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Synthesizing Information-Driven Insider Trade Signals

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Abstract

We propose a novel approach to synthesize presumably information-driven insider trading signals for the cross section of stocks. We find that the resulting straightforward composite strategy can often forecast returns in a global sample. This predictability is strongest in equal-weighted portfolios, short holding periods, and insider-buying signals, and it improves further with global diversification. Cross-country analysis reveals that varying insider trading restrictions between countries have limited explanatory power for the performance of the composite strategy. Overall, the results are consistent with a short-term informational advantage of insiders, which might be due to the skillful interpretation of non-private news.

I. Introduction

Corporate insiders may buy or sell their firms' 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

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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.

Existing work has mostly focused on individual signals to separate informative trades from noise. 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, Jiang, and Koch (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, Larcker, and Taylor (2011), Ben-David, Kim, Moussawi, and Roulstone (2023)) are more difficult to value, thus potentially resulting in higher insider trading profits. Nevertheless, due to the focus on individual signals and, furthermore, on the U.S. market, the literature remains partially fragmented. Several questions on how markets incorporate information from corporate insiders have not yet been conclusively resolved. How can these numerous economically plausible and conceptually diverse trading signals be integrated into a unified framework? How successful are such composite, information-based approaches? What additional insights can be gained from a global analysis? What are the economic determinants of the performance of information-driven insider trading? As outlined subsequently, our analysis aims to contribute to a more nuanced understanding of these issues.

Specifically, our first contribution to the literature is to propose straightforward and intuitive composite measures and to study their benefits and limitations. We test and largely confirm the hypothesis that the signal-to-noise ratio for information-driven trades can be improved if we synthesize many individual measures (see Section III.A 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. 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), and Malliouris, Vermorken, and Vermorken (2022)). In contrast, we composite individual cross-sectional methods to identify information-driven trades with the goal of predicting abnormal performance in the cross section of (international) stocks.

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

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

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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, Korczak, and Korczak (2013), Gebka, Korczak, Korczak, and Traczykowski (2017), Brochet (2019), and Hong, Li, and Zhu (2019), they have a different focus. Exceptions include Giamouridis, Liodakis, and Moniz (2008) and Dardas (2012), who employ multivariate regression models with firm and insider characteristics to identify "high conviction" insider trades in the United Kingdom and Western Europe, respectively. Our third contribution is to analyze the potential channels behind the performance of the composite approaches, in part by making use of cross-country heterogeneity.

The baseline composition approach, which we later benchmark against more complex methods, is straightforward. In each firm-month, we count how many of the presumably information-driven buy proxies are observed and subtract the number of observable sell signals.[3] If the resulting difference 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, that is, we assume a one-month holding period. In the 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 sample size and portfolio diversification). We find that this heuristic often has predictive power for both raw and abnormal returns. The predictability is particularly driven by small firms, that is, concentrated in equal-weighted portfolios, and by signals derived from insider buying, that is, concentrated in the long leg.

In equal-weighted portfolios, the one-month Fama and French (2018) 6-factor alphas[4] reach at least 1% for aggregations of both developed and emerging markets, which is also statistically significant at the 1% level. This finding applies regardless of whether the aggregation is based on firm-months, which favors large markets, or country-months, which favors small markets. In value-weighted portfolios, the corresponding results are considerably weaker at 0.23% to 0.79%. However, 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. Relative

[2]See, e.g., Bhattacharya and Daouk (2002), Bushman, Piotroski, and Smith (2005), and Fernandes and Ferreira (2009) on international differences in insider trading regulation and enforcement; Akbari, Ng, and Solnik (2020) on economic and financial international market integration; Griffin, Kelly, and Nardari (2010), Brockman, Chung, and Pérignon (2009), and Bris, Goetzmann, and Zhu (2007) for global differences in transaction costs, liquidity, and short-selling, respectively.

[3]Regarding the assumed mechanism, this approach has some parallels to Engelberg, McLean, and Pontiff (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.

[4]We use the country-specific or regional Fama and French (2018) 6-factor model to control for insiders' potentially contrarian trading behavior by incorporating the momentum factor from Jegadeesh and Titman (1993). The contrarian investment behavior of insiders has widely been documented; see, e.g., Lakonishok and Lee (2001), Jenter (2005), and Piotroski and Roulstone (2005).

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to this unconditional insider trading strategy, the outperformance of the composite approach is often in the range of 3% to 4% per year. Overall, these results illustrate the benefits of synthesizing individual trade signals, but they also reveal the limits of cross-sectional return predictability.

Further analyses show that more complex approaches to synthesize the individual trading signals do not lead to an overall improvement in performance. For roughly comparable average portfolio sizes, established machine learning methods perform mostly similarly to the baseline composition approach outlined previously. The machine learning approaches, in which no method emerges as the clear winner in a relative comparison, have more difficulties in predicting alphas in emerging markets. This lack of empirical superiority further justifies using the straightforward, economically intuitive baseline composition approach for the further analyses outlined subsequently.

What explains the performance of the composite measure? Given the elusive and likely multifaceted nature of insider trading, 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 utilizing public (or at least non-private) but typically locally limited information better than the market does. This line of reasoning is broadly consistent with findings in, for example, Kolasinski and Li (2010), Veenman (2013), Alldredge and Cicero (2015), Lambe, Li, and Qin (2022), or Contreras, Fidrmuc, and Kozhan (2026). Several results are in line with this assessment.

First, abnormal returns decrease considerably with longer time horizons. For example, at 6-month (as opposed to 1-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. Nevertheless, this short-term advantage does not appear to be related to earnings announcements, as trades in other months tend to yield at least similarly high alphas.

Second, this view is further supported by the strategy's implementability from an outsider's perspective. In the monthly baseline analysis, we rely on the actual trading date because our focus is on testing whether insiders have and exploit an information advantage. Switching to the outsider perspective, that is, conditioning only on signals arising from trades that have been reported before the end of the month, tends to decrease returns only slightly. In general, the results point to the importance 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 disclosure delays and short holding periods.

Third, we generally find considerably stronger risk-adjusted performance for regional strategies than for the more mixed country-level strategies. This pattern can be explained by international diversification benefits, as both the unconditional and composite strategies exhibit relatively low correlations between countries. This finding suggests that insiders likely leverage firm-specific, country-specific, or other forms of more locally limited information as opposed to (global) market-wide information for their profitable trades.

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Fourth, while the composite strategy tends to be stronger in aggregated emerging markets than in developed markets, the relative benefits, that is, 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, Daouk, Jorgenson, and Kehr (2000), Griffin, Hirschey, and Kelly (2011)) are not a main driver of the performance of the composite measure.

Fifth, a further cross-country analysis shows that country characteristics that proxy for insider trading restrictions and corporate governance have limited explanatory power for country differences in the performance of the composite measure. In particular, the composite measure provides only weak evidence for the monitoring hypothesis, which posits that insider trading regulations or stronger corporate governance prevent insiders from extracting rents, in contrast to the unconditional strategy, which is broadly consistent with it. These findings again indicate that better interpretation of public information, as opposed to opportunistic trading on private information, may be a driver of the composite results. Hence, they are consistent with the notion that insider trading can potentially improve price informativeness (see, e.g., Leland (1992), Bernhardt, Hollifield, and Hughson (1995), and Kacperczyk and Pagnotta (2024)).

The remainder of the article is organized as follows: Section II describes the data and Section III the methodology. Section IV provides the baseline results. Section V explores the statistical and economic mechanisms behind the findings. Section VI concludes.

II. Data

We use insider transactions data obtained from 2iQ Research, a company specialized in monitoring and analyzing 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 and 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 that can be identified as a private transaction either through their exchange or transaction label. We also exclude transactions if the transaction price is not within a 20% range of the daily closing price and if the trading volume exceeds the exchange volume for the day. To focus on more informative transactions, we also exclude all routine trades, following the trade-level approach of Cohen, Malloy, and Pomorski (2012). 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.

TABLE 1

Summary Statistics

Table 1 reports summary statistics for insider trades by country/region after applying the screens outlined in Section II. We report the respective start date, the total number of insider trades (purchases/sales in 1,000), 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 1,000 of U.S. dollars, respectively. Finally, we report the median reporting lag in days.

		Insider Trades ('000)					Insiders per Firm		Trades per Firm		Trades per Insider/ Firm		Mktcap (US$, '000000)		Value (US$, '000)		Rep. Lag
Country/Region	Start	Total	Buy	Sell	Firms	Insiders	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	14.5	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
United Kingdom	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
United States	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	4,964.0	1,135.6	3,506.8	152.2	1
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

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TABLE 1 (continued)

Summary Statistics

		Insider Trades ('000)					Insiders per Firm		Trades per Firm		Trades per Insider/ Firm		Mktcap (US$, '000000)		Value (US$, '000)		Rep. Lag
Country/Region	Start	Total	Buy	Sell	Firms	Insiders	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Median
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	13.0	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	2,610.4	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. United States	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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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.

We restrict the sample 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. A detailed description of all screens is provided in Table OA.2 of the Supplementary Material. The final sample consists of 34 countries and close to 40,000 stocks 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. The average number of trades per firm ranges between 27.65 and 185.82. Table OA.1 of the Supplementary Material reports the different insider relations (categories) and their distribution.

We use stock market and accounting data from Refinitiv Datastream and Worldscope. We apply comprehensive static and dynamic data cleaning procedures largely based on Landis and Skouras (2021), Ince and Porter (2006), Griffin et al. (2010), Lee (2011), and Karolyi, Lee, and van Dijk (2012), among others. Details are given in the stock market data screens Section OB in the Supplementary Material. Returns are calculated in USD. Table 1 provides descriptive statistics for the 18 developed and 16 emerging market countries (based on the MSCI classification) in the final sample. We use data from RavenPack News Analytics (see RavenPack-mapping Section OC in the Supplementary Material) to construct a few insider trading signals that take company-specific news into account. As asset pricing models, we either use the self-constructed country-specific Fama and French (2018) 6-factor model or the regional versions from Kenneth French's data library.

III. Methodology

A. Individual Measures of Information-Driven Insider Trading

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 but to provide a sufficiently wide range of individual measures for the construction of a meaningful composite. In this context, some signals suggested in the U.S.-based literature cannot be implemented appropriately in our global setting due to lack of sufficient data availability.[5] In addition, the individual signals must be consistent in

[5]Examples include Mansi, Peng, Qi, and Shi (2025), Gao, Ma, Ng, and Wu (2022), Hsieh, Ng, and Wang (2023), Ravina and Sapienza (2010), Fidrmuc, Goergen, and Renneboog (2006), El Ghoul, Guedhami, Nash, and Wang (2022), Massa, Qian, Xu, and Zhang (2015), Alldredge and Blank (2024), Liu (2016), Chung, Goh, Lee, and Shevlin (2019), Joseph and Wintoki (2013), Jiang, Wintoki, and Xi (2021), Inci, Narayanan, and Seyhun (2017), Jiang, John, Kim, and Zhang (2025), and Hillier, Korczak, and Korczak (2015), who rely on retail investor attention, shareholder litigation risk, analyst recommendations (downgrades), governance, ownership concentration, economic policy uncertainty,

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terms of their temporal availability to enter the resulting composite measure with a holding period of 1 month. The baseline composite measure always assumes that in 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. The 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 trades that occur 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 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, we focus more on investigating the existence of insiders' short-term informational advantages rather than the actual real-time implementability (see Section V.D).

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 particularly profitable trades shortly before quarterly earnings announcements (QEAs) 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 rationale to insider trades with greater market impact, that is, 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, that is, discontinuing to purchase (PPN) or sell (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, Shin, and Francis (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

short-selling, multinationals, corruption culture, corporate tax aggressiveness, advertising investments, legal expertise, gender, narcissism, and other personal attributes of corporate executives, respectively.

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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. (2023)): We assume that higher stock-level idiosyncratic volatility leads to higher information asymmetries regarding future developments or to more pronounced mispricing, both of which increase the likelihood of information-driven insider trades (IVOL).
- "Clustered trades" (Alldredge and Blank (2019)): We assume that insider trades in the same 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 suggests that the same (shared) 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, Parwada, and Zhang (2015), Sun, Dutta, Huang, and Zhu (2021), and Kyung and Nam (2023)): 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, that is, 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 more difficult for insiders to speculate on negative news when these are incorporated in the accounting numbers in a timely manner, that is, in times of high conditional accounting conservatism. Therefore, we regard sales of insiders as more likely to be information-driven if the company has low conditional conservatism. 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 (CONS).
- "Multiple firm insider sales" (Karamanou, Pownall, and Prakash (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).

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- "Persistently profitable trades" (Cline, Gokkaya, and Liu (2017)): We assume that insiders with persistently high abnormal returns might exploit information (PROF).

Following economic logic, we interpret sell (buy) transactions as a negative (positive) signal for future performance. We provide a detailed description of the implementation of all information-driven trade measures adapted to our global sample in Table OA.4 of the Supplementary Material. Tables OA.5 and OA.6 of the Supplementary Material provide descriptive statistics for the appearance of each information-driven buy and sell signal across countries, respectively.

B. Composite Measures of Information-Driven Insider Trading

The likelihood that information about a stock's future performance can reliably be drawn from insider trades presumably increases with the number of trade signals. In addition, 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 based on a total of 16 buy measures and 17 sell measures:

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

where $BuySignal_{j,i,t}$ is a dummy variable equal to 1 if any information-driven insider buy occurred in firm i during month t according to the individual information-driven buy measure j, $SellSignal_{k,i,t}$ is a dummy variable equal to 1 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 the 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 three information-driven buy signals and no more than one information-driven sell signal occurred in that month.

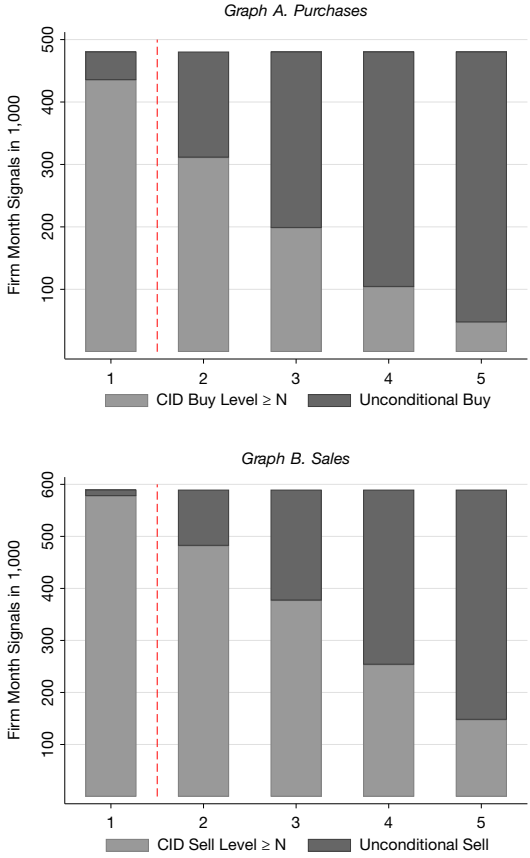
To better understand the operation of CID in equation (1), Figure 1 illustrates how many trade signals are generated in the pooled country data set depending on the surplus requirements ($N \geq 1,2,3,4,5$) of an information-driven insider trading signal. Graphs A and B clearly show that, for both purchase and sale signals, the absolute threshold of 1, that is, an excess of one purchase ($N \geq 1$) or sale ($N \leq -1$) signal, does not lead to a meaningful signal reduction compared to the number of unconditional signals. As surplus requirements increase, correspondingly clearer signals, that is, larger absolute surpluses of individual information-driven purchase or sale signals, are generated. However, a clearer signal also substantially decreases the sample size. Considering this trade-off, we use a CID greater than or equal to

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FIGURE 1

Composite Firm-Month Signals

Figure 1 shows the total number of firm-month signals over the sample period from 2000 to 2021 for the pooled country sample. We show unconditional trade firm-month signals, that is, all months in which at least one insider traded. Furthermore, we report composite firm-month signals greater than or equal to ($N \geq$) 1, 2, 3, 4, 5, respectively. A composite firm-month signal (see equation (1)) greater than or equal to 2 shows the number of firm-month with a surplus, that is, absolute value of individual information-driven purchases—individual information-driven sale firm-month signals being greater than or equal to 2 ($N \geq 2$). Graphs A and B show purchases and sales, respectively. We only consider firm-month signals with a minimum absolute surplus of 2 as information-driven (the area to the right of the dashed red line).



2 (CID^2) as the baseline approach. This choice is also motivated by the heterogeneous appearance of individual information-driven signals both across measures and across countries (see Tables OA.5 and OA.6 of the Supplementary Material). As such, a *CID* greater than or equal to 2 prevents the composite signal from being driven by the more prevalent individual information-driven purchase or sale signals. Consequently, combinations of less common signals can also generate a valid composite information-driven signal, thus enabling the use of the full breadth of individual measures. 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 surplus requirements (N) greater than or equal to 3 (CID^3) and 4 (CID^4) in Section V.A.

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IV. Baseline Results

A. Unconditional Insider Trading

We start by analyzing unconditional (for brevity henceforth *UNC*) insider trades as a benchmark. More precisely, 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 $t-1$. The *UNC* strategy considers 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 $t-1$.

Table 2 shows the raw and abnormal returns (6-factor alphas following Fama and French (2018), henceforth FF6 alphas) of the *UNC* strategy as well as the performance of the long and short legs separately for each country. The t-statistics are Newey and West (1987) adjusted.[6]

Only eight (eight) countries exhibit significantly positive value-weighted raw (abnormal) returns, respectively. The only countries whose raw and abnormal returns are both significantly greater than 0 at the 5% level are France, Germany, Malaysia, Poland, South Korea, Spain, and Turkey. The results are substantially stronger for equal-weighted *UNC* portfolios, where 26 (raw) and 28 (abnormal) of the *UNC* equal-weighted long–short returns are positively significant at the 5% level, respectively. The only countries that exhibit insignificant equal-weighted abnormal returns are Denmark, Egypt, Finland, Indonesia, Israel, and the Philippines. In general, the return dispersion is large, both across value-weighted and equal-weighted strategies.

Almost all long legs have positive raw returns and alphas. The performance is especially strong among equal-weighted *UNC* portfolios, where almost all alphas are statistically significantly positive. The patterns in the short leg are less pronounced. The returns and alphas tend to be more dispersed, but they are statistically insignificant in the majority of cases.

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.

B. Composite Measures of Information-Driven Insider Trading

We use the composite approach developed in Section III.B to identify information-driven insider trades. Following the same timing and portfolio construction as described in Section IV.A 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

[6]We use the following formula to calculate the optimal number of lags (L) for the Newey and West (1987), (1994) adjustment: $L = \lfloor 4\left(\frac{N}{100}\right)^{2/9} \rfloor$, where N is the reported monthly sample length in the respective tables for each country or region.

TABLE 2

Unconditional Performance

Table 2 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- (VW) and equal-weighted (EW) raw returns and FF6 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 number of firms (*F*) in each respective portfolio. Finally, we report the total positive and negative significant performances. A performance is counted as significant if it is significant at the 5% level. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
Australia	0.165	0.973***	0.444	0.995***	227	152	1.056**	2.199***	0.328*	1.213***	227	121	0.891	1.226	−0.116	0.218	227	31
	(0.59)	(3.43)	(1.39)	(3.49)			(2.01)	(2.71)	(1.68)	(5.73)			(1.60)	(1.62)	(−0.53)	(0.72)		
Belgium	−0.657	0.850***	−0.210	1.020***	172	19	0.325	0.802	0.257	0.583*	179	8	0.958*	−0.006	0.255	−0.543***	180	10
	(−1.25)	(3.35)	(−0.38)	(3.88)			(0.38)	(1.32)	(0.54)	(1.81)			(1.80)	(−0.01)	(0.84)	(−2.76)		
Brazil	0.476	1.134***	0.314	1.029***	203	49	1.510*	2.352***	0.509*	1.515***	203	21	1.034	1.218	0.195	0.486**	203	28
	(1.41)	(4.04)	(1.03)	(3.43)			(1.83)	(2.60)	(1.77)	(5.76)			(1.42)	(1.46)	(0.96)	(2.44)		
Canada	0.214	1.350***	0.207	1.379***	227	722	0.992**	2.604***	0.045	1.847***	227	412	0.778*	1.255*	−0.162***	0.467***	227	309
	(1.49)	(6.62)	(1.37)	(7.28)			(2.05)	(3.22)	(0.30)	(9.49)			(1.82)	(1.75)	(−2.64)	(2.98)		
Chile	0.046	0.680*	0.049	1.044**	106	19	−0.255	0.210	0.064	0.737**	121	12	−0.104	−0.237	0.181	−0.091	106	7
	(0.11)	(1.74)	(0.09)	(2.03)			(−0.40)	(0.29)	(0.28)	(2.42)			(−0.14)	(−0.27)	(0.39)	(−0.20)		
China	−0.296	0.492***	−0.330	0.539***	191	223	1.224	2.129**	0.214*	0.670***	191	87	1.520*	1.638**	0.545**	0.131	191	136
	(−1.15)	(2.61)	(−1.43)	(3.23)			(1.61)	(2.56)	(1.75)	(3.97)			(1.72)	(2.00)	(2.51)	(0.70)		
Denmark	−0.581	0.032	−0.024	0.419	155	22	0.361	0.468	−0.143	0.182	172	14	1.183**	0.514	0.199	−0.154	160	8
	(−1.31)	(0.10)	(−0.05)	(1.09)			(0.53)	(0.75)	(−0.39)	(0.73)			(2.42)	(1.00)	(0.67)	(−0.43)		
Egypt	0.284	0.518	0.305	0.854*	117	30	0.463	1.138	0.317	0.671**	117	16	0.179	0.619	0.011	−0.182	117	13
	(0.53)	(1.00)	(0.58)	(1.93)			(0.67)	(1.39)	(0.87)	(2.32)			(0.23)	(0.67)	(0.03)	(−0.49)		
Finland	−0.016	0.238	0.288	0.371	176	27	0.793	1.141**	0.228	0.528***	185	16	0.700	0.842	−0.138	0.135	176	10
	(−0.04)	(0.83)	(0.58)	(1.22)			(1.37)	(2.00)	(0.75)	(2.90)			(1.35)	(1.43)	(−0.40)	(0.50)		
France	0.656**	1.103***	0.734***	1.036***	203	84	1.175**	1.284**	0.532***	0.630***	203	42	0.519	0.181	−0.202	−0.405***	203	41
	(2.51)	(5.76)	(3.15)	(5.61)			(2.39)	(2.50)	(2.67)	(4.18)			(1.20)	(0.35)	(−1.43)	(−3.40)		
Germany	0.886**	1.306***	1.266**	1.303***	232	49	1.393***	1.898***	0.522**	1.033***	233	33	0.520	0.604	−0.741*	−0.258	232	16
	(2.16)	(4.72)	(2.38)	(4.05)			(2.88)	(3.56)	(2.23)	(5.07)			(0.89)	(1.15)	(−1.76)	(−0.88)		
Greece	0.277	1.501***	0.223	1.354***	178	42	0.438	1.505*	0.429	1.414***	183	27	−0.218	−0.318	0.256	0.021	179	15
	(0.48)	(3.04)	(0.36)	(2.66)			(0.39)	(1.83)	(1.11)	(3.95)			(−0.20)	(−0.35)	(0.50)	(0.05)		

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TABLE 2 (continued)

Unconditional Performance

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
Hong Kong	−0.335*	0.599***	−0.299	0.520***	224	236	1.003*	1.241**	0.225	0.602***	225	136	1.326**	0.669	0.508**	0.092	224	100
	(−1.72)	(3.11)	(−1.52)	(2.66)			(1.90)	(1.98)	(1.32)	(5.31)			(2.51)	(0.97)	(2.44)	(0.45)		
India	0.183	1.099***	0.128	1.040***	182	211	1.073	2.263**	0.031	1.172***	183	105	1.297*	1.520*	0.244	0.385*	187	106
	(0.79)	(5.35)	(0.60)	(5.40)			(1.33)	(2.39)	(0.11)	(5.69)			(1.85)	(1.77)	(1.18)	(1.82)		
Indonesia	0.749	0.688	0.562	0.974*	138	59	1.675**	2.320***	0.442	1.241***	145	32	0.987*	1.625**	−0.018	0.327	142	26
	(1.24)	(1.37)	(0.97)	(1.74)			(2.14)	(3.13)	(1.17)	(3.30)			(1.75)	(2.36)	(−0.05)	(0.66)		
Israel	−0.155	0.033	−0.051	0.178	209	32	1.386**	1.917***	0.443	0.909***	211	18	1.522***	1.840***	0.476	0.713**	215	13
	(−0.68)	(0.16)	(−0.22)	(0.74)			(2.19)	(3.27)	(1.46)	(3.49)			(2.64)	(3.11)	(1.50)	(2.45)		
Italy	0.097	1.212***	0.126	1.226***	226	56	0.567	1.142**	0.062	0.752***	227	33	0.488	−0.044	−0.068	−0.470**	226	22
	(0.36)	(5.34)	(0.43)	(4.40)			(1.08)	(2.13)	(0.33)	(4.62)			(0.94)	(−0.08)	(−0.30)	(−1.97)		
Malaysia	0.499**	0.533***	0.569**	0.623***	203	168	0.985*	1.527***	0.396**	1.051***	203	96	0.485	0.995*	−0.173	0.428**	203	71
	(2.52)	(3.34)	(2.35)	(4.09)			(1.92)	(2.89)	(2.20)	(6.98)			(1.08)	(1.81)	(−1.33)	(2.42)		
Netherlands	0.161	1.172***	−0.017	1.032***	185	13	1.276*	1.251*	0.715**	0.889***	199	6	0.992*	0.495	0.181	−0.201	243	7
	(0.33)	(2.70)	(−0.04)	(2.66)			(1.92)	(1.93)	(2.02)	(3.05)			(1.95)	(0.98)	(0.42)	(−0.67)		
Norway	0.736**	0.502	0.607	0.777**	201	42	0.978	1.083	0.234	0.548**	203	28	0.146	0.542	−0.388	−0.220	201	13
	(2.20)	(1.33)	(1.63)	(2.00)			(1.52)	(1.58)	(1.15)	(2.41)			(0.21)	(0.73)	(−1.27)	(−0.58)		
Pakistan	0.208	1.184***	0.131	1.013**	105	32	1.054	2.034**	0.411	1.024***	106	19	0.737	0.787	0.242	−0.022	106	12
	(0.58)	(3.08)	(0.34)	(2.43)			(1.37)	(2.18)	(1.20)	(3.73)			(1.06)	(0.85)	(0.75)	(−0.07)		
Philippines	0.371	0.690*	0.387	0.609	188	39	1.391**	2.177***	0.438**	1.123***	190	22	0.948*	1.414**	0.005	0.440	188	17
	(1.10)	(1.76)	(1.19)	(1.54)			(2.46)	(3.30)	(2.33)	(4.97)			(1.77)	(2.28)	(0.02)	(1.37)		
Poland	1.492***	0.986**	1.771***	1.100**	177	49	1.504*	1.966**	1.474***	2.063***	177	31	0.012	0.980	−0.297	0.963**	177	18
	(2.99)	(2.10)	(3.18)	(2.53)			(1.89)	(2.04)	(4.66)	(5.95)			(0.01)	(0.99)	(−0.79)	(2.09)		
Singapore	0.677*	0.693**	0.575	0.640**	259	48	0.952**	1.252**	0.318	0.942***	261	34	0.391	0.601	−0.033	0.394	259	14
	(1.87)	(2.44)	(1.49)	(1.99)			(2.04)	(2.18)	(0.93)	(3.67)			(0.64)	(0.90)	(−0.10)	(1.04)		
South Africa	0.436	0.740**	0.715**	0.978**	221	38	1.588**	1.765***	0.716***	0.929**	222	15	1.169**	1.019*	0.022	−0.027	226	23
	(1.28)	(2.38)	(2.10)	(2.44)			(2.49)	(2.60)	(2.59)	(2.47)			(2.24)	(1.82)	(0.10)	(−0.18)		
South Korea	0.937***	2.032***	0.718**	1.703***	262	213	1.512**	2.108***	0.677**	1.350***	263	121	0.335	−0.071	−0.353	−0.516**	262	91
	(2.95)	(7.79)	(2.32)	(6.75)			(2.47)	(3.63)	(1.99)	(4.80)			(0.50)	(−0.11)	(−1.31)	(−2.44)		

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TABLE 2 (continued)

Unconditional Performance

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
Spain	0.779*** (2.76)	0.935*** (3.87)	0.850*** (3.21)	0.877*** (3.37)	189	32	0.803 (1.32)	0.853 (1.35)	0.563*** (2.76)	0.738*** (3.35)	191	21	0.000 (0.00)	−0.109 (−0.17)	−0.277 (−1.10)	−0.125 (−0.45)	189	10
Sri Lanka	0.705 (1.43)	1.362*** (3.25)	0.836* (1.89)	1.216*** (2.90)	115	21	0.451 (0.69)	1.190 (1.45)	−0.065 (−0.28)	0.526 (1.64)	141	15	−0.093 (−0.13)	0.004 (0.01)	−0.828* (−1.93)	−0.541 (−1.26)	115	6
Sweden	0.267 (1.13)	1.122*** (5.65)	0.313 (1.33)	1.174*** (6.38)	215	119	1.234** (2.35)	1.775*** (3.15)	0.129 (0.95)	0.628*** (4.19)	215	80	0.968* (1.91)	0.653 (1.29)	−0.183 (−1.12)	−0.546*** (−4.06)	215	39
Switzerland	0.560* (1.68)	0.711*** (3.41)	0.664* (1.76)	0.711*** (3.31)	195	44	1.390*** (2.89)	1.378*** (2.58)	0.682** (2.16)	0.497*** (2.66)	195	18	0.801** (2.27)	0.625 (1.36)	0.020 (0.13)	−0.218 (−1.56)	197	25
Thailand	0.359 (1.31)	1.171*** (5.27)	0.273 (1.07)	1.051*** (5.27)	263	94	1.470** (2.33)	2.398*** (3.82)	0.340* (1.89)	1.107*** (5.97)	263	52	1.112** (1.99)	1.227** (2.00)	0.067 (0.34)	0.057 (0.30)	263	42
Turkey	1.268*** (2.97)	2.400*** (5.98)	1.416*** (3.15)	2.220*** (5.10)	151	42	0.693 (0.98)	1.992** (2.22)	0.219 (0.61)	0.968*** (2.80)	153	23	−0.237 (−0.29)	−0.134 (−0.14)	−1.092*** (−3.12)	−1.135*** (−2.73)	153	18
United Kingdom	0.236 (1.30)	0.465*** (2.82)	0.224 (1.16)	0.524*** (4.15)	227	163	0.829* (1.83)	1.162** (2.12)	0.256* (1.65)	0.450*** (3.33)	227	91	0.593 (1.55)	0.697 (1.52)	0.032 (0.29)	−0.075 (−0.73)	227	72
United States	0.075 (0.44)	0.805*** (4.11)	−0.027 (−0.22)	0.912*** (6.03)	227	1,666	1.046*** (2.65)	1.928*** (3.75)	0.014 (0.11)	1.037*** (6.17)	227	386	0.971*** (3.20)	1.123*** (2.80)	0.041 (0.73)	0.126** (2.23)	227	1,280
Total > 0 [Sig.]	28 [8]	34 [26]	27 [8]	34 [28]			33 [14]	34 [25]	32 [10]	34 [31]			30 [7]	27 [6]	18 [2]	16 [6]		
Total < 0 [Sig.]	6 [0]	0 [0]	7 [0]	0 [0]			1 [0]	0 [0]	2 [0]	0 [0]			4 [0]	7 [0]	16 [2]	18 [6]		

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2 (less than or equal to −2). Table 3 shows the monthly raw returns and FF6 alphas for the *CID* trading strategy separately for each country.[7]

In total, 9 (10) of the value-weighted raw (abnormal) *CID* returns are significantly positive at the 5% level. For the equal-weighted *CID* portfolios, we observe a clearer picture with 22 and 23 statistically significant positive raw and abnormal returns at the 5% level, respectively.

To identify the performance drivers of the *CID* strategy, we analyze the long and short legs separately. Almost all of the value-weighted raw and abnormal returns of the long legs are positive. Furthermore, 15 and 16 of these value-weighted raw and abnormal *CID* returns are significant at the 5% level. For equal-weighted portfolios, we observe greater economic magnitude and significance of abnormal returns. In total, 29 countries show significantly positive (at the 5% level) abnormal returns in the long leg. Looking at the short legs, there are only five and seven statistically significant negative value- and equal-weighted abnormal returns at the 5% level, respectively.

Table OA.7 of the Supplementary Material provides an overview of the performance differences at the country level by investing in a portfolio that goes long the respective composite *CID* approach and short the unconditional *UNC* benchmark strategy. The comparison at the country level does not provide a conclusive picture. Noticeably, at least three-quarters of the countries show positive improvements (point estimates) in value- and equal-weighted raw and abnormal performance. However, only one-third of the countries show significant positive improvements for equal-weighted raw and abnormal returns, while seven and six 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 the *CID* strategy, we analyze the performance of all countries in aggregate regions. In Table 4, we report value- and equal-weighted FF6 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 alphas for a long–short strategy (*CID* − *UNC*) that goes long the respective *CID* long–short, long, and short strategies and short the respective *UNC* long–short, long, and short strategies. To account for structural differences between countries, we distinguish between developed markets (DM) and emerging markets (EM). We use the following two aggregation methods: We aggregate all firm-months across all countries in the respective region (DM or EM) to create a regional monthly sample that includes all information-driven (or unconditional) insider trade firm-month signals. This "pooled" sample is dominated by countries with a greater number of information-driven (unconditional) firm-month observations. To weaken the influence of countries with many monthly signals, we additionally calculate "country-neutral" regional results by averaging the respective *UNC*, *CID*, and *CID* − *UNC* monthly country strategy return time series in each month. Thus, in the "country-neutral" approach, each country with a valid monthly return receives the same weight in the month under consideration. For both approaches,

[7]As with the *UNC* strategy, we require at least three stocks per country month to construct valid long and short portfolios, respectively.

TABLE 3

Composite Performance

Table 3 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 equation (1) was generated in the previous month. We report monthly value- (VW) and equal-weighted (EW) raw returns and FF6 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 number of firms (F) in each respective portfolio. Finally, we report the total positive and negative significant performances. A performance is counted as significant if it is significant at the 5% level. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
Australia	0.333	1.570***	0.649*	1.441***	227	104	1.350**	2.458***	0.581***	1.441***	227	80	1.017*	0.888	−0.067	0.000	227	23
	(0.90)	(4.96)	(1.92)	(4.45)			(2.37)	(2.95)	(2.66)	(5.73)			(1.78)	(1.17)	(−0.30)	(0.00)		
Belgium	−0.560	1.128***	−0.053	1.346***	157	14	0.667	1.039*	0.776	0.995**	164	6	1.126**	0.039	0.447	−0.492**	178	8
	(−0.91)	(3.84)	(−0.10)	(4.00)			(0.82)	(1.77)	(1.62)	(2.31)			(2.08)	(0.09)	(1.36)	(−2.25)		
Brazil	0.928*	1.419***	0.822*	1.371***	194	36	1.742*	2.389**	0.668**	1.522***	197	14	0.591	0.844	−0.236	0.127	200	21
	(1.93)	(3.48)	(1.84)	(3.26)			(1.95)	(2.51)	(2.07)	(4.83)			(0.84)	(1.02)	(−0.83)	(0.53)		
Canada	0.373*	1.904***	0.376**	1.925***	227	500	1.083**	2.951***	0.148	2.206***	227	257	0.710*	1.048	−0.228***	0.281*	227	243
	(1.78)	(7.29)	(1.97)	(7.83)			(2.03)	(3.58)	(0.85)	(9.58)			(1.66)	(1.49)	(−3.56)	(1.79)		
Chile	0.316	0.374	0.449	1.026	87	14	0.030	0.142	0.374	0.739*	116	8	−0.245	−0.106	−0.131	−0.228	90	5
	(0.59)	(0.64)	(0.61)	(1.36)			(0.04)	(0.20)	(1.12)	(1.92)			(−0.35)	(−0.12)	(−0.27)	(−0.41)		
China	−0.301	0.368	−0.420	0.480*	190	146	0.869	1.937**	−0.177	0.542**	191	52	1.206	1.562*	0.290	0.050	190	93
	(−0.89)	(1.24)	(−1.38)	(1.83)			(1.14)	(2.30)	(−0.83)	(2.35)			(1.64)	(1.95)	(1.53)	(0.24)		
Denmark	−0.216	0.223	0.818	0.957**	134	17	0.514	0.600	0.341	0.446	154	10	1.273**	0.827	0.155	−0.094	146	6
	(−0.40)	(0.51)	(1.52)	(2.04)			(0.71)	(0.89)	(0.70)	(1.23)			(2.55)	(1.53)	(0.44)	(−0.24)		
Egypt	0.464	0.445	0.430	0.984	114	21	0.894	1.289	0.772*	0.913**	115	11	0.404	0.894	0.273	−0.017	115	9
	(0.64)	(0.56)	(0.59)	(1.51)			(1.22)	(1.58)	(1.68)	(2.16)			(0.47)	(0.86)	(0.56)	(−0.04)		
Finland	0.045	0.362	0.316	0.522	161	21	1.048*	1.173*	0.527*	0.553**	174	13	1.106*	0.939	0.254	0.100	167	8
	(0.09)	(0.96)	(0.60)	(1.26)			(1.76)	(1.92)	(1.76)	(2.42)			(1.90)	(1.48)	(0.60)	(0.33)		
France	0.354	1.292***	0.454*	1.215***	203	63	1.069**	1.365***	0.471**	0.720***	203	30	0.715*	0.073	0.017	−0.495***	203	33
	(1.27)	(5.71)	(1.87)	(5.56)			(2.07)	(2.71)	(2.46)	(4.33)			(1.71)	(0.14)	(0.12)	(−3.54)		
Germany	0.738*	1.457***	0.952**	1.276***	228	38	1.478***	1.993***	0.635**	1.054***	233	25	0.848*	0.608	−0.323	−0.226	228	13
	(1.83)	(5.11)	(2.06)	(3.70)			(2.78)	(3.78)	(2.24)	(4.82)			(1.78)	(1.14)	(−0.97)	(−0.64)		

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TABLE 3 (continued)

Composite Performance

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
Greece	1.700**	2.334***	1.631**	2.221***	162	33	1.268	1.980**	1.165***	1.859***	178	21	−1.055	−0.859	−0.336	−0.272	165	11
	(2.22)	(4.58)	(2.01)	(4.00)			(1.16)	(2.36)	(2.95)	(5.20)			(−0.94)	(−0.97)	(−0.52)	(−0.66)		
Hong Kong	−0.340	0.834***	−0.324	0.724***	224	158	0.914	1.340**	0.099	0.671***	224	85	1.255**	0.506	0.424*	−0.053	224	72
	(−1.36)	(3.74)	(−1.23)	(3.29)			(1.55)	(2.10)	(0.63)	(4.89)			(2.40)	(0.74)	(1.81)	(−0.24)		
India	0.333	1.379***	0.126	1.268***	180	162	1.258	2.479***	0.109	1.314***	180	74	0.912	1.078	−0.014	0.038	182	88
	(0.86)	(5.67)	(0.35)	(6.05)			(1.47)	(2.60)	(0.33)	(6.62)			(1.37)	(1.26)	(−0.12)	(0.25)		
Indonesia	0.343	−0.077	0.043	−0.144	118	39	1.222*	1.101*	0.446	0.086	120	20	1.039*	1.376*	0.455	0.614	132	18
	(0.53)	(−0.11)	(0.06)	(−0.19)			(1.83)	(1.66)	(0.98)	(0.26)			(1.81)	(1.82)	(1.15)	(0.92)		
Israel	−0.078	0.123	0.088	0.230	169	22	1.393**	1.742***	0.634**	0.836***	179	12	1.652***	1.922***	0.620	0.765**	185	10
	(−0.23)	(0.36)	(0.26)	(0.61)			(2.06)	(2.61)	(1.99)	(2.72)			(2.70)	(3.01)	(1.48)	(2.12)		
Italy	0.412	1.396***	0.266	1.337***	223	41	0.764	1.260**	0.106	0.836***	227	23	0.309	−0.188	−0.114	−0.469*	223	17
	(1.46)	(5.40)	(0.83)	(4.24)			(1.44)	(2.29)	(0.49)	(4.57)			(0.61)	(−0.32)	(−0.46)	(−1.73)		
Malaysia	0.871***	0.982***	0.854***	0.953***	203	109	1.173**	1.624***	0.583***	1.122***	203	59	0.302	0.641	−0.270**	0.169	203	50
	(3.60)	(4.44)	(3.48)	(4.50)			(2.34)	(3.07)	(3.56)	(5.55)			(0.67)	(1.13)	(−1.98)	(0.81)		
Netherlands	−0.684	0.373	−0.778	0.328	121	11	0.142	0.206	0.103	0.340	144	5	0.812	0.392	0.026	−0.355	209	6
	(−0.97)	(0.73)	(−1.14)	(0.63)			(0.17)	(0.28)	(0.18)	(0.83)			(1.49)	(0.73)	(0.06)	(−0.94)		
Norway	1.352***	0.830	1.236***	0.990*	198	29	1.290*	1.378*	0.479*	0.708***	203	20	−0.001	0.744	−0.820**	−0.228	198	9
	(3.33)	(1.55)	(2.73)	(1.91)			(1.79)	(1.94)	(1.87)	(2.61)			(−0.00)	(0.97)	(−2.22)	(−0.51)		
Pakistan	0.481	1.053**	0.288	0.917*	99	21	1.228	2.251**	0.470	1.230***	102	11	0.539	0.943	0.032	0.120	103	10
	(0.85)	(2.00)	(0.52)	(1.70)			(1.25)	(2.05)	(0.99)	(2.94)			(0.74)	(0.98)	(0.08)	(0.39)		
Philippines	0.660	0.905*	0.482	0.799	179	28	1.658**	2.328***	0.594**	1.227***	185	16	0.875	1.297*	0.077	0.367	184	12
	(1.28)	(1.74)	(1.02)	(1.45)			(2.36)	(3.14)	(2.22)	(3.90)			(1.54)	(1.88)	(0.24)	(0.93)		
Poland	1.804***	1.325**	2.177***	1.621***	174	33	1.548*	1.889*	1.660***	2.073***	174	20	−0.230	0.575	−0.523	0.455	177	13
	(2.95)	(2.29)	(3.49)	(3.08)			(1.80)	(1.87)	(4.45)	(5.76)			(−0.28)	(0.58)	(−1.38)	(0.99)		
Singapore	0.950**	1.149***	0.717*	1.401***	251	33	1.117***	1.139**	0.583***	0.788***	257	23	0.184	−0.039	−0.148	−0.657**	254	10
	(2.47)	(3.18)	(1.79)	(3.83)			(2.58)	(2.09)	(2.87)	(3.55)			(0.29)	(−0.06)	(−0.41)	(−2.02)		
South Africa	0.301	0.475	0.529	0.656*	193	30	1.615**	1.452**	0.739**	0.616**	194	11	1.311**	1.013*	0.185	−0.054	221	19
	(0.63)	(1.25)	(1.17)	(1.66)			(2.16)	(2.06)	(1.97)	(2.08)			(2.43)	(1.83)	(0.75)	(−0.31)		

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TABLE 3 (continued)

Composite Performance

	Long–Short						Long						Short					
	Raw Returns		FF6α				Raw Returns		FF6α				Raw Returns		FF6α			
Country	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*	VW	EW	VW	EW	*N*	*F*
South Korea	1.621*** (4.16)	2.536*** (7.14)	1.340*** (3.52)	2.112*** (6.51)	261	139	1.825*** (2.85)	2.174*** (3.86)	0.894*** (3.39)	1.368*** (6.60)	261	74	0.329 (0.49)	−0.262 (−0.42)	−0.342 (−1.23)	−0.650*** (−2.58)	262	64
Spain	1.514*** (4.10)	1.732*** (5.25)	1.469*** (4.22)	1.555*** (4.51)	180	23	0.915 (1.50)	1.080 (1.62)	0.699*** (4.01)	0.946*** (4.05)	190	15	−0.490 (−0.81)	−0.561 (−0.83)	−0.746** (−2.52)	−0.637** (−2.17)	181	7
Sri Lanka	0.329 (0.49)	1.453* (1.96)	0.761 (1.14)	1.383** (1.96)	82	14	0.693 (0.83)	1.355 (1.47)	0.065 (0.23)	0.643** (2.11)	130	10	−0.357 (−0.41)	−0.679 (−0.62)	−0.839 (−1.25)	−0.756 (−1.13)	83	4
Sweden	0.332 (1.11)	1.514*** (6.08)	0.400 (1.45)	1.524*** (6.47)	215	82	1.457** (2.56)	1.879*** (3.19)	0.419** (2.15)	0.739*** (4.30)	215	56	1.125** (2.22)	0.365 (0.71)	0.018 (0.11)	−0.784*** (−5.30)	215	26
Switzerland	0.388 (0.97)	0.665*** (2.78)	0.513 (1.16)	0.646** (2.48)	191	36	1.294** (2.40)	1.317** (2.41)	0.579* (1.67)	0.390* (1.88)	191	14	0.833** (2.27)	0.579 (1.23)	0.038 (0.23)	−0.260 (−1.63)	197	22
Thailand	0.633 (1.63)	1.641*** (5.41)	0.433 (1.18)	1.356*** (5.00)	262	63	1.699*** (2.78)	2.571*** (4.19)	0.573** (2.44)	1.308*** (6.30)	263	33	1.014* (1.80)	0.877 (1.44)	0.221 (1.05)	−0.074 (−0.43)	262	30
Turkey	1.717*** (3.15)	2.844*** (6.89)	1.767*** (3.16)	2.815*** (6.03)	149	29	1.216 (1.50)	1.844** (2.19)	0.578 (1.44)	0.975*** (2.69)	149	15	−0.629 (−0.82)	−1.089 (−1.48)	−1.210*** (−3.24)	−1.837*** (−5.27)	150	13
United Kingdom	0.668** (2.41)	0.625*** (2.95)	0.646** (2.38)	0.712*** (4.15)	227	124	1.134** (2.15)	1.282** (2.26)	0.537** (2.42)	0.587*** (3.52)	227	64	0.466 (1.16)	0.657 (1.45)	−0.109 (−0.82)	−0.125 (−1.03)	227	59
United States	0.241 (1.02)	1.031*** (4.65)	0.113 (0.52)	1.183*** (6.95)	227	1,378	1.191*** (2.70)	2.121*** (3.98)	0.141 (0.64)	1.266*** (6.79)	227	245	0.951*** (3.16)	1.090*** (2.72)	0.027 (0.44)	0.083 (1.52)	227	1,132
Total > 0 [Sig.]	28 [9]	33 [22]	30 [10]	33 [23]			34 [15]	34 [23]	33 [16]	34 [29]			27 [8]	26 [2]	17 [0]	13 [1]		
Total < 0 [Sig.]	6 [0]	1 [0]	4 [0]	1 [0]			0 [0]	0 [0]	1 [0]	0 [0]			7 [0]	8 [0]	17 [5]	21 [7]		

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TABLE 4

***CID* − *UNC* Performance Difference Alphas**

Table 4 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 on the composite measure (*CID*) of information-driven (see Table 3) trade signals. Additionally, we report alphas for a long–short strategy (*CID* − *UNC*) that goes long the respective *CID* long–short, long, and short strategies and short the respective *UNC* long–short, long, and short strategies (see Table OA.7 of the Supplementary Material for country-level results). We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas (see Table OA.8 of the Supplementary Material for raw returns) for the long–short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report the number of months (*N*) with a valid portfolio. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	UNC FF6α		*CID* FF6α		*CID* − *UNC* FF6α		
	VW	EW	VW	EW	VW	EW	*N*
Panel A. Long–Short							
			Pooled				
DM	−0.049	0.724***	0.226	1.011***	0.275***	0.286***	227
	(−0.56)	(4.18)	(1.51)	(4.92)	(2.98)	(6.84)	
EM	0.466***	1.004***	0.789***	1.387***	0.323**	0.383***	227
	(2.59)	(7.37)	(3.01)	(8.80)	(2.32)	(4.72)	
			Country-Neutral				
DM	0.282***	0.883***	0.418***	1.165***	0.136**	0.282***	227
	(3.75)	(11.57)	(4.41)	(13.91)	(2.25)	(6.72)	
EM	0.462***	1.044***	0.794***	1.313***	0.332***	0.269**	227
	(4.93)	(8.99)	(6.23)	(10.46)	(3.45)	(2.22)	
Panel B. Long							
			Pooled				
DM	0.046	0.924***	0.301***	1.134***	0.255***	0.210***	227
	(0.71)	(4.47)	(2.75)	(5.02)	(2.86)	(5.73)	
EM	0.335	1.168***	0.516	1.277***	0.181	0.109**	227
	(1.22)	(6.88)	(1.60)	(7.54)	(1.34)	(2.23)	
			Country-Neutral				
DM	0.187	0.702***	0.313**	0.832***	0.126**	0.130***	227
	(1.25)	(4.15)	(2.03)	(4.78)	(2.24)	(3.64)	
EM	0.317**	1.186***	0.598***	1.196***	0.282***	0.010	227
	(2.41)	(7.71)	(3.40)	(7.55)	(2.74)	(0.11)	
Panel C. Short							
			Pooled				
DM	0.095	0.200*	0.075	0.124	−0.019	−0.076***	227
	(1.56)	(1.67)	(1.11)	(1.10)	(−1.19)	(−3.44)	
EM	−0.131	0.164	−0.273	−0.110	−0.142	−0.275***	227
	(−0.55)	(0.68)	(−1.52)	(−0.51)	(−1.47)	(−3.84)	
			Country-Neutral				
DM	−0.098	−0.166	−0.107	−0.339**	−0.009	−0.173***	227
	(−0.78)	(−1.08)	(−0.87)	(−2.22)	(−0.27)	(−5.41)	
EM	−0.093	0.180	−0.232*	−0.093	−0.139**	−0.273***	227
	(−0.66)	(1.08)	(−1.66)	(−0.57)	(−2.10)	(−3.59)	

we require at least 15 stocks per month for a valid long (short) portfolio construction. All abnormal returns for the "pooled" and "country-neutral" regions are calculated using the regional U.S. dollar Fama and French (2018) 6-factor model obtained from Kenneth French's data library.

Panel A of Table 4 reports the FF6 long–short alphas for the value- and equal-weighted *UNC* and *CID* strategies, respectively. In the pooled DM sample, the long–short returns for value- and equal-weighted *UNC* portfolios are −0.05% and 0.72%, respectively. The corresponding returns for the *CID* DM strategies are 0.23% and 1.01%, respectively. In both cases, only equal-weighted portfolios show

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significant alphas. The value-weighted (0.28%) and equal-weighted (0.29%) *CID* − *UNC* alphas are significantly positive, indicating an outperformance of the *CID* strategies in the pooled DM samples. For the pooled EM samples, we observe similar results with higher absolute alphas. The value- and equal-weighted *UNC* alphas are 0.47% and 1.00%, respectively. The corresponding EM *CID* alphas are higher with 0.79% and 1.39% for the value- and equal-weighted portfolios, respectively. The value-weighted and equal-weighted *CID* − *UNC* alphas are 0.32% and 0.38%, statistically significant at the 5% and 1% levels, respectively. In sum, the pooled DM and EM samples reveal a significant outperformance of the *CID* strategies.

In the country-neutral DM samples, the value- and equal-weighted long–short *UNC* (*CID*) alphas are 0.28% and 0.88% (0.42% and 1.17%), all of which are significant at the 1% level. Furthermore, the *CID* − *UNC* differences are significant for both equal- (0.28%) and value-weighted (0.14%) DM portfolios. Similarly, for EM, both the country-neutral value-weighted (0.33%) and equal-weighted (0.27%) *CID* − *UNC* alpha differences are significant. In sum, the alternative aggregation method, that is, country-neutral DM and EM portfolios, also suggests a significant outperformance of the *CID* strategies.

Relative to the more mixed country-level results in Tables 2 and 3 and OA.7 of the Supplementary Material, the high statistical significance of the pooled and country-neutral regional strategies can be explained by international diversification benefits. More precisely, most country-level *UNC*, *CID*, and *CID* − *UNC* strategies exhibit low correlation between countries. These findings suggest that informed insider trading tends to be based rather on firm-specific (or country-specific or industry-specific) information as opposed to market or regional information.

Panels B and C of Table 4 report the FF6 alphas for the long and short legs separately. Noticeably, for equal-weighted portfolios, we observe significant *CID* − *UNC* alphas for almost all pooled and country-neutral long–short, long, and short portfolios, respectively. This finding suggests that among small firms, the outperformance of *CID* relative to the unconditional strategy stems from its ability to identify both information-driven buys and sells. Overall, however, the significant *UNC*, *CID*, and *CID* − *UNC* long–short alphas are often driven by their long legs, suggesting that insider buying generally has more return predictive ability. Table OA.8 of the Supplementary Material shows similar results for raw returns. In Table OA.9 of the Supplementary Material, we benchmark the *CID* strategy against the performance obtained from averaging the returns of the individual presumably information-driven strategies outlined in Section III.A.[8] For this high-hurdle robustness check, we find a statistically significant and economically relevant (often several percent p.a.) superiority of the *CID* strategy only for equal-weighted portfolios. Notably, the outperformance can be found in all specifications

[8]We use *UNC* as the baseline benchmark because Table 2 shows that unconditional insider strategies —especially purchases and equal-weighted portfolios—deliver economically and statistically strong returns, consistent with existing U.S. findings (e.g., Lakonishok and Lee (2001), Jeng, Metrick, and Zeckhauser (2003)). Therefore, *UNC* is a demanding benchmark. Conceptually, *UNC* is model-free and independent of our composition logic; hence, benchmarking *CID* against *UNC* focuses the comparison on *CID*'s incremental information. Practically, *UNC* offers uniform coverage and implementability across countries and over time, whereas the individual component signals can be heterogeneous and sparse. Few studies explicitly control for unconditional predictability when assessing new measures; a notable exception is Akbas et al. (2020).

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with equal-weighted returns, and it increases with the extent of the signal surplus of the composite strategy (see also Section V.A). In summary, the advantages of signal synthesis materialize in both developed markets and emerging markets but are predominantly found among smaller stocks. In the following, we examine potential statistical and economic mechanisms behind the performance of the *CID* strategy in more detail.

V. Statistical and Economic Mechanisms

A. More Restrictive Composition Approaches

We test more restrictive versions of the (CID^2) measure, that is, signal surplus requirements larger than $N = 2$. Specifically, we set $N = 3$ or $N = 4$ (see equation (1)). Note that even higher surplus requirements, such as $N = 5$, would not be consistently possible due to the often sparse and heterogeneous signal appearances across countries (see Figure 1).

Table 5 shows the resulting performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) samples. The results show that the more restrictive versions (CID^3 and CID^4) of the composite measure of information-driven trades uniformly, that is, regardless of the country aggregation scheme, show significant positive abnormal long–short returns for equal-weighted portfolios. However, pooled DM value-weighted CID^3 and CID^4 portfolios and the pooled EM value-weighted CID^4 portfolio show insignificant (but still positive) long–short FF6 alpha estimates, which is largely consistent with the baseline measure CID^2 in Panel A of Table 4. Evaluating the effectiveness of CID^3 and CID^4 to improve on the unconditional predictability by looking at the $CID^3 - UNC$ and $CID^4 - UNC$ alphas shows substantial differences across samples. These

TABLE 5

More Restrictive Composition Approaches

Table 5 reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of more restrictive versions (CID^3 and CID^4) of our original composite measure of information-driven trades (see Figure 1). Additionally, we report alphas for a long–short strategy (e.g., $CID^3 - UNC$) that goes long the respective more restrictive long–short *CID* strategy and short the respective long–short *UNC* strategy. We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas for the long–short portfolios. Furthermore, we report the number of months (*N*) with a valid portfolio. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CID^3 FF6α		$CID^3 - UNC$ FF6α			CID^4 FF6α		$CID^4 - UNC$ FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
	Pooled					Pooled				
DM	0.334*	1.086***	0.382***	0.362***	227	0.240	1.269***	0.273	0.554***	225
	(1.86)	(5.35)	(3.01)	(6.36)		(0.95)	(5.12)	(1.31)	(4.37)	
EM	0.909***	1.430***	0.443**	0.426***	227	0.745	1.497***	0.264	0.431***	214
	(2.79)	(8.98)	(2.02)	(4.64)		(1.57)	(10.63)	(0.66)	(3.38)	
	Country-Neutral					Country-Neutral				
DM	0.565***	1.371***	0.283***	0.487***	227	0.674***	1.769***	0.376**	0.892***	224
	(4.76)	(12.83)	(3.09)	(6.12)		(3.60)	(6.15)	(2.30)	(3.54)	
EM	0.965***	1.359***	0.504**	0.315**	227	1.328***	1.601***	0.861***	0.568***	214
	(4.46)	(8.06)	(2.52)	(2.08)		(4.50)	(9.44)	(3.05)	(3.22)	

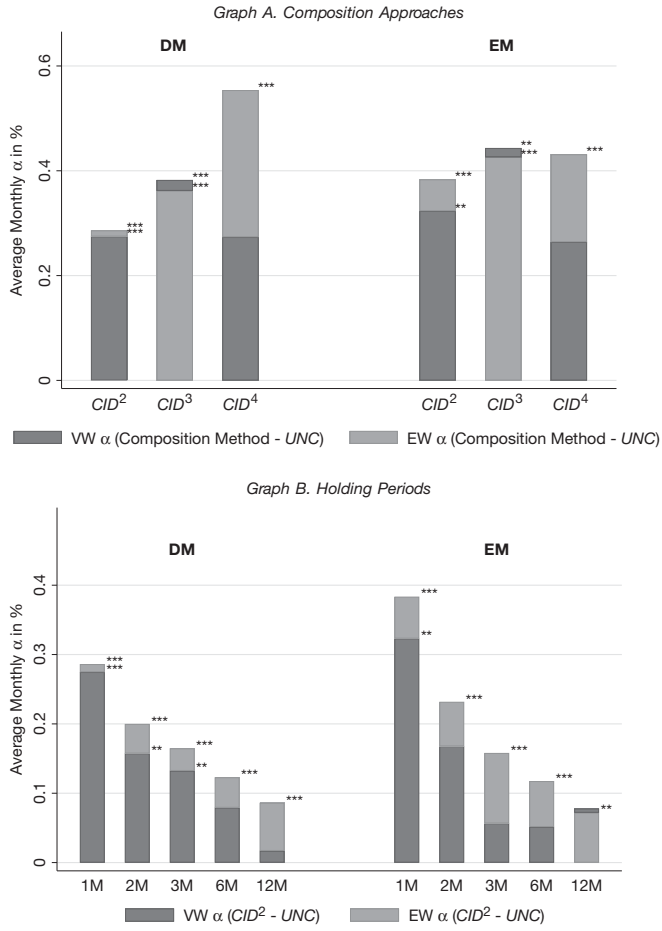
findings are broadly comparable to the baseline measure CID^2 in Panel A of Table 4.

Graph A of Figure 2 shows the difference between the unconditional (*UNC*) and all versions of *CID* (CID^2, CID^3, and CID^4) alphas for the pooled DM and EM samples. Graph 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

FIGURE 2

Composition Benefits

Figure 2 shows the benefits of our composite measures by displaying the monthly value- (VW) and equal-weighted (EW) FF6 alphas of long–short strategies that go long the long–short composition measure (CID^2, CID^3, CID^4) and short the long–short unconditional strategy (*UNC*) for pooled developed (DM) and emerging market (EM) samples in Graph A. Graph B shows the potential benefits of a change in holding periods for our baseline composite measure CID^2 by displaying the monthly equal- and value-weighted FF6 alphas of long–short strategies that go long the long–short composition measure (CID^2) and short the long–short unconditional strategy (*UNC*) for various holding periods (1, 2, 3, 6, and 12 months) for pooled developed (DM) and emerging market (EM) samples. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.



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increased benefits from CID^2 to CID^3, but not additional benefits for the CID^4 strategy. The value-weighted pooled EM and DM samples show similar increased benefits from CID^2 to CID^3, but reversals back to comparable CID^2 alphas for the CID^4 strategy.

In contrast, the value- and equal-weighted DM and EM country-neutral portfolios show that more restrictive *CID* strategies outperform more or less monotonically. We conjecture that the different pooled versus 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 portfolios, which are United States (DM) and China/India (EM) dominated. Overall, the results indicate that the baseline results are robust to the choice of the surplus requirement of the composite measure (N in equation (1)).

B. Composition Approaches Using Machine Learning

Can more complex methods enhance return predictability? Following Gu, Kelly, and Xiu (2020), Drobetz and Otto (2021), Leippold, Wang, and Zhou (2022), and Hanauer, Soebhag, Stam, and Hoogteijling (2025), among others, we implement a variety of machine learning techniques. Specifically, we employ ordinary least squares (*OLS*), least absolute shrinkage and selection operator (*LASSO*), elastic net (*ENET*), random forest (*RF*), gradient boosting regression trees (*GBR*), and neural networks with three layers (*NN*3). For all algorithms, we apply an expanding-window approach with disjoint training and testing samples. The initial training period spans 5 years and expands annually. Stock portfolios are formed monthly by sorting stocks into terciles based on their predicted returns. Unlike most of the machine learning literature (e.g., Rasekhschaffe and Jones (2019), Freyberger, Neuhierl, and Weber (2020), Tobek and Hronec (2021), and Hanauer and Kalsbach (2023)), we do not use quintile or decile splits in the baseline analysis. Tercile splits result in similar portfolio sizes as in the *CID* approaches and thus allow for better comparability.[9] We report quintile split results in Table OA.11 of the Supplementary Material. Further details on the implementation of the machine learning models are provided in Section OA.2 of the Supplementary Material.

Table 6 shows the value- and equal-weighted FF6 alphas for the machine learning-based long–short portfolios (*ML*), along with alphas for long–short strategies ($ML - UNC$) that go long the long–short machine learning strategies and short the long–short unconditional strategies. We implement the strategies separately for pooled developed (DM) and emerging markets (EM) samples. We do not consider country-neutral approaches, as the limited data, especially in the smaller countries, often do not satisfy the requirements for adequate training of the respective models. Due to the (at least) 5-year training period, the sample period starts in 2008 instead of 2003. This sample period adjustment also affects *CID* and $CID - UNC$ alphas (see Table 4) that act as a benchmark. These values are therefore shown at the

[9]The machine learning tercile splits result in long–short legs with on average around 2000 and 800 stocks for developed and emerging markets, respectively, which is close to the original CID^2 long–short construction with 2,658 (DM) and 786 (EM) stocks (see Table 9).

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TABLE 6

Alternative Composition Approaches Using Machine Learning

Table 6 reports performance statistics for pooled developed (DM) and emerging market (EM) implementations for monthly rebalanced insider trading strategies based on machine learning (*ML*) composite measures of information-driven trade signals and on a long–short strategy (*ML* − *UNC*) that goes long the respective long–short machine learning strategy and short the long–short unconditional strategy. We report results for the following machine learning return prediction models: ordinary least squares (*OLS*), LASSO regression (*LASSO*), elastic net (*ENET*), random forest (*RF*), gradient boosting regression trees (*GBR*), and neural networks (*NN*3). We form long and short portfolios based on tercile splits of the respective models' return predictions. For comparability, we report the *CID* results for the same time-series length as the aforementioned *ML* strategies. We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas for the long–short portfolios. Furthermore, we report the number of months (*N*) with a valid portfolio. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	OLS FF6α		*OLS* − *UNC* FF6α			*LASSO* FF6α		*LASSO* − *UNC* FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
DM	0.078	0.927***	0.213	0.365**	168	0.157	0.945***	0.292*	0.383**	168
	(0.45)	(4.98)	(1.14)	(1.99)		(1.03)	(5.04)	(1.83)	(2.17)	
EM	0.355	0.835***	0.037	−0.199	168	0.340	0.840***	0.023	−0.194	168
	(1.12)	(5.17)	(0.13)	(−1.09)		(1.04)	(5.68)	(0.08)	(−1.09)	
	ENET FF6α		*ENET* − *UNC* FF6α			*RF* FF6α		*RF* − *UNC* FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
DM	0.008	0.715***	0.143	0.154	168	0.008	0.929***	0.144	0.367**	168
	(0.05)	(4.48)	(0.94)	(1.17)		(0.05)	(4.42)	(0.94)	(2.50)	
EM	0.469	0.459***	0.151	−0.575***	168	0.574*	0.958***	0.256	−0.076	168
	(1.36)	(2.72)	(0.51)	(−2.89)		(1.76)	(4.29)	(0.99)	(−0.35)	
	GBR FF6α		*GBR* − *UNC* FF6α			*NN*3 FF6α		*NN*3 − *UNC* FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
DM	0.062	0.897***	0.197	0.335*	168	0.125	0.838***	0.260*	0.276*	168
	(0.45)	(4.72)	(1.40)	(1.76)		(0.87)	(4.48)	(1.80)	(1.77)	
EM	0.553*	0.868***	0.235	−0.165	168	0.158	0.750***	−0.159	−0.284*	168
	(1.76)	(4.76)	(0.82)	(−0.80)		(0.67)	(5.38)	(−0.66)	(−1.71)	
	CID FF6α		*CID* − *UNC* FF6α							
	VW	EW	VW	EW	*N*					
DM	−0.019	0.775***	0.117	0.213***	168					
	(−0.12)	(3.39)	(1.40)	(5.55)						
EM	0.460*	1.284***	0.142	0.250***	168					
	(1.75)	(8.13)	(1.12)	(4.30)						

bottom of Table 6. For DM (EM), the value- and equal-weighted FF6 *CID* alphas change to −0.02% and 0.78% (0.46% and 1.28%). The *CID* − *UNC* alphas remain statistically significant at the 1% level for equal-weighted portfolios, amounting to 0.21% in DM and 0.25% in EM. For value-weighted portfolios, however, the *CID* − *UNC* alpha spreads become statistically insignificant, at 0.12% (DM) and 0.14% (EM), respectively.

Turning to the machine learning approaches in Table 6, we observe highly significant equal-weighted alphas around 0.9% in DM across most models, while value-weighted alphas remain insignificant around 0%. In EM, equal-weighted alphas remain significant but are slightly lower at around 0.8% for most models, while value-weighted alphas in EM are around 0.4%, but statistically insignificant. Hence, the machine learning models produce comparable alphas to the *CID* strategy for DM samples, but much lower alphas for EM samples.

When comparing the machine learning *ML* − *UNC* strategies with the *CID* − *UNC* strategy, we find only significant and comparable alphas in equal-weighted

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DM samples for the linear regression (*OLS*), *LASSO*, and random forest (*RF*) models. Notably, the equal-weighted $ML - UNC$ alphas in EM are uniformly negative. Value-weighted $ML - UNC$ alphas are mostly positive, but statistically insignificant in all models and in both DM and EM, ranging between −0.16% and 0.29%. Therefore, the machine learning models produce $ML - UNC$ alphas comparable to those of the $CID - UNC$ strategies for value-weighted DM and EM samples and equal-weighted DM samples, but underperform significantly in equal-weighted EM samples. We report statistical tests for the $ML - CID$ return differences in Table OA.23 of the Supplementary Material, which show that none of the machine learning models significantly outperform the straightforward baseline strategy across regions and weighting schemes. Furthermore, a direct comparison of the machine learning models reveals no definitive superior performer.

Notably, the machine learning alpha spreads increase materially for more restrictive quintile splits in the pooled DM sample, but still remain insignificant or negative for the pooled EM sample (see Table OA.11 of the Supplementary Material). Overall, under comparable conditions, more complex methods[10] do not outperform the baseline composite strategy ($CID - UNC$), which we therefore concentrate on in the remainder of the article.

C. Long Versus 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 also implement an analogous portfolio approach for *UNC* trades, which allows us to study the $CID - UNC$ performance difference.

In Table 7, we report value- and equal-weighted FF6 alphas separately for pooled and country-neutral developed (DM) and emerging market (EM) *CID* (Panel A) and $CID - UNC$ strategies (Panel B) for different holding periods. We report the *UNC* alphas for different holding periods in Table OA.12 of the Supplementary Material.

The main finding is that for both *CID* and $CID - UNC$ strategies, irrespective of the region or country aggregation scheme, equal-weighted alphas decrease with longer time horizons by half or more, but largely remain significant. For example, the equal-weighted alphas of *CID* trades in the pooled DM and EM portfolios fall from highly significant 1.01% and 1.39%, respectively, in the 1-month holding period, to still highly significant 0.34% and 0.48%, respectively, in the 12-month holding period. Value-weighted *CID* alphas are mostly significant with the exception of pooled DM samples and also decrease with longer time horizons. Value-weighted $CID - UNC$ alphas are often significant, but also decrease with longer time horizons, the exception being the country-neutral DM alphas.

[10]Section OA.1 and Table OA.10 of the Supplementary Material show that comparable insights are also obtained for two further alternative composition approaches such as attaching higher weights to signals that occur less frequently.

TABLE 7

Longer Holding Periods

Table 7 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, that is, 1 to 12 months, in the respective portfolios. Furthermore, Panel B reports long–short alphas for a strategy that goes long the respective information-driven long–short *CID* strategy and short the long–short *UNC* strategy for different holding periods. We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas for the long–short portfolios. Finally, we report the number of available months (*N*) with a valid portfolio. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	1 Month		2 Months		3 Months		6 Months		12 Months		
	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	*N*
Panel A. CID FF6 α (Long–Short)											
						Pooled					
DM	0.226	1.011***	0.068	0.768***	0.021	0.663***	0.001	0.459***	−0.053	0.337***	227
	(1.51)	(4.92)	(0.52)	(4.49)	(0.19)	(4.35)	(0.01)	(3.70)	(−0.74)	(3.35)	
EM	0.789***	1.387***	0.510***	1.177***	0.368**	0.966***	0.147	0.655***	0.143*	0.477***	227
	(3.01)	(8.80)	(2.82)	(8.19)	(2.28)	(7.15)	(1.25)	(6.15)	(1.79)	(5.62)	
						Country-Neutral					
DM	0.418***	1.165***	0.246***	0.831***	0.240***	0.768***	0.130**	0.553***	0.033	0.394***	227
	(4.41)	(13.91)	(3.53)	(11.67)	(3.43)	(10.07)	(2.54)	(9.24)	(0.78)	(8.71)	
EM	0.794***	1.313***	0.523***	1.053***	0.400***	0.878***	0.297***	0.664***	0.205***	0.480***	227
	(6.23)	(10.46)	(4.98)	(10.84)	(4.50)	(11.73)	(3.80)	(10.59)	(3.48)	(10.03)	
Panel B. CID – UNC FF6 α (Long–Short)											
						Pooled					
DM	0.275***	0.286***	0.157**	0.200***	0.132**	0.165***	0.079	0.123***	0.017	0.086***	227
	(2.98)	(6.84)	(2.11)	(6.00)	(2.15)	(5.41)	(1.30)	(4.12)	(0.35)	(3.18)	
EM	0.323**	0.383***	0.168	0.232***	0.057	0.158***	0.051	0.117***	0.078	0.072**	227
	(2.32)	(4.72)	(1.48)	(4.49)	(0.57)	(3.39)	(0.68)	(2.95)	(1.34)	(2.09)	
						Country-Neutral					
DM	0.136**	0.282***	0.093	0.192***	0.173***	0.198***	0.107**	0.164***	0.044	0.105***	227
	(2.25)	(6.72)	(1.63)	(5.11)	(3.43)	(6.67)	(2.48)	(9.02)	(1.47)	(5.44)	
EM	0.332***	0.269**	0.212***	0.216***	0.113*	0.095	0.089	0.069	0.062	0.010	227
	(3.45)	(2.22)	(3.01)	(2.85)	(1.78)	(1.41)	(1.17)	(0.98)	(1.05)	(0.15)	

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Collectively, the economic difference between $CID - UNC$ alphas tends to become smaller over time, which suggests that *CID* insider trades capture partly a short-term information advantage. Graph B of Figure 2 illustrates this negative relation between time horizon and $CID - UNC$ alphas 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 alphas. Nevertheless, the equal-weighted $CID - UNC$ alphas 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.

D. Real-Time Perspective and Earnings Months

In this section, we analyze two further aspects regarding the timing of insider transactions. In Panel A of Table 8, we first report the performance of a real-time implementable version of our baseline strategy to outside investors (CID_O), which includes only trades that have been reported to the respective authorities before the end of the previous month, that is, before the portfolio construction. Furthermore, we report in Panel A the performance of a pure insider version of our baseline strategy (CID_I), which includes only trades that have been reported to the respective authorities after the end of the previous month. These trades are therefore not available to outside investors at the time of portfolio formation.[11]

The CID_O alpha (averaged across all EM and DM pooled and country-neutral specifications) decreases by approximately 6 bps, while the $CID_O - UNC_O$ alpha spreads closely resemble the baseline results in Table 4 across both regions and weighting schemes. The CID_I alpha (averaged across all EM and DM pooled and country-neutral specifications) increases often significantly by approximately 43 bps,[12] while the $CID_I - UNC_I$ alpha spreads again closely resemble the baseline results in Table 4, with the exception of the value-weighted DM alpha spread becoming insignificant. In Table OA.22 of the Supplementary Material, we formally test whether the pure outsider strategy and pure insider strategy differ from one another and from the baseline strategy. For the *CID* alphas, we find mainly significant outperformance in equal-weighted DM samples, with the pure insider strategy outperforming the baseline ($CID_I - CID$) and the outsider strategy ($CID_I - CID_O$),[13] and the baseline strategy outperforming the outsider strategy ($CID - CID_O$). For the $CID - UNC$ alpha spreads, we find no significant differences, except for significantly lower returns of the value-weighted pure insider strategy relative to the baseline strategy in developed markets. Overall, the slightly

[11]We note that this pure insider strategy is materially more restrictive and severely less diversified than the outsider CID_O or the baseline *CID* strategy, which limits direct comparability.

[12]Since the needed reporting delay going over the end of the month is highly correlated with late filing, the pure insider strategy mechanically gets exposure to the well-documented late filing premium, see, e.g., Jackson, Lynch-Levy, and Taylor (2022) and Cline and Houston (2023). This exposure explains the increased CID_I alphas in Table 8 relative to our *CID* baseline strategy.

[13]The significance of the differences of the pure insider strategy to the baseline and outsider strategy is largely driven by the aforementioned mechanical exposure to the late filing premium.

decreased outsider results again point to a short-term information advantage of insiders. Although the pure insider results might suggest a similar interpretation, we cannot directly make this link as the baseline and the pure insider strategy are by design far less comparable than the baseline to the outsider strategy.

In Panel B of Table 8, we perform a similar variation of the baseline strategy to investigate the influence of QEAs. Specifically, we rerun the analysis separately for trades in earnings announcement months on the one hand (CID_Q) and all other months on the other hand (CID_{nQ}). The alphas of trades initiated in months without an earnings announcement are at least as large as, if not larger than, the alphas in earnings months (all respective tests for significant differences in Table OA.22 of the Supplementary Material are insignificant), suggesting that the latter are not a major driver of the success of the baseline analysis.

TABLE 8

Real-Time Perspective and Earnings Months

Table 8 reports performance statistics for pooled and country-neutral developed (DM) and emerging market (EM) implementations of variations of the baseline composite measure (*CID*). We report alphas for a long–short strategy (e.g., $CID_O - UNC_O$) that goes long the respective variations of the long–short *CID* strategy and short the respective long–short *UNC* strategy. Panel A reports a version of the baseline composite measure that only considers individual signals for the composite measure if the trades were observable in real-time at portfolio construction (i.e., the outsider perspective CID_O) and if the trades were not observable in real-time at portfolio construction (i.e., the insider perspective CID_I). Panel B reports a version of the baseline composite measure that only considers individual signals for the composite measure if the trades happened in months with (CID_Q) or without (CID_{nQ}) a quarterly earnings announcement. We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas for the long–short portfolios. Furthermore, we report the number of months (*N*) with a valid portfolio. We report Newey and West (1987) adjusted *t*-statistics (in parentheses). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A. Outsider vs. Insider Perspective (Long–Short)

	CID_O FF6α		$CID_O - UNC_O$ FF6α			CID_I FF6α		$CID_I - UNC_I$ FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
			Pooled					Pooled		
DM	0.285*	0.842***	0.319***	0.262***	227	0.282	1.849***	0.082	0.272***	227
	(1.67)	(3.99)	(2.87)	(5.67)		(1.40)	(8.71)	(0.76)	(5.07)	
EM	0.654***	1.274***	0.301**	0.395***	227	1.084***	1.629***	0.439***	0.377***	227
	(2.78)	(6.58)	(2.02)	(4.03)		(3.28)	(9.55)	(2.90)	(3.65)	
			Country-Neutral					Country-Neutral		
DM	0.473***	1.048***	0.197**	0.278***	227	0.852***	2.222***	0.157	0.351***	227
	(3.72)	(9.70)	(2.50)	(5.24)		(5.21)	(11.39)	(1.51)	(3.44)	
EM	0.791***	1.253***	0.399***	0.310**	227	1.024***	1.621***	0.096	0.290**	227
	(4.81)	(7.51)	(3.63)	(2.10)		(4.47)	(8.85)	(0.59)	(2.31)	

Panel B. QEA (Long–Short)

	CID_Q FF6α		$CID_Q - UNC_Q$ FF6α			CID_{nQ} FF6α		$CID_{nQ} - UNC_{nQ}$ FF6α		
	VW	EW	VW	EW	*N*	VW	EW	VW	EW	*N*
			Pooled					Pooled		
DM	0.231	0.803***	0.293*	0.189**	167	0.175	0.880***	0.248**	0.256***	226
	(1.13)	(3.24)	(1.75)	(2.02)		(0.99)	(4.75)	(2.35)	(5.40)	
EM	−0.185	1.350***	0.167	0.116	114	0.707***	1.436***	0.174	0.359***	221
	(−0.39)	(2.83)	(0.65)	(0.87)		(2.92)	(7.43)	(1.38)	(4.36)	
			Country-Neutral					Country-Neutral		
DM	0.305	0.989***	0.067	0.280*	167	0.559***	1.181***	0.298***	0.405***	226
	(0.95)	(4.45)	(0.39)	(1.85)		(4.65)	(12.46)	(3.14)	(5.58)	
EM	0.479	0.997***	0.093	0.058	114	0.772***	1.449***	0.261**	0.250*	221
	(0.99)	(2.70)	(0.31)	(0.25)		(3.64)	(8.60)	(2.07)	(1.78)	

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E. Developed Versus Emerging Markets

The information environment in emerging markets (EM) is likely to be different from that in developed markets (DM) (see also Section V.F). For example, Brochet (2019) shows that institutions in EM demand less transparency regarding insider trades, which, in turn, increases the predictability of returns. Bhattacharya et al. (2000) find that stock prices in Mexico hardly reacted 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. In this respect, the question arises whether the outperformance of *CID* trades compared to *UNC* trades is also driven by this mechanism. However, Table 9, which reports tests for differences in abnormal returns between pooled and country-neutral EM and DM portfolios for the *UNC*, *CID*, and *CID* − *UNC* strategies, shows that this is unlikely to be the case.

Panel A reveals that insiders in emerging markets achieve higher long–short alphas, sometimes significantly, than in developed markets for both unconditional insider trades (*UNC*) and the composite measure (*CID*). However, all *CID* − *UNC* alphas show small and insignificant differences between EM and DM, suggesting

TABLE 9

Developed Versus Emerging Markets

Table 9 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 of the *CID* − *UNC* long–short strategies. We report monthly value- (VW) and equal-weighted (EW) FF6 factor alphas for the long–short (Panel A), long (Panel B), and short (Panel C) portfolios, respectively. Furthermore, we report the monthly average number of firms (F) in each respective portfolio and the number of months (*N*) with a valid portfolio. We report *z*-statistics (in parentheses) for Wald tests of equality of coefficients (alphas), based on seemingly unrelated regressions. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	UNC				*CID*				*CID* − *UNC*		
	VW	EW	*F*(EM)	*F*(DM)	VW	EW	*F*(EM)	*F*(DM)	VW	EW	*N*
Panel A. FF6 α Long – Short											
					Pooled						
EM – DM	0.514**	0.280	1,155	3,484	0.563*	0.377	786	2,658	0.048	0.097	227
	(2.33)	(1.25)			(1.77)	(1.48)			(0.30)	(1.13)	
					Country-Neutral						
EM – DM	0.180	0.161	93	213	0.376**	0.148	64	166	0.196	−0.013	227
	(1.34)	(1.13)			(2.23)	(1.05)			(1.57)	(−0.10)	
Panel B. FF6 α Long											
					Pooled						
EM – DM	0.289	0.244	606	1,478	0.215	0.143	387	966	−0.074	−0.102*	227
	(0.97)	(0.88)			(0.63)	(0.50)			(−0.52)	(−1.73)	
					Country-Neutral						
EM – DM	0.129	0.484**	49	90	0.285	0.364*	32	60	0.156	−0.120	227
	(0.61)	(2.42)			(1.26)	(1.69)			(1.46)	(−1.15)	
Panel C. FF6 α Short											
					Pooled						
EM – DM	−0.225	−0.035	549	2,006	−0.348	−0.234	400	1,692	−0.123	−0.199**	227
	(−0.97)	(−0.14)			(−1.63)	(−1.03)			(−1.40)	(−2.41)	
					Country-Neutral						
EM – DM	0.005	0.346	44	123	−0.124	0.246	33	106	−0.130	−0.100	227
	(0.03)	(1.58)			(−0.61)	(1.17)			(−1.53)	(−1.13)	

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that differences in the information environment between EM and DM are not the main performance driver of the increased predictability of the *CID* 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 almost equally driven by the long and short legs (see Panels B and C). The respective estimate for *CID* trades is 0.56%, which is again driven by both the long and short legs (see Panels B and C), leading to an insignificant $CID - UNC$ alpha of 0.05%. In the country-neutral equal-weighted strategy, the alpha difference is 0.16% for *UNC* trades and 0.15% for *CID* trades, again leading to an insignificant $CID - UNC$ alpha of -0.01%.

Overall, higher informational advantages in EM manifest themselves already in the performance of unconditional insider trading, not additionally through the composite measure. In summary, there is 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.

F. Cross-Country Analysis

1. Hypothesis Development and Country Characteristics

In the following, we explore whether selected country characteristics, that is, proxies for insider trading regulation and corporate governance, may explain the variation in performance, as reported in Tables 2 and 3. 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, Fu, Kang, and Lee (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. The results of Cziraki, De Goeij, and Renneboog (2014) support this hypothesis by showing that

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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, that is, committing their 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 can 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 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 a 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.

Empirically, we test whether country characteristics that proxy for insider trading restrictions and corporate governance, that is, 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 34 developed and emerging market countries.[14] 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 OA.14 and OA.17 of the Supplementary Material. To proxy for insider trading restrictions and corporate governance, we use the anti-self-dealing (AS) index from Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2008). AS is a survey-based measure of the legal protection of minority shareholders against expropriation. The index ranges from

[14]We note that an important aspect of regulation is arguably the amount/degree of specific insider trading laws (e.g., measured by the insider trading law index from Beny (2005), (2007)) as well as the enforcement of such laws (e.g., enforcement dummy used in Bhattacharya and Daouk (2002), Fernandes and Ferreira (2009)). However, we could not obtain reliable, comprehensive coverage of the insider trading law index for our 34-country sample and time period. With regard to enforcement, the cited sources and our own checks (Internet search) suggest limited exploitable cross-country heterogeneity as almost all sample countries had already enforced insider trading laws at the beginning of our sample period.

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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 1 if class action lawsuits are possible against illegal corporate insider trading, and 0 otherwise. We conjecture that the litigation risk corporate insiders must face will restrain corporate insiders more from opportunistic insider trading (e.g., Cheng, Huang, and Li (2016), Adhikari, Agrawal, and Sharma (2025)) 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 periods (i.e., shortly before a QEA). We calculate blackout periods (BLACKOUT) following Brochet (2019) as the difference between the percentage of insider trades that occur within 1 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 to trade or are restricted from trading shortly before the announcement, it becomes less likely that the information advantage still remains after the QEA.[15] 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, that is, 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 construct a combined insider regulation index (IRI) using all aforementioned individual cross-country variables (AS, CLASSA, BLACKOUT, ITR). We provide further details on the aggregated IRI measure in Table OA.17 of the Supplementary Material.

2. Analysis Based on Insider Trading Restrictions

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 across countries. Therefore, the dependent variables are the country-level long–short raw returns obtained from Tables 2 and 3. Consequently, the independent variables are country

[15]Additionally, we test another measure of indirect insider trading regulation following Gorbenko (2026) and find similar results to the BLACKOUT measure. Gorbenko (2026) measures the extent of insider trade reporting as the share of firms with at least one reported insider trade in a given country and year, where higher shares suggest stronger regulation and enforcement.

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characteristics comprising the time-invariant AS, CLASSA, and ITR, the time-averaged BLACKOUT, and the composite IRI (a standardized index of the preceding four proxies). Following Kolasinski and Yang (2018) and Cochrane (2005), we estimate a one-step panel regression framework that jointly identifies the country-level risk-adjusted returns and their relation to country characteristics, using country-specific FF6 factor loadings (implemented via country-factor interactions):

$$R^{LS}_{c,t} = b_0 + \boldsymbol{\gamma}'\mathbf{X}_c + \boldsymbol{\beta}'_c\mathbf{F}_{c,t} + \varepsilon_{c,t}, \tag{2}$$

where $R^{LS}_{c,t}$ is the value-weighted (equal-weighted) monthly long–short return in country c and month t, based on the country-level portfolios reported in Tables 2 and 3, respectively. The vector $\mathbf{X}_c$ contains the time-invariant country-level insider regulation proxies and the vector $\mathbf{F}_{c,t}$ contains the country-specific monthly FF6 factor returns. The factor-loading vector $\boldsymbol{\beta}_c$ is allowed to vary by country, so that each country has its own exposure to the FF6 factors. The coefficient vector $\boldsymbol{\gamma}$ captures the relation between the insider regulation proxies and cross-country differences in risk-adjusted long–short returns. Standard errors are double-clustered by country and month.

Table 10 reports the empirical results with respect to unconditional (*UNC*, in Panel A) or composite (*CID*, in Panel B) information-driven long–short insider trading strategies. In Table OA.15 of the Supplementary Material, we provide the same analysis separately for the long and short portfolios.

Assuming that the *monitoring hypothesis* is correct, one would expect AS, CLASSA, BLACKOUT, ITR, and IRI to take negative values, as an increase in all of them indicates higher insider trading restrictions.

Panels A and B of Table 10 report the results of the regressions for the value- and equal-weighted long–short implementations of the unconditional (*UNC*) and composite (*CID*) information-driven insider trading strategies, respectively. The univariate regressions of Panel A show consistent results in line with the *monitoring hypothesis*, that is, consistently negative although only sometimes significant coefficients.[16] We only find a significant (at the 5% level) relationship between the equal-weighted *UNC* strategy and the anti-self-dealing index (AS), the occurrence of blackout periods (BLACKOUT), and the composite insider regulation index (IRI), respectively. This suggests that the abnormal performance of the equal-weighted *UNC* strategy is greater in countries with lower insider trading restrictions. Judging the explanatory power of insider trading restrictions based on the multiple regression framework which jointly includes all four original proxies reveals no significant relation with respect to the value-weighted *UNC* strategy and a negative relation (at the 5% level) between the equal-weighted *UNC* strategy and BLACKOUT only. Nevertheless, at least most of the signs remain negative across proxies and specifications.

[16]Looking at the long and short legs in Table OA.15 of the Supplementary Material 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.

TABLE 10

Cross-Country Analysis

Table 10 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. Following Kolasinski and Yang (2018) and Cochrane (2005), we estimate a one-step panel regression that jointly identifies the country-level risk-adjusted returns and their relation to country characteristics, using country-specific FF6 factor loadings (implemented via country-factor interactions) and two-way clustering by country and month. The dependent variables are the value- (VW) and equal-weighted (EW) long–short returns of the 34 countries from 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 combined insider regulation index (IRI) constructed from the four aforementioned proxies. All explanatory variables are described in detail in Table OA.17 of the Supplementary Material. The actual variable values are reported in Table OA.14 of the Supplementary Material. Table OA.15 of the Supplementary Material provides the same analysis for the long and short portfolios, respectively. The *t*-statistics reported (in parentheses) are computed using two-way clustered standard errors by country and month. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	VW						EW					
Panel A. UNC (Long–Short)												
AS	−0.530					−0.507	−0.644***					−0.397*
	(−1.55)					(−1.20)	(−2.88)					(−1.83)
CLASSA		−0.256				−0.196		−0.114				−0.052
		(−1.58)				(−1.14)		(−0.76)				(−0.41)
BLACKOUT			−0.210			0.161			−0.979**			−0.887**
			(−0.54)			(0.30)			(−2.55)			(−2.17)
ITR				−0.047		−0.032				−0.053		0.045
				(−0.55)		(−0.32)				(−0.67)		(0.73)
IRI					−0.199*						−0.260**	
					(−1.73)						(−2.19)	
N	6,210	6,210	6,210	6,029	6,210	6,029	6,210	6,210	6,210	6,029	6,210	6,029
R^2	0.101	0.101	0.101	0.098	0.101	0.099	0.099	0.097	0.099	0.099	0.099	0.101
Panel B. CID (Long–Short)												
AS	−0.743					−0.715	−0.541					−0.257
	(−1.65)					(−1.28)	(−1.52)					(−0.66)
CLASSA		−0.225				−0.123		−0.066				−0.004
		(−1.07)				(−0.55)		(−0.33)				(−0.03)
BLACKOUT			−0.502			0.064			−0.962*			−1.148*
			(−1.07)			(0.10)			(−1.75)			(−1.93)
ITR				−0.103		−0.084				−0.014		0.102
				(−0.90)		(−0.71)				(−0.13)		(1.17)
IRI					−0.281*						−0.209	
					(−1.72)						(−1.24)	
N	6,210	6,210	6,210	6,029	6,210	6,029	6,210	6,210	6,210	6,029	6,210	6,029
R^2	0.102	0.101	0.101	0.098	0.102	0.099	0.090	0.089	0.090	0.089	0.090	0.091

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Assuming that the relative outperformance of the *CID* strategy originates from insiders using nonpublic information, we conjecture that the explanatory power of insider trading restriction proxies is stronger for these trading strategies. Contradicting this conjecture, Panel B shows fewer (i.e., no) significant coefficients (at the 5% level) for the insider regulation proxies. This is also confirmed by the insignificant coefficients in all specifications of the cross-country analysis for the long–short *CID* − *UNC* strategy in Table OA.16 of the Supplementary Material.[17]

Finally, as an alternative test to the regression-based cross-country analysis, we use the composite insider regulation index (IRI) to create high (HIRI) and low (LIRI) regulation regions via a tercile split to replicate the main DM versus EM analysis of Tables 4 and 9 for the high and low regulation samples. The results are reported in Table OA.21 of the Supplementary Material.[18] Overall, the high versus low insider regulation sample tests only show limited evidence for a greater outperformance in low regulation regions, as only the value-weighted country-neutral *CID* − *UNC* spreads are statistically significant.

Overall, the comparatively weaker findings for the *CID* strategies in Panel B of Table 10 and the insignificant results for the performance differences between high and low regulation samples may imply that regulatory differences of insider trading restrictions across countries are not a key driver of the strategy performance. Rather than exploiting nonpublic information, informative insiders in the *CID* strategies may achieve their outperformance primarily through a superior interpretation of public information compared to outside investors.

VI. 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 novel approach by synthesizing a substantial subset of previously proposed signals into an overall cross-sectional measure and show that it tends to perform well in a global sample, especially for smaller stocks. 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, similar composite approaches could be applied to the performance prediction of other presumably informed market participants, such as mutual funds, hedge funds, or analysts.

[17]We also run the cross-country analysis with a two-step procedure in Tables OA.18, OA.19, and OA.20 of the Supplementary Material, where we use the FF6 alphas from Tables 2 and 3 (first-step) and regress them on the time-invariant country-level insider regulation proxies (second-step). This approach yields similar results, but is less suitable as it may be exposed to an errors-in-variables bias and as it has lower statistical power.

[18]The results for a country median split and for using a combined EM + DM 12-factor model instead of the FF6 factor regional models yield similar results. We use EM (DM) FF6 models for the LIRI (HIRI) sample, as the overlap between the respective samples is the greatest.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109026103366.

References

Aboody, D., and B. Lev. "Information Asymmetry, R&D, and Insider Gains." *Journal of Finance*, 55 (2000), 2747–2766. https://doi.org/10.1111/0022-1082.00305.

Adhikari, B. K.; A. Agrawal; and B. Sharma. "Does Litigation Risk Deter Insider Trading? Evidence from Universal Demand Laws." *Journal of Financial and Quantitative Analysis*, (2025), 1–49. https://doi.org/10.1017/S0022109025102482.

Akbari, A.; L. Ng; and B. Solnik. "Emerging Markets Are Catching up: Economic or Financial Integration?" *Journal of Financial and Quantitative Analysis*, 55 (2020), 2270–2303. https://doi.org/10.1017/S0022109019000681.

Akbas, F.; C. Jiang; and P. D. Koch. "Insider Investment Horizon." *Journal of Finance*, 75 (2020), 1579–1627. https://doi.org/10.1111/jofi.12878.

Ali, U., and D. Hirshleifer. "Opportunism as a Firm and Managerial Trait: Predicting Insider Trading Profits and Misconduct." *Journal of Financial Economics*, 126 (2017), 490–515. https://doi.org/10.1016/j.jfineco.2017.09.002.

Alldredge, D. M., and D. B. Blank. "Do Insiders Cluster Trades with Colleagues? Evidence from Daily Insider Trading." *Journal of Financial Research*, 42 (2019), 331–360. https://doi.org/10.1111/jfir.12172.

Alldredge, D. M., and D. B. Blank. "Insider Trading in Multinational Firms." *European Financial Management*, 30 (2024), 314–345. https://doi.org/10.1111/eufm.12415.

Alldredge, D. M., and D. C. Cicero. "Attentive Insider Trading." *Journal of Financial Economics*, 115 (2015), 84–101. https://doi.org/10.1016/j.jfineco.2014.09.005.

Ben-David, I.; B. Kim; H. Moussawi; and D. Roulstone. "Corporate Transactions in Hard-to-Value Stocks." *Review of Corporate Finance Studies*, 12 (2023), 539–580. https://doi.org/10.1093/rcfs/cfab025.

Beneish, M. D., and M. E. Vargus. "Insider Trading, Earnings Quality, and Accrual Mispricing." *Accounting Review*, 77 (2002), 755–791. https://doi.org/10.2308/accr.2002.77.4.755.

Beny, L. N. "Do Insider Trading Laws Matter? Some Preliminary Comparative Evidence." *American Law and Economics Review*, 7 (2005), 144–183. https://doi.org/10.1093/aler/ahi002.

Beny, L. N. "Insider Trading Laws and Stock Markets Around the World: An Empirical Contribution to the Theoretical Law and Economics Debate." *Journal of Corporation Law*, 32 (2007), 237–300.

Bergstresser, D., and T. Philippon. "CEO Incentives and Earnings Management." *Journal of Financial Economics*, 80 (2006), 511–529. https://doi.org/10.1016/j.jfineco.2004.10.011.

Bernhardt, D.; B. Hollifield; and E. Hughson. "Investment and Insider Trading." *Review of Financial Studies*, 8 (1995), 501–543. https://doi.org/10.1093/rfs/8.2.501.

Bhattacharya, U., and H. Daouk. "The World Price of Insider Trading." *Journal of Finance*, 57 (2002), 75–108. https://doi.org/10.1111/1540-6261.00416.

Bhattacharya, U.; H. Daouk; B. Jorgenson; and C.-H. Kehr. "When an Event Is Not an Event: The Curious Case of an Emerging Market." *Journal of Financial Economics*, 55 (2000), 69–101. https://doi.org/10.1016/S0304-405X(99)00045-8.

Bris, A.; W. N. Goetzmann; and N. Zhu. "Efficiency and the Bear: Short Sales and Markets Around the World." *Journal of Finance*, 62 (2007), 1029–1079. https://doi.org/10.1111/j.1540-6261.2007.01230.x.

Brochet, F. "Aggregate Insider Trading and Market Returns: The Role of Transparency." *Journal of Business Finance and Accounting*, 46 (2019), 336–369. https://doi.org/10.1111/jbfa.12357.

Brockman, P.; D. Y. Chung; and C. Pérignon. "Commonality in Liquidity: A Global Perspective." *Journal of Financial and Quantitative Analysis*, 44 (2009), 851–882. https://doi.org/10.1017/S0022109009990123.

Bushman, R. M.; J. D. Piotroski; and A. J. Smith. "Insider Trading Restrictions and Analysts' Incentives to Follow Firms." *Journal of Finance*, 60 (2005), 35–66. https://doi.org/10.1111/j.1540-6261.2005.00724.x.

Cheng, C. S. A.; H. H. Huang; and Y. Li. "Does Shareholder Litigation Deter Insider Trading?" *Journal of Law, Finance, and Accounting*, 1 (2016), 275–318. https://doi.org/10.1561/108.00000007.

Cheng, Q., and K. Lo. "Insider Trading and Voluntary Disclosures." *Journal of Accounting Research*, 44 (2006), 815–848. https://doi.org/10.1111/j.1475-679X.2006.00222.x.

https://doi.org/10.1017/S0022109026103366

Chung, S. G.; B. W. Goh; K. B. J. Lee; and T. Shevlin. "Corporate Tax Aggressiveness and Insider Trading." *Contemporary Accounting Research*, 36 (2019), 230–258. https://doi.org/10.1111/1911-3846.12422.

Cline, B. N.; S. Gokkaya; and X. Liu. "The Persistence of Opportunistic Insider Trading." *Financial Management*, 46 (2017), 919–964. https://doi.org/10.1111/fima.12177.

Cline, B. N., and C. Houston. "Insider Filing Violations and Illegal Information Delay." *Journal of Financial and Quantitative Analysis*, 58 (2023), 2262–2297. https://doi.org/10.1017/S0022109022000953.

Cochrane, J. H. *Asset Pricing*. Princeton, NJ: Princeton University Press (2005).

Cohen, L.; C. Malloy; and L. Pomorski. "Decoding inside Information." *Journal of Finance*, 67 (2012), 1009–1043. https://doi.org/10.1111/j.1540-6261.2012.01740.x.

Contreras, H.; J. P. Fidrmuc; and R. Kozhan. "Insiders' Information Advantage: Evidence from Competition with Short Sellers." *Journal of Financial and Quantitative Analysis*, 61 (2026), 1841–1880. https://doi.org/10.1017/S0022109025102287.

Cziraki, P.; P. De Goeij; and L. Renneboog. "Corporate Governance Rules and Insider Trading Profits." *Review of Finance*, 18 (2014), 67–108. https://doi.org/10.1093/rof/rft001.

Dai, L.; R. Fu; J.-K. Kang; and I. Lee. "Corporate Governance and the Profitability of Insider Trading." *Journal of Corporate Finance*, 40 (2016), 235–253. https://doi.org/10.1016/j.jcorpfin.2016.08.002.

Dai, L.; J. T. Parwada; and B. Zhang. "The Governance Effect of the Media's News Dissemination Role: Evidence from Insider Trading." *Journal of Accounting Research*, 53 (2015), 331–366. https://doi.org/10.1111/1475-679X.12073.

Dardas, K. "Identifying Profitable Insider Transactions." *Journal of Investing*, 21 (2012), 61–75. https://doi.org/10.3905/joi.2012.21.2.061.

Dardas, K., and A. Güttler. "Are Directors' Dealings Informative? Evidence from European Stock Markets." *Financial Markets and Portfolio Management*, 25 (2011), 111–148. https://doi.org/10.1007/s11408-011-0156-z.

Denis, D. J., and J. Xu. "Insider Trading Restrictions and Top Executive Compensation." *Journal of Accounting and Economics*, 56 (2013), 91–112. https://doi.org/10.1016/j.jacceco.2013.04.003.

Djankov, S.; R. La Porta; F. Lopez-de-Silanes; and A. Shleifer. "The Law and Economics of Self-Dealing." *Journal of Financial Economics*, 88 (2008), 430–465. https://doi.org/10.1016/j.jfineco.2007.02.007.

Drobetz, W., and T. Otto. "Empirical Asset Pricing via Machine Learning: Evidence from the European Stock Market." *Journal of Asset Management*, 22 (2021), 507–538. https://doi.org/10.1057/s41260-021-00237-x.

Durnev, A. A., and A. S. Nain. "Does Insider Trading Regulation Deter Private Information Trading? International Evidence." *Pacific-Basin Finance Journal*, 15 (2007), 409–433. https://doi.org/10.1016/j.pacfin.2006.10.003.

El Ghoul, S.; O. Guedhami; R. Nash; and H. H. Wang. "Economic Policy Uncertainty and Insider Trading." *Journal of Financial Research*, 45 (2022), 817–854. https://doi.org/10.1111/jfir.12299.

Ellul, A., and M. Panayides. "Do Financial Analysts Restrain Insiders' Informational Advantage?" *Journal of Financial and Quantitative Analysis*, 53 (2018), 203–241. https://doi.org/10.1017/S0022109017000990.

Engelberg, J.; R. D. McLean; and J. Pontiff. "Anomalies and News." *Journal of Finance*, 73 (2018), 1971–2001. https://doi.org/10.1111/jofi.12718.

Fama, E. F., and K. R. French. "Choosing Factors." *Journal of Financial Economics*, 128 (2018), 234–252. https://doi.org/10.1016/j.jfineco.2018.02.012.

Fernandes, N., and M. A. Ferreira. "Insider Trading Laws and Stock Price Informativeness." *Review of Financial Studies*, 22 (2009), 1845–1887. https://doi.org/10.1093/rfs/hhn066.

Fidrmuc, J. P.; M. Goergen; and L. Renneboog. "Insider Trading, News Releases, and Ownership Concentration." *Journal of Finance*, 61 (2006), 2931–2973. https://doi.org/10.1111/j.1540-6261.2006.01008.x.

Fidrmuc, J. P.; A. Korczak; and P. Korczak. "Why Does Shareholder Protection Matter for Abnormal Returns After Reported Insider Purchases and Sales?" *Journal of Banking and Finance*, 37 (2013), 1915–1935. https://doi.org/10.1016/j.jbankfin.2012.06.019.

Frankel, R., and X. Li. "Characteristics of a Firm's Information Environment and the Information Asymmetry Between Insiders and Outsiders." *Journal of Accounting and Economics*, 37 (2004), 229–259. https://doi.org/10.1016/j.jacceco.2003.09.004.

Freyberger, J.; A. Neuhierl; and M. Weber. "Dissecting Characteristics Nonparametrically." *Review of Financial Studies*, 33 (2020), 2326–2377. https://doi.org/10.1093/rfs/hhz123.

Gao, G. P.; Q. Ma; D. T. Ng; and Y. Wu. "The Sound of Silence: What Do We Know When Insiders Do Not Trade?" *Management Science*, 68 (2022), 4835–4857. https://doi.org/10.1287/mnsc.2021.4113.

https://doi.org/10.1017/S0022109026103366

Gebka, B.; A. Korczak; P. Korczak; and J. Traczykowski. "Profitability of Insider Trading in Europe: A Performance Evaluation Approach." *Journal of Empirical Finance*, 44 (2017), 66–90. https://doi.org/10.1016/j.jempfin.2017.08.001.

Giamouridis, D.; M. Liodakis; and A. Moniz. "Some Insiders Are Indeed Smart Investors." Working Paper, Bank of America, Citigroup, Acadian Asset Management (2008).

Gorbenko, A. "Short Selling Around News in International Stock Markets." *Review of Asset Pricing Studies*, 16 (2026), 95–132. https://doi.org/10.1093/rapstu/raaf011.

Griffin, J. M.; N. H. Hirschey; and P. J. Kelly. "How Important Is the Financial Media in Global Markets?" *Review of Financial Studies*, 24 (2011), 3941–3992. https://doi.org/10.1093/rfs/hhr099.

Griffin, J. M.; P. J. Kelly; and F. Nardari. "Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets." *Review of Financial Studies*, 23 (2010), 3225–3277. https://doi.org/10.1093/rfs/hhq044.

Gu, S.; B. Kelly; and D. Xiu. "Empirical Asset Pricing via Machine Learning." *Review of Financial Studies*, 33 (2020), 2223–2273. https://doi.org/10.1093/rfs/hhaa009.

Hanauer, M. X., and T. Kalsbach. "Machine Learning and the Cross-Section of Emerging Market Stock Returns." *Emerging Markets Review*, 55 (2023), 101022. https://doi.org/10.1016/j.ememar.2023.101022.

Hanauer, M. X.; A. Soebhag; M. Stam; and T. Hoogteijling. "Do Machine Learning Models Need to Be Sector Experts?" Working Paper, Technische Universität München (TUM), Erasmus University Rotterdam, Tilburg University, Robeco Quantitative Investments (2025).

Hillier, D.; A. Korczak; and P. Korczak. "The Impact of Personal Attributes on Corporate Insider Trading." *Journal of Corporate Finance*, 30 (2015), 150–167. https://doi.org/10.1016/j.jcorpfin.2014.12.003.

Hong, C. Y., and F. W. Li. "The Information Content of Sudden Insider Silence." *Journal of Financial and Quantitative Analysis*, 54 (2019), 1499–1538. https://doi.org/10.1017/S0022109018001059.

Hong, C. Y.; F. W. Li; And Q. Zhu. "Do Foreign Institutional Investors Deter Opportunistic Insider Trading?" Working Paper, Shanghai Jiao Tong University, Singapore Management University, Nanyang Business School (2019).

Hsieh, J.; L. Ng; and Q. Wang. "How Informative Are Insider Trades and Analyst Recommendations?" *Journal of Banking and Finance*, 149 (2023), 106787. https://doi.org/10.1016/j.jbankfin.2023.106787.

Ince, O. S., and R. B. Porter. "Individual Equity Return Data from Thomson Datastream: Handle with Care!" *Journal of Financial Research*, 29 (2006), 463–479. https://doi.org/10.1111/j.1475-6803.2006.00189.x.

Inci, A. C.; M. P. Narayanan; and H. N. Seyhun. "Gender Differences in Executives' Access to Information." *Journal of Financial and Quantitative Analysis*, 52 (2017), 991–1016. https://doi.org/10.1017/S0022109017000266.

Jackson, R.; B. Lynch-Levy; and D. Taylor. "Late Filings and Insider Trading: Broken Windows or Opportunism?" Working Paper, NYU School of Law and The Wharton School, University of Pennsylvania (2022).

Jagolinzer, A. D.; D. F. Larcker; and D. J. Taylor. "Corporate Governance and the Information Content of Insider Trades." *Journal of Accounting Research*, 49 (2011), 1249–1274. https://doi.org/10.1111/j.1475-679X.2011.00424.x.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x.

Jeng, L. A.; A. Metrick; and R. Zeckhauser. "Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective." *Review of Economics and Statistics*, 85 (2003), 453–471. https://doi.org/10.1162/003465303765299936.

Jenter, D. "Market Timing and Managerial Portfolio Decisions." *Journal of Finance*, 60 (2005), 1903–1949. https://doi.org/10.1111/j.1540-6261.2005.00783.x.

Jiang, C.; K. John; J. J. Kim; and J. Zhang. "CEOs' Narcissism and Opportunistic Insider Trading." *Journal of Corporate Finance*, 91 (2025), 102695. https://doi.org/10.1016/j.jcorpfin.2024.102695.

Jiang, C.; M. B. Wintoki; and Y. Xi. "Insider Trading and the Legal Expertise of Corporate Executives." *Journal of Banking and Finance*, 127 (2021), 106114. https://doi.org/10.1016/j.jbankfin.2021.106114.

Joseph, K., and M. B. Wintoki. "Advertising Investments, Information Asymmetry, and Insider Gains." *Journal of Empirical Finance*, 22 (2013), 1–15. https://doi.org/10.1016/j.jempfin.2013.02.004.

Kacperczyk, M., and E. S. Pagnotta. "Legal Risk and Insider Trading." *Journal of Finance*, 79 (2024), 305–355. https://doi.org/10.1111/jofi.13299.

https://doi.org/10.1017/S0022109026103366

Karamanou, I.; G. Pownall; and R. Prakash. "Asymmetric Information Consolidation and Price Discovery: Inferring Bad News from Insider Sales." *Journal of Business Finance and Accounting*, 48 (2021), 230–268. https://doi.org/10.1111/jbfa.12476.

Karolyi, G. A.; K.-H. Lee; and M. A. van Dijk. "Understanding Commonality in Liquidity Around the World." *Journal of Financial Economics*, 105 (2012), 82–112. https://doi.org/10.1016/j.jfineco.2011.12.008.

Kelly, P. "The Information Content of Realized Losses." *Review of Financial Studies*, 31 (2018), 2468–2498. https://doi.org/10.1093/rfs/hhy013.

Khalilov, A., and B. G. Osma. "Accounting Conservatism and the Profitability of Corporate Insiders." *Journal of Business Finance and Accounting*, 47 (2020), 333–364. https://doi.org/10.1111/jbfa.12438.

Kolasinski, A. C., and X. Li. "Are Corporate Managers Savvy About Their Stock Price? Evidence from Insider Trading After Earnings Announcements." *Journal of Accounting and Public Policy*, 29 (2010), 27–44. https://doi.org/10.1016/j.jaccpubpol.2009.10.004.

Kolasinski, A. C., and N. Yang. "Managerial Myopia and the Mortgage Meltdown." *Journal of Financial Economics*, 128 (2018), 466–485. https://doi.org/10.1016/j.jfineco.2017.03.010.

Kyung, H., and J. S. Nam. "Insider Trading in News Deserts." *Accounting Review*, 98 (2023), 299–325. https://doi.org/10.2308/TAR-2020-0799.

Lakonishok, J., and I. Lee. "Are Insider Trades Informative?" *Review of Financial Studies*, 14 (2001), 79–111. https://doi.org/10.1093/rfs/14.1.79.

Lambe, B.; Z. Li; and W. Qin. "Uncertain Times and the Insider Perspective." *International Review of Financial Analysis*, 81 (2022), 102138. https://doi.org/10.1016/j.irfa.2022.102138.

Landis, C., and S. Skouras. "Guidelines for Asset Pricing Research Using International Equity Data from Thomson Reuters Datastream." *Journal of Banking and Finance*, 130 (2021), 106128. https://doi.org/10.1016/j.jbankfin.2021.106128.

Lee, K.-H. "The World Price of Liquidity Risk." *Journal of Financial Economics*, 99 (2011), 136–161. https://doi.org/10.1016/j.jfineco.2010.08.003.

Leippold, M.; Q. Wang; and W. Zhou. "Machine Learning in the Chinese Stock Market." *Journal of Financial Economics*, 145 (2022), 64–82. https://doi.org/10.1016/j.jfineco.2021.08.017.

Leland, H. E. "Insider Trading: Should It Be Prohibited?" *Journal of Political Economy*, 100 (1992), 859–887. https://doi.org/10.1086/261843.

Leuz, C. "Different Approaches to Corporate Reporting Regulation: How Jurisdictions Differ and Why." *Accounting and Business Research*, 40 (2010), 229–256. https://doi.org/10.1080/00014788.2010.9663398.

Liu, X. "Corruption Culture and Corporate Misconduct." *Journal of Financial Economics*, 122 (2016), 307–327. https://doi.org/10.1016/j.jfineco.2016.06.005.

Malliouris, D. D.; A. T. Vermorken; and M. A. Vermorken. "Aggregate Insider Trading and Future Market Returns in the United States, Europe, and Asia." *International Journal of Finance and Economics*, 27 (2022), 802–821. https://doi.org/10.1002/ijfe.2178.

Mansi, S.; L. Peng; J. Qi; and H. Shi. "Investor Attention and Insider Trading." *Journal of Financial and Quantitative Analysis*, 60 (2025), 2293–2333. https://doi.org/10.1017/S0022109024000450.

Massa, M.; W. Qian; W. Xu; and H. Zhang. "Competition of the Informed: Does the Presence of Short Sellers Affect Insider Selling?" *Journal of Financial Economics*, 118 (2015), 268–288. https://doi.org/10.1016/j.jfineco.2015.08.004.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708. https://doi.org/10.2307/1913610.

Newey, W. K., and K. D. West. "Automatic Lag Selection in Covariance Matrix Estimation." *Review of Economic Studies*, 61 (1994), 631–653. https://doi.org/10.2307/2297912.

Piotroski, J. D., and D. T. Roulstone. "Do Insider Trades Reflect Both Contrarian Beliefs and Superior Knowledge About Future Cash Flow Realizations?" *Journal of Accounting and Economics*, 39 (2005), 55–81. https://doi.org/10.1016/j.jacceco.2004.01.003.

Rasekhschaffe, K. C., and R. C. Jones. "Machine Learning for Stock Selection." *Financial Analysts Journal*, 75 (2019), 70–88. https://doi.org/10.1080/0015198X.2019.1596678.

Ravina, E., and P. Sapienza. "What Do Independent Directors Know? Evidence from their Trading." *Review of Financial Studies*, 23 (2010), 962–1003. https://doi.org/10.1093/rfs/hhp027.

Seyhun, H. N. "The Information Content of Aggregate Insider Trading." *Journal of Business*, 61 (1988), 1–24. https://doi.org/10.1086/296417.

Sun, F.; S. Dutta; H. Huang; and P. Zhu. "News Media and Insider Trading Profitability: An Emerging Country Perspective." *Emerging Markets Review*, 49 (2021), 100795. https://doi.org/10.1016/j.ememar.2021.100795.

https://doi.org/10.1017/S0022109026103366

Tobek, O., and M. Hronec. "Does It Pay to Follow Anomalies Research? Machine Learning Approach with International Evidence." *Journal of Financial Markets*, 56 (2021), 100588. https://doi.org/10.1016/j.finmar.2020.100588.

Veenman, D. "Do Managers Trade on Public or Private Information? Evidence from Fundamental Valuations." *European Accounting Review*, 22 (2013), 427–465. https://doi.org/10.1080/09638180.2012.683664.

Wang, W.; Y.-C. Shin; and B. B. Francis. "Are CFOs' Trades More Informative than CEOs' Trades?" *Journal of Financial and Quantitative Analysis*, 47 (2012), 743–762. https://doi.org/10.1017/S0022109012000257.

https://doi.org/10.1017/S0022109026103366