Synthesizing Information-driven Insider Trade Signals

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Abstract

We propose a simple approach to synthesize presumably information-driven insider trading signals for the cross-section of stocks. We find that the resulting composite strategy can predict returns, predominantly in equal-weighted portfolios, in our global sample. The results indicate that the benefits of our composite strategy reflect a short-term informational advantage of insiders. Finally, cross-country analysis reveals that varying insider trading restrictions between countries have limited explanatory power for the benefits of the composite strategy.

Keywords: Informed trading; insider trading; return predictability; global markets.

JEL Classification Codes: G12; G14.

Attachments: Appendix (43 pages)

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1 Introduction

Corporate insiders may buy or sell their firm's stocks for various reasons, which could range from diversification motives or liquidity considerations to regulatory aspects or signaling effects to perceived or actual informational advantages. Given these possible motives and constraints, a large literature proposes a broad range of methods and ideas to extract the information-driven component. In this study, we composite a variety of these information-driven measures into an overall proxy at the firm-month level, document its performance in a global context, and analyze its economic drivers.

The question of whether and how those who make use of an information advantage can be identified from the multitude of insider trades has not yet been conclusively resolved. So far the literature has approached this question with economically plausible and in their logic diverse ideas and individual measures. For example, if trades by multiple insiders go in the same direction (Alldredge and Blank 2019), then the likelihood of information-based as opposed to personal motives might, all else equal, be higher. A similar argument can be made for insiders with a high trading frequency and, therefore, a short investment horizon (Akbas et al. 2020). The historical profitability of trades prior to earnings announcements may indicate a private information advantage (Ali and Hirshleifer 2017). Firms with high R&D expenditures (Aboody and Lev 2000) or high idiosyncratic volatility (Jagolinzer et al. 2011, Ben-David et al. 2021) are more difficult to value, thus potentially resulting in higher insider trading profits.

Against this background, our rationale is simple: we test and largely confirm the hypothesis that the signal-to-noise ratio for information-driven trades can be improved if we composite these and other individual measures (see, Section 3.1 for an overview) at the firm-month level. Therefore, we attempt to combine different trading patterns as well as multiple insider and firm characteristics, which have been largely considered in isolation in the literature so far, into a more precise overall firm-level measure of informed trading to predict abnormal returns. In total, we consider 16 information-driven buy proxies and 17 information-driven sell proxies, respectively. Note that both the composite method and its goal conceptually differ from existing approaches that construct bottom-up measures of total insider trading activity to predict the market return (e.g., Seyhun 1988, Lakonishok and Lee 2001, Brochet 2019, Malliouris et al. 2020). In contrast, we composite individual cross-section-based methods to identify information-driven trades with the goal of predicting abnormal performance in the cross-section.

Proposing simple and intuitive composite measures and studying their benefits and limitations is our first contribution to the literature. The second contribution is an analysis on a global scale, since the literature on information-driven insider measures has so far mostly concentrated on the U.S. market. Non-U.S. countries on average account for 75% of the global gross domestic product and 60% of the world market capitalization during our sample period from 2000 to 2021[1] and differ from the U.S. market in a variety of ways.[2] A more comprehensive view thus helps to provide insight into the existence and determinants of information-driven trades. In total, we analyze 3.7 million daily aggregated insider transactions from more than 350,000 insiders in 34 countries. Although there are studies on international or global insider trading, such as Durnev and Nain (2007), Dardas and Güttler (2011), Fidrmuc et al. (2013), Gebka et al. (2017), Brochet (2019) and Hong et al. (2019), they have a different focus. Exemptions include Giamouridis et al. (2008) and Dardas (2012) who employ multivariate regression models with firm and insider characteristics to identify "high conviction" insider trades in the U.K. and Western Europe, respectively. Our third contribution is to analyze the potential economic channels behind the performance of the composite approaches, in part by making use of cross-country heterogeneity.

Our basic composition approach is straightforward. In each company month, we count how many of the information-driven buy proxies derived from the insider trading literature are observed and subtract the number of observable information-driven sell signals. Regarding the assumed mechanism, this approach has some parallels to Engelberg et al. (2018) who, in a different context, net the number of factor long and short leg appearances for each firm-month to construct a more powerful cross-sectional return predictor. In our approach, if the resulting difference between information-driven insider buy and sell signals is greater than or equal to N (less than or equal to $-N$), we assume that there is a composite information-driven buy (sell) signal and consequently buy (sell) and hold the stock in the next calendar month, i.e., we assume a one-month holding period. In our baseline analysis, we set N to (only) 2 to achieve a balance between signal strength (and its presumed implication for abnormal returns) and signal frequency (and its implications for a sufficient sample size, especially at the country-level, and portfolio diversification). We find that this heuristic has predictive power for both raw and abnormal returns in our global sample. The predictability is particularly driven by small firms, i.e., concentrated in equal-weighted portfolios, and by the long leg, i.e., signals derived from insider buying. Twenty-one (24) of the 34 countries in our sample generate statistically significant long-short returns (Carhart 1997[3] alphas) in

[1] See, World Bank data for global gross domestic product and global market capitalization.

[2] See, e.g., Bhattacharya and Daouk (2002), Bushman et al. (2005), Fernandes and Ferreira (2008) on international differences in insider trading regulation and enforcement; Akbari et al. (2020) on economic and financial international market integration; Griffin et al. (2010), Brockman et al. (2009) and Bris et al. (2007) for global differences in transaction costs, liquidity and short-selling, respectively.

[3] We use a local Carhart (1997) factor model to control for insiders' potentially contrarian trading behavior by incorporating the momentum factor from Jegadeesh and Titman (1993). The contrarian invest-

equal-weighted portfolios. In value-weighted portfolios driven by large firms with presumably lower information asymmetries among market participants, 10 (8) countries generate statistically significant long-short returns (Carhart 1997 alphas).

The one-month alphas are also economically significant, again especially among small stocks. In equal-weighted portfolios, they amount to at least 1% for aggregations of both developed and emerging markets, which is also statistically significant at the one-percent level. This finding applies regardless of whether the aggregation is based on firm-months ("pooled") or country-months ("country-neutral"). The first approach is dominated by large markets and the second by small markets. In value-weighted portfolios, the corresponding results are considerably or much weaker at 0.15% to 0.87%, depending on the sample. However, in most samples, the return predictability of the composite approach is still statistically significantly greater than the predictability of an unconditional benchmark strategy that mimics insider buying and selling regardless of its presumed information content. A relative alpha difference, often in the range of 2.5% to 3.5% annualized, can be found in pooled and country-neutral samples, in developed and emerging markets, for equal-weighted and value-weighted portfolios and (approximately half) in both the long and short legs. These results again illustrate the benefits of synthesizing individual trade signals, but they also reveal the limits of return predictability.

Furthermore, alternative composition approaches yield robust results in line with our baseline composition approach in all pooled regional samples, but are unable to produce reliable benefits relative to the unconditional insider trading strategy for the "signal-weighted" and "expected-return" approaches in the country-neutral regional samples. These findings suggest that the benefits of composition, particularly at the country-level, are especially noticeable when applying approaches that are based on basic economic logic, whereas approaches that require potentially outlier-dominated and thus more extreme signal weight calculations are often unable to robustly produce significant benefits across all countries.

What explains the performance of the composite measure? Given the elusive and likely multifaceted nature of insider trading signals, our tests cannot provide a conclusive answer. Nevertheless, in the overall picture, they are at least consistent with an economic mechanism: insiders on average appear to have short-term informational advantages, especially among small firms, by assessing and exploiting public (or at least non-private) information better than the market does. This line of reasoning is broadly consistent with findings in, e.g., Jenter (2005), Kolasinski and Li (2010), Veenman (2013), Alldredge and Cicero (2015), or Lambe et al. (2022). Several results are in line with this assessment. Abnormal returns decrease con-

ment behavior of insiders has widely been documented; See, e.g., Lakonishok and Lee (2001), Jenter (2005), Piotroski and Roulstone (2005).

siderably with longer time horizons. For example, at six-month (as opposed to one-month) holding periods, the average monthly alpha in equal-weighted portfolios is roughly halved; the effect is even stronger for value-weighted portfolios. This finding suggests a primarily short-term informational advantage. It is also consistent with the idea of limits to arbitrage. Implementation costs, such as search costs, spreads, market impact, idiosyncratic risk, or shorting availability and costs, are likely particularly large for small firms in combination with short holding periods. With respect to cross-country variation in the baseline analyses, two results can be noted. First, while the composite strategy tends to be stronger in aggregated emerging markets than in developed markets, the relative benefits, i.e., the difference between the composite and unconditional insider trading profitability, are similar across both markets. At the country level, there are many developed (emerging) markets with high (low) alphas. In summary, these results suggest that general differences between emerging and developed markets with respect to the information environment and, in particular, the exploitability of private information (e.g., Bhattacharya 2000, Griffin et al. 2011) are not a main driver of the performance of the composite measure. Consistent with this view, second, a further cross-country analysis shows that country characteristics that proxy for insider trading restrictions and corporate governance do not have significant explanatory power for country differences in the performance of the composite measure. Partially diverging from the results for unconditional insider trading, we therefore find no reliable evidence for the monitoring hypothesis, which argues that insider trading regulations or better corporate governance prevent insiders from rent extraction. These findings suggest that a better interpretation of public information, as opposed to opportunistic trading on private information, is more likely to be the driver of the results.

The remainder of the paper is organized as follows. Section 2 describes our data and Section 3 our methodology. Section 4 provides the baseline results. Section 5 explores the statistical and economic mechanisms behind our findings. Section 6 concludes.

2 Data

2.1 Insider trade data

We construct the measures of information-driven insider trading from insider transactions obtained by 2iQ Research, a company specialized in monitoring and analyzing millions of global insider trading activities. For most countries, the sample begins around 2003. The specific sample start dates are shown in Table 1. Start dates vary between 2000 to 2013 and are chosen to ensure a comparable quality and quantity of insider transactions in the cross-section as well as in the time series. The end of the sample period is 2021. We only consider open-market purchases and sales reported to local regulators for which we have valid return and market capitalization data. Specifically, in each country sample, we only consider purchases and sales if either the source of an insider transaction is equal to the local regulator or if the transaction was placed on a local exchange. Furthermore, we exclude all transactions not labeled as equity transactions by 2iQ and all transactions which can be identified as a private transaction either through their exchange or transaction label. As the availability of exchange and transaction labels varies greatly between countries, we also implement our own private transactions screen by excluding transactions which have both an unusual transaction price and trading volume for the given trading day, i.e., the transaction price is not within a 20% range of the daily closing price and the volume exceeds the exchange volume for the day. Furthermore, we exclude all trades that are considered routine trades following the trade-level approach of Cohen et al. (2012) to focus on the most informative transactions. These screens imply that we exclude, among others, private transactions, awards, and option exercises. Finally, we aggregate purchases and sales by an individual insider to obtain net shares bought or sold during a given day. When calculating the information-driven measures, we aggregate purchases and sales by an individual insider to obtain net shares bought or sold during a given month if not stated otherwise.

[Please insert Table 1 near here]

We restrict our final data set to countries that have at least 5,000 valid (after screens) open-market purchases/sales transactions and a minimum of 100 stocks over the entire sample period to ensure that all individual measures can be reliably constructed for each country. A detailed description of all the screens applied is provided in Table A.1 of the Appendix. The applied screens lead to a sample of 34 countries covering 39,827 stocks (EM: 14,772; DM: 25,055) with more than 3.7 million daily aggregated insider transactions from more than 350,000 corporate insiders. As Table 1 shows, the mean number of insiders per firm varies between 2.7 and 19.5. Accordingly, the average number of trades per firm ranges between 27.65 and 185.82.

2.2 Stock market data

We use stock market and accounting data from Refinitiv Datastream and Worldscope. We clean the data using static and dynamic screens largely based on Landis and Skouras (2021), Ince and Porter (2006), Griffin et al. (2010), Lee (2011), and Karolyi et al. (2012), among others. Details are given in stock market data screens Appendix. We use both general and country-specific static screens. The general screens aim to filter out non-common stocks, cross-listed stocks, or stocks with incorrect geographic allocation. The country-specific screens focus on the correct mapping of currencies and exchanges, as well as country-specific terms that suggest the stock is not common equity. After all screens, our data set comprises a total of 18 developed and 16 emerging market countries based on the MSCI classification. Table 1 provides descriptive statistics. We perform all portfolio return calculations in U.S. dollars and calculate abnormal returns using self-constructed country-specific Carhart (1997) factor models for the individual country and regional country-neutral analyses. We obtain the regional factor models for the pooled analysis from Kenneth French's data library.

2.3 News data

The construction of some of our information-driven insider trading measures takes into account the amount and sentiment of different types of company-specific news articles. We rely on RavenPack News Analytics, which provides textual analysis of time-stamped comprehensive global news in a standardized form. In the finance and accounting literature, RavenPack is increasingly used not only for the U.S. stock market, but also for international markets. Examples include Blankespoor et al. (2018), Bushee et al. (2020), Dai et al. (2021), Dang et al. (2015), Shroff et al. (2014) or You et al. (2018), among others. The advantages of this data for our analysis include the broad coverage of companies, countries, and sources, ranging from newswires to newspapers to company-initiated news (i.e., press releases), resulting in millions of eligible articles. Details on our company matching and the inclusion of news data in the insider trading measures can be found in the RavenPack mapping Appendix and in Table A.3 of the Appendix.

3 Methodology

3.1 Individual measures of information-driven insider trading

Our goal is to construct a simple composite measure of information-driven insider trading that attempts to eliminate noise from the individual information-driven insider measures. The resulting composite measure should thereby produce a significantly better signal for identifying information-driven insider trades, i.e., significantly improve the signal-to-noise ratio. Intuitively, this means that not every identification methodology can always ensure a correct classification into information-driven and non-information-driven insider trades, as these measures are usually heuristics stemming from economic logic and/or intuition. For example, although the likelihood of information-driven insider trades may generally be higher for insiders with a short investment horizon (Akbas et al. 2020, Fu et al. 2020), this does not mean that every trade made by an insider with a short investment horizon must always be information-driven, as even such insiders will, for example, execute liquidity or diversification-induced trades from time to time. The same could apply to insiders who in the past have executed particularly profitable trades prior to quarterly earnings announcements (Ali and Hirshleifer 2017). The concept of the composite measure is quite simple: we conjecture that an insider trade executed by, for example, an insider who satisfies both of the above conditions will be more often, in fact, information-driven, and thus the number of insider trades falsely identified as information-driven will decrease significantly.

Consequently, to exploit the full potential of this composite measure, a first step is to identify a variety of individual information-driven insider trading measures. The literature offers a plethora of different methodologies for the identification of potentially information-driven insider trades, covering, for example, insider trading patterns, the timing of insider trades, the general profitability of past insider trades, the nature of the insider position in the company, and general firm characteristics which are associated with greater information asymmetries.

Our goal is not to implement all proposed information-driven measures in the literature but to provide a sufficiently wide range of individual measures for the construction of a meaningful composite. In this context, some information-driven insider trading measures suggested in the U.S.-based literature cannot be implemented appropriately in our global setting due to lack of sufficient data availability.[4] In addition, the individual measures (signals) included in the composite measure must be consistent in terms of their temporal availability to be able to generate a trading strategy based on the resulting composite measure.[5] Our baseline composite measure always assumes that in the calendar month t following the information-driven insider trade (signal) in month $t-1$, a long or short position is established according to the expected predictive power of the transaction (signal) direction. Our monthly rebalanced trading strategy is based on the actual trade date disregarding the reporting lag of the transaction. This implies that the strategy mimics information-driven insider trades with some delay for information-driven insider trades that occurred at the beginning of month $t-1$. Note that an outside investor would potentially not be able to mimic insider trades that occur at the end of month $t-1$ or trades with greater reporting lags, as

[4] Examples include Ravina and Sapienza (2010), Fidrmuc et al. (2006), Ghoul et al. (2022), Massa et al. (2015), Jiang et al. (2021), and Hillier et al. (2015), who rely on governance, ownership concentration, economic policy uncertainty, short-selling, legal expertise and other personal attributes of corporate executives, respectively.

[5] Therefore, among others, we cannot implement the isolated trade and trade sequences measures of Biggerstaff et al. (2020) appropriately, since it requires to wait two more months after the trading month to make an appropriate classification.

those trades would not be observable in real-time at the beginning of month t (see, Table 1 for the median reporting lags of each country). Consequently, with our simple strategy, we focus more on investigating the existence of insiders' short-term informational advantages rather than the actual real-time implementability of such a strategy.

Given the aforementioned constraints, we implement the following individual measures to identify information-driven insider trades and provide a brief description of the particular economic logic and/or intuition behind the identification:

- "Opportunistic trades" (Ali and Hirshleifer 2017): We assume that trades of insiders who have traded particularly profitable shortly before quarterly earnings announcements are more likely to be information-driven trades **(Q3)**.
- "Strong trades", "Short horizon trades" and "Unexpected trades" (Akbas et al. 2020): We assume that insiders with a high trading frequency, and therefore a short investment horizon, are more likely to execute information-driven trades **(SHOR)**. We apply a similar rational to insider trades with greater market impact, i.e., high daily volume **(STRO)**, and insider trades that are unexpected given the regular trading behavior of an insider **(UNEX)**.
- "Insider silence" (Hong and Li 2019): We assume that sudden insider silence, i.e., discontinuing to purchase **(PPN)** or sale **(SSN)**, following several consecutive purchases/sales, is informative.
- "Realized loss sales" (Kelly 2018): We assume that a sale at a loss is more "painful" than a sale at a gain, and thus it is assumed to have a higher (negative) information-content **(LOSS)**.
- "CFO purchases" (Wang et al. 2012): We assume insider purchases by CFOs to be more likely information-driven, as CFOs are in the best position among corporate insiders to have access to informational advantages and also to use them effectively **(CFO)**.
- "Accrual trades" (e.g., Beneish and Vargus 2002, Bergstresser and Philippon 2006): We assume that insider transactions by top-level executives are more likely to be information-driven if all company insiders as a group trade in the same direction, while the level of accruals in the last fiscal year suggests a possible manipulation of accruals in favor of the transaction direction **(ACC)**.
- "Research & Development trades" (Aboody and Lev 2000): We assume that higher R&D expenditures lead to higher information asymmetries regarding future developments, which increase the likelihood of information-driven insider trades by corporate officers **(R&D)**.
- "Idiosyncratic volatility trades" (e.g., Jagolinzer et al. 2011, Ben-David et al. 2021): We assume that higher idiosyncratic volatility leads to higher information asymme-

tries regarding future developments or to more pronounced mispricing, both of which increase the likelihood of information-driven insider trades in these firms with high idiosyncratic volatility **(IVOL)**.

- "Clustered trades" (Alldredge and Blank 2019): We assume that insider trades in the same trade direction made by multiple insiders of the same firm within a certain temporal proximity are more likely to be information-driven, as this synchronous trading of insiders suggests that the same (shared) nonpublic information might be exploited by multiple insiders **(CLUS)**.
- "Analyst coverage trades" (e.g., Frankel and Li 2004, Ellul and Panayides 2018): We assume that an unusually high degree of analyst coverage (controlling for firm size) may indicate greater public interest in and scrutiny of the firm, which makes it harder to exploit nonpublic information for insiders. On the contrary, less attention from analysts might result in more information-driven trades **(ANA)**.
- "Residual media coverage trades" and "Selected residual media coverage trades" (e.g., Dai et al. 2015, Sun et al. 2021): We assume that an unusually high degree of media coverage (controlling for firm size) may indicate greater public interest in and scrutiny of the firm, which makes it harder to exploit nonpublic information for insiders. On the contrary, less press attention could result in more information-driven trades **(RMC)**. We apply the same rationale to narrower press coverage dealing with insider trades and related topics **(SRMC)** such as corporate responsibility or investor relations.
- "Press release trades" (e.g., Cheng and Lo 2006): We assume that voluntary firm-initiated news disclosure, i.e., press releases, in advance of a planned insider transaction could be motivated to influence the stock price in a favorable direction **(VOLD)**.
- "Conditional conservatism trades" (Khalilov and Osma 2020): We assume it to be difficult for insiders to speculate on negative news when those are timely incorporated in the accounting numbers, i.e., in times of high conditional accounting conservatism. Therefore, we regard sales of insiders as more likely to be information-driven if the company had low conditional conservatism, assuming that in these cases it is more likely that insiders can successfully speculate on bad news. On the other hand, we assume that high conditional conservatism leads to a potential undervaluation, as profits are not recognized until the associated cash flows are realized, which offers the opportunity to speculate on good news, especially in times of high conditional conservatism **(CONS)**.
- "Multiple firm insider sales" (Karamanou et al. 2021): We assume that when an insider who is active in multiple firms executes a sale transaction in one firm that is accompanied by at least one purchase transaction in one of his or her other firms in

the same month, it is less likely that the sale transaction is liquidity-driven. Therefore, we assume the sale to be information-driven **(MFS)**.

- "Persistently profitable trades" (Cline et al. 2017): We assume that insiders with persistently high abnormal returns might exploit nonpublic information leading to their superior performance **(PROF)**.

The simultaneous and global implementation of the above discussed information-driven measures allows the calculation of a particularly versatile composite, which we hope will provide a new perspective in assessing the information content of insider trades. The individual information-driven measures provide information on the future development of a stock based on the type of transaction. Following the economic logic of the identification, sell transactions indicate a negative future stock price development, whereas buy transactions indicate a positive future stock price development. The indicators emerging from our various measures of information-driven insider trades are composited for each company on a monthly basis, so that we can derive a composite signal for future positive (surplus of information-driven buy signals) or negative (surplus of information-driven sell signals) stock price development. We provide a detailed description of the implementation of all individual information-driven trade measures adapted to an international sample with a very heterogeneous composition of individual country data sets in Table A.3 of the Appendix. Tables A.4 and A.5 of the Appendix provide descriptive statistics for the appearance of each information-driven buy and sell signal across countries, respectively.

3.2 Composite measures of information-driven insider trading

The individual insider measures aim to identify information-driven trades. However, each individual measure has a considerable amount of noise, since trading patterns, past performance, or information asymmetries are not necessarily a clear indicator of information-driven trades. Nevertheless, the likelihood that information about a stock's future performance can reliably be drawn from insider trades presumably increases with the number of information-driven insider trade signals. Therefore, we synthesize individual measures of information-driven insider trades to obtain a clearer picture. Furthermore, individual information-driven signals are not necessarily unambiguous. Hence, different measures can indicate opposing trade directions. Composition rules out such ambiguities by requiring a certain number of unique signals to be considered relevant. We classify each firm-month as information-driven (Buy=1/Sell=−1) or non-information-driven (0) using the following composition methodology:

$$CID^N_{i,t} = \begin{cases} 1 & \text{if } \sum_{j=1}^{16} Buy\ Signal_{j,i,t} - \sum_{k=1}^{17} Sell\ Signal_{k,i,t} \geq \quad N \quad (Buy) \\ -1 & \text{if } \sum_{j=1}^{16} Buy\ Signal_{j,i,t} - \sum_{k=1}^{17} Sell\ Signal_{k,i,t} \leq -N \quad (Sell) \\ 0 & \text{else,} \end{cases} \tag{1}$$

where $Buy\ Signal_{j,i,t}$ is a dummy variable equal one if any information-driven insider buy occurred in firm i during month t according to the individual information-driven buy measure j, $Sell\ Signal_{k,i,t}$ is a dummy variable equal one if any information-driven insider sell occurred in firm i during month t according to the individual information-driven sell measure k, and N is the required surplus needed to qualify as an information-driven composite buy ($CID = 1$) or sell ($CID = -1$) signal, respectively. In our baseline approach, we use $N = 2$, which is denoted CID^2, for brevity henceforth CID. For example, we would consider a firm-month to have an information-driven buy signal if 3 information-driven buy signals and no more than 1 information-driven sell signal occurred in that month. We consider a total of 16 information-driven buy measures and 17 information-driven sell measures, respectively.

[**Please insert Figure 1 near here**]

To better understand the operation of CID in Eq. (1), Figure 1 illustrates how many trade signals are generated in the pooled country data set depending on the surplus requirements ($N \geq 1, 2, 3, 4, 5$) of an information-driven insider trading signal. Subfigures 1 (a) and 1 (b) clearly show that for both purchase and sale signals, the absolute threshold of 1, i.e., an excess of one purchase ($N \geq 1$) or sale ($N \leq -1$) signal, does not produce a meaningful signal reduction compared to the number of unconditional signals. With increasing surplus requirements, correspondingly clearer signals, i.e., larger absolute surpluses of individual information-driven purchase or sale signals, are generated; however, a clearer signal is accompanied by an increasing reduction of our composite information-driven purchase or sale signals. Considering this trade-off, we use a CID greater than or equal to 2 (CID^2) as our baseline composite measure of information-driven trades to account for the heterogeneous appearance of individual information-driven signals both across measures and across countries (see, Tables A.4 and A.5 of the Appendix). As such, a CID greater than or equal to 2 prevents our composite information-driven signal from being driven by individual information-driven purchase or sale signals, which are more prevalent. Consequently, in our baseline measure, combinations of information-driven signals that are not as numerous can also generate a composite information-driven signal, thus enabling the use of the full breadth of all our individual measures of information-driven insider trades. On the contrary, this implies that a CID greater than or equal to 3, 4 or 5 is increasingly driven by the most prevalent signals and could potentially not be implementable in countries with low or poorer signal appearances. We report the results of our composite information-driven insider trading strategies with surplus requirements (N) greater than or equal to 3 (CID^3) and 4 (CID^4) in Section 5.1.

4 Baseline results

4.1 Unconditional insider trading

First, we investigate the predictive power of unconditional (UNC) insider trades. Our idea is that these serve as a benchmark against information-driven insider trades. We construct a simple trading strategy in which we buy stocks in month t that were bought by (any) insiders in the previous month $t-1$ and short-sell stocks that were sold, respectively. We use the actual trade date to determine whether an unconditional signal was generated in month $t-1$ disregarding the reporting lag of the transaction. Thus, the UNC strategy mimics unconditional insider trades with some delay for insider trades that occurred at the beginning of month $t-1$. It potentially renders trades that occur at the end of month $t-1$ or trades with greater reporting lags infeasible for outside investors, as those trades would not be observable in real-time, at the beginning of month t (see, Table 1 for the median reporting lags of each country). Consequently, with this simple strategy, we focus more on investigating the existence of unconditional short-term informational advantages of insiders rather than the actual real-time implementability of such a strategy.

Furthermore, it should be emphasized that our unconditional strategy deviates from the large number of aggregated insider trading strategies, e.g., based on intensive trading criteria (see, e.g., Seyhun 1986, Seyhun 1988, Seyhun 1992). Since we study the predictive power in the cross-section of stocks and not in aggregate, the corresponding benchmark strategy (UNC) should also consider all individual insider signals before generating a firm-month signal. Thus, we hold a firm in both the long and short legs in month t if at least one insider in that firm was a net buyer and another insider a net seller in month $t-1$.

In Table 2, we report the performance of the UNC strategy as well as the performance of the respective long and short legs separately for each country. Raw and abnormal returns (4-factor alphas following Carhart 1997, henceforth CH4 alphas) are shown individually for each country to reveal country-specific differences. Additionally, we report the average number of companies in the UNC portfolios and their respective long and short legs, respectively, to illustrate how portfolio construction differs between countries. Looking at the number of firms in each UNC portfolio reveals a significant dispersion between countries. We observe small averages of 14 and 19 firms, respectively, for the Netherlands and Belgium, whereas Canada and the U.S. exhibit large portfolios of 722 and 1,666 firms on average, respectively.

[Please insert Table 2 near here]

Looking at the value-weighted results shows that only 9 (7) countries exhibit significantly positive raw (abnormal) returns, respectively. The only countries whose raw and abnormal returns are both significantly greater than zero are France, Poland, South Africa, South Korea, Spain, and Turkey. The return dispersion is large. For example, Belgium shows raw and abnormal value-weighted long-short returns of -0.66% and -0.30%, respectively, while Poland shows returns of 1.49% and 1.71%, respectively. In total, 6 (5) of the raw (abnormal) value-weighted returns are negative, all of them being statistically insignificant. The results look different for equal-weighted UNC portfolios, where all returns, raw and abnormal, are positive. Furthermore, 25 (raw) and 27 (abnormal) of the UNC equal-weighted long-short returns are significant, respectively. The only countries that exhibit insignificant equal-weighted abnormal returns are Denmark, Egypt, Finland, Indonesia, Israel, Norway, and the Philippines. Again, we have a large dispersion of monthly returns between countries. Denmark and Israel have the lowest raw (abnormal) returns with 0.03% (0.38%) and 0.08% (0.20%), respectively. The economically most predictive UNC countries are South Korea with raw and abnormal returns of 2.03% and 1.72% and Turkey with 2.40% and 2.22%, respectively. Considering the long and short legs separately shows the performance drivers of the UNC strategies. First, the value-weighted long legs show only a few insignificant raw and abnormal negative returns. Equal-weighted, no returns are negative. On the other hand, countries such as South Africa and Indonesia have value-weighted raw returns in the long leg of 1.59% and 1.68%, respectively. For abnormal returns, the only country with average returns greater than 1% per month is Poland with 1.44%. The economic magnitude of returns is much higher for equal-weighted portfolios. For example, in the case of raw returns, only four countries show returns smaller than 1% per month. Those are Chile (0.21%), Denmark (0.47%), Belgium (0.80%), and Spain (0.85%). Noticeably, 10 countries are above the 2% level per month. To get a clearer picture, we analyze the short legs as well. No value-weighted or equal-weighted raw returns have significant negative returns. Canada, Sri Lanka, and Turkey are the only countries with significant negative abnormal returns for value-weighted short portfolios. For equal-weighted short portfolios, only Belgium, France, Italy, South Korea, Sweden, and Turkey exhibit significant negative returns. In general, the long-short returns of the UNC strategies are mainly driven by their long legs, as the short legs barely reveal any significant negative returns.

Overall, the profitability of the UNC strategies appears to be limited for value-weighted portfolios. However, there seems to be predictive power for equal-weighted unconditional insider trades in most countries.

4.2 Composite measures of information-driven insider trading

We use the composite approach developed in Section 3.2 to identify information-driven insider trades. Following the same timing and portfolio construction as described in Section 4.1 for the UNC strategy, we construct the CID strategy by buying (selling) a stock if the difference between information-driven insider buying and selling signals in the previous month is greater than or equal to 2 (less than or equal to -2).

Table 3 shows the monthly raw returns and CH4 alphas for the CID trading strategy as well as the performance of the respective long and short legs separately for each country. Furthermore, it shows the average number of firms in the CID portfolios and their respective long and short legs, respectively. The dispersion across countries in the number of average firms for the CID strategy is large, but, as expected, at a lower absolute level compared to the UNC strategy. It ranges from 14 and 15 firms on average for Chile and Belgium, respectively, to 501 firms for Canada, which is only exceeded by the U.S. with on average 1,378 firms in the monthly long-short portfolios.

[Please insert Table 3 near here]

Looking at monthly value-weighted raw and abnormal long-short returns, we observe 6 and 4 negative returns, respectively. The Netherlands (-0.88%), Hong Kong (-0.34%), Belgium (-0.20%), and China (-0.19%) exhibit the lowest abnormal returns, but none of them are significant. On the other hand, 7 countries generate abnormal value-weighted long-short returns above 1% per month. The most predictive countries are Turkey and Poland with 1.80% and 2.11%, respectively. In total, 10 (8) of the value-weighted raw (abnormal) CID returns are significantly positive. For the equal-weighted CID portfolios, we observe a clearer picture with 21 and 24 statistically significant positive raw and abnormal returns, respectively. The only country that shows negative equal-weighted CID returns is Indonesia with insignificant raw and abnormal returns of -0.08% and -0.07%, respectively. However, 19 countries exceed a monthly return level of 1% for both raw and abnormal returns. The countries with the highest abnormal returns are South Korea (2.08%), Greece (2.15%), and Turkey (2.75%). All are significant at the one-percent level.

To identify the performance drivers of the CID strategy, we analyze the long and short legs separately. First, looking at the value-weighted raw and abnormal returns of the long legs reveals that all returns are positive, with the exception of China showing a negative abnormal return. Furthermore, 18 and 14 of these value-weighted raw and abnormal CID returns are significant. China and Hong Kong exhibit the lowest abnormal returns with -0.05% and 0.06%, respectively. We observe the only value-weighted abnormal long returns above 1% in Greece and Poland with 1.28% and 1.63%, respectively. For equal-weighted portfolios, we observe greater economic magnitude and significance of abnormal returns. In total, 30 countries show significant abnormal long returns. Indonesia and the Netherlands have the lowest equal-weighted abnormal long returns with 0.02% and 0.34%, respectively, while Poland and Canada have the highest returns with 2.02% and 2.09%, respectively. Looking at the short legs, there are only 3 and 7 statistically significant negative value- and equal-weighted abnormal returns, respectively. However, compared to Table 2 we see a slight improvement in the number of negative returns and fewer significant positive short legs which both benefit the long-short CID strategies. We provide an overview of the performance differences between the UNC and CID strategy on country-level in Table A.6 of the Appendix. However, the comparison at the country-level does not provide a conclusive picture on whether the CID strategy improves the return predictive power of insider transactions. Noticeably, at least three-quarters of the countries show positive improvements in value- and equal-weighted raw and abnormal long-short differences. Albeit, only one third of the countries show significant positive improvements for equal-weighted raw and abnormal returns, while 7 and 6 countries show significant positive improvements for value-weighted raw and abnormal returns.

In the following, to provide a more general and potentially more meaningful perspective on the improvements produced by our CID strategy, we analyze the performance of all countries in aggregate regions. In Table 4, we report value- and equal-weighted CH4 alphas for the UNC and CID strategies for the long-short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report the differences between UNC and CID alphas, as well as a test for significant differences. To account for structural differences between countries, we distinguish between developed markets (DM) and emerging markets (EM). We use the following two aggregation methods for the DM and EM regions: We aggregate all firm-months across all countries in the respective region to create a regional monthly sample that includes all information-driven (unconditional) insider trade firm-month signals. This "pooled" sample is dominated by countries with a greater number of information-driven (unconditional) firm-month observations. All abnormal returns for the "pooled" regions are calculated using regional U.S. dollar Carhart (1997) 4-factor models obtained from Kenneth French's data library. To weaken the influence of countries with many monthly signals, we additionally calculate "country-neutral" regional results. All abnormal returns and t-statistics for the "country-neutral" regions are calculated by averaging the abnormal returns and t-statistics across all individual country results in the respective region.

[Please insert Table 4 near here]

Panel A reports the CH4 long-short alphas for the value- and equal-weighted UNC and CID strategies, respectively. Starting with our pooled sample, we see that for DM, the long-short returns for value- and equal-weighted UNC portfolios are -0.08% and 0.75%, respectively. For the CID DM strategies, the returns are 0.15% and 1.00%, respectively. In both cases, only equal-weighted portfolios show significant alphas, with the CID strategies having absolute higher alphas compared to the UNC strategies. The value-weighted (0.23%) and equal-weighted (0.27%) CID-UNC alpha spreads are significantly positive, indicating an outperformance of the CID strategies in the pooled DM samples. Looking at the pooled EM samples, we observe similar results with higher absolute alphas. The value- and equal-weighted UNC alphas are 0.43% and 1.03%, respectively. The alphas of the EM CID strategies are higher with 0.70% and 1.40% for the value- and equal-weighted portfolios, respectively. The value-weighted and equal-weighted CID-UNC alpha spreads are 0.26% and 0.37% being statistically significant at the ten- and one-percent level, respectively. Therefore, the pooled DM and EM samples reveal a significant outperformance of the CID strategies. Considering the country-neutral samples, the value- and equal-weighted long-short UNC and CID alphas of the DM portfolios are 0.34% and 0.86% and 0.43% and 1.11%, respectively. However, the CID-UNC alpha spreads are only significant for equal-weighted DM portfolios (0.25%). For EM, both the country-neutral value-weighted (0.36%) and equal-weighted (0.20%) CID-UNC alpha spreads are significant. The respective value- and equal-weighted alphas of the UNC and CID strategies are 0.51% and 1.02% and 0.87% and 1.22%, respectively. The country-neutral UNC and CID strategies have almost consistently higher alphas with the exception of the equal-weighted EM strategies. CID-UNC alpha spreads are significantly higher in both pooled and country-neutral samples, except for the value-weighted country-neutral DM alpha spread.

Panels B and C report the CH4 alphas for the long and short legs separately, to identify the drivers of the long-short performance. Looking at the long legs, we see that for the DM pooled samples, all alphas (UNC and CID), except the value-weighted UNC alpha, are significantly positive. The alphas are slightly higher than the long-short alphas, suggesting that the short legs have little impact. The CID-UNC alpha spreads are significant for both value- and equal-weighted pooled DM samples with differences of about 0.2%. In pooled EM samples, the long leg alphas are on average higher but less significant. Only the equal-weighted portfolios show significance, both in alphas and in the CID-UNC spreads. However, we see economically higher CID-UNC spreads in DM suggesting higher relative CID benefits in pooled DM long portfolios. In country-neutral portfolios, the equal-weighted alphas for UNC and CID are significant, for both DM and EM portfolios, albeit the alphas of the EM portfolios are consistently higher. Country-neutral CID alphas are always higher than their UNC counterparts, with the exception of the equal-weighted EM alpha. Hence, the CID-UNC alpha spreads are significant, with the exception of the equal-weighted country-neutral EM alpha. In EM, the CID-UNC alpha spreads are 0.28% for value-weighted and -0.01% for equal-weighted portfolios. For DM, the CID-UNC alpha spreads are around 0.11% for both value- and equal-weighted portfolios.

For the short legs, we find no unconditional or information-driven negative (positive) predictability, as none of the alphas, regardless of the country aggregation or weighting scheme, are negative (positive) statistically significant. However, we observe that CID-UNC alpha spreads are predominantly negative. In particular, the CID-UNC alpha spreads for equal-weighted portfolios are significantly negative in both DM and EM pooled and country-neutral samples. This reveals that insider sales generally do not have a significant negative predictability in both EM and DM; however, the equal-weighted long-short CID strategies improve significantly in both EM and DM due to a relatively weaker positive predictability of the short legs compared to the respective unconditional short leg performances.

Overall, we observe that the significant CID-UNC long-short alpha spreads are mainly driven by the predictability of their long legs. Noticeably, for equal-weighted portfolios, we observe significant CID-UNC alpha spreads for almost all pooled and country-neutral long-short, long, and short portfolios, respectively. Table A.7 of the Appendix shows similar results for raw returns. For both regions, we observe that the long-short CID strategies perform significantly better than the UNC strategies. In the following, to better understand what drives the documented outperformance of our constructed CID strategy, we examine potential statistical and economic mechanisms.

5 Statistical and economic mechanism

5.1 Alternative composition approaches

In addition to our composite baseline measure (CID^2), we subsequently test the performance of alternative composition approaches. These include more restrictive versions of our CID measure, i.e., larger signal surplus requirements. First, we test CID measures with $N = 3$ and 4 (see, Eq. (1)), but refrain from implementing a CID measure with $N = 5$. A cross-country implementation with a CID^5 would not be consistently possible due to the very sparse and heterogeneous signal appearances across countries (see, Figure 1).

Another alternative composition approach is not to assign equal weights to individual information-driven insider trade signals as in our CID measure, but to assign higher weights to signals that occur less frequently.[6] The underlying assumption is that signals that occur less (more) frequently might have a better (worse) signal-to-noise ratio and should be over-weighted (under-weighted) accordingly. Therefore, we calculate every month the absolute number of all information-driven insider buy and sell signal appearances and scale all signals by dividing this absolute number for all signals by the buy and sell signals with the highest signal frequency. Finally, we multiply these scaled weights by the dummy variables of information-driven buy (1) and sell (-1) signal occurrences and sum them up to construct the signal-weighted measure. To maintain the composition idea, we calculate this signal-weighted measure only for stock months in which at least two information-driven buy or sell signals are present. In a final step, we assume that the stocks in the top (only for signal-weighted measures > 0) and bottom (only for signal-weighted measures < 0) terciles of our signal-weighted measure generate information-driven buy and sell signals, respectively, which we use to construct our long-short SW strategy.

Furthermore, we apply a composition approach that is solely data-driven.[7] Data-driven approaches for identifying more profitable and potentially information-driven trades have been used by Giamouridis et al. (2008) and Dardas (2012) who use multivariate regression models with firm and insider characteristics to identify "high conviction" insider trades in the U.K. and Western Europe, respectively. We construct a measure based on expected return (ER) forecasts similar to the approaches applied in Lewellen (2015) and Green et al. (2017). To identify information-driven trades in month t to later evaluate the predictive power of this signal in $t+1$, we estimate monthly cross-sectional one-month ahead return regressions in month t using our individual information-driven insider trading measures from month $t-1$ as predictors. This results in regression coefficients for each insider measure that indicate how important the respective insider trading measure was for return predictability in the previous month. To limit the effect of outliers on these monthly regression coefficients, we use the mean regression coefficients over an expanding window requiring at least 12 months of data. In a next step, we multiply these mean regression coefficients with the individual measures (dummies) of information-driven trades from month t to estimate the expected return for month $t+1$ for all stocks in our sample, ensuring that the inputs of our forecast are observable in real-time. In order not to undermine the composition idea, we only estimate the expected

[6] The weighting scheme is motivated by a similar approach to factor portfolio construction used in Frazzini and Pedersen (2014), where higher-beta securities have larger weights in the high-beta portfolio.

[7] A data-driven approach implies that even a signal that we use to construct information-driven buy signals could possibly, contrary to economic reasoning, generate an information-driven sell signal.

returns for companies in months with at least two individual information-driven signals. This ensures that no single signal maintains the power to individually mark a firm-month as information-driven. In a final step, we consider that the stocks in the top (only for expected returns > 0) and bottom (only for expected returns < 0) terciles of these expected returns generate information-driven buy and sell signals, respectively, which we use to construct our ER strategy.

In Table 5, we report performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of the described alternative composition approaches. Panel A reveals that the more restrictive versions (CID^3 and CID^4) of our original composite measure of information-driven trades uniformly, i.e., regardless of the country aggregation scheme, show significant positive abnormal long-short returns for equal-weighted portfolios. However, most value-weighted CID^3 and CID^4 portfolios show positive but insignificant long-short CH4 alpha estimates, which is consistent with our baseline measure CID^2 in Panel A of Table 4. Judging the effectiveness of CID^3 and CID^4 to improve the unconditional predictability by looking at the difference between the unconditional (UNC) and information-driven (CID^3 and CID^4) alphas shows significant differences comparable to our baseline measure CID^2 in Panel A of Table 4.

[Please insert Table 5 near here]

Subfigure 2 (a) illustrates the difference between the unconditional (UNC) and all versions of our information-driven CID (CID^2, CID^3 and CID^4) alphas for the pooled DM and EM samples. Subfigure 2 (a) shows that a more restrictive CID monotonically increases the benefits of our CID strategy relative to the UNC strategy for the equal-weighted pooled DM sample. However, the equal-weighted pooled EM sample shows increased benefits from CID^2 to CID^3, but a reversal back to comparable CID^2 alphas for the CID^4 strategy. The value-weighted pooled EM and DM samples show similar increased benefits from CID^2 to CID^3, but also reversals back to comparable CID^2 alphas for the CID^4 strategies.

[Please insert Figure 2 near here]

The value- and equal-weighted DM and EM country-neutral portfolios show that for more restrictive CID strategies the benefits of our CID strategies relative to UNC strategies increase more or less monotonically. We conjecture that the different pooled vs. country-neutral results indicate that increasing the CID restrictions works better on a country-level basis and has a somewhat limited ability to increase the benefits in our value-weighted pooled, U.S. (DM) and China/India (DM) dominated, portfolios. Overall, the results indicate that our baseline results are robust to the choice of the surplus requirement of our composite measure (N in Eq. (1)).

Panel B reports a signal-weighted (SW) and an expected return (ER) based approach, respectively. Looking at the pooled EM and DM SW and ER strategies in Subfigure 2 (a) and Panel B of Table 5 reveals that different weighting schemes, which differ from our baseline economic logic-based approach, also generate significant benefits that are comparable to our baseline CID^2 approach. However, the country-neutral EM and DM SW and ER strategies show a much weaker picture with only one positive significant alpha difference. This suggests that our signal-weighted and expected return approaches do not work equally efficient in creating benefits relative to the UNC strategies across all countries, but do produce benefits in those countries that dominate value- and equal-weighted pooled EM and DM portfolios. We conjecture that both weighting schemes are less reliable when applied on individual country-level data sets as those smaller data sets suffer more from potentially noisy or outlier-dominated weight calculations required in both approaches.

Overall, our alternative composition approaches show robust results similar to our baseline composition measure in all value- and equal-weighted pooled EM and DM portfolios, but do not show robust results for the SW and ER value- and equal-weighted country-neutral EM and DM portfolios. This indicates that the benefits of composition, especially at the country-level, are primarily prevalent when using approaches which are based on simple economic logic/intuition as well as less extreme signal weights.

5.2 Long vs. short term information

Our results so far concentrate on one-month ahead performance. However, an information advantage could also be of a longer-term nature. To test this possibility, we examine the profitability of CID insider trades based on longer holding periods ranging from 2 to 12 months. In other words, if a stock has at least two excess buy or sell signals in a month, it is assigned to the long or short portfolio accordingly and remains there for 2, 3, 6, or 12 months. We implement an analogous portfolio approach for UNC trades to assess whether the time pattern of possible informational advantages differs from that of CID insider trades by assessing the alpha spreads (CID-UNC) at longer time horizons.

In Table 6, we report value- and equal-weighted CH4 alphas separately for pooled and country-neutral developed (DM) and emerging market (EM) CID (Panel A) portfolios and CID-UNC alpha spreads (Panel B) for different holding periods. We report the UNC results for different holding periods in Table A.8 of the Appendix.

[Please insert Table 6 near here]

The main finding is that for both CID portfolios and CID-UNC alpha spreads, irrespective of the region or country aggregation scheme, abnormal equal-weighted alphas decrease with longer time horizons by half or more, but remain significant. For example, the equal-weighted alphas of CID trades in the pooled DM and EM portfolios fall from highly significant 1.00% and 1.40%, respectively, in the one-month holding period, to still highly significant 0.38% and 0.49%, respectively, in the 12-month holding period. Value-weighted CID alphas are mostly insignificant even in the short run, but nevertheless also decrease with longer time horizons. Value-weighted CID-UNC alpha spreads are often significant, but also decrease with longer time horizons, the exception being the country-neutral DM alpha spreads.

Collectively, the economic difference between CID-UNC alpha spreads tends to become smaller over time, which suggests that CID insider trades capture partly a short-term information advantage, especially among small firms. Subfigure 2 (b) graphically illustrates this negative relation between time horizon and performance differences between CID and UNC trades for the pooled DM and EM portfolios. The results of the country-neutral portfolios are qualitatively comparable with the exception of the country-neutral DM alpha spreads. Nevertheless, the equal-weighted CID-UNC alpha spreads remain statistically significant at long time horizons, indicating that the CID measure also outperforms the equal-weighted UNC strategies at longer time horizons. In summary, we can confirm the hypothesis that CID trades contain an important short-term information component.

5.3 Developed vs. emerging markets

The information environment in emerging markets (EM) is likely to be different from that in developed markets (DM) (see, also Section 5.4). For example, Brochet (2019) shows that institutions in EM demand less transparency regarding insider trades, which, in turn, increases the predictability of returns. Bhattacharya (2000) find that stock prices in Mexico hardly react to usually value-relevant corporate news in the period between 1994 and 1997. Griffin et al. (2011) show that stock prices in DM move more strongly on public news, especially on earnings announcements. These results suggest that insiders in EM, in particular, may have private information advantages.[8] In this respect, the question arises whether the outperformance of CID trades compared to UNC trades is also driven by this mechanism. However, Table 7, which computes differences in abnormal returns between pooled and country-neutral EM and DM portfolios for the UNC and CID strategies as well as for the CID-UNC alpha

[8] Nevertheless, most of the literature does not focus on the strong form of market efficiency, i.e., on the incorporation of private information into prices, but on the weak or semi-strong form by studying seemingly abnormal international return predictability based on observable firm characteristics. Table A.9 of the Appendix shows that the literature finds on average that cross-sectional factor-based return predictability in DM is at least as high as in EM.

spreads, shows that this is unlikely to be the case.

[Please insert Table 7 near here]

Panel A reveals that insiders in emerging markets achieve higher alphas, often significantly, than in developed markets for both unconditional insider trades (UNC) and the composite measure (CID). However, the CID-UNC alpha spreads are only significantly positive for the country-neutral value-weighted strategy, which is due to the weak performance of the country-neutral CID DM strategy in our baseline analysis. All other CID-UNC alpha spreads, especially those of the overall good performing equal-weighted strategies, show small and insignificant differences between EM and DM, suggesting that differences in the information environment between EM and DM are not the main performance driver of the increased predictability of our CID strategies relative to the unconditional UNC strategies.

For example, in the pooled analysis with value-weighted returns, the alpha of UNC trades is 0.51% higher in EM than in DM, which is driven mainly by the long leg (see, Panels B and C). The respective estimate for CID trades is 0.55%, which is driven by both the long and short legs (see, Panels B and C), leading to an insignificant CID-UNC alphas spread of 0.03%. In the county-neutral equal-weighted strategy, the alpha difference is 0.16% for UNC trades and 0.11% for CID trades, again leading to an insignificant CID-UNC alphas spread of -0.05%.

Overall, higher informational advantages in EM do seem to exist on average, but they manifest themselves already in the performance of insider trading in general, not additionally through the composite measure. In summary, the analysis provides limited to no evidence for the conjecture that stronger private information advantages, or other possible differences in the information environment between EM and DM, lead to stronger return predictability for information-driven CID trades.

5.4 Cross-country analysis

5.4.1 Hypothesis development and country characteristics

Given the mixed performance at the country level of our unconditional (UNC) and composite (CID) information-driven insider trading strategies in Tables 2 and 3, we try to exploit the heterogeneity of performance in different countries to explore whether various country characteristics, i.e., proxies for insider trading regulation and corporate governance, may explain the variation in performance. The literature (e.g., Durnev and Nain 2007, Fidrmuc et al. 2013) offers a variety of explanation channels leading to multiple possible hypotheses about the link between insider trading regulations (corporate governance) and abnormal returns following transactions by corporate insiders.

The first hypothesis (*monitoring hypothesis*) predicts a negative relationship between insider trading regulation (corporate governance) and abnormal returns. If insider regulations or corporate governance limit opportunistic insider trading on nonpublic information, we expect larger positive abnormal returns after purchases and more negative abnormal returns after sales in countries with weaker insider regulations (corporate governance). We develop this more general hypothesis on a rationale similar to Fidrmuc et al. (2013) with respect to investor protection. The U.S. country-level results of Ravina and Sapienza (2010) and Dai et al. (2016) support this hypothesis by showing that executives and independent directors generate higher returns in firms with the weakest governance and that corporate governance significantly reduces the profitability of insider sales. A second hypothesis which also argues from a rent extraction perspective (*substitution hypothesis*) predicts a positive relationship only between corporate governance and abnormal returns. If strong corporate governance limits the direct extraction of private benefits from insiders and, consequently, insiders engage more in opportunistic insider trading as an alternative source of wealth extraction, we expect larger positive abnormal returns after purchases and more negative abnormal returns after sales in countries with stronger corporate governance.[9] The results of Cziraki et al. (2013) support this hypothesis by showing that for Dutch firms with better investor protection standards, abnormal returns following insider transactions are higher.

Another possible hypothesis (*information-content hypothesis*) predicts a positive relationship between insider trading regulation (corporate governance) and abnormal returns following purchases, while predicting a negative relationship following sales. If insider regulations or corporate governance limit opportunistic insider trading on nonpublic information, outside investors could view insider purchases, i.e., committing own funds and bearing diversification losses, as an especially strong sign regarding the future of a firm. Therefore, we expect higher positive abnormal returns after purchases in countries with stronger insider regulations (corporate governance). The information-content hypothesis suggests a somewhat different reasoning for sale transactions. As insiders could sell for various reasons including liquidity and diversification, the negative signaling effect of insider sales to outside investors could potentially be mitigated. If insider regulations or corporate governance limit opportunistic insider trading on nonpublic information in countries with stronger regulations (governance), the hypothesis assumes that the mitigating effect will be stronger, leading to

[9] Noticeably, this prediction can only be valid if corporate governance measures limit the extraction of direct private benefits from insiders through better investor protection while the substitution channel remains open, i.e., the governance measures do not impose restrictions on insider trading that prevent a profitable substitution.

sale transactions being perceived as a trustworthy liquidity- or diversification-driven trade signal. Therefore, we expect less (more) negative abnormal returns after sales in countries with stronger (weaker) insider regulations. Once again, we develop this more general hypothesis on a rationale similar to Fidrmuc et al. (2013) with respect to investor protection. The cross-country results of Fidrmuc et al. (2013) support this hypothesis by documenting a positive (negative) relationship between investor protection and the informativeness of insider purchases (sales) using an European/U.S. country sample. Gebka et al. (2017) document that the profitability of insider purchases is higher in countries with better investor protection also for a sample of European countries.[10]

We contribute to the literature by testing whether country characteristics that proxy for insider trading restrictions and corporate governance, i.e., investor protection (AS), litigation risk (CLASSA), timing restrictions on trades (BLACKOUT), and the general prevalence of insider trading (ITR), are related to the performance of our insider trading strategies in a broader set of 34 developed and emerging market countries. Therefore, we hope to gain new insights into which of the proposed channels might explain the differences in the profitability of insider trading strategies.

In the following, we explain the reasoning behind the selection of each variable in the cross-country analysis. We provide a detailed description of the variables and summary statistics for the cross-country variables in Tables A.10 and A.12 of the Appendix. To proxy for insider trading restrictions and corporate governance, we use the anti self-dealing (AS) index from Djankov et al. (2008). AS is a survey-based measure of the legal protection of minority shareholders against expropriation. The index ranges from 0 (weak control of self-dealing transactions) to 1 (strong control). We conjecture that the more laws that are in place to protect minority shareholders, the more difficult it will generally be for corporate insiders to profitably exploit private information advantages. The second proxy is the class action dummy (CLASSA) of Leuz (2010). CLASSA is equal to one if class action lawsuits are possible against illegal corporate insider trading and zero otherwise. We conjecture that the litigation risk corporate insiders must face will restrain corporate insiders more from opportunistic insider trading (e.g., Cheng et al. 2016) in countries where class action lawsuits are possible. This variable is likely to express its effect mainly through the short side, as investors are more likely to be severely disturbed by the avoided losses of insiders in the event of their own losses. The third proxy is a variable proposed by Brochet (2019) that measures timing restrictions on insider trades by determining whether insiders trade during blackout

[10] Noticeably, the *information-content hypothesis* does not imply that insiders no longer seek to extract rents, but suggests that signals to outside investors by insider purchases are particularly credible when insider regulations (corporate governance) are high.

periods, i.e., shortly before a quarterly earnings announcement (QEA). We calculate blackout periods (BLACKOUT) following Brochet (2019) as the difference between the percentage of insider trades that occur within one month after a QEA and the month before, aggregated by country quarter. The blackout period measure ranges from -1 (only trades before the QEA in a given quarter = low insider trading restrictions) to 1 (only trades after the QEA in a given quarter = high insider trading restrictions). We conjecture that if insiders must wait until after the QEA to trade because they are not allowed or restricted to trade shortly before the announcement, it becomes less likely that the information advantage still remains after the QEA. The fourth proxy is the insider trading restriction index (ITR) of Denis and Xu (2013). ITR measures the "perceived" degree of insider trading restrictions through a global survey of corporate officers. We conjecture that insider trading is more restricted in countries in which top executives, i.e., corporate officers, themselves view insider trading not to be common in the respective domestic market. Therefore, higher ITR values indicate a more restrictive insider trading environment, as insider trading is not common in this case. Our conjectures for all four variables (AS, CLASSA, BLACKOUT, ITR) are in line with the *monitoring hypothesis* and with respect to the short legs also in line with the *information-content hypothesis*. Finally, we use a developed market dummy (DEV) to account for the general performance differences shown in Section 5.3. DEV is equal to one for developed markets and zero (emerging markets) otherwise. Cross-country studies that use a developed market dummy (see, e.g., Titman et al. 2013, Watanabe et al. 2013) implicitly consider developed stock markets to be more informationally efficient.

The cross-country analysis aims to identify cross-country differences that are able to explain the varying abnormal performance of the unconditional (UNC) and composite (CID) information-driven insider trading strategies between countries. Therefore, the variable of interest is the country-level long-short CH4 alpha obtained from the factor regressions in Tables 2 and 3, which has a cross-sectional data structure with only a country dimension. Consequently, using the long-short CH4 alpha as a dependent variable only allows for investigating the cross-country relationship between the time-averaged abnormal performance measure of our insider trading strategies and the time-averaged values of the country characteristics. Hence, the cross-sectional regressions that are applied in the following are designed to measure the between-country effect. Although some country characteristics are time-varying (i.e., DEV and BLACKOUT), the usage of a time-invariant dependent variable does not allow us to investigate the within-country relation between the time variation of the alphas and the time variation of the country characteristics. Therefore, when the country characteristics are time-varying, the independent variables are the time-series averages of the country characteristics over the respective time horizon of the abnormal performance measurement.

5.4.2 Analysis based on insider trading restrictions

In Table 8, we report the empirical results of the cross-country relationship between the time-averaged performance measure (CH4 alpha) of our unconditional (UNC) and composite (CID) information-driven long-short insider trading strategies and the time-averaged proxies for insider trading restrictions. In Table A.11 of the Appendix, we provide the same analysis separately for the long and short portfolios.

Assuming that the *monitoring hypothesis* is correct, one would expect to see signs for the insider trading restriction proxies that indicate a higher abnormal performance for both insider trading strategies in countries with lower insider trading restrictions. In particular, consistent with the hypothesis, one would expect AS, CLASSA, BLACKOUT, and ITR to take negative values, as an increase in all of them indicates higher insider trading restrictions. Panels A and B of Table 8 report the results of the cross-sectional regressions for the value- and equal-weighted long-short implementations of the unconditional (UNC) and composite (CID) information-driven insider trading strategies, respectively.

[Please insert Table 8 near here]

The univariate regressions of Panel A show consistent results in line with the *monitoring hypothesis*, i.e., consistently negative although rarely significant coefficients.[11] We only find a significant relationship between the equal-weighted UNC strategy and the anti self-dealing index (AS) and the occurrence of blackout periods (BLACKOUT), respectively. This suggests that the abnormal performance of the equal-weighted UNC strategy is greater in countries with lower insider trading restrictions. Consistent with our results in Section 5.3, DEV is negative but insignificant, suggesting a potentially higher performance of the UNC strategy in emerging markets. Judging the explanatory power of insider trading restrictions based on the multiple regression framework, where all proxies are jointly included as explanatory variables, reveals no significant relation between the value- and equal-weighted UNC strategies and the proxies for insider trading restrictions. Nevertheless, at least the signs, with the exception of the ITR variables, remain negative across all proxies and specifications.

Assuming that the documented relative outperformance of the CID strategy originates from insiders using nonpublic information, we conjecture that the explanatory power of

[11] Looking at the long and short legs in Table A.11 of the Appendix also reveals coefficient estimates, although rarely significant, that are in line with the *monitoring hypothesis* and at least for the short legs in line with the *information-content hypothesis*, i.e., mostly negative estimates in the long legs and positive estimates in the short legs.

insider trading restriction proxies is stronger for these trading strategies. Overall, the univariate and mutltivariate regressions of Panel B show, contradicting our conjecture, fewer (no) significant coefficients and almost uniformly a lower explanatory power, indicated by the lower R^2 in comparison to Panel A, of the insider regulation proxies for all implementations of the CID strategies. We interpret these weaker results for the CID strategies to imply that an increased exploitation of nonpublic information is unlikely to explain the relative outperformance. A possible explanation for the relative outperformance of CID strategies is the possibility that informative insiders achieve their outperformance through a superior interpretation of public information compared to outside investors.

Overall, the results suggest that insider trading restrictions (the *monitoring hypothesis*) only have a limited ability to explain the varying abnormal performance of the unconditional (UNC) and composite information-driven (CID) insider trading strategies between countries and that the relative outperformance of the information-driven insider trading strategy is likely not driven by regulatory differences of insider trading restrictions across countries.

6 Conclusion

How to identify information-driven trades by insiders is a long-standing question in the literature. Previous work typically addresses this research question by proposing individual presumably information-driven signals for the U.S. market. We suggest a different approach by synthesizing a substantial subset of previously proposed signals into an overall cross-sectional measure and show that it performs well in a global sample. Further tests find no direct evidence of exploitation of private information, although we caution that private information (exploitation) cannot be measured directly. Instead, they are consistent with the notion that insiders may interpret short-term public information particularly well. Our work suggests different directions for future research. First, the precise information that insiders use to make their buying and selling decisions remains largely unknown. Second, we focus on simple, intuitive heuristics for synthesizing trade signals. How more complex methods, such as machine learning approaches, perform could be the subject of future research. Finally, the reasoning could be applied to the performance prediction of other presumably informed market participants, such as mutual funds, hedge funds, or analysts.

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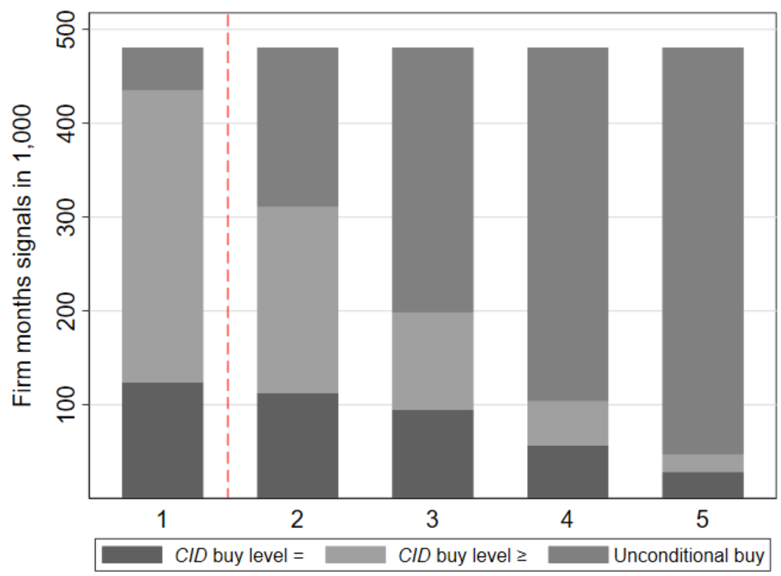
Figure 1: Composite firm months signals

This figures shows the total amount of firm months signals over the sample period from 2000 to 2021 for the pooled country sample. We show unconditional trade firm months signals, i.e., all months in which at least one insider traded. Furthermore, we report composite firm months signals greater and equal to 1, 2, 4, 5, respectively. A composite firm months signal greater (equal) to 2 shows the number of firm months with a surplus, i.e., absolute value of individual information-driven purchases - information-driven sale firm months signals, of greater (exactly) 2. Subfigures (a) and (b) show purchases and sales, respectively. We only consider firm months signals with a minimum absolute surplus of 2 as information-driven (the area to the right of the dashed red line).

(a) Purchases



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(b) Sales

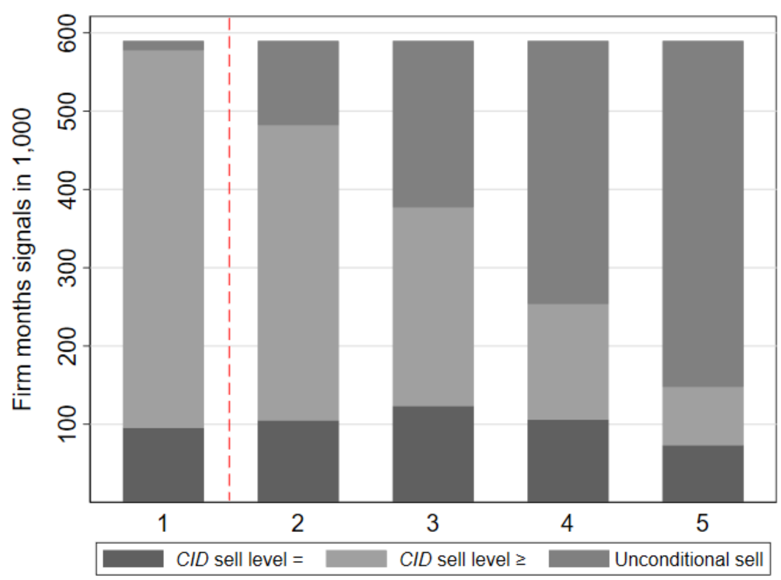

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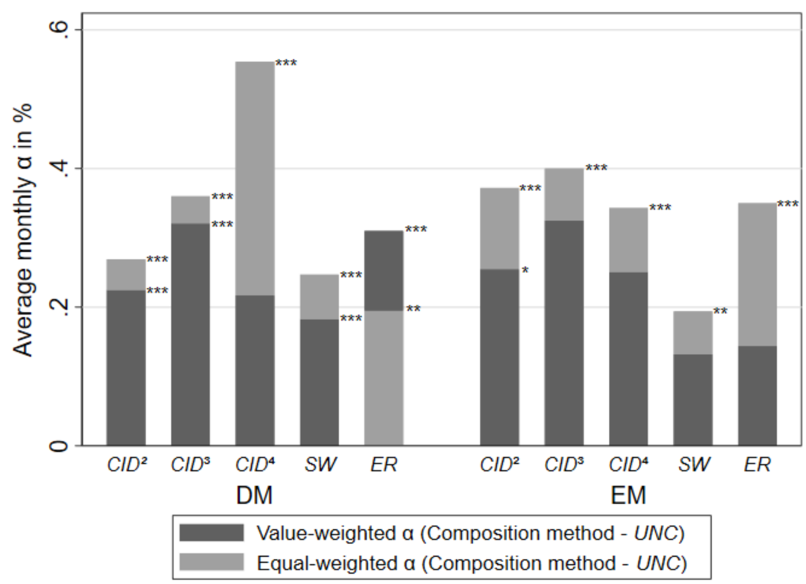
Figure 2: Composition benefits

This figure illustrates the benefits of our composite measures by displaying the monthly equal- and value-weighted alpha spreads between all composition approaches (CID^2, CID^3, CID^4, SW, ER) and the unconditional strategy (UNC) for pooled developed (DM) and emerging market (EM) samples in Subfigure (a). Subfigure (b) shows the potential benefits of a change in holding periods for our baseline composite measure by displaying the monthly equal- and value-weighted alpha spreads between various holding periods (1, 2, 3, 6, and 12-months) of CID^2 and holding period-matched unconditional (UNC) strategies for pooled developed (DM) and emerging market (EM) samples. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

(a) Composition approaches



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(b) Holding periods

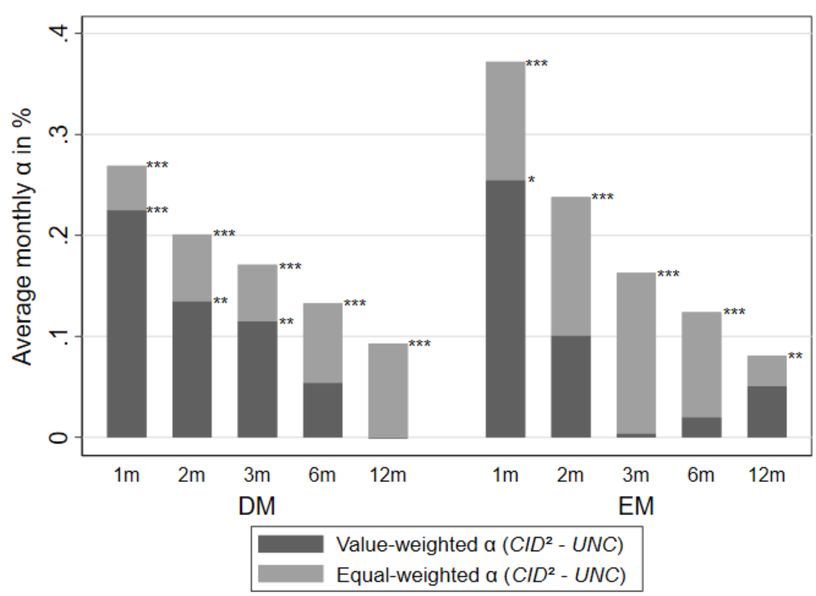

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Table 1: Summary statistics

This table reports summary statistics for insider trades by country/region after applying the screens outlined in Section 2.1. We report the respective start date, the total number of insider trades (purchases/sales) in thousands of shares and the number of unique firms and insiders. Furthermore, we report mean and median values for insiders per firm, trades per firm and trades per insider/firm. We also report mean and median trade-weighted market capitalization of all traded firms over all trades in millions of U.S. dollars and the mean and median trade size in thousands of U.S. dollars, respectively. Finally, we report the median reporting lag in days.

Country/ Region	**Start**	**Insider trades ('000)**			**Firms**	**Insiders**	**Insiders per firm**		**Trades per firm**		**Trades per insider/firm**		**Mktcap (US$, '000000)**		**Value (US$, '000)**		**Rep. Lag**
		Total	**Buy**	**Sell**			**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Median**
Australia	2003	66.1	53.8	12.4	2,293	9,638	6.2	5	28.85	19	4.7	2	1,043.0	42.5	557.0	18.5	4
Belgium	2006	9.9	5.0	4.9	145	1,316	9.8	7	68.26	42	7.0	2	7,993.3	1,047.4	1,038.2	83.2	5
Canada	2003	551.7	289.4	262.3	4,406	39,880	13.5	10	125.22	75	9.3	3	2,070.0	49.1	779.0	12.3	3
Denmark	2007	9.9	4.7	5.1	230	2,121	10.3	8	42.85	18	4.1	2	5,091.4	1,132.0	881.0	76.4	1
Finland	2006	13.3	8.3	5.1	203	2,279	13.2	12	65.69	44	5.0	2	2,017.2	267.4	334.9	19.6	2
France	2005	58.4	31.4	27.0	833	4,940	6.9	4	70.06	35	10.2	2	5,085.4	307.4	1,224.7	33.3	8
Germany	2002	26.6	18.1	8.4	847	4,609	6.0	4	31.35	15	5.3	2	5,417.9	220.3	827.8	42.2	3
Hong-Kong	2003	160.9	103.7	57.2	2,088	13,598	10.0	7	77.06	41	7.7	2	1,941.3	214.1	4,069.1	156.5	3
Israel	2003	30.1	16.5	13.6	432	1,846	6.7	5	69.68	14	10.4	2	912.3	449.3	384.5	20.7	1
Italy	2003	61.4	40.2	21.3	489	4,060	9.2	5	125.64	65	13.6	3	3,115.5	390.6	674.1	38.2	6
Netherlands	2000	8.4	3.3	5.1	160	1,813	11.8	7	52.19	28	4.4	2	8,670.0	1,496.0	4,405.8	117.3	8
Norway	2005	17.0	11.5	5.6	485	5,524	14.2	10	35.15	20	2.5	1	1,558.4	272.5	1,596.2	53.3	0
Singapore	2000	35.1	26.9	8.2	762	3,939	6.4	4	46.07	20	7.3	2	1,202.4	199.4	3,616.4	69.9	1
Spain	2006	23.1	16.2	6.9	183	2,142	13.4	11	126.26	65	9.5	2	6,965.7	1,269.8	1,792.6	70.7	6
Sweden	2004	61.3	41.6	19.6	1,043	11,888	14.6	9	58.74	29	4.0	2	2,459.5	192.6	849.0	20.0	2
Switzerland	2005	21.2	9.0	12.1	293	784	2.7	2	72.20	49	26.7	10	9,019.1	916.8	1,048.5	117.8	1
U.K.	2003	76.1	37.5	38.6	2,274	17,632	9.8	6	33.48	14	3.4	2	8,758.8	939.6	816.9	71.1	1
U.S.	2003	1,466.0	256.1	1,209.9	7,889	119,198	19.5	17	185.82	117	9.5	4	8,973.4	1,202.2	1,744.6	106.5	2
Brazil	2005	37.6	15.1	22.5	298	1,094	3.8	3	126.27	53	33.6	7	6,944.3	1,590.0	2,244.9	50.4	27
Chile	2011	8.1	5.8	2.3	129	1,209	10.3	5	62.53	32	6.1	2	2,999.6	919.5	1,488.1	51.7	2
China	2006	128.1	48.4	79.7	3,441	25,055	7.7	6	37.22	20	4.8	2	4,964.1	1,135.6	3,506.8	152.2	6
Egypt	2012	13.4	8.2	5.2	197	1,106	6.1	5	68.05	50	11.2	3	175.2	49.3	592.3	20.9	1
Greece	2005	40.1	30.1	10.0	292	2,426	8.9	5	137.38	64	15.5	3	1,084.0	133.0	578.1	14.7	3
India	2006	214.4	67.0	147.4	2,678	31,385	13.1	4	80.07	16	6.1	2	13,049.5	1,330.7	783.4	23.1	4
Indonesia	2009	24.6	13.9	10.6	619	2,464	4.7	3	39.69	13	8.4	2	1,448.0	259.2	3,191.6	35.6	9
Malaysia	2005	145.6	90.7	54.9	1,081	7,671	8.8	7	134.72	64	15.3	4	707.5	134.1	861.3	32.8	3
Pakistan	2013	9.0	5.0	4.0	327	1,741	6.0	3	27.65	11	4.6	2	418.7	179.5	77.4	5.0	2
Philippines	2006	30.6	17.5	13.1	242	2,140	10.6	7	126.62	46	11.9	3	1,894.4	449.7	742.5	13.8	6
Poland	2007	24.1	15.7	8.4	786	3,111	4.6	3	30.72	16	6.7	2	463.0	27.6	515.3	5.8	4
South Africa	2003	23.1	8.0	15.1	351	3,599	11.6	8	65.69	35	5.7	3	2,610.5	685.8	339.4	53.7	2
South Korea	2000	224.4	140.5	83.8	2,902	24,291	9.3	6	77.32	37	8.3	2	1,884.2	107.0	590.0	33.3	6
Sri Lanka	2010	7.8	5.9	2.0	231	692	4.3	3	33.97	17	7.9	2	71.3	23.2	118.6	3.0	4
Thailand	2000	75.8	44.5	31.3	789	6,082	8.7	7	96.05	47	11.0	4	840.0	112.2	181.5	12.5	2
Turkey	2009	22.1	13.9	8.2	409	1,900	5.7	4	54.08	25	9.5	3	499.4	92.4	501.3	60.1	1
DM	2003	2,696.4	972.9	1,723.5	25,055	241,082	13.1	9	107.62	47	8.2	3	6,226.1	563.4	1,564.1	60.3	2
DM ex. U.S.	2003	1,230.5	716.9	513.6	17,166	125,316	10.1	7	71.68	31	7.1	2	2,976.5	145.5	1,349.1	28.0	3
EM	2003	1,029.0	530.3	498.7	14,772	115,699	8.8	5	69.66	26	7.9	2	4,425.2	282.5	1,118.1	29.6	3

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Table 2: Unconditional performance

This table reports summary performance statistics for an unconditional (UNC) monthly rebalanced insider trading strategy by country. We buy (sell) a stock if any company insider has bought (sold) the company stock in the previous month. We report monthly value- and equal-weighted raw returns and CH4 factor alphas for the long-short, long, and short portfolios, respectively. Furthermore, we report the number of available months (N) with a valid portfolio and the monthly average amount of firms (F) in each respective portfolio. Finally, we report the total positive and negative significant performances. Statistical significance at the five-percent level is needed to be counted as a significant performance. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Country	**Long-Short**						**Long**						**Short**					
	Raw returns		**CH4 α**				**Raw returns**		**CH4 α**				**Raw returns**		**CH4 α**			
	vw	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**
Australia	0.165	0.973***	0.405	0.955***	227	152	1.056**	2.199***	0.311*	1.126***	227	121	0.891*	1.226**	-0.094	0.171	227	31
	(0.55)	(3.11)	(1.38)	(3.27)			(2.29)	(3.53)	(1.75)	(5.45)			(1.80)	(2.00)	(-0.44)	(0.59)		
Belgium	-0.657	0.850***	-0.302	0.945***	172	19	0.325	0.802	0.241	0.594*	179	9	0.958*	-0.006	0.322	-0.459**	180	10
	(-1.21)	(2.73)	(-0.57)	(3.68)			(0.43)	(1.48)	(0.50)	(1.86)			(1.81)	(-0.01)	(1.08)	(-2.24)		
Brazil	0.476	1.134***	0.261	1.023***	203	49	1.510**	2.352***	0.419	1.339***	203	21	1.034	1.218*	0.157	0.316	203	28
	(1.43)	(4.06)	(0.85)	(3.87)			(2.06)	(3.07)	(1.50)	(5.44)			(1.49)	(1.69)	(0.76)	(1.60)		
Canada	0.214	1.350***	0.250*	1.413***	227	722	0.992**	2.604***	0.092	1.754***	227	412	0.778**	1.254**	-0.158***	0.340**	227	310
	(1.45)	(8.49)	(1.73)	(7.78)			(2.34)	(4.33)	(0.65)	(8.84)			(2.05)	(2.23)	(-2.71)	(2.16)		
Chile	0.046	0.680*	0.081	1.018**	106	20	-0.255	0.210	-0.108	0.668**	121	12	-0.104	-0.237	0.032	-0.154	106	7
	(0.11)	(1.69)	(0.16)	(2.29)			(-0.39)	(0.31)	(-0.44)	(2.29)			(-0.14)	(-0.28)	(0.07)	(-0.41)		
China	-0.296	0.492**	-0.211	0.567***	191	224	1.224**	2.129***	0.304**	0.625***	191	88	1.520**	1.638**	0.516**	0.058	191	136
	(-1.05)	(2.43)	(-0.84)	(3.30)			(1.98)	(3.12)	(2.24)	(3.70)			(2.31)	(2.35)	(2.19)	(0.31)		
Denmark	-0.581	0.032	-0.182	0.382	155	23	0.361	0.468	-0.262	0.174	172	14	1.183**	0.514	0.276	-0.098	160	8
	(-1.30)	(0.10)	(-0.41)	(1.01)			(0.64)	(0.96)	(-0.69)	(0.71)			(2.57)	(1.11)	(0.86)	(-0.29)		
Egypt	0.365	0.507	0.372	0.869*	117	31	0.652	1.179	0.373	0.687**	117	17	0.288	0.671	0.001	-0.182	117	14
	(0.60)	(1.08)	(0.73)	(1.94)			(0.82)	(1.54)	(1.09)	(2.57)			(0.32)	(0.73)	(0.00)	(-0.47)		
Finland	-0.016	0.238	0.215	0.366	176	28	0.793	1.141**	0.244	0.523***	185	17	0.700	0.842*	-0.065	0.133	176	11
	(-0.04)	(0.82)	(0.44)	(1.19)			(1.41)	(2.35)	(0.80)	(2.88)			(1.21)	(1.65)	(-0.19)	(0.49)		
France	0.646***	1.102***	0.763***	1.104***	203	85	1.171***	1.284***	0.537***	0.637***	203	43	0.525	0.182	-0.226	-0.467***	203	42
	(2.85)	(6.10)	(3.06)	(5.87)			(2.62)	(2.96)	(2.64)	(4.06)			(1.30)	(0.43)	(-1.54)	(-3.70)		
Germany	0.886**	1.306***	0.953*	1.190***	232	49	1.393***	1.898***	0.550**	0.936***	233	33	0.520	0.604	-0.401	-0.245	232	16
	(2.26)	(4.31)	(1.77)	(3.47)			(2.83)	(4.30)	(2.29)	(4.84)			(1.00)	(1.26)	(-0.86)	(-0.77)		
Greece	0.632	1.502***	0.118	1.329***	178	42	0.559	1.353**	0.557	1.513***	183	26	-0.567	-0.509	0.517	0.133	179	15
	(1.12)	(3.33)	(0.19)	(2.64)			(0.59)	(2.03)	(1.38)	(4.17)			(-0.56)	(-0.67)	(0.94)	(0.33)		
Hong Kong	-0.335	0.599***	-0.291	0.555***	224	237	1.003**	1.241**	0.187	0.588***	225	136	1.326***	0.669	0.463**	0.044	224	100
	(-1.54)	(3.61)	(-1.46)	(2.79)			(2.29)	(2.51)	(1.08)	(5.06)			(2.94)	(1.25)	(2.05)	(0.21)		
India	0.183	1.099***	0.093	1.088***	182	215	1.073	2.263***	0.111	1.328***	183	105	1.297**	1.519**	0.221	0.388**	187	106
	(0.70)	(6.31)	(0.46)	(5.81)			(1.46)	(2.87)	(0.50)	(6.88)			(2.05)	(2.05)	(1.30)	(2.18)		
Indonesia	0.749	0.688	0.667	0.964	138	62	1.675**	2.320***	0.522	1.094***	145	33	0.987*	1.625**	-0.060	0.167	142	27
	(1.42)	(1.49)	(1.04)	(1.63)			(2.34)	(3.47)	(1.36)	(2.95)			(1.82)	(2.39)	(-0.15)	(0.33)		
Israel	-0.138	0.080	-0.022	0.198	209	33	1.333***	1.853***	0.477	0.934***	211	18	1.454***	1.733***	0.487	0.728**	215	14
	(-0.56)	(0.34)	(-0.10)	(0.88)			(2.68)	(3.90)	(1.52)	(3.20)			(2.92)	(3.44)	(1.51)	(2.37)		

Table 2: (continued)

Country	Long-Short						Long						Short					
	Raw returns		CH4 α				Raw returns		CH4 α				Raw returns		CH4 α			
	vw	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**
Italy	0.097	1.212***	0.182	1.260***	226	57	0.567	1.142**	0.057	0.629***	227	34	0.488	-0.044	-0.129	-0.624***	226	22
	(0.38)	(5.62)	(0.61)	(5.08)			(1.18)	(2.54)	(0.30)	(3.88)			(1.04)	(-0.10)	(-0.62)	(-2.67)		
Malaysia	0.499**	0.533***	0.426*	0.607***	203	168	0.985**	1.527***	0.245	1.006***	203	97	0.485	0.995**	-0.181	0.399**	203	72
	(2.14)	(3.55)	(1.87)	(4.25)			(2.24)	(3.37)	(1.51)	(7.20)			(1.28)	(2.04)	(-1.44)	(2.27)		
Netherlands	0.161	1.172***	0.043	1.070***	185	14	1.276*	1.251**	0.769**	0.872***	199	6	0.992*	0.495	0.230	-0.248	243	7
	(0.31)	(3.07)	(0.09)	(2.82)			(1.88)	(2.14)	(2.16)	(2.97)			(1.90)	(1.09)	(0.60)	(-0.88)		
Norway	0.736**	0.502	0.665*	0.748*	201	43	0.978*	1.083*	0.179	0.458*	203	29	0.146	0.542	-0.512	-0.272	201	14
	(2.10)	(1.28)	(1.78)	(1.90)			(1.66)	(1.89)	(0.90)	(1.85)			(0.24)	(0.81)	(-1.64)	(-0.74)		
Pakistan	0.208	1.184**	0.227	1.004**	105	32	1.054	2.034**	0.442	0.976***	106	20	0.737	0.787	0.179	-0.051	105	13
	(0.57)	(2.57)	(0.61)	(2.59)			(1.51)	(2.62)	(1.36)	(3.72)			(0.99)	(0.91)	(0.60)	(-0.18)		
Philippines	0.371	0.690*	0.581	0.649	188	40	1.391***	2.177***	0.581**	1.041***	190	23	0.948*	1.414***	-0.042	0.323	188	17
	(1.14)	(1.93)	(1.59)	(1.61)			(3.02)	(4.25)	(2.56)	(4.53)			(1.93)	(2.75)	(-0.18)	(1.03)		
Poland	1.492***	0.986**	1.712***	0.981**	177	50	1.504**	1.966***	1.443***	1.969***	177	31	0.012	0.980	-0.270	0.987**	177	18
	(3.05)	(2.37)	(3.14)	(2.17)			(1.99)	(2.65)	(4.80)	(6.17)			(0.02)	(1.28)	(-0.70)	(2.20)		
Singapore	0.677**	0.693*	0.606	0.761**	259	49	0.952**	1.252***	0.297	0.850***	261	34	0.391	0.601	-0.095	0.179	259	14
	(2.27)	(1.93)	(1.58)	(2.52)			(2.21)	(2.71)	(0.82)	(3.20)			(0.79)	(1.00)	(-0.27)	(0.48)		
South Africa	0.436	0.740**	0.709**	0.969**	221	39	1.588***	1.765***	0.692**	0.911**	222	15	1.169**	1.019**	0.008	-0.034	226	23
	(1.27)	(2.35)	(2.07)	(2.41)			(2.81)	(3.10)	(2.46)	(2.40)			(2.21)	(2.06)	(0.04)	(-0.23)		
South Korea	0.937***	2.033***	0.733**	1.717***	262	214	1.512**	2.108***	0.709*	1.357***	263	122	0.335	-0.071	-0.364	-0.540**	262	91
	(2.70)	(8.47)	(2.37)	(6.85)			(2.47)	(3.89)	(1.96)	(4.70)			(0.60)	(-0.12)	(-1.30)	(-2.59)		
Spain	0.779***	0.935***	0.863***	0.899***	189	32	0.803	0.853	0.587***	0.731***	191	22	0.0003	-0.109	-0.266	-0.155	189	11
	(2.64)	(3.37)	(3.11)	(3.71)			(1.46)	(1.61)	(2.82)	(3.37)			(0.00)	(-0.21)	(-1.09)	(-0.57)		
Sri Lanka	0.705	1.362**	1.075**	1.280***	115	23	0.451	1.190*	-0.030	0.573*	141	16	-0.093	0.004	-0.894**	-0.527	115	6
	(1.31)	(2.50)	(2.16)	(2.96)			(0.77)	(1.81)	(-0.12)	(1.70)			(-0.13)	(0.01)	(-1.98)	(-1.24)		
Sweden	0.267	1.122***	0.300	1.150***	215	119	1.234***	1.775***	0.120	0.597***	215	80	0.968**	0.653	-0.180	-0.553***	215	39
	(1.19)	(6.61)	(1.28)	(6.11)			(2.62)	(3.67)	(0.88)	(3.86)			(2.00)	(1.45)	(-1.11)	(-4.16)		
Switzerland	0.560*	0.711***	0.639*	0.678***	195	44	1.390***	1.378***	0.671**	0.485***	195	18	0.801**	0.625*	0.033	-0.199	197	26
	(1.76)	(3.44)	(1.71)	(3.48)			(3.06)	(3.24)	(2.14)	(2.68)			(2.44)	(1.66)	(0.22)	(-1.44)		
Thailand	0.359	1.171***	0.228	1.089***	263	95	1.470***	2.398***	0.326*	1.116***	263	53	1.112**	1.227**	0.097	0.027	263	42
	(1.45)	(5.91)	(0.87)	(5.43)			(2.75)	(4.87)	(1.76)	(6.03)			(2.26)	(2.50)	(0.48)	(0.14)		
Turkey	1.268***	2.400***	1.385***	2.218***	151	42	0.693	1.992**	0.194	0.939***	153	23	-0.237	-0.134	-1.095***	-1.148***	153	19
	(2.62)	(5.26)	(3.22)	(5.51)			(0.94)	(2.54)	(0.58)	(2.80)			(-0.29)	(-0.16)	(-3.22)	(-2.85)		
U.K.	0.236	0.465***	0.280	0.525***	227	164	0.829**	1.162***	0.327**	0.539***	227	91	0.593*	0.697*	0.047	0.014	227	72
	(1.35)	(2.93)	(1.56)	(3.88)			(2.22)	(2.69)	(2.24)	(3.65)			(1.78)	(1.93)	(0.44)	(0.13)		
U.S.	0.075	0.805***	0.021	0.895***	227	1666	1.046***	1.928***	0.048	0.988***	227	386	0.971***	1.124***	0.028	0.094	227	1280
	(0.51)	(5.57)	(0.16)	(5.59)			(3.07)	(4.80)	(0.37)	(5.52)			(3.50)	(3.12)	(0.52)	(1.63)		
Total>0 [Sig.]	28 [9]	34 [25]	29 [7]	34 [27]			33 [20]	34 [27]	31 [10]	34 [30]			30 [11]	27 [11]	17 [2]	17 [5]		
Total<0 [Sig.]	6 [0]	0 [0]	5 [0]	0 [0]			1 [0]	0 [0]	3 [0]	0 [0]			4 [0]	7 [0]	17 [3]	17 [6]		

(Go back to text)

Table 3: Composite performance

This table reports summary performance statistics for the monthly rebalanced insider trading strategy based on the composite measure (CID) of information-driven trades by country. We buy (sell) a stock if a composite information-driven buy (sell) signal CID^2 according to Eq. (1) was generated in the previous month. We report monthly value- and equal-weighted raw returns and CH4 factor alphas for the long-short, long, and short portfolios, respectively. Furthermore, we report the number of available months (N) with a valid portfolio and the monthly average amount of firms (F) in each respective portfolio. Finally, we report the total positive and negative significant performances. Statistical significance at the five-percent level is needed to be counted as a significant performance. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Country	**Long-Short**						**Long**						**Short**					
	Raw returns		**CH4 α**				**Raw returns**		**CH4 α**				**Raw returns**		**CH4 α**			
	vw	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**	**vw**	**ew**	**vw**	**ew**	**N**	**F**
Australia	0.333	1.566***	0.512	1.349***	227	104	1.350***	2.458***	0.457**	1.368***	227	80	1.017**	0.892	-0.055	0.019	227	24
	(0.83)	(4.44)	(1.58)	(4.11)			(2.73)	(3.90)	(2.05)	(5.54)			(1.99)	(1.49)	(-0.25)	(0.06)		
Belgium	-0.560	1.128***	-0.196	1.258***	157	15	0.667	1.039*	0.751	0.991**	164	6	1.126**	0.039	0.565*	-0.380*	178	9
	(-0.92)	(2.85)	(-0.42)	(4.12)			(0.84)	(1.75)	(1.64)	(2.35)			(2.09)	(0.09)	(1.72)	(-1.70)		
Brazil	0.928**	1.421***	0.760*	1.410***	194	37	1.743**	2.391***	0.625*	1.408***	197	14	0.591	0.844	-0.209	-0.033	200	22
	(2.16)	(3.53)	(1.73)	(3.74)			(2.26)	(2.98)	(1.94)	(4.85)			(0.86)	(1.15)	(-0.73)	(-0.15)		
Canada	0.375*	1.904***	0.384**	1.954***	227	501	1.084**	2.952***	0.150	2.094***	227	258	0.710*	1.048*	-0.234***	0.140	227	243
	(1.68)	(9.07)	(2.05)	(8.24)			(2.27)	(4.79)	(0.86)	(9.09)			(1.87)	(1.88)	(-3.63)	(0.91)		
Chile	0.316	0.374	0.322	0.910	87	14	0.030	0.142	0.241	0.675*	116	8	-0.245	-0.106	-0.212	-0.262	90	6
	(0.59)	(0.66)	(0.50)	(1.41)			(0.05)	(0.22)	(0.79)	(1.87)			(-0.33)	(-0.12)	(-0.54)	(-0.60)		
China	-0.301	0.368	-0.191	0.535**	190	147	0.869	1.937***	-0.054	0.519**	191	53	1.206*	1.562**	0.186	-0.029	190	94
	(-0.81)	(1.27)	(-0.59)	(2.06)			(1.33)	(2.84)	(-0.24)	(2.27)			(1.92)	(2.19)	(1.02)	(-0.13)		
Denmark	-0.216	0.223	0.659	0.814*	134	19	0.514	0.600	0.212	0.367	154	11	1.273**	0.827	0.236	-0.017	146	7
	(-0.37)	(0.48)	(1.21)	(1.71)			(0.82)	(1.04)	(0.46)	(1.03)			(2.57)	(1.60)	(0.62)	(-0.04)		
Egypt	0.599	0.441	0.577	0.993	114	21	0.925	1.296*	0.818*	0.940**	115	11	0.301	0.904	0.200	0.002	115	10
	(0.78)	(0.64)	(0.80)	(1.46)			(1.17)	(1.70)	(1.80)	(2.21)			(0.34)	(0.92)	(0.42)	(0.00)		
Finland	0.045	0.362	0.278	0.527	161	22	1.048*	1.173**	0.526*	0.546**	174	13	1.106*	0.939*	0.314	0.101	167	8
	(0.09)	(0.99)	(0.52)	(1.23)			(1.88)	(2.30)	(1.74)	(2.38)			(1.75)	(1.70)	(0.74)	(0.32)		
France	0.361	1.292***	0.421	1.288***	203	64	1.069**	1.364***	0.421**	0.732***	203	30	0.707*	0.072	-0.0003	-0.555***	203	33
	(1.41)	(6.14)	(1.58)	(5.74)			(2.35)	(3.11)	(2.00)	(4.29)			(1.81)	(0.17)	(-0.00)	(-3.70)		
Germany	0.738*	1.457***	0.630	1.218***	228	38	1.478***	1.993***	0.664**	1.002***	233	25	0.848*	0.608	0.043	-0.217	228	13
	(1.77)	(3.99)	(1.37)	(3.46)			(3.01)	(4.58)	(2.23)	(4.74)			(1.79)	(1.19)	(0.12)	(-0.58)		
Greece	1.940***	2.383***	1.431*	2.152***	162	33	1.140	1.796**	1.278***	1.993***	178	21	-1.332	-0.920	-0.020	-0.086	165	12
	(2.86)	(4.61)	(1.67)	(3.91)			(1.29)	(2.58)	(2.88)	(5.63)			(-1.31)	(-1.19)	(-0.03)	(-0.21)		
Hong Kong	-0.340	0.834***	-0.335	0.769***	224	158	0.914**	1.340***	0.058	0.639***	224	86	1.255***	0.506	0.393	-0.130	224	73
	(-1.25)	(3.68)	(-1.20)	(3.28)			(1.98)	(2.73)	(0.35)	(4.41)			(2.78)	(0.92)	(1.59)	(-0.57)		
India	0.333	1.379***	0.183	1.302***	180	164	1.258	2.479***	0.237	1.452***	180	74	0.912	1.078	0.055	0.138	182	89
	(0.90)	(6.24)	(0.53)	(6.17)			(1.65)	(3.13)	(0.74)	(7.36)			(1.52)	(1.48)	(0.46)	(0.90)		
Indonesia	0.343	-0.077	0.176	-0.074	118	41	1.222*	1.101*	0.450	0.016	120	21	1.039*	1.376*	0.401	0.398	132	19
	(0.55)	(-0.11)	(0.24)	(-0.09)			(1.68)	(1.74)	(0.93)	(0.04)			(1.81)	(1.88)	(1.02)	(0.58)		
Israel	-0.079	0.123	0.084	0.222	169	23	1.393**	1.742***	0.661**	0.881**	179	12	1.563***	1.727***	0.665	0.844**	185	10
	(-0.21)	(0.33)	(0.27)	(0.61)			(2.34)	(3.06)	(2.16)	(2.55)			(2.95)	(3.03)	(1.54)	(2.03)		

Table 3: (continued)

Country	Long-Short						Long						Short					
	Raw returns		CH4 α				Raw returns		CH4 α				Raw returns		CH4 α			
	vw	ew	vw	ew	N	F	vw	ew	vw	ew	N	F	vw	ew	vw	ew	N	F
Italy	0.412	1.396***	0.345	1.397***	223	41	0.764	1.260***	0.147	0.752***	227	23	0.309	-0.188	-0.158	-0.625**	223	18
	(1.35)	(5.20)	(1.08)	(4.89)			(1.59)	(2.73)	(0.69)	(4.15)			(0.65)	(-0.39)	(-0.71)	(-2.46)		
Malaysia	0.872***	0.982***	0.744***	0.995***	203	110	1.174***	1.624***	0.482***	1.085***	203	60	0.302	0.641	-0.262*	0.090	203	50
	(3.43)	(5.11)	(2.95)	(5.11)			(2.73)	(3.60)	(3.09)	(6.01)			(0.82)	(1.32)	(-1.90)	(0.45)		
Netherlands	-0.684	0.373	-0.875	0.289	121	12	0.142	0.206	0.088	0.344	144	5	0.812	0.392	0.112	-0.396	209	7
	(-0.97)	(0.74)	(-1.27)	(0.54)			(0.18)	(0.31)	(0.16)	(0.85)			(1.43)	(0.79)	(0.28)	(-1.09)		
Norway	1.352***	0.830	1.317***	1.074**	198	30	1.290**	1.378**	0.414	0.667**	203	20	-0.0008	0.744	-0.950**	-0.325	198	9
	(3.08)	(1.50)	(2.93)	(1.99)			(2.16)	(2.34)	(1.65)	(2.21)			(-0.00)	(0.96)	(-2.53)	(-0.74)		
Pakistan	0.481	1.053*	0.338	0.916*	99	22	1.228	2.251**	0.498	1.196***	102	11	0.539	0.943	-0.044	0.103	103	10
	(0.83)	(1.77)	(0.60)	(1.70)			(1.51)	(2.56)	(1.06)	(2.69)			(0.69)	(1.04)	(-0.10)	(0.36)		
Philippines	0.660	0.905*	0.845	0.890*	179	29	1.658***	2.328***	0.776**	1.157***	185	17	0.875*	1.297**	-0.086	0.201	184	12
	(1.44)	(1.80)	(1.52)	(1.66)			(3.24)	(4.20)	(2.27)	(3.73)			(1.72)	(2.24)	(-0.28)	(0.55)		
Poland	1.804***	1.325**	2.110***	1.570***	174	34	1.548*	1.889**	1.628***	2.018***	174	20	-0.230	0.575	-0.489	0.449	177	14
	(3.12)	(2.56)	(3.33)	(2.99)			(1.89)	(2.47)	(4.29)	(5.90)			(-0.31)	(0.71)	(-1.29)	(1.04)		
Singapore	0.950***	1.149***	0.701*	1.411***	251	34	1.117***	1.139**	0.480**	0.700***	257	24	0.184	-0.039	-0.205	-0.749**	254	10
	(2.68)	(3.06)	(1.77)	(3.97)			(2.73)	(2.55)	(2.10)	(2.97)			(0.36)	(-0.07)	(-0.52)	(-2.25)		
South Africa	0.301	0.475	0.548	0.646	193	32	1.615**	1.452**	0.718*	0.600**	194	11	1.311**	1.013**	0.168	-0.058	221	19
	(0.70)	(1.38)	(1.21)	(1.63)			(2.50)	(2.45)	(1.91)	(1.99)			(2.36)	(2.00)	(0.70)	(-0.34)		
South Korea	1.621***	2.536***	1.339***	2.083***	261	140	1.825***	2.174***	0.876***	1.367***	261	75	0.329	-0.262	-0.359	-0.639**	262	65
	(4.32)	(7.98)	(3.52)	(6.29)			(3.14)	(4.04)	(3.43)	(6.59)			(0.57)	(-0.42)	(-1.24)	(-2.46)		
Spain	1.514***	1.732***	1.382***	1.608***	180	23	0.915*	1.080**	0.703***	0.941***	190	16	-0.490	-0.561	-0.649*	-0.659**	181	7
	(3.93)	(4.82)	(3.63)	(4.91)			(1.67)	(1.99)	(3.98)	(4.05)			(-0.88)	(-1.04)	(-1.92)	(-2.18)		
Sri Lanka	0.329	1.453*	1.078	1.476**	82	16	0.693	1.355*	0.208	0.735**	130	10	-0.357	-0.679	-0.853	-0.719	83	5
	(0.44)	(1.73)	(1.59)	(2.05)			(1.00)	(1.86)	(0.62)	(2.14)			(-0.41)	(-0.62)	(-1.26)	(-1.13)		
Sweden	0.332	1.514***	0.384	1.514***	215	83	1.457***	1.879***	0.394**	0.702***	215	56	1.125**	0.365	0.009	-0.812***	215	26
	(1.18)	(6.83)	(1.39)	(6.39)			(3.01)	(3.79)	(2.09)	(3.99)			(2.31)	(0.80)	(0.05)	(-5.69)		
Switzerland	0.388	0.665***	0.512	0.614***	191	37	1.294***	1.317***	0.580*	0.381**	191	14	0.833**	0.579	0.043	-0.246	197	22
	(1.10)	(2.80)	(1.21)	(2.65)			(2.70)	(2.99)	(1.77)	(1.99)			(2.47)	(1.50)	(0.25)	(-1.55)		
Thailand	0.633*	1.641***	0.376	1.460***	262	64	1.699***	2.571***	0.603**	1.324***	263	34	1.014**	0.877*	0.305	-0.138	262	30
	(1.75)	(6.27)	(0.88)	(5.51)			(3.28)	(5.26)	(2.42)	(6.30)			(2.08)	(1.78)	(1.13)	(-0.81)		
Turkey	1.717***	2.844***	1.796***	2.752***	149	30	1.216	1.844**	0.607	0.902***	149	16	-0.629	-1.089	-1.218***	-1.846***	150	14
	(2.96)	(5.71)	(3.33)	(6.38)			(1.51)	(2.32)	(1.62)	(2.66)			(-0.77)	(-1.40)	(-3.22)	(-5.56)		
U.K.	0.668**	0.625***	0.752***	0.673***	227	125	1.134**	1.282***	0.660***	0.645***	227	65	0.466	0.657*	-0.092	-0.028	227	60
	(2.46)	(3.10)	(2.84)	(3.77)			(2.57)	(2.84)	(3.00)	(3.67)			(1.36)	(1.81)	(-0.71)	(-0.21)		
U.S.	0.241	1.031***	0.142	1.159***	227	1378	1.191***	2.122***	0.152	1.212***	227	246	0.951***	1.090***	0.010	0.053	227	1133
	(1.05)	(5.82)	(0.68)	(6.37)			(3.02)	(5.15)	(0.73)	(6.02)			(3.44)	(3.01)	(0.18)	(0.95)		
Total>0 [Sig.]	28 [10]	33 [21]	30 [8]	33 [24]			34 [18]	34 [27]	33 [14]	34 [30]			27 [10]	26 [5]	16 [0]	12 [1]		
Total<0 [Sig.]	6 [0]	1 [0]	4 [0]	1 [0]			0 [0]	0 [0]	1 [0]	0 [0]			7 [0]	8 [0]	18 [3]	22 [7]		

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Table 4: $CID - UNC$ performance differences

This table reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations for monthly rebalanced insider trading strategies based on the unconditional trade (UNC) signals (see, Table 2) and based on the composite measure (CID) of information-driven (see, Table 3) trade signals. We report monthly value- and equal-weighted CH4 factor alphas (see, Table A.7 for raw returns) for the long-short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report the differences between unconditional and information-driven alphas, a test for significant differences, and the number of months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: Long-Short

	UNC CH4 α		CID CH4 α		$CID - UNC$		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
				Pooled			
DM	-0.082	0.754***	0.153	1.002***	0.225***	0.269***	227
	(-0.96)	(4.18)	(1.12)	(4.79)	(2.78)	(8.30)	
EM	0.429**	1.032***	0.699***	1.396***	0.255*	0.372***	227
	(2.39)	(7.02)	(2.65)	(8.31)	(1.93)	(5.24)	
				Country-neutral			
DM	0.338	0.861***	0.434	1.112***	0.096	0.251***	227
	(0.98)	(3.61)	(1.18)	(3.78)	(1.62)	(6.29)	
EM	0.510	1.021***	0.872	1.221***	0.362***	0.200**	227
	(1.28)	(3.45)	(1.49)	(3.25)	(3.86)	(2.11)	

Panel B: Long

	UNC CH4 α		CID CH4 α		$CID - UNC$		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
				Pooled			
DM	0.011	0.836***	0.250**	1.034***	0.211***	0.197***	227
	(0.17)	(3.92)	(2.26)	(4.52)	(2.72)	(6.36)	
EM	0.399	1.194***	0.515	1.288***	0.119	0.107**	227
	(1.37)	(7.00)	(1.54)	(7.59)	(1.13)	(2.21)	
				Country-neutral			
DM	0.323	0.786***	0.440	0.893***	0.117**	0.107***	227
	(1.29)	(3.77)	(1.65)	(3.68)	(2.29)	(3.50)	
EM	0.462	1.096***	0.745*	1.085***	0.283***	-0.011	227
	(1.53)	(4.20)	(1.85)	(3.89)	(3.83)	(-0.15)	

Panel C: Short

	UNC CH4 α		CID CH4 α		$CID - UNC$		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
				Pooled			
DM	0.093	0.082	0.097	0.033	-0.013	-0.071***	227
	(1.59)	(0.78)	(1.28)	(0.33)	(-0.78)	(-3.26)	
EM	-0.030	0.162	-0.184	-0.108	-0.137	-0.264***	227
	(-0.12)	(0.67)	(-1.03)	(-0.50)	(-1.57)	(-4.14)	
				Country-neutral			
DM	-0.018	-0.063	0.004	-0.189	0.022	-0.126***	227
	(-0.18)	(-0.52)	(-0.18)	(-1.03)	(0.59)	(-3.42)	
EM	-0.005	0.108	-0.110	-0.118	-0.105*	-0.227***	227
	(-0.16)	(0.15)	(-0.37)	(-0.47)	(-1.88)	(-4.05)	

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Table 5: Alternative composition approaches

This table reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of alternative composition approaches. Panel A reports more restrictive versions (CID^3 and CID^4) of our original composite measure of information-driven trades (see, Figure 1). Panel B reports a signal-weighted (SW) and an expected return (ER) based approach, respectively. We report monthly value- and equal-weighted CH4 factor alphas for the long-short portfolios. Furthermore, we report the differences between unconditional (UNC) and all information-driven alphas, a test for significant differences, and the number of months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: Stronger composite measures (Long-Short)

	CID^3 CH4 α		$CID^3 - UNC$			CID^4 CH4 α		$CID^4 - UNC$		
	vw	ew	vw	ew	N	vw	ew	vw	ew	N
	Pooled					**Pooled**				
DM	0.239	1.114***	0.321***	0.360***	227	0.149	1.294***	0.217	0.554***	225
	(1.52)	(5.54)	(2.94)	(6.75)		(0.73)	(5.55)	(1.40)	(5.74)	
EM	0.788***	1.426***	0.325	0.400***	227	0.678	1.485***	0.251	0.343***	214
	(2.64)	(8.57)	(1.61)	(4.05)		(1.53)	(9.57)	(0.84)	(2.54)	
	Country-neutral					**Country-neutral**				
DM	0.576	1.267***	0.238***	0.406***	227	0.594	1.595***	0.258*	0.721***	225
	(1.16)	(3.37)	(2.70)	(5.19)		(0.96)	(2.71)	(1.95)	(4.51)	
EM	0.885	1.226***	0.375**	0.205*	227	1.068*	1.583***	0.578**	0.573***	227
	(1.42)	(2.85)	(2.39)	(1.65)		(1.67)	(3.21)	(2.35)	(3.18)	

Panel B: Alternative composition methods (Long-Short)

	SW CH4 α		$SW - UNC$			ER CH4 α		$ER - UNC$		
	vw	ew	vw	ew	N	vw	ew	vw	ew	N
	Pooled					**Pooled**				
DM	0.120	0.979***	0.183***	0.247***	227	0.216*	0.974***	0.310***	0.195**	227
	(0.98)	(4.93)	(2.54)	(5.51)		(1.89)	(4.77)	(2.54)	(1.98)	
EM	0.577**	1.216***	0.132	0.194**	227	0.598**	1.366***	0.144	0.350***	227
	(2.32)	(7.62)	(0.94)	(2.21)		(2.08)	(9.33)	(0.63)	(2.57)	
	Country-neutral					**Country-neutral**				
DM	0.409	1.007***	0.071	0.146**	227	0.092	0.757**	-0.247*	-0.104	227
	(0.99)	(3.06)	(1.02)	(2.56)		(0.30)	(2.38)	(-1.69)	(-0.80)	
EM	0.671	1.107***	0.160	0.086	227	0.567	0.843**	0.057	-0.178	227
	(1.15)	(3.05)	(1.52)	(0.86)		(1.08)	(2.01)	(0.32)	(-1.06)	

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Table 6: Longer holding periods

This table reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of the information-driven (CID) monthly rebalanced insider trading strategy for different holding periods in Panel A. We still rebalance the portfolios monthly but keep the stocks longer, i.e., 1 to 12 months, in the respective portfolios. We report monthly value- and equal-weighted CH4 factor alphas for the long-short portfolios. Furthermore, in Panel B, we report the differences between unconditional and information-driven alphas and a test for significant differences. Finally, we report the number of available months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: CID CH4 α (Long-Short)

	1 month		2 months		3 months		6 months		12 months		N
	vw	ew	vw	ew	vw	ew	vw	ew	vw	ew	
						Pooled					
DM	0.153	1.002***	0.048	0.777***	0.016	0.680***	0.005	0.495***	-0.036	0.381***	227
	(1.12)	(4.79)	(0.39)	(4.41)	(0.15)	(4.24)	(0.05)	(3.78)	(-0.48)	(3.50)	
EM	0.699***	1.396***	0.432**	1.195***	0.304*	0.969***	0.136	0.662***	0.130	0.485***	227
	(2.65)	(8.31)	(2.32)	(7.94)	(1.92)	(6.96)	(1.13)	(6.18)	(1.57)	(5.47)	
						Country-neutral					
DM	0.434	1.112***	0.325	0.832***	0.325	0.800***	0.197	0.569***	0.089	0.403***	227
	(1.18)	(3.78)	(1.03)	(3.71)	(1.09)	(3.86)	(0.88)	(3.65)	(0.47)	(3.17)	
EM	0.872	1.221***	0.496	0.958***	0.350	0.831***	0.260	0.663***	0.187	0.483***	227
	(1.49)	(3.25)	(1.00)	(3.20)	(1.01)	(3.37)	(1.04)	(3.10)	(0.94)	(2.91)	

Panel B: $CID - UNC$ (Long-Short)

	1 month		2 months		3 months		6 months		12 months		N
	vw	ew	vw	ew	vw	ew	vw	ew	vw	ew	
						Pooled					
DM	0.225***	0.269***	0.135**	0.201***	0.115**	0.171***	0.054	0.133***	-0.001	0.092***	227
	(2.78)	(8.30)	(2.02)	(7.30)	(2.03)	(6.60)	(1.06)	(5.45)	(-0.03)	(3.89)	
EM	0.255*	0.372***	0.101	0.238***	0.004	0.163***	0.020	0.124***	0.051	0.081**	227
	(1.93)	(5.24)	(0.80)	(4.32)	(0.03)	(3.32)	(0.20)	(2.98)	(0.66)	(2.26)	
						Country-neutral					
DM	0.096	0.251***	0.096	0.180***	0.167***	0.209***	0.111***	0.163***	0.043	0.102***	227
	(1.62)	(6.29)	(1.69)	(4.94)	(3.30)	(6.64)	(2.94)	(7.29)	(1.41)	(5.83)	
EM	0.362***	0.200**	0.217***	0.188***	0.150**	0.155**	0.128**	0.138***	0.114**	0.104**	227
	(3.86)	(2.11)	(2.88)	(3.00)	(2.08)	(2.56)	(2.05)	(2.67)	(2.06)	(2.19)	

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Table 7: Developed vs. Emerging markets

This table reports the difference between emerging market (EM) and developed market (DM) alphas for the unconditional (UNC) and information-driven (CID) monthly rebalanced insider trading strategy for pooled and country-neutral implementations. Additionally, we report differences between EM and DM alpha spreads ($CID-UNC$). We report monthly value- and equal-weighted CH4 factor alphas for the long-short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report a test statistic for significant differences, the monthly average amount of firms (F) in each respective portfolio, and the number of months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

	UNC CH4 α				CID CH4 α				$CID-UNC$		
	vw	**ew**	**F(EM)**	**F(DM)**	**vw**	**ew**	**F(EM)**	**F(DM)**	**vw**	**ew**	**N**
Panel A: Long - Short											
Pooled											
EM - DM	0.511**	0.279	1155	3484	0.547**	0.395*	783	2646	0.031	0.103	227
	(2.66)	(1.44)			(2.04)	(1.84)			(0.21)	(1.34)	
Country-neutral											
EM - DM	0.172	0.160	74	196	0.438***	0.109	58	150	0.266**	-0.051	227
	(1.35)	(1.33)			(2.80)	(0.86)			(2.48)	(-0.49)	
Panel B: Long											
Pooled											
EM - DM	0.388	0.359	606	1478	0.265	0.254	385	962	-0.093	-0.090	227
	(1.59)	(1.55)			(0.98)	(1.07)			(-0.74)	(-1.62)	
Country-neutral											
EM - DM	0.139	0.311***	39	87	0.305**	0.193*	29	55	0.166*	-0.118	227
	(1.47)	(3.11)			(2.62)	(1.94)			(1.86)	(-1.41)	
Panel C: Short											
Pooled											
EM - DM	-0.123	0.080	549	2006	-0.281	-0.141	398	1684	-0.124	-0.193***	227
	(-0.63)	(0.37)			(-1.53)	(-0.69)			(-1.15)	(-2.87)	
Country-neutral											
EM - DM	0.013	0.172*	35	116	-0.114	0.071	29	95	-0.127*	-0.100	227
	(0.14)	(1.87)			(-1.03)	(0.73)			(-1.90)	(-1.44)	

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Table 8: Cross-country analysis

This table reports the results of the cross-country regressions examining the relation between various proxies for insider trading restrictions and the potential benefits of the unconditional (UNC) and composite information-driven (CID) insider trading strategies. The dependent variables are the equal- and value-weighted long-short within-country alphas of the 34 countries from the CH4 factor regressions in Tables 2 and 3, respectively. Panel A and Panel B report the regression results for the unconditional (UNC) and the composite (CID) strategy, respectively. The explanatory variables are the time series averages (if time varying) of various insider trading restriction proxies, including an anti self-dealing (AS) index, a class action dummy (CLASSA), blackout periods (BLACKOUT), an insider trading restriction index (ITR), and a developed-market dummy (DEV). All explanatory variables are described in detail in Table A.12 of the Appendix. The actually variables values are report in Table A.10 of Appendix. Table A.11 of the Appendix provides the same analysis for the long and short portfolios, respectively. The t-statistics reported in parentheses are computed using robust standard errors. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: *UNC* (Long-Short)																
	Value-weighted								**Equal-weighted**							
AS	-0.555*					-0.432	-0.434	-0.490	-0.502***					-0.301	-0.286	-0.323
	(-1.87)					(-1.26)	(-1.14)	(-1.31)	(-2.75)					(-1.57)	(-1.49)	(-1.55)
CLASSA		-0.239*				-0.199	-0.143	-0.121		-0.067				-0.024	0.007	0.022
		(-1.81)				(-1.44)	(-0.97)	(-0.79)		(-0.51)				(-0.20)	(0.06)	(0.19)
BLACKOUT			-0.472			-0.229	-0.140	-0.118			-0.878**			-0.731*	-0.792	-0.777
			(-1.23)			(-0.50)	(-0.24)	(-0.21)			(-2.29)			(-1.76)	(-1.49)	(-1.55)
ITR				-0.092			-0.057	0.083				-0.086			-0.001	0.091
				(-1.12)			(-0.52)	(0.69)				(-1.11)			(-0.01)	(0.75)
DEV					-0.229			-0.335					-0.190			-0.219
					(-1.41)			(-1.41)					(-1.35)			(-1.04)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.087	0.065	0.035	0.033	0.066	0.139	0.134	0.188	0.098	0.007	0.167	0.038	0.059	0.200	0.204	0.234
Panel B: *CID* (Long-Short)																
	Value-weighted								**Equal-weighted**							
AS	-0.675					-0.545	-0.620	-0.652	-0.517					-0.332	-0.291	-0.297
	(-1.50)					(-0.99)	(-1.05)	(-1.08)	(-1.44)					(-0.74)	(-0.61)	(-0.64)
CLASSA		-0.276				-0.227	-0.149	-0.136		-0.070				-0.026	0.020	0.022
		(-1.35)				(-0.99)	(-0.61)	(-0.55)		(-0.35)				(-0.13)	(0.10)	(0.11)
BLACKOUT			-0.526			-0.224	0.115	0.128			-0.829			-0.667	-0.959	-0.956
			(-1.20)			(-0.41)	(0.18)	(0.20)			(-1.42)			(-0.97)	(-1.30)	(-1.29)
ITR				-0.162			-0.151	-0.071				-0.049			0.052	0.067
				(-1.54)			(-1.35)	(-0.37)				(-0.42)			(0.54)	(0.31)
DEV					-0.260			-0.193					-0.050			-0.035
					(-1.21)			(-0.52)					(-0.23)			(-0.10)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.074	0.049	0.025	0.056	0.046	0.11	0.136	0.145	0.046	0.003	0.067	0.005	0.002	0.085	0.103	0.104

(Go back to text)

Appendix "Synthesizing Information-driven Insider Trade Signals"

Abstract

This document describes the cleaning of the insider trading data from 2iQ, the detailed implementation of all individual information-driven trade measures in our global sample, and includes various additional materials and results beyond the content of the main paper. Screens and filtering rules are intended to clear the sample of undesired transactions and ensure consistent and unambiguous allocation of insider trades to individual countries. They also aim to provide a comparable and sufficient quantity and quality of data across countries. All screens are performed at the level of an individual country. Table A.1 reports general and specific insider transaction data screens. Table A.2 reports all publishing sources of insider transactions provided by 2iQ and the considered country exchanges. Table A.3 reports all individual information-driven trade measures, including a detailed description of their implementation. Tables A.4 and A.5 report descriptive statistics for the buy and sell signal appearances of the individual information-driven trade measures, respectively. Table A.6 reports the difference in performance between the unconditional and composite information-driven insider trading strategies at the country-level. Table A.7 reports a version of Table 4 using raw returns instead of alphas. Table A.8 shows the unconditional results for the longer holding periods analysis in Table 6. Table A.9 shows a literature overview of return predictability studies in emerging vs. developed markets. Table A.10 reports the country-level variable values of the proxies for insider trading restrictions. Table A.11 reports an additional cross-country analysis investigating long and short portfolios separately. Table A.12 reports further variable definitions.

Table A.1: Insider data screens

The table reports the data screens which are uniformly applied to the international insider trading data set from 2iQ. Additionally, the table reports further (not uniformly applied) screens which are only applied when necessary and thus explicitly stated in the construction of a specific information-driven insider trade measure in Table A.3.

No.	Name	Description	(Exemplary) reference(s)
		Uniformly applied screens	
(1)	Transaction type	Exclusion of all insider transaction which are not flagged as either purchase (transaction type = "Buy") or sale (transaction type = "Sell"), i.e., exclusion of awards ("Award") and options exercises ("Exercise").	Aboody and Lev (2000), Jeng et al. (2003), Cheng and Lo (2006), Ravina and Sapienza (2010), Cohen et al. (2012), Dai et al. (2015), Hong and Li (2019), Akbas et al. (2020), Afzali and Martikainen (2021)
(2)	Equity data availability	Exclusion of all insider purchases and sales for which there is no valid (see, Table B.5 for equity data screens) return and market capitalization during the month of the insider trade. The data from 2iQ and Datastream was merged based on ISINs/SEDOLs.	Aboody and Lev (2000), Jeng et al. (2003), Dai et al. (2015), Ali and Hirshleifer (2017), Hong and Li (2019)
(3)	Only local source	Exclusion of all insider purchases and sales for which the publishing source of the insider transaction is not equal to the local (national) regulator code, except when the transaction has been placed on a local exchange indicated by the transaction exchange variable. The considered source codes and transaction exchanges for each country are listed in Table A.2. Together with the equity data merge in screen (2) this ensures that we only consider insider transactions in the home country where the firm is listed and where the transaction occurred and was announced.	Hong et al. (2019)

Table A.1: (continued)

No.	Name	Description	(Exemplary) reference(s)
(4)	Only Equity	Exclusion of all purchases and sales which are not labeled as equity (asset class = "Equity") transactions by 2iQ.	Afzali and Martikainen (2021)
(5)	No private transactions	Exclusion of all purchases and sales which can be identified as a private transaction either through their exchange or transaction label. Exclusion if transaction exchange label is equal to "OTC" or "off exchange" and if the transaction label is equal to or contains "OTC", "PR", "PP", "PRN".	Beneish and Vargus (2002), Ravina and Sapienza (2010), Cohen et al. (2012), Hong et al. (2019), Hong and Li (2019), Akbas et al. (2020), Afzali and Martikainen (2021)
		Additionally, we exclude remaining transactions which have both an unusual transaction price (Bad price screen) and trading volume (Volume too high screen) for the day of the insider trade.	Lakonishok and Lee (2001), Jeng et al. (2003)
(6)	No routine trades	Exclusion of all insider transactions which are considered to be routine trades following the trade-level approach of Cohen et al. (2012).	Alldredge and Cicero (2015), Alldredge and Blank (2019), Khalilov and Osma (2020), Afzali and Martikainen (2021), Cziraki and Gider (2021)
(7)	Start date	Not all countries have sufficient data from the sample start in 2000. Therefore, each country has its own start date. We exclude observations prior to the start date specified in Table 1.	Afzali and Martikainen (2021)
(8)	Sufficient data	Exclusion of countries which have fewer than 5,000 valid insider transactions and/or less than 100 stocks over the sample period after applying screens (1)-(7) and (9)-(11).	Hong et al. (2019)

Table A.1: (continued)

No.	Name	Description	(Exemplary) reference(s)
		Additional (not uniformly applied) screens	
(9)	Non-trading day	Exclusion of all insider purchases and sales which occurred on a day in 2iQ that is considered a non-trading day or a day with missing price and volume data in Datastream. We do not apply this screen for transactions that were executed over multiple days which is indicated by a non-missing "max trade date" in 2iQ.	Lakonishok and Lee (2001), Jeng et al. (2003)
(10)	Volume too high	Exclusion of all insider purchases and sales whose transaction volume (shares traded) in 2iQ exceeds the daily market trading volume in Datastream.	Jeng et al. (2003), Dai et al. (2015)
(11)	Bad price	Exclusion of all insider purchases and sales whose transaction price in 2iQ is not within a 20% range of Datastream's daily closing price if both prices are quoted in the same currency and non-missing.	Lakonishok and Lee (2001), Jeng et al. (2003), Cline et al. (2017), Gao et al. (2022)

(Go back to text)

Table A.2: Insider data sources and exchanges

The table reports all publishing sources (2iQ abbreviations) of insider transactions provided by 2iQ. Furthermore, the table reports the respective country exchanges which are accepted under the only local source screen (3) in Table A.1 when the publishing source is not from a local regulator.

Country	Sources	Transaction exchanges
Australia	ASX	ASX, XASX
Belgium	BEL	Euronext Bruxelles
Brazil	BRA	
Canada	CAN	TSE-Toronto
Chile	CHI	
China	SSE, SSX, HKE	
Denmark	DAN	OMX-Copenhagen, XCSE - OMX-Copenhagen
Egypt	EGY	
Finland	FIN	XHEL - NASADQ Helsinki
France	Frau	Euronext Paris
Germany	ADH, EQU	Tradegate Exchange, XETRA
Greece	GRE	
Hong Kong	HKE	HKE (Hong Kong)
India	IND, NSE	Bombay
Indonesia	IDN	
Israel	ISR	Tel Aviv Stock Exchange
Italy	ITA	
Korea	KRX	
Malaysia	MYX	Kuala Lumpur
Netherlands	NET	XAMS, Euronext Amsterdam
Norway	NOR	
Pakistan	KSE	
Philippines	PHE	
Poland	PAP, TSE	XWAR, Warsaw Stock Exchange
Singapore	SGP	Singapore Exchange
South Africa	JSE	XJSE, JSE-Johannesburg
Spain	ESP	Bolsa De Madrid
Sri Lanka	SRL	
Sweden	SWE	XSTO, NASDAQ Stockholm, XSAT, Sweden, OMX-Stockholm, First North NASDAQ Sweden
Switzerland	SWI	SIX
Thailand	THA	
Turkey	KAP	
U.K	LSE	
U.S.	SEC	NASDAQ, NYSE, AMEX, XNYS

(Go back to text)

Table A.3: Individual information-driven trade measures

The table reports all individual information-driven trade measures including a detailed description of their implementation adapted to an international sample with a very heterogeneous composition of individual country data sets. We aggregate purchases and sales by an individual insider for all individual information-driven trade measures to obtain split-adjusted net shares bought or sold during a given month if not otherwise stated.

No.	Measure	Description
(1)	**Opportunistic Trades (Q3)** Ali and Hirshleifer (2017)	Following Ali and Hirshleifer (2017), we examine the historical profitability of insider trades executed in the 21 days prior to a quarterly earnings announcement (pre-QEA) over the entire history of all pre-QEA trades (at least 3 years) up to the current year to identify "opportunistic" traders. Opportunistic traders are all traders who belong to the top tercile according to their historical pre-QEA trade profitability before the beginning of the respective year of classification. Note that when calculating pre-QEA trade profitability, only pre-QEA trades are used, while the classification into "opportunistic" traders/trades applies to all future trades, including non-pre-QEA trades. We use terciles instead of quintiles as in Ali and Hirshleifer (2017) to ensure that this identification strategy is feasible even in countries with a low number of pre-QEA trades. The profitability of each pre-QEA trade is defined as the average market adjusted return in the five-day window centered at the QEA date: $$Profit = \sum_{j=-2}^{j=2} (r_{i,t+j} - r_{m,t+j})/5, \quad (A.1)$$ where t is the QEA date, $r_{i,t}$ is the return of stock i on day t, and $r_{m,t}$ is the value-weighted market return on day t. The average profitability of the insider's past pre-QEA trades is calculated each year for each insider as follows: $$Average\ Profit = (\sum^{B} Profit_{Buy} - \sum^{S} Profit_{Sell})/(B+S), \quad (A.2)$$ where B is the total number of buy and S the total number of sell pre-QEA trades made by the insider prior to the start of the year. Using the entire available history to calculate the average historical profitability in Eq. (A.2), implies that the initial information content of the first profitability calculated after a three-year formation period is potentially updated each year if a new pre-QEA trade occurs during the year.

Table A.3: (continued)

No.	Measure	Description
		We identify QEA dates for each firm through the Worldscope variables WC05901, WC05902, WC05903, and WC05904. We exclude all firm years with a missing fiscal year end date (WC0350), and all QEA dates that are dated before or more than one year after the fiscal quarter end date. Finally, after these screens, we only consider firm years with at least two valid QEA dates. The deviation from the four required QEA dates as in Ali and Hirshleifer (2017) is due to the fact that quarterly reporting is not mandatory in all countries in our sample. We define a pre-QEA trade as a trade that occurs during the 21 trading days before the QEA date, excluding the last two days before the QEA. Furthermore, we aggregate multiple trades made by the same insider on the same day into one trade and use split-adjusted shares to aggregate trades if an insider made multiple trades in a particular pre-QEA window. Finally, we exclude all trades by beneficial owners and (aggregated) transactions with a value of less than 5,000 in local currency. In a final step, we identify all firm-months in which at least one "opportunistic" insider traded to obtain an aggregate firm-month data set, marking each firm-month with an information-driven insider purchase or sale. (Go back to text)
(2)	**Strong trades (STRO)** Akbas et al. (2020)	Following Akbas et al. (2020), we construct a relative strength measure of each insider transaction to identify "strong" purchases and sales assuming that more impact-full transactions contain more information. Noteworthy, we do not implement the strength measure in combination with the "short horizon" measure to identify "strong short horizon" trades as in Akbas et al. (2020), but instead decided to implement both measures individually. The reason we decided to do this is that we ultimately want to use individual measures to implement a composite measure of information-driven trades, and thus both information measures are ultimately combined anyway, and also because a similar implementation as in Akbas et al. (2020) would not have been feasible in countries with a smaller number of transactions. We calculate the relative trading strength measure as follows: $$STRO_{i,j,t} = \frac{P_{i,j,t} - S_{i,j,t}}{VOL_{j,t}}, \qquad \text{(A.3)}$$

Table A.3: (continued)

No.	Measure	Description
		where $P_{i,j,t}$ is the number of shares purchased by insider i at firm j in month t, $S_{i,j,t}$ is the number of shares sold by insider i at firm j in month t, and $VOL_{j,t}$ is the total volume of shares traded by all investors in firm j during month t. We apply screens (9) and (10) of Table A.3 to ensure that we have non-missing volume data and to not falsely identify potential private transactions, i.e., trades that exceed the overall daily trading volume, as "strong" trades. Furthermore, we split-adjust the shares bought, sold, and the overall daily trading volume prior to calculating Eq. (A.3). The resulting measure is defined from -1 ("strong" sales) to 1 ("strong" purchases). Finally, we calculate monthly expanding window medians separately for sales (negative $STRO$ values) and purchases (positive $STRO$ values) to define a "strong" sale as a trade with a $STRO$ value smaller than the sale median and a "strong" purchase as a trade with a $STRO$ value greater than the purchase median, respectively. In a final step, we identify all firm-months in which at least one "strong" insider traded to obtain an aggregate firm-month data set, marking each firm-month with an information-driven ("strong") insider purchase or sale. (Go back to text)
(3)	**Short horizon trades (SHOR)** Akbas et al. (2020)	Following Akbas et al. (2020), we construct a measure that aims to capture the investment horizon of an insider to identify information-driven trades by investors with a shorter investment horizon. This approach assumes that "short-horizon traders" focus more on dynamic short-term information flows that force them to switch more frequently between buying and selling to realize trading profits. Such a behavior would lead to a balanced net order flow, i.e., close to zero, whereas annual net order flows close to 1 (-1) would indicate that the insider only engaged in buying (selling) over the year. For each year, we calculate the annual net order flow using split-adjusted shares as follows: $$IOF_{i,j,y} = \frac{P_{i,j,y} - S_{i,j,y}}{P_{i,j,y} + S_{i,j,y}}, \qquad \text{(A.4)}$$ where $P_{i,j,y}$ is the number of split-adjusted shares purchased by insider i at firm j in year y and $S_{i,j,y}$ is the number of split-adjusted shares sold by insider i at firm j in year y.

Table A.3: (continued)

No.	Measure	Description
		In order to classify an insider as a "short horizon" trader we define the investment horizon of an insider each year as his or her average annual net order flow over the last 10 calendar years prior to year y as follows: $$HOR_{i,j,t} = \left| \frac{\sum_{y=T-10}^{year(t-1)} IOF_{i,j,y}}{N} \right| \times (-1), \quad \text{(A.5)}$$ where $IOF_{i,j,y}$ is the annual net insider order flow as defined in Eq. (A.4) of insider i at firm j in year y and N is the number of calendar years the insider traded over the 10 years prior to year y. We require the insider to have traded in at least three of the last 10 years to be included in our sample, but use an expanding window approach so that the first HOR measure could already be constructed after the first three years given that the insider traded in all three years. We deviate from the implementation in Akbas et al. (2020), i.e., requiring 4 trades and a full history of 10 years, because such an implementation would not have been feasible in countries with shorter insider trading histories. We do follow the original paper in excluding smaller trades with less than 100 split-adjusted shares. The resulting HOR measure is defined from 0 (short horizon) to -1 (long horizon) and subsequently used to define "short horizon" trades as traders with a HOR greater than (i.e., closer to zero) the yearly expanding median of all non-long horizon traders (HOR = -1). The remaining traders with a HOR smaller or equal to the median (i.e., closer to -1) of all non-long horizon traders are considered to be medium horizon traders. In a final step, we identify all firm-months in which at least one "short horizon" insider traded to obtain an aggregate firm-month data set, marking each firm-month with an information-driven ("short horizon") insider purchase or sale. (Go back to text)
(4)	**Unexspected trades (UNEX)** Akbas et al. (2020)	Following Akbas et al. (2020), we construct a measure that aims to capture to what extent an insider transaction is unexpected considering the expectation associated with the insider's investment horizon. This approach assumes that "unexspected" trades are more likely information-driven.

Table A.3: (continued)

No. Measure	Description
	It is important to emphasize that this approach is useful to identify information-driven trades beyond the investment horizon ($SHOR$) approach. While it is correct that short horizon traders are generally more likely to execute unexpected trades, long horizon traders who deviate from their trading direction only once, i.e., act very unexpectedly, would not be considered to be carrying out information-driven trades. In order to classify a trade as unexpected we define the measure of unexpected insider trading as follows: $$UNEX_{i,j,t} = CURRENT_{i,j,t} - \frac{\sum_{y=T-10}^{year(t-1)} IOF_{i,j,y}}{N}, \quad (A.6)$$ where $CURRENT_{i,j,t} = +1$ (-1) if insider i has net purchases (sales) of stock j in month t, $IOF_{i,j,y}$ is the annual net insider order flow of insider i at firm j in year y as defined in Eq. (A.4) and N is the number of calendar years the insider traded over the 10 years prior to year y. We require the insider to have traded in at least three of the last 10 years to be included in our sample using an expanding window approach so that the first $UNEX$ measure could already be constructed after the first three years given that the insider traded in all three years. It appears that Akbas et al. (2020) only looks at the last 10 years without specifying a minimum number of trades to establish an expectation. We deviate from this implementation because we believe that assessing the unexpectedness of a trade relative to only one or two trades does not seem very revealing. We do follow the original paper in excluding smaller trades with less than 100 split-adjusted shares. The resulting $UNEX$ measure is defined from -2 (more unexpected sales) to 2 (more unexpected purchases). Finally, we calculate monthly expanding window medians separately for sales (negative $UNEX$ values) and purchases (positive $UNEX$ values) to define an "unexpected" sale as a trade with an $UNEX$ value smaller than the sale median and an "unexpected" purchase as a trade with an $UNEX$ value greater than the purchase median, respectively. In a final step, we identify all firm-months in which at least one "unexpected" insider trade occurred to obtain an aggregate firm-month data set, marking each firm-month with an information-driven ("unexpected") insider purchase or sale.

(Go back to text)

Table A.3: (continued)

No.	Measure	Description
(5)	**Insider silence (PPN/SSN)** Hong and Li (2019)	Following Hong and Li (2019), we construct a measure that attempts to extract information from the absence of a trade that would be expected given the trading pattern of previous years, i.e., the sudden silence of an insider. The intuition is that a sudden omission, e.g., of a January purchase (sale) that seems to have been routine in the past, is a negative (positive) signal for the future stock price development. This silence could reveal nonpublic information that lead the insider to deviate from his or her routine trading pattern. If an insider has made a purchase (sale) in the same month in each of the last two years and has not traded in that month this year, we mark the non-transaction month as informative. We denote these non-transaction months as PPN (Purchase, Purchase, No-Purchase) and SSN (Sale, Sale, No-Sale), respectively. We do not apply screen (6) of Table A.3 before determining whether an insider unexpectedly remained silent after two consecutive same-month trades over the previous two years, because excluding non-routine trades would otherwise construct a salient signal in months in which the trader actually did continue to trade. We recognize that this approach also marks non-informative silence, e.g., when an insider loses his or her insider status because he or she leaves the company, however, within the framework of our implemented trading strategy (trade in the month after a signal or the absence of a signal) we cannot take into account the information whether an insider has traded at all again in the current year or in any year after the trade as this would induce a look-ahead bias. In a final step, we identify all firm-months in which at least one insider unexpectedly remained silent to obtain an aggregate firm-month data set, marking firm-months without an insider purchase or sale as informative. (Go back to text)
(6)	**Realized loss trades (LOSS)** Kelly (2018)	Following Kelly (2018), we construct a measure that attempts to differentiate information-driven from non-information-driven sales by identifying sales that are realized at a loss relative to a recent reference price. The intuition is that (informed) investors (insiders) do not like to realize losses (see, disposition effect, e.g., Odean (1998)) and thus must foresee especially negative information about their company when they are willing to realize such a "loss" trade anyways.

Table A.3: (continued)

No. Measure	Description
	We deviate from the original implementation in Kelly (2018) by using the moving-average split-adjusted local month-end prices over the previous six months to calculate a reference price. We cannot use the preferred methodologies of Kelly (2018), i.e., the FIFO reference price (First-In-First-Out) or the last purchase price, as using either of these for our international insider data set would lead to a very small number of classified sales. It is not possible to categorize a sale as a loss or gain trade without knowing the purchase or acquisition history of the respective position. Using the moving average of the split-adjusted local month-end price does not require any knowledge of the transaction history of the shares and, more importantly, seems to be a particularly suitable reference price for insiders. Insiders, more than retail investors, are regularly confronted with the current stock price of their company, making it particularly plausible that an insider would not use the actual purchase price potential dating back several years, but most likely a price more prevalent in his or her memory to judge whether a sale at the current price is perceived as a loss or a gain. A sale is only categorized if we have a valid moving-average split-adjusted month-end price over the last six months from Datastream and a split-adjusted sale price from 2iQ in the same dominated currency. The 2iQ transaction price is split adjusted using the Datastream adjustment factor. We aggregate all sales by an insider on a daily basis. Consequently, we use a share-weighted average split-adjusted transaction price to compute the daily transaction price for all insider sales. Importantly, we do not implement the "active" trader screen used in Kelly (2018). An argument for not using the "active" trader screen in our setting is that especially "active" traders might be prone to turn to a more recent reference price (six months moving-average) as it may be difficult for them to keep track of their actual reference price due to intensive trading. Another concern with the "active" trader screen is that the implementation in Kelly (2018) uses a full-sample approach to judge whether a trader has been "active". This look-ahead bias could be mitigated by judging the activeness based on the past trading history of an insider. In a final step, we identify all firm-months in which at least one insider sold a stock at a "loss" to obtain an aggregate firm-month data set, marking firm-months with insider sales at a "loss" as information-driven.

(Go back to text)

Table A.3: (continued)

No.	Measure	Description
(7)	**CFO purchases (CFO)** Wang et al. (2012)	Following Wang et al. (2012), we assume insider purchases of CFOs to be more likely information-driven. The intuition behind this rather easy approach is that CFOs are in a sense in the best position among corporate insiders to have access to information advantages and also to use those effectively. CFOs are responsible for the financial strategy, in charge of the financial reporting, and have immediate information on all financial details regarding the firm. This information, coupled with their often superior financial skills/education, makes CFOs the most likely insiders to profitably exploit private information. The focus on purchases is due to the inability to distinguish between liquidity-driven CFO sales and information-driven CFO sales. We aggregate insider purchases by every CFO in a given month, rather than using net share purchases or sales to assess whether a CFO traded (bought) stocks in a given month, to avoid losing signals accompanied by larger liquidity-driven sales in the same month. CFO trades are identified by the following insider relation labels: "CFO"; "President, CFO"; "Acting CFO"; "Founder, CFO"; "Founder, President, CFO"; "CFO, Division/Unit/Subsidiary"; "Co-CEO, CFO"; "Deputy CFO". In a final step, we identify all firm-months in which at least one CFO purchased a stock to obtain an aggregate firm-month data set, marking firm-months with CFO purchases as information-driven. (Go back to text)
(8)	**Accrual trades (ACC)** Beneish and Vargus (2002), Bergstresser and Philippon (2006)	In a similar rationale to Beneish and Vargus (2002) and Bergstresser and Philippon (2006), we construct a measure that attempts to identify potentially information-driven purchases and sales using the accounting (accrual) practice of a firm paired with the top-level insider trading behavior as an identification strategy. The intuition behind this measure is that top-level executives could manipulate earnings through the use of accruals to present the stock in a better (worse) light before selling (buying) it. Following this rational, we regard sales of individual insiders as information-driven if the company had high accruals in the last fiscal year and the respective sale is accompanied by net selling of all top-level insiders in the same month, i.e., top-level insiders as a whole are selling the stock.

Table A.3: (continued)

No.	Measure	Description
		We apply the same reasoning for insider purchases assuming that purchases are information-driven if the company had low accruals in the last fiscal year and an insider purchase is accompanied by net buying of all top-level insiders in the same month. High (low) accruals are defined by performing a monthly tercile split for all companies with non-missing non-discretionary accruals and at least one purchase/sale of a top-level executive insider (i.e., all insider relation labels containing the words: “Founder”; “CFO”; “CEO”;“COO”; “Chairman”; “President”; “Board of Directors”; “Executive Committee”) in the respective month. We only perform the split for months with at least 9 firm-level observations. Net selling (buying) is defined as a negative (positive) value of shares sold (bought) across all top-level insiders in the respective month, i.e., subtracting the amount of shares bought from the amount of shares sold for all company insiders in a month. We calculate total accruals as the change in current assets ($CA = WC02201$) minus the change in cash and short-term investments ($CSTI = WC02001$) minus the change in current liabilities ($CL = WC03101$) plus the change in debt of short-term liabilities ($DSTL = WC03051$, 0 if missing) plus the change in income taxes payable ($ITP = WC03063$, 0 if missing) minus depreciation ($DEP = WC01151$, 0 if missing) divided by lagged total assets ($TA = WC02999$): $$A_{i,t} = \frac{\Delta CA - \Delta CSTI - \Delta CL + \Delta DSTL + \Delta ITP - DEP_t}{TA_{t-1}}. \quad \text{(A.7)}$$ In a next step, following Bergstresser and Philippon (2006) we regress the total accruals ($A_{i,t}$) on the change in sales ($Sales = WC01001$) normalized by lagged total assets ($WC02999_{t-1}$), lagged firm size ($Size = 1/WC02999_{t-1}$), and gross property, plant, and equipment ($PPE = WC02301$) normalized by lagged total assets ($WC02999_{t-1}$): $$A_{i,t} = \alpha_i + \beta_{Sales}\Delta Sales_{i,t} + \beta_{Size}Size_{i,t} + \beta_{PPE}PPE_{i,t} + u_{i,t}. \quad \text{(A.8)}$$ The estimated coefficients of this regression are then used to calculate our non-discretionary accruals (NDA) as follows: $$NDA_{i,t} = \hat{a}_i + \hat{\beta}_{Sales}Sales_{i,t} + \hat{\beta}_{Size}Size_{i,t} + \hat{\beta}_{PPE}PPE_{i,t}. \quad \text{(A.9)}$$

Table A.3: (continued)

No.	Measure	Description
		In a final step, we identify all firm-months in which at least one insider sold (bought) a stock with high (low) non-discretionary accruals while all insiders as a group were net sellers (buyers) of the stock in the same month to obtain an aggregate firm-month data set, marking firm-month with high or low "accrual" trades as information-driven. (Go back to text)
(9)	**Research & Development trades (R&D)** Aboody and Lev (2000)	Following Aboody and Lev (2000), we assume insider transactions by officers in firms with higher research and development expenditures to be more likely information-driven. The intuition behind this approach is that research and development expenditures lead to greater information asymmetries that could be exploited by insiders. We define R&D expenditures as the ratio of R&D expenditures ($WC01201$) to total assets ($WC02999$) to account for the relative importance of the expenditures given the size of a company. High R&D expenditure ratios are defined by performing a monthly median split for all companies with non-missing and non-zero R&D expenditures and at least one purchase/sale of a top-level executive/officer (i.e., all insider transactions with an insider level label equal to "A") in the respective month. We use an expanding window approach to calculate the monthly median R&D expenditure ratios. We only perform the split for months with at least 5 firm-level observations. In a final step, we identify all firm-months in which at least one insider (top-level executive/officer) traded in a company with an above median ratio of research and development expenditures to total assets to obtain an aggregate firm-month data set, marking each firm-month with higher "R&D" insider purchases or sales as information-driven. (Go back to text)
(10)	**Idiosyncratic volatility trades (IVOL)** Jagolinzer et al. (2011)	In a similar rationale to Jagolinzer et al. (2011), we assume insider trades of firms with high idiosyncratic volatility to be more likely information-driven. The intuition behind this approach is that higher idiosyncratic volatility leads to greater information asymmetries that could be exploited by insiders. We define idiosyncratic volatility as the standard deviation of the residuals from a local Fama and French (1993) three-factor regression over the last 12 months.

Table A.3: (continued)

No. Measure	Description
	High idiosyncratic volatility is defined by performing a monthly quintile split for all companies with a non-missing idiosyncratic volatility over the last 12 months and at least one purchase/sale of an insider in the respective month. All companies in quintile 5 are considered to be high idiosyncratic volatility firms. We only performed the split for months with at least 15 firm-level observations. In a final step, we identify all firm-months in which at least one insider traded in a company with high idiosyncratic volatility to obtain an aggregate firm-month data set, marking each firm-month with high idiosyncratic volatility insider purchases or sales as information-driven. (Go back to text)
(11) **Clustered trades (CLUS)** Alldredge and Blank (2019)	Following Alldredge and Blank (2019), we assume insider trades which cluster around other insider trades at the same firm to be more likely information-driven. The intuition behind this approach is that we suspect that insiders within a company share their information and, therefore, act in a somewhat similar time frame to exploit the shared information. Noteworthy, we do not implement the clustered trade identification as in Alldredge and Blank (2019) using a specific amount (e.g., 10 days) of days before and after an insider trade to determine whether other insiders at the same firm also traded. We use a somewhat simpler approach by checking each month whether at least two insiders at the same firm were net buyers/sellers of the stock to determine whether insiders clustered their trades in the same month. More specifically, this means that if, e.g. 3 insiders purchase and 1 insider sells in the same month, this would still be considered a clustered trade month, as 2 net insiders have traded in the same direction. We opted for this less precise approach to be able to implement our information-driven signal in real-time and with the same timing across all used information-driven trade measures, i.e., we need to make sure that we identify a firm-month as information-driven at the end of the month in order to buy or sell the company stock according to the signal at the beginning of the next month. Consequently, we define a clustered purchase/sale month as a month in which at least two insiders were net buying/selling the company stock, marking each firm-month with "clustered" insider purchases or sales as information-driven. (Go back to text)

Table A.3: (continued)

No.	Measure	Description
(12)	**Analyst coverage trades (ANA)** Ellul and Panayides (2018), Frankel and Li (2004)	In a similar rationale to Ellul and Panayides (2018) and Frankel and Li (2004), we assume that an usually low degree of analyst coverage may indicate weaker public interest in and scrutiny of the firm, which consequently makes it easier and more likely for insiders to exploit nonpublic information. The intuition is that relatively low analyst coverage could make the insider feel less watched, and therefore more willing to exploit private information. Residual analyst coverage is defined as the residual from a monthly cross-sectional regression of log analyst coverage on log size following Conrad et al. (2014). As in Hong et al. (2000), log analyst coverage is the log of 1 + the number of analysts obtained from Datastream, where the number of analysts is set to zero if it is missing. Log size is the log of the market capitalization. Consequently, low (negative) values of residual analyst coverage indicate that the firm receives less attention from analysts than would be expected given the size of the company. Low residual analyst coverage is defined by performing a monthly quintile split for all companies with a non-missing residual analyst coverage and at least one purchase/sale of an insider in the respective month. All companies in quintile 1 are considered to be low residual analyst coverage firms. We only performed the split for months with at least 15 firm-level observations. In a final step, we identify all firm-months in which at least one insider traded a stock with low residual analyst coverage to obtain an aggregate firm-month data set, marking firm-months with low analyst coverage trades as information-driven. (Go back to text)
(13)	**Residual media coverage trades (RMC)** Dai et al. (2015), Sun et al. (2021)	In a similar rationale to Dai et al. (2015) and Sun et al. (2021), we assume that (unusually) high media coverage reduces information asymmetries, consequently lowering the profitability of insider trades. The intuition is that relatively high media coverage leads to deeper public interest which makes it harder to exploit nonpublic information for insiders. Therefore, we assume that companies with lower media coverage increase an insider's ability to exploit nonpublic information. To examine the relationship between media coverage and trading profitability, we use the residual media coverage of a company over the last 12 months. The residual media coverage indicates the amount of media coverage for the respective firm controlling for firm size.

Table A.3: (continued)

No.	Measure	Description
		More specifically, in each country month, we regress the log of 1 + number of firm-specific articles on the log of lagged firm size and compute the residual. We then averaged the residual over the previous 12 months on a rolling basis as our proxy for residual media coverage. We only consider article news stories with full text, a firm relevance score of at least 75 and an event relevance score of at least 80, as defined by RavenPack. Low residual media coverage is defined by performing a monthly quintile split for all companies with a non-missing residual media coverage over the last 12 months and at least one purchase/sale of an insider in the respective month. All companies in quintile 1 are considered low residual media coverage firms. We only perform the split for months with at least 15 firm-level observations. In a final step, we identify all firm-months in which at least one insider traded in a company with low residual media coverage to obtain an aggregate firm-month data set, marking firm-months with low media coverage trades as information-driven. (Go back to text)
(14)	**Selected residual media coverage trades (SRMC)** Dai et al. (2015), Sun et al. (2021)	In addition to the overall media coverage measure described above, we calculate a second measure based on firm-specific media coverage of topics particularly relevant to insiders. Therefore, the second measure is based on a subset of the articles used for the first measure. Specifically, we only consider articles that deal with (at least) one of the following topics according to the RavenPack event group classification: "insider trading", "corporate responsibility", "crime", "investor relations", "labor issues", "legal", "regulatory". With this company-specific article universe, the selected residual media coverage measure and the relevant insider trades are calculated analogously to our procedure for residual media coverage trades described above. (Go back to text)
(15)	**Press release trades (VOLD)** Cheng and Lo (2006)	In a similar rationale to Cheng and Lo (2006), we assume that voluntary firm-initiated news disclosure in advance to an insider transaction might be motivated to influence the stock price in a favorable direction to exploit private information. The intuition is that when insiders want to buy (sell) shares of their company, they want to do so at a particularly low (high) price. One way to lower the price of the stock before buying is to publish voluntarily bad news about the company, like Cheng and Lo (2006) show.

Table A.3: (continued)

No. Measure	Description
	Bad news causes the share price to fall, but favorable future news is expected to cause the price to rise, in turn. Therefore, we assume that insiders' voluntary publication of bad news before buying a stock will lead to future positive stock performance. This could also apply in the opposite sense to a planned sale of shares. Voluntary disclosure of positive news can lead to price increases that allow for a sale at a higher price. However, the reason for the sale may be that bad news is expected in the future, so we assume a negative development of the share in the future. The degree of residual, i.e., unusual, press coverage for a given firm month is computed as log of 1 + number of press releases on lagged firm size in a cross-sectional regression for all firms in that country month. The residual of this monthly regression is then averaged over the previous 12 months, resulting in our measure of residual press releases. Whether the releases are positive or negative in a given month is expressed by the average RavenPack event sentiment score (ESS) for the firm under consideration minus the average ESS for all firms in that country month. Again, we averaged this measure of residual sentiment over the previous 12 months. In addition, we are interested in sell transactions that follow positive reporting and buy transactions that follow negative reporting. We identify these trading patterns with the assumption that such sell transactions lead to a future negative development of the share and such buy transactions lead to a positive development.In a final step, we identify all firm-months in which at least one insider bought (sold) a company with negative (positive) residual press coverage over the last 12 months to obtain an aggregate firm-month data set, marking firm-months with purchases (sales) following negative (positive) voluntary press releases as information-driven. (Go back to text)
(16) **Conditional conservatism trades (CONS)** Khalilov and Osma (2020)	Following Khalilov and Osma (2020), we construct a measure that attempts to identify potentially information-driven purchases and sales using an accounting measure (conditional conservatism) of a firm as an identification strategy. The intuition behind this measure is that it is very difficult for insiders to speculate on negative news when unfavorable economic news are timely recognized in the accounting numbers, which is proxied by high conditional accounting conservatism.

Table A.3: (continued)

No.	Measure	Description
		Following this rationale, we regard sales of individual insiders as information-driven if the company had low conditional conservatism over the last three fiscal years assuming that in these cases it is more likely that insiders can successfully speculate on bad news. On the other hand, we assume that high conditional conservatism leads to a potential undervaluation, as gains are only recognized when their associated cash flows are realized, i.e., with a leg, which creates opportunities to speculate on good news especially in times of high conditional conservatism. Therefore, we regard purchases of individual insiders as information-driven if the company had high conditional conservatism over the last 3 fiscal years assuming that in these cases it is more likely that insiders can successfully speculate on good news. High (low) conditional conservatism is defined by performing a median split for all companies with non-missing conditional conservatism in the respective month. We use an expanding-window approach to calculate the monthly median. We only perform the split for months with at least 5 firm-level observations. We calculate conditional conservatism following Khalilov and Osma (2020) and Banker et al. (2016) by estimating an augmented Basu (1977) model with the Khan and Watts (2009) adjustment for the timeliness of good news and timeliness of bad news:

$$\begin{aligned} E_{i,t}/P_{i,t-1} = {} & \alpha_0 + \alpha_1 DR_{i,t} + \alpha_2 RET_{i,t} + \alpha_3 DR_{i,t} RET_{i,t} \\ & + BM_{i,t-1} \times (\alpha_4 DR_{i,t} + \alpha_5 RET_{i,t} + \alpha_6 DR_{i,t} RET_{i,t}) \\ & + LEV_{i,t-1} \times (\alpha_7 DR_{i,t} + \alpha_8 RET_{i,t} + \alpha_9 DR_{i,t} RET_{i,t}) \\ & + SIZE_{i,t-1} \times (\alpha_{10} DR_{i,t} + \alpha_{11} RET_{i,t} + \alpha_{12} DR_{i,t} RET_{i,t}) \\ & + \gamma_1 BM_{it-1} + \gamma_2 LEV_{it-1} + \gamma_3 SIZE_{it-1} \\ & + \beta_1 DS_{i,t} + \beta_2 \Delta S_{i,t}/P_{i,t-1} + \beta_3 DS_{i,t} \times \Delta S_{i,t}/P_{i,t-1} \\ & + BM_{i,t-1} \times (\beta_4 DS_{i,t} + \beta_5 \Delta S_{i,t}/P_{i,t-1} + \beta_6 DS_{i,t} \times \Delta S_{i,t}/P_{i,t-1}) \\ & + LEV_{i,t-1} \times (\beta_7 DS_{i,t} + \beta_8 \Delta S_{i,t}/P_{i,t-1} + \beta_9 DS_{i,t} \times \Delta S_{i,t}/P_{i,t-1}) \\ & + SIZE_{i,t-1} \times (\beta_{10} DS_{i,t} + \beta_{11} \Delta S_{i,t}/P_{i,t-1} + \beta_{12} DS_{i,t} \times \Delta S_{i,t}/P_{i,t-1}) \\ & + \epsilon_{i,t}, \end{aligned} \tag{A.10}$$

where $E_{i,t}/P_{i,t-1}$ is earnings ($WC01751$) in year t scaled by the market value of equity at the beginning of the fiscal year. RET is the compounded market-adjusted (i.e., return in excess of the value-weighted market return) stock return over the fiscal year t. DR is a dummy variable equal to one if RET is negative (i.e., in the case of bad news) and zero otherwise (i.e., good news).

Table A.3: (continued)

No.	Measure	Description
		DS is a dummy variable equal to one if there is a decrease in sales from year $t-1$ to t and zero otherwise. $\Delta S_{i,t}/P_{i,t-1}$ is the change in sales ($WC01001$) from year $t-1$ to year t that is scaled by the market value of equity at the beginning of the fiscal year. $BM_{i,t-1}$, $LEV_{i,t-1}$, and $SIZE_{i,t-1}$ are the book-to-market ratio (book-equity = $WC03501$ plus $WC03263$, zero if missing), leverage (= $WC03251$ plus $WC03101$, zero if missing divided by $WC02999$), and size (log of market equity), respectively, at the beginning of the fiscal year. We winsorize all continuous variables at the 1%-level. Finally, we construct our firm-year measure of conditional conservatism as follows: $$C_{Score} = \alpha_3 + \alpha_6 BM_{i,t} + \alpha_9 LEV_{i,t} + \alpha_{12} SIZE_{i,t}. \quad \text{(A.11)}$$ Our firm-year measure of conditional conservatism is the three-year average of the C_{Score} (e.g., for year t, C_{Score} is the average over years t, $t-1$, and $t-2$) with a minimum of two valid scores to calculate the average. In a final step, we identify all firm-months in which at least one insider sold (bought) a stock with low (high) conditional conservatism to obtain an aggregate firm-month data set, marking firm-month with high or low "conditional conservatism" trades as information-driven. (Go back to text)
(17)	**Multiple firm insider sales (MFS)** Karamanou et al. (2021)	Following Karamanou et al. (2021), we assume insider sales of multiple-firm insiders to be more likely information-driven if a sale in one affiliated firm is accompanied by a purchase of another affiliated firm in the same month. The intuition behind this approach is that, unlike most sales, a sale whose proceeds are immediately reinvested in another company is most likely not liquidity-driven. The trading behavior indicates that the insider does not need the liquidity of the sale proceeds, which implies that the sale was probably made only for information purposes. Therefore, a sale accompanied by a purchase may indicate a negative future performance of the sold firm. We identify these sales by first filtering out all multi-firm insiders, i.e., marking all insiders who trade at least two different stocks in a given month. We also mark firm-months in which a multi-firm insider sold one stock while purchasing two or more other stocks in the same month.

Table A.3: (continued)

No. Measure	Description
	We do not mark firm-months in which a multi-firm insider sold two different stocks while purchasing a third stock in the same month. In a final step, we identify all firm-months in which at least one multi-firm insider sold a stock in one firm while purchasing at least one other stock in a different firm to obtain an aggregate firm-month data set, marking firm-months with sales by insiders who simultaneously made purchases as information-driven. (Go back to text)
(18) **Persistently profitable trades (PROF)** Cline et al. (2017)	Following Cline et al. (2017), we assume that insiders that have been persistently profitable with their past trades have exploited nonpublic information. Therefore, we consider future trades of "persistently profitable" insiders to be information-driven. An insider is considered "persistently profitable" if he or she has made two or more trades in the last 36 months, of which more than 50% have produced an abnormal performance, i.e., in the case of only two trades, both trades. The intuition is that the probability of an abnormal performance should be 0.5 (50%) if we assume no information-driven insider trading. Therefore, we regard an insider to be using nonpublic information if he or she has outperformed the market consistently, i.e., beyond what would be expected by pure chance (> 0.5). The abnormal performance measure is defined as the cumulative abnormal 6-month return following each trade. Consequently, when calculating the probability of abnormal performance for an insider, we do not consider trades made in the last 6 months. A purchase (sale) is considered to have an abnormal performance if the cumulative 6-month abnormal return is positive (negative). Abnormal return (AR) for each month is calculated as follows: $$AR_{i,t} = RET_{i,t} - MKT_t \times \hat{\beta}_{iMKT} - SMB_t \times \hat{\beta}_{iSMB} - HML_t \times \hat{\beta}_{iHML} - \hat{\alpha}_i, \quad \text{(A.12)}$$ where $RET_{i,t}$ is the stock return of stock i in month t, MKT_t is the return of the value-weighted market portfolio in month t, SMB_t is the return of the small minus big factor in month t, and HML_t is the return of the high minus low factor in month t, respectively.

Table A.3: (continued)

No.	Measure	Description
		$\hat{\beta}_{iMKT}$, $\hat{\beta}_{iSMB}$, $\hat{\beta}_{iHML}$, and $\hat{\alpha}_i$ are the historic betas and the historic alpha of stock i over the last 36 months estimated using a local Fama and French (1992) 3-factor model. We require at least 24 months of data for the regression. We winsorize all estimators at the 1%-level before calculating the abnormal return in Eq. (A.12). In a final step, we identify all firm-months in which at least one "persistently profitable" insider traded to obtain an aggregate firm-month data set, marking each firm-month with an information-driven insider purchase or sale.
		(Go back to text)

Table A.4: Descriptive statistics buy signal appearances

This table reports by country summary statistics for the appearances of the individual information-driven buy signals (16) used to construct the composite measure of information-driven trading (CID). We report the monthly average signal appearances and the total signal appearances (in parenthesis) over the entire sample period, respectively. Furthermore, we report the monthly average of unconditional buy signal appearances (Buys) and the total unconditional buy signal appearances (in parenthesis), respectively. Finally, we report the number of firms months used to calculate the respective buy signal appearances.

Country	**VOLD**	**ACC**	**PROF**	**IVOL**	**CFO**	**R&D**	**CONS**	**CLUS**	**ANA**	**SRMC**	**RMC**	**SSN**	**UNEX**	**SHOR**	**STRO**	**Q3**	**Buys**	**N**
Australia	1.7	10.87	13.63	24.73	1.11	4.84	45.23	25	23.93	19.18	20.55	1.83	3.32	3.17	65.82	3.73	121.75	228
	(388)	(2478)	(3108)	(5639)	(253)	(1103)	(10312)	(5699)	(5457)	(4372)	(4686)	(418)	(756)	(722)	(15006)	(850)	(27760)	
Belgium	0.51	0.41	1.53	1.74	0.6	0.3	3.6	1.46	2.68	1.17	1.86	1.2	0.42	0.39	4.37	0.39	8.67	189
	(96)	(77)	(289)	(329)	(114)	(57)	(681)	(276)	(506)	(222)	(352)	(227)	(80)	(73)	(825)	(74)	(1638)	
Brazil	1.07	3.44	6.48	4.26	0.02	0.37	9.04	3.06	4.75	3.75	3.42	6.5	4.96	4.99	10.19	5.2	21.16	203
	(217)	(698)	(1316)	(865)	(4)	(75)	(1835)	(622)	(965)	(761)	(695)	(1319)	(1006)	(1013)	(2068)	(1055)	(4296)	
Canada	36.83	21.07	73.68	116.28	28.41	11.04	113.88	95.23	94.57	33.26	60.46	46.29	34.69	39.82	231.67	31.67	414.07	228
	(8397)	(4803)	(16800)	(26512)	(6478)	(2517)	(25964)	(21713)	(21562)	(7583)	(13785)	(10555)	(7909)	(9078)	(52821)	(7220)	(94409)	
Chile	0.26	0.03	2.02	1.87	0.31	0	5.59	2.31	3.52	1.81	2.75	0.61	0.52	0.54	7.32	1.42	12.02	129
	(33)	(4)	(260)	(241)	(40)	(0)	(721)	(298)	(454)	(233)	(355)	(79)	(67)	(70)	(944)	(183)	(1550)	
China	4.39	8.62	9.11	13.28	4.85	11.86	39.02	18.07	18.82	21.06	17.98	11.09	6.49	5.88	46.1	5.53	87.77	192
	(843)	(1655)	(1750)	(2550)	(931)	(2278)	(7492)	(3470)	(3614)	(4043)	(3453)	(2130)	(1246)	(1129)	(8851)	(1062)	(16851)	
Denmark	1.01	0.93	1.57	2.62	1.22	0.77	7.01	3.97	3.26	2.18	2.59	0.91	0.27	0.24	7.48	0.25	13.73	179
	(180)	(166)	(281)	(469)	(218)	(137)	(1255)	(710)	(583)	(390)	(464)	(164)	(49)	(43)	(1339)	(45)	(2458)	
Egypt	0.03	0.02	3.39	2.75	0	0	8.96	2.83	3.67	3.37	3.27	0.87	1.58	1.15	9.28	1.98	17	120
	(3)	(2)	(407)	(330)	(0)	(0)	(1075)	(339)	(441)	(404)	(392)	(104)	(190)	(138)	(1114)	(238)	(2040)	
Finland	2.09	1.59	2.26	2.94	1.92	2.23	9.03	4.08	3.28	2.84	3.13	0.73	0.52	0.43	10.48	0.77	16.05	192
	(402)	(306)	(433)	(565)	(368)	(429)	(1734)	(783)	(629)	(545)	(600)	(141)	(100)	(83)	(2013)	(148)	(3082)	
France	3.49	4.87	7.41	8.59	0.95	2.26	19.94	5.36	10.94	7.01	8.59	4.34	2.05	2.37	21.99	3.05	42.99	204
	(712)	(994)	(1512)	(1753)	(194)	(461)	(4068)	(1094)	(2232)	(1431)	(1752)	(886)	(418)	(484)	(4486)	(623)	(8769)	
Germany	2.42	5.63	4.9	6.68	4.14	4.95	11.59	6.95	8.72	5.68	6.66	1.01	1.59	1.03	16.03	2.7	33.13	235
	(569)	(1324)	(1151)	(1570)	(973)	(1164)	(2723)	(1634)	(2050)	(1335)	(1564)	(237)	(373)	(241)	(3767)	(635)	(7786)	
Greece	0.31	3.4	6.97	5.74	0.42	2.01	16.77	4.92	6.38	3.6	4.69	1.76	2.88	3.08	17.59	3.95	26.32	197
	(62)	(669)	(1374)	(1130)	(82)	(395)	(3304)	(970)	(1257)	(710)	(923)	(346)	(568)	(606)	(3465)	(779)	(5186)	
Hong Kong	10.86	14.51	20.76	20.74	0.35	7.31	52.26	24.37	30.15	25.56	27.96	5.68	10.31	9.38	63.65	6.22	135.44	228
	(2475)	(3309)	(4733)	(4729)	(80)	(1666)	(11916)	(5556)	(6875)	(5827)	(6376)	(1295)	(2351)	(2139)	(14512)	(1419)	(30880)	
India	1.72	6.35	13.93	38.79	2.16	4.16	55.85	21.56	41.18	5.38	26.02	11.66	2.39	2.59	54.73	6.89	101.86	191
	(328)	(1213)	(2660)	(7409)	(412)	(794)	(10667)	(4118)	(7866)	(1027)	(4969)	(2227)	(456)	(495)	(10454)	(1316)	(19455)	
Indonesia	0.23	1.08	5.01	5.05	0.4	0.33	10.93	4.44	6.12	5.82	6.05	2.05	1.97	1.88	13.93	4.26	31.22	153
	(35)	(165)	(767)	(772)	(61)	(50)	(1673)	(679)	(936)	(890)	(925)	(316)	(302)	(288)	(2132)	(652)	(4777)	
Israel	0.23	0.1	2.39	3.55	0.35	0.49	8.66	2.96	3.25	2.6	2.82	2.25	0.83	0.66	10.04	2.35	17.99	220
	(51)	(23)	(526)	(781)	(78)	(108)	(1906)	(651)	(714)	(572)	(620)	(496)	(182)	(146)	(2208)	(516)	(3957)	
Italy	1.02	3.24	6.59	6.36	1.07	1.19	12.07	6.74	8.37	5.29	6.08	2.48	2.44	2.31	21.54	4.07	34.03	228
	(232)	(738)	(1502)	(1449)	(243)	(272)	(2751)	(1537)	(1909)	(1207)	(1386)	(565)	(556)	(527)	(4910)	(927)	(7758)	

Table A.4: (continued)

Country	VOLD	ACC	PROF	IVOL	CFO	R&D	CONS	CLUS	ANA	SRMC	RMC	SSN	UNEX	SHOR	STRO	Q3	Buys	N
Korea	1.56	9.02	17.97	20.03	0.64	14.88	38.7	19.64	25.15	20.29	22.03	6.92	4.51	3.89	59	7.61	122.12	264
	(412)	(2382)	(4745)	(5287)	(170)	(3929)	(10216)	(5186)	(6639)	(5357)	(5815)	(1826)	(1190)	(1026)	(15577)	(2008)	(32239)	
Malaysia	0.29	8.03	21.58	18.13	1	1.74	44.8	17.58	20.8	14.39	16.65	8.24	10.55	9.5	45.63	13.71	97.37	204
	(60)	(1638)	(4403)	(3698)	(203)	(354)	(9139)	(3586)	(4244)	(2935)	(3397)	(1680)	(2153)	(1939)	(9309)	(2797)	(19863)	
Netherlands	0.59	0.55	0.68	0.69	1.1	0.36	2.1	1.09	1.14	0.74	0.99	0.87	0.17	0.18	2.74	0.19	5.05	256
	(151)	(142)	(174)	(176)	(281)	(93)	(538)	(280)	(292)	(190)	(254)	(231)	(43)	(46)	(704)	(51)	(1292)	
Norway	3.02	2.64	2.27	5.39	3.06	1.2	12.34	7.43	7.28	4.95	5.85	0.56	0.51	0.38	16.19	1.11	29.11	204
	(617)	(538)	(463)	(1099)	(625)	(245)	(2517)	(1516)	(1485)	(1009)	(1193)	(115)	(104)	(77)	(3303)	(227)	(5938)	
Pakistan	0.08	0.06	2.76	4.49	0.75	0.37	2.69	3.44	5.22	3.3	3.99	0.84	0.4	0.45	11.19	1.45	19.8	108
	(9)	(7)	(298)	(485)	(81)	(40)	(290)	(371)	(564)	(356)	(431)	(91)	(43)	(49)	(1208)	(157)	(2138)	
Philippines	0.35	1.65	5.37	4.61	1.21	0.29	14.97	5.44	5.58	2.73	4.91	2.44	2.28	2.23	13.51	4.33	22.51	191
	(67)	(316)	(1025)	(881)	(231)	(56)	(2860)	(1039)	(1066)	(521)	(938)	(466)	(435)	(426)	(2580)	(827)	(4300)	
Poland	0.06	2.08	4.16	5.6	0.53	0.19	12.34	4.28	6.89	4.6	5.05	1.22	1.04	1.23	18.29	1.92	30.99	180
	(11)	(375)	(749)	(1008)	(96)	(35)	(2222)	(771)	(1240)	(828)	(909)	(219)	(188)	(221)	(3292)	(346)	(5578)	
Singapore	0.26	2.82	4.65	6.2	0.21	0.51	18.12	5.89	8.15	6.29	7.12	0.77	1	0.91	19.05	3.37	34.47	262
	(68)	(738)	(1218)	(1625)	(54)	(134)	(4747)	(1544)	(2134)	(1649)	(1865)	(202)	(263)	(239)	(4992)	(884)	(9030)	
South Africa	0.82	1.18	2.45	4.66	1.21	0.36	6.06	3.08	4.22	1.9	2.29	3.24	1.27	1.15	8.54	0.28	15.02	228
	(188)	(269)	(558)	(1063)	(275)	(82)	(1382)	(703)	(962)	(434)	(521)	(738)	(290)	(262)	(1948)	(63)	(3425)	
Spain	1.3	1.32	4.44	4.14	0.77	0.41	11.57	5.79	4.94	4.05	4.84	1.07	1.23	1.09	13.71	2.63	21.77	192
	(249)	(253)	(852)	(794)	(147)	(78)	(2222)	(1111)	(949)	(777)	(929)	(205)	(237)	(210)	(2632)	(504)	(4179)	
Sri Lanka	0	0.19	3.2	2.49	0.01	0.04	6.76	2.16	3.17	3.62	3.33	0.38	0.79	0.76	8.57	1.54	15.61	143
	(0)	(27)	(458)	(356)	(2)	(6)	(966)	(309)	(454)	(517)	(476)	(55)	(113)	(108)	(1225)	(220)	(2232)	
Sweden	7.04	5.5	10.54	18.03	6.56	3.45	33.31	22.55	17.54	12.91	15.08	2.34	2.88	3.08	52.88	2.99	80.86	216
	(1521)	(1189)	(2277)	(3895)	(1416)	(745)	(7196)	(4871)	(3789)	(2788)	(3258)	(506)	(622)	(665)	(11421)	(645)	(17466)	
Switzerland	0.79	0	5.7	3.94	0.05	1.61	9.97	1.79	5.06	2.63	3.11	4.56	3.02	3.85	8.3	1.66	18.01	199
	(157)	(0)	(1135)	(784)	(10)	(320)	(1984)	(357)	(1007)	(523)	(619)	(907)	(600)	(766)	(1652)	(331)	(3584)	
Thailand	0.17	5.38	11.77	10.16	1.07	0.01	16.27	9.66	12.27	8.77	9.34	4.35	6.59	6.5	28.4	8.92	52.99	264
	(45)	(1421)	(3108)	(2682)	(283)	(2)	(4295)	(2549)	(3238)	(2314)	(2467)	(1149)	(1740)	(1715)	(7498)	(2356)	(13990)	
Turkey	0.1	0.64	5.3	3.3	0.28	1.15	10.15	4.21	5.52	5.03	5.29	1.35	1.68	1.42	14.06	2.04	23.48	155
	(15)	(99)	(822)	(511)	(43)	(179)	(1573)	(653)	(856)	(779)	(820)	(209)	(261)	(220)	(2179)	(316)	(3640)	
U.K.	9.59	11.02	9.26	25.44	9.53	7.92	38.27	25.14	23.4	12.55	16.77	9.34	2.79	2.96	53.7	0.48	91.25	228
	(2187)	(2512)	(2112)	(5801)	(2173)	(1806)	(8725)	(5733)	(5336)	(2861)	(3823)	(2130)	(637)	(674)	(12243)	(109)	(20805)	
U.S.	78.53	22.91	69.08	119.95	40.44	24.8	183.61	99.05	118.87	49.93	86.35	305.54	24.96	21.99	208.93	24.63	387.32	228
	(17904)	(5223)	(15751)	(27349)	(9220)	(5654)	(41862)	(22584)	(27103)	(11384)	(19688)	(69664)	(5690)	(5014)	(47636)	(5616)	(88310)	
Total	5.08	4.74	10.67	15.39	3.43	3.34	26.22	13.87	16.14	9.07	12.29	13.39	4.20	4.16	35.14	4.80	64.79	201
	(38684)	(35753)	(79017)	(114587)	(25839)	(25264)	(192811)	(103312)	(119408)	(66774)	(90700)	(101898)	(31218)	(30932)	(260314)	(35199)	(480661)	6838

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Table A.5: Descriptive statistics sell signal appearances

This table reports by country summary statistics for the appearances of the individual information-driven sell signals (17) used to construct the composite measure of information-driven insider trading (CID). We report the monthly average signal appearances and the total signal appearances (in parenthesis) over the entire sample period, respectively. Furthermore, we report the monthly average of unconditional sell signal appearances (Sells) and the total unconditional sell signal appearances (in parenthesis), respectively. Finally, we report the number of firms months used to calculate the respective sell signal appearances.

Country	**VOLD**	**ACC**	**PROF**	**IVOL**	**MFS**	**R&D**	**CONS**	**CLUS**	**ANA**	**SRMC**	**RMC**	**LOSS**	**PPN**	**UNEX**	**SHOR**	**STRO**	**Q3**	**Sells**	**N**
Australia	1.13	2.39	5.01	5.31	0.67	1.5	13.76	3.85	7.36	9.27	8.54	10.81	9.99	3.28	2.69	15.18	0.96	31.17	228
	(258)	(546)	(1143)	(1210)	(152)	(341)	(3137)	(878)	(1679)	(2114)	(1947)	(2465)	(2277)	(747)	(614)	(3461)	(219)	(7107)	
Belgium	1.31	0.37	2.68	1.81	0.04	0.88	4.84	2.88	1.98	2.55	2.32	3.08	0.82	0.87	0.6	6.1	0.78	9.73	188
	(247)	(69)	(503)	(341)	(8)	(166)	(910)	(542)	(373)	(479)	(437)	(579)	(155)	(164)	(113)	(1146)	(147)	(1830)	
Brazil	1.43	3.85	8.95	4.84	0.05	0.43	10.88	4.99	5.17	6.33	6.65	11.52	3.74	7.97	7.63	12.58	7.53	28.23	203
	(291)	(782)	(1817)	(983)	(10)	(87)	(2209)	(1012)	(1049)	(1284)	(1349)	(2339)	(759)	(1617)	(1548)	(2553)	(1529)	(5730)	
Canada	68.43	16.26	97.82	64.47	16.62	7.05	104.83	96.5	70.99	57.2	65.46	128.49	58.81	50.8	43.45	198.21	29.44	311.95	228
	(15603)	(3708)	(22303)	(14699)	(3790)	(1608)	(23901)	(22002)	(16185)	(13042)	(14926)	(29295)	(13409)	(11583)	(9907)	(45192)	(6713)	(71124)	
Chile	0.43	0.02	1.28	1.21	0.16	0	2.34	1.48	1.3	1.62	1.63	3.14	1.34	0.51	0.34	4.36	0.95	6.57	125
	(54)	(3)	(160)	(151)	(20)	(0)	(292)	(185)	(163)	(202)	(204)	(393)	(171)	(64)	(43)	(545)	(119)	(821)	
China	4.15	9.12	17.47	29.69	2.23	22.14	40.67	36.93	27.25	22.77	23.91	38.43	7.01	7.87	6.96	73.35	10.16	136.88	192
	(797)	(1751)	(3354)	(5700)	(428)	(4251)	(7809)	(7091)	(5232)	(4371)	(4591)	(7378)	(1345)	(1511)	(1337)	(14083)	(1950)	(26280)	
Denmark	1.92	0.37	1.59	0.91	0.07	0.95	4.19	2	1.32	2.16	1.86	2.56	1.19	0.74	0.47	4.44	0.16	7.66	178
	(342)	(65)	(283)	(162)	(13)	(169)	(746)	(356)	(235)	(384)	(331)	(455)	(212)	(131)	(83)	(790)	(29)	(1364)	
Egypt	0.04	0.02	2.11	2.44	0.19	0	3.63	2.17	2.9	3.6	3.48	5.69	1.38	1.7	1.45	8.12	1.98	13.97	120
	(5)	(2)	(253)	(293)	-23	(0)	(435)	(260)	(348)	(432)	(418)	(683)	(166)	(204)	(174)	(974)	(237)	(1676)	
Finland	1.77	0.53	2.1	1.59	0.06	1.03	3.88	1.8	2.4	2.54	2.64	3.94	1.61	0.61	0.72	5.75	0.81	10.14	187
	(331)	(100)	(392)	(298)	(11)	(193)	(726)	(336)	(448)	(475)	(493)	(737)	(301)	(115)	(135)	(1075)	(152)	(1897)	
France	7.12	5.07	10.39	8.24	0.37	4.62	17.43	8.61	7.6	9.21	8.51	13.34	4	3.43	2.9	21.51	3.32	41.83	204
	(1452)	(1034)	(2119)	(1681)	(75)	(942)	(3556)	(1757)	(1551)	(1878)	(1736)	(2721)	(816)	(700)	(592)	(4388)	(678)	(8534)	
Germany	2.56	2.33	3.06	3.27	0.06	2.55	7.74	3.17	3.13	3.85	3.68	4.3	2.8	1.38	0.71	6.98	1.24	16.04	234
	(600)	(545)	(716)	(765)	(14)	(597)	(1811)	(742)	(732)	(901)	(860)	(1007)	(656)	(324)	(166)	(1634)	(291)	(3754)	
Greece	0.31	1.09	3.64	3.14	0.27	0.87	4.93	3.74	2.97	3.07	3.15	5.86	4.36	1.88	1.58	9.64	1.26	14.74	196
	(60)	(213)	(714)	(615)	(53)	(170)	(967)	(734)	(582)	(601)	(618)	(1149)	(860)	(369)	(309)	(1890)	(247)	(2889)	
Hong Kong	11.73	3.79	15.45	20.68	5.67	5.07	42.22	20.25	18.82	22.19	21.19	46.68	13.94	8.33	9.46	44.26	5.56	98.93	228
	(2675)	(864)	(3523)	(4715)	(1293)	(1156)	(9627)	(4616)	(4290)	(5059)	(4832)	(10644)	(3178)	(1899)	(2157)	(10092)	(1267)	(22555)	
India	7.9	4.18	20.97	31.48	1.64	4.17	30.04	41.15	31.69	13.2	30.68	40.01	7.64	3.91	3.4	84.07	10.25	104.67	192
	(1516)	(803)	(4027)	(6044)	(314)	(800)	(5767)	(7901)	(6085)	(2535)	(5891)	(7682)	(1466)	(751)	(653)	(16142)	(1968)	(20097)	
Indonesia	0.17	0.31	3.98	4.73	0.86	0.12	9.26	3.35	5.45	4.59	4.63	11.9	2.95	1.99	1.88	12.71	3.42	25.8	150
	(25)	(47)	(597)	(710)	(129)	(18)	(1389)	(502)	(817)	(688)	(695)	(1786)	(451)	(299)	(282)	(1907)	(513)	(3870)	
Israel	0.71	0.06	2.52	2.39	0.88	0.2	5.29	2.85	3.1	3.13	3.21	5.6	2.26	0.81	0.65	7.37	2.25	13.71	223
	(159)	(13)	(563)	(534)	(197)	(45)	(1180)	(636)	(692)	(697)	(716)	(1248)	(504)	(180)	(146)	(1644)	(502)	(3057)	
Italy	1.18	1.73	5.08	5.59	0.33	0.87	9.59	4.94	4.09	4.73	4.68	9.17	4.66	1.96	2.19	14.89	3.03	22.42	228
	(268)	(395)	(1158)	(1274)	(75)	(199)	(2186)	(1126)	(933)	(1078)	(1068)	(2091)	(1063)	(448)	(499)	(3395)	(690)	(5112)	

Table A.5: (continued)

Country	VOLD	ACC	PROF	IVOL	MFS	R&D	CONS	CLUS	ANA	SRMC	RMC	LOSS	PPN	UNEX	SHOR	STRO	Q3	Sells	N
Korea	1.69	2.69	11.91	22.55	1.11	8.3	34.93	13.95	18.92	16.14	17.31	37.73	13.93	4.22	4.15	44.17	5.16	91.18	264
	(446)	(709)	(3145)	(5954)	(292)	(2190)	(9222)	(3684)	(4996)	(4261)	(4569)	(9961)	(3678)	(1115)	(1095)	(11662)	(1361)	(24071)	
Malaysia	0.35	3.48	16.53	15.41	2.95	1.05	30.88	14.38	13.88	16.07	15.42	30.88	13.07	9.2	8.69	37.16	9.1	71.93	204
	(72)	(709)	(3372)	(3143)	(601)	(215)	(6299)	(2933)	(2832)	(3278)	(3145)	(6299)	(2666)	(1877)	(1773)	(7580)	(1856)	(14674)	
Netherlands	1.43	0.55	1.55	1.04	0	0.78	2.87	2.54	1.29	1.3	1.27	2.38	0.33	0.45	0.47	4.02	0.4	6.95	263
	(377)	(144)	(408)	(273)	(1)	(205)	(755)	(667)	(338)	(341)	(334)	(626)	(86)	(118)	(123)	(1057)	(106)	(1829)	
Norway	2.02	0.74	1.14	2.62	0.31	0.48	5.22	3.11	2.69	3.41	2.89	4.98	1.4	0.75	0.69	7.6	0.41	13.56	204
	(413)	(151)	(233)	(535)	(63)	(97)	(1064)	(635)	(548)	(695)	(589)	(1015)	(285)	(152)	(140)	(1550)	(84)	(2766)	
Pakistan	0.12	0.02	1.96	2.58	0.15	0.2	7.95	2.24	2.59	2.56	2.44	5.09	0.89	0.45	0.4	8.98	1.11	12.44	108
	(13)	(2)	(212)	(279)	(16)	(22)	(859)	(242)	(280)	(276)	(263)	(550)	(96)	(49)	(43)	(970)	(120)	(1343)	
Philippines	0.27	0.53	4.7	4.34	0.52	0.04	2.55	4.27	3.61	3.49	3.57	7.05	3.02	2.06	2.16	11.44	2.94	17.05	191
	(52)	(102)	(897)	(829)	(100)	(8)	(487)	(816)	(690)	(667)	(682)	(1347)	(576)	(393)	(412)	(2185)	(561)	(3257)	
Poland	0.28	0.78	2.75	3.77	0.24	0.07	5.78	2.43	3.33	4.82	4.63	8.37	2.52	1.17	0.79	10.61	1.14	18.35	180
	(50)	(141)	(495)	(679)	(44)	(13)	(1041)	(438)	(600)	(868)	(834)	(1506)	(454)	(211)	(143)	(1909)	(206)	(3303)	
Singapore	0.38	0.3	1.93	3.21	0.71	0.24	3.9	2.13	2.29	3.43	2.97	6.35	3.25	1.17	1.04	8.31	1.37	14.51	262
	(99)	(79)	(505)	(841)	(186)	(63)	(1021)	(559)	(600)	(899)	(777)	(1665)	(851)	(307)	(272)	(2177)	(360)	(3802)	
South Africa	2.71	1.32	5.55	3.57	0.11	1.02	11.76	9.07	4.69	5.43	5.53	7.69	1.22	2.02	2.07	12.85	0.44	23.25	228
	(617)	(300)	(1265)	(814)	(26)	(232)	(2682)	(2069)	(1069)	(1237)	(1260)	(1753)	(279)	(460)	(472)	(2929)	(100)	(5301)	
Spain	0.9	0.29	2.2	2.32	0.17	0.14	3.06	1.38	2.3	2.52	2.11	4.95	2.84	1.05	1.05	5.29	1.35	10.53	192
	(173)	(55)	(422)	(445)	(33)	(27)	(588)	(264)	(442)	(484)	(406)	(950)	(546)	(202)	(202)	(1016)	(260)	(2022)	
Sri Lanka	0.01	0.04	0.96	1.11	0.4	0.01	1.68	0.55	0.96	1.09	0.87	2.31	1.74	0.55	0.5	2.87	0.3	5.56	141
	(1)	(6)	(135)	(157)	(57)	(2)	(237)	(77)	(136)	(154)	(123)	(326)	(253)	(77)	(70)	(405)	(42)	(784)	
Sweden	5.93	1.55	6.12	7.79	1.03	1.27	15.25	7.48	9.75	7.36	8.63	14.49	6.74	3.54	3.32	22.75	1.3	39.25	216
	(1280)	(335)	(1322)	(1682)	(223)	(274)	(3295)	(1615)	(2107)	(1589)	(1865)	(3129)	(1455)	(764)	(717)	(4913)	(280)	(8479)	
Switzerland	3.97	0	10.41	4.35	0	5.27	13.41	3.06	4.47	6.29	6.1	7.94	2.24	6.31	5.42	12.16	1.83	25.42	202
	(802)	(0)	(2102)	(878)	(0)	(1064)	(2708)	(618)	(902)	(1271)	(1233)	(1603)	(453)	(1274)	(1094)	(2457)	(369)	(5134)	
Thailand	0.29	1.87	8.91	8.17	0.51	0.05	18.42	9.13	8.12	8.97	8.61	14.7	6.82	5.79	5.66	22.82	7.41	42.19	264
	(76)	(494)	(2352)	(2158)	(134)	(14)	(4863)	(2409)	(2143)	(2367)	(2274)	(3881)	(1801)	(1529)	(1493)	(6025)	(1957)	(11139)	
Turkey	0.1	0.32	3.16	4.38	0.68	0.64	6.71	2.89	3.13	3.9	3.73	8.01	2.57	1.24	1.46	10.91	1.79	18.44	156
	(16)	(50)	(493)	(683)	(106)	(100)	(1047)	(451)	(489)	(609)	(582)	(1250)	(401)	(193)	(227)	(1702)	(280)	(2876)	
U.K.	19.73	7.35	17.75	9.63	0.49	6.32	33.57	27.57	13.35	17.76	16.36	23.43	5.19	8.68	8.2	43.66	1.25	72.7	228
	(4498)	(1676)	(4048)	(2195)	(112)	(1441)	(7654)	(6287)	(3043)	(4050)	(3729)	(5343)	(1183)	(1979)	(1870)	(9955)	(285)	(16576)	
U.S.	466.57	152.34	514.45	245.72	8.8	151.85	556.26	696.04	249.33	261.56	265.42	481.25	40.65	118.39	106.61	768.97	203.45	1292.1	228
	(106377)	(34734)	(117294)	(56025)	(2006)	(34622)	(126827)	(158697)	(56847)	(59635)	(60516)	(109725)	(9269)	(26994)	(24308)	(175326)	(46386)	(294599)	
Total	18.21	6.64	24.00	15.72	1.42	6.77	31.46	30.67	15.95	15.83	16.59	29.77	6.97	7.80	7.05	46.00	9.53	78.53	201
	(140045)	(50627)	(182325)	(117745)	(10605)	(51331)	(237297)	(233137)	(119456)	(118901)	(124293)	(223581)	(52121)	(58800)	(53212)	(344729)	(71864)	(589652)	6835

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Table A.6: $CID - UNC$ performance differences country-level

This table reports the performance differences between the insider trading strategy based on the composite measure (CID) of information-driven trades and the unconditional (UNC) insider trading strategy by country. We report monthly value- and equal-weighted raw returns and CH4 factor alphas for the long-short, long, and short portfolios, respectively. Furthermore, we report the number of months (N) with a valid difference, i.e., a non-missing return/alpha for both the composite and unconditional strategy. Finally, we report the total positive and negative significant performance differences. Statistical significance at the five-percent level is needed to be counted as a significant performance difference. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Country	**Long-Short**					**Long**					**Short**				
	Raw returns		**CH4 α**			**Raw returns**		**CH4 α**			**Raw returns**		**CH4 α**		
	vw	**ew**	**vw**	**ew**	**N**	**vw**	**ew**	**vw**	**ew**	**N**	**vw**	**ew**	**vw**	**ew**	**N**
Australia	0.168	0.594***	0.107	0.394**	227	0.294	0.259**	0.147	0.242**	227	0.126	-0.334**	0.039	-0.152	227
	(0.70)	(3.41)	(0.45)	(2.31)		(1.36)	(2.37)	(0.68)	(2.23)		(1.06)	(-2.23)	(0.34)	(-1.04)	
Belgium	0.172	0.258	0.120	0.276	157	0.424	0.429**	0.487*	0.491***	164	0.148	0.074	0.209	0.091	178
	(0.56)	(1.45)	(0.39)	(1.57)		(1.47)	(2.28)	(1.72)	(2.70)		(0.89)	(0.75)	(1.30)	(0.91)	
Brazil	0.467**	0.227	0.505**	0.320	194	0.188	-0.009	0.194	0.019	197	-0.285**	-0.244	-0.305**	-0.297*	200
	(2.26)	(0.88)	(2.48)	(1.26)		(1.04)	(-0.06)	(1.07)	(0.13)		(-2.18)	(-1.37)	(-2.37)	(-1.69)	
Canada	0.161	0.554***	0.135	0.54***	227	0.093	0.348***	0.059	0.340***	227	-0.068*	-0.207***	-0.076**	-0.200***	227
	(1.03)	(5.68)	(0.94)	(5.61)		(0.61)	(4.24)	(0.41)	(4.16)		(-1.94)	(-3.10)	(-2.19)	(-3.06)	
Chile	0.390	-0.200	0.311	-0.086	87	0.366	-0.002	0.300	-0.027	116	-0.151	0.047	-0.193	-0.065	90
	(1.61)	(-0.62)	(1.26)	(-0.27)		(1.34)	(-0.01)	(1.14)	(-0.12)		(-0.71)	(0.18)	(-0.89)	(-0.25)	
China	-0.024	-0.135	0.000	-0.049	190	-0.355**	-0.193	-0.359**	-0.106	191	-0.278	-0.047	-0.301	-0.045	190
	(-0.08)	(-0.91)	(0.00)	(-0.36)		(-2.22)	(-1.39)	(-2.25)	(-0.83)		(-0.91)	(-0.46)	(-1.03)	(-0.45)	
Denmark	-0.014	0.057	0.445	0.274	134	-0.077	0.149	0.297	0.228	154	0.200	0.207	0.091	0.038	146
	(-0.04)	(0.31)	(1.15)	(1.48)		(-0.22)	(0.91)	(0.86)	(1.37)		(1.46)	(1.64)	(0.68)	(0.31)	
Egypt	0.256	-0.153	0.237	0.047	114	0.264	0.144	0.408*	0.251	115	0.020	0.307	0.176	0.234	115
	(0.90)	(-0.43)	(0.86)	(0.14)		(0.88)	(0.52)	(1.76)	(0.95)		(0.06)	(1.17)	(0.69)	(0.93)	
Finland	0.195	0.099	0.240	0.160	161	0.247	-0.030	0.269	0.004	174	0.222	-0.074	0.243	-0.111	167
	(0.60)	(0.65)	(0.77)	(1.10)		(0.88)	(-0.25)	(1.01)	(0.04)		(1.04)	(-0.54)	(1.17)	(-0.83)	
France	-0.285	0.191**	-0.342*	0.184**	203	-0.102	0.081	-0.116	0.095	203	0.182*	-0.110**	0.226**	-0.088	203
	(-1.41)	(2.20)	(-1.71)	(2.12)		(-0.59)	(1.12)	(-0.67)	(1.33)		(1.89)	(-1.97)	(2.38)	(-1.60)	
Germany	0.026	0.183	-0.136	0.067	228	0.085	0.095	0.114	0.065	233	0.064	-0.095	0.252*	-0.012	228
	(0.10)	(1.29)	(-0.52)	(0.49)		(0.42)	(0.98)	(0.57)	(0.71)		(0.45)	(-0.84)	(1.69)	(-0.11)	
Greece	1.379***	0.46*	1.194**	0.444	162	0.492	0.304	0.639*	0.342*	178	-0.621*	-0.031	-0.651*	-0.046	165
	(2.79)	(1.67)	(2.41)	(1.60)		(1.15)	(1.55)	(1.69)	(1.71)		(-1.79)	(-0.18)	(-1.90)	(-0.27)	
Hong Kong	-0.005	0.235*	-0.044	0.214*	224	-0.077	0.072	-0.116	0.040	224	-0.072	-0.163*	-0.071	-0.175*	224
	(-0.04)	(1.92)	(-0.33)	(1.78)		(-0.63)	(0.81)	(-0.95)	(0.47)		(-1.03)	(-1.80)	(-1.03)	(-1.95)	
India	0.157	0.283**	0.095	0.216**	180	0.112	0.121	0.081	0.095	180	-0.043	-0.171**	0.026	-0.118*	182
	(0.54)	(2.57)	(0.34)	(2.05)		(0.40)	(1.28)	(0.30)	(1.03)		(-0.76)	(-2.59)	(0.42)	(-1.77)	
Indonesia	0.147	-0.589	-0.057	-0.903**	118	0.344	-0.585*	0.291	-0.873***	120	0.221	-0.076	0.324*	0.069	132
	(0.56)	(-1.32)	(-0.21)	(-2.01)		(1.49)	(-1.74)	(1.23)	(-2.72)		(1.27)	(-0.22)	(1.82)	(0.20)	
Israel	0.092	0.142	0.135	0.089	169	0.168	-0.002	0.149	-0.068	179	0.143	-0.044	0.180	0.080	185
	(0.42)	(0.65)	(0.61)	(0.42)		(0.82)	(-0.01)	(0.73)	(-0.37)		(1.26)	(-0.21)	(1.59)	(0.41)	

Table A.6: (continued)

Country	Long-Short					Long					Short				
	Raw returns		CH4 α			Raw returns		CH4 α			Raw returns		CH4 α		
	vw	ew	vw	ew	N	vw	ew	vw	ew	N	vw	ew	vw	ew	N
Italy	0.269	0.164	0.114	0.115	223	0.197	0.118	0.090	0.123	227	-0.038	-0.028	0.022	0.022	223
	(1.53)	(1.42)	(0.67)	(1.00)		(1.33)	(1.29)	(0.63)	(1.34)		(-0.35)	(-0.35)	(0.20)	(0.28)	
Malaysia	0.373***	0.450***	0.318**	0.388***	203	0.189	0.097	0.238**	0.078	203	-0.183**	-0.353***	-0.080	-0.310***	203
	(2.90)	(4.45)	(2.48)	(3.90)		(1.56)	(1.33)	(2.00)	(1.10)		(-2.46)	(-4.44)	(-1.22)	(-3.96)	
Netherlands	(0.10)	-0.444*	-0.089	-0.50**	121	0.079	-0.284	-0.012	-0.310	144	0.066	-0.002	0.099	0.007	209
	(0.25)	(-1.87)	(-0.22)	(-2.13)		(0.20)	(-1.24)	(-0.03)	(-1.36)		(0.40)	(-0.02)	(0.60)	(0.05)	
Norway	0.66***	0.296	0.694***	0.287	198	0.312*	0.295**	0.235	0.209	203	-0.372**	0.001	-0.490***	-0.083	198
	(2.75)	(1.24)	(2.92)	(1.26)		(1.71)	(2.22)	(1.31)	(1.60)		(-2.00)	(0.01)	(-2.70)	(-0.41)	
Pakistan	0.349	-0.152	0.201	-0.078	99	0.212	0.136	0.066	0.169	102	-0.173	0.214	-0.203	0.230	103
	(0.93)	(-0.49)	(0.55)	(-0.25)		(0.60)	(0.45)	(0.19)	(0.56)		(-0.95)	(1.25)	(-1.12)	(1.36)	
Philippines	0.247	0.149	0.235	0.169	179	0.175	0.071	0.153	0.040	185	-0.037	-0.090	-0.044	-0.156	184
	(1.17)	(0.72)	(1.12)	(0.82)		(1.16)	(0.53)	(1.02)	(0.30)		(-0.21)	(-0.51)	(-0.25)	(-0.89)	
Poland	0.300	0.299	0.39*	0.544*	174	0.083	-0.080	0.185	0.020	174	-0.243**	-0.405*	-0.219**	-0.538**	177
	(1.27)	(0.88)	(1.67)	(1.68)		(0.34)	(-0.33)	(0.77)	(0.09)		(-2.17)	(-1.72)	(-1.99)	(-2.35)	
Singapore	0.247	0.286	0.071	0.473*	251	-0.003	-0.228	0.039	-0.248*	257	-0.180	-0.506**	-0.062	-0.758***	254
	(1.05)	(1.14)	(0.31)	(1.88)		(-0.01)	(-1.63)	(0.22)	(-1.81)		(-1.19)	(-2.08)	(-0.41)	(-3.17)	
South Africa	-0.164	-0.036	-0.169	-0.024	193	0.074	0.020	0.059	-0.018	194	0.130	0.021	0.148	-0.011	221
	(-0.54)	(-0.24)	(-0.56)	(-0.15)		(0.26)	(0.15)	(0.21)	(-0.13)		(1.17)	(0.27)	(1.36)	(-0.14)	
South Korea	0.577***	0.499***	0.495**	0.362**	261	0.465**	0.261**	0.332	0.188	261	-0.006	-0.191	0.004	-0.099	262
	(2.67)	(3.02)	(2.30)	(2.22)		(2.38)	(2.09)	(1.59)	(1.45)		(-0.03)	(-1.43)	(0.03)	(-0.76)	
Spain	0.664**	0.734***	0.439*	0.655***	180	0.119	0.203**	0.116	0.180*	190	-0.486*	-0.506***	-0.306	-0.469***	181
	(2.44)	(4.27)	(1.75)	(4.10)		(0.86)	(2.13)	(0.86)	(1.90)		(-1.93)	(-3.09)	(-1.38)	(-3.08)	
Sri Lanka	0.094	0.430	0.445	0.578	82	0.415	0.318	0.297	0.175	130	0.049	-0.142	-0.063	-0.208	83
	(0.35)	(0.97)	(1.61)	(1.35)		(1.14)	(0.97)	(0.83)	(0.53)		(0.22)	(-0.44)	(-0.32)	(-0.66)	
Sweden	0.066	0.393***	0.084	0.364***	215	0.223*	0.104	0.274**	0.105	215	0.157	-0.288***	0.190	-0.258***	215
	(0.39)	(3.61)	(0.50)	(3.38)		(1.74)	(1.51)	(2.17)	(1.53)		(1.26)	(-3.12)	(1.53)	(-2.82)	
Switzerland	-0.184	-0.037	-0.138	-0.058	191	-0.147	-0.080	-0.111	-0.106	191	0.032	-0.046	0.010	-0.047	197
	(-0.88)	(-0.41)	(-0.67)	(-0.65)		(-0.75)	(-0.98)	(-0.58)	(-1.31)		(0.47)	(-0.99)	(0.15)	(-1.02)	
Thailand	0.313	0.465***	0.169	0.372***	262	0.229	0.173	0.277	0.208*	263	-0.060	-0.298***	0.180	-0.178*	262
	(1.47)	(3.61)	(0.81)	(3.06)		(1.17)	(1.52)	(1.47)	(1.89)		(-0.45)	(-3.22)	(1.40)	(-1.95)	
Turkey	0.354	0.463	0.310	0.552	149	0.315	-0.221	0.253	-0.095	149	-0.039	-0.680*	-0.042	-0.671**	150
	(1.05)	(1.13)	(0.93)	(1.37)		(1.18)	(-0.83)	(0.95)	(-0.41)		(-0.17)	(-1.91)	(-0.18)	(-2.03)	
U.K.	0.432**	0.160**	0.472**	0.147**	227	0.305	0.12*	0.333*	0.105*	227	-0.127**	-0.040	-0.139**	-0.042	227
	(2.08)	(2.20)	(2.36)	(2.07)		(1.51)	(1.95)	(1.72)	(1.74)		(-2.20)	(-0.95)	(-2.42)	(-1.02)	
U.S.	0.166	0.227***	0.121	0.264***	227	0.146	0.194***	0.104	0.224***	227	-0.020	-0.033**	-0.017	-0.040**	227
	(1.13)	(3.69)	(0.86)	(4.41)		(0.99)	(3.15)	(0.74)	(3.74)		(-1.53)	(-1.96)	(-1.36)	(-2.44)	
Total>0 [Sig.]	28 [7]	26 [11]	26 [6]	27 [11]		28 [1]	23 [7]	29 [2]	25 [4]		14 [0]	7 [0]	17 [1]	8 [0]	
Total<0 [Sig.]	6 [0]	8 [0]	8 [0]	7 [2]		6 [1]	11 [0]	5 [1]	9 [1]		20 [5]	27 [10]	17 [5]	26 [8]	

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Table A.7: $CID - UNC$ performance differences raw returns

This table reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations for monthly rebalanced insider trading strategies based on the unconditional trade (UNC) signals and based on the composite measure (CID) of information-driven trade signals. We report monthly value- and equal-weighted raw returns (see, Table 4 for alphas) for the long-short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report the differences between the unconditional and informative raw returns, a test for significant differences, and the number of months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: Long-Short							
	***UNC* raw returns**		***CID* raw returns**		***CID − UNC***		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
			Pooled				
DM	-0.017	0.803***	0.253	1.042***	0.262***	0.258***	227
	(-0.15)	(5.68)	(1.55)	(6.50)	(3.11)	(7.85)	
EM	0.370**	0.941***	0.644**	1.318***	0.263**	0.383***	227
	(1.98)	(7.36)	(2.47)	(9.17)	(1.97)	(5.34)	
			Country-neutral				
DM	0.267	0.822***	0.405	1.085***	0.138**	0.264***	227
	(0.83)	(3.52)	(1.05)	(3.66)	(2.24)	(6.39)	
EM	0.535	1.024***	0.946*	1.249***	0.411***	0.226**	227
	(1.29)	(3.46)	(1.63)	(3.20)	(4.30)	(2.20)	
Panel B: Long							
	***UNC* raw returns**		***CID* raw returns**		***CID − UNC***		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
			Pooled				
DM	0.908***	1.917***	1.156***	2.084***	0.238***	0.175***	227
	(2.68)	(4.48)	(3.20)	(4.89)	(2.97)	(5.55)	
EM	1.609***	2.060***	1.741***	2.161***	0.138	0.111**	227
	(3.46)	(4.78)	(3.56)	(5.06)	(1.30)	(2.23)	
			Country-neutral				
DM	1.160**	1.646***	1.287**	1.769***	0.127**	0.124***	227
	(2.05)	(2.87)	(2.10)	(2.89)	(2.41)	(3.78)	
EM	1.520*	2.169***	1.795*	2.137**	0.274***	-0.032	227
	(1.71)	(2.84)	(1.89)	(2.75)	(3.46)	(-0.39)	
Panel C: Short							
	***UNC* raw returns**		***CID* raw returns**		***CID − UNC***		
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**N**
			Pooled				
DM	0.925***	1.114***	0.902***	1.042***	-0.024	-0.083***	227
	(3.28)	(3.01)	(3.24)	(2.85)	(-1.34)	(-3.72)	
EM	1.239***	1.119***	1.097***	0.843**	-0.125	-0.272***	227
	(3.00)	(2.62)	(2.71)	(2.02)	(-1.42)	(-4.16)	
			Country-neutral				
DM	0.879	0.831	0.866	0.692	-0.013	-0.139***	227
	(1.74)	(1.34)	(1.71)	(1.08)	(0.31)	(-3.41)	
EM	1.023	1.188	0.864	0.946	-0.159**	-0.241***	227
	(1.01)	(1.22)	(0.72)	(0.81)	(-2.39)	(-3.71)	

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Table A.8: Longer holding periods for *UNC* strategy

This table reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of the unconditional (*UNC*) monthly rebalanced insider trading strategies for different holding periods. We still rebalance the portfolios monthly but keep the stocks longer, i.e., 1 to 12 months, in the respective portfolios. We report monthly value- and equal-weighted CH4 factor alphas for the long-short portfolios. Furthermore, we report the number of available months (N) with a valid portfolio. The reported t-statistics (in parentheses) are robust to heteroskedasticity. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

***UNC* CH4 α (Long-Short)**											
	1 month		**2 months**		**3 months**		**6 months**		**12 months**		**N**
	vw	**ew**	**vw**	**ew**	**vw**	**ew**	**vw**	**ew**	**vw**	**ew**	
					Pooled						
DM	-0.082	0.754***	-0.111	0.589***	-0.124*	0.522***	-0.077	0.367***	-0.063*	0.286***	227
	(-0.96)	(4.18)	(-1.54)	(3.88)	(-1.90)	(3.81)	(-1.61)	(3.42)	(-1.91)	(3.34)	
EM	0.429**	1.032***	0.320***	0.969***	0.291***	0.822***	0.115	0.555***	0.080*	0.417***	227
	(2.39)	(7.02)	(2.85)	(7.43)	(2.93)	(6.73)	(1.51)	(6.35)	(1.68)	(5.95)	
					Country-neutral						
DM	0.338	0.861***	0.229	0.652***	0.158	0.592***	0.086	0.406***	0.046	0.302***	227
	(0.98)	(3.61)	(0.90)	(3.47)	(0.67)	(3.64)	(0.61)	(3.37)	(0.29)	(2.96)	
EM	0.510	1.021***	0.279	0.770***	0.201	0.676***	0.133	0.526***	0.072	0.379***	227
	(1.28)	(3.45)	(0.89)	(3.33)	(0.95)	(3.37)	(0.85)	(3.09)	(0.64)	(2.79)	

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Table A.9: Return predictability in emerging vs. developed markets

This table lists papers published in the Financial Times Top 50 Journal List that examine abnormal return predictability in numerous countries, thus allowing for a comparison of anomalies between developed markets and emerging markets. As our focus is on market (in)efficiency, papers with a focus on return predictors widely interpreted as risk premia are not considered. Note that not all of the studies pursue the goal of directly comparing the efficiency of developed markets and emerging markets. In many cases, the comparison is indirect, arising as a "byproduct" of a different research question. In this respect, the results and the estimation of the differences often leave room for interpretation. The last column shows our interpretation of the respective findings.

Study	**Cross-sectional anomaly / Return predictive factor**	**Results**
Barber et al. (2013)	Earnings announcement premium anomaly	Return predictability in DM>EM
Bartram and Grinblatt (2021)	Composite predictor	Return predictability in DM<EM
Cai et al. (2022)	Composite predictor	Return predictability in DM>=EM
Cakici and Zaremba (2022)	Salience theory anomaly	Return predictability in DM<=EM
Cheon and Lee (2018)	Lottery anomaly	Return predictability in DM>EM
Chui et al. (2010)	Momentum anomaly	Return predictability in DM>EM
Dou et al. (2016)	Post-earnings-announcement drift anomaly	Return predictability in DM>=EM
Gao et al. (2018)	Financial distress anomaly	Return predictability in DM>EM
Goyal and Wahal (2015)	Intermediate horizon return anomaly	Return predictability in DM>EM
Griffin et al. (2003)	Momentum anomaly	Return predictability in DM>EM
Griffin et al. (2010)	Several anomalies / proxies for mispricing	Return predictability in DM≈EM
Jacobs (2016)	Composite predictor	Return predictability in DM>=EM
Han et al. (2015)	Idiosyncratic volatility anomaly	Return predictability in DM>=EM
Hollstein (2022)	Large number of anomalies	Return predictability in DM<=EM
Hou et al. (2011)	Several anomalies	Return predictability in DM≈EM
Hou et al. (2022)	R&D intensity anomaly	Return predictability in DM≈EM
Hung et al. (2015)	Post-earnings-announcement drift anomaly	Return predictability in DM≈EM
Jensen et al. (2023)	Large number of anomalies	Return predictability in DM≈EM
Kaniel et al. (2012)	High volume anomaly	Return predictability in DM>=EM
Li et al. (2023)	Large number of anomalies	Return predictability in DM>=EM
Manconi et al. (2019)	Buyback anomaly	Return predictability in DM<=EM
Mclean et al. (2009)	Share issuance anomaly	Return predictability in DM>EM
Pincus et al. (2007)	Accruals anomaly	Return predictability in DM>EM
Titman et al. (2013)	Asset growth anomaly	Return predictability in DM>EM
Hou and van Dijk (2019)	Size anomaly	Return predictability in DM<EM
Watanabe et al. (2013)	Asset growth anomaly	Return predictability in DM>EM

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Table A.10: Descriptive statistics: Cross-country variables

This table reports summary statistics for the cross-country variables (see, cross-country analysis in Table 8 and Table A.11) for a set of 34 countries. The columns report static values for the non-changing cross-country variables and time-series averages for the monthly, quarterly or yearly time-varying cross-country variables, respectively. A detailed description of the variables is provided in Table A.12. Additionally, we report variable averages (standard deviations), the variable averages (standard deviations) for developed and emerging markets, and their differences.

Country	**AS**	**CLASSA**	**BLACKOUT**	**ITR**	**DEV**
Australia	0.76	1	0.57	5.59	1
Belgium	0.54	0	0.35	5.41	1
Brazil	0.27	1	0.08	3.72	0
Canada	0.64	1	0.27	5.55	1
Chile	0.63	0	0.11	4.16	0
China	0.76	0	0.15	3.45	0
Denmark	0.46	0	0.57	6.00	1
Egypt	0.20	0	0.16	3.77	0
Finland	0.46	0	0.36	5.53	1
France	0.38	0	0.18	5.17	1
Germany	0.28	0	0.21	5.24	1
Greece	0.22	0	0.16	3.41	1
Hong Kong	0.96	0	0.34	3.94	1
India	0.58	1	0.18	3.53	0
Indonesia	0.65	0	-0.03	3.56	0
Israel	0.73	1	0.27	4.39	1
Italy	0.42	1	0.15	4.38	1
Korea	0.47	0	0.02	4.10	0
Malaysia	0.95	1	0.32	3.42	0
Netherlands	0.20	1	0.32	5.20	1
Norway	0.42	0	0.28	4.24	1
Pakistan	0.41	1	-0.03	-	0
Philippines	0.22	0	0.06	3.48	0
Poland	0.29	0	0.28	3.88	0
Singapore	1.00	0	0.20	5.58	1
South Africa	0.81	0	0.73	3.74	0
Spain	0.37	1	0.13	4.68	1
Sri Lanka	0.39	0	0.24	-	-
Sweden	0.33	0	0.41	5.58	1
Switzerland	0.27	0	0.29	4.67	1
Thailand	0.81	0	0.17	3.29	0
Turkey	0.43	0	0.02	3.58	0
U.K.	0.95	1	0.66	5.85	1
U.S.	0.65	1	0.28	5.64	1
Avg. (SD)	0.53 (0.24)	0.35 (0.49)	0.25 (0.18)	4.49 (1.38)	0.58 (0.50)
Avg. DM (SD)	0.53 (0.25)	0.42 (0.51)	0.32 (0.15)	5.06 (0.71)	1.00 (0.00)
Avg. EM (SD)	0.52 (0.24)	0.27 (0.46)	0.16 (0.19)	3.67 (1.31)	0.00 (0.00)
Diff. DM-EM	0.004	0.15	0.15	1.39	

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Table A.11: Cross-country analysis long and short leg

This table reports the results of the cross-country regressions examining the relation between various proxies for insider trading restrictions and the potential benefits of the unconditional (UNC) and composite information-driven (CID) insider trading strategies. The dependent variables are the equal- and value-weighted long and short within-country alphas of the 34 countries from the CH4 factor regressions in Tables 2 and 3, respectively. Panel A and Panel C report the regression results for the long and short unconditional (UNC) strategies, respectively. Panel B and Panel D report the regression results for the long and short composite (CID) strategies, respectively. The explanatory variables are the time series averages (if time varying) of various insider trading restriction proxies, including an anti self-dealing (AS) index, a class action dummy (CLASSA), blackout periods (BLACKOUT), an insider trading restriction index (ITR), and a developed-market dummy (DEV). All explanatory variables are described in detail in Table A.12 of the Appendix. The actually variables values are report in Table A.10 of Appendix. The t-statistics reported in parentheses are computed using robust standard errors. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: UNC (Long)																
	Value-weighted								**Equal-weighted**							
AS	-0.376**					-0.365	-0.473*	-0.479*	-0.113					-0.001	-0.114	-0.157
	(-2.12)					(-1.69)	(-1.89)	(-1.80)	(-0.48)					(-0.004)	(-0.40)	(-0.54)
CLASSA		-0.055				-0.026	-0.019	-0.016		0.185				0.203	0.255*	0.272**
		(-0.55)				(-0.27)	(-0.18)	(-0.16)		(1.43)				(1.62)	(2.02)	(2.32)
BLACKOUT			-0.190			-0.011	0.366	0.369			-0.623**			-0.662*	-0.329	-0.312
			(-0.65)			(-0.03)	(0.90)	(0.89)			(-2.12)			(-1.92)	(-0.76)	(-0.75)
ITR				-0.094*			-0.125*	-0.11				-0.154**			-0.144	-0.037
				(-1.76)			(-1.83)	(-1.26)				(-2.05)			(-1.66)	(-0.24)
DEV					-0.131			-0.036					-0.290**			-0.256
					(-1.16)			(-0.21)					(-2.28)			(-0.93)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.086	0.007	0.012	0.073	0.046	0.088	0.199	0.20	0.005	0.054	0.086	0.122	0.141	0.151	0.234	0.275
Panel B: CID (Long)																
	Value-weighted								**Equal-weighted**							
AS	-0.442*					-0.427	-0.537*	-0.547*	-0.271					-0.253	-0.339	-0.352
	(-1.80)					(-1.53)	(-1.74)	(-1.72)	(-0.87)					(-0.64)	(-0.81)	(-0.85)
CLASSA		-0.17				-0.139	-0.128	-0.124		0.252				0.283	0.315*	0.321*
		(-1.61)				(-1.27)	(-1.12)	(-1.07)		(1.52)				(1.65)	(1.81)	(1.83)
BLACKOUT			-0.123			0.106	0.503	0.507			-0.466			-0.400	-0.093	-0.088
			(-0.55)			(0.35)	(1.40)	(1.38)			(-1.16)			(-0.88)	(-0.16)	(-0.15)
ITR				-0.100			-0.133*	-0.107				-0.100			-0.118	-0.085
				(-1.58)			(-1.89)	(-0.82)				(-0.96)			(-1.10)	(-0.40)
DEV					-0.145			-0.062					-0.155			-0.08
					(-1.17)			(-0.26)					(-0.90)			(-0.23)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.099	0.058	0.004	0.066	0.045	0.14	0.247	0.251	0.019	0.064	0.031	0.033	0.025	0.116	0.14	0.142

Table A.11: (continued)

Panel C: *UNC* (Short)

	Value-weighted								Equal-weighted							
AS	0.312					0.226	0.133	0.179	0.441*					0.360	0.243	0.231
	(1.43)					(0.92)	(0.60)	(0.95)	(1.92)					(1.46)	(0.85)	(0.76)
CLASSA		0.131				0.108	0.068	0.049		0.243*				0.213	0.245*	0.250*
		(1.22)				(0.98)	(0.64)	(0.44)		(1.79)				(1.67)	(1.82)	(1.99)
BLACKOUT			0.324			0.195	0.492	0.474			0.266			0.054	0.438	0.443
			(1.16)			(0.63)	(1.35)	(1.44)			(0.84)			(0.16)	(0.88)	(0.85)
ITR				-0.012			-0.072	-0.187*				-0.071			-0.145*	-0.114
				(-0.18)			(-1.07)	(-1.72)				(-0.98)			(-1.72)	(-1.07)
DEV					0.072			0.276					-0.118			-0.074
					(0.60)			(1.36)					(-0.77)			(-0.31)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.046	0.032	0.027	0.001	0.012	0.076	0.097	0.165	0.068	0.082	0.014	0.024	0.021	0.131	0.187	0.19

Panel D: *CID* (Short)

	Value-weighted								Equal-weighted							
AS	0.387*					0.293	0.258	0.280	0.323					0.175	0.049	0.043
	(1.73)					(1.17)	(1.00)	(1.08)	(1.14)					(0.55)	(0.18)	(0.15)
CLASSA		-0.002				-0.036	-0.095	-0.104		0.246				0.224	0.221	0.223
		(-0.02)				(-0.28)	(-0.71)	(-0.77)		(1.59)				(1.46)	(1.43)	(1.54)
BLACKOUT			0.530			0.398	0.427	0.419			0.420			0.294	0.841	0.843
			(1.64)			(1.08)	(1.05)	(1.03)			(0.95)			(0.59)	(1.45)	(1.43)
ITR				0.058			0.020	-0.034				-0.053			-0.164**	-0.149
				(0.87)			(0.31)	(-0.27)				(-0.60)			(-2.11)	(-1.37)
DEV					0.113			0.131					-0.098			-0.036
					(0.81)			(0.53)					(-0.56)			(-0.16)
N	34	34	34	32	33	34	32	32	34	34	34	32	33	34	32	32
R^2	0.053	0	0.056	0.017	0.021	0.082	0.097	0.107	0.028	0.064	0.026	0.01	0.011	0.092	0.149	0.15

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Table A.12: Further variable definitions

This table reports detailed variable descriptions for the cross-country variables used in the analysis of Table 8 and Table A.11. The respective values of the cross-country variables are reported in Table A.10.

Variable	**Description**
Developed market dummy (DEV)	The developed market dummy (DEV) is equal to one for developed markets and zero (emerging markets) otherwise. The data is obtained from the MSCI market classification which is updated at the end of June each year. For the cross-country analysis of Table 8, we use the time series average of the developed market dummy. For countries that have a change in their classification over time (time series average unequal to 0 or 1), countries are only considered to be a developed country if the time series average of the MSCI classification indicates the developed status for more than 50% of the sample period (time series average greater than 0.5). Developed stock markets are considered to be more informationally efficient. This country-specific variable is frequently used in cross-country financial studies, see, e.g., Titman et al. (2013), Watanabe et al. (2013).
Anti self dealing (AS)	The anti self-dealing (AS) index is a survey-based measure of legal protection of minority shareholders against expropriation, i.e., ex ante and ex post restrictions on controlling shareholders' self-dealing, by corporate insiders developed in the seminal study of Djankov et al. (2008). The index ranges from 0 (weak control of self-dealing transactions) to 1 (strong control). The data is obtained from Andrei Shleifer's institutional homepage. For the cross-country analysis of Table 8, we argue that these legal protections against self-dealing can be used as a general proxy for insider trading restrictions or higher corporate governance standards. The intuition is that the more laws are in place to protect minority shareholders, the more difficult it will generally be for corporate insiders to profitably exploit private information advantages. This interpretation is in line with the *monitoring hypothesis* which argues that insider trading regulations or better corporate governance prevents insiders from rent extraction consequently leading to lower returns after insider trading in countries with higher insider regulations or better corporate governance. For a discussion and an overview of the variety of proposed explanations (hypotheses) of the prospective relation between insider trading regulations/corporate governance and the informativeness of insider trades, see Fidrmuc et al. (2013).

Table A.12: (continued)

Variable	Description
	Previous studies (e.g., Fidrmuc et al. 2013, Gebka et al. 2017) have used the anti self-dealing index in a similar rationale as a proxy for shareholder protection/corporate governance quality. This country-specific variable is frequently used in cross-country financial studies, see, e.g., Watanabe et al. (2013), Fidrmuc et al. (2013), Gebka et al. (2017), Brochet (2019).
Class action lawsuits (CLASSA)	The class action dummy is equal to one if class action lawsuits are possible against illegal corporate insider trading and zero otherwise. The data is obtained from Leuz (2010) and updated according to Brochet (2019). For the cross-country analysis of Table 8, we argue that these potential lawsuits can be used as a general proxy for insider trading restrictions or higher corporate governance standards. The intuition is that the litigation risk corporate insiders have to face will restrain corporate insiders more from opportunistic insider trading (e.g., Cheng et al. 2016) in countries where class action lawsuits are possible. This interpretation is in line with the *monitoring hypothesis*. This country-specific variable is used in a similar rationale in Brochet (2019) to construct a governance transparency score.
Blackout periods (BLACKOUT)	We calculate blackout periods (BLACKOUT) following Brochet (2019) as the difference between the percentage of insider trades that occur within one month after a quarterly earnings announcement (QEA) and the month before, aggregated by country quarter. We identify the QEA dates for each firm through the Worldscope variables WC05901, WC05902, WC05903, and WC05904. We exclude all firm years with a missing fiscal year end date (WC0350), and all QEA dates that are dated before or more than one year after the fiscal quarter end date. The blackout period measure ranges from -1 (only trades before the earnings announcement in a given quarter = low insider trading restrictions) to 1 (only trades after the earnings announcement in a given quarter = high insider trading restrictions). The intuition is that if insiders must wait until after the earnings announcements to trade because they are not allowed or restricted to trade shortly before the announcement, it becomes less likely that the information advantage still remains after the announcement. For the cross-country analysis of Table 8, we therefore use the extent of timing restrictions on corporate insider trades (Blackout periods) as a proxy for insider trading restrictions or higher corporate governance standards.

Table A.12: (continued)

Variable	Description
	This interpretation is in line with the *monitoring hypothesis*. This country-specific variable is used in a similar rationale in Hong et al. (2019).
Insider trading restriction index (ITR)	The insider trading restriction index (ITR) following Denis and Xu (2013), measures the "perceived" degree of insider trading restrictions through a global survey on corporate officers. The data is obtained from Denis and Xu (2013) Appendix B. The intuition is that insider trading is more restricted in countries in which top executives, i.e., corporate officers, themselves view insider trading not to be common in the respective domestic market. Therefore, larger values of the ITR indicate a more restrictive insider trading environment, as insider trading is not common in this case. This interpretation is in line with the *monitoring hypothesis*. This country-specific variable is used in a similar rationale in Brochet (2019) to construct an investor protection factor.

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