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Indirect Insider Trading

Brad Goldie
Miami University Farmer School of Business
goldieba@miamioh.edu

Chao Jiang
University of South Carolina Darla Moore School of Business
chao.jiang@moore.sc.edu

Paul Koch
Iowa State University Ivy College of Business
pkoch@iastate.edu (corresponding author)

M. Babajide Wintoki
University of Kansas School of Business
jwintoki@ku.edu

Abstract

Insiders must disclose indirect trades made through accounts they control, including family, trust, retirement, and foundation accounts. Indirect trades through these accounts are more profitable than direct trades in the insider's own account. They are also more likely to be made by "opportunistic" insiders who make nonroutine trades, or who trade profitably before earnings announcements, or who have a short investment horizon. These trades contain more predictive information about earnings surprises and large price changes, and they tend to be made by insiders at firms with high information asymmetry. Insiders also make fewer indirect trades following periods of intense regulatory scrutiny.

I. Introduction

The privilege of corporate insiders' access to material nonpublic information attracts the attention of scholars, market participants, and regulators who wish to know whether insider trades convey predictive information about forthcoming firm performance and stock price movements. Prior studies glean the sample of all

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publicly disclosed insider trades in an attempt to find groups of unusual trades that contain more predictive information about stock prices. For example, recent work identifies subsets of insiders and their trades that tend to be particularly opportunistic (i.e., profitable), including nonroutine insiders (Cohen, Malloy, and Pomorski (2012)), insiders who trade profitably before earnings announcements (Ali and Hirshleifer (2017)), and insiders with a short investment horizon (Akbas, Jiang, and Koch (2020)).[1]

However, insiders also trade for reasons not driven by information, including a desire for liquidity, diversification, or corporate control. These alternative rationales make it difficult for market participants and regulators to detect subsets of insiders or their trades that are more likely to signal private information. This concern highlights the need for more research to advance further our understanding of the economic motivation and predictive information embodied in various aspects of insider trading behavior.

This article breaks new ground by examining a different group of unusual insider trades. We compare the information content of direct trades made in the insider's own account versus indirect trades made in the accounts of family members, trusts, retirement accounts, and foundations. We hand-collect data on all U.S. corporate insider trades from files containing the individual Form 4s filed by insiders electronically, which have been available on the Securities and Exchange Commission (SEC) EDGAR website since July 2003.[2] From these files, we also gather information about whether an insider trade is direct (for the insider's own account), or an indirect trade for a family member, trust, retirement account, or foundation, which is disclosed on the Form 4 in field #7 and its footnotes.

Although direct and indirect trades represent two distinct categories of insider trades, it is not immediately obvious which, if either, should be more informed ex ante. Indeed, there are three broad possibilities. First, opportunistic insiders may randomly distribute informed trades across their direct and indirect accounts. In this case, there should be no difference in the average abnormal returns earned following their direct trades versus their indirect trades.

A second possibility is that indirect trades may, on average, be less informed than direct trades. Indirect trades are often made on behalf of entities or individuals who are not corporate insiders themselves, and are thus less informed than the insider making trades on their behalf. These noncorporate beneficiaries of indirect accounts may persuade the informed insider who controls the account to execute the timing of trades in a manner that meets their wishes, but does not exploit the

[1]See also Jaffe (1974), Seyhun (1986), (1988), (1992), Lee, Mikkelson, and Partch (1992), Agrawal and Jaffe (1995), Aboody and Lev (2000), Bettis, Coles, and Lemmon (2000), Lakonishok and Lee (2001), Jeng, Metrick, and Zeckhauser (2003), Frankel and Li (2004), Jenter (2005), Piotroski and Roulstone (2005), Fidrmuc, Goergen, and Renneboog (2006), Huddart, Ke, and Shi (2007), Marin and Olivier (2008), Ravina and Sapienza (2010), Jagolinzer, Larcker, and Taylor (2011), Skaife, Veenman, and Wangerin (2013), Bhattacharya (2014), Cziraki, De Goeij, and Renneboog (2014), Alldredge and Cicero (2015), Kelly (2018), Wu (2018), Amel-Zadeh, Faasse, and Lotz (2019), Ben-David, Birru, and Rossi (2019), Hong and Li (2019), and Jagolinzer, Larcker, Ormazabal, and Taylor (2020). There is also a large literature on illegal insider trading. For example, see Cornell and Sirri (1992), Meulbroek (1992), Fishe and Robe (2004), Ahern (2017), (2020), and Kacperczyk and Pagnotta (2019).

[2]In July 2003, the SEC began requiring insiders to disclose their insider trades by submitting Form 4 electronically (https://www.sec.gov/edgar/search-and-access).

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insider's access to private information. For example, the beneficiary of a foundation or trust may seek to access the funds in their indirect account by asking the insider to sell stocks, without regard to private information possessed by the insider executing the trade on their behalf.

Finally, a third possibility is that indirect trades may, on average, be more informed than direct trades. Although we cannot directly observe the precise reasons for any particular insider's informed trades, there are three potential theoretical rationales for expecting a higher proportion of informed trading through indirect accounts relative to direct accounts.

First, indirect trades may contain more information than direct trades because they are less likely to be motivated by reasons unrelated to information, such as a desire for liquidity, diversification, or corporate control. For instance, although insiders commonly make uninformed sales through direct accounts to achieve diversification or liquidity, they are unlikely to make such uninformed sales through indirect accounts. As an example, insiders are unlikely to sell shares from a retirement account to meet immediate liquidity needs. On the other hand, insiders typically accumulate large direct shareholdings from their compensation packages. This concentration of direct shareholdings motivates selling from the insider's own account to obtain diversification or liquidity, rather than because of bad news. Most prior work concludes that, for this reason, the average insider sale is uninformed.[3] Similarly, insiders who make open market purchases over time to build a large stake in a quest for corporate control are more likely to use their direct accounts.[4] These motives for uninformed trading are less likely to apply to indirect trades.

Second, insiders who use their information advantage to build wealth, either directly for themselves or for eventual bequests, may trade through indirect accounts to minimize the impact of personal, estate, or gift taxes. Consistent with this view, Yermack (2009) finds that Chairs and CEOs donate shares to foundations just before sharp drops in the share price to maximize their own personal income tax benefits from charitable giving. Dambra, Gustafson, and Quinn (2020) find that 23% of CEOs use tax-advantaged pre-IPO trusts, and share transfers into such trusts are positively associated with CEO equity wealth, estate taxes, and post-IPO stock price appreciation. Brown, Huston, and Wenzel (2018) analyze a small hand-collected sample of CEO stock gifts to family members, and show that the timing of these gifts precedes significant price appreciation over long horizons, thereby avoiding estate and gift taxes. While these three studies only look at limited samples of stock donations, transfers, and gifts, insiders may also use open market purchases and sales through indirect accounts to obtain the same tax benefits. For example, they may buy shares for a family account prior to positive news, to avoid estate or gift taxes. Alternatively, insiders may sell holdings in a trust or retirement account

[3]Some early studies find that insider sales contain negative information about future returns (see, e.g., Jaffe (1974), Seyhun (1986)). However, more recent work generally finds that only insider purchases contain predictive information about future stock returns (see, e.g., Lakonishok and Lee (2001), Jeng et al. (2003)).

[4]Akbas et al. (2020) find that such purchases by insiders with a long investment horizon are less informed.

before a price decline, to preserve the tax benefits embedded in the accumulated wealth of such accounts.[5]

Third, consider indirect trades made through family accounts. The subset of insiders who open accounts on behalf of family members may be more opportunistic, on average, and channel a disproportionate amount of their informed trades through family accounts. This view is consistent with the work of Berkman, Koch, and Westerholm (2014), who find that the small subset of all Finnish retail investors who open accounts on behalf of young children outperform other individual investors, and they tend to make their best trades through these underaged accounts. In addition, although illegal insider trading through family accounts may seem unlikely, the Appendix documents several recent U.S. insider trading cases that involve the accounts of family members.

We begin our analysis by comparing the performance of all *direct* trades made in the insider's own account with all *indirect* trades made through other accounts, using a calendar-time portfolio approach. We find that the portfolio of stocks where insiders make *direct* purchases each month has an alpha of 0.65%, whereas the portfolio of all *indirect* purchases has a larger monthly alpha of 0.89%, significantly outperforming direct purchases by 25 bps. We further analyze subsets of indirect trades and find that different groups outperform direct trades by a greater amount, on either the buy side or the sell side, depending on the trade category. For example, portfolios of indirect purchases made in *family* accounts earn a monthly alpha of 1.09%, which significantly outperforms direct purchases by 45 bps, whereas subsets of family purchases made for a *spouse* or *child* earn an even higher alpha of 1.27% or 1.30%, respectively, outperforming direct purchases by 63 or 65 bps. On the sell side, indirect sales made in *nonfamily trusts* or *retirement accounts* significantly outperform direct sales by −22 to −67 bps.

We next use a regression framework that accounts for the strength of the information signal conveyed by the size of insider trades. This analysis confirms the evidence from our portfolio approach, indicating that different groups of *indirect* trades significantly outperform *direct* trades after controlling for other firm attributes. For example, the results imply that a hedge portfolio that is long the subset of large *direct* purchases and short large *direct* sales earns an abnormal return of 0.36%–0.40% per month, after controlling for firm attributes. However, the analogous hedge portfolio of large purchases and sales in *any indirect* account earns a larger abnormal return of 0.90% in the following month, which significantly outperforms direct trades by 50 bps.

Furthermore, we show that this outperformance of indirect trades persists for up to 2 years, and does not reverse over longer horizons. For example, the 1-month abnormal return of 0.40% for the hedge portfolio of large *direct* insider purchases and sales accumulates to 2.17% after 24 months. However, the analogous hedge portfolio based on all *indirect family* trades accumulates to 6.34% after 2 years, which significantly outperforms the hedge portfolio of *direct* trades. In addition,

[5]Insiders who wish to exploit positive private information are likely to find a lower tax incidence for long-term capital gains arising from share purchases in an indirect account, compared with their direct account. Likewise, the after-tax loss avoided from a price decline is larger in tax-advantaged retirement and trust accounts, relative to direct accounts.

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after 2 years, the hedge portfolio of large purchases and sales in *nonfamily trusts* earns even more, at 10.48%, whereas analogous trades made in *nonfamily retirement accounts* earn 7.22%, both of which significantly outperform direct trades over this 2-year period. Importantly, we find no evidence of outperformance for indirect trades on behalf of a foundation, and no evidence of return reversals in any account over longer horizons.

We also examine the relative information content of direct versus indirect insider trades regarding future firm-specific information events. We find that indirect trades contain significantly more predictive information than direct trades about upcoming quarterly earnings surprises and large idiosyncratic price changes. These results suggest that insiders tend to place their trades strategically through indirect accounts, rather than direct accounts, prior to imminent firm events. Consequently, the superior performance of indirect trades appears to arise at least partially from exploiting inside information about forthcoming firm-specific information events.

Prior research suggests that insiders are less likely to make informed trades when the risk of doing so is made more salient (e.g., during periods of intense scrutiny by the SEC (Cohen et al. (2012), Del Guercio, Odders-White, and Ready (2017)). We follow this research to investigate whether intensified SEC enforcement activity deters insider trading through indirect accounts moreso than through direct accounts. We find that insiders make a significantly smaller proportion of all their insider trades through indirect accounts, relative to direct accounts, following months with more cases released by the SEC against illegal insider trading. This outcome suggests that insiders are more reluctant to make opportunistic trades through indirect accounts when litigation risk is especially salient.

We further explore how the attributes of insiders or their firms are associated with the inclination to make indirect trades versus direct trades. We find that indirect trades are more likely to be made by insiders from firms that are subject to greater information asymmetry (i.e., with smaller size, higher asset growth, more volatile stock prices, and lower institutional ownership). This evidence is consistent with the view that greater information asymmetry offers more trading opportunities and less scrutiny for insiders who wish to make informed trades through indirect accounts. In addition, indirect trades tend to be made by insiders who are older, or have longer tenure, more experience, and compensation packages that are more closely tied to the firm's stock price. Indirect trades are also more likely to be made by the CEO or Chair of the Board, and less likely by insiders who serve as General Counsel or are female. Furthermore, while insiders who trade through indirect accounts tend to trade more shares overall, they do so in smaller trade sizes, suggesting that opportunistic insiders tend to break up their informed trades over several accounts. This finding is consistent with prior work contending that informed investors disguise their activity by trading when liquidity is high and by splitting large orders into smaller trades.[6] Finally, indirect trades are more likely

[6]See Kyle (1985), Admati and Pfleiderer (1988), Barclay and Warner (1993), Hasbrouck (1995), Keim and Madhavan (1995), Chakravarty (2001), Garfinkel and Nimalendran (2003), and Collin-Dufresne and Fos (2015), (2016).

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to be made by "opportunistic" insiders who make nonroutine trades (Cohen et al. (2012)), or who trade profitably before earnings announcements (Ali and Hirshleifer (2017)), or have a short investment horizon (Akbas et al. (2020)).

Given the last result above, it is conceivable that indirect trades could be more informed, on average, merely because they are more likely to be made by these three aforementioned types of opportunistic insiders. In this case, indirect trades may simply correlate with these other aspects of opportunistic insider trading that have already been documented in the literature. We examine this potential explanation for our results by replicating our analysis after excluding nonroutine insiders, insiders who trade profitably before earnings announcements, and insiders with a short investment horizon. Although the subset of remaining insiders does not make these three types of opportunistic trades, their indirect trades still significantly outperform their own direct trades. This evidence establishes that indirect trades indeed represent a novel, unique form of opportunistic insider trading that has been heretofore unexplored in the insider trading literature.

Our results generally support the theoretical rationales we propose to explain why various categories of indirect trades are more likely to be informed than direct trades. For example, our finding that indirect purchases made in family accounts outperform direct purchases supports the conjecture that these indirect purchases offer a tax-advantaged mechanism to bequest wealth via informed trading. Similarly, the finding that sales made in nonfamily trust and retirement accounts significantly outperform direct sales (which are not informed, on average) is consistent with the view that insiders make informed sales to preserve the wealth accumulated in these tax-advantaged indirect accounts. Finally, trades in these indirect accounts are less likely to be made by routine insiders, who are prone to make uninformed trades to achieve liquidity or diversification (Cohen et al. (2012)).

Our analysis of the incremental information content of different categories of indirect trades significantly advances our understanding of the economic motivation and predictive information embodied in various aspects of insider trading behavior. The prior literature generally relies on the Thomson Financial insider trading database, and does not distinguish between direct insider trades versus indirect trades (made on behalf of families, trusts, retirement accounts, or foundations). One exception is Jeng, Metrick, and Zeckhauser (2003), who briefly mention that they find no significant difference in the performance of direct trades versus all indirect trades when they analyze data from 1975 to 1996.[7] We emphasize that they analyze data prior to 2003, the distinction between direct and indirect trades is not a focus of their work, and they do not separately investigate the relative information content of different types of indirect accounts.

Furthermore, although the Thomson insider trading database contains a variable that denotes every trade as direct or indirect, this variable is missing for nearly half of all insider trades prior to 2003. These missing data on indirect insider trades help to explain the paucity of prior work or evidence regarding the relative information content of indirect trades versus direct trades. In contrast, we rely on the actual

[7]Their discussion of their analysis of indirect trades is only presented briefly as an untabulated result, and is not part of their main analysis or findings.

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Form 4s filed by insiders electronically since 2003, which contain nonmissing information on indirect trades, as well as detailed information about trades made in different types of indirect accounts that does not appear in the Thomson database. Our analysis of these data establishes that an insider's inclination to make different types of indirect trades represents a unique and important behavioral attribute that can help both market participants and regulators to identify subsets of insiders and their trades that are significantly more informative.

Our article is related to research on personal finance decisions and studies on illegal trading that exploit private information. Private information often flows within personal networks, and individuals tend to use the accounts of others to hide their transactions when such trades are associated with private information and litigation risk. For example, Ahern (2017) collects data from illegal insider trading cases and shows that these cases often involve family members, friends, and other social networks. Berkman et al. (2014) find that trades made through underaged accounts earn abnormal returns, on average, and conjecture that guardians of these children try to hide their informed trades through the child's account. These findings are intuitive since informed individuals (whether or not they are corporate insiders) have the incentive to obfuscate their informed trades through the accounts of others, who are naturally prone to be family members or friends. However, this rationale for hiding illegal trades does not apply to our context or analysis, since both direct and indirect trades made by corporate insiders are reported to the SEC using the same Form 4, under the corporate insider's name.

II. Data and Description of Variables

A. Data on Indirect Trades

U.S. corporate insiders are required to disclose any personal trades made in their company's stock within 2 business days of the trade's execution. Insiders comply with this regulation by electronically submitting a Form 4 that describes the transaction details.

Figure 1 provides an actual example of this document with the insider's personal information redacted, to illustrate how we construct the data used in this study. The top portion of the Form 4 provides personal information about the insider and her/his firm. The middle panel of the Form 4 then lists information about the trades disclosed by the insider. Field #6 requires the insider to indicate whether each transaction is a "direct" trade for the insider's own account or an "indirect" trade through another account associated with the insider. If a transaction is identified as an indirect trade, the insider is given the opportunity to elaborate on the nature of this indirect ownership in field #7, as well as in footnotes to this field.

Since July 2003, the SEC has required insiders to submit Form 4 electronically, and makes these Form 4s available to the public on EDGAR. We download the files containing all individual Form 4s submitted by corporate insiders over the period of July 2003 to Dec. 2017. From these files, we identify different categories of indirect insider trades, by using text processing software to parse any information provided in field #7 of Form 4 and its related footnotes. Specifically, we search for words that indicate trades made on behalf of a spouse, child, or other family members, as well

FIGURE 1

Example of Form 4 with Indirect Trades, with Personal Information Redacted

Figure 1 provides an actual example of a Form 4 (with the insider's personal information redacted) to illustrate how we construct the data used in our study.

SEC Form 4

FORM 4

UNITED STATES SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549

OMB APPROVAL	
OMB Number:	XXXX-XXXX
Estimated average burden hours per response:	0.5

☐ Check this box if no longer subject to Section 16. Form 4 or Form 5 obligations may continue. *See* Instruction 1(b).

STATEMENT OF CHANGES IN BENEFICIAL OWNERSHIP

Filed pursuant to Section 16(a) of the Securities Exchange Act of 1934
or Section 30(h) of the Investment Company Act of 1940

1. Name and Address of Reporting Person*
XXXXXXXXXXXXX
(Last) (First) (Middle)
XXXXX XXXXX XXXXX
(Street)
XXXXXXXXXX XXXXX XXXXX
(City) (State) (Zip)

2. Issuer Name and Ticker or Trading Symbol
XXXXXXXXXXXXXXXXX [XXXX]

3. Date of Earliest Transaction (Month/Day/Year)
XX/XX/XXXX

4. If Amendment, Date of Original Filed (Month/Day/Year)

5. Relationship of Reporting Person(s) to Issuer (Check all applicable)
√ Director √ 10% Owner
Officer (give title below) Other (specify below)

6. Individual or Joint/Group Filing (Check Applicable Line)
√ Form filed by One Reporting Person
Form filed by More than One Reporting Person

Table I - Non-Derivative Securities Acquired, Disposed of, or Beneficially Owned

1. Title of Security (Instr. 3)	2. Transaction Date (Month/Day/Year)	2A. Deemed Execution Date, if any (Month/Day/Year)	3. Transaction Code (Instr. 8)		4. Securities Acquired (A) or Disposed Of (D) (Instr. 3, 4 and 5)			5. Amount of Securities Beneficially Owned Following Reported Transaction(s) (Instr. 3 and 4)	6. Ownership Form: Direct (D) or Indirect (I) (Instr. 4)	7. Nature of Indirect Beneficial Ownership (Instr. 4)
			Code	V	Amount	(A) or (D)	Price			
Common Stock	XX/XX/XXXX		P		7,308	A	$12.65	11,335,586	I	By XXXXXXX Living Trust(1)(5)
Common Stock								635,722	I	Family Foundation(2)(5)
Common Stock								689,355	I	By XXXXXXX Grandchildren LLC(3)(5)
Common Stock								689,355	I	By XXXXXXX Continuation Trust(4)(5)

Table II - Derivative Securities Acquired, Disposed of, or Beneficially Owned (e.g., puts, calls, warrants, options, convertible securities)

1. Title of Derivative Security (Instr. 3)	2. Conversion or Exercise Price of Derivative Security	3. Transaction Date (Month/Day/Year)	3A. Deemed Execution Date, if any (Month/Day/Year)	4. Transaction Code (Instr. 8)		5. Number of Derivative Securities Acquired (A) or Disposed of (D) (Instr. 3, 4 and 5)		6. Date Exercisable and Expiration Date (Month/Day/Year)		7. Title and Amount of Securities Underlying Derivative Security (Instr. 3 and 4)		8. Price of Derivative Security (Instr. 5)	9. Number of derivative Securities Beneficially Owned Following Reported Transaction(s) (Instr. 4)	10. Ownership Form: Direct (D) or Indirect (I) (Instr. 4)	11. Nature of Indirect Beneficial Ownership (Instr. 4)
				Code	V	(A)	(D)	Date Exercisable	Expiration Date	Title	Amount or Number of Shares				

Explanation of Responses:

1. Mr. XXXXXXX has sole voting and dispositive power with respect to such shares in his capacity as trustee of the XXXXXXX Living Trust.
2. Mr. XXXXXXX has sole voting and dispositive power with respect to such shares in his capacity as President of the XXXXXXX Family Foundation.
3. Mr. XXXXXXX has sole voting and dispositive power with respect to such shares in his capacity as manager of XXXXXXX Grandchildren LLC.
4. Mr. XXXXXXX has shared voting and dispositive power with respect to such shares in his capacity as the grantor of XXXXXXX GC 2010 Continuation Trust.
5. The reporting person disclaims beneficial ownership of these securities except to the extent of his pecuniary interest therein, and the inclusion of these shares in this report shall not be deemed an admission of beneficial ownership of all of the reported shares for purposes of Section 16 or for any other purpose.

/s/ XXXXX XXXXXXX, attorney-in-fact XX/XX/XXXX
** Signature of Reporting Person Date

Reminder: Report on a separate line for each class of securities beneficially owned directly or indirectly.
* If the form is filed by more than one reporting person, *see* Instruction 4 (b)(v).

http://www.sec.gov/Archives/edgar/data/XXXXXX/XXXXXXXXXXXXXXXXXX/xslFXXXXXX/vXXXXXX_X.xml 1/2

as trades allocated to a trust, retirement account, or foundation. In the top half of Table 1, we describe each category of indirect insider trades that we analyze.[8]

[8]In Table 1, we provide a list of key words used to identify these categories of indirect insider trades.

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TABLE 1

Categories of Insider Trades and Descriptions of Monthly Variables

Table 1 defines the different categories of direct and indirect insider trades analyzed in this study and the monthly variables used in our panel regression analysis. When categorizing the subsets of family trades, we search for the following lists of keywords for each respective dummy variable. This search pertains to the insider's response to both Question 7 of Table 1 in Form 4, *Nature of Indirect Beneficial Ownership*, and in any footnoted responses to the question in the *Explanation of Responses*, found at the end of Form 4. Our search requires appropriate spaces at the beginning and end of words, is case insensitive, and allows for plural or possessive versions of words where appropriate.

Category	Key Words
Child	Son, Daughter, Child(ren)
Spouse	Wife, Husband, Spouse
Family	Son, Daughter, Child(ren), Wife, Husband, Spouse, Family, Mom, Mother, Dad, Father, Niece, Nephew, Aunt, Uncle, Grandchild(ren), Granddaughter, Grandson
Retirement	401, ESOP, Profit Sharing, Pension, Retirement, IRA
Foundation	Foundation, Charity
Trust	Trust

Categories of Insider Trades

INSIDER (me): *Direct trades* for the insider's own account.

OTHER: *Indirect trades* by the insider for any other account controlled by the insider.

Subsets of Indirect Trades

ANY_FAMILY: For a spouse, child, or any other family member.

SPOUSE: For a spouse.

CHILD: For a child.

OTH_FAM: For a family member other than a spouse or child, or with no mention of a spouse or child.

TRUST: For a trust account.

$\text{TRUST}_{\text{FAM}}$: For the trust account of a family member, including a spouse, child, or any other family.

$\text{TRUST}_{\text{SPOUSE}}$: For the trust account of a spouse.

$\text{TRUST}_{\text{CHILD}}$: For the trust account of a child.

$\text{TRUST}_{\text{NOTFAM}}$: For a trust account with no reference to a family member.

RETIREMENT: For a retirement account.

$\text{RETIREMT}_{\text{FAM}}$: For a retirement account with reference to a family member.

$\text{RETIREMT}_{\text{NOTFAM}}$: For a retirement account with no reference to a family member.

FOUND: For the account of a foundation.

Monthly Dependent and Control Variables

$\text{AR}_{j,t+1}$: Future Fama–French 4-factor alphas for firm j in month $t+1$, following the month (t) in which the insider trades. Following Brennan, Chordia, and Subrahmanyam (1998), we compute the firm's monthly factor loadings using 60-month rolling windows while requiring at least 24 nonmissing months in each 60-month period.

$\text{CAR}_{j,t+1,t+a}$: Future cumulative Fama–French 4-factor alphas for firm j over months $t+1$ through $t+a$, following the month (t) in which the insider trades.

ASSETGR: Annual asset growth.

B/M: Book-to-market ratio. We take the natural logarithm of this variable in the analysis.

PROFIT: Firm profitability, measured by the gross profit (SALES − COGS)/AT.

$\text{RET}_{j,t}$: Lagged 1-month stock return for firm j in month t.

$\text{RET}_{j,t-6,t-1}$: Recent cumulative (i.e., momentum) stock return for firm j from month $t-6$ through month $t-1$.

$\text{SIZE}_{j,t}$: The firm's market capitalization, measured as the total number of shares outstanding for firm j ($\text{SHROUT}_{j,t}$) multiplied by price per share (abs($\text{PRC}_{j,t}$)) at the end of month t. We take the natural logarithm of this variable in the analysis.

$\text{STDRET}_{j,t}$: Volatility of daily stock returns for firm j during month t, measured as the standard deviation across daily returns during the month.

$\text{SUE}_{j,q}$: Standardized unexpected earnings for firm j during quarter q, following Bernard and Thomas (1990): $\text{SUE} = \frac{\text{EPS}_{j,q} - \text{EPS}_{j,q-4} - \mu_{q-7,q}}{\sigma_{q-7,q}}$, where $\text{EPS}_{j,q}$ is earnings per share for firm j in quarter q announced following the trades of insider i during month t, and $\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of ($\text{EPS}_{j,q} - \text{EPS}_{j,q-4}$) in the past 8 quarters, respectively.

$\text{TRADE\_SIZE\_}k_{i,j,t}$: Our measure of trade size for trades of type k by insider i of firm j in month t is $\text{TRADE\_SIZE\_}k_{\text{i,j,t}} = \frac{P_{k,i,j,t} - S_{k,i,j,t}}{\text{VOL}_{j,t}}$, where $P_{k,i,j,t}$ is the number of shares of each trade type (k) purchased by insider i at firm j in month t, $S_{k,i,j,t}$ is the number of shares of each trade type (k) sold, and $\text{VOL}_{j,t}$ is the total share volume by all investors in firm j during month t.

$\text{TRSIZE\_}k\text{\_RK}_{i,j,t}$ or $\text{TRSIZE\_RK}_{i,j,t}$: Adjusted rank of $\text{TRADE\_SIZE\_}k_{i,j,t}$ or $\text{TRADE\_SIZE}_{i,j,t}$, for every category ($k$) of trades by insider i of firm j during month t, or for all trade categories, constructed as follows: First, for each category of trades (k), $\text{TRADE\_SIZE}_{i,j,t}$ is ranked across all insiders who buy or sell in month t into terciles, which are assigned values from 0 to 2. Second, these ranked values are scaled by 2 to obtain the adjusted rank measure for insider purchases (or sales), which ranges from 0 to 1.

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B. Variables

Our sample of insider trades is limited to open market purchases and sales of common stocks. Following prior literature, we examine monthly data on aggregate net purchases or sales by individual insiders, for each trade category listed in the top half of Table 1. During a given month, we sum across all purchases and sales by every insider to obtain net shares traded in each type of account. The unit of measurement is net shares of type (k) purchased or sold by a given insider (i) at firm (j) during month (t). Following prior work, the final sample excludes small trades of less than 100 shares. We obtain firm financial statement data from Compustat and stock return data from CRSP. Our main sample spans the period between July 2003 and Dec. 2017.

The bottom half of Table 1 describes our monthly variables. Dependent variables for our panel regression approach include the 1-month-ahead Carhart (1997) 4-factor alphas ($\text{AR}_{j,t+1}$) following a trade of any type (k) by insider (i) in stock (j) during month (t), as well as the cumulative abnormal return implied by these alphas covering the following a months ($\text{CAR}_{j,t+1,t+a}$). Firm-specific control variables include firm size (SIZE), book-to-market ratio (B/M), short-term lagged returns (during the current month, $\text{RET}_{j,t}$), momentum returns over the previous 6 months ($\text{RET}_{j,t-6,t-1}$), asset growth (ASSETGR), stock return volatility (STDRET), and firm profitability (PROFIT). We also construct a variable that measures the magnitude of a given insider's net trading activity of type (k) during the month (TRADE_SIZE_k), as net shares purchased or sold on behalf of account type (k) scaled by the total share volume from all investors in firm (j) during month (t).

Panel A of Table 2 presents the relative frequency of insider trades made in each category. For example, roughly 18% of all insider trades are made through another indirect account. A lower proportion of 8.2% is allocated to the account of a family member, whereas 8.1% is allocated to a trust, with 4.4% made in a family trust. Finally, a smaller proportion of insider trades are made through retirement accounts (0.4%) or foundations (0.3%). We also provide analogous statistics for the subsets of insider purchases and sales separately, and find that indirect trades account for a larger fraction of purchases (33.2%) compared with sales (16.0%).

In Panel B of Table 2, we present descriptive statistics and correlations for our key variables. The mean net trade size for all insider trades is negative (−0.17), which indicates that the typical insider trade is a sale. We find a similar negative mean net trade size for the subsets of direct trades and indirect trades, respectively, although this value is much larger in magnitude for direct trades (−0.26), compared with indirect trades (−0.03). This outcome reflects the fact that insiders often obtain shares in their direct account as part of their compensation packages, and are thus more likely to make direct sales for diversification or liquidity purposes.

III. Calendar-Time Portfolios: The Relative Performance of Different Trade Categories

In our first set of tests, we analyze calendar-time portfolios of stocks purchased or sold by insiders, either directly for their own accounts or indirectly on behalf of family members, trusts, retirement accounts, or foundations. We also examine

TABLE 2
Sample Composition and Summary Statistics

Panel A of Table 2 presents the total number of trades for each category of insider trades, along with the percentage of trades for each type relative to all trades in that group, and relative to all insider trades. We provide the results for these subsets of all trades, as well as for the finer subsets of insider purchases and sales, separately. Panel B provides summary statistics and correlations for the key variables, including the 1-month-ahead abnormal return (AR), size of insider trades regardless of account types (TRADE_SIZE), size of direct insider trades (TRADE_SIZE_ME), size of all indirect insider trades (TRADE_SIZE_OTHER), book-to-market ratio (B/M), short-term returns in month t (RET_t), momentum returns over the previous 6 months ($RET_{t-6,t-1}$), asset growth (ASSETGR), firm profitability (PROFIT), and stock return volatility (STDRET). The sample period covers July 2003 to Dec. 2017. Numbers appearing in bold in Panel B are significant at the 5% level.

Panel A. Relative Frequencies for the Different Categories of Insider Trades

	Subsets of All Trades			Subsets of All Purchases			Subsets of All Sales		
Group of Trades for	No. of Trades	% of Group	% of All Trades	No. of Purchases	% of Group	% of All Buys	No. of Sales	% of Group	% of All Sales
Insider (direct)	1,297,414	100%	81.8%	135,823	100%	66.8%	1,161,591	100%	84.0%
Other (indirect)	288,794	100%	18.2%	67,407	100%	33.2%	221,387	100%	16.0%
Any family	129,957	100%	8.2%	28,224	100%	13.9%	101,733	100%	7.4%
Spouse	32,389	24.9%	2.0%	4,990	17.7%	2.5%	27,399	26.9%	2.0%
Child	81,703	62.9%	5.2%	21,326	75.6%	10.5%	60,377	59.3%	4.4%
Other family	46,908	36.1%	3.0%	6,245	22.1%	3.1%	40,663	40.0%	2.9%
Trust	127,731	100%	8.1%	18,239	100%	9.0%	109,492	100%	7.9%
For family	69,459	54.4%	4.4%	12,186	66.8%	6.0%	57,273	52.3%	4.1%
Spouse	11,619	9.1%	0.7%	1,731	9.5%	0.9%	9,888	9.0%	0.7%
Child	45,519	35.6%	2.9%	9,693	53.1%	4.8%	35,826	32.7%	2.6%
Not family	58,272	45.6%	3.7%	6,053	33.2%	3.0%	52,219	47.7%	3.8%
Retirement	6,828	100%	0.4%	4,198	100%	2.1%	2,630	100%	0.2%
For family	1,921	28.1%	0.1%	1,218	29.0%	0.6%	703	26.7%	0.1%
Not family	4,907	71.9%	0.3%	2,980	71.0%	1.5%	1,927	73.3%	0.1%
Foundation	4,901	100%	0.3%	222	100%	0.1%	4,679	100%	0.3%
All trades	1,586,208	–	–	203,230	–	–	1,382,978	–	–

Panel B. Summary Statistics and Correlations

Variables	Mean	Std. Dev.	Correlations										
			AR	TRADE_SIZE	TRADE_SIZE_ME	TRARDE_SIZE_OTHER	B/M	SIZE	RET_t	$RET_{t-6,t-1}$	PROFIT	ASSETGR	STDRET
AR	0.12	11.70	1.00	0.00	0.00	0.01	0.00	0.00	–0.01	0.00	0.01	**–0.01**	0.00
TRADE_SIZE (all)	–0.17	61.00	**0.01**	1.00	**0.26**	**0.28**	**0.01**	**0.01**	0.00	**–0.02**	**–0.01**	0.00	**0.02**
TRADE_SIZE_ME (direct)	–0.26	1.40	**0.01**	**0.83**	1.00	**0.01**	–0.01	**0.05**	**0.01**	**–0.05**	**–0.04**	0.00	**0.05**
TRADE_SIZE_OTHER (indirect)	–0.03	1.15	**0.01**	**0.35**	**–0.08**	1.00	**0.01**	**0.01**	**0.01**	**–0.05**	**–0.03**	0.00	**0.02**
B/M	0.56	0.58	0.00	**0.03**	**0.05**	**0.05**	1.00	**–0.11**	0.01	**–0.03**	**–0.22**	**–0.11**	**0.09**
SIZE	8,318	21,476	**0.01**	**0.13**	**0.05**	**–0.06**	**–0.29**	1.00	0.00	–0.01	**–0.01**	0.00	**–0.23**
RET_t	2.61	11.46	**–0.02**	**–0.05**	**–0.07**	**–0.01**	0.00	**0.06**	1.00	0.01	**0.02**	**–0.02**	**0.13**
$RET_{t-6,t-1}$	14.31	31.07	0.00	**–0.18**	**–0.17**	**–0.08**	**–0.04**	**0.12**	0.01	1.00	**0.03**	**–0.03**	0.00
PROFIT	34.50	25.89	0.01	**–0.11**	**–0.11**	**–0.04**	**–0.34**	**–0.04**	**0.02**	**0.05**	1.00	**–0.08**	**–0.03**
ASSETGR	15.38	34.96	0.00	**–0.04**	**–0.05**	**–0.04**	**–0.21**	**0.12**	0.00	–0.01	**0.03**	1.00	**0.04**
STDRET	2.56	1.48	**–0.03**	**0.06**	**0.10**	**0.03**	0.01	**–0.50**	**0.05**	–0.03	0.01	0.00	1.00

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portfolios based on subsets of family trades made in the account of a spouse or child, as well as subsets of trades in trust or retirement accounts that are devoted to family members. We begin by building portfolios of stocks based on all insider purchases or sales in each trade category (k) during any given 1-month period. We then examine the time series of 1-month-ahead portfolio returns for each type of insider transaction.

The first column of Table 3 presents the monthly Carhart (1997) 4-factor alpha for portfolios based on every category of insider purchases (α_k).[9] The second column compares this performance with the alpha for the portfolio of direct insider purchases (α_{ME}). That is, for each type of indirect purchase (k), we also provide the alpha of a hedge portfolio that is long stocks with that type of indirect purchase and short stocks with direct purchases made in the insider's own account ($\alpha_k - \alpha_{\mathrm{ME}}$). The third and fourth columns provide the same information for each category of indirect sales. Finally, the fifth column presents the performance of a hedge portfolio that is long insider purchases and short insider sales, for every category of indirect trades (k), whereas the sixth column compares this performance with the analogous long-short hedge portfolio based on direct trades.

In the top row of Table 3, we document the performance of all insider purchases or sales. Consistent with prior work, calendar-time portfolios of all stocks bought by insiders in 1 month earn a 4-factor alpha (α_{ALL}) of 0.70% in the following month (t-stat = 4.18), whereas all stocks sold by insiders yield an insignificant α_{ALL} of −0.03% (t = −0.47). As a result, the combined hedge portfolio that is long all stocks purchased and short all stocks sold by insiders is dominated by the performance of insider purchases, earning an α_{ALL} of 0.73% (t = 4.57).

When we distinguish between direct and indirect insider trades, their performance diverges. For example, the subset of *direct* purchases made in the insider's own account have a slightly smaller alpha (α_{ME}) of 0.65% per month (t = 3.63). In contrast, insider purchases made through any *indirect* account have a significantly larger alpha (α_{OTHER}) of 0.89% (t = 4.99), which outperforms *direct* purchases by ($\alpha_{\mathrm{OTHER}} - \alpha_{\mathrm{ME}}$ =) 25 bps (t = 1.97). Once again, insider sales do not significantly outperform, when made either *directly* through the insider's own account (α_{ME} = −0.02, t = −0.32) or *indirectly* through any other account (α_{OTHER} = −0.10, t = −1.11). As a result, the combined hedge portfolio that replicates both *direct* purchases and sales earns an alpha (α_{ME}) of 0.67% (t = 3.96), whereas the analogous hedge portfolio of *indirect* purchases and sales has a significantly larger alpha (α_{OTHER}) of 0.99% (t = 4.98), which outperforms *direct* trades by ($\alpha_{\mathrm{OTHER}} - \alpha_{\mathrm{ME}}$ =) 33 bps (t = 2.10).

We next analyze the subset of indirect trades made through family accounts. For example, the portfolio of indirect purchases made in *any family* account earns an alpha (α_{FAM}) of 1.09% (t = 4.37) in the following month, significantly outperforming direct purchases by ($\alpha_{\mathrm{FAM}} - \alpha_{\mathrm{ME}}$ =) 45 bps (t = 3.12). Moreover, the subset of family purchases made on behalf of a *spouse* earns an even larger alpha (α_{SPOUSE}) of 1.27% (t = 4.65), which outperforms direct purchases by ($\alpha_{\mathrm{SPOUSE}} - \alpha_{\mathrm{ME}}$ =) 63 bps (t = 2.48), whereas purchases for a *child* earn an alpha (α_{CHILD}) of 1.30% (t = 3.91),

[9]We find similar results when we use the Fama–French 3-factor or 5-factor model (Fama and French (1993), (2015)).

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TABLE 3

Calendar-Time Portfolio Approach: Performance of Indirect Insider Trades

Table 3 analyzes calendar-time portfolios of stocks purchased or sold by insiders, either directly for their own accounts or indirectly on behalf of family members, trusts, retirement accounts, or foundations. We also examine portfolios based on subsets of indirect trades made in trust or retirement accounts that are devoted to family members. We begin by building portfolios of stocks based on all insider purchases or sales in each trade category (k) during any given 1-month period. We then examine the time series of monthly portfolio returns for every type of insider transaction. The first column presents the monthly 4-factor alpha for every portfolio of insider purchases (α_k). The second column compares this performance (α_k) with the alpha for a portfolio comprising the insider's own direct purchases (α_{ME}). That is, for each type of indirect purchase (k), we also provide the alpha of a hedge portfolio that is long stocks that experience that type of indirect purchase and short stocks with direct purchases made in the insider's own account ($\alpha_k - \alpha_{\text{ME}}$). The third and fourth columns provide the same information for each category of indirect sales. Finally, the fifth column presents the performance of a hedge portfolio that is long insider purchases and short insider sales, for every category of indirect trades (k), whereas the sixth column compares this performance with the alpha of the analogous long-short hedge portfolio based on direct trades. The t-statistics are based on Newey and West (1987) robust standard errors with 12 monthly lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Purchases		Sales		Purchases − Sales	
Insider Trades for (Type k)	α_k (%)	$\alpha_k - \alpha_{\text{ME}}$	α_k (%)	$\alpha_k - \alpha_{\text{ME}}$	α_k (%)	$\alpha_k - \alpha_{\text{ME}}$
	1	2	3	4	5	6
All trades (α_{ALL})	0.70***		−0.03		0.73***	
	(4.18)		(−0.47)		(4.57)	
For me (direct, α_{ME})	0.65***		−0.02		0.67***	
	(3.63)		(−0.32)		(3.96)	
Other (indirect, α_{OTHER})	0.89***	0.25*	−0.10	−0.08	0.99***	0.33**
	(4.99)	(1.97)	(−1.11)	(−0.98)	(4.98)	(2.10)
Any family (α_{FAM})	1.09***	0.45***	0.07	0.09	1.02***	0.35*
	(4.37)	(3.12)	(0.53)	(0.78)	(3.68)	(1.80)
Spouse (α_{SPOUSE})	1.27***	0.63**	0.08	0.10	1.19***	0.53*
	(4.65)	(2.48)	(0.48)	(0.72)	(3.65)	(1.94)
Child (α_{CHILD})	1.30***	0.65***	−0.03	−0.01	1.33***	0.67**
	(3.91)	(2.76)	(−0.19)	(−0.08)	(3.83)	(2.24)
Other family ($\alpha_{\text{OTH\_FAM}}$)	0.47	−0.18	0.14	0.16	0.33	−0.34
	(1.27)	(−0.50)	(0.72)	(0.99)	(0.94)	(−0.96)
Trust (α_{TRUST})	1.05***	0.40*	−0.05	−0.03	1.10***	0.44**
	(4.73)	(1.82)	(−0.52)	(−0.42)	(4.75)	(2.10)
Trust for family ($\alpha_{\text{TRUST\_FAM}}$)	1.39***	0.74**	0.16	0.18*	1.23***	0.56
	(3.71)	(2.08)	(1.19)	(1.82)	(2.96)	(1.43)
Trust for spouse ($\alpha_{\text{TRUST\_SPOUSE}}$)	1.55**	0.91	−0.22	−0.20	1.78***	1.11
	(2.36)	(1.29)	(−0.88)	(−0.88)	(2.74)	(1.64)
Trust for child ($\alpha_{\text{TRUST\_CHILD}}$)	1.35**	0.71	0.13	0.15	1.22**	0.56
	(2.50)	(1.29)	(0.72)	(1.05)	(2.06)	(0.93)
Trust not family ($\alpha_{\text{TRUST\_NOTFAM}}$)	0.73***	0.09	−0.25*	−0.22*	0.98***	0.31
	(3.03)	(0.32)	(−1.77)	(−1.68)	(3.84)	(1.23)
Retirement (α_{RETIREMT})	0.76***	0.11	−0.73***	−0.71***	1.49***	0.82***
	(2.81)	(0.46)	(−2.95)	(−2.98)	(4.48)	(2.98)
Retirement for family ($\alpha_{\text{RET\_FAM}}$)	0.24	−0.40	−0.87	−0.85	1.11	0.44
	(0.62)	(−1.27)	(−1.11)	(−1.15)	(1.32)	(0.55)
Retirement not family ($\alpha_{\text{RET\_NOTFAM}}$)	0.82***	0.17	−0.69***	−0.67**	1.51***	0.85***
	(3.05)	(0.67)	(−2.75)	(−2.55)	(4.61)	(3.11)
Foundation (α_{FOUND})	0.75	0.10	−0.27	−0.24	1.02	0.35
	(0.94)	(0.12)	(−0.46)	(−0.45)	(1.07)	(0.36)

which outperforms by ($\alpha_{\text{CHILD}} - \alpha_{\text{ME}} =$) 65 bps ($t = 2.76$). On the sell side, no subset of family trades generates a significant alpha. As a result, the combined hedge portfolio that replicates both purchases and sales in *any family* account is dominated by the performance of family purchases, earning an alpha of 1.02%, which outperforms the analogous hedge portfolio of purchases and sales made through *direct* accounts by 35 bps. When we narrow this analysis further, we find that hedge portfolios replicating both purchases and sales in the account of a *spouse*

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or *child* earn alphas of 1.19% or 1.33%, outperforming the analogous hedge portfolio of trades made through *direct* accounts by 53 or 67 bps, respectively.

Consider next the performance of indirect trades made through trust accounts. Purchases in *any trust* generate a 1-month alpha (α_{TRUST}) of 1.05% ($t = 4.73$), which outperforms direct purchases by (α_{TRUST}–α_{ME} =) 0.40% (t = 1.82). This outperformance is larger for the subset of purchases made in *family trusts* ($\alpha_{\text{TRUST\_FAM}}$ = 1.39%, t = 3.71), which outperforms direct purchases by ($\alpha_{\text{TRUST\_FAM}} - \alpha_{\text{ME}}$ =) 0.74% (t = 2.08). In contrast, although purchases in *nonfamily trusts* also generate a significant alpha ($\alpha_{\text{TRUST\_NOTFAM}}$ = 0.73%, t = 3.03), this portfolio does not significantly outperform direct purchases ($\alpha_{\text{TRUST\_NOTFAM}} - \alpha_{\text{ME}}$ = 0.09%, t = 0.32). On the sell side, indirect sales through *family trusts* do not outperform. On the other hand, sales in the insider's own *nonfamily trust* generate a marginally significant negative alpha ($\alpha_{\text{TRUST\_NOTFAM}}$) of −0.25% ($t$ = −1.77), which outperforms direct insider sales ($\alpha_{\text{TRUST\_NONFAM}}$–$\alpha_{\text{ME}}$ = −0.22%, t = −1.68). This latter evidence is consistent with insiders avoiding estate and gift taxes by conducting informed selling through nonfamily trusts, in order to preserve the wealth accumulated in these tax-advantaged accounts.[10]

Next, we examine the sample of indirect trades made through *retirement* accounts. Purchases in retirement accounts earn an alpha (α_{RETIREMT}) of 0.76% (t = 2.81), which only slightly outperforms the alpha for direct purchases (α_{RETIREMT}–α_{ME} = 0.11%, t = 0.46). On the sell side, trades in *retirement* accounts significantly outperform direct sales (i.e., α_{RETIREMT} = −0.73%, t = −2.95; and α_{RETIREMT}–α_{ME} = −0.71%, t = −2.98). As a result, the combined hedge portfolio that duplicates insider purchases and sales in *retirement* accounts generates a significant monthly alpha (α_{RETIREMT}) of 1.49% (t-ratio = 4.48), which outperforms the analogous hedge portfolio of direct trades (α_{RETIREMT}–α_{ME} = 0.82%, t = 2.98). This impressive outperformance for retirement accounts is in large part driven by sales in *nonfamily retirement* accounts, which generate an alpha of α_{RETIREMT} = −0.69% (t-ratio = −2.75), and is also consistent with insiders selling before large price declines to preserve the wealth in these tax-advantaged accounts.[11] Finally, there is no evidence to indicate that insider trades on behalf of a foundation significantly outperform, on either the buy side or the sell side.

Although our tests cannot single out one, and exclude others, from our list of potential theoretical motivations for insiders to make informed trades through

[10]We conjecture that, if nonfamily trusts are mainly for charity, this would help to explain the difference in results for sales in family trusts versus nonfamily trusts documented in Table 3. However, although it is possible that the majority of insider trades made in nonfamily trusts are for charity, only 1.7% of these trades made in nonfamily trusts are explicitly labeled as "charitable." Thus, given the lack of data regarding whether nonfamily trusts are for charity, we cannot confirm this conjecture based on the limited data available in the Form 4s.

[11]We presume that trades in nonfamily retirement accounts are for the insiders themselves, although they are made in retirement accounts rather than the insider's own direct brokerage account. Typical language on the Form 4 for these trades refers to a 401(k), ESOP, or IRA. Sometimes the insider is identified in these retirement account trades, such as "G. Deems IRA." We take these labels to indicate that the trade is for the insider herself or himself. Table 2 reports that insider trades made in retirement accounts on behalf of family members are less common than trades made in nonfamily retirement accounts.

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indirect accounts, the evidence in Table 3 supports several different information-based motives to varying degrees. For example, we find strong evidence that indirect *purchases* through *family* accounts significantly outperform direct purchases in the insiders' own account. This outcome supports the conjecture that family accounts offer one mechanism by which insiders can build wealth for eventual bequests while avoiding estate or gift taxes. In addition, although we do not find that *indirect sales* outperform direct sales in general, we do find that the subsets of *indirect sales* made in *nonfamily trust* or *retirement* accounts significantly outperform sales in direct accounts. This evidence provides additional support for our conjecture that insiders use these tax-advantaged structures to preserve the tax benefits embedded in the accumulated wealth of such accounts. Taken together, the results in Table 3 provide our first significant body of compelling evidence indicating that insider trades made in accounts the insider controls indirectly outperform direct insider trades, on either the buy side or the sell side, depending on the type of indirect account used.

IV. Monthly Panel Regression: The Relative Performance of Different Trade Categories, Accounting for Trade Size and Firm Attributes

In Section IV, we estimate panel regressions to assess whether the superior profitability of indirect trades relative to direct trades, documented in Table 3, is robust when we control for other firm attributes that have been shown to predict returns. In this analysis, we also account for the strength of the signal revealed by the *size* of an insider's trades in each category. In particular, we follow Akbas et al. (2020) to measure the magnitude of the insider's net order flow in each category during any month, as a proportion of total trading volume in the stock. Specifically, for insider i of firm j in month t, the insider's net trade size in each category (k) is defined as

$$\text{TRADE\_SIZE\_}k_{i,j,t} = \frac{P_{k,i,j,t} - S_{k,i,j,t}}{VOL_{j,t}},$$

where $P_{k,i,j,t}$ is the number of shares of type k purchased by insider i at firm j in month t, $S_{k,i,j,t}$ is the number of shares sold, and $\text{VOL}_{j,t}$ is total share volume from all investors in firm j in month t.

We then construct the scaled rank of this insider trade size variable, as follows: First, in each month t, the cross section of insiders who make trades of type k (across all insiders i and firms j) is ranked into terciles by trade size ($\text{TRADE\_SIZE\_}k_{i,j,t}$), and the individuals in each tercile are assigned the values, 0, 1, or 2. Second, these tercile ranks are divided by 2 to form the scaled rank, TRSIZE_k_RK, which ranges from 0 (for the lowest tercile with *large sales*) to +1 (for the highest tercile with *large purchases*). This scaled rank variable offers a straightforward interpretation: A 1-unit increase in TRSIZE_k_RK ranges from the tercile of insiders making large sales (*LS*) to the tercile making large purchases (*LP*) during month t.

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A. Regression Approach: Short-Run Trading Performance

In Section IV.A, we estimate the relative short-run trading profitability for every category of insider trades (k) in the month following the trades ($t+1$) while controlling for firm attributes. We accomplish this task by regressing the 1-month-ahead abnormal return on the scaled rank of trade size (TRSIZE_k_RK) for each trade category (k), along with other control variables, as follows:

$$\text{AR}_{j,t+1} = \alpha_t + \sum_{k=1}^{15} \beta_k \text{TRSIZE\_}k\text{\_RK}_{i,j,t} + \text{Controls}_{j,t} + \varepsilon_{i,j,t}, \tag{1}$$

where k indexes the 15 categories of direct and indirect insider trades listed in Table 1.

The dependent variable, $\text{AR}_{j,t+1}$, is the Fama–French 4-factor alpha for firm j in month $t+1$, following the month (t) in which the insider (i) trades.[12] We multiply $\text{AR}_{j,t+1}$ by 100 to reflect performance in percentage terms. TRSIZE_k_RK is the scaled rank of trade size for each category of insider trades (k = 1–15). The control variables include the firm's book-to-market ratio (B/M), firm size (SIZE), the short-term lagged return in month t ($\text{RET}_{j,t}$), momentum returns over the previous 6 months ($\text{RET}_{j,t-6,t-1}$), gross profits (PROFIT), asset growth (ASSETGR), and the volatility of daily stock returns (STDRET). These controls help to establish whether the predictive information contained in each category of indirect trades (k) remains after accounting for other firm attributes that prior research shows to predict returns. We also include monthly fixed effects.

Following Akbas et al. (2020), the coefficient of the scaled rank of trade size (β_k) is analogous to the return on a hedge portfolio that is long the tercile of large purchases of type k and short the tercile of large sales (LP − LS). To understand this interpretation, observe that the association between the scaled rank for each trade size measure and future returns implied by equation (1) is given by the partial derivative, $\frac{\partial \text{AR}_{j,t+1}}{\partial \text{TRSIZE\_}k\text{\_RK}_{i,j,t}} = \beta_k$. According to this partial derivative, a 1-unit increase in the scaled rank of trade size (i.e., changing TRSIZE_k_RK from 0 to +1, which compares the tercile of large sales with large purchases) is associated with a change in $\text{AR}_{j,t+1}$ of β_k percent.

In Table 4, we present results from estimating nine different specifications of this panel regression model that include the trade size variables for various subsets of the 15 categories listed in Table 1. The top row of Table 4 presents the coefficient of the scaled rank of trade size for *direct* insider trades (β_1) across these nine specifications. These nine coefficients lie within a narrow range, from 0.36 to 0.40, all with t-ratios above 3.5. This evidence implies that, after controlling for firm attributes, a hedge portfolio that duplicates large *direct* purchases and sales by insiders (LP − LS) earns significant abnormal returns of 0.36%–0.40% in the following month.

The next 14 rows in Table 4 reveal coefficients for the 14 categories of *indirect* trades (β_k) that are mostly larger in magnitude than the coefficient for *direct* trades in

[12] In Table IA.1 of the Supplementary Material, we also analyze raw stock returns as the dependent variable and find similar results.

the top row (β_1). Indeed, the F-tests at the bottom of each column in Table 4 confirm that, for most categories of *indirect* trades (k), these regression coefficients are significantly greater than the coefficient for *direct* trades (i.e., $\beta_k > \beta_1$). For example, in column 1, the (LP − LS) hedge portfolio based on *all indirect* trades earns ($\beta_2 =$) 0.90% per month (t = 4.70), which significantly outperforms direct trades by ($\beta_2 - \beta_1 =$) 50 bps (p-value < 0.01). Likewise, column 2 indicates that the analogous hedge portfolio of indirect trades made in *any family* account earns ($\beta_3 =$) 0.93% per month (t = 3.81), which significantly outperforms direct trades by ($\beta_3 - \beta_1 =$) 55 bps (p = 0.02). Similarly, column 3 shows that trades on behalf of a *child* earn even

TABLE 4

Panel Regression Approach: The Short-Run Relative Performance of Direct Versus Indirect Trades

Table 4 estimates the short-run (1-month-ahead) relative trading profitability of large purchases versus large sales (LP − LS), for every category of direct or indirect insider trades (k), in the month following the trades. We regress the 1-month-ahead market-adjusted abnormal stock return on the scaled rank of insider trade size for each category of insider trades, along with other control variables, as follows:

$$\mathrm{AR}_{j,t+1} = \alpha_t + \sum_{k=1}^{15} \beta_k \mathrm{TRSIZE\_}k\mathrm{\_RK}_{i,j,t} + \mathrm{CONTROLS}_{j,t} + \varepsilon_{i,j,t},$$

where k indexes the 15 categories of direct and indirect trades by insider (i) analyzed here. The control variables are listed in Table 1. The dependent variable, $\mathrm{AR}_{j,t+1}$, is the leading 1-month-ahead Fama–French 4-factor alpha for the firm (j). We multiply $\mathrm{AR}_{j,t+1}$ by 100 to reflect performance in percentage terms. TRSIZE_k_RK is the scaled tercile rank of trade size for each category of trades analyzed (k = 1–15). For each category of direct or indirect trades (k), the coefficient of the scaled rank of trade size (β_k) is analogous to the return on a hedge portfolio that is long the tercile of large purchases of type k and short the tercile of large sales (LP − LS). To see this result, consider the association between the scaled rank of each trade size measure and future returns implied by equation (1): $\frac{\partial \mathrm{AR}(j,\ t+1)}{\partial \mathrm{TRSIZE\_}k\mathrm{\_RK}(j,\ t)} = \beta_k$. This partial derivative shows that a 1-unit increase in the scaled rank of trade size, which compares the tercile of large sales with the tercile of large purchases (i.e., changing TRSIZE_k_RK from 0 to 1), is associated with a change in $\mathrm{AR}_{j,t+1}$ of β_k percent. Monthly fixed effects are included, and standard errors are clustered by time at the monthly level. The t-statistics are provided in parentheses below the parameter estimates. At the bottom of each column, we provide F-statistics that test the equality of different pairs of regression coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Trade Category Variables		1	2	3	4	5	6	7	8	9
TRSIZE_ME_RK	β_1	0.400***	0.379***	0.372***	0.403***	0.403***	0.400***	0.356***	0.356***	0.398***
(all direct trades)		(3.84)	(3.69)	(3.63)	(3.84)	(3.84)	(3.85)	(3.53)	(3.52)	(3.81)
TRSIZE_OTHER_RK	β_2	0.895***								
(all indirect trades)		(4.70)								
TRSIZE_FAM_RK	β_3		0.932***							0.910***
			(3.81)							(3.73)
TRSIZE_SPOUSE_RK	β_4			0.652*						
				(1.66)						
TRSIZE_CHILD_RK	β_5			1.204***						
				(3.38)						
TRSIZE_OTH_FAM_RK	β_6			−0.141						
				(−0.33)						
TRSIZE_TRUST_RK	β_7				1.135***					
					(4.68)					
TRSIZE_TRUST_FAM_RK	β_8					0.981***				
						(3.15)				
TRSIZE_TRUST_NOTFAM_RK	β_9					1.220***	1.218***			1.170***
						(4.33)	(4.31)			(4.14)
TRSIZE_TRUST_SPOUSE_RK	β_{10}						1.619**			
							(2.57)			
TRSIZE_TRUST_CHILD_RK	β_{11}						1.112**			
							(1.97)			
TRSIZE_RETIREMENT_RK	β_{12}							1.080**		
								(2.21)		
TRSIZE_RET_FAM_RK	β_{13}								0.946	
									(0.73)	
TRSIZE_RET_NOTFAM_RK	β_{14}								1.184**	1.006*
									(2.24)	(1.90)
TRSIZE_FOUND_RK	β_{15}									−0.573
										(−0.94)

(continued on next page)

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TABLE 4 (continued)

Panel Regression Approach: The Short-Run Relative Performance of Direct Versus Indirect Trades

Control Variables		1	2	3	4	5	6	7	8	9
B/M	β_{16}	3.613	3.669	3.748	3.702	3.725	3.708	3.944	3.940	3.569
		(0.34)	(0.35)	(0.36)	(0.35)	(0.36)	(0.35)	(0.38)	(0.38)	(0.34)
SIZE	β_{17}	−11.970***	−12.156***	−12.203***	−12.152***	−12.147***	−12.195***	−12.216***	−12.204***	−11.972***
		(−2.73)	(−2.77)	(−2.78)	(−2.77)	(−2.77)	(−2.78)	(−2.78)	(−2.78)	(−2.73)
$RET_{j,t}$	β_{18}	−3.629**	−3.639**	−3.643**	−3.635**	−3.635**	−3.638**	−3.649**	−3.649**	−3.627**
		(−2.32)	(−2.32)	(−2.33)	(−2.32)	(−2.32)	(−2.32)	(−2.33)	(−2.33)	(−2.32)
$RET_{j,t-6,t-1}$	β_{19}	−0.263	−0.282	−0.284	−0.282	−0.282	−0.283	−0.297	−0.297	−0.271
		(−0.72)	(−0.78)	(−0.78)	(−0.78)	(−0.78)	(−0.78)	(−0.82)	(−0.82)	(−0.74)
PROFIT	β_{20}	0.410	0.396	0.396	0.400	0.400	0.402	0.388	0.388	0.408
		(1.16)	(1.12)	(1.12)	(1.13)	(1.13)	(1.13)	(1.09)	(1.09)	(1.15)
ASSETGR	β_{21}	−0.378**	−0.382**	−0.384**	−0.382**	−0.383**	−0.385**	−0.388**	−0.388**	−0.381**
		(−2.20)	(−2.22)	(−2.24)	(−2.23)	(−2.23)	(−2.25)	(−2.27)	(−2.27)	(−2.22)
STDRET	β_{22}	1.843	2.081	2.109	1.850	1.849	1.840	2.233	2.234	1.826
		(0.16)	(0.18)	(0.18)	(0.16)	(0.16)	(0.16)	(0.19)	(0.19)	(0.15)
No. of obs.		323,832	323,832	323,832	323,832	323,832	323,832	323,832	323,832	323,832
Adj. R^2		0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
						$\beta_1 = \beta_8$	$\beta_1 = \beta_9$	$\beta_1 = \beta_{12}$	$\beta_1 = \beta_{13}$	$\beta_1 = \beta_3$
F-statistic (*p*-value)		7.9	5.8	5.5	11.5	4.0	9.3	2.2	0.2	4.9
		(.00)***	(.02)**	(.02)**	(.00)***	(.05)**	(.00)***	(.14)	(.65)	(.03)**
						$\beta_1 = \beta_9$ 9.3(.00)***	$\beta_1 = \beta_{10}$ 3.6(.06)*		$\beta_1 = \beta_{14}$ 2.4(.14)	$\beta_1 = \beta_9$ 8.2(.00)***
							$\beta_1 = \beta_{11}$ 1.7(.19)			$\beta_1 = \beta_{14}$ 1.3(.26)
										$\beta_1 = \beta_{15}$ 2.6(.11)

more, at ($\beta_5 =$) 1.20% per month ($t = 3.38$), which outperforms by ($\beta_5 - \beta_1 =$) 83 bps ($p = 0.02$). Furthermore, in column 5, the hedge portfolio that duplicates the large purchases and sales made in a *family trust* earns ($\beta_8 =$) 0.98% per month ($t = 3.15$), which outperforms direct trades by ($\beta_8 - \beta_1 =$) 58 bps ($p = 0.05$). Likewise, comparable trades through a *nonfamily trust* earn even more at ($\beta_9 =$) 1.22% ($t = 4.33$), which outperforms by ($\beta_9 - \beta_1 =$) 82 bps ($p = 0.00$).

Finally, the last column of Table 4 presents our baseline model, which includes multiple scaled rank variables that span the different categories of indirect trades while limiting the overlap across more than one category that involves family trades. In particular, we include the scaled rank of trades for *any family* member, as well as trades in *nonfamily trust* or *retirement accounts*, along with trades on behalf of *foundations.* Column 9 reveals that, once again, the performance of *direct* trades ($\beta_1 = 0.40\%$, $t = 3.81$) is significantly dominated by trades on behalf of *any family* member ($\beta_3 = 0.91\%$, $t = 3.73$) and *nonfamily trusts* ($\beta_9 = 1.17\%$, $t = 4.14$). Trades through the insider's own (*nonfamily*) *retirement* account also earn a higher alpha ($\beta_{14} = 1.00\%$, $t = 1.90$), although the excess return over direct trades ($\beta_{14} - \beta_1$) is not statistically significant ($p = 0.26$). As before, trades on behalf of a foundation do not outperform ($\beta_{15} = -0.57\%$, $t = -0.94$).

This regression analysis in Table 4 confirms that our major findings and conclusions from the portfolio approach in Table 3 remain after accounting for trade size, and controlling for other firm attributes that also predict stock returns. In addition, the coefficients of the control variables are consistent across the columns of Table 4, and generally support our expectations. For example, firms

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that outperform in month $t + 1$ tend to have a smaller size, a lower lagged 1-month return, and lower asset growth.[13]

B. Regression Approach: Long-Run Trading Performance

In Section IV.B, we examine the longer-run performance of indirect trades versus direct trades. The evidence from Sections III and IV.A indicates a tendency for indirect trades in family accounts, trusts, and retirement accounts to outperform direct trades over the next month, but it is not clear whether this performance is based on information that is short-lived or more long-lasting. Here, we investigate whether this short-run outperformance continues to accumulate over longer periods that extend up to 2 years following the insider trades.

For this analysis, we focus on our baseline specification of equation (1) in column 9 of Table 4, which includes the nonoverlapping categories of trade size variables. We then replace the 1-month-ahead abnormal return ($\text{AR}_{j,t+1}$) as dependent variable with the cumulative abnormal return extending further into the future ($\text{CAR}_{j,t+1,t+a}$), as follows:

$$(2)\quad \begin{aligned} \text{CAR}_{j,t+1,t+a} = \alpha_t &+ \beta_1 \text{TRSIZE\_ME\_RK}_{i,j,t} + \beta_2 \text{TRSIZE\_FAM\_RK}_{i,j,t} \\ &+ \beta_3 \text{TRSIZE\_TRUST\_NOTFAM\_RK}_{i,j,t} \\ &+ \beta_4 \text{TRSIZE\_RET\_NOTFAM\_RK}_{i,j,t} \\ &+ \beta_5 \text{TRSIZE\_FOUND\_RK}_{i,j,t} + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t}, \end{aligned}$$

where $\text{CAR}_{j,t+1,t+a}$ is the Fama–French 4-factor alpha for firm j over months $t + 1$ through $t + a$, following the month (t) in which insider i trades.[14] Once again, monthly fixed effects are included.

In Table 5, we present 4 columns of coefficients (β_k) that reflect the performance of long-short hedge portfolios (LP $-$ LS) for different categories of insider trades over future periods that extend up to 2 years later. The first column of Table 5 reproduces the 1-month-ahead results from our baseline model from column 9 of Table 4, whereas the remaining columns present the analogous results over longer periods extending further into the future. For brevity, we do not present the estimated coefficients of the control variables in this table.

The top row of Table 5 presents the coefficient of the scaled rank for *direct* trades (β_1) that pertains to future periods that range from 1 month to 2 years ahead. These results indicate that the performance of the (LP $-$ LS) hedge portfolio comprised of *direct* trades grows in magnitude monotonically, from 0.40% (t = 3.81) over the next month to 2.17% (t = 3.43) after 2 years. This evidence is

[13]In untabulated results, we examine whether our main results differ across three subsets of registered insiders: officers, directors, and blockholders. For example, officers and directors are likely to be more informed than some types of blockholders such as institutional investors, who are subject to Reg FD. We find that, although indirect trades are generally more informed than direct trades for all three types of insiders, there are no significant differences in the incremental information content of indirect versus direct trades across these different subsets of insiders.

[14]We repeat this analysis using raw returns and find similar results, provided in Table IA.2 in the Supplementary Material.

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TABLE 5

Panel Regression: The Long-Run Performance of Direct Versus Indirect Trades

Table 5 presents the long-run relative trading performance of direct versus indirect trades over different periods that extend from month $t+1$ to month $t+a$. In this table, we analyze whether the short-run performance documented in Table 4 extends beyond 1 month, by considering the cumulative abnormal returns measured over time frames that span different subsets of the 2 years following insider trades. For this analysis, we estimate a revised version of equation (1) that replaces $\text{AR}_{j,t+1}$ as the dependent variable with $\text{CAR}_{j,t+1,t+a}$, as follows:

$$\text{CAR}_{j,t+1,t+a} = \alpha_t + \beta_1 \text{TRSIZE\_ME\_RK}_{i,j,t} + \beta_2 \text{TRSIZE\_FAM\_RK}_{i,j,t} + \beta_3 \text{TRSIZE\_TRUST\_NOTFAM\_RK}_{i,j,t} + \beta_4 \text{TRSIZE\_RET\_NOTFAM\_RK}_{i,j,t} + \beta_5 \text{TRSIZE\_FOUND\_RK}_{i,j,t} + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t}.$$

The first column reproduces the results for 1-month-ahead abnormal returns ($\text{AR}_{j,t+1}$), from our main model in column 9 of Table 4. The remaining columns present the analogous results for performance measured over longer time frames that extend up to 24 months in the future. We include the same controls as our analysis of equation (1) in Table 4. The coefficients of the controls have similar implications to those presented in Table 4, and are omitted here for brevity. All variables are defined in Table 1. Monthly fixed effects are included, and standard errors are clustered by time at the monthly level. The t-statistics are provided in parentheses below the parameter estimates. At the bottom of each column, we provide F-statistics that test the equality of different pairs of parameter estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables		$\text{AR}_{j,t+1}$	$\text{CAR}_{j,t+1,t+6}$	$\text{CAR}_{j,t+1,t+12}$	$\text{CAR}_{j,t+1,t+24}$
		1	2	3	4
TRSIZE_ME_RK	β_1	0.398***	1.055***	1.883***	2.169***
(all direct trades)		(3.81)	(4.10)	(4.36)	(3.43)
TRSIZE_FAM_RK	β_2	0.910***	3.656***	4.330***	6.339***
		(3.73)	(4.58)	(4.37)	(4.60)
TRSIZE_TRUST_NOTFAM_RK	β_3	1.170***	1.788**	4.174***	10.479***
		(4.14)	(2.29)	(4.16)	(6.03)
TRSIZE_RET_NOTFAM_RK	β_4	1.006*	2.108	4.917**	7.221**
		(1.90)	(1.47)	(2.55)	(2.57)
TRSIZE_FOUND_RK	β_5	−0.573	0.316	0.200	0.216
		(−0.94)	(0.18)	(0.07)	(0.05)
Controls		Yes	Yes	Yes	Yes
No. of obs.		323,832	319,439	301,727	264,788
Adj. R^2		0.011	0.011	0.011	0.009
H_i: Testing equality; F-statistic (p-value)					
1. $\beta_1 = \beta_2$		4.9 (.03)**	11.0 (.00)***	6.9 (.01)**	10.5 (.00)***
2. $\beta_1 = \beta_3$		8.2 (.00)***	1.0 (.33)	5.8 (.02)**	26.7 (.00)***
3. $\beta_1 = \beta_4$		1.3 (.26)	0.5 (.46)	2.2 (.14)	3.3 (.07)*
4. $\beta_1 = \beta_5$		2.6 (.11)	0.2 (.68)	0.4 (.53)	0.2 (.63)

consistent with prior work that generally finds insider purchases outperform sales over relatively long horizons that extend up to a year or more.[15]

In contrast, the second row of coefficients in Table 5 reports that the abnormal performance of *any family* trades (β_2) reveals stronger growth over the following 2 years, from 0.91% ($t = 3.73$) over the next month to 6.34% ($t = 4.60$) after 24 months. The third row similarly reveals that the abnormal performance of indirect trades for *nonfamily trusts* (β_3) grows from 1.17% ($t = 4.14$) after 1 month to 10.48% ($t = 6.03$) after 24 months. In the fourth row, the abnormal performance of trades for the insider's own (*nonfamily*) *retirement account* (β_4) also grows from 1.01% ($t = 1.90$) after 1 month to 7.22% ($t = 2.57$) after 2 years. As in Table 4, trades made on behalf of a *foundation* (β_5) never significantly outperform for any time frame.

The F-tests at the bottom of each column of Table 5 indicate that indirect trades for *family* members (β_2) significantly outperform direct trades (β_1) for all periods over the next 2 years. Similarly, trades made in a *nonfamily trust* (β_3) outperform over the next month, as well as longer periods that extend beyond 1 year

[15]We refer the reader to the references cited in footnote 1.

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into the future. In contrast, trades made in the insider's own (*nonfamily*) *retirement account* (β_4) only significantly outperform direct insider trades over longer periods that extend 2 years, whereas trades for a foundation never outperform direct trades.

Taken together, the regression analyses in this section corroborate and extend the calendar-time portfolio analysis in Table 3. These results establish that indirect trades through the accounts of family members, nonfamily trusts, and retirement accounts outperform direct trades in the insider's own account, after accounting for trade size and controlling for other firm attributes that prior research shows to predict returns. This outperformance is both economically and statistically significant, and it extends for up to 2 years following the trades.

V. Indirect Insider Trading and the Use of Private Information

In Section V, we compare the predictive information contained in direct trades versus indirect trades made ahead of firm-specific information events, including earnings announcements and large idiosyncratic price changes. If the superior performance of indirect trades arises from strategic timing by insiders prior to the arrival of such pertinent information, we would expect indirect transactions to contain more predictive information about these events than direct trades.

A. Quarterly Earnings Surprises

We first relate the firm's forthcoming earnings surprise to the information contained in recent insider trading activity through direct versus indirect accounts, with the following model:

$$
\begin{aligned}
(3)\quad \text{SURPRISE}_{j,q} = {} & \alpha_t + \beta_1\text{TRSIZE\_ME\_RK}_{i,j,t} + \beta_2\text{TRSIZE\_OTHER\_RK}_{i,j,t} \\
& (\text{or} + \beta_3\text{TRSIZE\_FAM\_RK}_{i,j,t} + \beta_4\text{TRSIZE\_TRUST\_NOTFAM\_RK}_{i,j,t} \\
& + \beta_5\text{TRSIZE\_RET\_NOTFAM\_RK}_{i,j,t} + \beta_6\text{TRSIZE\_FOUND\_RK}_{i,j,t}) \\
& + \beta_7\text{SURPRISE}_{j,q-1} + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t},
\end{aligned}
$$

where $\text{SURPRISE}_{j,q}$ is the earnings surprise of firm j at the next quarterly earnings announcement that occurs in quarter q, following trades made by insider i in month t. We measure SURPRISE using the standardized unexpected earnings (SUE) model of Bernard and Thomas (1990), as defined in Table 1. Our main independent variables of interest are the scaled rank variables for trade size in a given month (t), based on direct trades, TRSIZE_ME_RK, versus all indirect trades, TRSIZE_OTHER_RK (or the subsets of indirect trades made through family accounts, nonfamily trusts, nonfamily retirement accounts, and foundations). In addition to the standard control variables from equation (1), we also control for the lagged 1-quarter earnings surprise, $\text{SURPRISE}_{j,q-1}$, and include monthly fixed effects.

We conjecture that, if the subset of trades made through all indirect accounts (or through specific categories of indirect accounts) in 1 month contain more predictive information about the firm's next quarterly earnings surprise, then β_2 (or β_3–β_6) should be larger than β_1. We present the results of this analysis in Panel A

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of Table 6. Column 1 compares the information content of direct trades (TRSIZE_ME_RK) with that of all other indirect trades (TRSIZE_OTHER_RK). The results indicate a slightly negative relation between net order flow through direct accounts and the next earnings surprise ($\beta_1 = -0.006$, $t = -0.61$), but a positive relation for net order flow through all indirect accounts ($\beta_2 = 0.027$, $t = 1.54$). Although β_2 is not significantly different from 0 at conventional levels, β_2 is significantly greater than β_1 ($p = 0.05$). This evidence indicates that net order flow through all indirect accounts contains significantly more predictive information than direct trades, regarding the firm's next earnings surprise.

In column 2 in Panel A of Table 6, we present the analogous results comparing the predictive ability of direct trades (TRSIZE_ME_RK) with the subsets of indirect trades made through family accounts (TRSIZE_FAM_RK) and nonfamily indirect

TABLE 6

Direct Versus Indirect Trades and Future Firm-Specific Informational Events

Panel A of Table 6 reports the results from the following panel regression analysis that relates direct trades and the nonoverlapping categories of indirect trades to the firm's next earnings surprise:

$$\begin{aligned}\text{SURPRISE}_{j,q} = {} & \alpha_t + \beta_1 \text{TRSIZE\_ME\_RK}_{i,j,t} + \beta_2 \text{TRSIZE\_OTHER\_RK}_{i,j,t} \\ & (\text{or} + \beta_3 \text{TRSIZE\_FAM\_RK}_{i,j,t} + \beta_4 \text{TRSIZE\_TRUST\_NOTFAM\_RK}_{i,j,t} + \beta_5 \text{TRSIZE\_RET\_NOTFAM\_RK}_{i,j,t} \\ & + \beta_6 \text{TRSIZE\_FOUND\_RK}_{i,j,t}) + \beta_7 \text{SURPRISE}_{j,q-1} + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t}.\end{aligned}$$

The dependent variable is the earnings surprise for the next earnings announcement by firm j in quarter q, following the trades of insider i during month t, measured by standardized unexpected earnings (SUE).

Panel B presents the results of probit regression analysis that relates direct and indirect trades to the likelihood of an imminent large idiosyncratic stock price change within the next 10 days following an insider trade:

$$\begin{aligned}\Phi^{-1}(+/-\Delta P_{j,t}) = {} & \alpha_t + \beta_1 \text{TRSIZE\_ME\_RK}_{i,j,t} + \beta_2 \text{TRSIZE\_OTHER\_RK}_{i,j,t} \\ & (\text{or} + \beta_3 \text{TRSIZE\_FAM\_RK}_{i,j,t} + \beta_4 \text{TRSIZE\_TRUST\_NOTFAM\_RK}_{i,j,t} + \beta_5 \text{TRSIZE\_RET\_NOTFAM\_RK}_{i,j,t} \\ & + \beta_6 \text{TRSIZE\_FOUND\_RK}_{i,j,t}) + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t}.\end{aligned}$$

$\Phi(.)$ represents the cumulative distribution function for the standard normal distribution. The sample of large price change events is identified as follows: First, for each firm, we compute the 3-day CAR around every trading day during a given year. If the CAR for a given day is among the top (bottom) 5% among all trading days in the year, that day is identified as having a large positive (negative) price change. If such a large price increase (decrease) occurs within 10 days following an insider trade, the dummy variable $+\Delta P$ ($-\Delta P$) is assigned a value of 1, and 0 otherwise. We also present the marginal effects implied by this probit analysis. We include the same control variables as our analysis of equation (1) in Table 4. Monthly fixed effects are included, and standard errors are clustered by time at the monthly level. The t-statistics are provided in parentheses below the parameter estimates. At the bottom of each column, we also provide F-statistics or χ^2-statistics that test the equality of different pairs of parameter estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Standardized Unexpected Earnings (SUE)

Variables		Dependent Variable: SUE 1	2
TRSIZE_ME_RK (all direct trades)	β_1	−0.006 (−0.61)	−0.006 (−0.65)
TRSIZE_OTHER_RK (all indirect trades)	β_2	0.027 (1.54)	
TRSIZE_FAM_RK	β_3		0.057** (2.33)
TRSIZE_TRUST_NOTFAM_RK	β_4		−0.005 (−0.14)
TRSIZE_RET_NOTFAM_RK	β_5		0.031 (0.50)
TRSIZE_FOUND_RK	β_6		−0.052 (−0.56)
SUE_{q-1}	β_7	0.297*** (34.14)	0.297*** (34.14)
Controls		Yes	Yes
No. of obs.		190,009	190,009
Adj. R^2		0.124	0.124
H_1: testing equality		$\beta_1 = \beta_2$	$\beta_1 = \beta_3$
F-statistic (p-value)		4.0 (.05)**	7.3 (.01)***

(continued on next page)

TABLE 6 (continued)

Direct Versus Indirect Trades and Future Firm-Specific Informational Events

Panel B. Large Idiosyncratic Stock Price Changes (ΔP)

Variables		+ΔP	+ΔP	+ΔP	+ΔP	−ΔP	−ΔP	−ΔP	−ΔP
		1	2	3	4	5	6	7	8
TRSIZE_ME_RK	β_1	0.269***	0.135***	0.267***	0.134***	−0.046***	−0.076***	−0.044***	−0.074***
(all direct trades)		(20.42)	(11.92)	(20.19)	(11.77)	(−3.90)	(−6.24)	(−3.76)	(−6.14)
TRSIZE_OTHER_RK	β_2	0.363***	0.250***			−0.136***	−0.143***		
(all indirect trades)		(16.81)	(11.73)			(−6.36)	(−6.92)		
TRSIZE_FAM_RK	β_3			0.327***	0.228***			−0.108***	−0.109***
				(10.26)	(7.20)			(−3.34)	(−3.36)
TRSIZE_TRUST_NOTFAM_RK	β_4			0.366***	0.224***			−0.097***	−0.139***
				(10.51)	(6.20)			(−3.43)	(−4.99)
TRSIZE_RET_NOTFAM_RK	β_5			0.242***	0.124**			−0.076	−0.076
				(4.19)	(2.05)			(−1.19)	(−1.15)
TRSIZE_FOUND_RK	β_6			0.210*	0.157			0.087	0.035
				(1.88)	(1.36)			(0.80)	(0.32)
Controls		No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.		323,832	323,832	323,832	323,832	323,832	323,832	323,832	323,832
Pseudo-R^2		0.036	0.064	0.035	0.063	0.035	0.047	0.035	0.047
Marginal effects	β_1	0.075	0.037	0.075	0.036	−0.013	−0.021	−0.012	−0.020
	β_2	0.101	0.068	–	–	−0.037	−0.039	–	–
	β_3	–	–	0.091	0.062	–	–	−0.030	−0.030
	β_4	–	–	0.102	0.061	–	–	−0.027	−0.038
	β_5	–	–	0.068	0.034	–	–	−0.021	−0.021
	β_6	–	–	0.059	0.042	–	–	0.024	0.010
H_i: testing equality		χ^2 (*p*-value)							
1. $\beta_1 = \beta_2$		21.4(.00)***	31.0(.00)***	–	–	20.0(.00)***	10.4(.00)***	–	–
2. $\beta_1 = \beta_3$		–	–	4.0(.05)**	9.0(.00)***	–	–	4.0(.05)**	1.1(.29)
3. $\beta_1 = \beta_4$		–	–	8.1(.00)***	6.6(.01)***	–	–	3.4(.06)*	5.2(.02)**
4. $\beta_1 = \beta_5$		–	–	0.2(.66)	0.0(.87)	–	–	0.3(.61)	0.0(.99)
5. $\beta_1 = \beta_6$		–	–	0.3(.61)	0.0(.84)	–	–	1.4(.23)	1.0(.31)

accounts (TRSIZE_TRUST_NOTFAM_RK, TRSIZE_RET_NOTFAM_RK, and TRSIZE_FOUND_RK). We find that the coefficient of the scaled rank of trade size for family trades (β_3) is positive and significant ($t = 2.33$), which shows that an increase in net purchases made through family accounts is followed by a significantly larger upcoming earnings surprise (SUE). Moreover, β_3 is again significantly greater than β_1 ($p = 0.01$), indicating that net order flow through family accounts contains significantly more predictive information than direct trades about future earnings.

B. Large Stock Price Changes

Next, we examine the relative information content of direct trades versus indirect trades regarding imminent large idiosyncratic stock price changes. We identify large price change events as follows: For each firm, we compute the 3-day CAR around every trading day during a given year. If this CAR for a given day is among the top (bottom) 5% among all trading days in the year, we classify that day as having a large positive (negative) price change. We then create 2 indicator variables, $+\Delta P$ or $-\Delta P$, for the subsets of such large positive or negative price changes that occur shortly after insider trades. Specifically, if a large price increase (decrease) occurs within 10 days following an insider trade, the dummy variable $+\Delta P$ ($-\Delta P$) is assigned a value of 1, and 0 otherwise. We then perform the

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following probit regression analysis for trades made by insider i at firm j during month t:

$$
\begin{aligned}
(4)\quad \Phi^{-1}\left(+/-\Delta P_{j,t}\right) = {} & \alpha_t + \beta_1 \text{TRSIZE\_ME\_RK}_{I,j,t} + \beta_2 \text{TRSIZE\_OTHER\_RK}_{I,j,t} \\
& (\text{or } + \beta_3 \text{TRSIZE\_FAM\_RK}_{I,j,t} \\
& + \beta_4 \text{TRSIZE\_TRUST\_NOTFAM\_RK}_{I,j,t} \\
& + \beta_5 \text{TRSIZE\_RET\_NOTFAM\_RK}_{I,j,t} \\
& + \beta_6 \text{TRSIZE\_FOUND\_RK}_{I,j,t}) \\
& + \text{CONTROLS}_{j,t} + \varepsilon_{i,j,t},
\end{aligned}
$$

where $\Phi(.)$ represents the cumulative distribution function for the standard normal distribution. We again incorporate all control variables in model (1), and include monthly fixed effects.[16]

We present the results from this probit regression in Panel B of Table 6. We also provide the marginal effects implied by the insider trading signals from direct trades, as well as the different categories of indirect trades, along with the χ^2 tests for the null hypotheses that the individual coefficients for each category of indirect trades are equal to that for direct trades. Columns 1–4 provide the evidence for large positive price changes, whereas columns 5–8 present the analogous results for large negative price changes.

Across columns 1–4 in Panel B of Table 6, the coefficients β_1–β_5 are all significantly *positive.* This evidence indicates that, in general, *greater purchases* (*sales*) in these five types of insider accounts are associated with a higher (lower) likelihood of an imminent large price *increase.* Furthermore, in columns 1–4, the impacts for all indirect trades, family trades, and trades through nonfamily trust accounts (β_2–β_4) are significantly larger than the impact for direct trades (β_1). For example, in column 2, the marginal effect for direct trades (β_1) indicates that an increase in TRSIZE_ME_RK of 1 unit (i.e., changing from the tercile of large direct sales to large direct purchases) increases the probability of an imminent large positive stock price change by 3.7%. However, the analogous effect for all indirect trades is larger, at 6.8%. Furthermore, the difference between β_2 and β_1 is statistically significant at the 1% level (χ^2 = 31.0, $p < 0.01$). This evidence indicates that large net purchases through any indirect account are significantly more likely to precede large stock price increases than those through the insider's own direct account.

Columns 5–8 in Panel B of Table 6 provide similar results for large stock price declines. Now, the coefficients β_1–β_4 are all significantly *negative.* This evidence indicates that *greater sales* (*purchases*) of each type predict a higher (lower) likelihood of an imminent price *decline.* Once again, the effect is significantly larger for indirect trades, family trades, and trades through nonfamily trust accounts when compared with direct trades. For instance, in column 6, the marginal effect

[16]Due to the potential "incidental parameters problem" when estimating probit models with fixed effects (see Greene (2004)), we repeat this analysis using a linear probability model in Table IA.3 in the Supplementary Material, with robust results.

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associated with β_1 indicates that changing from large purchases to large sales through direct accounts (i.e., a *decrease* in TRSIZE_ME_RK from +1 to 0) increases the likelihood of an imminent large price decline by 2.1%. The same evidence for all indirect trades (β_2) increases the chance of a large price decline by 3.9%. Once again, this difference between β_2 and β_1 is statistically significant (χ^2 = 10.4, $p < 0.01$). Finally, column 7 indicates that family trades and trades through nonfamily trust accounts also contain significantly more predictive information than direct trades about large price declines, although the difference between β_3 and β_1 becomes insignificant when we include the controls in column 8 (i.e., χ^2 = 1.1, p = 0.29).

The analyses in Section V show that net order flow through indirect accounts contains significantly more predictive information than direct trades, with regard to future firm-specific information events. Overall, these results are consistent with our main findings above, indicating that insider trades through various indirect accounts tend to have better stock return performance than trades through insiders' own account. Furthermore, this evidence suggests that insiders strategically time their trades through indirect accounts just prior to major firm-specific information events, implying that the superior performance of indirect trades arises, at least partially, from the insider's privileged access to private information about firm performance.[17]

VI. The Intensity of SEC Scrutiny and Indirect Insider Trading

In Section VI, we investigate whether the ratio of indirect trades to direct trades varies over time with the intensity of SEC scrutiny against illegal insider trading. Adhikari, Agrawal, and Sharma (2021) document that a decrease in litigation risk leads to more profitable insider trades. Alternatively, Del Guercio et al. (2017) find that an increase in litigation risk, proxied by more aggressive SEC enforcement activity, deters illegal insider trading. Similarly, Cohen et al. (2012) show that opportunistic insiders trade less in the months following an increase in the number of SEC investigations regarding illegal insider trading, arguing that such intensified scrutiny makes the risks of illegal insider trading particularly salient.

Our analysis thus far indicates that insiders tend to use direct accounts more for uninformed trades (e.g., for diversification or liquidity purposes) and indirect accounts more for informed trades. Thus, following the above literature, we conjecture that insiders are more likely to reduce their indirect trades when there is an increase in litigation risk. Put another way, if opportunistic insiders channel a greater proportion of their most informed trades through indirect accounts, and if increased SEC scrutiny serves as an effective deterrent to informed trading (as the prior literature suggests), then we would expect the ratio of indirect trades

[17]This finding is also consistent with Cheng and Lo (2006), who document that insiders strategically time their trades and disclosures to maximize trading profits.

[18]We do not assert that regulators scrutinize indirect trades either more or less carefully than they scrutinize direct trades. Indeed, insiders report both types of trades essentially in the same way on the Form 4. See Figure 1 for an example of such a Form 4 that includes indirect trades.

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to direct trades to decline in the months following more aggressive SEC enforcement activity.[18]

We follow the approach in Cohen et al. (2012), and test this conjecture by examining whether the frequency of indirect trades relative to direct trades is sensitive to the recent intensity of SEC enforcement activity. The model is specified as follows:

$$(5)\qquad \mathrm{RATIO}_t = \alpha + \beta_1 \mathrm{SEC}_{t-1} + \beta_2 \mathrm{SEC}_{t-2} + \beta_3 \mathrm{SEC}_{t-3} + \beta_4 \mathrm{MKTRET}_{t-1} + \beta_5 \mathrm{MKTRET}_{t-13,t-2} + \varepsilon_t.$$

where RATIO_t is the total number insider trades through any indirect account divided by the total number of direct trades during month t. SEC_t is the number of SEC investigations against illegal insider trading in month t. To construct the SEC_t variable, we proceed in a similar fashion to Cohen et al. (2012) and screen the headlines of SEC press release for the phrases "Insider Trading," "Insider Trader," and "Insider Traders," and then verify that the identified releases indeed cover enforcement actions.[19] We also control for the lagged 1-month market return (MKTRET_{t-1}), as well as the cumulative market return over the prior 12 months ($\mathrm{MKTRET}_{t-13,t-2}$).

Table 7 presents the analysis. The first 3 columns report that more aggressive SEC enforcement in 1 month is associated with less insider trading through indirect accounts in each of the next 3 months. In column 4, when all three monthly lags on SEC are included, only the coefficient at lag 1 month is significantly negative. The economic impact of these lagged effects is large. For example, column 4 indicates that one more case against illegal insider trading in month t is associated with a 0.60% decline in the ratio of indirect trades to direct trades in month $t + 1$. Column 4 also reports that this deterrence effect is temporary, since the coefficient of the SEC variable declines in magnitude and statistical power after 1 month.

This analysis indicates that insiders reduce their trading activity through indirect accounts, relative to their direct trading activity, following periods of intensified scrutiny by the SEC. The evidence is again in line with our main findings above, which indicate that insiders are more likely to place informed trades through indirect accounts. These results further suggest that insiders become more hesitant to trade through indirect accounts relative to direct accounts when litigation risk is greater, such that informed trading through indirect accounts is effectively deterred by greater EC enforcement activity.

VII. Direct Trades Versus Indirect Trades and the Attributes of Insiders or Their Firms

In Section VII, we explore how the attributes of insiders or their firms affect the likelihood of an insider making indirect trades. Specifically, we estimate probit

[18]We do not assert that regulators scrutinize indirect trades either more or less carefully than they scrutinize direct trades. Indeed, insiders report both types of trades essentially in the same way on the Form 4. See Figure 1 for an example of such a Form 4 that includes indirect trades.

[19]The SEC makes press releases available at https://www.sec.gov/news/pressreleases.

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TABLE 7

The Intensity of SEC Scrutiny and Indirect Insider Trading

Table 7 estimates a time series regression model to analyze whether the ratio of indirect trades to direct trades in a given month (t) is sensitive to the extent of recent SEC enforcement activity regarding insider trading abuse. The dependent variable is the ratio of the number of insider trades in any indirect account to the number of direct insider trades during month t. The independent variables of interest include 3 monthly lagged values of the number of SEC investigations against insider trading during months $t-1$, $t-2$, and $t-3$, respectively (i.e., SEC_{t-1}, SEC_{t-2}, and SEC_{t-3}). We also control for the 1-month lagged stock market return (i.e., MKTRET_{t-1}), and the previous cumulative stock market return from month $t-13$ to month $t-2$ (i.e., $\text{MKTRET}_{t-13,t-2}$). The model is specified as follows:

$$\text{RATIO}_t = \alpha + \beta_1 \text{SEC}_{t-1} + \beta_2 \text{SEC}_{t-2} + \beta_3 \text{SEC}_{t-3} + \beta_4 \text{MKTRET}_{t-1} + \beta_5 \text{MKTRET}_{t-13,t-2} + \varepsilon_t.$$

The sample period is determined by the availability of SEC investigation data, which spans the period of 2003 to 2012. Newey and West (1987) adjusted t-statistics appear in parentheses (with 12 monthly lags). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: RATIO = No. of Indirect Trades/No. of Direct Trades			
	1	2	3	4
SEC_{t-1}	−0.007***			−0.006**
	(−3.86)			(−2.56)
SEC_{t-2}		−0.005*		−0.002
		(−1.94)		(−0.87)
SEC_{t-3}			−0.005**	−0.002
			(−2.10)	(−0.64)
MKTRET_{t-1}	−0.225***	−0.227***	−0.225***	−0.224***
	(−4.06)	(−3.86)	(−3.48)	(−3.90)
$\text{MKTRET}_{t-13,t-2}$	−0.059***	−0.059***	−0.058***	−0.059***
	(−3.83)	(−3.69)	(−3.45)	(−3.91)
No. of obs.	114	114	114	114
Adj. R^2	0.293	0.250	0.251	0.287

models where the dependent variable is an indicator that takes a value of 1 if a trade is an indirect trade, and 0 otherwise, whereas the independent variables reflect the characteristics of insiders and their firms.

The results are presented in Table 8. We begin by examining whether the attributes of an insider's firm are associated with the likelihood of an insider making indirect trades. Column 1 reports that indirect trades are more likely to originate from insiders at firms subject to greater information asymmetry, characterized by smaller size, higher asset growth, and higher stock return volatility. This greater information asymmetry may offer insiders more opportunities to make informed trades. Column 2 reveals that indirect trades also tend to originate from insiders at firms with lower institutional ownership, which are subject to less monitoring by institutional investors, and thus less likely to attract attention and scrutiny from the public.

Next, we turn to the attributes of insiders themselves. Indirect trades are more likely to originate from insiders who are older (column 3 of Table 8) and have more experience on the job (column 4). Indirect trades are also more likely to come from insiders who serve as CEO or Chair of the Board (column 5). In contrast, insiders who serve as the General Counsel, or are female, are less likely to make indirect trades (columns 6 and 7). Furthermore, insiders who have lower total compensation but greater pay-for-performance sensitivity (i.e., delta) are more likely to make indirect trades (column 8). We also find (in column 9) that, all else equal (especially controlling for the total shares traded, TOTSHR), the likelihood of an insider making indirect trades is positively associated with the frequency of trades relative

TABLE 8

The Attributes of Insiders and Their Firms, for Subsets of Insiders Who Make Direct Trades Versus Indirect Trades

Table 8 relates the personal attributes of insiders and their respective firms to the likelihood of making direct trades versus indirect trades, in a probit regression framework. The dependent variable is an indicator variable that takes a value of 1 if a trade is an indirect trade. IO is the percentage institutional ownership in the insider's firm. The other firm attributes are described in Table 1. The remaining variables pertain to the attributes of the insiders themselves, as follows: AGE is the insider's age. YEAR_EXP is the number of years of experience since the insider's first year of insider trading. TIMEROLE is the number of years since the insider's first year in the current position. CEOCB is an indicator variable that takes a value of 1 if the insider is the CEO or Chair of the Board. GCOUNSEL is a dummy variable that takes a value of 1 if the insider is the general counsel. FEMALE is a dummy variable for female insiders. COMPEN is the total compensation of the insider, and DELTA is a measure of pay-performance sensitivity following Coles, Daniel, and Naveen (2006). TOTSHR is the total number of shares traded by the insider in month *t*, scaled by the total trading volume by all investors. N_MTH_VOL is constructed as the number of trades made by the insider during month *t*, scaled by the total trading (share) volume across all investors in the same month. We take the natural logarithm of N_MTH_VOL. TRADENO is the total number of trading months for the insider during the past 3 years. NONROUTINE_CMP is an indicator variable for nonroutine (or opportunistic) insiders, following Cohen et al. (2012). OPPORT_AH is an indicator variable that identifies opportunistic insiders, based on Ali and Hirshleifer (2017). SHORT_HORIZON is a rank variable that takes a value of 1, 2, or 3 for insiders with a long, medium, or short investment horizon, respectively, following Akbas et al. (2020). The sample period covers July 2003 to Dec. 2017. Monthly fixed effects are included, and standard errors are clustered by time at the monthly level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
B/M	0.154	−0.191	−0.987*	−1.145*	0.367	0.042	−0.155	6.212***	0.133	6.744***	1.946***	6.252***
	(0.27)	(−0.33)	(−1.72)	(−1.95)	(0.64)	(0.07)	(−0.27)	(5.06)	(0.23)	(6.94)	(3.39)	(7.89)
SIZE	−7.687***	−5.192***	−4.808***	−5.222***	−7.475***	−4.619***	−4.838***	−9.415***	−1.075***	−5.718***	−8.020***	−5.035***
	(−26.53)	(−17.19)	(−16.15)	(−17.37)	(−25.71)	(−15.14)	(−16.15)	(−10.08)	(−2.61)	(−12.28)	(−28.99)	(−16.19)
$RET_{j,t}$	−0.110***	−0.136***	−0.066*	−0.077**	−0.104***	−0.070**	−0.072**	−0.076	−0.188***	−0.008	−0.101***	−0.084*
	(−3.26)	(−4.16)	(−1.89)	(−2.16)	(−3.08)	(−2.04)	(−2.08)	(−0.95)	(−4.91)	(−0.10)	(−3.04)	(−1.67)
$RET_{j,t-6,t-1}$	−0.003	−0.020	0.027**	0.022	−0.002	0.016	0.017	0.159***	−0.020	0.047*	0.005	0.008
	(−0.21)	(−1.22)	(2.03)	(1.63)	(−0.15)	(1.24)	(1.29)	(5.22)	(−1.12)	(1.80)	(0.28)	(0.45)
PROFIT	−0.130***	−0.103***	−0.078***	−0.111***	−0.129***	−0.083***	−0.085***	−0.104**	−0.173***	−0.094***	−0.148***	−0.004
	(−7.15)	(−5.80)	(−4.04)	(−5.58)	(−7.04)	(−4.29)	(−4.40)	(−2.54)	(−10.60)	(−2.97)	(−8.15)	(−0.17)
ASSETGR	0.037***	0.047***	0.057***	0.073***	0.035***	0.053***	0.049***	−0.063**	0.034***	0.006	0.020**	0.020
	(3.70)	(4.82)	(4.78)	(6.12)	(3.43)	(4.49)	(4.14)	(−2.37)	(3.15)	(0.32)	(1.98)	(1.35)
STDRET	2.107***	1.980***	1.453***	1.840***	2.112***	1.233***	1.236***	3.973***	3.548***	2.150***	2.333***	2.308***
	(6.25)	(6.49)	(4.05)	(4.84)	(6.31)	(3.60)	(3.54)	(5.22)	(6.56)	(4.20)	(7.16)	(5.68)
		IO	AGE	YEAR_EXP	CEOCB	GCOUNSEL	FEMALE	COMPEN	TOTSHR	TRADENO	TRADENO	TRADENO
		−0.341***	0.008***	0.017***	0.170***	−0.513***	−0.051***	−0.079***	4.368***	0.030***	0.018***	0.019***
		(−22.55)	(14.94)	(21.34)	(17.72)	(−15.10)	(−3.00)	(−7.86)	(14.52)	(24.33)	(24.14)	(26.31)
				TIMEROLE				DELTA	N_MTH_VOL	NONROUTINE_CMP	OPPORT_AH	SHORT_HORIZON
				0.004***				0.267***	0.034***	0.091***	0.093***	0.099***
				(4.05)				(33.24)	(10.21)	(5.46)	(8.94)	(11.46)
No. of obs.	323,818	323,804	157,342	159,417	323,818	159,417	157,475	63,744	323,799	76,847	323,818	135,042
Pseudo-R^2	0.016	0.019	0.010	0.013	0.018	0.008	0.006	0.067	0.045	0.031	0.022	0.021

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to total volume (N_MTH_VOL). Thus, if insiders trade more frequently but in smaller amounts during a given month, they are more likely to be making trades through indirect accounts. This outcome supports the inference that, holding constant the number of shares traded (TOTSHR), insiders who make indirect trades are more likely to break up their most informed trades and place them through different accounts to reduce the price impact of such trades.[20]

Finally, in columns 10–12 of Table 8, we consider 3 subsets of insiders who exhibit other aspects of trading behavior that have been associated with opportunistic insider trading, and we examine whether these opportunistic insiders are more likely to make indirect trades. We find that indirect trades are more likely to be made by nonroutine insiders (Cohen et al. (2012)), insiders who trade profitably before earnings announcements (Ali and Hirshleifer (2017)), and insiders who have a short investment horizon (Akbas et al. (2020)).[21]

The findings in columns 10–12 of Table 8 raise the possibility of an alternative potential explanation for our finding that indirect trades are more informed than direct trades. Given that indirect trading is associated with these 3 subsets of opportunistic insiders identified in prior literature, it is conceivable that the greater information content of indirect trades we find could merely reflect the coincidence of indirect trading with these 3 subsets of opportunistic insiders. We assess this potential alternative explanation by replicating the analysis specified in equation (1) while excluding: i) nonroutine insiders as defined by Cohen et al. (2012), ii) insiders who trade profitably before earnings announcements as defined by Ali and Hirshleifer (2017), and iii) insiders with a short investment horizon as defined by Akbas et al. (2020). The results are provided in Table IA.5 of the Supplementary Material. The evidence indicates that, although the remaining insiders in the sample do not make these three types of opportunistic trades, their indirect trades still significantly outperform their own direct trades. This evidence establishes that indirect insider trades indeed represent a novel, unique form of opportunistic insider trading that has been heretofore unexplored in the insider trading literature.

VIII. Indirect Trades and the Likelihood of Subsequent Litigation and Enforcement Action

Our evidence indicating that indirect trades tend to be more profitable than direct trades raises the possibility that these insiders are more likely to be eventual

[20]We find similar results when we replace our measure of trading frequency relative to total volume, N_MTH_VOL (measured as the number of trades made by each insider in a given firm during month *t*, scaled by total trading volume by all investors), with either of the following: i) the total number of trades made by the insider in month *t* (N_MTH) or ii) N_MTH scaled by share turnover in the stock across all investors, where share turnover is total shares traded by all investors divided by shares outstanding.

[21]Since all three of these aspects of insider opportunism are based on the insider's own past trading behavior, we also control for the total number of trades made by the insider during the previous 3 years (TRADENO) in columns 10–12. Again, due to the potential "incidental parameters problem" when estimating probit models with fixed effects (see Greene (2004)), we also repeat this analysis using a linear probability model. The results are provided in Table IA.4 in the Supplementary Material, and are robust.

targets of SEC enforcement actions against illegal insider trading, or that their firms are more likely to be targets of class action lawsuits. We test these possibilities by examining whether the making of indirect trades is associated with a greater likelihood of either subsequent SEC enforcement action against illegal insider trading, or shareholder class action lawsuits against the insider's firm.

We begin by analyzing SEC enforcement actions against illegal insider trading. For this analysis, we use the sample from Ahern (2017), who collects data on enforcement actions against illegal insider trading from SEC filings, DOJ filings, Factiva, and Lexis Nexis over the years 2009–2013. As Ahern (2017) notes, his sample begins in 2009 because the SEC and DOJ reclassified how cases were handled in 2008. We match this sample with our insider trading database using first and last names. We then create 2 alternative binary variables to indicate the release of these SEC enforcement actions. The first is a binary variable that equals 1 (0 otherwise) if the insider is named in an SEC enforcement action against illegal insider trading, within the next 60 months following the trade of insider i in firm j during month t. The second is a binary variable that equals 1 (0 otherwise) if the insider's firm is involved in such an SEC enforcement action within the next 60 months. Using our monthly panel of all insider trades, we then estimate a probit model that regresses each of these binary variables against an indicator variable that distinguishes whether the insider trade is indirect or direct (as measured by the indicator variable INDIRECT), along with a set of control variables.

The results are presented in Table 9, and document a significant positive association between indirect trading and the likelihood of subsequent SEC enforcement action against illegal insider trading, at both the insider level and the firm level. That is, the likelihood of an insider (columns 1 and 2 of Table 9) or the insider's firm (columns 3 and 4) being involved in a subsequent SEC enforcement action against illegal insider trading is significantly greater if the insider has made an indirect trade within the previous 60 months.

We next turn to shareholder lawsuits. Our database containing shareholder lawsuits is taken from the Stanford Securities Class Action Clearing House. This data set covers the period of 1996 to 2021 and includes 6,063 class action lawsuits. Among these lawsuits, 389 mention the terms "insider," "inside," or "insiders" in their case summaries, and are thus classified as potential "insider trading-related class action lawsuits." Our sample of firms includes all publicly traded firms in the U.S. (listed in CRSP with data in Compustat). The sample is indexed on the firm level because shareholder lawsuits generally target the firm rather than individual insiders.

We again create 2 alternative binary variables that indicate whether a firm is the subject of a shareholder lawsuit. The first (SCA_ALL) is a binary variable that equals 1 (0 otherwise) if a firm faces any class action lawsuit in month t, whereas the second (SCA_INSIDER_TRADING) is another binary variable that equals 1 (0 otherwise) if the firm faces an insider trading-related class action lawsuit during that month, as described above. We also create 2 explanatory variables: N_OTHER is the number of insider months with indirect trades during the past 60 months, whereas N_ME is the analogous number for direct trades (made in the insiders' own accounts). We take the natural logarithm of 1 plus the actual numbers for both variables, N_OTHER and N_ME. We then estimate a probit model that regresses

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TABLE 9

Indirect Trading and SEC Enforcement Action Against Illegal Insider Trading

In Table 9, we examine whether indirect insider trading is associated with the likelihood of subsequent SEC enforcement action against illegal insider trading, using probit regressions based on insider-month-level panel data. In columns 1 and 2 (or columns 3 and 4), the dependent variable takes a value of 1 if insider *i* (or anyone) in firm *j* is involved in an SEC enforcement action against illegal insider trading within 5 years (60 months) following his or her trade in month *t*, and 0 otherwise. The independent variable, INDIRECT, is an indicator variable that takes a value of 1 if a trade is an indirect trade, and 0 otherwise. We also include the other standard control variables from Table 4. Since the litigations data cover the years 2009–2013 and we analyze litigation cases within 60 months following insider trades, the insider trading sample period for this analysis covers the years 2004–2013. We include monthly fixed effects, and cluster standard errors by time at the monthly level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Insider Level		Firm Level	
Variables	1	2	3	4
INDIRECT	0.182***	0.193***	0.069***	0.177***
	(3.10)	(3.47)	(3.27)	(7.31)
B/M		20.025***		−10.528***
		(8.31)		(−5.90)
SIZE		5.517**		23.182***
		(2.49)		(17.22)
$\text{RET}_{j,t}$		−0.547**		−0.020
		(−2.38)		(−0.16)
$\text{RET}_{j,t-6,t-1}$		−0.163**		0.041
		(−1.99)		(0.92)
PROFIT		−0.203**		0.157***
		(−2.56)		(2.81)
ASSETGR		0.150***		0.206***
		(5.02)		(8.29)
STDRET		1.110		5.665***
		(0.88)		(5.38)
No. of obs.	149,330	149,330	217,541	217,541
Pseudo-R^2	0.023	0.053	0.034	0.137

each binary variable (SCA_ALL or SCA_INSIDER TRADING) against these 2 explanatory variables and a set of control variables.[22] The results are presented in Table 10, and document a significant positive association between indirect trading activity and the likelihood of facing any shareholder lawsuit in general, or of facing an insider-trading-related shareholder lawsuit specifically.

Taken together, the results in Tables 9 and 10 suggest that insiders who have engaged in indirect insider trading (or their firms) are more likely to be subsequent parties to SEC enforcement actions against illegal insider trading (or shareholder lawsuits). This evidence provides support for our conjecture that insiders who make indirect trades tend to be more "opportunistic" overall and, as a result, are more likely to be the eventual targets of such SEC enforcement actions or shareholder lawsuits. This result is consistent with Ali and Hirshleifer (2017), who show that firms with opportunistic insiders are more likely to be involved in SEC enforcement actions for alleged misstatements in financial reports, as well as shareholder litigation, such that insider opportunism could be considered a "domain-general trait."

We wish to draw attention to some caveats regarding interpretation of the results from this analysis. First, consider our analysis of SEC investigations against

[22]We also control for an indicator variable, NOTRAD, which equals 1 (0 otherwise) if there is no insider trading in the past 60 months, to capture potential differences between firms with or without insider trading. We find similar results when we do not include the NOTRAD variable.

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TABLE 10

Indirect Insider Trading and Securities Class Action Lawsuits

In Table 10, we examine whether insider trades are associated with the likelihood of subsequent securities class action lawsuits against the insider's firm, using probit regressions based on firm-month-level panel data. In columns 1 and 2, the dependent variable (SCA_ALL) takes a value of 1 if there is a securities class action lawsuit involving firm *i* in month *t*, and 0 otherwise. In columns 3 and 4, the dependent variable (SCA_INSIDER_TRADING) takes a value of 1 if the lawsuit case summary mentions any of the terms, "insider," "inside," or "insiders," at least once in the associated legal documents. The independent variable, N_OTHER, is defined as the number of insider months when indirect trades are made in the past 60 months prior to month *t*, whereas N_ME is the analogous number of direct trades made in the insiders' own accounts. We take the natural logarithm of 1 plus the actual numbers for both N_OTHER and N_ME. NOTRAD is an indicator variable that takes a value of 1 (0 otherwise) for firms with no insider trades made during the past 60 months. We also include the other standard control variables from Table 4. The sample period covers the period of July 2003 to Dec. 2017. Monthly fixed effects are included, and standard errors are clustered by time at the monthly level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	SCA_ALL		SCA_INSIDER_TRADING	
Variables	1	2	3	4
N_OTHER	0.029***	0.030***	0.096***	0.083**
(all indirect trades)	(3.07)	(3.12)	(2.69)	(2.31)
N_ME		−0.005		0.051
(all direct trades)		(−0.47)		(1.18)
B/M	−0.057***	−0.057***	−0.076***	−0.074**
	(−6.04)	(−6.06)	(−2.60)	(−2.46)
SIZE	0.076***	0.077***	0.086***	0.079***
	(10.46)	(10.28)	(5.59)	(4.77)
$RET_{j,t}$	−0.718***	−0.719***	−0.360	−0.355
	(−6.61)	(−6.61)	(−1.39)	(−1.37)
$RET_{j,t-6,t-1}$	−0.086*	−0.086**	−0.351**	−0.349**
	(−1.96)	(−1.96)	(−2.50)	(−2.50)
PROFIT	0.012	0.014	0.061	0.052
	(0.38)	(0.42)	(0.56)	(0.47)
ASSETGR	0.006***	0.006***	0.003**	0.004**
	(6.53)	(6.50)	(2.36)	(2.46)
STDRET	4.257***	4.256***	4.955***	4.974***
	(6.27)	(6.27)	(6.70)	(6.73)
NOTRAD	0.134***	0.121***	0.147	0.271*
	(4.49)	(2.85)	(1.47)	(1.85)
No. of obs.	517,335	517,335	207,447	207,447
Pseudo-R^2	0.061	0.061	0.070	0.071

illegal insider trading. We emphasize that insiders are rarely investigated for illegal insider trading. Furthermore, when they are investigated, it is often because they tip someone else rather than for trading illegally. In the rare cases when insiders are investigated for making illegal trades, they typically did not report these trades on a Form 4. The result is that our indicator variable to identify trades disclosed by insiders who are the subject of SEC investigations is rarely assigned a value of 1, relative to our overall insider trading data sample.[23]

Second, consider our analysis of class action lawsuits. These lawsuits generally target the firm rather than the insider, and they rarely involve complaints about insider trading. Even when a lawsuit mentions insider trading, it generally means that the litigants aggressively listed all possible offenses that might pertain to the firm involved. Importantly, since these lawsuits do not target individuals, we cannot conduct analysis that attempts to relate indirect trades to class action lawsuits against a specific corporate insider.

[23]The binary variable for insiders (or firms) involved in SEC enforcement actions is assigned a value of 1 only 116 (or 3,372) times in our overall sample.

IX. Conclusion

We compare the information content of direct insider trades made in an insider's own account versus indirect trades made in the accounts of family members, trusts, retirement accounts, and foundations. Portfolio analysis reveals that the subset of all *indirect* trades made through accounts controlled by an insider significantly outperforms *direct* trades made in the insider's own account. Further analysis shows that finer subsets of indirect trades made through *family* accounts outperform direct trades by a greater amount on the buy side, whereas indirect trades through *nonfamily trust* and *retirement* accounts outperform direct trades on the sell side. Our results are robust when we apply regression analysis that accounts for trade size, and controls for firm attributes that prior research shows to predict returns.

Various tests support several potential theoretical rationales to explain why different categories of indirect trades are more likely to be informed than direct trades. For example, our finding that indirect purchases made in family accounts outperform direct purchases supports the conjecture that these indirect purchases offer a tax-advantaged means to bequest wealth via informed trading. Similarly, the finding that sales made in nonfamily trust and retirement accounts significantly outperform direct sales is consistent with the view that insiders make informed sales to preserve the wealth accumulated in these tax-advantaged indirect accounts. Furthermore, trades in any indirect account are less likely to be made by "routine insiders," who are prone to make uninformed trades to achieve liquidity or diversification (Cohen et al. (2012)).

We further investigate potential sources of the superior performance of indirect trades relative to direct trades. We find that indirect trades convey significantly more information about future firm-specific information events, such as earnings surprises and large idiosyncratic stock price changes. Furthermore, insiders tend to reduce their trading activity through indirect accounts relative to direct accounts, when there is greater litigation risk associated with more SEC enforcement activity against illegal insider trading. This evidence corroborates the view that insider trades through indirect accounts are more likely to be based on nonpublic information, and suggests that SEC enforcement actions effectively deter such informed trading activity.

Finally, we show that insiders are more likely to make indirect trades if they have more experience, or they are male, or serve as CEO or Chair of the Board. In addition, insiders are more prone to make indirect trades if they work for firms that are subject to greater information asymmetry embodied in smaller size, greater asset growth, higher stock return volatility, or lower institutional ownership. This evidence is consistent with the view that greater information asymmetry offers more trading opportunities and less scrutiny for insiders who wish to make informed trades through indirect accounts. In addition, while insiders who use indirect accounts trade more shares overall, they do so in smaller trade sizes, suggesting that opportunistic insiders tend to break up their informed trades over several accounts.

This article contributes to the substantial body of prior work on the information content of insider trades with regard to future stock returns, which does not distinguish between direct and indirect insider trades. For example, previous work

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documents opportunistic trading by three groups of insiders, including nonroutine insiders (Cohen et al. (2012)), insiders who profit by trading before earnings announcements (Ali and Hirshleifer (2017)), and insiders with a short investment horizon (Akbas et al. (2020)). We show that indirect trades are more likely to originate from these 3 subsets of opportunistic insiders. On the other hand, after omitting these three groups of opportunistic traders from our analysis, we still find that indirect trades made by the remaining insiders significantly outperform their own direct trades. Our analysis establishes that insider trading through various categories of indirect accounts represents another unique dimension of managerial opportunism. Insider transactions made through indirect accounts contain more information than direct trades about both future stock prices and the prospects for firm performance.

This article should be of interest to regulators and other market participants, who could be justified in applying more scrutiny to insider trades made through indirect accounts. Such indirect trades represent a relatively small portion of all insider transactions, but they are more likely to convey private information. In addition, this article should be of interest to other stakeholders involved in corporate governance. For example, when implementing internal policies related to insider trading, governance committees may wish to devote more resources to monitor transactions made through indirect accounts controlled by insiders. Finally, we note that, as McLean and Pontiff (2016) point out with respect to market anomalies, the publication of our findings could potentially have an effect on the future behavior of market participants, including insiders, investors, and regulators. As such, the outperformance of indirect insider trades over direct trades documented here may diminish in the future.

Appendix. Documented U.S. Cases of Informed Insider Trading Through Family Accounts

There have been numerous documented cases of illegal insider trading in which the alleged informed trading was carried out through indirectly controlled family accounts. The following discussion summarizes four such cases that involve corporate executives trading through the accounts of family members, which ultimately led to SEC charges.

1. SEC v. Peter C. Chang (09/20/2017)

This case involved alleged serial insider trading in the securities of Alliance Fiber Optic Products, Inc. (AFOP) by Defendant Peter C. Chang, who served as the company's Chairman of the Board, Chief Executive Officer, and President from its formation in 1995 until its acquisition in 2016 by Corning, Inc.

According to the SEC, "in 2015 and 2016, Chang, by virtue of his leadership positions at AFOP, acquired material nonpublic information about AFOP's earnings results and financial performance, as well as the intended acquisition of AFOP by Corning, all of which were significant, market moving information. Chang was the largest holder of AFOP stock and was required to disclose his ownership of AFOP securities as an officer and director in accordance with the federal securities laws. But to capitalize on the highly sensitive information he learned about AFOP without detection, Chang secretly traded AFOP shares in two nominee accounts – *one held in his wife's name, and the other in his brother's name* – in advance of two public earnings announcements and the public acquisition announcement" In addition to this, the SEC complaint also highlighted that fact that "Chang allegedly tried to hide his control over one of the accounts by posing as his brother in communications with one of the brokerage firms, and he allegedly obscured his relationship with his wife in response to a market surveillance inquiry by the Financial Industry Regulatory Authority" The SEC also alleged that "In total, Chang's insider trading scheme generated more than $2 million in illicit profits and losses avoided, with at least $1.5 million for Chang's nominee accounts, and more than $600,000 for Chang's brother's account" On Feb. 21, 2018, Peter C. Chang pleaded guilty to illegal insider trading and tender offer fraud. As part of his guilty plea, Chang admitted that he traded AFOP stock through brokerage accounts in the names of his wife and brother (https://www.sec.gov/litigation/litreleases/2017/lr23937.htm).

2. SEC v. Alexander J. Yaroshinsky (06/23/2006)

This case involved transactions in the securities of Connetics Corp. by Alexander J. Yaroshinsky, the former Vice President of Biostatistics and Clinical Operations (and another defendant, Victor E. Zak). The SEC complaint alleges that, in 2005 "between April 13 and June 10, Yaroshinsky and Zak executed numerous trades. Yaroshinsky purchased put contracts in his own account and in a nominee account *opened in the name of his mother-in-law* and sold shares of Connetics common stock in his own account. Zak purchased put contracts, sold short Connetics shares, and sold his long position of Connetics shares. All of the trading by defendants was conducted in advance of a June 13, 2005 public announcement by Connetics stating that it had received a 'not approvable' letter from the Food and Drug Administration ('FDA') concerning Velac Gel. After the announcement, Connetics' stock price fell 27%"

In 2008, Alexander J. Yaroshinsky agreed to pay $723,000 to settle charges that he and a neighbor traded on nonpublic information (https://www.sec.gov/litigation/litreleases/2006/lr19738.htm).

3. SEC v. Jorge Eduardo Ballesteros (05/08/2001)

The SEC complaint alleges that Jorge Ballesteros (the former Chairman of Grupo Mexicano de Desarrollo, S.A., a major Mexican construction company) received a tip from his brother, the late Jose Luis Ballesteros, who was then a director of Nalco Chemical Company. The complaint stated that Jorge Ballesteros was tipped about a possible acquisition of Nalco prior to the June 28, 1999 public announcement that Nalco would be acquired by Suez Lyonnaise des Eaux, S.A. Following the tip, Jorge Ballesteros placed orders to purchase over $5.7 million in Nalco stock through Swiss accounts controlled by offshore trusts and nominee companies *in the names of his wife and mother, respectively*, resulting in illegal profits of over $2 million. In 2003, without admitting or denying the allegations of the SEC's complaint, Jorge Ballesteros agreed to pay a penalty of $2,573,875, as one part of settling the case (https://www.sec.gov/litigation/litreleases/lr18441.htm).

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4. SEC v. Saleem Khan (06/13/2014)

This case alleges that Khan was repeatedly tipped by his friend, Roshanlal Chaganlal, a director at headquarters of Ross Stores in Dublin, CA. Khan allegedly traded more than 40 times in advance of the company's disclosure of its ongoing financial performance. In addition to trading in his own account, *Khan traded in the account of his brother-in-law*, as well as another acquaintance. He also tipped two work colleagues who also traded on the nonpublic information. This insider trading activity led to more than $12 million in collective profits (https://www.sec.gov/news/press-release/2014-117).

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001119.

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