0.192	-0.016
	(-0.413)	(-0.447)	(-0.331)	(-0.352)	(-1.070)	(-0.792)	(-0.925)	(-1.068)	(-0.770)	(-0.559)	(-0.327)
RatioMB	0.002	0.002	0.000***	0.000***	3.03E-4	2.93E-4	0.000	0.000	0.000	0.004	0.000
	(0.672)	(0.684)	(2.878)	(3.204)	(1.189)	(1.212)	(1.192)	(1.220)	(1.271)	(0.641)	(1.522)
PriorPerf	-0.458*	-0.445*	-0.147*	-0.143*	0.033	0.063	0.007	0.029	0.075	-0.761*	0.041
	(-1.735)	(-1.672)	(-1.801)	(-1.760)	(0.435)	(0.798)	(0.089)	(0.378)	(0.924)	(-1.699)	(0.558)
ROA	-0.249	-0.032	-0.067	-0.028	-1.111	-1.005	-1.157	-1.117	-1.010	0.395	-0.538
	(-0.187)	(-0.024)	(-0.170)	(-0.074)	(-1.609)	(-1.534)	(-1.595)	(-1.618)	(-1.546)	(0.173)	(-0.932)
Deal Completion Controls	Yes	Yes	Yes	Yes						Yes	
Abnormal Ret Controls					Yes	Yes	Yes	Yes	Yes		Yes
LR-ratio	67.35	73.01								77.77	
Estrella R^2	0.059	0.064								0.068	
Adjusted R^2	0.071	0.077	0.057	0.061	0.403	0.415	0.383	0.402	0.415	0.082	0.409
Liklihood	-536.21	-533.38								-531.00	
N_{obs}	945	945	945	945	1295	1295	1295	1295	1295	945	1295

Conclusion

In the first chapter, we examine seasonality and momentum jointly across national equity markets, confirm their existence at the index level, and find that seasonality and momentum have little or no correlation and may emanate from separate global or local risk factors, rather than from different loadings on the same risk factor(s). Employing a parametric trading strategy that enables combining seasonality and momentum, we confirm the conclusion about the relationship between seasonality and momentum. In addition, the combination trading strategy shows statistically and economically significant trading returns and outperforms the corresponding pure seasonality and pure momentum strategies, and potentially could be useful in practice as part of a global asset allocation strategy.

In the second chapter, we find empirically that incorporating intra-industry peer information by employing earnings mimicking portfolio returns can generate model forecasts that are significantly better than without use of the earnings mimicking portfolio returns. The difference in forecast accuracy is economically important as we can exploit it with a simple trading strategy that generates significant annual returns of 11.5%, although it is difficult to implement in practice due to high trading costs. The results demonstrate that financial analysts may not fully integrate and incorporate interim industry-wide financial market information into their earnings forecasts.

In the third chapter, our study provides new insights on informed trading activities by corporate insiders. Following the intuition that corporate insiders would maintain and increase their information advantage to achieve higher trading profits, we exploit the unique setting of trading suspensions in China to identify separate windows of insider private operational efforts and insider trading activities. Our results reveal that corporate insiders not only choose to trade on deals that are more profitable based on their fundamentals, but also insert private efforts to increase the probability of deal closure and achieve higher abnormal returns. Meanwhile, insider private effort fails to improve acquirer long-term operational performance. These results imply that acquirer insider efforts are misdirecting in nature and do not significantly improve acquirer shareholder welfare by enhancing deal fundamentals.

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Appendix A

Chapter 2 Supplement

A1 Industry Definitions

This table presents the brief definitions of the 9 industries used in Chapter 2. It is based on the 12-industry classification of Fama and French, with Utilities, Finance, and Others being excluded. More comprehensive information can be accessed at Kenneth R. French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

Industry	Name	Description
1	NoDur	Consumer Nondurables (e.g., Food, Tobacco, Textiles, Apparel, Toys)
2	Durbl	Consumer Durables (e.g., Cars, TVs, Furniture, Household Appliances)
3	Manuf	Manufacturing (e.g., Machinery, Trucks, Planes, Paper, Com Printing)
4	Enrgy	Oil, Gas, and Coal Extraction and Products
5	Chems	Chemicals and Allied Products
6	BusEq	Business Equipment (e.g., Computers, Software, Electronic Equipment)
7	Telcm	Telephone and Television Transmission
8	Shops	Wholesale, Retail, and Some Services
9	Hlth	Healthcare, Medical Equipment, and Drugs

A2 Characteristics and CMP

The optimality of extracting industry peer information for the characteristic (earnings) forecast by using the CMP return. Returns have a time-varying link to the characteristic:

$$\mathbf{r_t} = c_t \mathbf{Z_t} + \mathbf{e_t}, \qquad \mathbf{e_t} \sim N(0, \mathbf{D_e}) \tag{A.1}$$

Note that normality may not be needed. $\mathbf{D}$ indicates a diagonal matrix.

$$\mathbf{z_t} = \mathbf{z} + \mathbf{u_t}, \qquad \mathbf{u_t} \sim N(0, \mathbf{D_u}) \tag{A.2}$$

Note that $\mathbf{z}$ indicates the prior mean of $\mathbf{z_t}$.

$$c_t = c + v_t, \qquad v_t \sim N(0, \sigma_v^2) \tag{A.3}$$

Here c is the prior mean of c_t.

Find best linear estimator $\hat{\mathbf{z}}_\mathbf{t}$ for $\mathbf{z_t}$:

$$\hat{\mathbf{z}}_\mathbf{t} = \mathbf{a} + \mathbf{B}\mathbf{r_t} \tag{A.4}$$

$$\min_{\mathbf{a},\mathbf{B}} \Big(E\{Tr[(\hat{\mathbf{z}}_\mathbf{t} - \mathbf{z_t})(\hat{\mathbf{z}}_\mathbf{t} - \mathbf{z_t})^T]\} \Big) \tag{A.5}$$

$$2E[(\hat{\mathbf{z}}_\mathbf{t} - \mathbf{z_t})^T] = 0 \quad \text{(first-order condition for } \mathbf{a}) \tag{A.6}$$

From euqation A.6:

$$\mathbf{c} = \mathbf{z} - c\mathbf{B}\mathbf{z} \tag{A.6'}$$

$$\min_{\mathbf{B}} (E\{Tr[\mathbf{B}(\mathbf{r_t} - c\mathbf{z})(\mathbf{r_t} - c\mathbf{z})^T \mathbf{B}^T - 2\mathbf{B}(\mathbf{r_t} - c\mathbf{z})\mathbf{u_t}^T + \mathbf{u_t}\mathbf{u_t}^T]\}) \tag{A.5'}$$

$$E[2\mathbf{B}(\mathbf{r_t} - c\mathbf{z})(\mathbf{r_t} - c\mathbf{z})^T - 2(\mathbf{r_t} - c\mathbf{z})\mathbf{u_t}^T] = 0 \tag{A.7}$$

$$\mathbf{B}E[(\mathbf{r_t} - c\mathbf{z})(\mathbf{r_t} - c\mathbf{z})^T] = E[(\mathbf{r_t} - c\mathbf{z})\mathbf{u_t}^T] = c\mathbf{D_u} \tag{A.7'}$$

Since,

$$\mathbf{B} = c\mathbf{D_u}\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}, \qquad \text{with } \boldsymbol{\Sigma}_{\mathbf{r}}^{-1} = (\mathbf{c^2} + \sigma_{\mathbf{v}}^{\mathbf{2}})\mathbf{D_u} + \mathbf{D_e} + \sigma_{\mathbf{v}}^{\mathbf{2}}\mathbf{z}\mathbf{z}^{\mathbf{T}} \tag{A.7”}$$

Define:

$$\mathbf{Q} = \boldsymbol{\Sigma}_{\mathbf{r}} - \sigma_v^2\mathbf{z}\mathbf{z}^T = (c^2 + \sigma_v^2)\mathbf{D_u} + \mathbf{D_e} \tag{A.8}$$

By the Sherman-Morrison identity:

$$\mathbf{Q}^{-1} = \boldsymbol{\Sigma}_{\mathbf{r}}^{-1} + \frac{\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\sigma_v^2\mathbf{z}\mathbf{z}^T\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}}{1 - \sigma_v^2(\mathbf{z}^T\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\mathbf{z})} \tag{A.9}$$

Define the CMP:

$$\mathbf{s} = \frac{\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\mathbf{z}}{\mathbf{z}^T\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\mathbf{z}}, \qquad \mathbf{r}_{\mathbf{t}}^{\mathbf{CMP}} = \mathbf{r_t}^T\mathbf{s} \tag{A.10}$$

From equation A.4 and A.6’

$$\hat{\mathbf{z}}_{\mathbf{t}} - \mathbf{z} = \mathbf{B}(\mathbf{r_t} - c\mathbf{z}) \tag{A.11}$$

Then use equation A.7”, A.9 and A.10 to obtain:

$$\hat{\mathbf{z}}_{\mathbf{t}} - \mathbf{z} = c\mathbf{D_u}\mathbf{Q}^{-1}(\mathbf{r_t} - c\mathbf{z}) - \frac{c\mathbf{D_u}\mathbf{s}(r_t^{CMP} - \mu^{CMP})}{(1/\sigma_v^2) - (\mathbf{z}^T\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\mathbf{z})} \tag{A.12}$$

For an individual asset’s characteristic:

$$\hat{\mathbf{z}}_t^i - \mathbf{z}^i = \left(\frac{cd_u^i}{(c^2 + \sigma_v^2)d_u^i + d_e^i}\right)(\mathbf{r}_t^i - c\mathbf{z}^i) - \left(\frac{cd_u^i s^i}{1/\sigma_v^2) - (\mathbf{z}^T\boldsymbol{\Sigma}_{\mathbf{r}}^{-1}\mathbf{z})}\right)(r_t^{CMP} - \mu^{CMP}) \tag{A.13}$$

For each firm i the optimal characteristic forecast is determined by the most recent characteristic observation, the firm’s observed stock return since the last characteristic observation, and the CMP return since the last characteristic observation in conjunction with the firm’s historical CMP loadings.

Appendix B

Chapter 3 Supplement

B1 Variable Definition

This table presents the variable definitions in Chapter 3.

Variable	**Definition**
Insider	Using PIN as proxy or using dummy variable *Convicted* as proxy. Details about PIN and *Convicted* are presented in this table.
PIN	10-day average probability of informed trading (PIN) before trading suspension, following Easley et al., 1996.
CAR(-A,+B)	Cumulative Abnormal Return (CAR) from trading day $t - A$ to trading day $t + B$, where day t is the trading resumption day and the abnormal return is in excess of Fama-French 3-factor model.
TotalAsset	Nature log of the total assets of the listed company at the end of quarter $t - 1$.
Leverage	Leverage of the listed company, defined as total debt scaled by total assets at the end of quarter $t - 1$.
BusiLendingRate	Business lending rate, which is yield to maturity on 1-year, AAA rated corporate bond in China in year t.
RatioMB	Ratio between market value and book value of the company at the end of quarter $t - 1$.
PriorPerf	Prior performance, 30-day CAR based on Fama-French 3-factor model.
SOSPctg	State owned share percentage, which is the percentage of the state-owned shares of the listed company before the deal.
HHI	Herfindahl-Hirschman Index of the listed company's industry.
ROA	Return on assets of the listed company at the end of quarter $t - 1$, defined as net income / total assets.
SuspDuration	Suspension duration, number of trading days suspended for the company.
RetBeforeSusp	Return before suspension, which is 5-day return before trading suspension.
MktRetDurSusp	Market return during suspension, which is the broad market return during the suspension of the listed company.
PctgAcquired	Percentage of target company's ownership acquired during the transaction.
Short-term performance	Three-day (-1,+1), five-day (-2,+2) and seven-day (-3,+3) cumulative abnormal returns around trading suspension and resumption in excess of Fama-French 3-factor model.
Long-term performance	One, two, and three-year monthly excess returns based on Fama-French 3-factor model.
Convicted	Equal to 1 if the deal involves convicted case of insider trading by CSRC, 0 otherwise.
SOEDummy	Equal to 1 if the company is a state-owned-enterprise, 0 otherwise.
ConnectedTrade	Equal to 1 if the acquirer and target companies are related (e.g., controlled by same shareholders), 0 otherwise.
MentionDummy	Equal to 1 if the deal is announced as M&A at trading suspension, 0 otherwise.
SuccessDummy	Equal to 1 if the deal is completed, 0 otherwise.

B2 Sample Case: New Sun Equity Investment Co.[1]

In July 2009, Jiashou Xiao, President of New Sun Equity Investment Co. (NSEI), learned that Hengli of Ningxia (HLN) was considering a potential merger. NSEI's intention to participate was communicated with HLN during the months of July 2009 and January 2010. The potential deal was put on hold by local government in early April of 2010, given that a portion of HLS is state-owned while NSEI is private.

Nevertheless, Jiashou Xiao, President of NSEI, insisted on the potential deal and actively promoted the deal to HLN and its corresponding local government in Ningxia Province, China. On May 13th, 2010, a national regulatory change encouraging privately-owned firms to invest in firms with state ownership made the potential deal possible. Thereafter, Jiashou Xiao made several trips from NSEI's headquarters in Shanghai to Ningxia Province to discuss the feasibility of the deal with HLS and the Ningxia provincial government during the months of April 2010 and August 2010. The local regulatory agency approved the deal on August 24th, 2010. Trading in HLN stock was suspended on September 1st, 2010, and resumed on September 28th, 2010. To further safeguard the local government's support of the deal, Jiashou Xiao also assisted in another acquisition deal in Ningxia Province.

Meanwhile, Lili Zhou, Jiashou Xiao's wife, purchased a total of 362,700 HLN shares over the period May 20th to August 25th, 2010. The stocks were later sold for a profit of 134,773.84 Chinese Yuan. In the Administrative Penalty Decision published by CSRC, Jiashou Xiao and Lili Zhou's plea of innocence was denied, because

[1] This sample case is a brief summary from the Administrative Penalty Decision on the insider trading case, which is published by CSRC. For further details on this case, please see http://www.csrc.gov.cn/csrc/c101928/c1043192/content.shtml

> "...based on testimonial and flight records, Jiashou Xiao was continuously involved in the HLN merger deal, including communicating with HLN and leadership of the local government to facilitate the successful merger. ...In addition, as part of the agreement, Jiashou Xiao also facilitated the deal for Ningxia Electricity Investment ... Although Lili Zhou returned all trading profits to HLN as demanded by Jiashou Xiao, Jiashou Xiao failed to fulfill his duty and responsibilities as a core member of the deal."

The deal was successfully closed on June 27th, 2011, shortly after the 2011 regulatory change. Jiashou Xiao and Lili Zhou were found guilty of insider trading on June 5th, 2012. The couple were together fined 300,000 Chinese Yuan. In the penalty decision, it was stated that even though Jiashou Xiao denied the implied motivation of his private efforts and returned all trading profits to HLN, he was considered guilty as he failed to fulfill his duty and responsibilities. Therefore, Jiashou Xiao was ordered to pay an additional fine of 150,000 Chinese Yuan.