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Essays on the Tax Policy and Insider Trading

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by

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DEDICATION

I would like to dedicate this dissertation to my grandmom (late Mrs. Shao Chen He), mother (Shaohua Fu), my wife (Mrs. Amanda Lyn Patterson), my cousin (Mr. Kang Fu), my uncle (Mr. Weiming Fu), and all my friends (especially Miss Xiaojing Yuan and Mr. Rui Jing). Thank you very much for your encouragements and supports, which keep me working hard so that I am eventually able to reach the finish-line of this long journey.

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Abstract

In the first essay I examine the relation between firm advertising and tax aggressiveness. Advertising increases firm visibility in both the product and the financial market. While investors would appreciate more tax savings, they are aware of the negative impact of tax aggressiveness on consumers' views of the firm and hence its competitive positions in the product market. We find that firms that spend more on advertising have fewer tax sheltering activities, lower book-tax differences, and higher cash effective tax rates. Specifically, an increase of 1% on $Advertising_{i,t}$ ($ADVGP_{i,t}$), the firm pays an additional tax of $0.70 million ($10.92 million). However, the negative impact of advertising on tax aggressiveness becomes weaker (and even reverses) for firms having great transparency, more public scrutiny, or strong external monitoring. We control for endogeneity using propensity score matching and an instrumental variable approach. Our findings are consistent with the argument that advertising enhances corporate reputation and is an important determinant in firms' tax planning.

In the second essay I document a significant increase in opportunistic insider trades when retail investors are paying greater attention to the stock. Using Google SVI to proxy for their level of attention, we find that a higher (lower) SVI on a stock is associated with more insider sales (purchases) of the stock and greater abnormal returns on the sales (purchases). A value-weighted long-short portfolio mimicking insider trades would earn an abnormal return of 1.19% per month (14.28% per year), excluding transaction costs. We also fund that the SVI-related insider traders tend to be non-independent directors who have long tenures but no senior executive positions in their firm and the firm tends to exhibit weaker governance, lower reputation, and poorer social responsibility. Our results are more pronounced for lottery-type stocks but are weaker for stocks with large attention of local investors. Interestingly, the risk of SEC investigation and litigation is lower on SVI-related insider sales and this type of sales actually rises following an increase in news releases of SEC enforcement action. Overall, certain insiders appear to engage in trades to take advantage of variations of retail investors' attention to their stock.

Essay 1- Advertising and Firm Tax Aggressiveness

Introduction

Corporate advertising helps the firm shape its image and convey tailor-made messages to an audience that includes consumers as well as investors. Marketing research identifies a number of benefits of product market advertising such as providing useful information about the firm, its products and their quality (Nelson, 1974; Grossman and Shapiro, 1984), and engaging customers in a dialogue and gaining their trust (Keller, 2001; Smith et al., 2014). In particular, firms use advertising to promote product differentiation and create barriers to entry (Comanor and Wilson, 1974; Rumelt, 1987), to build and enhance firm and product reputation (Klein and Leffler, 1981; Kreps and Spence, 1985; Jorgensen and Isaaksson, 2008), and to project attractive images of corporate citizenship and responsibilities (Fombrun et al., 2000; Pashupati et al., 2002).

More recently, research recognizes the spillover effect of product market advertising on the investment community. Advertising affects investors' interests in the firm's securities and influence their investment decisions. For example, advertising helps to attract investors' attention, lower their information search costs, and enhance the firm's overall visibility in the financial market (Sirri and Tufano, 1998; Grullon et al., 2004; Frieder and Subrahmanyam, 2005; Lou, 2014). A firm may also use advertising to signal its quality (Chemmanur and Yan, 2009) and to influence investors' perceptions of its long-term prospect (Pauwels, 2004). Given the importance of advertising in attracting *both* consumers and investors' attention to the firm and shaping their views, an interesting question concerns how advertising affects the firm's corporate decisions and especially its tax policy. In particular, does a greater extent of advertising make a firm more or less aggressive in pursuing strategies that would lower its tax liabilities? This is an interesting question because the firm's customers (or potential customers) and its investors may draw very different conclusions when they become aware of its tax aggressiveness.

The key objective of product market advertising is to expand the reach of firm products (or services) to consumers. To achieve this goal, a firm often spends a significant amount of advertising dollars to portray it as committing to good product quality, great customer services, and meeting or exceeding consumers' high expectations about the firm's corporate responsibilities and overall reputation. A public exposure of negative incidents or breaches of these commitments may jeopardize the firm's reputation in the eyes of consumers and affect their general interests in the firm's products. Indeed, a public revelation that a firm explores various tax loopholes to avoid paying a "fair" share of corporate taxes may cause consumers to view the firm negatively and to react poorly to its products, in light of the perception of the firm's poor corporate citizenship and ethics. Now, with a greater extent of product market advertising that increases a firm's public exposure and visibility to consumers, the cost would be greater if the firm is perceived to be a poor corporate citizen that does not pay its share of taxes. In this sense, firms that spend more on advertising would have the greater incentive to refrain from employing aggressive strategies to lower taxes. In other words, product market advertising may serve as a commitment to a reputation of not engaging in aggressive tax activities, and we refer to this effect of advertising on tax aggressiveness as *Product Market Commitment (PMC)*.[1]

Product market advertising can spill over to the financial market, causing more investors to pay attention to the firm and generating greater investor interests in its securities (primarily, stock). But, what is the effect of tax aggressiveness on firm investors? On one hand, the negative effect of firm tax aggressiveness on consumers' product-purchase decisions would adversely affect the firm's investors by lowering its sales and profits. Thus, the PMC effect of advertising on tax aggressiveness would carry over to the financial market, as investors recognize the threat of firm tax avoidance to its product market positions. On the other hand, a policy of pursuing legal tax avoidance (not illegal tax evasion) would improve the firm's tax efficiency and benefit its shareholders by lowering the firm's tax liabilities and increasing its after-tax income. Therefore, it is possible that greater advertising by a firm could increase investors' awareness of the firm's tax efficiency. In contrast to the PMC effect, the benefit to

[1] Fombrun and Shanley (1990) define corporate reputation as a cognitive representation of a firm's actions and results that crystallizes its ability to deliver valued outcomes to its stakeholders. As an example of a firm's sensitivity to corporate citizenship concerns, consider Starbucks' response to allegations by U.K. politicians that it was avoiding U.K. taxes (http://www.dailymail.co.uk/news/article-2606274/Starbucks-pay-tax-Britain-relocates-European-headquarters-London-following-customer-boycott.html). To defuse the adverse publicity, Starbucks volunteered to pay more taxes in the U.K. than were required by the tax code (http://www.nytimes.com/2012/12/07/business/global/07iht-uktax07.html).

shareholders of improved corporate tax efficiency suggests that advertising may serve as an alternative commitment to lowering the firm's tax liabilities, and we refer to the latter effect of advertising on tax aggressiveness as *Tax Efficiency Commitment (TEC)*.

While it is generally ambiguous which effect – PMC or TEC – of advertising on tax aggressiveness dominates, the tax aggressiveness literature in accounting offers some tentative suggestions. Desai and Dharmapala (2009a) observe that a common characteristic of aggressive tax strategies is their general complexity and ambiguity, and firms that employ these strategies also tend to be involved in earnings management, in withholding certain information from investors, and in managers' abusing corporate resources for personal gains. Desai and Dharmapala (2009b) show that a firm's overall transparency and governance is an important determinant on whether its tax aggressiveness benefits shareholders; in particular, strategies that result in lower corporate tax liabilities are more likely to be value enhancing if the firm has in place a good and non-opaque governance and oversight structure. Their results suggest that for advertising to have a positive effect on tax aggressiveness – for the TEC effect to dominate the PMC – firms must have sufficiently good managerial oversight and corporate transparency. In contrast, for firms with murky governance structures and generally opaque informational environments, managers have more opportunities to take actions that benefit them personably. In the accounting literature, aggressive tax strategies are associated with the kind of activities that thrive in opacity, raising the question of whether agency considerations may be in play when managers pursue such strategies. Since for firms that are a priori opaque, advertising can significantly enhance these firms' public visibility and exposure, thereby improving their transparency, for such firms, the PMC effect of advertising on tax aggressiveness would likely be more important than that of TEC; that is, advertising would reduce the firms' tax aggressiveness.

Using a large sample of U.S. public firms over the period of 1995 to 2013, we find that firms that spend more on advertising are generally less tax aggressive; the firms have lower probabilities of engaging in tax sheltering activities, lower book-tax differences, and higher cash-effective tax rates, after controlling for firm characteristics and for year and industry effects. The negative impact of adverting on tax aggressiveness is also stronger for firms having greater informational opacity in the first place. Overall, our findings support the PMC effect that product market advertising reduces tax aggressiveness. Hanlon and Heitzman (2010) raise an under-sheltering puzzle by asking the question of "why do some corporations avoid more taxes than others." Our paper addresses this question by proposing a cost and benefit tradeoff when management makes decisions on the firm's tax policy. Essentially, management weighs the direct benefit of lower tax liabilities against the potential cost of adverse consumer reactions toward a tax aggressive firm. Our results suggest that by increasing a firm's product market exposure, advertising serves as a commitment to less tax aggressiveness.

Interestingly, our subsample analyses reveal that for certain types of firms, the TEC effect can dominate the PMC – increased advertising can lead to more aggressive tax planning. In particular, when firms that have large reputation capital in place or that face strong public pressure or external monitoring (e.g., those in the S&P 1500 index or with large institutional ownerships) increase advertising, the firms are more likely to engage in planning strategies to lower their tax liabilities. In other words, for these types of firms advertising actually has a positive impact on their tax aggressiveness.

In the subsample of firms with family ownerships, our evidence also shows a positive effect of advertising on tax aggressiveness. We find that family firms with high advertising expenditures are no longer less tax aggressive than non-family firms. This finding contrasts to Chen et al.'s (2010) result that family firms are less tax aggressive than non-family firms; they argue that family firms' concerns for valuation discounts make them less interested in having a complex informational environment that may be needed to facilitate aggressive tax strategies. Our result suggests that a greater extent of advertising may sufficiently increase the information flow and overall transparency of family firms, making valuation discounts less a concern, and therefore, these firms no longer need to be more conservative in their tax planning. Moreover, the unique ownership structure of family firms suggests that the firms' tax aggressive strategies are likely to improve corporate tax efficiency, benefiting the firms' shareholders (as well as their managers).

A firm's advertising expenditure, of course, is at management's discretion and is not exogenous. It is possible that managers of firms that are prone to aggressive tax planning may choose to decrease advertising spending, so as to reduce public attention to the firms and to limit the public exposure of tax aggressiveness. We address the endogeneity issue in two ways. First, we utilize the instrumental variable (IV) approach. The IV we choose is the number of (significant) customers that a firm reports; this number is highly correlated with the firm's advertising expenditure but has little or no relation with its tax planning. Additional tests further support the quality of our instrument. Second, we use the propensity score matching method to isolate the effect of advertising on tax aggressiveness while controlling for firm characteristics at the same time. In both cases, our results are qualitatively unchanged and remain both statistically and economically significant.

There is a growing stream of research on how product market advertising affects financial markets. Closely related is Grullon et al. (2004) who find that higher advertising spending helps to generate greater interests of individual as well as institutional investors to the firm's stock and to increase the stock's liquidity.[2] As in theirs, increased advertising in our analysis improves the firm's informational environment; however, the improved informational environment here affects the firm's tax policy. To our knowledge, our paper is the first to link firm advertising to its tax planning.

Another closely related paper is Gallemore et al. (2014) who examine whether corporate reputation concerns deter firms' tax sheltering activities; they find that such concerns appear to have little impact. Our paper is similar in that we too address how

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[2] See also Srinivasan et al. (2009). Relatedly, Jain and Wu (2000) find that mutual fund managers use advertising to attract the interests of potential investors in spite of no significant differences in their post-advertisement performance.

product market reputation may be a concern for a firm's tax aggressiveness, but it differs in two important ways. First, our sample consists of a broad spectrum of firms, instead of limiting it only to firms that are involved in tax sheltering activities. Our broad sample reduces a potential self-selection bias that firms which are involved in tax sheltering activities might have less concern for reputation. Second, unlike Gallemore et al.'s (2014) use of the Fortune magazine ranking as proxy for firm reputation, a firm's advertising expenditure seems to be a more direct measure of its public visibility and reputation because of advertising's wide reach to consumers and investors. Using our advertising measures, we find that firms that spend more on advertising – thus likely having greater concerns for potentially negative product market reactions upon unflattering tax avoidance allegations – are indeed less aggressive in their tax planning.

The rest of the paper is organized as follows. The next chapter reviews the related literature on advertising and tax aggressiveness and develops testable hypotheses. Chapter three describes the sample selection procedures and provides summary statistics. Chapter four presents the empirical model and discusses variable construction. Chapter five shows the empirical findings. Chapter six concludes.

Literature Review and Hypothesis Development

Advertising

A large literature on advertising examines its impacts on the product market (e.g., Nelson, 1974; Mcleod and Kunita, 1994; Keller, 2001; Smith et al., 2014) and its spillover effects on the financial market (e.g., Grullon et al., 2004). The basic observation is that advertising enhances the visibility of the firm by drawing more attention of consumers and investors to the firm, its products, and its stock. An important implication is that firms that spend more on advertising will have at stake greater reputation capital if they take actions that may be perceived by the public to be unethical.

It is well known that companies use advertising to convey important messages to their constituents, striving to influence the audience's perceptions and decisions (Mizruchi and Schwartz, 1992). Examining the long term impact of advertising on the market capitalization of firm, Joshi and Hanssens (2010) find that advertising increases firm value by improving its risk and return profile. Lou (2014) argues that advertising increases investors' interest in the firm's stock, which causes a short-term rise in the stock price; consistent with this view, Lou (2014) finds that firms increase their advertising expenditures prior to the firms' seasoned equity offerings (SEOs) and their insiders' sales of stocks. Similarly, Fich et al. (2016) show that merger and acquisition target firms increase their advertising spending, so as to secure higher takeover premiums or to attract more bidders. While our analysis is similar in that it too examines the spillover effects of product market advertising, our focus is the impact of advertising on tax policy.

That advertising attracts people's attention stems from the view that individuals have limited attention spans and attention-grabbing news or events influence their purchase or investment decisions. Seasholes and Wu (2005) document greater buying interests by individual investors of a firm's stock when there are attention-grabbing events or news on the firm, possibly because such occurrences lower the investors' costs of searching for investment opportunities. Barber and Odean (2008) argue that individual investors have "limited cognitive abilities and preferences on their choice sets" and are net buyers of attention-grabbing stocks.[3] Fang and Peress (2008) find that media coverages on particular firms affect their stock prices even when the coverages contain no genuine news about the firms. Research has also shown that investors tend to focus on "familiar firms" with the consequence that many investors' portfolios are overly concentrated on the familiar stocks and are not sufficiently diversified. For examples, Frieder and Subrahmanyam (2005) report that individual investors are more likely to hold stocks of firms that have strong brand recognitions, and Keloharju et al. (2012) document a direct link between individuals' product choices and their investment decisions. In particular, investors are more likely to buy, and less likely to sell, a firm's stock if they are frequent customers of the firm's products. This relationship is also stronger, the greater the customers' product preferences.

Tax Aggressiveness

Corporate income taxes represent significant costs to successful companies by reducing their free cash flows that would otherwise be available for investments or other discretionary uses by managers. For this reason, managers of firms have the incentive to engage in tax planning activities to minimize the firms' tax liabilities. Some may even attempt aggressive tax strategies that are unethical or may end up being

[3] Barber and Odean (2008) define attention-grabbing stocks as those appearing in the news, experiencing high abnormal trading volume, or having extreme one day returns.

impermissible by the Internal Revenue Services (IRS). According to a report by the Citizens for Tax Justice,[4] although the U.S. has long had a high corporate income tax rate of 34% or 35%, Fortune 500 U.S. companies pay an average tax rate of only 18.5% and 30 of the companies actually have a negative income tax due. A key issue in aggressive tax planning is the difference between (legal) tax avoidance and (illegal) tax evasion. In reality, it is often very hard to make a distinction; as Denis Healey (a British politician) puts it, the difference between what is and is not legal is "the thickness of a prison wall." To deter and detect abusive tax strategies by U.S. corporations, the IRS has been increasing its enforcement actions, including various attempts to uncover corporate offshore tax avoidance schemes.

Given the importance of tax, it is not surprising that firms' tax policy, particularly their incentive for tax aggressiveness, has received considerable attention from researchers and regulators alike. A number of papers examine tax aggressiveness in a managerial agency framework. In a model linking managerial incentive compensation to corporate tax planning, Slemond (2004) argues that incentive compensation should motivate managers to make tax-efficient decisions that benefit shareholders. Consistent with this argument, Armstrong et al. (2012) find that firms that provide incentive contracts to tax directors observe lower reported tax expenses. Of course, there are potentially high costs, direct and indirect, to tax aggressiveness. The direct costs arise from increased personnel and budget in the tax department – hiring and paying very expensive fees to tax specialists or consultants. The indirect costs

[4] See http://money.cnn.com/2011/11/03/news/economy/corporate_taxes/index.htm?iid=HP_LN.

include potentially costly future lawsuits, fines and penalties by the IRS for abusive tax reporting, as well as reputation costs to the firm and its executives (Chen et al., 2010). With the increased risk of IRS enforcement, a firm's tax aggressive behavior may also distort its management's effort incentive (Chen and Chu, 2005).

A firm's governance structure and general informational opacity affects its policy on tax aggressiveness. Desai and Dharmapala (2006) suggest a positive feedback between a firm's tax sheltering and its managers' rent extraction; the relationship, however, is weaker for firms having better corporate governance. Desai et al. (2007) find that when managers want to reduce corporate taxes and divert resources for personal use, they structure the firm in a very complex manner; this diversion problem becomes more serious, the weaker the firm's corporate governance. Comparing tax aggressiveness behaviors of family versus non-family firms, Chen et al. (2010) find that family firms are generally less tax aggressive; they argue that family firms forgo tax savings from complex tax planning to avoid significant stock price discounts that outside investors would demand in light of the additional complexity. Kim et al. (2011) document a close association between a firm's tax avoidance and its stock-crashing risk; their result is supportive of the view that tax avoidance is a means of managerial rent extraction by withholding bad news, and the stock crashes when hoarding from investors the accumulated bad news is no longer possible.

There is an extensive literature in finance examining how tax planning affects corporate decisions on capital structure, payout, compensation, risk management, and even organizational form (for a comprehensive review, see Graham, 2003). The tax benefit of debt is known to significantly influence corporate capital structure decisions. Concerning how firm debt use affects tax aggressiveness, Graham and Tucker (2006) find a negative relationship between debt levels of firms and the firms' tax sheltering activities. Lin et al. (2014) report a lower extent of tax aggressiveness by more levered firms. The results suggest a substitution effect between tax-shield benefits of debt and tax savings from aggressive planning. There is also evidence that this substitution effect is intensified in the presence of outside directors (Rchardson et al., 2014).

Hypothesis Development

The perception of a firm, positive or negative, by its customers has a significant impact on the firm's future. According to a recent survey by accounting firm PricewaterhouseCoopers (PWC 16th Annual Global CEO Survey), 80% of the CEOs agree that customers and clients exert significant influence on their business strategies, and the CEOs are very aware of the importance of public opinions and perceptions to the future of their firms. Clearly, individuals are more likely to buy a firm's products if they have a positive view of the firm, and to distrust the firm and its products if their perception of the firm is negative – for example, if the firm is viewed as having poor corporate ethics. A key aspect of firm tax aggressiveness is that it is often associated with a high degree of public beliefs of corporate greed, perceiving firms that are involved in aggressive tax activities to be socially irresponsible and unethical. Indeed, Senator Carl Levin recently quoted a survey showing that two-thirds of Americans believe that U.S. corporations should bear a larger share of the tax burden. In academic research, tax aggressive activities are also found to have a negative impact on the firm when they are associated with hidden actions of management (Scholes et al., 2005; Desai et al., 2007).

Since advertising has been shown to increase firm visibility (e.g., Grullon, 2004) and to enhance its reputation capital (e.g., Klein and Leffler, 1981), it is plausible that managers of firms that spend more on advertising would be more conservative in their firms' tax reporting. This is because customers' knowledge of a firm's tax aggressiveness and their subsequent negativity towards the firm can damage its reputation and result in possibly lost sales. The personal reputation of the firm's managers may also be at stake. Fich and Shivdasani (2007) document a substantial impact to firms' outside directors following financial fraud allegations against the firms; the directors experience a marked decline in their subsequent appointments to other corporate boards following such allegations. In a similar vein, Borghesi et al. (2014) argue that managers may pursue corporate social responsibility activities to enhance their personal as well as their firms' reputation; they find that firms with higher advertising outlays are associated with higher levels of socially responsible corporate activities. Now, if a greater extent of advertising increases a firm's public exposure and helps it better reach consumers, the cost becomes higher if the firm is viewed as being a poor corporate citizen that does not pay its "fair" share of tax. With this in mind, firms that spend more on advertising should have a stronger incentive not to engage in aggressive strategies to lower taxes. Thus, we hypothesize that advertising by firms serves as a commitment to a conservative corporate tax policy, and we refer to this effect of advertising on tax aggressiveness as Product Market Commitment (PMC).

Hypothesis 1 (H1): Higher advertising expenditures by firms are associated with less occurrence of their managers' pursuing aggressive tax strategies – the PMC effect.

The existing literature suggests that tax aggressiveness is linked to a high level of information asymmetry and possibly also to more severe managerial agency problems. For examples, Desai and Dharmapala (2006) argue that effective tax avoidance strategies require concealment of the underlying transactions, and Bushman et al. (2004) show that operational complexity of firms is usually associated with an extensive corporate engagement to arbitrage tax codes and financial regulations.[5] Balakrishnan et al. (2012) find that tax aggressiveness reduces corporate reporting transparency and managers of tax aggressive companies often have to make additional tax related disclosures. Since operational complexity and general opacity appears almost to be a precondition for tax aggressiveness, we hypothesize that the Product Market Commitment (PMC) effect of advertising on tax aggressiveness is stronger for firms that are informationally more opaque a priori.

Hypothesis 2 (H2): The PMC effect is stronger for firms having a higher degree of opacity at the outset.

[5] Apple Inc.'s complex tax planning has been alleged to complicate efforts by its shareholders and board members to comprehend the firm's foreign operations (http://www.forbes.com/sites/beltway/2013/05/21/the-real-story-about-apples-tax avoidance-how-ordinary-it-is/).

Tax aggressiveness may simply reflect managers' maximizing shareholder wealth by lawfully reducing their firms' tax liabilities (Slemrod, 2004). In other words, tax avoidance does not have to entail a managerial agency consideration (Hanlon and Heitzman, 2010). Similarly, Frank et al. (2009) define aggressive tax reporting as a "downward manipulation of taxable income" that may not be fraudulent. Indeed, if investors view tax aggressiveness as management pursuing legal strategies to improve corporate tax efficiency, they should appreciate and even reward management for engaging in such activities. In this regard, by enhancing firms' visibility to the investment community, advertising may commit the firms to pursuing an efficient tax policy, and we refer to this effect of advertising on tax aggressiveness as Tax Efficiency Commitment (TEC).[6]

We have proposed a negative (PMC) and a positive (TEC) effect of advertising on tax aggressiveness. While it is generally ambiguous which of the effects would dominate, the literature on tax aggressiveness suggests that the TEC could dominate the PMC when firms have in place strong governance structures or face great external monitoring by large shareholders (institutional investors). Examining the effect of institutional ownership on tax aggressiveness, Khurana and Moser (2009) find that higher institutional ownerships are generally associated with increased tax aggressive activities; their result is consistent with the argument that institutional investors pressure managers to act in shareholders' interest by reducing corporate taxes. Desai

[6] The same Apple story alleged that the firm reduced its tax liabilities in 2012 by reporting as much income as allowed in countries with lower tax rates while expensing as much costs as permitted in countries (e.g., the U.S.) that have much higher tax rates.

and Dharmapala (2009b) argue that good corporate governance is another determinant that makes tax aggressiveness beneficial to shareholders. Thus, for firms with a priori good governance and strong external monitoring, a greater amount of advertising spending may reflect the firms' commitment to engaging in aggressive tax planning that improves their tax efficiency. Evidently, this alternative relationship between advertising and tax aggressiveness is more likely to be important when there is a greater shareholder pressure on management. For these firms, it is possible that the net effect is positive of advertising on tax aggressiveness; that is, the TEC effect may dominate the PMC.

Hypothesis (H3): The PMC effect is less pronounced or even dominated by the TEC effect for firms that a priori face greater shareholder pressure or public scrutiny.

An interesting case to examine the opposing PMC and TEC effects of advertising on tax aggressiveness is to look at family versus non-family firms. Chen et al. (2010) show that family firms are generally less tax aggressive than non-family firms because family firms are more concerned with valuation discounts and are therefore less interested in having complex informational environments that would be needed to facilitate aggressive tax strategies. Now, if a greater extent of advertising sufficiently increases the information flow and the overall transparency of family firms, thereby adequately addressing outside investors' concerns, the family firms may no longer need to be conservative in their tax planning. Moreover, the unique ownership structure of family firms suggests that these firms' aggressive tax planning that improves tax efficiency is likely to benefit their shareholders (not just managers). Taken together, our last hypothesis posits that for family firms, the TEC effect is more dominant than the PMC.

Hypothesis (H4): The TEC effect should be more pronounced for family firms than non-family firms.

Sample Selection and Descriptive Statistics

<u>Data</u>

Our initial sample contains all companies that appear in the Compustat North American Annual File during the sample period of 1995 to 2013. As Kim et al. (2011), we begin our sample period in 1995 to minimize potential impacts on the consistency of our tax avoidance measures from two regulatory changes in 1993 – FAS 109 that altered the accounting for income taxes and an increase from 34% to 35% of top corporate income tax rate. Advertising expenditure (item 45) is a key variable in our analysis, representing the firm's spending on all sorts of advertising media (radio, television, newspapers, periodicals, etc.) and promotional activities. After excluding observations that have missing values on the key advertising variable, our sample size drops substantially. We exclude financial and utility firms (SIC between 6000-6999 and between 4900-4999) [7] as well as firms incorporated outside the U.S. (ones with Foreign Incorporation Codes-FIC). To be included in the sample, firms must be at least one year old since the first-year data tend to contain more errors. Moreover, our analysis is based

[7] Advertising expense (item 45) is not available for banks or utility firms, and therefore, our final sample excludes these firms.

only on firms that report a positive amount of advertising expenditure since we cannot differentiate between ones that report a zero advertising expense and others that do not report any. We exclude firms with missing observations on the right-hand size of baseline regression.[8] All variables are winsorized at 1% and 99% to mitigate potential outliers. Our final sample consists of 14,871 firm-year observations.

We construct two variables to indicate the degree of external monitoring and that of corporate informational opacity. The first is based on institutional holdings from 13F institutional filings that begin in 1980. This dataset is formerly known as CDA/Spectrum 34 and includes institutional managers who have at least $100 million of assets under management. As Anderson et al. (2009), we construct an opacity index at the firm level using CRSP (Center for Research in Security Prices) and IBES (Institutional Brokers' Estimate System) datasets.

Measuring Tax Aggressiveness

We apply five different measures of tax aggressiveness to triangulate the results since each measure has its own limitations and may not capture perfectly the degree to which a firm is involved in tax aggressive activities (Hanlon and Hertzman, 2010). We discuss each measure briefly here with a detailed variable definition provided in Appendix A. Our first measure is the sheltering probability ($Shelter\_Prob_{i,t}$) introduced by Wilson (2009) to capture the likelihood of most egregious tax aggressive activities, which is computed as follows:

[8] We also use the unbalanced panel sample, and the inference from our main regression is unaltered.

$$Shelter\_Prob_{i,t} = -4.86 + 5.20 \times BTD_{i,t} + 4.08 \times DA_{i,t} - 0.41 \times LEV_{i,t} + 0.76 \times AT_{i,t}$$

$$+3.51 \times ROA_{i,t} + 1.72 * FI_{i,t} + 2.43 \times RD_{i,t}$$

Our second measure of tax aggressiveness is the cash effective tax rate ($CETR_{i,t}$) which is affected by tax deferral strategies of the firm:

$$CETR_{i,t} = Cash\ Taxes\ Paid_{i,t}(\#\ 317)/Pretax\ Income_{i,t}(\#170)$$

This measure captures a broader scale of tax avoidance, including both permanent and temporary differences. Since this measure focuses on the amounts of tax payments, it emphasizes managerial discretions at actual taxes paid to tax authorities. A lower cash effective tax rate, a smaller CETR, implies a higher level of tax aggressiveness.

The next two measures of tax aggressiveness are based on a book-tax difference (BTD) which captures the difference between income reported to investors and that to tax authorities. Wilson (2009) finds that firms with a higher probability of tax sheltering activities are likely to have a larger BTD, and Mills (1998) reports that large BTD firms are likely to be audited by the IRS and see a significant audit adjustment. Our first book-tax difference measure is $KIMBTD_{i,t}$ constructed by Kim et al. (2011).[9] A large BTD may reflect accrual manipulation or earnings management (Desai and Dharmapala, 2009). Many studies suggest that such manipulation is likely to occur on accruals that

[9] We have to exclude Manzon and Plesko's (2002) measure because it uses only U.S. numbers to compute book-tax differences and thus fails to capture the total tax aggressive of many multinational firms.

are under managerial discretion. Thus, our next measure of tax aggressiveness is $DDKIMBTD_{i,t}$, the residual of KIMBTD after controlling for earnings management.[10]

The last measure of tax aggressiveness is based on the discretionary permanent book-tax difference for firm i in year t ($DTAX_{i,t}$), following Frank et al. (2009). This measure, relying on permanent book-tax differences, is free of earnings management bias, is less spurious than other measures (e.g., the ETR) when firms manage pre-tax earnings upwards, and captures more in-depth tax shelter activities.

Table 1 displays the descriptive statistics of our initial sample. Due to data requirements in the estimation procedures, the sample sizes for these measures vary, for example, from 9,937 for $CETR_{i,t}$, to 14,256 for $KIMBTD_{i,t}$. Our sample statistics for aggressive tax avoidance measures are consistent with those in the literature. Panel A of Table 1 shows cross-sectional differences for the tax aggressive measures of our sample firms. For instance, between the 25th (Column P25) and 75th percentile (Column P75), the range is 0.156 to 0.376 for $CETR_{i,t}$, 0.013 to 0.476 for $KIMBTD_{i,t}$, and –0.020 to 0.060 for $DTAX_{i,t}$. On our advertising measures, the mean (median) of advertising expenditure, $Advertising_{i,t}$, is \$51.719 million (\$2.3 million), and the mean (median) of the ratio of advertising expenditure to gross profits, $ADVGP_{i,t}$, is 0.080 (0.035). Thus, firms' average advertising spending is \$51.719 million, about 8% of their gross profits. There are also significant cross-sectional differences on control variables such as ROA, age, leverage, size, and MTB, indicating a wide variety of characteristics of our sample firms. Panel B

[10] We use the total accrual, constructed as in Hribar and Collins (2002), to proxy for earnings management (see Appendix A for a detailed description).

of Table 1 displays the Pearson correlation matrix for our five tax aggressive measures. As expected, there are negative correlations between the cash effective tax rate and each of the other four tax aggressive measures, and positive correlations between any pairs of the other four.

To investigate whether tax aggressiveness diminishes with advertising, we first control for firm size by partitioning the overall sample into quintiles based on market capitalization, and then group each market value portfolio into five sub-quintiles based on the amount of advertising expenditure. Table 2 presents the results of this univariate test. Controlling for size, a larger amount of advertising spending is associated with a lower level of tax aggressiveness – a smaller $SHELTER_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ but a larger $CETR_{i,t}$. The differences in means between the largest and smallest advertising quintiles are both economically and statistically significant in all market capitalization quintiles.[11] The univariate test results are supportive of the PMC effect (H1): an increase in advertising reduces management's incentive for aggressive tax planning. Looking at each advertising quintile more closely, we see that on all five measures of tax aggressiveness, the effect of advertising tends to be smaller as firm size gets larger. In other words, the product market commitment value of advertising to lower tax aggressiveness tends to be stronger, the smaller the firm size. This finding is supportive of our second hypothesis (H2) that smaller firms a priori exhibit greater opacity and therefore the impact of advertising is greater for these firms. Overall, our

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[11] We observe a similar pattern by partitioning the sample based on the advertising expenditure to gross profit measure.

results in Table 2 are consistent with the argument that greater advertising in magnitude and in intensity (see footnote 11) is related to fewer tax aggressive activities, irrespective of firm size.

Empirical Model

To rigorously test our hypotheses, we employ the following regression model:

$$TaxAgg_{i,t} = \alpha_0 + \beta_1[Log(ADV)_{i,t}\ or\ ADVGP_{i,t}] + \beta_2 ROA_{i,t} + \beta_3 LEV_{i,t} + \beta_4 NOL_{i,t} + \beta_5 \Delta NOL_{i,t} + \beta_6 FI_{i,t} + \beta_7 PPE_{i,t} + \beta_8 INTANG_{i,t} + \beta_9 EQINC_{i,t} + \beta_{10}\log(AGE)_{i,t} + \beta_{11}\,(RD)_{i,t} + +\beta_{12} DIV_{i,t} + \ \beta_{13} Size_{i,t} + \beta_{14} MB_{i,t-1} + \beta_{15} TaxAgg_{i,t-1} + YearDummies + IndustryDummies + \varepsilon_{i,t} \quad (1)$$

The dependent variable, $\mathrm{TaxAgg}_{i,t}$, represents one of the five measures of tax aggressiveness. The key independent variable is one of the two measures of advertising: the log of advertising expenditure, $\mathrm{LOG(ADV)}_{i,t}$, or a measure of advertising intensity, $\mathrm{ADVGP}_{i,t}$, which equals to advertising expenditure divided by gross profits. The definitions of all other variables in Equation (1) are provided in Appendix A. Now, if a higher level of advertising spending or advertising intensity is to result in fewer tax aggressive activities, we expect coefficient β_1 to be negative on the shelter probability ($\mathrm{SHELTER}_{i,t}$), on the book-tax differences ($\mathrm{KIMBTD}_{i,t}$ and $\mathrm{DDKIMBTD}_{i,t}$), and on the discretionary permanent book-tax difference ($\mathrm{DTAX}_{i,t}$), but to be positive on the cash effective tax rate ($\mathrm{CETR}_{i,t}$).

Our advertising variables include both the actual amount of advertising expenditure and the scaled measure of advertising spending to gross profits. These two advertising measures capture different dimensions of corporate strategies on advertising. While the scaled advertising measure reflects how intensive the firm desires to reach the product market, the actual advertising spending indicates the depth of reach in the marketplace. For example, in 2012, General Motors Company (GM) spent about $5.37 billion on advertising, which is about 26.82% of its gross profits, while CenturyLink, Inc. (CTL) spent $189 million on advertising and this amount accounts for 1.75% of its gross profits. In term of the reach to consumers, there is no doubt that GM's advertising is much more significant than CTL's. Incidentally, GM's advertising intensity is also substantially higher than that of CTL.

We employ a number of variables in the regressions to control for firm characteristics. We control for profitability (ROA, NOI, and ΔNOI), leverage (LEV), foreign operation (FI), firm size (Size), firm growth opportunity (MTB), payout policy (DIV), as well as other firm-specific characteristics (PPE, INTANG, EQINC, RD, and Age). As Manzon and Plesko (2002) and Chen et al. (2010), we include lagged tax aggressive measures to control for their potential persistence over time.[12] Additionally, we include dummy variables to control for year fixed effects and the two-digit SIC industry code to control for industry fixed effects. Except for MTB and lagged tax

[12] We also carry out a sensitivity analysis by excluding the lag of book-tax differences from our baseline regressions. Our inferences on the two measures of advertising remain unchanged.

aggressive measures, all other control variables are measured contemporaneously with our main dependent variables.[13]

Empirical Findings

The Effect of Advertising on Tax aggressiveness

To test the validity of hypothesis 1 (H1), we run the baseline logistic and OLS regressions of Equation (1) with clustered standard errors at the firm level, and report the results in Table 3. The dependent variable for tax aggressiveness is $SHELTER_{i,t}$ for the logistic regressions, and is $CETR_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ for the OLS regressions. The main independent variable is either the log of advertising expenditure, $LOG(ADV)_{i,t}$, or the advertising intensity, $ADVGP_{i,t}$.[14] As seen in Table 3, the coefficient on either $LOG(ADV)_{i,t}$ or $ADVGP_{i,t}$ is as expected, negative and statistically significant when the tax aggressive variable is the sheltering probability or one of the three book-tax differences, and is positive and significant when it is the cash effective tax rate. The results support the PMC effect of advertising (H1) that a higher level of advertising spending (intensity) lowers firms' tax aggressiveness as it enhances the firms' overall visibility and commits them to greater product market reputation.

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[13] We use the lag of advertising expenditure as additional robustness check, and our results remain consistent.

[14] For additional robustness check, we create the high advertising dummy $HADVDUM_{i,t}$, which is equal to one if advertising expenditure is above the median level. The results are consistent with our baseline regressions.

The results in Table 3 are economically significant. For example, after controlling for other factors that might affect tax avoidance, the coefficient in Model 1 of Panel A (B) indicates that when a firm increases by 1% its advertising spending (advertising intensity $ADVGP_{i,t}$), its probability of engaging in tax sheltering activities is lowered by 0.80% (6.35%).[15] The difference in probability is economically meaningful particularly since the sample's mean sheltering probability is only 30.5%. The implied effects on cash effect tax rates are also economically significant. The coefficient in Model 2 of Panel A (B) indicates that a firm that spends 1% more on advertising (advertising intensity) sees an increased cash effective tax rate of 0.5% (7.8%). This implies that for an increase of 1% on $Advertising_{i,t}$ ($ADVGP_{i,t}$), the firm pays an additional tax of $0.70 million ($10.92 million) since our sample's mean pre-tax income is $140 million. Our results are broadly consistent with those in Chen et al. (2010) and Hoi et al. (2013), considering that there are more small firms in our sample than in theirs.

Corporate Opacity, Advertising and Tax Aggressiveness

We now address how firms' degrees of opacity affect the impact of advertising on tax aggressiveness. All else the same, we expect the impact of advertising to be stronger for firms that are less transparent at the outset. As Anderson et al. (2009), we construct an opacity index based on four components, using the CRSP and IBES datasets. The first component is trading volume measured by the natural logarithm of average daily trading volume during the fiscal year. Trading volume is viewed as a

[15] The decrease in sheltering probability is computed as the estimated marginal effect of $LOG(ADV)_{i,t}$ (or $ADVGP_{i,t}$) on tax sheltering probability – i.e., the expected decrease in sheltering probability as a function of variable $LOG(ADV)_{i,t}$ (or $ADVGP_{i,t}$), holding all other variables in Equation (1) at the sample mean.

proxy for informational uncertainty (Lo et al., 2004). The second component is bid-ask spread defined as the difference of ask and bid prices divided by the median of bid and ask prices. The bid-ask spread is considered to be a proxy for informational asymmetry among investors. Following Anderson et al. (2009), for each firm, we choose from CRSP only data from the third Wednesday of the month and then average the 12 monthly observations for the year. The third and fourth components of our opacity index are analyst coverage and analyst forecast errors, respectively. To arrive at an index value, we first rank each component into decile based on the magnitude of information content each component proxies for;[16] we then sum the rank values of all four components; finally, we divide this sum by 40, so that the index value is normalized to between 0 and 1, with 1 being most opaque and 0 most transparent.

Table 4 presents our findings in this part. For parsimony reasons, we do not tabulate the results on the control variables. The coefficients on advertising variables $LOG(ADV)_{i,t}$ and $ADVGP_{i,t}$ retain the correct signs and significance. The coefficients on the opacity index $OPACITY_{i,t}$ show that more opaque firms are generally more tax aggressive. However, the coefficients on interaction terms between advertising $LOG(ADV)_{i,t}$ (or $ADVGP_{i,t}$) and opacity $OPACITY_{i,t}$ are significant and positive for tax aggressive measure $CETR_{i,t}$, and significant and negative for the other tax aggressive measures $SHELTER_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$, all indicating that the negative effect of advertising on tax aggressiveness – the PMC effect – is greater for firms that are less transparent in the first place.

[16] A higher rank is associated with a higher level of opacity – a lower trading volume, a greater bid-ask spread, fewer analyst coverages, or higher analyst forecast errors.

The Effect of Public Scrutiny and External Monitoring

We have shown a negative effect of advertising on tax aggressiveness that is both statistically and economically significant, and particularly so for firms having more opaque environments at the outset. Our third hypothesis (H3) argues that for firms that face strong public scrutiny or external monitoring, it is also possible that advertising may serve as a commitment (to the investment community) of more efficient corporate tax planning which lowers the firms' tax liabilities – the Tax Efficiency Commitment (TEC). For such firms, it may be that the PMC effect is weaker or is even dominated by the TEC. To check this possibility, we identify two subsamples of firms for which public scrutiny or external monitoring are likely to be considerably stronger. Our first subsample consists of firms listed in the S&P 1500 index. The index firms, which cover about 90% of market capitalization of all publicly listed stocks in the U.S., are exposed to greater public pressure and scrutiny because they are generally large, well-established firms. Our second subsample of firms is comprised of those having a high level of institutional ownership; larger institutional ownerships impose greater discipline on firms' managements since institutional investors are more likely to engage in shareholder activism and carry out external monitoring. We measure institutional ownership as the average of total institutional ownership stakes in the firm divided by the number of common shares outstanding over a given firm-year, and we interact this institutional ownership variable (INST. $OWN_{i,t}$) with our advertising variable ($LOG(ADV)_{i,t}$ or $ADVGP_{i,t}$).

Table 5 presents the results of our subsample analysis on firms facing the greater pressure of public scrutiny or external monitoring. Panel A shows the regression results from the subsample of S&P 1500 firms; we see positive interaction terms of $LOG(ADV)_{i,t}$ or $ADVGP_{i,t}$ with $SHELTER_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ (and negative with $CETR_{i,t}$). The results suggest that higher advertising spending or intensity by the S&P 1500 firms (i.e., the large firms which are subject to greater public scrutiny) are actually associated with greater tax aggressiveness. Similarly, in Panel B of Table 5, firms with higher institutional ownerships (i.e., those facing stronger external monitoring) also exhibit a positive relationship between advertising expenditure or intensity and tax aggressiveness. The coefficients of $INST.OWN_{i,t}$ are significant and negative on $SHELTER_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ (and positive on $CETR_{i,t}$). Overall, our results support hypothesis 3 (H3) that for firms facing strong public scrutiny or external monitoring, the value of advertising that commits the firms to tax efficiency can become more significant than that of its product market commitment. That is, for these firms, the TMC (positive) effect of advertising on tax aggressiveness now dominates the PMC (negative) effect. It is possible that strong external scrutiny or monitoring deters managerial agency considerations, ensuring that managers sufficiently value their own as well as their firms' reputation. An important implication of this observation is that tax planning by firms that already face sufficiently great public pressure is likely to benefit the firms' shareholders by making the firms more tax efficient. In other words, high advertising expenditures by such firms actually showcase shareholder friendliness of the firms' aggressive tax activities.

Can Advertising Mitigate Agency Issues of Family Firms?

We now turn to the incremental impact of advertising on family firms' tax planning. Chen et al. (2010) find that family firms (those with a high level of family ownership) are generally less tax aggressive than non-family firms. They argue that because family firms tend to suffer from valuation discounts by outside investors, the firms choose to be less tax aggressive to avoid even deeper discounts. Now, if advertising helps to improve corporate transparency and thereby to reduce agency problems between family firms' insiders and outside investors, it seems that advertising may lessen the negative effect of family ownership on firm tax aggressiveness.

Table 6 shows the results of our analysis on family versus non-family firms. Our family firm sample is considerably smaller than the overall sample because we have access only to the family ownership data of S&P 500 companies from 1996 to 2006. The smaller sample size reduces our statistical inferences, but its effect actually biases against our finding a relationship. As in Chen et al. (2010), family firms in our sample are generally less tax aggressive. However, we find that advertising reduces family firms' aversion to tax aggressiveness. In particular, the coefficients of interaction terms between Family $Firm_{i,t}$ and $LOG(ADV)_{i,t}$ or $ADVGP_{i,t}$ are positive and significant on $SHELTER_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ (and negative and significant on $CETR_{i,t}$). The results support hypothesis 4 (H4) that the TEC (positive) effect of advertising is more pronounced for family firms because advertising helps reduce outside investors' agency concerns and thereby enhance their confidence on the firms' tax aggressive policies.

Endogeneity Concerns

A firm's advertising expenditure, of course, is at the discretion of management and is not exogenous. It is possible that managers who are prone to taking tax aggressive actions may choose to limit their firms' public exposure by spending less on advertising. In other words, our study potentially has an endogeneity problem. We employ two standard methods to address this problem. The first is the instrument variable (IV) approach. The IV we use is the natural logarithm of the number of (significant) customers that each of our sample firms has. We obtain the customer dataset from the Compustat Customer Segment database from 1995 to 2013. Regulation SFAS No. 131 requires that a firm report information about a customer which represents more than 10% of the firm's sales. We exclude firms that have contracts with U.S. government since Kim and Zhang (2016) document a strong relationship between the number of governmental customers and the firm's tax aggressiveness.[17] In our first stage regression, the dependent variable is as before, $\mathrm{LOG(ADV)}_{i,t}$ or $\mathrm{ADVGP}_{i,t}$, and the independent variables include Log(Number of $\mathrm{Customers}_{i,t}$), $\mathrm{ROA}_{i,t}$, $\mathrm{CASH}_{i,t}$, $\mathrm{LEMP}_{i,t}$, $\mathrm{LEV}_{i,t}$, $\mathrm{SIZE}_{i,t}$, $\mathrm{MTB}_{i,t-1}$, $\mathrm{RD}_{i,t}$, $\mathrm{PPE}_{i,t}$, $\mathrm{INTANG}_{i,t}$, $\mathrm{DIV}_{i,t}$, $\mathrm{LAGE}_{i,t}$, and year as well as industry dummies. As shown in Panel A of Table 7, the results are consistent with those of our earlier baseline regressions.

There are two reasons why the number of customers would be a good IV for our study. One, a firm's advertising expenditure tends to be highly correlated with the

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[17] Specifically, we exclude firms that fall into the categories of GOVDOM, GOVFRN, GOVLOC, and GOVSTATE in the Compustat Customer Segment dataset.

number of its customers since more advertising spending would likely be needed to reach more customers. Two, we have little reason to expect that the customer number would have a relationship with the firm's tax aggressiveness.[18] In addition, we perform an F-test by excluding the instrument from the first-stage regression. For all specifications, F statistics are much higher than 10, the critical value for the weak instrument (Staiger and Stock, 1997). For example, when we use $\mathrm{LOG(ADV)}_{i,t}$ as the dependent variable in the first stage regression, the F-value is 309.15 on $SHELTER_{i,t}$, 259.26 on $CETR_{i,t}$, 151.26 on $KIMBTD_{i,t}$, 151.42 on $DDKIMBTD_{i,t}$, and 282.61 on $DTAX_{i,t}$. We also perform a Stock and Yogo (2005) test for all linear models and the Cragg-Donald F-statistics are much higher than the critical value of 19.93.[19] These results suggest that our instrument is not weak, and therefore, our instrumental variable estimates are unlikely to be biased toward OLS estimates.

Our second approach to address the endogeneity issue is the propensity score matching method (PSM). A key advantage of applying PSM in our study is that we can isolate the effect of advertising on tax aggressiveness while controlling for firm characteristics with one single propensity score. We compute the propensity score using a logit model on high advertising dummy $HADVDUM_{i,t}$ and the independent variables of $ROA_{i,t}$, $CASH_{i,t}$, $LEMP_{i,t}$, $LEV_{i,t}$, $SIZE_{i,t}$, $MTB_{i,t-1,}$ $RD_{i,t}$, $PPE_{i,t}$, $INTANG_{i,t}$, $DIV_{i,t}$, $LAGE_{i,t}$, and year as well as industry dummies. We first match without replacement a firm-year observation with $HADVDUM_{i,t}$=1, and a treatment observation to another firm-year

[18] We also empirically validate the conditions of instrument exogeneity and relevance.

[19] When we use $\mathrm{LOG(ADV)}_{i,t}$ as the dependent variable in the first stage regression, the Cragg-Donald F-statistics on $CETR_{i,t}$, $KIMBTD_{i,t}$, $DDKIMBTD_{i,t}$, and $DTAX_{i,t}$ are 37.68, 48.70, 48.67, and 21.63, respectively.

observation with $HADVDUM_{i,t}$=0. We then pool the treatment and control observations for each of our five tax aggressive measures. As seen in Panel B of Table 7, the estimates on $HADVDUM_{i,t}$ are all significant and have the signs that are consistent with the results of our earlier baseline regressions.

Additional Robustness Tests

We carry out several additional robustness tests on the baseline analysis. First, we perform the firm-level regression using the averages of our empirical measures over the whole sample period. The results are shown in Panel A of Table 8. Second, we use the Fama-MacBeth (1973) method to address the concern of serial dependence of regression errors.[20] Running this regression, we exclude the year dummies from the baseline model and estimate the model by each year, and test the statistical significance of average coefficients using a t-test.[21] The Fama-MacBeth regression results are presented in Panel B of Table 8. Third, we run Heckman's two-stage model and insert the Inverse-Mills ratio as an additional control in the baseline model to address the sample self-selection bias. Lastly, we rerun the baseline regression controlling for firms' fixed effect. Overall, our basic results remain unchanged, irrespective of model specifications.

[20] Following Fama and French (2001), we estimate the logit regressions each year and report the average coefficients and pseudo R-square. T-value is estimated based on the time-series standard deviations of the regression coefficients.
[21] We follow the Newey-West adjustment for standard errors using three lags.

Conclusions

We document strong evidence that firm advertising reduces its tax aggressiveness. The results support our contention that advertising serves as a commitment to product market reputation – what we refer to as the Product Market Commitment (PMC). This negative effect of advertising on tax aggressiveness is also stronger for firms that have a priori a higher degree of corporate opacity, a lower level of public scrutiny, or a weaker extent of external monitoring, suggesting that advertising helps to improve corporate transparency and thereby to reduce concerns for managerial agency. However, for subsamples of firms that face greater public exposure and external monitoring – S&P 1500 firms as well as firms with large institutional ownership stakes – we find that advertising can actually lead to more tax planning activities that reduce the firms' tax liabilities. The latter finding is consistent with our alternative argument that advertising by these firms commits them to more efficient tax planning that benefits the firms' shareholders – what we refer to as the Tax Efficiency Commitment (TEC). Addressing the question of tax aggressiveness of family firms, we find that advertising lessens family firms' concerns for valuation discounts, and as a result, family firms with high advertising expenditures are no longer less tax aggressive than non-family firms. Our finding on family firms' tax aggressiveness augments that in Chen et al. (2010) who find that family firms are generally less tax aggressive because of their desire to avoid greater valuation discounts.

The basic contribution of our study is to show that by increasing firms' visibility and exposure to product market consumers as well as financial market investors, advertising affects the firms' tax policy in different ways. While investors would appreciate more tax savings, they are aware of the potentially negative impact of tax aggressive activities on consumers' views of the firms and hence the firms' competitive positions in the product market. This tradeoff determines the effect of advertising, positive or negative, on tax aggressiveness.

Essay 2- Retail Investors' Attention and Insider Trading

Introduction

Insider trades have long been documented to earn significant abnormal returns (e.g., Seyhun, 1986). Insiders possess superior information about their firm and therefore are able to exploit their informational advantage for profitable trades. More recently, Alldredge and Cicero (2015) show that insiders may also profitably trade on publicly available information that has implications for their firm value. Alldredge and Cicero find that supplier firm insiders earn positive abnormal returns on sales of their firm's stock when newly public information indicates bad news for major customers of the firm. Alldredge and Cicero attribute the abnormal returns to supplier firm insiders' better and faster appreciation of interconnectness between the supplier and its customers. We build on the idea that certain public information may be relevant to insiders' trades by examining whether insider trading may be linked to retail investors' interest in – or attention to – the stock. Unlike in Alldredge and Cicero (2015), the information pertaining to retail investors' attention may or may not have any bearing on the fundamental value of the firm.

We conjecture a link between investor attention and insider trading because varying levels of investor attention to a particular stock has been found to affect its price. Using a stock's Google Search Volume Index (SVI) to proxy for retail investors' attention to it, Da, Engelberg, and Gao (2011) find that a higher SVI is associated with a transient rise in the stock's price. This finding is consistent with Barber and Odean's (2008) argument that investors' attention is a scarce resource and retail investors, in particular, pay attention only to stocks that they are interested in trading. Since retail investors usually sell only stocks they already own, an increase in their attention to a particular stock indicates that the stock will likely experience a greater buying pressure, resulting in a (temporary) spike in its price. Now, if this buying pressure causes the stock price to deviate from its fundamental value, the firm's insiders may be in a unique position to engage in trades that take advantage of this mispricing. For example, a spike in stock price that is unsupported by the firm's fundamentals may provide insiders with an opportunity to unload their shares at an attractive price.

We test our conjecture by investigating whether a change of Google SVI on a stock affects the direction (buy or sell), volume, and profitability of insider trading on the stock. As Da, Engelberg, and Gao (2011), we use the SVI to capture retail investors' attention to the stock because searches by individual investors account for a vast majority of stock search volume at Google. To measure changes in investors' attention, we first compute the stock's monthly SVI as the arithmatic mean of its weekly SVI in the month; we then calculate its monthly abnormal SVI (ABSVI) – its monthly SVI scaled by the previous month's SVI. Thus, an increase (a decrease) in a stock's SVI means that its ABSVI in the month will be greater (lower) than one. Following Cohen, Malloy, and Pomorski (2012), we are interested only in non-routine, i.e., opportunistic, insider trades. Obviously, insider trading that is motivated by an actual or perceived mispricing, for example, that which arises from greater retail investors' attention, is a textbook definition of an opportunitistic behavior.

Our results support a link between the ABSVI and insider trading activities. We find that a higher ABSVI in a month predicts a lower abnormal return on the stock in the subsequent month, suggesting for example, that insiders would benefit by selling (or refraining from buying) shares when the ABSVI is high – when the volume of Google search is high on the stock. Indeed, a higher (lower) ABSVI is associated with more (fewer) insider sales and fewer (more) insider purchases; that is, the pattern of insider trades is contrarian to retail investors' attention level. The contrarian insider trades also generate significant abnormal returns. While the observation that insider trades tend to be contrarian is broadly in line with the findings in other studies (e.g., Lakonishok and Lee, 2001; Jeng, Metrick, and Zeckhauser, 2003; Cohen, Malloy, and Pomorski, 2012), our focus on how retail investors' attention affects insider trading is new and interesting. Further, potential profits of such insider trades are substantial. We show that a long-short portfolio mimicking attention-based insider trading would generate an abnormal return of about 119 basis points per month (14.28 % per year), excluding transaction costs.

An interesting question concerns what insiders are likely to engage in SVI-related trades. We find that the insider traders tend to be non-independent directors who have long tenures but no senior positions (CEO, CFO, COO, and Chair of the board) in their firms. The firms tend to exhibit weaker governance, lower reputation, and poorer social responsibility. They also operate in more states, have more concentrated product sales, and are healthier financially. All these are largely consistent with the characteristics of opportunistic insider traders and their firms documented in Cohen, Malloy, and Pomorski (2012).

Research has found that lottery-type stocks, ones that have a low price, high idiosyncratic volatility and skewness, tend to attract less sophisticated retail investors (Kumar, 2009). If a lottery-type stock's SVI reflects the level of interest of less sophisticated investors in the stock, the firm's insiders may be able to benefit more from SVI-related trades. Consistent with this prediction, we find that our basic results are more pronounced for lottery-type stocks. In particular, this type of stock is more likely to be sold (bought) by insiders when the stock's SVI – retail investors' attention to it – is higher (lower).

Research also documents that local investors earn higher returns on local stocks. An explanation is that physical proximity of local investors to a local firm facilitates their acquisition of "soft information", thereby providing them with an informational advantage over non-local investors (e.g., Seasholes and Zhu, 2010; Engelberg and Parsons, 2011; Shive, 2012; Berry and Gamble, 2013). If this informational advantage exists, we expect that an increase in local investors' attention to a local stock would not create as great an opportunity for insider trading as would an increase in the attention of non-local investors. In other words, opportunity for profitable insider trading is more limited based on local investors' attention. We use a stock's local Google SVI to proxy for local investors' attention, and our results are supportive of this expectation.

Other measures have been used to proxy for investor attention, including news and media headlines or reports (Barber and Odean, 2008; Yuan, 2008; Fang and Peress, 2009), extreme returns or trading volumes (Gervais, Kaniel, and Mingelgrin, 2001; Barber and Odean, 2008; Hou, Xiong, and Peng, 2009), and advertising expenditure (Grullon, Kanatas, and Weston, 2004; Chemmanur and Yan, 2009; Lou, 2014). Da, Engelberg, and Gao (2011) point out that Google SVI is a better measure of investor attention because it is a direct, reliable, and timely reflection of genuine investor interest in the stock. Clearly, individuals who take time and effort to Google-search a stock are self-revealing of their interest in the stock (Ding and Hou, 2015). The other measures either do not capture this interest in a timely manner, or they fail to explain a large variation of SVI. For example, news coverage is a popular proxy for investor attention but it fails to explain a large volume of Google searches. The SVI measure also possesses two additional advantages: it is a continuous measure and it makes no assumption that investors are actually aware of the news.

It is possible that a stock's abnormal SVI (ABSVI) may simply reflect investors' reactions to the flow of public information such as news, reports or other items that impact the stock. An implication is that if the effect of the information flow is accounted for, the ABSVI would have little relevance to insider trading. We address this issue with two additional analyses. First, we control for factors that have been suggested to have an effect on the ABSVI, such as earnings surprise, advertising expenditure to sales, as well as macro variables on GDP data and FOMC interest rate decisions. After controlling for these factors, the unexplained component of ABSVI remains significant to opportunistic insider trades. To the extent that the unexplained part of ABSVI reflects changes in retail investors' sentiment towards the stock, which go beyond what arise from the information flow, our results suggest that opportunistic insider trading may be taking advantage of retail sentiment which is unsubstantiated by the stock's fundamentals. Second, we perform a subsample analysis by classifying a firm-month as either an earnings news month if the firm releases its earnings in the month, or a non-earnings news month if it does not. While our results are more pronounced for the subsample of earnings news month – indicating the importance of the news – they remain significant with the same signs for the subsample of non-earnings news month.

Another concern is that the SVI may be influenced by insider trading activities. For example, an increase in insider trading activities may cause investors to pay more attention to the stock by increasing their Google searches. To address this issue, we perform two checks, using regulatory changes as exogeneous shocks. Our first check utilizes a political regime change. We decompose our sample period of 2004-2014 into two subsample periods of 2004-2008 and 2009-2014, with the former being the years of the more laissez faire Republican Bush Administration and the later being those of the more activist Democratic Obama Administraion. The presumption is that the Obama Administration would be more active in taking enforcement actions against questionable insider trading and thus would have a stronger deterrence on opportunistic insider sales. However, our results remain unchanges during the two subsample periods. In our second check, we use as exogneous shocks the number of news releases of SEC investigation and litigation against illegal insider trading. More SEC activities would presumably have a greater deterence effect on insider sales in the subsequent month. Indeed, Cohen, Malloy, and Pomorski's (2012) document an overall reduction in opportunistic insider sales following an increase in SEC investigation and litigation.[22] Now, if insider sales were to affect the SVI, we would expect a lower SVI, following the month of more active SEC. This is not the case; there are no discernible changes in the SVI surrounding SEC actions.

Interestingly, when we classify opportunistic insider sales as being either SVI-related or non-SVI-related. We find that following the month of increased SEC enforcement activities, while insiders' non-SVI-related sales decline, their SVI-related sales actually rise. The latter is in contrast to Cohen, Malloy, and Pomorski's (2012)

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[22] The SEC defines illegal insider trading as insiders buy or sell a security, in breach a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security. For examples, on September 14, 2014, the SEC charged two former Wells Fargo employees for trading on an analyst rating change on their firm's stock before the report was publicly available, and on November 21, 2014, the SEC charged a former CEO of GenTek, who had tipped a close friend of non-public information concerning his firm's forthcoming merger.

finding of an overall decline in opportunitistic insider sales. It is possible that insiders view the SVI-related sales as relying more on publicly available information and therefore being less likely to be subject to regulatory sanctions. Supporting this point of view, we find that SVI-related insider sales indeed have a lower risk of being subject to SEC investigation and litigation.

The rest of the paper is organized as follows. Chapter two reviews the literature on investor attention and on insider trading and develops testable hypotheses. Chapter three describes the sample selection procedures and methodology and provides summary statistics. Chapter four presents the empirical findings. Chapter five concludes.

Literature Review and Hypothesis Development

Investor Attention

Merton (1987) introduces the concept of investors' attention to the field of finance, arguing that their attention is relevent to stock market activities because stock price is affected by the firm's general visibiliy in the marketplace such as its publicity, popularity, and social image.[23] Hirshleifer (2001) argues that investors have limited attention and thus focus only on a subset of available information, leading to the

[23] Merton's argument builds on a large body of psychological research suggesting that human attention is a scarce resource. The scarcity of attention refers to both selection and intensity since one always has alternatives to engage in (Kahneman,1973). Pashler & Johnston (1998) argue that human beings are constrained by their cognitive limits, so that mutiple tasking often does not work out successfully. Fischhoff, Slovic, and Lichtenstein (1977) argue that people often fail to filter in relevent information when they allocate their attention and hence underweigh the probablities of contingencies that are not explicitly available at the time of decision making.

potential misvaluation of assets. Limited attention or increased market-wide uncertainty also causes investors to pay more attention to the information that has broader sector or market implications and less on that of firm-specific nature (Peng and Xiong, 2006; Peng, Xiong, and Bollerslev, 2007). Barber and Odean (2008) find that individual investors increase their informational searches on a stock that catches their attention and are predisposed to buy the stock, exerting an upward pressure on its price.

What attracts individual investors' attention to a particular stock? Keloharju, Knupfer, and Linnainmaa (2012) suggest that individuals' familarity with a firm's products spills over to their interest in the stock. Fang and Peress (2009) argue that news or media coverage is another channel that alerts individuals to a stock, and this channel is especially important for stocks of small firms or with large individual ownerships, low analyst coverage, and high idiosyncratic risk. Indeed, Engelberg and Parsons (2011) show that local press coverage has a strong influence on local investors' trading interest in the stock. A feedback loop may also emerge when media coverage, investor sentiment, and stock prices. For example, media pessimism may exert downward pressure on the price of stock, resulting in poor stock returns, and the poor returns may give rise to additional media pessimism. With this in mind, firms may choose to manage messages or inflence media coverage. Ahern and Sosyura (2014) report that during important corporate events such as mergers and acquisitions, managers actively use media coverage to affect their stock prices. Gurun and Butler

(2012) find that advertising spending steers local media to put more “postive slant” in its reporting of local firms.

Although media coverage has been used to proxy for investor attention, the availability of Google Search Volume Index (SVI) on individual stocks offers a direct measure of investor interest in particular stocks. Da, Engelberg, and Gao (2011) argue that a stock’s SVI captures primarily small (retail) investors’ interest in – or attention to – the stock because small investors are numerous and rely on public domain searches to obtain information. In contrast, institutional, large or sophisticated investors often have access to in-house or proprietary sources of information. Consistent with this argument, Da, Engelberg, and Gao (2011) find that a higher SVI on a stock is associated with more contemporary retail purchases of the stock, resulting in a temporary spike in the stock price. Relatedly, Joseph and Zhang (2011) suggest that the SVI reflects retail investors’ sentiment on the stock; they find that the SVI predicts stock returns and trading volume, especially for more volatile or difficult-to-arbitrage stocks. In Vozlyublennaia (2014), the SVI is seen to reflect investors’ demand for information.

Since retail investors do not usually possess superior information when they trade, more trades as a result of their greater attention suggests an increase in “noise trading” and hence liquidity on the stock. Consistent with this view, Ding and Hou (2015) document a negative relationship between a stock’s SVI and its bid-ask spreads; that is, a larger volunme of Google searches on a stock improves its liquidity. Now, it is well known that noise trading provides camouflage for informed trades, enabling informed traders (e.g., insiders) to profit from trading on their private information (e.g., Kyle, 1985; Kyle and Wang, 1997).[24] Moreover, noise trading arising from retail investors' changes of sentiment can affect stock price by making rational arbitrage riskier (Shleifer and Summers, 1990), and noise trading in general can have a greater impact on stock price than implied by its size because uninformed but rational investors may take noise as containing real information (Mendel and Shleifer, 2012).[25]

Insider Trading

Empirical studies on insider trading in the U.S. has long established that corporate insiders have better information about their firm and earn significant abnormal returns on their trades of their own firm's stock (e.g., Seyhun, 1986). Further research documents asymmetric profits and informativeness between insider buying and selling of shares. Lakonishok and Lee (2001) find that insider buying is more informative than selling, and Jeng, Metrick, and Zeckhauser (2003) show that insiders earn significant abnormal returns only on their purchases of shares. An explanation for the apparent lack of information content on insiders' sales of shares is that insiders may have other important reasons to sell shares – for example, to reduce a portfolio

[24] In an equilibrium model, Kyle (1985) shows that insider trading is profitable only at the expenses of noise traders, and the higher the level of noise trading, the greater are the insider profits. To the extent that a rise (fall) in the Google SVI predicts an increased (a decreased) level of noise trading, our empirical findings are consistent with the implication of the Kyle model. Informed traders who profit from noise traders are sometimes referred to as "smart money." For example, Individual Investor (in its February 1998 issue, pp. 54) summarizes the smart money as "company executives and directors" who "know their business more intimately than any Wall Street analyst even would" and "know when a new product is flying out the door, when inventories are pilling up, whether profit magins are expanding or wheter production costs are raising."

[25] In this model, unlike insiders who possess valuable information or noise traders who are vulnerable to sentiment shocks, rational outsiders are only able to learn information from the stock price they observe.

concentration of their own firm's shares. More recently, Cohen, Malloy, and Pomorski (2012) classify insider trades into "routine" and "non-routine" types; they show that only non-routine (or opportunistic) trades are informative and generate abnormal returns. Additionally, the opportunistic traders tend to be non-independent directors who have long tenures but no senior executive responsibilities in their firms, and the firms also tend to have weaker governance. Hillier, Korczak, and Korczak (2015) examine how insiders' attributes affect the performance of their trades; they show that personal traits such as age, gender, and education are important to the performance.

Our paper is closely related to two recent papers. As Cohen, Malloy, and Pomorski (2012), we also classify all insider trades as being either routine or opportunistic (non-routine). Clearly, insider trades that are based on Google SVI must be opportunistic in nature. Because the SVI information on individual stocks are publicly available, our study relates to Alldredge & Cicero (2015) in that this type of insider trading is connected more to publicly available information. In Alldredge and Cicero (2015), supply firm insiders profit by selling their own firm's shares when newly public information is negative on the firm's major customers. While we similarly examine the link between publicly available information and insiders' trading ideas, the kind of information in our study – Google SVI – does not have a clear implication for firm value. In this regard, our paper relates also to the insider trading literature that emphasizes that it is the liquidity or noise traders who provide the basis for insiders' trading profits.

Other research suggests that insiders time their trades to certain corporate activities. Lo and Cheng (2006) find that managerial insiders time the release of their firm's bad news before purchases of shares. Bonaime & Ryngaert (2013) document more frequent insider trades in quarters when their firm is buying back shares. Moreover, insiders who buy shares when their firm is repurchasing earn higher abnormal returns on the purchases while insiders who sell when their firm is buying back shares are likely from a firm that offers a large quantity of executive stock options, has low stock liquidity and a low equity book-to-market ratio. There is also evidence suggesting that managerial insiders take strategic actions to generate profitable trading opportunities. Lou (2014) finds that managers increase their firm's advertising expenditure before the firm's equity issues and before their sales of shares. Ahern and Sosyura (2014) find that managers manipulate media coverage to influence stock price during important corporate events such as mergers and acquisitions. We too examine how insiders may time their trades to increase trading profits. We differ in that argue that insiders' opportunistic trades can be based on shifting interests of retail investors, as proxied by the stock's SVI. Such trades may be less likely to be subject to regulatory enforcement actions against illegal insider trading.

Hypothesis Development

Researchers have identified a number of pitfalls of retail investors that more sophisticated investors may be able to exploit. Retail investors are informationally disadvantaged (Kyle, 1985). They may be less than fully rational in their investment decisions. For example, retail investors may exhibit overconfident (Fischhoff, Slovic, and Lichtenstein, 1977); they tend to trade aggressively and take excessive risks (Hirshleifer and Teoh, 2003); they are overly speculative and earn negative alphas (Han and Kumar, 2013); their trades are significantly influenced by sentiments (Shleifer and Summers, 1990). Furthermore, trading behaviors of retail investors may result in misleading signals to rational but insufficiently informed investors, affecting the latter's ability to arbitrage (Mendel and Shleifer, 2011). All these suggest that corporate insiders, with their informational advantage, may be in a unique position to exploit the pitfalls of retail investors. Indeed, Lo and Cheng (2006) find that managerial insiders manipulate the content or timing of financial disclosure to take advantage of retail investors. Such manipulations, however, run the risk of investor lawsuit and regulatory enforcement. With this in mind, insiders may prefer to engage in trades that profit from the behavior biases of retail investors but that do not involve a manipulation of firm-specific information. In this context, an increase in the buying (selling) interest of retail investors that is driven by their changing sentiments, and not by the fundamental value of the stock, may present insiders with good selling (buying) opportunities.

As Da, Engelberg, and Gao (2011), we use Google SVI to capture retail investors' level of attention to, or interest in, a particular stock. Since retail investors are net buyers of stock that catches their attention (Barber and Odean, 2008; Joseph, Wintoki, and Zhang, 2011), their aggregate buying could exert pressure on the stock's price, causing it to deviate from its intrisic value. In particular, if an increase in a stock's SVI indicates a rising interest of retail investors in the stock, it could cause a (temporary) rise in the stock's price and thereby provide opportunities for the firm's insiders to trade on this mispricing. Thus, our first hypothesis contends that an increase in the level of retail investors' attention to a stock – a higher ABSVI – is associated with more frequent and more profitable insider trades.

Hypothesis 1 (H1): A higher level of retail investors' attention (a higher Abnormal Google SVI, ABSVI) leads to a larger volume and greater profit of insider trading.

It is also possible that the greater attention of investors may stimulate the flow and dissemination of firm-specific information, making stock price more informative and reducing opportunities for profitable insider trading. If this is the case, a higher ABSVI – an increase in investor attention – would be associated with fewer and less profitable insider trades. Related to this point of view, several studies suggest that insufficient attention of investors can be detrimental to their welfare. For example, Daniel and Hirshleifer (2002) argue that inattentive investors provide more opportunities for the firm to exploit them by issuing overvalued equity shares, by managing earnings upward or guiding analyst forecasts, and by lobbying to alter accounting regulations. Hirshleifer and Teoh (2003) argue that investors' limited attention could be a source of mispricing because it can cause them to allocate insufficient time and effort to understand the salient content of firm disclosures. Vozlyublennaia (2014) shows that a higher level of investor attention is associated with a lower predictability of stock returns. Based on these observations, we propose a competing hypothesis that an increase in retail investors' attention to a stock – a higher ABSVI – may diminish opportunities for profitable insider trading.

Hypothesis 2 (H2): A higher level of retail investors' attention (a higher Abnormal Google SVI, ABSVI) leads to a smaller volume and lower profit of insider trading.

Data and Methodology

<u>Data</u>

The data for our analysis are obtained from several sources. Insider trading data is from Table 1 of the Thomson Reuters Insider Database, which includes all equity-related transactions filed by insiders to the U.S. Securities and Exchange Commission (SEC) via Forms 3, 4, and 5.[26] To ensure accuracy of insider trading data, we retain only transactions that are verified by Thomson Reuters based on a cleanse code of R, H, L, C, or Y. We exclude observations with transaction prices that are either more than three times or less than one third of the closing price on the transaction day since they are very likely to have resulted from data errors.

To focus on opportunistic (non-routin) insider trades, we exclude trades that are deemed routine. As in Cohen, Malloy, and Pomorski (2012), a routine trade is one executed by an insider who made a similar trade in the same month of the year for the last three years. Cohen, Malloy, and Pomorski find no abnormal returns on routine

[26] Form 3 includes all insiders who register equity securities for the first time with the SEC. Form 4 documents any changes of ownership upon a transaction that must be reported within two business days. Form 5 reports any missing transactions on Form 4 from those insiders who are eligible for deferred reporting.

trades. We also drop trades that are linked to insiders' stock options transactions. With these exclusions, our sample consists of only opportunistic open-market buying or selling by insiders. We aggregate insider trading data at a monthly firm level. Seyhun (1998) argues that aggregate insider trading predicts stock movement and may be used to time the market**.** We define a sale (purchase) month as a calendar month in which at least one insider trades his/her firm's shares, resulting in a net decrease (increase) in his/her equity stake. If we observe a net sale by one insider and a net purchase by another at the same firm-month, this observation is excluded because of its ambiguity concerning the direction of insider trades.

As Da, Engelberg, and Gao (2011), we use Google's Search Volume Index (SVI) to proxy for retail investors' attention to a particular stock since most Google stock searches are carried out by individual investors having an interest in the stock.[27] The SVI captures the level of investor attention to the stock in a more direct and timely fashion than measures such as extreme returns or news items.[28] We collect SVI information on individual stocks between years 2004 and 2014 by manually inputting a stock's ticker symbol into the Google Trend and downloading its SVI data into a CSV file. After compiling the data for all tickers, they are separated into two groups based on how frequent of their SVI data are available. An "attention" sample consists of all stocks of tickers that have a weekly SVI, indicating frequent searches on their tickers. A "non-

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[27] The SVI is a relative measure that is constructed by Google Trends as the search interest relative to the highest point on the chart.

[28] Da, Engelberg, and Gao (2011) show a postive but weak correlation between Google SVI and other attention measures such as news coverage. They argue that this is because Google SVI is a continuous measure and news coverage does not guarantee investors' attention unless they are actually aware of the news.

attention" sample, on the other hand, contains stocks of tickers that do not have a weekly SVI; that is, these tickers are searched so infrequently that they have either no SVI or only a monthly SVI.[29] As Da, Engelberg, and Gao (2011), we exclude ambigious tickers such as A, AUTO, ALL, B, BABY, BED, DNA, GPS, GAS, and GOLF since they may be associated with things that are unrelated to stock.[30] We collect a stock's SVI at two different points in time to ensure that our sample is fairly representative of investor attention over time.

Stock market return data and delisting information are obtained from the Center for Research in Security Prices (CRSP), and firm characteristic data (balance sheet and income statement items) from the Compustat North America. Our sample contains only common stocks (CRSP share codes 10 and 11) and excludes illiquid stocks (those with a price of less than $5 or a market capitalization of less than $100 million). All variables are winsorized at 1% and 99% to minimize outlier effects. Combining the SVI and insider trading data with the information on stock returns and firm characteristics results in a total of 92,834 firm-month observations from January 2004 through November 2014.[31] The attention sample has 52,477 net sale months (3,096 unique firms) and 16,997 net purchase months (2,667 unique firms) while the non-attention sample

[29] For Robustness checks, our inferences do not vary if monthly SVI firms are excluded from the non-attention sample and included in attention sample although significance levels become weaker because we include low attention firms.
[30] We also run the same regressions without excluding those ambiguous tickers, our results remain unchanged.
[31] Our sample ends on November 2014 because monthly CRSP return data are available only till December 2014.

has 15,739 net sale months (1,224 unique firms) and 7,621 net purchase months (1,063 unqiue firms).

A stock's monthly SVI is the arithmatic mean of its weekly SVI in the month,[32] and the stock's abnormal monthly SVI (ABSVI) is its SVI in the month scaled by that in the previous month. Figure 1 illustrates Apple stock's SVI (ticker: AAPL) between January 2004 and December 2004, where Panel A displays its weekly SVI and Panel B shows its monthly SVI derived from the weekly SVI. Comparing Panels A and B, we see that the monthly SVI preserves the shifts of investor attention, especially during the months of significant increase or decrease. Checking further Apple insiders' trading patterns following each monthly SVI and using a + (-) sign to denote a net sale (purchase) month, we see in Panel B that insiders appeared to time their trades with peaks and troughes of investor attention (monthly SVI). In particular, Apple insiders executed more sell (buy) orders during peak (trough) SVI months. The aggregate volume of sales on peak months were substantially higher than that on trough months, and the total volume of insider trading decreased dramatically after peak months. Apple insiders' trading patterns are suggestive of correlation between their trades and retail investors' attention (proxied by its ABSVI). The Apple example is also consistent with Barber & Odean's (2008) observation that retail investors are net buyers of

[32] There are instances where weekly SVI data near the end of a calendar month encompass the beginning days of next month. In such instances, we use a simple proportion to the number of days in a month to achieve the closest approximation of investor attention in the month. For example, between September 28th and October 4th of 2008, Apple has a weekly SVI of 69, and the portion of SVI that is allocated to September is 30 (3/7 of 69) and to October 39 (4/7 of 69).

attention-grabbing stocks, and their concentrated purchases result in a (temporary) rise in the stock price.[33]

Methodology

Our approach to empirically test whether abnormal returns of opportunistic insider trades are related to retail investors' attention is as follows. First, we investigate abnormal returns following trades by insiders of firms in our attention sample vis-à-vis those in our non-attention sample. Next, within the attention sample, we check abnormal returns of insider trades when there is an abnormal level of attention. We compute abnormal returns of stocks in two ways. In the first, we compute stock return in the calendar month subsequent to a trading month, adjusting for the return of a comparable size decile profolio based on NYSE breakpoints. This method controls for market-related risk factors that affect firms of similar size. In the second, we calculate excess stock return as the stock's return minus the risk-free rate and use the excess return as dependent variable in our baseline regression.[34] To address the question of whether investor attention affects insider trading, we regress one-month excess returns following the trade month onto equal-weighted market returns (to control for market risk) as well as control variables that count for risk factors such as firms' market values, book-to-market ratios, and past stock returns. Similar regressions are employed in Cohen, Malloy, and Pomorski (2011) and Alldredge and Cicero (2015).

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[33] They define an attention-grabbing stock as one having an extreme one-day return, experiencing an abnormal trading volume, or being in the news.

[34] A stock's excess return is defined as its monthly return minus the one-month risk-free rate reported in Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.

Table 9 presents the summary statistics of our sample. Panel A of Table 9 shows that our sample contains no sample selection bias because its characteristics are generally similar to the insider trading universe. Panel B shows that firms in the attention sample are substantially larger than those in the non-attention sample. The mean market capitalization is $6.74 billion ($5.48 billion) for attention sample firms with insider sales (purchases), but is only $1.07 billion ($0.66 billion) for non-attention firms with insider sales (purchases). Bigger firms have a larger investor base, and therefore, are more likely to attract investors' attention and have more active Google searches. However, the book-to-market ratio is only marginally different between attention and non-attention sample firms. Interestingly, attention firms with insider sales have more non-routine *traders* but fewer non-routine *trades* per firm-month than do non-attention firms with insider sales. This difference suggests that although attention firms have more opportunistic insider traders, the insiders engage in sales only when circumstances warrant the sales. In comparison, attention firms with insider purchases have fewer non-routine traders and fewer non-routine trades per firm-month than do non-attention firms with insider purchase. These observations appear to support Barber & Odean's (2008) argument that retail investors' attention results in net buying interests, which exert an upward pressure on stock price, creating opportunities for insider sales rather than purchases.

Figure 2 illustrates the time-series patterns of insider trading for years 2004 through 2014. Attention sample firms have fewer trades per insider in sale months and in most purchase months than non-attention firms. The number of insider trades is also smaller for attention firms. These patterns are consistent with our contention that attention firm insiders are more likely to engage in opportunistic trades, for example, when greater investor attention creates tradable opportunities. Our prelimiary observations remain consistent throughout the sample period.

Table 10 reports the distribution and average monthly SVI of our sample firms across the Fama and French 17 industry classifications. Panel A shows that our attention sample includes more financial companies (16.40%) and machinery and business equipment firms (12.05%) than our non-attention sample. In the attention sample, 74.5% of financial companies are commercial banks (e.g., Bank of America Corp.: BAC) while the rest are insurance and other financial companies; 20.2% of the machinery and business equipment firms are producers of eletronic components (e.g., Microchip Technology: MCHP). These two industries are also the largest segments in the non-attention sample (financial companies 27.51% and machinery and business equipment firms 10.90%). In the non-attention sample, 60.6% of the financial companies are commercial banks (e.g., First United bankcorp: FUBC); 29.1% of the machinery and business equipment firms are manufactuers of eletronic components (e.g., CHIPPAC, Inc.: CHPC). The retail stores industry constitutes only a relatively small percentage in both attention and non-attention samples.

Panel B of Table 10 depicts the level of attention – the average monthly SVI – during insider purchase and sale months across the 17 industries. Sale months are more likely than purchase months to be associated with higher levels of investor attention. Indeed, 8 out of 17 industries have a statistically significant higher attention level in sale months than in purchase months while only 5 out of 17 industries see more attention (statistically significant) in purchase months. Firms that operate in relatively small industries of mining and minerals, steel, and fabricated products have highest levels of investor attention during insider sale as well as purchase months, suggesting that these industries' insiders trade more during the months of high investor attention.

Empirical Findings

Table 11 reports one-month cumulative abnormal returns (CARs) following the insider trade month, adjusted by NYSE size decile portfolio returns, where Panel A (B) displays the results following the insider sale (purchase) month. As mentioned, NYSE size decile portfolios control for market factors that affect firms of similar size. Overall, insider sales earn higher abnormal returns when investors' attention to the stock is greater – when there is an increase in the Google SVI. In particular, following insiders' sale months, CARs on average are -0.688% per month for our attention firm sample and only -0.495% for our non-attention firm sample. The difference of CAR of 0.193% per month is statistically significant (T-statistics = 3.78). CARs are also less negative (-0.541%) in months in which attention firms receive no attention, and the difference of 0.147% per month (between -0.541% and -0.688%) is also statistically significant (T-statistics = 2.56). These results suggest that investors' attention, measured by the SVI, appears to be an important indicator of profitability of insider sales.

Panel A of Table 11 also details abnormal returns of sales by insider types. The difference of CAR between our attention and non-attention samples stems mainly from sales by attention firms' non-executive directors and other non-executive insiders, whose sales earn 0.446% and 0.249% more, respectively, than those of the same types of insiders of non-attention firms. In comparison, sales by top executives of attention firms earn only 0.215% more than those of their counterparts in non-attention firms. The results suggest that senior management insiders are less keen to engage in opportunistic sales to profit at the expense of retail investors, possibly because top executives are more concerned about poor perception and reputation this sort of sales may entail. In both attention and non-attention samples, however, when top-level officers do sell shares, their sales generate greater CARs than those of other insiders, consistent with top managers having better information on their firms.

Panel B of Table 11 presents the results of parallel tests on insider purchases. Consistent with the findings in previous research, average CARs following insider purchases are generally greater than those following insider sales. Within purchase firms, however, CARs of our attention sample are smaller than those of non-attention sample. Average size-adjusted CARs following the insider purchase month are 1.010% for attention firms and 1.215% for non-attention firms, and the difference of 0.205% is statistically significant (T-statistics = 3.12). Similar patterns are also evident on different classifications of insiders. Thus, when investors are paying greater attention (when the SVI is higher), purchases by insiders of all types earn lower CARs. The results again supports the argument that greater investor attention puts an upward pressure on stock price, making insider purchases (sales) less (more) profitable.

Return Analysis

We now perform mutivariate regressions to examine whether insiders could profit from trading on varying investor attention. Our empirical approach is similar to that in Cohen, Malloy, and Pomorski (2011) and Alldredge and Cicero (2015). As outlined earlier, we define a calendar month as an insider sale (purchase) month if there is at least one net insider seller (buyer) of shares but no net insider buyer (seller) in the same month. We regress stock excess returns onto various explanatory varables including size and book-to-market ratio. Table 12 presents the results of the return analysis, where Panel A (B) presents abnormal returns following the insider sale (purchase) month. Column 1 in Panel A (B) presents a strong evidence of abnormal returns following the insider sale (puchase) month with the intercept being a statistically significant amount of 0.0169 (0.1133). Cohen, Malloy, & Pomorski (2011) also find that opportunistic insider sales lead to positive abnormal returns in the following month. An explanation for this finding is that insiders have other reasons to sell shares, for example, to diversify their porfolio holdings. Thus, sales by insiders while investor attention is high present them with opportunities to unload their shares at lower opportunity costs (less foregone returns).

Insider trading is subject to significant regulatory and policy constratins. Many large corporations put in place strict compliance policy to deter questionable insider trading (Lakonisjok and Lee, 2001) and a big part of securities regulation is enforcement by the SEC agains illegal trading. Since SEC actions tend to focus more on insider sales than purchases (Agrawal & Cooper, 2015), when insiders sell shares, they would want to do so in a way to minimize potential issues with the SEC. In this regard, insider sales that mainly take advantage of investors' level of attention may pose a lower risk of violating insider trading regulation.[35] Our evidence is consistent with this view. In Panel A of Table 4, the coefficient on the attention dummy, indicating greater investor attention, is -0.0022 (T-statistics = 3.143) on insider sales, and in Panel B, it is -0.0035 (T-statistics = 2.917) on insider purchases. The negative coefficients suggest that a higher level of investors attention lowers the opportunity costs of insider sales as well as the potential profits of insider purchases.

We next test how the extent of investor attention impacts returns of insider trades by examining the effect of abnormal investor attention. Column 2 in Table 12 presents the regression results, where the coefficient of Log(ABSVI) is highly significant and negative on both insider sales (-0.0059 in Panel A) and purchases (-0.0140 in Panel B). Column 3 includes additional explanatory variables such as SVI Duration – the number of months between a trade month and the first month when a valid SVI was available. This variable can have two opposite effects on insiders' trading profits. On one hand, the SVI Duration reflects a lengthy or durable interest of investors in the stock, creating more opportnities for insider trades. On the other hand, a sustained

[35] There are a substantial number of insiders who sell (purchase) shares when investors' attention is low (high). In later tests, we classify them as non-SVI-related trades.

interest of investors may enable them to learn from experience and become more sophisticated investors, reducing insider trading opportunities. Our evidence supports the latter conjecture. The coefficent of Log(SVI Duration) is positive on sales (0.0048 in Panel A) but negative on purchases (-0.0107 in Panel B), both statistically significant. That is, insiders' abnormal returns diminish on both their sales and purchases as the length of investors' attention increases. We include in Column 3 the Log(Analysts) variable, capturing the number of analysts covering the stock, to control for publicly available information which may affect retail investors' attention. We expect insiders' abnormal profits to diminish when more analysts cover the stock since more analysts provide more information to the public, thereby reducing insiders' informational advantage and dimishing their opportunities for profitable trading. Consistent with this prediction, the coefficient on Log(Analysts) is significant and positive on insider sales (0.0029 in Panel A), although the coefficient is insignificant on insider purchases (in Panel B).

For the last two model specifications, Columns 4 and 5 in Table 12, the sample is split on the basis of abnormal SVI (ABSVI) to disentangle the impact of SVI-related verses non-SVI-related trading on next month's excess returns. We find that our results are mainly driven by insider sales when the ABSVI is greater than one – when the month's SVI is greater than that of last month – and by insider purchases when the ABSVI is less than one. In Panel A's Column 4, the coefficient of Log(ABSVI) is negative (-0.0194) and statistically significant (T-value = 3.18). The results in Column 5 of Panel A suggest that insiders' sales generate abnormal returns following their trades that do not take advantage of heightened investors' attention. In Panel B's Columns 4 and 5, we see that insider purchases are generally more informative and generate abnormal returns following their trades. However, taking advantaging of lower investors' attention (depressed stock price) would also yield higher abnormal returns. Overall, our results indicate that a higher (lower) Google SVI benefits insiders' sales (purchases). The results are consistent with our hypothesis that insiders profit by engaging in opportunistic trades that take advantage of stock price variations arising from changing levels of investor attention.

Insider Trading Patterns

We perform Probit and Tobit regressions to explore further how investors' attention levels affect the likelihood and amount of insiders' trades. We measure trades by the volume of insiders' sales or purchases in a given month. We conjecture that insiders execute trades when retail interest exerts a price pressure on the stock. Table 13 presents the results of limited dependent variable regressions that predict insider trading. The dependent variable in Probit regressions is a Sale (Purchase) dummy, which equals one if a firm-month is a net sale (purchase) month. The dependent variable in Tobit regressions is Shares Sold (Purchased), which equal the number of shares, in thousands, that insiders sell (buy) during a sale (purchase) month. In all regressions, independent variables include Log(Size), Log(BM), the contemporaneous equally weighted market return $Market_t$, Advertising/Sales ratio, Log(Price), and

Log(Turnover). In Appendix: Variable Definitions and Sources of Main Variables, we provide the detailed definitions of all these and other variables. The independent variable of particular interest is either Log(ABSVI) or a dummy variable indicating whether Log(ABSVI) is positive (predicting sales) or is negative (predicting purchases). If the coefficients of these variables have correct signs and are statistically significant, the results would further support the argument that insiders trade when abnormal investor attention presents a profitable trading opportunity.

Table 13 displays the results of Probit and Tobit regressions, where Columns 1 through 4 show predictions on insider sales, and Columns 5 through 8 on insider purchases. Overall, insiders trade more often and transact more shares when there is abnormal investor attention (when their trades would be more likely to be profitable). The marginal effect associated with the Log(ABSVI) Positive dummy in Column 2 shows that insiders are 11.6% more likely to sell shares when there is an increase in investor attention.[36] Similarly, the same coefficient of Tobit regression in Column 4 shows that insiders sell 27,464 more shares when Log(ABSVI) is positive. On the purchase side, insiders buy more shares and more frequently when investors are less attentive. The marginal effect associated with the Log(ABSVI) Negative dummy in Column 6 shows that insiders are 3.37% more likely to buy shares when there is a lack of investor attention, and the same coefficient of Tobit model in Column 8 indicates that insiders buy 4,518 more shares under the same circumstance.

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[36] The marginal effect presented here is derived using the Stata program mfx.

Which Insiders Take the Trading Opportunities?

Our preliminary results in Table 11 suggest that insiders who are non-executive, non- independent directors are more likely to engage in trades that are linked to investors' attention. We now carefully examine this possibility, using limited dependent variable regressions. For this purpose, we classify insiders as top level officers, insider directors, independent directors, and others, based on the role classification codes defined in the insider filing database. Top level officers are the firm's chief executive officer, chief financial officer, chief operating officer, and the chair of its board (role classification codes: CEO, CFO, CO, and CB). Insider directors are those who have an employment contract with or a beneficial interest in the firm, excluding the top level officers (role classification codes: DO, H, and OD). All other directors are taken to be independent directors.

To test the role played by insider type, we interact each role classification dummy with the variable of interest, Log(ABSVI). Table 14 presents the results of Logit regressions, where in Columns 1, 3, and 5, the dependent variable is the sale dummy, and in Columns 2, 4, and 6, it is the number of shares sold (in thousands). The coefficients of the interaction terms on Columns 1, 3, and 5 are negative on Top-level Officers and on Independent Directors, but are positive on Insider Directors, confirming our initial observation that non-senior-executive, inside directors are the insiders who are likely to trade to take advantage of investors' attention. Top executives and independent directors are less likely to engage in such opportunistic trades possbily because of their greater concerns for reputation. The results of Tobit regressions in Columns 2, 4 and 6 support a simlar conclusion.

Characteristics of the Opportunistic Traders and their Firms

Having identified that non-senior-executive, non-independent directors tend to engage in opportunistic trades related to investor attention, we now explore the insider traders' individual as well as firm characteristics. We employ a logit model where the dependent variable is a dummy that equals one if an insider is a non-senior-executive, non-independent director. Independent variables in the regression include major categories of insider and firm level characteristics such as the insider's tenure in the firm as well as the firm's geographical dispersion, governance, financial constraints, product dispersion, social responsibility, reputation and fame. We measure insider tenure as the log of the number of years the insider is active in the firm. Geographical dispersion is measured as the log of the number of states in which the firm operates. Governance is based on the G-index from Gompers, Ishii, & Metrick (2003), with the poor governance dummy equal to one if the firm's G-index is 90 percentile or higher of the distribution (G-index >= 12 and a larger number indicating poorer governance). Financial constraint is based on the SA index introduced by Hadlock & Pierce (2010).[37] Corporate social responsibility is measured by the KLD index from the KLD Social

[37] The SA Index is computed as (-0.737*Size) + (0.043* Size^2)-(0.040* Age), where Size is the log of inflation-adjusted book asset, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. The size is capped at the log of \$4.5 billion, and age is winsorized at thirty-seven years.

Ratings database.[38] Product dispersion is the product-sales based Herfindahl-Hirschman index from Compustat Product database. For the reputation and fame variable, we manually collect the Fortune magazine ranked 100 best companies to work for between 2004 and 2014 and we create the Fortune100 dummy to proxy for good corporate reputation.

Table 15 shows that the non-senior-executive, non-independent insider traders are more likely to have a longer tenure in their firms and to be from firms that have poor governance, are socially less responsible, and are not in the list of Fortune 100 best companies. Moreover, their firms also operate in more states, have more concentrated product-sales, and are financially less constrained. Specifically, the coefficient of Log(Number of Years Active) in Column 1 is positive and significant, indicating the insider trader's longer tenure in the firm. As Cohen, Malloy, & Pomorski (2011), we include the number of trades to isolate the effect of time in the firm, conditional on the trading activity of individual insider. Here, the coefficient of Log(Number of Trades) is negative and significant, suggesting that while the insider trades less in general, he/she actively trades when an attention-related opportunity presents itself. Thus, conditioned on the same amount of trades, our results indicate that an insider who has a longer tenure in a firm is more likely to trade opportunistically.

[38] The KLD index is computed by considering seven dimensions: Corporate Governance, Human Rights, Community, Diversity, Employee Relations, Environment, and Product. The KLD is computed by subtracting total weaknesses from total strengths from the seven dimensions.

Column 2 of Table 15 examines the effect of firm geographical dispersion: the log of the number of states the firm operates. The coefficient is positive and significant, suggesting that the number of states in which a firm operates positively predicts the likelihood that a non-senior-executive, non-independent insider of the firm will engage in an opportunistic trade. This finding differs somewhat from that in Cohen, Malloy, and Pomorski (2011) possibly because we focus only on certain opportunistic traders. In particular, firms that operate in more states are likely to attract a larger base of retail investors, creating more opportunities for profitable insider trades.

The effects of corporate governance, financial constraints, and product concentration are shown in Columns 3 through 5 of Table 15. In Column 3, the coefficent of the poor governance dummy is positive and significant, indicating that an opportunistic trader is more likely associated with a poorly govened firm. In Column 4, an opportunistic insider trader is more likely linked to a financially less constrained firm. This result is consistent with the argument that retail investors are more likely to be interested in firms that are doing well financially. In Column 5, we see a positive, although weakly significant, coefficient on product concentration. It is possible that when a firm's revenue source is concentrated from fewer products, less corporate diversification might motivate insiders to engage in more trades when the opportunities are present. Overall, our results support that opportunistic insider traders are more likely from firms that have a poorer governance, that are financially less constrained, and that have more concentrated products.

Columns 6 through 8 turn to aspects of social responsibility and reputation of firms. The result in Column 6 is based on the KLD-corporate social responsibility of companies. The KLD measure is an aggregate on seven dimensions: corporate governance, human rights, community, diversity, employee relations, environment, and product. A higher KLD index means a higher level of social awareness and integrity. The negative coefficient on this measure suggests that opportunistic insiders are more likely to be from social less responsible firms. In Columns 7 and 8, we check whether a firm in our sample has been in the list of Fortune 100 best companies to work for. The best companies may attract more investors' attention, thereby creating more opportunities for insider trading. However, such firms may also bear greater reputation costs if opportunistic insider trades are exposed. The negative coefficients of the Fortune100 dummy and Log(Nomination Ranks) support the latter argument that reputable firms value more highly their public image and reputation, and therefore, their insiders of all types are less likely to engage in trades that take advantage of retail investors.

Do Lottery-type Stocks Have More SVI-related Insider Trading?

Kumar (2009) finds that individual investors who are young, urban, single, relatively poor and less educated tend to overweigh stocks with lottery features in their portfolios. Kumar labels a stock as lottery-type if it has a low per share price, high idiosyncratic volatility and skewness. The idea is that a lottery-type stock, like a lottery ticket, can provide the buyer with a huge reward but only with a very low probability.

An implication of Kumar’s study is that lottery stock buyers are generally less sophisticated investors who may have limited resources and abilities to process relevant information. If this implication is true, we expect that insiders of lottery-stock firms would have greater opportunities to engage in SVI-related trades that take advantage of varying attention of individual investors on the stocks.

We follow Kumar’s (2009) approach to identify lottery-type stocks. We first compute idiosyncratic volatility and skewness for each stock at month t using the CRSP return data of previous six months (t-6 to t-1). As in Kumar (2009) and Ang, Xing, & Zhang (2006), idiosyncratic volatility is calculated as follows:

$$Idovol_{i,t} = \frac{\sum_{d \epsilon T_i(t)} \varepsilon_{i,d}^2}{D_i(t)}, \tag{1}$$

where stock price in month t is the closing price at the end of month t-1, $T_i(t)$ is the set of CRSP daily returns for firm i in month t, $D_i(t)$ is the number of trading days for firm i in month t, and $\varepsilon_{i,d}$ is the residual on trading day d for firm i from regressing firm i’s daily return on the four factor model over the period $T_i(t)$. For idiosyncratic skewness, we follow Harvey and Siddique (2000) and Kumar (2009), and use the following equation:

$$Idovol_{i,t} = \frac{\sum_{d \epsilon T_i(t)} \varepsilon_{i,d}^3}{\sigma_{i,t}^3}, \tag{2}$$

where $T_i(t)$, $D_i(t)$, and $\varepsilon_{i,d}$ are the same as in Equation (1), and $\sigma_{i,t}$ is the squared root of $Idovol_{i,t}$ estimated from Equation (1). A stock in our sample is lottery-type if its price is in the bottom half of distribution while its idiosyncratic volatility and skewness are both in the top half. All other stocks in our sample are classified as non-lottery type stocks.[39]

Table 16 presents the descriptive statistics of lottery-type stocks and the results of firm-level regressions. In Panel A, we compare lottery-type and non-lottery stocks based on the three characteristics of stock price, idiosyncratic volatility and skewness. Our sample has 1,093 lottery-type stocks and 4,029 non-lottery stocks. Lottery-type stocks have a much lower average price (6.40 vs. 23.68), much higher average idiosyncratic volatility (21.99 vs. 8.11) and skewness (2.10 vs. 0.29). In our firm-level regressions, we introduce a dummy variable, Lottery, which equals one if the stock is lottery-type at the end of month t-1.[40] Our main interests are the lottery dummy and its interaction term with Log(ABSVI): the Log(ABSVI) Positive or Log(ABSVI) Negative dummy. We also construct a jump (fall) dummy to capture an extreme increase (decrease) in the level of investor attention over that of the previous month. The Jump (Fall) dummy equals one when the ABSVI is in the top (bottom) 10 percentile. Panel B (C) of Table 16 presents the results of our Logit and Tobit regressions on net sales (purchases). The coefficient of Lottery is negative (positive) in Panel B (C), indicating that insiders sell less (buy more) of lottery-type stocks compared with insider trading on non-lottery stocks. Panel B also shows highly positive and significant coefficients of the interaction terms between Lottery and Log(ABSVI), Log(ABSVI) Positive, and Jump,

[39] Kumar (2009) defines non-lottery type stocks as those that belong to none of the three categories. In our paper, our main interest is to examine the impact of lottery-type stocks on SVI-related trades, and our grouping approach is not expected to result in biased results.
[40] We use the lottery dummy at the end of month t-1 to regress on the month t's insider trading activity in order to establish a causality relationship.

providing further support to our conjecture. Indeed, a greater interest of retail investors in a lottery-type stock (a higher ABSVI on the stock) appears to create more profitable opportunities for insider trading.

Local Investors and SVI-related Insider Trading

Research has documented that local investors are better informed, for example, because of local media's coverage on local firms (Engelberg and Parsons, 2011). Because of this informational advantage, local investors face less adverse selection and contribute to price discovery of local stocks (Shive, 2012). Their portfolios overweigh local stocks (Seasholes and Zhu, 2010) and earn superior returns (Berry and Gamble, 2013). Taken together, local investors appear to be better investors of local stocks with their local investments driven more by the fundamantal information than by other factors. An implication is that the interest of local investors in –their attention to – local stocks would be less likely to create opportunities for profitable insider trades.

We test this implication, using both Compustat state (STATE) and city (CITY) information on firms to define a firm's locality. We manually collect from Google Trends firm local SVI information (at the state level: SVI_State, and at the metropolitian statistics area level: SVI_Metro),[41] and use the information to construct two abnormal local SVI measures. The results in Table 17 support our expectations. Panel A shows the mean comparisons between two local SVI measures and the aggregated SVI. Both SVI_State and SVI_Metro are significantly smaller than the SVI of all Google searches,

[41] We use the local SVI at the State and Metro level to ensure sufficient data availability.

indicating that local investors rely less on Internet searches than do non-local investors. Thus, local investors' investment decisions are more likely influenced by their local information or knowledge. Panel B (C) presents the results of our Logit and Tobit regressions on Sales Dummy and Shares Sold (Purchase Dummy and Shares Bought). As expected, we observe weaker (and even insignificant) coefficients, implying that better informed trading by local investors presents fewer opportunities for profitable insider trades.

SEC Enforcement Activities and Opportunistic Insider Sales

In this section, we examine whether insiders change their SVI-related trading behaviors upon the news releases of SEC enforcement actions on illegal insider trading activities. We focus on the impact of SEC actions on opportunistic insider sales because such sales are most likely to trigger SEC investigations (Cohen, Malloy, and Pomorski, 2012). We classify opportunistic insider sales into two categories: SVI-related and non-SVI-related. An opportunistic sale is SVI-related if it takes place in a month when there is an increase in investors' searches on the stock – when Log(ABSVI) > 0. All other opportunistic sales are defined as non-SVI-related. It is possible that insiders may believe that the sales of shares when retail investors are paying more attention are less likely to be subject to SEC investigation. If this view is correct, we expect insiders to engage in *more* SVI-related sales following the releases of SEC actions on illegal insider trading, in contrast to Cohen, Malloy, and Pomorski's (2012) finding that there is an overall reduction in opportunistic insider sales following such releases.

To test this conjecture, we regress the ratio of SVI-related sales to total opportunistic sales in month t onto the number of releases of SEC litigation on illegal insider trading in month t-1. The independent variable of interest is the natural log of one plus the number of releases of SEC cases against insider trading in month t-1. We include in the regression the fraction of positive Log(ABSVI) at month t and t-1, where the fraction of positive Log(ABSVI) is defined as the number of months that have positive Log(ABSVI) divided by the total number of months that ABSVIs are available. Control variables include an equally weighted market return in month t, the standard deviation of daily market returns in month t-1, and cumulative equally weighted market returns of past 3, 6, and 12 months.

We report the results of the test in Table 18. Panel A shows that SVI-related sales increase significantly following the news releases of SEC actions. The evidence indicates that SEC cases result in more SVI-related insider sales even though they dampen overall opportunistic sales. In other words, when there are greater concerns about regulatory scrutiny of insider trading, insiders appear to prefer SVI-related sales to other opportunistic sales. The coefficient of the number of SEC releases (Num SEC Release_{t-1}) is 0.073 (t = 4.37).[42] The coefficient of the fraction of positve Log(ABSVI) at month t is positive and significant, suggesting that abnormal investors' attention attracts more SVI-related insider sales. Interestingly, the coefficient of the fraction of positve Log(ABSVI) at month t-1 is negative and significant, indicating that after taking

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[42] Summary Statistics for our litigation data are as follows: the average number of insider trading-related cases the SEC makes in a given month is 5.6 (median 5.5), with a standard deviation of 2.61(max=12, 75th percentile=7, 25th percentile=4, min=0).

advantage of heightened retail investors' attention, insiders reduce their sales, presumably to reduce the risk of SEC action since the other forms of sales may be riskier.

In Panel B of Table 18, we rerun firm-level Probit and Tobit regressions where the dependent variables are the sales dummy and the number of shares sold, respectively. The coefficients of Num SEC Release$_{t-1}$ are negative and significant, consistent with a deterrence effect on overall opportunistic sales. However, the coefficients of interaction term between Log(ABSVI)$_t$ and Num SEC Release$_{t-1}$ are positive and significant, indicating that insiders change their trading behaviors by trading more on the basis of retail interest.

Panel C examines the probability of an insider trader being investigated by the SEC. The observations are at the insider level, and insider characteristics are constructed based on all trades and sales of each insider.[43] Column 1 shows that an insider who engages in SVI-related trades has a lower likelihood of subsequently being investigated or sued by the SEC. In Column 2, we partition the number of insider trades on the basis of being SVI-related and non-SVI-related. The coefficient on the number of Non_SVI_Related Trades is positive and significant (t=2.56) while that on SVI_Related Trades remain insignificant. The result suggests that it is the *non-SVI-related trades* that trigger SEC actions. We also construct the percentage of SVI-related sales dummy (% SVI_Related) which equals one when the number of SVI-related sales (trades) is greater

[43] We define the number of trades here as the number of an insider executing each transaction and the number of sales as the total number of shares sold.

than that of non-SVI-related sales (trades). The coefficients of % SVI_Related sales and trades dummies are negative and marginally significant. Overall, our evidence supports the argument that SVI-related sales are less likely to face SEC actions, and therefore, such sale activities actually increase following the news of SEC actions.

Information or Sentiment and Additional Robustness Checks

One concern is that Google's SVI simply reflects investors' interest in real news or information relevant to the stock. In other words, the SVI represents the variation of flow of publicly available firm-level information. To check whether our results are mainly driven by the flow of public information about particular stocks or by changing sentiments of retail investors on these stocks, we regress Log(ABSVI) onto such variables that are known to affect the SVI as earning surprise, advertising to sales, major macro variables of GDP final and FOMC rate decisions, as well as year and industry dummies. We extract the information about firms' earning announcements from I/B/E/S and adjust the announcement days into the CRSP trading days. The magnitude of earnings surprise is constructed, using the following equation:

$$SUE_{i,q} = \frac{Actual\ EPS_{i,q} - Median\ Forecasted\ EPS_{i,q}}{P_{i,q}} \tag{3}$$

In the above, $Actual\ EPS_{i,q}$ is actual earnings per share (EPS) for firm i at quarter q, $Median\ Forecasted\ EPS_{i,q}$ is the median estimate of EPS among those posted 90 days prior to the earnings report day, and $P_{i,q}$ is the price per share for firm i at the end of quarter q from Compustat. We include two manually collected major macro news variables: GDP final and FOMC rate decisions, which are considered by Bloomberg to have most relevance to investors. We run the following regression to decompose Log(ABSVI):

$$Log(ABSVI)_{i,t} = \alpha_i * SUE_{i,Q(t)-1} + \beta_i * \frac{Adv}{sale}_{i,Y(t)-1} + \gamma_i * GDP_{Final_{t-1}} + \delta_i * FOMC_{t-1} + Year + Industry + \varepsilon_{i,t} \tag{2}$$

where $SUE_{i,Q(t)-1}$ is firm i's earnings surprise at the quarter immediately before month t, $Adv/sale_{i,Y(t)-1}$ is the firm's advertising to sale ratio in the previous year, and GDP_Final_{t-1} and $FOMC_{t-1}$ are dummy variables that equal one if there is a release of the macro information in month t-1. We take the predicted value as the information component of Log(ABSVI) – denoted Log(ABSVI-Information) – and the residual value as its non-information or sentiment component – denoted Log(ABSVI-Sentiment). Table 19 presents the effects of the two components of ABSVI on insider trading. As shown in their respective coefficients, the sentiment component delivers stronger and more consistent impacts than do the information component. Thus, our results are more in line with retail investors' shifting sentiments creating opportunities for profitable insider trades.

To address concerns of causality as well as endogeneity, we perform two sub-sample analyses. The first is based on a political regime change that serves as an exogenous shock. In particular, we decompose our whole sample period of 2004-2014 into two subsample periods of 2004-2008 and 2009-2014 with the former being under the more laissez faire Republican Bush Administration and the later under the more activist Democratic Obama Administraion. Presumably, the Obama Administration would be more active at taking enforcement actions against legally questionable insider trading and thus would have a stronger deterrence effect on opportunistic trades. However, our results remain essentially the same for the two subsample periods, suggesting that the SVI is not affected by insider trading. In our second sub-sample analysis, we create one subsample for months of earnings annoucements and another for months of no earnings annoucements. Our results remain significant in the months of no earnings annoucement, although they are stronger in the months of earnings annoucement.

Portfolio Returns from SVI-Based Trading Strategy

We now examine the returns of portfolios formed according to our SVI-related trading classifications. The main question is whether insiders' SVI-based trading behaviors predict future returns. To address this question, we create quintiles using the monthly ABSVI and each firm's monthly net transaction volume (net sales or purchases). Specifically, we base the portfolios on our classifications of SVI-related trades at the firm level rather than the insider level. We focus on firm-months that have either a positive or a negative Log(ABSVI) by excluding those that have a zero Log(ABSVI). For each subsample, we classify a firm based on its net transaction volume (number of shares). For example, if a firm has more insider sales (purchases) than purchases (sales), we group the firm into a net sale (purchase) portfolio. In essence, we create two portfolios for net sale: one insider sale portfolio when Log(ABSVI) is positive and another insider sale portfolio when Log(ABSVI) is negative. Likewise, we also create two net purchase portfolios: one when Log(ABSVI) is positive and another when it is negative. We hold these four portfolios over the month following insider trades, and then rebalance all portfolios at the end of month, using new information on each firm's Log(ABSVI) and net transaction volume for the month.

Table 20 shows the portfolio returns of SVI-based trading strategy. We see that future one-month returns are monotonically decreasing in the ABSVI and in net transaction positions. In particular, firms at the highest net sales and the lowest ABSVI quintile experience the highest average returns (1.85%), indicating that insiders who sell their firm's shares when investors' attention (ABSVI) is extremely low will experience the greatest opportunity cost of trading by forgoing the highest positive return in the following month. In contrast, if insiders sell at a higher ABSVI, their opportunity cost of selling will be lower. The results are similar on net insider purchase. A higher average return is realized when the ABSVI is lower; that is, insiders who buy their firm's shares when investors' attention is lower will earn higher returns. Overall, the results reinforce the argument that the ABSVI presents meaningful opportunities for profitable insider trades.

Table 21 presents raw portfolio returns and risk-adjusted alphas for the CAPM, Fama-French, Carhart four-factor, as well as five-factor model which includes the Pastor-Stambaugh liquidity factor. It also reports on both value-weighted and equal-weighted portfolios. We see that a portfolio strategy based on opportunistic insider trades when the ABSVI is low would earn significant and large abnormal returns. In comparison, a portfolio strategy based on opportunistic trades when the ABSVI is high would only earn insignificant and sometimes even negative risk-adjusted returns. Furthermore, an equally weighted long-short portfolio that is long on what insiders buy when Log(ABSVI) is negative and short on what insiders sell when Log(ABSVI) is positive would generate a five-factor alpha of 232 basis points (t = 7.08) or 27.84% per year before transaction costs. A one directional portfolio strategy, be it based on buy or sell, however, would generate a consistently negative alpha for all model specifications. In the lower half of Table 13, we present the return results of value-weighted portfolios; here, the five-factor alpha is 119 basis points (t = 3.08) or 14.28% per year before transaction costs. Taken together, our return analysis suggests that a trading strategy that follows insiders' SVI-related trades would earn economically and statistically significant abnormal returns.

Conclusion

This paper explores how insiders may engage in opportunistic trades to take advantage of varying attention of retail investors to their firm's stock. Our analysis rests on the premise that retail investors exhibit behavior biases that could result in mispricing and create opportunities for profitable insider trades. Our result indicates that insiders can indeed profit by timing their sales of shares when there is an increase in retail investors' attention (proxied by the ABSVI). Exploring further this finding using the Limited Depedent Variable regression, we show that a higher level of abnormal investor attention increases the likelihood of insiders' selling and also the quantity of their sales while decreasing the likelihood of insiders' buying and the quantity of their purchases. In other words, we document a pattern of opportunistic insider trades that are contrarian to the level of retail interest in the stock.

While the level of investor attention is significantly and positively associated with insiders' abnormal returns on sales, we observe no significant relationship between the attention level and abnormal returns on insiders' purchases. This result is consistent with the contention that retail investors' attention affects mostly their buying rather than selling decisions, with a higher attention level predicts a short-term price rise. Exploring further this finding using multivariate regressions, we show that investors' abnormal attention has a significant negative effect on the following month's excess returns. This negative effect, however, appears to be attenuated by the longevity of attention, implying that as retail investors' active searches on the same firm persists, they may be learning from their experience and becoming less sentimental and more rational in making their trading decisions.

We find that insiders who are involved in the SVI-related opportunistic trades tend to be non-senior-executive, non-independent directors. Such insiders may be less concerned about firm and individual repuation and may therefore value more the opportunistic trading profits. In particular, exploring the mechinism behind our return analysis, we find that the opportunistic traders are more likely to have a long tenure in their firm, and to be from a firm that has weak corporate governance, low awareness of corporate social responsibility, and low reputation costs in the eyes of the public. The firm also operates in more states, has a high product sale concentration, and is less financial constrained.

We conduct subsample analyses to address several issues. One is that retail investors may find lottery-type stocks more appealing and hence their optimistic sentiment on such stocks may create even greater opportunities for profitable insider trades. Our evidence supports this conjecture. Another issue concerns that our results might be driven by local sentiment because local investors prefer and overweigh local stocks in their portfolio, presumably because they are better informed about local stocks. Our results that are based on the local ABSVI are indeed much weaker and less significant, indicating that local investors are less driven by sentiment than non-local investors and thus there are fewer opportunities for profitable insider trades based on local attention. We also explore SEC enforcement risk associated with SVI-related trades. Interestingly, we find supportive evidence that insider trading motivated by an abnormal SVI faces a lower risk of SEC litigation, and thus, the amount of SVI-related trades actually increases following the releases of SEC litigation cases.

It is possible that investors' level of attention may simply refect their demand for newly public information about the firm; that is, corporate news or events rather than investor sentiment may be driving the level of attention. To address this issue, we disentangle the ABSVI into two components: the first is part of ABSVI that is explained by arrivals of firm or market information while the second is the part that is left unexplained – which we refer to as the sentiment component. We show that our results are driven more by the sentiment component. We carry out additional subsample analyses based on the change of political administration and earnings news releases. The results show that the SVI is unlikely to be affected by insider trading and remain significant even after controlling for the news element.

We show that the potential profits of the insider trades are both statistically and economically significant. For example, a value-weighted (equal-weighted) mimicking portfolio that is long on what insiders buy when the ABSVI is negative and is short on what they sell when the ABSVI is positive would generate a significant five-factor alpha of about 119 (232) basis points per month, or 14.28 % (27.84%) per year, before transaction costs. Overall, we provide strong evidence that insiders strategically exploit mispricing of their firm’s stock arising from retail investors’ shifting sentiment, perhaps believing (correctly) that this type of trades is less likely to subject them to investor litigation and SEC enforcement actions.

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Appendix A

Essay1_Variable Definitions

Variable	Definition	Source
	Measures of Tax Aggressiveness and Advertising	
$SHELTER_{i,t}$	Wilson's (2009) sheltering probability is computed using the following regression model (Table 5 Column 3): $SHELTER\_PROB_{it} = -4.86 + 5.20 \times BTD_{i,t} + 4.08 \times DA_{i,t} - 0.41 \times LEV_{i,t} + 0.76 \times AT_{i,t} + 3.51 \times ROA_{i,t} + 1.72 * FI_{i,t} + 2.43 \times RD_{i,t}$ In the above, $SHELTER\_PROB_{it}$ is the sheltering probability from firm i in year t. $KIMBTD_{i,t}$ is a book-tax difference measure defined in Kim et al. (2011). $DA_{i,t}$ is discretionary accruals from the performance-adjusted modified cross-sectional Jones Model. $LEV_{i,t}$ is the long-term debt scaled by lagged asset (#9/#6). $AT_{i,t}$ is the log of total asset (#6). $ROA_{i,t}$ is return on assets measured as operating income (#170 minus #192) scaled by lagged assets (#6). $FI_{i,t}$ (#273) is a dummy variable, equals to one for a firm-year that reports foreign income and zero otherwise. $RD_{i,t}$ is research and development expense scaled by lagged total assets (#46/#6). We follow Rego and Wilson (2012) and rank $SHELTER\_PROB_{it}$ each year and create a dummy variable to capture firms that have a high sheltering probability. $SHELTER_{i,t}$ is an indicator variable that equals to one if the firm's estimated sheltering probability is in the top quartile in that year and is zero if otherwise.	Compustat
$CETR_{i,t}$	Cash Taxes Paid/Pretax Income (#317 divided by #170). $CETR_{i,t}$ is set to missing when the denominator is zero or negative. It is truncated to the range of [0, 1].	Compustat
$KIMBTD_{i,t}$	Defined as book income (#170) minus taxable income over lagged assets (#6). Taxable income is computed as the sum of current federal tax expense (#63) and current foreign tax expense (#64) divided by the statutory tax rate, and then subtracted the change in net operating loss carryforwards (#52). If current deferral tax expense is missing, total	Compustat

	current tax expense is calculated by subtracting deferred taxes (#50), state income taxes (#173), and other income tax (#211) from total income taxes (#16) in year t.	
$DDKIMBTD_{i,t}$	Desai and Dharmapala's (2006) residual book-tax difference, which equals the residual of firm fixed effect regression: $KIMBTD_{i,t} = \beta_1 TACC_{i,t} + \mu_i + \varepsilon_{i,t}$, where $TACC_{i,t}$ is total accruals measured using the cash flow method of Hribar and Collins (2002). Both variables are scaled by lagged total assets (#6) and are winsorized at the 1% and 99% levels.	Compustat
$DTAX_{i,t}$	Frank et al.'s (2009) discretionary permanent book-tax difference for firm i in year t. $DTAX_{i,t}$ is the ε_{it} from the following regression estimated by 2-digit SIC code and fiscal year: $PERMDIFF_{it} = \beta_0 + \beta_1 INTANG_{it} + \beta_2 UNCON_{it} + \beta_3 MI_{it} + \beta_4 CSTS_{it} + \beta_5 \Delta NOL_{it} + \beta_6 LAGPERM_{it} + \varepsilon_{it};$ where: $PERMDIFF_{it} = BI_{it} - [(CFTE_{it} + CFOR_{it})/STR_{it}) - (DTE_{it}/STR_{it});$ BI_{it}= pre-tax book income (#170) for firm i in year t; $CFTE_{it}$= current federal tax expense (#63) for firm i in year t; $CFOR_{it}$= current foreign tax expense (#64) for firm i in year t; STR_{it}= statutory tax rate in year t; DTE_{it}= deferred tax expense (#50) for firm i in year t; $INTANG_{it}$= good will and other intangibles (#33) for firm i in year t; $UNCON_{it}$= income (loss) reported under the equity method (#55) for firm i in year t; MI_{it}= income (loss) attributable to minority interest (#49) for firm i in year t; $CSTE_{it}$= current state income tax expense (#173) for firm i in year t; ΔNOL_{it}= change in net operating expense (#52) for firm i in year t; $LAGPERM_{it}$ = one-year lagged PERMDIFF firm i in year t; Following Frank et al. (2009), we handle the missing value problems as follows: if MI_{it}, $CFOR_{it}$, $UNCON_{it}$, or $CSTE_{it}$ is missing, it is set to zero. If $CFTE_{it}$ (#63) is missing, then $CFTE_{it}$ is computed as total tax expense (#16) less current	Compustat

	foreign tax expense (#64), less current state tax expense (#173), and less deferred tax expense (#50). If INTANG_{it} (#33) is missing, then it is set to zero. If INTANG_{it} (#33) = "C", then it equals that for good will (#204).	
$\mathrm{LOG(ADV)}_{i,t}$	Natural logarithm of one plus advertising expenditure (#45) times 1,000,000	Compustat
$\mathrm{ADVGP}_{i,t}$	Ratio of advertising (#45) to gross profits (#12-#41)	Compustat
$\mathrm{HADVDUM}_{i,t}$	Dummy variable that equals one if advertising expenditure is above the median	Compustat
	Firm Specific Variables	
$\mathrm{OPACITY}_{i,t}$	We follow Anderson et al. (2009) and compute opacity by aggregating the decile ranks from the variables: bid-ask spread, trading volume, analyst coverage, and analyst forecast errors, and then dividing the sum by 40. Trading volume is the nature logarithm of average daily trading volume during a fiscal year. Bid-ask spread is ask-price minus bid-price over the average of bid-ask prices, computed by averaging all trades for each firm from the third Wednesday of each month and then calculated a yearly average based on these 12 observations. Analyst coverage is the natural logarithm of the number of analysts following each firm, and analyst forecast error is the square of difference between the mean analysts' earnings forecast and actual firms' earnings scaled by the firm's stock price.	CRSP, IBES
$\mathrm{SP1500}_{i,t}$	Dummy variable that equals one if a firm is listed in the S&P 1500 over a firm year	Compustat
$\mathrm{INST.\ OWN}_{i,t}$	Percentage of shares owned by institutional investors scaled by common shares outstanding	13 f
$\mathrm{FAMILY\ FIRM}_{i,t}$	Dummy variable that equals one for family firms listed in the S&P 500, where founding family is defined as that with an equity ownership of 5% or more. Data for family firms are from 1995 to 2006	Hand Collected
$\mathrm{ROA}_{i,t}$	Return on assets measured as operating income (#170 minus #192) scaled by lagged assets (#6)	Compustat
$\mathrm{LEV}_{i,t}$	Leverage ratio measured as long-term debt (#9) scaled by lagged asset (#6)	Compustat
$\Delta\mathrm{NOI}_{i,t}$	Change in loss carry forward (#52) scaled by lagged asset (#6)	Compustat
$\mathrm{NOI}_{i,t}$	Dummy variable that equals one if loss carry forward (#52) is positive as of the beginning of the year	Compustat

$FI_{i,t}$	Foreign income (#273) for firm i, year t, scaled by lagged assets (#6)	Compustat
$PPE_{i,t}$	Property, plant, and equipment (#8) scaled by lagged assets (#6)	Compustat
$INTANG_{i,t}$	Intangible assets (#33) scaled by lagged assets (#6)	Compustat
$EQINC_{i,t}$	Equity income in earnings (#55) scaled by lagged assets (#6)	Compustat
$SIZE_{i,t}$	Natural logarithm of firm i's total assets (#6)	Compustat
$MTB_{i,t-1}$	Market-to-book ratio for firm i, at the beginning of year t, measured as market value of equity [(#199) × (#25)], scaled by book value of equity (#60)	Compustat
$RD_{i,t}$	Research and development ratio measured as research and development expense (#46) scaled by lagged total assets (#6). Missing values are set to zero.	Compustat
$CASH_{i,t}$	Cash and cash equivalents (#1) scaled by lag of total assets (#6) net of cash	Compustat
$LAGE_{i,t}$	Natural logarithms of firm age in Compustat	Compustat
$DIV_{i,t}$	Dummy variable that equals one if a firm pays dividends (#201)	Compustat
$EMP_{i,t}$	Number of employees in the firm (#29) in thousands	Compustat

Appendix B

Essay 2_Variable Definitions

Variable	Definition	Source
Panel A: Investors' Attention Measure		
Monthly SVI	Arithmetic average of weekly SVI	Google Trends
Log(ABSVI)	Natural logarithm of monthly SVI scaled by previous month's SVI	Google Trends
Log(SVI Duration)	Natural logarithm of number of months that separate the trade month and first valid SVI month	Google Trends
Log(ABSVI_City) /Log(ABSVI_Metro)	Natural logarithm of ABSVI that matches search interests of city/metropolitan statistical	Google Trends

	areas where the firm's headquarter is located	
Attention Dummy	Indicator variable that equals one (zero) if the firm is (is not) in the attention sample	Google Trends
Log(ABSVI) Positive[44]	Indicator variable that equals one (zero) if Log(ABSVI) is (is not) positive	Google Trends
Log(ABSVI) Negative	Indicator variable that equals one (zero) if Log(ABSVI) is (is not) negative	Google Trends
Jump	Indicator variable that equals one (zero) if the ABSVI is (is not) at the top 10 percentile	Google Trends
Fall	Indicator variable that equals one (zero) if the ABSVI is (is not) at the bottom 10 percentile	Google Trends
Fraction Positive Log(ABSVI)	Number of months that have positive Log(ABSVI) scaled by total number of months that ABSVIs are available	Google Trends
Panel B: Insider Trading and Characteristics		
Number of Shares Sold/Bought	Number of shares sold/bought by insiders, in thousands	Thomson Reuters Insider Database
Sales/Purchase Dummy	Indicator variable that equals one (zero) if firm-month is (is not) a net sale/purchase month	Thomson Reuters Insider Database
Top-level/Inside/Independent director	Indicator variable equals to one if a top-level/inside/independent director trade in a firm-month, and zero if otherwise	Thomson Reuters Insider Database
Number of Year Active	Number of years that an insider has been trading	Thomson Reuters Insider Database
Number of Trades	Numbers of trades an insider executes.	Thomson Reuters Insider Database
Panel C: Stock and Firm Characteristics		

[44] We use a similar approach to define the local ABSVI dummies.

Book-to-Market Ratio	The firm's book value scaled by its market value	CRSP, Compustat
Size	Previous year-end market value: share price times number of shares outstanding	CRSP
Log(Analysts)	Natural logarithm of 1+number of analysts covering the firm	IBES
Advertising/Sales	Advertising Expenditure scaled by sales	Compustat
Log(Price)	Natural logarithm of stock price at previous year's end	Compustat
CAR	Firm market adjusted return	CRSP
Turnover	Average monthly turnover scaled by share outstanding	CRSP
Std Market Return	Standard deviation of equally weighted market returns	CRSP
Market	Equally-weighted market return	CRSP
Excess Return	Stock return minus risk-free rate	CRSP, Fama French Data Library
Geo Dispersion	Natural logarithm of 1+number of states in which the firm operates	Compustat Segment
Poorly Governed Firms	Indicator variable that equals one (zero) if G-index is equal or larger than (less than) 12	ISS (Formerly Risk Metrics)
SA Index	Computed as (-0.737*Size) + (0.043* Size^2)-(0.040* Age), where Size is the log of inflation-adjusted book asset, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. The size is capped at the log of $4.5 billion, and age is winsorized at thirty-seven years.	Compustat
KLD Index	KLD is computed by subtracting total concerns from total strength from those seven dimensions.	KLD Social Ratings Database
Product Dispersion: HHI	Herfindahl-Hirschman Index based on product sales	Compustat Product

Fortune100_DUM	Indicator variable that equals one (zero) if a firm is (is not) one of Fortune 100 best companies to work for	Fortune Magazine
Fortune100_Rank	Natural logarithm of ranks of 100 best companies to work for	Fortune Magazine
Lottery	Indicator variable that equals one (zero) if a stock is (is not) a lottery-type stock as defined in Kumar (2009)	CRSP
SUE	Actual EPS minus median forecasted EPS over those posted 90 days prior to the earnings report day scaled by the price per share	IBES, Compustat
Panel D: SEC Litigation		
Number of SEC Release	Natural logarithm of 1+number of releases of SEC litigation cases	SEC
Panel E: Macro News		
GDP Final	Indicator variable that equals one (zero) if there is (is not) an announcement on the GDP Final	Bloomberg
FOMC	Indicator variable that equals one (zero) if there is (is not) an FOMC rate decision announcement	Bloomberg

Appendix C: Tables and Figures

Table 1: Sample Statistics

This table provides sample statistics. Panel A presents descriptive statistics on the tax aggressiveness measures for the observations used in the baseline regression analysis as well as advertising expenditure and all control variables. Panel B shows the Pearson correlation of tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations for which data for advertising expenditure, control variables of our baseline regression, and at least one tax aggressive variable are available. Appendix A provides detailed definitions on all the variables.

Table 1 (Continued)

Panel A. Descriptive Statistics

Variable	**N**	**Mean**	**Std Dev**	**P25**	**Median**	**P75**
$SHELTER_{i,t}$	13,118	0.305	0.460	0.000	0.000	1.000
$CETR_{i,t}$	9,937	0.277	0.171	0.156	0.281	0.376
$KIMBTD_{i,t}$	14,256	0.621	1.269	0.013	0.078	0.476
$DDKIMBTD_{i,t}$	14,247	0.649	1.272	0.030	0.104	0.517
$DTAX_{i,t}$	13,735	0.014	0.148	-0.020	0.015	0.060
$ADVERTISING_{i,t}$						
(Million $)	14,871	51.719	232.957	0.300	2.300	17.229
$LOG(ADV)_{i,t}$	14,871	14.393	3.386	12.612	14.648	16.662
$ADVGP_{i,t}$	14,807	0.080	0.141	0.011	0.035	0.098
$ASSET_{i,t}$ (Million $)	14,871	1835.040	7753.270	30.364	171.318	854.500
$ROA_{i,t}$	14,871	0.033	0.162	-0.096	0.041	0.130
$LEV_{i,t}$	14,871	0.191	0.286	0.000	0.078	0.275
$CNOI_{i,t}$	14,871	0.131	0.500	-0.001	0.000	0.064
$NOI_{i,t}$	14,871	0.687	0.464	0.000	1.000	1.000
$FI_{i,t}$	14,871	0.007	0.024	0.000	0.000	0.000
$PPE_{i,t}$	14,871	0.239	0.233	0.067	0.165	0.327
$INTANG_{i,t}$	14,871	0.179	0.234	0.002	0.078	0.276
$EQINC_{i,t}$	14,871	0.000	0.004	0.000	0.000	0.000
$RD_{i,t}$	14,871	0.181	1.174	0.000	0.000	0.080
$LAGE_{i,t}$	14,871	2.510	0.841	1.946	2.565	3.135
$DIV_{i,t}$	14,871	0.244	0.430	0.000	0.000	0.000
$SIZE_{i,t}$	14,871	18.847	2.423	17.229	18.959	20.566
$MTB_{i,t-1}$	14,871	2.834	6.150	0.975	1.891	3.572
$CASH_{i,t}$	14,871	0.230	0.320	0.028	0.108	0.308
$EMP_{i,t}$ (Thousands)	14,497	7.400	18.445	0.167	0.924	4.950

Table 1 (Continued)

Panel B: Pearson Correlations

	$CETR_{i,t}$	$SHELTER_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$
$SHELTER_{i,t}$	-0.094			
	(0.00)			
$KIMBTD_{i,t}$	-0.283	0.513		
	(0.00)	(0.00)		
$DDKIMBTD_{i,t}$	-0.289	0.508	0.999	
	(0.00)	(0.00)	(0.00)	
$DTAX_{i,t}$	-0.189	0.136	0.069	0.051
	(0.00)	(0.00)	(0.00)	(0.00)

Table 2: Univariate Analysis

This table presents a comparison of equally weighted portfolio means for five measures of tax aggressiveness by quintile of firms' market value and advertising expenditure. The portfolios are formed by first dividing the sample into five quintiles based on the market capitalization. Then each market value quintile is sub-divided into five quintiles based on the advertising expenditure. Advertising expenditures and firms' market values are obtained from COMPUSTAT. The significant levels for the differences are computed based on two tails t-test, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Market Value Quintile				
Advertising Quintile	Smallest	2	3	4	Largest
$SHELTER_{i,t}$					
Smallest	0.497	0.492	0.353	0.283	0.571
2	0.375	0.352	0.285	0.215	0.318
3	0.377	0.264	0.211	0.160	0.307
4	0.317	0.188	0.184	0.152	0.281
Largest	0.202	0.144	0.119	0.157	0.291
Difference (largest-Small)	-0.295***	-0.348***	-0.234***	-0.126***	-0.280***
$CETR_{i,t}$					
Smallest	0.193	0.240	0.267	0.253	0.265
2	0.201	0.294	0.306	0.305	0.297
3	0.239	0.285	0.306	0.303	0.302
4	0.247	0.278	0.329	0.314	0.301
Largest	0.263	0.326	0.326	0.327	0.301
Difference (largest-Small)	0.070***	0.086***	0.059***	0.074***	0.036***
$KIMBTD_{i,t}$					
Smallest	2.121	1.828	1.112	0.492	0.245
2	1.567	1.209	0.721	0.294	0.143
3	1.424	0.712	0.488	0.224	0.077
4	1.177	0.583	0.365	0.161	0.078
Largest	0.690	0.309	0.174	0.128	0.077
Difference (largest-Small)	-1.431***	-1.519***	-0.938***	-0.364***	-0.168***
$DDKIMBTD_{i,t}$					

Smallest	2.160	1.865	1.137	0.514	0.278
2	1.607	1.236	0.750	0.320	0.170
3	1.456	0.740	0.513	0.253	0.101
4	1.205	0.615	0.393	0.188	0.102
Largest	0.720	0.340	0.201	0.152	0.101
Difference (largest-Small)	-1.440***	-1.525***	-0.936***	-0.362***	-0.177***

Table 2 (Continued)

$DTAX_{i,t}$					
Smallest	0.017	0.006	0.007	0.014	0.015
2	0.022	0.003	0.005	0.011	0.009
3	0.010	0.003	0.004	0.005	0.008
4	0.007	0.004	0.005	0.002	0.007
Largest	0.006	0.000	0.000	0.003	0.008
Difference (largest-Small)	-0.011**	-0.006**	-0.007**	-0.011**	-0.007***

Table 3: Baseline Regression

Table 3 provides regression results on the relation between advertising and various tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations covering the period 1995-2013 for which data for advertising expenditure, control variables of our baseline regression and at least one tax aggressive measure is available. Appendix A provides detailed definitions on all the variable. Year and industry dummies (based on two-digit SIC industry code) are included in each specification. The t-statistics and z-statistics, reported in parentheses, are based on standard errors clustered at the firm level, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Log of Advertising

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$LOG(ADV)_{i,t}$	-0.046***	0.005**	-0.017***	-0.016***	-0.004***
	(-3.79)	(2.03)	(-4.31)	(-4.11)	(-3.85)
$ROA_{i,t}$	1.091***	-1.145***	0.108**	-0.001	0.228***
	(5.89)	(-28.10)	(2.17)	(-0.01)	(14.77)
$LEV_{i,t}$	0.149	0.003	0.154***	0.135***	0.012
	(1.55)	(0.13)	(5.19)	(4.81)	(1.44)
$\Delta NOI_{i,t}$	1.188***	0.220***	0.707***	0.703***	-0.059***
	(15.49)	(5.37)	(20.53)	(20.28)	(-7.39)
$NOI_{i,t}$	0.863***	-0.029***	0.090***	0.092***	0.041***
	(12.78)	(-3.72)	(9.98)	(10.55)	(15.01)
$FI_{i,t}$	5.724***	-0.630***	0.479**	0.538***	0.164***
	(5.96)	(-4.54)	(2.41)	(2.77)	(2.71)
$PPE_{i,t}$	-0.033	-0.071***	-0.100***	-0.083***	-0.006
	(-0.22)	(-2.82)	(-3.29)	(-2.84)	(-0.69)
$INTANG_{i,t}$	-0.363***	-0.081***	-0.160***	-0.155***	-0.020**
	(-3.19)	(-4.34)	(-5.14)	(-5.11)	(-2.54)
$EQINC_{i,t}$	13.044**	-2.841***	1.580	1.558	-1.076***
	(2.29)	(-3.51)	(1.57)	(1.60)	(-3.09)
$SIZE_{i,t}$	0.049***	-0.011***	-0.032***	-0.032***	0.001
	(2.70)	(-3.07)	(-5.72)	(-5.92)	(0.66)
$RD_{i,t}$	0.044*	0.105**	-0.031***	-0.032***	-0.009***
	(1.78)	(2.09)	(-3.13)	(-3.22)	(-2.89)
$LAGE_{i,t}$	0.131***	-0.019***	0.041***	0.038***	0.001
	(3.69)	(-4.00)	(6.11)	(5.70)	(0.61)
$MTB_{i,t-1}$	0.008**	0.004***	-0.005***	-0.005***	-0.001*
	(2.04)	(4.76)	(-3.63)	(-3.50)	(-1.69)
$DIV_{i,t}$	0.030	0.004	-0.001	0.000	-0.013***
	(0.44)	(0.48)	(-0.09)	(0.04)	(-4.85)
Lag(DepVar)	1.801***	0.293***	0.837***	0.796***	-0.132***

	(37.68)	(13.37)	(69.81)	(72.22)	(-8.72)
Observations	13,118	9,937	14,256	14,247	13,735
(Pseudo) R-square	0.239	0.358	0.838	0.845	0.117

Table 3 (Continued)
Panel B: Advertising Intensity

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$ADVGP_{i,t}$	-0.401**	0.078*	-0.169***	-0.170***	-0.047***
	(-2.04)	(1.88)	(-3.57)	(-3.59)	(-3.26)
$ROA_{i,t}$	0.687***	-1.137***	0.098*	-0.011	0.223***
	(3.56)	(-27.56)	(1.95)	(-0.23)	(14.41)
$LEV_{i,t}$	0.174*	0.003	0.153***	0.135***	0.011
	(1.72)	(0.16)	(5.20)	(4.82)	(1.39)
$\Delta NOI_{i,t}$	1.237***	0.229***	0.712***	0.709***	-0.057***
	(14.81)	(5.47)	(20.67)	(20.41)	(-7.19)
$NOI_{i,t}$	0.754***	-0.029***	0.091***	0.093***	0.041***
	(10.52)	(-3.65)	(10.09)	(10.67)	(15.06)
$FI_{i,t}$	5.845***	-0.632***	0.483**	0.543***	0.164***
	(5.75)	(-4.54)	(2.43)	(2.79)	(2.71)
$PPE_{i,t}$	1.345***	-0.073***	-0.089***	-0.073**	-0.005
	(8.39)	(-2.91)	(-2.95)	(-2.50)	(-0.56)
$INTANG_{i,t}$	-0.239**	-0.083***	-0.152***	-0.147***	-0.019**
	(-1.99)	(-4.47)	(-4.91)	(-4.88)	(-2.37)
$EQINC_{i,t}$	-0.767	-2.910***	1.607	1.589*	-1.124***
	(-0.12)	(-3.59)	(1.63)	(1.67)	(-3.23)
$SIZE_{i,t}$	-0.099***	-0.006**	-0.049***	-0.049***	-0.003***
	(-7.00)	(-2.52)	(-11.74)	(-11.72)	(-3.06)
$RD_{i,t}$	0.058**	0.105**	-0.031***	-0.032***	-0.010***
	(1.96)	(2.09)	(-3.11)	(-3.21)	(-2.93)
$LAGE_{i,t}$	0.187***	-0.019***	0.037***	0.034***	0.001
	(4.92)	(-3.84)	(5.60)	(5.19)	(0.39)
$MTB_{i,t-1}$	0.020***	0.004***	-0.005***	-0.005***	-0.001*
	(4.57)	(4.82)	(-3.61)	(-3.47)	(-1.70)
$DIV_{i,t}$	-0.062	0.005	-0.001	0.000	-0.014***
	(-0.84)	(0.57)	(-0.11)	(0.03)	(-4.98)
Lag(DepVar)	1.868***	0.294***	0.839***	0.798***	-0.130***
	(37.01)	(13.39)	(70.66)	(73.08)	(-8.63)
Observations	13,110	9,937	14,234	14,247	13,723
(Pseudo) R-square	0.300	0.359	0.838	0.845	0.116

Table 4: Opacity, Advertising and Tax Aggressiveness

This table provides regression results on the relation between advertising and various tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations covering the period 1995-2013 for which data for advertising expenditure, control variables of our baseline regression and at least one tax aggressive measure is available. The variable $OPACITY_{i,t}$ is constructed using daily CRSP and IBES datasets Variable definitions are provided in Appendix A. Year and industry dummies (based on two-digit SIC industry code) are included in each specification. The t-statistics and z-statistics, reported in parentheses, are based on standard errors clustered on the firm level, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	Logit	OLS	OLS	OLS	OLS
$LOG(ADV)_{i,t}$	-0.153***	0.016***	-0.019**	-0.019**	-0.007***
	(-4.48)	(3.07)	(-2.52)	(-2.52)	(-3.61)
$OPACITY_{i,t}$	6.139***	-0.308**	1.083***	1.057***	0.039*
	(7.02)	(-2.33)	(5.36)	(5.20)	(1.84)
$LOG(ADV)_{i,t}$*$OPACITY_{i,t}$	-0.428***	0.023***	-0.071***	-0.070***	-0.004*
	(-7.60)	(2.73)	(-5.49)	(-5.38)	(1.66)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	8,174	5,745	8,919	8,913	8,716
(Pseudo) R-square	0.236	0.354	0.799	0.806	0.101

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	Logit	OLS	OLS	OLS	OLS
$ADVGP_{i,t}$	-1.67**	0.069*	-0.111**	-0.112**	-0.047**
	(-2.02)	(1.69)	(-2.06)	(-2.09)	(-2.22)
$OPACITY_{i,t}$	0.032	-0.061**	0.038	0.028	0.031***
	(0.86)	(-2.12)	(0.84)	(0.64)	(2.94)
$ADVGP_{i,t}$*$OPACITY_{i,t}$	-5.118***	0.173*	-0.513***	-0.506***	-0.124*
	(-2.83)	(1.70)	(-2.77)	(-2.88)	(-1.89)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	8,174	5,745	8,918	8,912	8,716

(Pseudo) R-square	0.270	0.236	0.800	0.804	0.098

Table 5: The Effects of Public Scrutiny and External Monitoring

This table provides regression results on the relation between advertising and various tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations covering the period 1995-2013 for which data for advertising expenditure, control variables of our baseline regression and at least one tax aggressive measure is available. The variable $SP1500_{i,t}$ is a dummy variable that equals one if a firm is listed in the S&P 1500 index within a firm year. INST. $OWN_{i,t}$ is the average of quarterly institutional holdings over the number of share outstanding within a firm year. Variable definitions are provided in Appendix A. Year and industry dummies (based on two-digit SIC industry code) are included in each specification. The t-statistics and z-statistics, reported in parentheses, are based on standard errors clustered at the firm level, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: S&P 1500

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$LOG(ADV)_{i,t}$	-0.055***	0.003	-0.018***	-0.017***	-0.004***
	(-4.49)	(1.23)	(-4.57)	(-4.37)	(-4.07)
$SP1500_{i,t}$	-3.719***	0.142*	-0.432***	-0.413***	-0.106***
	(-6.07)	(1.90)	(-5.53)	(-5.49)	(-4.22)
$LOG(ADV)_{i,t}$*$SP1500_{i,t}$	0.221***	-0.007*	0.028***	0.027***	0.006***
	(6.06)	(-1.68)	(5.96)	(5.89)	(4.12)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,118	9,937	14,256	14,247	13,735
(Pseudo) R-squared	0.241	0.502	0.838	0.845	0.118

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$ADVGP_{i,t}$	-0.437***	0.055*	-0.181***	-0.171***	-0.049***
	(-2.75)	(1.66)	(-3.67)	(-3.56)	(-3.23)
$SP1500_{i,t}$	-0.184*	0.025**	-0.001	-0.007	-0.010**

	(-1.85)	(2.20)	(-0.05)	(-0.52)	(-2.33)
$ADVGP_{i,t}*SP1500_{i,t}$	0.062	-0.075*	0.286***	0.346**	0.024
	(1.09)	(-1.92)	(3.65)	(2.49)	(1.56)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,110	9,937	14,234	14,247	13,723
(Pseudo) R-squared	0.289	0.502	0.838	0.845	0.117

Table 5 (Continued)

Panel B: Inst. Ownership

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$LOG(ADV)_{i,t}$	-0.116***	0.003**	-0.039***	-0.037***	-0.003*
	(-5.69)	(2.11)	(-5.62)	(-5.46)	(-1.68)
$INST.OWN_{i,t}$	-2.596***	0.083***	-0.794***	-0.739***	0.014
	(-5.18)	(3.09)	(-5.79)	(-5.49)	(0.44)
$LOG(ADV)_{i,t}$*$INST.OWN_{i,t}$	0.137***	-0.004***	0.053***	0.050***	0.002*
	(4.14)	(-2.62)	(5.90)	(5.66)	(1.77)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	10,252	8,160	11,166	11,160	10,876
(Pseudo) R-squared	0.236	0.476	0.814	0.821	0.109

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$ADVGP_{i,t}$	-0.456*	0.081*	-0.293***	-0.290***	-0.087***
	(-1.68)	(1.89)	(-3.74)	(-3.74)	(-3.01)
$INST.OWN_{i,t}$	-0.630***	0.019*	-0.041*	-0.028	-0.025***
	(-4.88)	(1.69)	(-1.80)	(-1.27)	(-3.90)
$ADVGP_{i,t}$* $INST.OWN_{i,t}$	0.628***	-0.087	0.448***	0.419***	0.118***
	(2.26)	(-1.06)	(3.30)	(3.11)	(2.72)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	10,251	8,160	11,160	11,157	10,874
(Pseudo) R-squared	0.233	0.477	0.814	0.821	0.108

Table 6: Family and Non-Family Firms

Note: This table provides regression results on the relation between advertising and various tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations covering the period 1995-2013 for which data for advertising expenditure, control variables of our baseline regression, and at least one tax aggressive measure is available. The variable FAMILY $FIRM_{i,t}$ is a dummy variable which equals one if founders or their family members (by either blood or marriage) are key executives, directors, or blockholders. Variable definitions are provided in Appendix A. Year and industry dummies (based on two-digit SIC industry code) are included in each specification. The t-statistics and z-statistics, reported in parentheses, are based on standard errors clustered at the firm level, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Variables	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	Logit	OLS	OLS	OLS	OLS
$LOG(ADV)_{i,t}$	-0.991**	0.016*	-0.013***	-0.011***	-0.005*
	(-2.30)	(1.82)	(-3.02)	(-2.65)	(-1.66)
FAMILY $FIRM_{i,t}$	-1.941***	0.455**	-0.221***	-0.209**	0.049
	(-2.89)	(2.03)	(-2.66)	(-2.57)	(0.35)
$LOG(ADV)_{i,t}$* FAMILY $FIRM_{i,t}$	1.071***	-0.022*	0.011**	0.010**	-0.003
	(3.00)	(-1.91)	(2.51)	(2.46)	(-1.46)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	341	376	430	430	429
(Pseudo) R-squared	0.483	0.333	0.766	0.795	0.276
	Logit	OLS	OLS	OLS	OLS
$ADVGP_{i,t}$	-3.160	0.131*	-0.021***	-0.020**	-0.032
	(-1.35)	(1.91)	(-2.78)	(-2.20)	(-1.14)
FAMILY $FIRM_{i,t}$	-1.293*	0.004	-0.015**	-0.017**	-0.007
	(-1.81)	(0.17)	(-2.55)	(-2.60)	(-0.84)
$ADVGP_{i,t}$ * FAMILY $FIRM_{i,t}$	6.124*	-0.238*	0.066*	0.071**	0.070**
	(1.65)	(-1.74)	(1.73)	(2.06)	(2.02)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	341	376	430	430	429
(Pseudo) R-squared	0.483	0.328	0.760	0.760	0.275

Table 7: Endogeneity Tests

This table provides regression results on the relation between advertising and various tax aggressiveness measures. The initial sample consists of 14,871 firm-year observations covering the period 1995-2013 for which data for advertising expenditure, control variables of our baseline regression, and at least one tax aggressive measure is available. Panel A presents the IV regression and we use the log of number of zero-political connection customers as our instrument variable. The controls from first-stage regressions include $ROA_{i,t}$, $CASH_{i,t}$, $LEMP_{i,t}$, $LEV_{i,t}$, $SIZE_{i,t}$, $MTB_{i,t-1}$, $RD_{i,t}$, $PPE_{i,t}$, $INTANG_{i,t}$, $DIV_{i,t}$ and $LAGE_{i,t}$ plus year and industry dummy (based on first two digit SIC code). Panel B shows the results from propensity score matching. Propensity scores are calculated using a logit model where the dependent variable is the high advertising dummy $HADVDUM_{i,t}$ and control variables are the same as in the IV regressions of Panel A plus year and industry dummy (based on two-digit SIC industry code). The t-statistics and z-statistics, reported in parentheses, are based on standard errors clustered at the firm level, and ***, **, and * denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Instrumental Variable

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$LOG(ADV)_{i,t}$	-0.228***	0.015**	-0.020**	-0.017**	-0.007***
	(-3.35)	(2.39)	(-2.41)	(-2.08)	(-3.19)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.415	0.509	0.841	0.848	0.112
N	6,199	4,533	6,635	6,632	5,367

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$ADVGP_{i,t}$	-5.868**	0.442***	-0.252**	-0.184*	-0.007***
	(-2.05)	(2.87)	(-2.31)	(-1.91)	(-3.19)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.288	0.499	0.849	0.847	0.112
N	6,199	4,533	6,635	6,632	5,367

Panel B: Propensity Score Matching

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$HADVDUM_{i,t}$	-0.011**	0.036**	-0.047**	-0.048**	-0.019***
	(-2.08)	(2.23)	(-2.23)	(-2.24)	(-3.25)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.239	0.444	0.757	0.760	0.152
N	1,615	1,768	1,954	1,954	1,882

Table 8: Additional Tests

This table reports the results of several additional analyses based on the baseline regressions. Panel A presents the results based on the firm level regression. All except dummy variables are averaged for the whole sample period between 1995 and 2013. Firm-level dummy variables such as $SHELTER_{i,t}$, $NOI_{i,t}$, and $DIV_{i,t}$ are denoted as 1 if those variables equal one at least half of the entire sample period, and equal zero if otherwise. We use those firm-level variables to run the firm-level regression. Panel B shows the results of running the Fama-MacBeth Regression. Panel C displays the results of using Hackman's two-stage procedure and the Inverse Mills Ratios are computed from the first-stage logit regression. The controls from first-stage regressions include $ROA_{i,t}$, $CASH_{i,t}$, $LEMP_{i,t}$, $LEV_{i,t}$, $SIZE_{i,t}$, $MTB_{i,t-1}$, $RD_{i,t}$, $PPE_{i,t}$, $INTANG_{i,t}$, $DIV_{i,t}$ and $LAGE_{i,t}$ plus year and industry dummy (based on two-digit SIC industry code). Panel D shows the results of baseline regression using firms' fixed effect.

Panel A: Firm level Regression

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
$LOG(ADV)_{i,t}$	-0.077***	0.003*	-0.014***	-0.013***	-0.002**
	(-3.15)	(1.66)	(-3.84)	(-3.71)	(-2.44)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.263	0.672	0.872	0.881	0.255
N	2,650	2,056	2,852	2,850	2,727
$ADVGP_{i,t}$	-1.440***	0.034*	-0.219***	-0.211***	-0.052***
	(-3.57)	(1.77)	(-3.89)	(-3.83)	(-4.25)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.265	0.419	0.873	0.881	0.266
N	2,645	2,056	2,842	2,841	2,722

Panel B: Fama-MacBeth Regressions

	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
$LOG(ADV)_{i,t}$	-0.051**	0.004*	-0.008**	-0.011**	-0.004***
	(-2.86)	(1.79)	(-2.43)	(-2.41)	(-6.34)
Controls	Yes	Yes	Yes	Yes	Yes
Average (Pseudo) R-square	0.544	0.497	0.839	0.860	0.148

N	13,118	9,937	14,256	14,247	13,735
$ADVGP_{i,t}$	-0.590***	0.060**	-0.083***	-0.082***	-0.039***
	(-3.42)	(2.54)	(-3.09)	(-3.08)	(-3.85)
Controls	Yes	Yes	Yes	Yes	Yes
Average (Pseudo) R-square	0.441	0.497	0.837	0.846	0.147
N	13,110	9,937	14,234	14,247	13,723
Panel C: Heckman Two Stage					
	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
$HADVDUM_{i,t}$	-0.209***	0.011**	-0.025**	-0.028**	-0.016***
	(-3.04)	(2.15)	(-2.11)	(-2.31)	(-4.61)

Table 8 (Continued)

$INVERSE\_MILLS\_RATIO_{i,t}$	1.286***	-0.015**	0.231***	0.225***	-0.133***
	(16.5)	(-2.07)	(9.88)	(9.69)	(-8.80)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.255	0.502	0.841	0.848	0.117
N	13,086	9,916	14,218	14,210	13,698
Panel D: Firms Fixed Effect					
	$SHELTER_{i,t}$	$CETR_{i,t}$	$KIMBTD_{i,t}$	$DDKIMBTD_{i,t}$	$DTAX_{i,t}$
$LOG(ADV)_{i,t}$	-0.053*	0.001	-0.025***	-0.024***	-0.003
	(-1.92)	(1.29)	(-2.93)	(-2.83)	(-1.35)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.547	0.696	0.910	0.914	0.408
N	7,599	9,937	14,256	14,247	13,735
$ADVGP_{i,t}$	-0.251	0.078*	-0.114**	-0.120**	-0.032
	(-0.97)	(1.69)	(-2.12)	(-2.05)	(-1.05)
Controls	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.529	0.696	0.910	0.914	0.407
N	7,013	9,937	14,234	14,247	13,723

Table 9: Summary Statistics

This table reports the summary statistics of sample firm-months for opportunistic insiders from January 2004 to November 2014. Panel A compares our sample's firm and insider characteristics with those in the insider universe. Panel B presents our attention and non-attention samples in firm-sale and firm-purchase months. Variable Size is based on the previous year-end market value (in millions of dollars). Variable BTM is the previous year-end book-to-market equity value ratio. Trades per firm-month, traders per firm month, and the number of firms per month are also reported. If a firm-month contains both an insider net sale and an insider net purchase, the observation is removed from the sample.

Non-routine Insiders (2004-2014)	**Our Sample (Jan. 2004-Nov. 2014)**			**Whole Sample (Jan. 1986-Nov. 2014)**	
Panel A: Attention Sample Vs Insider Universe	**Mean**	**Median**		**Mean**	**Median**
Size	4,599.44	923.31		4,297.72	751.96
BTM	0.56	0.47		0.57	0.47
Trades per firm-month	2.87	2.00		2.88	2.00
Traders per firm-month	1.71	1.00		1.72	1.00
Firms per month	708.66	698.00		621.79	622.00
Panel B: Decomposition of Our Sample	**Mean**	**P25**	**Median**	**Std.**	**P75**
SVI Firm Sales (3,096 firms, 52,477 firm-month observations)					
Size	6,741.29	514.10	1,457.19	15,994.14	4,604.91
BTM	0.54	0.27	0.45	0.38	0.70
Trades per firm-month	2.77	1.00	2.00	2.98	3.00
Traders per firm-month	1.70	1.00	1.00	1.15	2.00
Firms per month	399.21	318.00	381.00	120.04	492.00
No-SVI Firm Sales (1,224 firms,15,739 firm-month observations）					
Size	1,073.19	258.65	529.43	1,947.54	1,102.51
BTM	0.49	0.24	0.42	0.36	0.64
Table 9 (Continued)					
Trades per firm-month	2.95	1.00	2.00	3.08	4.00
Traders per firm-month	1.65	1.00	1.00	1.09	2.00
Firms per month	120.15	92.00	124.00	38.27	145.00

SVI Firm Purchase (2,667 firms and 16,997 firm-month observations)					
Size	5,477.28	312.48	892.26	15,557.39	2,988.72
BTM	0.65	0.35	0.57	0.43	0.84
Table 9 (Continued)					
Trades per firm-month	2.17	1.00	1.00	1.99	2.00
Traders per firm-month	1.52	1.00	1.00	0.99	2.00
Firms per month	129.75	87.00	119.00	64.63	161.00
No-SVI Firm Purchase (1,063 firms and 7,621 firm-month observations)					
Size	663.53	163.76	293.16	1,479.03	612.84
BTM	0.63	0.37	0.56	0.38	0.81
Trades per firm-month	2.44	1.00	2.00	2.11	3.00
Traders per firm-month	1.67	1.00	1.00	1.12	2.00
Firms per month	58.18	36.00	56.00	26.96	74.00

Table 10: Industry Classification

This table reports the distribution of firms in our sample based on Fama-French 17 industry Classifications. Panel A shows the percentage of firms in each classification and the difference between our attention and non-attention samples. Panel B shows the difference of monthly Google SVI between the purchase and sale months. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Sample Distribution	**No-SVI firms**	**SVI firms**	**Difference**
Food	1.40%	2.55%	-1.16%
Mining and minerals	0.51%	1.23%	-0.73%
Oil and petro products	1.88%	5.14%	-3.26%
Textiles, apparel, and footwear	0.58%	1.56%	-0.98%
Consumer duration	0.87%	1.56%	-0.70%
Chemicals	1.08%	2.31%	-1.23%
Drugs, soap, perfume, tobacco	6.06%	3.88%	2.19%
Construction	1.73%	2.70%	-0.97%
Steel	0.79%	1.26%	-0.47%
Fabricated products	0.36%	0.57%	-0.21%
Machinery and business equipment	10.90%	12.05%	-1.14%
Automobile	0.79%	1.47%	-0.68%
Transportation	2.17%	3.30%	-1.14%
Utilities	0.65%	2.91%	-2.26%
Retail stores	4.19%	6.01%	-1.82%
Financial Institutions	27.51%	16.40%	11.11%
Other	38.56%	35.09%	3.47%

Panel B: Average Monthly SVI	**Purchase**	**Sales**	**Difference**
Food	34.64	37.07	-2.43**
Mining and minerals	37.84	40.55	-2.71**
Oil and petro products	35.23	33.07	2.16***

Textiles, apparel, and footwear	33.49	37.31	-3.82***
Consumer duration	34.47	39.71	-5.24***
Chemicals	35.10	37.54	-2.43***
Drugs, soap, perfume, tobacco	28.85	34.42	-5.57***
Construction	39.45	39.36	0.08
Steel	41.01	36.15	4.86***
Fabricated products	44.53	46.90	-2.37**
Machinery and business equipment	32.86	31.85	1.01**
Automobile	35.66	36.48	-0.82
Transportation	32.79	32.40	0.39
Table 10 (Continued)			
Utilities	39.36	36.85	2.51***
Retail stores	36.28	34.76	1.52**
Financial Institutions	29.86	31.91	-2.05***
Other	32.70	32.45	0.24
Whole Sample	33.24	33.58	-0.34**

Table 11: Market-adjusted Returns Following Insider Trades

This table reports one-month NYSE size decile portfolio adjusted cumulative abnormal returns (CARs) following the insider trading month. CARs for trade months by insiders of attention firms are compared with those by insiders of non-attention firms. Panels A and B present the results for insider sales and purchases, respectively. In both panels, Column 1 reports results on all insiders, Column 2 on top-level officers (CEO, CFO, COO, and Chairman of the Board), Column 3 on directors in, and Column 4 on all other insiders. Standard errors are included in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Abnormal Returns	All Insiders (1)	Top-level officers (2)	Only directors (3)	Other Insiders (4)
Panel A: Sales				
SVI Firms				
Size_adj CAR(%)	-0.688***	-0.930***	-0.895***	-0.497***
Standard Deviation	(0.093)	(0.094)	(0.099)	(0.092)
Number of Observations	52,477	16,024	20,426	24,461
SVI firms in No-SVI months				
Size_adj CAR(%)	-0.541***	-0.747***	-0.614***	-0.490***
Standard Deviation	(0.094)	(0.098)	(0.096)	(0.093)
Number of Observations	4,626	1,608	1,992	2,479
No-SVI Firms				

Size_adj CAR(%)	-0.495***	-0.715***	-0.449***	-0.248***
Standard Deviation	(0.093)	(0.095)	(0.090)	(0.096)
Number of Observations	15,739	5,448	6,723	8,404
Panel B: Purchase				
SVI Firms				
Size_adj CAR(%)	1.010***	1.334***	0.777***	1.111***
Standard Deviation	(0.010)	(0.108)	(0.098)	(0.017)
Number of Observations	16,997	4,209	10,387	5,940
SVI Firms in No-SVI months				
Size_adj CAR(%)	1.140***	1.878***	0.792**	1.420***
Standard Deviation	(0.100)	(0.109)	(0.093)	(0.109)
Table 11 (Continued)				
Number of Observations	1,786	443	1,142	597
No-SVI Firms				
Size_adj CAR(%)	1.215***	1.424***	1.027***	1.625***
Standard Deviation	(0.115)	(0.118)	(0.109)	(0.126)
Number of Observations	7,621	2,113	4,903	2,616

Abnormal Returns	All Insiders		Top-level officers		Only directors
	(1)		(2)		(3)
Panel A: Sales					
SVI Firms					
Size_adj CAR(%)	-0.688***		-0.930***		-0.895***
Standard Deviation	(0.093)		(0.094)		(0.099)
Number of Observations	52,477		16,024		20,426
SVI firms in No-SVI months					
Size_adj CAR(%)	-0.541***		-0.747***		-0.614***
Standard Deviation	(0.094)		(0.098)		(0.096)
Number of Observations	4,626		1,608		1,992
No-SVI Firms					
Size_adj CAR(%)	-0.495***		-0.715***		-0.449***
Standard Deviation	(0.093)		(0.095)		(0.090)
Number of Observations	15,739		5,448		6,723

Panel B: Purchase						
SVI Firms						
Size_adj CAR(%)	1.010***		1.334***		0.777***	
Standard Deviation	(0.010)		(0.108)		(0.098)	
Number of Observations	16,997		4,209		10,387	
SVI Firms in No-SVI months						
Size_adj CAR(%)	1.140***		1.878***		0.792**	
Standard Deviation	(0.100)		(0.109)		(0.093)	
Number of Observations	1,786		443		1,142	
No-SVI Firms						
Size_adj CAR(%)	1.215***		1.424***		1.027***	
Standard Deviation	(0.115)		(0.118)		(0.109)	
Number of Observations	7,621		2,113		4,903	

Table 12: Return Analysis on Insider Trades

This table compares CARs following insider trades between our attention and non-attention firms. The dependent variable *Excess* Ret_{t+1} is the one-month excess return following trade month t. Attention dummy equals 1 (0) if a firm is in our attention (non-attention) sample. Log(ABSVI) is the log of monthly SVI scaled by the previous month's SVI. Log(ABSVI Duration) is the log of total number of months separating the trade month and the month of first valid ABSVI. Log(Analysts) is the log of number of analysts covering the firm. Log(Size) is the log of the previous year-end market value of firm. Log(BM) is the log of the previous year-end book-to-market equity value ratio. Advertising/Sales is the previous year-end ratio of advertisement expense to sales. $Market_{t+1}$ is the equal-weighted market return following trade month t. Log(Price) is the log of the previous year-end stock price. Log(Turnover) is the log of average monthly turnover in the previous year, where the monthly turnover is defined as the month's trading volume scaled by the number of shares outstanding: (VOL*100)/(SHROUT*1000). $CAR_{t-3,t-1}$ is the firm's three month market adjusted return from months t-3 to t-1. $CAR_{t-12,t-1}$ is the firm's one-year market adjusted return from month t-12 to t-1. Panels A and Panel B show results on insider sales and insider purchases, respectively. Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Insider Sales

Excess Ret_{t+1}	Attention and Non- Attention firms	Attention Firms	Attention Firms	Attention Firms	Attention Firms
	(1)	(2)	(3)	(4)	(5)
Constant	0.0169***	0.0238***	0.0156***	0.0094	0.0363***

	(0.0064)	(0.0077)	(0.0019)	(0.0067)	(0.0015)
Attention Dummy	-0.0022***				
	(0.0007)				
Log(ABSVI)		-0.0059***	-0.0071***	-0.0194***	0.0101*
		(0.0025)	(0.0020)	(0.0061)	(0.0061)
Log(SVI duration)			0.0048**	0.0015	0.0056**
			(0.0019)	(0.0025)	(0.0027)
Log(Analysts)			0.0029***	0.0038***	0.0009
			(0.0008)	(0.0011)	(0.0011)
Log(Size)	-0.0006*	-0.0002	-0.0010**	-0.0012*	-0.0005
	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Log(BM)	-0.0007	-0.0006	-0.0009	-0.0010	-0.0002
	(0.0006)	(0.0008)	(0.0009)	(0.0011)	(0.0011)
Advertising/sales	-0.0081	-0.0136	-0.0185	-0.0361	-0.0106
	(0.0149)	(0.0167)	(0.0182)	(0.0280)	(0.0239)
$Market_{t+1}$	1.0534***	1.0710***	1.0343***	1.0151***	1.0549***
Table 12 (Continued)	(0.0142)	(0.0151)	(0.0162)	(0.0218)	(0.0230)
Log(Price)	-0.0033***	-0.0034***	-0.0032***	-0.0039***	-0.0021
	(0.0008)	(0.0009)	(0.0010)	(0.0013)	(0.0014)
Log(Turnover)	-0.0030***	-0.0026***	-0.0027***	-0.0017	-0.0030**
	(0.0007)	(0.0008)	(0.0010)	(0.0013)	(0.0013)
$CAR_{t-3,t-1}$	0.0066**	0.0059	0.0022	0.0215***	0.0029
	(0.0031)	(0.0039)	(0.0041)	(0.0060)	(0.0055)
$CAR_{t-12,t-1}$	-0.0018	-0.0076***	-0.0071***	-0.0124***	0.0018
	(0.0015)	(0.0019)	(0.0021)	(0.0030)	(0.0028)
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	56,180	39,575	34,289	16,916	16,864
R^2	0.176	0.189	0.194	0.042	0.028

Panel B: Insider Purchase

$Excess\ Ret_{t+1}$	Attention and Non-Attention firms (1)	Attention Firms (2)	Attention Firms (3)	Attention Firms (4)	Attention Firms (5)
Constant	0.1133***	0.1189***	0.1572***	0.1338***	0.1898***
	(0.0123)	(0.0142)	(0.0216)	-0.0297	(0.0317)

Attention Dummy	-0.0035***				
	(0.0012)				
Log(ABSVI)		-0.0140***	-0.0146**	-0.0174	0.0261**
		(0.0054)	(0.0058)	(0.0128)	(0.0132)
Log(SVI duration)			-0.0107***	-0.0162***	-0.0074
			(0.0040)	(0.0053)	(0.0063)
Log(Analysts)			0.0007	-0.0000	0.0009
			(0.0016)	(0.0022)	(0.0022)
			-		
Log(Size)	-0.0038***	-0.0037***	0.0037***	-0.0021	-0.0052***
	(0.0007)	(0.0007)	(0.0009)	(0.0013)	(0.0013)
Log(BM)	-0.0012	-0.0014	-0.0020	-0.0017	-0.0020
	(0.0014)	(0.0016)	(0.0017)	(0.0023)	(0.0024)
Advertising/sales	0.0702*	0.0091	0.0284	-0.0430	0.1033*
	(0.0401)	(0.0411)	(0.0453)	(0.0556)	(0.0615)
$Market_{t+1}$	1.1314***	1.1483***	1.2149***	1.1835***	1.2090***
	(0.0227)	(0.0262)	(0.0304)	(0.0407)	(0.0412)
			-		
Log(Price)	-0.0101***	-0.0104***	0.0103***	-0.0096***	-0.0102***
	(0.0015)	(0.0017)	(0.0018)	(0.0025)	(0.0027)
Log(Turnover)	-0.0024**	-0.0015	-0.0017	-0.0057**	0.0020
	(0.0011)	(0.0013)	(0.0018)	(0.0025)	(0.0025)
$CAR_{t-3,t-1}$	-0.0099*	-0.0114*	-0.0131*	-0.0011	-0.0216**
Table 12 (Continued)	(0.0057)	(0.0068)	(0.0074)	(0.0109)	(0.0108)
$CAR_{t-12,t-1}$	-0.0063**	-0.0075**	-0.0060	-0.0034	-0.0090
	(0.0028)	(0.0035)	(0.0040)	(0.0058)	(0.0057)
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	15,262	10,749	8,895	4,282	4,483
R^2	0.242	0.281	0.309	0.323	0.298

Table 13: Predicting Insider Trading

This table presents the results of Logit and Tobit regressions that analyze the likelihood and quantity of insider trading. In Columns 1 and 2, the dependent variable is Sales dummy which equals 1 only if a firm-month is a net sale month. In Columns 3 and 4, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. In Columns 5 and 6, the dependent variable is Purchase dummy which equals 1 only if a firm-month is a net purchase month. In Columns 7 and 8, the dependent variable is the number of shares bought by all insiders (in thousands) for each firm-month observation. Log(ABSVI) is the natural log of monthly ABSVI. Log(ABSVI) Positive (Negative) is a dummy variable which equals 1 if Log(ABSVI) is positive (negative). Log(BM) is the log of the previous year-end book-to-market equity value ratio. Advertising/Sales is the previous year-end ratio of advertisement expense to sales. $Market_t$ is the equal-weighted market return. Log(Price) is the log of the previous year-end stock price. Log(Turnover) is the log of average monthly turnover in the previous year, where the monthly turnover is the month's trading volume scaled by the number of shares outstanding: (VOL*100)/ (SHROUT*1000). Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Probit Regression		Tobit Regression		Probit Regression		Tobit Regression	
	Sales Dummy		Shares Sold		Purchase Dummy		Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	0.087***		27.419***		-0.086***		-5.056**	
	(0.0333)		(7.8125)		(0.0334)		(2.1217)	
Log(ABSVI) Positive		0.041***		10.819***				
		(0.0128)		(2.9966)				
Log(ABSVI) Negative						0.043***		4.518***
						(0.0128)		(1.5824)
Log(Size)	0.011**	0.011**	17.555***	17.526***	-0.012**	-0.012**	0.443	0.764
	(0.0053)	(0.0053)	(1.2222)	(1.2222)	(0.0053)	(0.0053)	(0.6121)	(0.6435)
Log(BM)	-0.137***	-0.138***	-29.435***	-29.487***	0.137***	0.137***	11.538***	12.019***
	(0.0091)	(0.0091)	(2.1012)	(2.1012)	(0.0091)	(0.0091)	(1.0661)	(1.1205)

Advertising/Sales	1.186***	1.186***	438.613***	439.045***	-1.172***	-1.174***	-98.459***	-103.883***
	(0.2038)	(0.2038)	(44.2504)	(44.2506)	(0.2039)	(0.2039)	(23.9102)	(25.1360)

Table 13 (Continued)

$Market_t$	3.785***	3.795***	452.246***	454.008***	-3.772***	-3.784***	-392.012***	-415.846***
	(0.1372)	(0.1373)	(33.8714)	(33.8884)	(0.1373)	(0.1374)	(15.9847)	(16.8168)
Log(Price)	0.123***	0.124***	-48.489***	-48.440***	-0.120***	-0.120***	-22.1177***	-25.068***
	(0.0106)	(0.0106)	(2.4919)	(2.4918)	(0.0106)	(0.0106)	(1.2277)	(1.2904)
Log(Turnover)	0.082***	0.082***	0.034	0.006	-0.079***	-0.0793***	-4.654***	-4.383***
	(0.0087)	(0.0087)	(2.0927)	(2.0926)	(0.0087)	(0.0087)	(1.019)	(1.0711)
Constant	0.170*	0.152	-228.538***	-233.449***	-0.162	-0.186*	-41.964***	-46.262***
	(0.0994)	(0.0995)	(23.1477)	(23.1870)	(0.0995)	(0.0998)	(11.627)	(12.2543)
Obs	50,156	50,156	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.031	0.031	0.002	0.002	0.030	0.030	0.009	0.009

Table 14: Which Insiders Make Opportunistic Trades?

This table reports the results of Logit regressions that examine what types of insiders are likely to engage in opportunistic insider trades. In Columns 1, 3 and 5, the dependent variable is Sales dummy which equals 1 only if a firm-month is a net sale month. In Columns 2, 4 and 6, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. Log(ABSVI) is the natural log of monthly ABSVI. Top-level officer, Insider director, and Independent director are dummy variables equaling 1 if there is a trade in a firm-month by a top-level officer, an inside director, and an independent director, respectively. Log(BM) is the log of the previous year-end book-to-market equity value ratio. Advertising/Sales is the previous year-end ratio of advertisement expense to sales. $Market_t$ is the equal-weighted market return. Log(Price) is the log of the previous year-end stock price. Log(Turnover) is the log of average monthly turnover in the previous year, where the monthly turnover is the month's trading volume scaled by the number of shares outstanding: (VOL*100)/ (SHROUT*1000). We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Sales Dummy (1)	Shares Sold (2)	Sales Dummy (3)	Shares Sold (4)	Sales Dummy (5)	Shares Sold (6)
	Probit	Tobit	Probit	Tobit	Probit	Tobit
Log(Abnormal SVI)	0.128***	28.838***	0.122***	25.347***	0.086**	28.570***
	(0.0364)	(8.604)	(0.0402)	(8.9112)	(0.0344)	(8.0124)
Top Level officers	0.168***	38.264***				
	(0.0147)	(3.3402)				
Log (Abnormal SVI) *Top Level officers	-0.235***	-6.573***				
	(0.0862)	(1.9197)				
Independent Directors			-0.608***	-37.121***		
			(0.0132)	(3.1517)		
Log (Abnormal SVI) *Independent Directors			-0.147**	-5.640**		

			(0.0709)	(2.5627)		
Inside Directors					0.601***	289.832***
					(0.0397)	(7.766)
Log (Abnormal SVI) *Inside Directors					0.075	20.773
Table 14 (Continued)					(0.2003)	(44.5475)
Log(Size)	0.0159***	20.703***	0.0103*	18.957***	0.015***	22.060***
	(0.0053)	(1.2363)	(0.0054)	(1.2353)	(0.0053)	(1.2170)
Log(BM)	-0.133***	-28.870***	-0.1438***	-30.6424***	-0.135***	-28.452***
	(0.0091)	(2.0994)	(0.0092)	(2.1006)	(0.0091)	(2.0676)
Advertising/Sales	1.181***	424.188***	1.084***	420.737***	1.094***	367.028***
	(0.2044)	(44.2117)	(0.2085)	(44.3147)	(0.2045)	(43.6574)
$Market_t$	3.827***	451.840***	3.762***	440.560***	3.782***	436.633***
	(0.1374)	(33.8651)	(0.1400)	(33.9668)	(0.1375)	(33.4033)
Log(Price)	0.125***	-51.417***	0.1348***	-50.8260***	0.126***	-50.776***
	(0.0106)	(2.5260)	(0.0108)	(2.5325)	(0.0106)	(2.4921)
Log(Turnover)	0.077***	-1.633	0.0930***	0.201	0.087***	2.4046
	(0.0087)	(2.0913)	(0.0089)	(2.0957)	(0.0087)	(2.0640)
Constant	0.008	-300.057***	0.4187***	-239.060***	0.067	-325.820***
	(0.1005)	(23.5086)	(0.10223)	(23.4078)	(0.0998)	(23.0277)
Obs	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.0333	0.0018	0.0724	0.0018	0.0355	0.0039

Table 15: Insider Trader and Firm Characteristics

This table reports the results of Logit regressions of being non-senior-executive, non-independent insiders on a number of insider and firm characteristics during the 2004-2014 sample period. The dependent variable is a dummy at the insider level, which equals 1 only for a non-senior-executive, non-independent insider. The main independent variables are: the number of years an insider is active; the number of years an insider has been trading; the number of states a firm has operations; a Poorly Governed Firms dummy that equals 1 if the G-index (Gompers, Ishii, & Metrick, 2003) is greater than or equal to 12; Financial Constraints-SA Index (Hadlock & Pierce, 2010); Product Sales Herfindahl index; Social Responsibility-KLD Index; and a Fortune100 dummy and rankings. All other control variables are described in Table 4. Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of years active	0.361***							
	(0.0125)							
Number of Trades	-0.106***							
	(0.0262)							
Geo Dispersion: # States		0.346*						
		(0.2032)						
Poorly Governed Firm (Gindex>=90 Pecentile)			0.162**					
			(0.0784)					
SA Index (Financial Constraints)				-0.074***				
				(0.0225)				

Product Dispersion: HHI					0.084*			
					(0.0326)			
KLD Index						-0.023***		
						(0.0064)		
FORTUNE100_DUM							-0.238**	
							(0.1097)	
FORTUNE100_Rank								-0.082*
								(0.0467)
Log(Size)	-0.156***	-0.325***	-0.112***	-0.110***	-0.143***	-0.142***	-0.163***	-0.117*
	(0.0160)	(0.1106)	(0.0275)	(0.0250)	(0.0188)	(0.0180)	(0.0162)	(0.0667)
Table 15 (Continued)								
Log(BM)	-0.079***	-0.600***	-0.129***	-0.017	-0.057*	-0.072***	-0.056**	-0.061
	(0.0238)	(0.1808)	(0.0485)	(0.0279)	(0.0312)	(0.0282)	(0.0244)	(0.1723)
Advertising/Sales	-0.022	-32.416*	-1.327	-1.341***	-1.307*	-1.339**	-1.304**	-5.807*
	(0.1369)	(17.9263)	(1.3145)	(0.5706)	(0.7004)	(0.6277)	(0.5712)	(3.0283)
$Market_t$	-0.297	0.307	1.530	0.286	0.193	0.229	0.256	-5.033**
	(0.3329)	(3.9024)	(1.9919)	(0.3317)	(0.4007)	(0.3504)	(0.3294)	(2.2607)
Log(Price)	-0.026	0.418**	-0.036	0.0144	-0.013	0.008	0.020	0.228
	(0.0294)	(0.2007)	(0.0623)	(0.0303)	(0.0360)	(0.034)	(0.0297)	0.1726
Log(Turnover)	0.113***	0.072	0.086	0.142***	0.144***	0.138***	0.134***	0.294**
	(0.02)	(0.2321)	(0.0543)	(0.0211)	(0.0259)	(0.0241)	(0.0207)	(0.1467)
Past Firm Std Deviation	-0.415***	-2.031	-0.747	-0.890***	-0.841***	-0.992***	-0.974***	-0.675
	(0.1551)	(1.7720)	(0.8015)	(0.2473)	(0.3001)	(0.279)	(0.243)	(2.1066)
Constant	3.178***	5.310**	2.476***	2.747***	3.376***	3.243***	3.662***	2.633

	(0.3067)	(2.4163)	(0.5984)	(0.4652)	(0.3769)	(0.3596)	(0.3225)	(1.8283)
Obs	74,226	683	7,877	72,643	50,927	59,241	74,226	1,407
Pseudo R^2	0.0409	0.1127	0.0105	0.0128	0.0125	0.0121	0.0157	0.0291

Table 16: Lottery-type Stocks and Insider Trades

This table reports insider trading results in the subsample of lottery-type stocks. Lottery-type stocks are those with a price in the bottom half of distribution while its volatility and skewness are both in the top half. Panel A shows mean monthly characteristics of lottery-type and non-lottery-type stocks during the 2004-2014 sample period. In Columns 1 through 4 of Panel B (C), we run Logit regressions where the dependent variable is Sales (Purchase) dummy which equals 1 if a firm-month is a net sale (purchase) month. In Columns 5 through 8, we run Tobit regressions where the dependent variable is the number of shares sold (bought) by all insiders (in thousands) for each firm-month observation. Lottery dummy takes value 1 only if firm i's stock is a lottery stock at the end of month t-1. Log(ABSVI) is the natural log of monthly ABSVI. Log(ABSVI) Positive (Negative) is a dummy variable that equals 1 if Log(ABSVI) positive (negative). Jump dummy equals 1 if ABSVI is in the top 10% of distribution, and Fall dummy equals 1 if ABSVI is in the bottom 10%. Control variables include Advertising/Sales, Log(BM), the equal-weighted market return, Log(Price), and Log(Turnover). Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panal A: Lottery Vs Non-Lottery Stocks	Lottery Type	Non-Lottery Type
Number of Stocks	1,093	4,029
Price	6.40	23.68
Idiosyncratic Volatility	21.99	8.11
Idiosyncratic Skewness	2.10	0.29

Panel B: Sales Dummy/ Shares Sold	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	-0.173***	-0.268***	-0.102	- 0.230***	-23.121**	-57.249***	- 50.614*	-44.546**
	(0.0664)	(0.0744)	(0.0846)	(0.0690)	(10.352)	(21.0939)	(28.3731)	(19.5887)
Log(ABSVI)	0.081***				23.910***			
	(0.0301)				(7.3748)			
Log(ABSVI)*Lottery	0.241**				178.567**			
	(0.1015)				(70.1504)			
Log(ABSVI) Positive		0.036***				9.738***		
Table 16 (Continued)		(0.0123)				(2.8276)		
Log(ABSVI) Positive* Lottery		0.195**				68.3704**		
		(0.0861)				(29.8891)		
Log(ABSVI) Negative			- 0.040***				-10.416***	
							(2.8938)	

			(0.0124)					
Log(ABSVI) Negative*Lottery			-0.143				-58.6311**	
			(0.0889)				(29.5472)	
JUMP				0 .027*				12.917***
				(0.0165)				(3.5790)
JUMP *Lottery				0.259***				101.896***
				(0.1116)				(37.639)
Constant	0.341	0.324	0.362	0.328	-225.379***	-229.743***	-219.748	-231.914***
	(0.2767)	(0.2766)	(0.2765)	(0.2745)	(58.3314)	(58.4663)	58.14354	(57.957)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	50,156	50,156	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.031	0.031	0.030	0.031	0.002	0.002	0.002	0.002
Panel C: Puchase Dummy/ Shares Bought	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	0.153**	0.250***	0.073	0.208***	20.200**	30.064***	25.836**	20.544**
	(0.0658)	(0.0743)	(0.0849)	(0.0681)	(8.0768)	(9.2428)	(10.2457)	(8.5486)
Log(ABSVI)	-0.079**				-4.583**			
	(0.0318)				(2.000)			
Log(ABSVI)*Lottery	-0.264**				-18.005			
	(0.1174)				(30.4801)			
Log(ABSVI) Positive		-0.036***				-3.847**		
		(0.0123)				(1.4981)		

Table 16 (Continued)

Log(ABSVI) Positive* Lottery		-0.200**				-20.821*		
		(0.0887)				(11.1352)		
Log(ABSVI) Negative			0.040***				4.154***	
			(0.0124)				(1.505)	
Log(ABSVI) Negative*Lottery			0.160*				26.459**	
			(0.0912)				(11.2473)	
FALL				0.029*				4.94**
				(0.0166)				(2.0414)
FALL*Lottery				0.260**				3.034**
				(0.1118)				(1.4353)
Constant	-0.331	-0.314	-0.352	-0.318	-47.451	-45.666	-49.661	-47.336
	(0.2774)	(0.2774)	(0.2773)	(0.2752)	(31.7501)	(31.7331)	(31.7650)	(31.5079)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	50,156	50,156	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.030	0.030	0.030	0.030	0.009	0.009	0.009	0.009

Table 17: Local Investors and Insider Trades

This table reports the effect of local investors on opportunistic insider trading. Panel A makes mean comparisons between two measures of local SVI and the aggregated SVI during the 2004-2014 sample periods. In Columns 1 through 4 of Panel B (C), we run Logit regressions where the dependent variable is Sales (Purchase) dummy which equals 1 if a firm-month is a net sale (purchase) month. In Columns 5 through 8, we run Tobit regressions where the dependent variable is the number of shares sold (bought) by all insiders (in thousands) for each firm-month observation. Log(ABSVI _State) and Log(ABSVI _Metro) are the log of monthly ABSVI at the state and metro levels, respectively. Log(ABSVI _State) Positive (Negative) and Log(ABSVI_Metro) Positive (Negative) are dummy variables that equal 1 if the log values are positive (negative). Control variables include Advertising/Sales, Log(BM), the equal-weighted market return, Log(Price), and Log(Turnover). Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Local_SVI Vs Aggregate_SVI	SVI	SVI_State	SVI_Metro	Diff_SVI_State	Diff_SVI_Metro
SVI	33.50	23.68	23.96	-9.82***	-9.54***
N	69,440	29,388	19,673	-	-

Panel B: Sales Dummy/Shares Sold	Probit Regression Sales Dummy	Tobit Regression Shares Sold

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI_State)	0.058*				10.116*			
	(0.0313)				(6.2007)			
Log(ABSVI_State) Positive		0.057*				9.281		
		(0.0344)				(7.1110)		
Log(ABSVI_Metro)			0.043**				2.251	
			(0.0214)				(5.2193)	
Log(ABSVI_Metro) Positive				0.039				3.232
				(0.0259)				(6.2695)
Constant	0.6866	1.637***	0.660	1.616***	-173.289*	15.862	-173.129*	14.428
	(0.4650)	(0.5233)	(0.4651)	(0.5234)	(95.1718)	(96.8565)	(95.1012)	(97.7505)

Table 17 (Continued)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	17,041	17,041	11,121	11,121	17,041	17,041	11,121	11,121
Pseudo R^2	0.036	0.032	0.036	0.032	0.002	0.001	0.002	0.002

Panel C: Purchase Dummy/Shares Bought	Probit Regression Purchase Dummy				Tobit Regression Shares Bought			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI_State)	-0.049				-4.230			
	(0.0316)				(3.7654)			
Log(ABSVI_State) Negative		0.042*				5.679**		
		(0.0232)				(2.5307)		
Log(ABSVI_Metro)			-0.058*				-7.998*	
			(0.0343)				(4.3173)	

Log(ABSVI_Metro) Negative				0.053**				4.687
				(0.0261)				(3.1983)
Constant	-0.666	-0.708	-1.623***	-1.659***	-64.942	-66.9201	-171.998***	-174.077***
	(0.4674)	(0.4648)	(0.5282)	(0.5262)	(49.0662)	(49.0544)	(61.1809)	(61.1376)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	16,988	16,988	11,085	11,085	16,988	16,988	11,085	11,085
Pseudo R^2	0.035	0.035	0.032	0.032	0.011	0.011	0.011	0.011

Table 18: SEC Actions and Opportunistic Insider Trading

This table explores the link between SEC litigations and opportunistic insider trading during the 2004-2014 sample period. Panel A reports on regressions of the fraction of SVI-related sales on month t following news releases of SEC insider litigations at month t-1. The dependent variable is the number of opportunistic insider sales divided by the number of total opportunistic sales. The independent variable of interest is the Num SEC Releases in month t-1, which is the log of one plus the number of SEC releases on actions against illegal insider trading. We include control variables such as the fraction of positive Log(ABSVI) at month t and at month t-1, equally weighted market return, standard deviation of market return, and past cumulative market returns. Panel B reports the results of firm-level regressions where the dependent variables are Sales dummy (Columns 1-3) and Shares Sold (Columns 4-6). The independent variables of interest are the Num SEC Release and its interaction terms with Log(ABSVI). Panel C reports Logit regressions of SEC investigation. The observations are at the insider level and insider characteristics are constructed based on all trades and sales of each insider. SVI-relateded Sales dummy is equal to one if an insider sells in a month that has a positive Log(ABSVI), and % of SVI_induced traded (sales) dummy is equal to 1 if the number of SVI trades (sales) is more than the number of non-SVI trades (sales). Cluster standard errors are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Insider-level Regression	(1)	(2)	(3)	(4)	(5)	(6)
Num SEC Release$_{t-1}$	0.086***	0.055***	0.066***	0.073***	0.069***	0.073***
	(0.0217)	(0.0173)	(0.0190)	(0.0156)	(0.0188)	(0.0167)
Fraction Positive Log(ABSVI)$_t$		0.282***	0.264***	0.264***	0.265***	0.264***
		(0.0369)	(0.0329)	(0.0327)	(0.0334)	(0.0321)
Fraction Positive Log(ABSVI)$_{t-1}$			-0.078***	-0.081***	-0.080***	-0.081***
			(0.0186)	(0.0177)	(0.0175)	(0.0176)
Market Return$_{t-1}$				0.141	0.092	0.137
				(0.3099)	(0.3345)	(0.2948)
Std Market Return$_{t-1}$				3.223**	4.292*	3.069
				(1.5228)	(2.1646)	(2.6544)
Market Return$_{t-4,t-2}$				0.114		
				(0.2786)		
Market Return$_{t-7,t-2}$					0.147	
Table 18 (Continued)					(0.1222)	
Market Return$_{t-13,t-2}$						0.171
						(0 .1172)
Obs	130	130	129	129	129	129
R^2	0.039	0.547	0.585	0.594	0.595	0.594

Panel B: Firm-level Regressions	Probit Regression Sales Dummy			Tobit Regression Shares Sold		
	(1)	(2)	(3)	(4)	(5)	(6)
Num SEC Release$_{t-1}$	-0.051***	-0.065***	-0.063***	-3.232	-5.639*	-5.541*

	(0.0104)	(0.0130)	(0.0131)	(2.5189)	(3.1685)	(3.1696)
Log(Abnormal SVI)$_t$		0.081***	0.640***		27.972***	118.071***
		(0.0313)	(0.1055)		(7.4658)	(26.5771)
Log(ABSVI)$_t$*Num SEC Release$_{t-1}$			0.326***			52.216***
			(0.0591)			(14.8172)
Constant	- 0.051	0.204	0.203	66.1598***	76.331***	76.460***
	(0.2417)	(0.2771)	(0.2764)	(13.0303)	(16.4054)	(16.4046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	71,582	50,156	50,156	71,582	50,156	50,156
Pseudo R^2	0.027	0.031	0.032	0.001	0.001	0.001
Panel C: Probability of Being Investigated by the SEC						
	(1)	(2)	(3)	(4)		
SVI-Induced Sales Dummy	-0.812**	-1.456*	-0.104	-0.034		
	(0.40873)	(0.7601)	(0.4493)	(0.4493)		
Total Number of Insider Sales	0.434***					
	(0.1075)					
Num of SVI_Induced Trades		0.326				
		(0.2140)				
Num of Non_SVI_Induced Trades		0.336**				
		(0.1323)				
% SVI_Induced Trades Dummy			-1.307*			
Table 18 (Continued)			(0.6902)			
% SVI-Induced Sales Dummy				-1.125*		
				(0.6802)		
Obs	38,193	38,193	38,193	38,193		
Pseudo R^2	0.0348	0.0383	0.0125	0.0101		

Table 19: Public Information Flow or Investor Sentiment

This table reports on the effects SVI components: investor sentiment and public information on insider trading. We run following equation to decompose Log($ABSVI$): $Log(ABSVI)_{i,t} = \alpha_i * SUE_{i,Q(t)-1} + \beta_i * \frac{Adv}{sale}_{i,Y(t)-1} + \gamma_i * GDP_{Final_{t-1}} + \delta_i * FOMC_{t-1} + Year + Industry + \varepsilon_{i,t}$, where $SUE_{i,Q(t)-1}$is the previous quarter q of month t's earnings surprise for firm i. In Columns 1-3, the dependent variable is Sales (Purchase) dummy which equals 1 if a firm-month is a net sale (purchase) month. In Columns 4-6, the dependent variable is *the number of shares sold (bought)* by all insiders (in thousands) for each firm-month observation. $Adv/sale_{i,Y(t)-1}$ is the previous year-end advertising expenditure to sales ratio, GDP_Final_{t-1} and $FOMC_{t-1}$ are dummy variables that equal 1 if any macro news is release in month t-1. We take the predicted value as the information component denoted by Log(ABSVI-Information) and the residual value as the sentiment component denoted by Log(ABSVI-Sentiment). In all specifications, control variables include Log(Size), Log(BM), equally weighted market return, Log(Price), and Log(Turnover). Cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Sales	Probit Regression			Tobit Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ABSVI-Information)	1.186**		1.208**	35.317		38.183
	(0.5963)		(0.5640)	(125.3903)		(125.2870)
Log(ABSVI-Sentiment)		0.067**	0.068**		25.634***	25.616***
		(0.0263)	(0.0283)		(7.0948)	(6.1449)
Constant	0.418	0.401	0.419	-197.389***	-164.752***	-196.828***
	(0.2866)	(0.2871)	(0.2866)	(55.5111)	(24.9630)	(55.5026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	43,144	43,144	43,144	43,144	43,144	43,144
Pseudo R^2	0.0287	0.0293	0.0296	0.0012	0.0011	0.0011
Panel B: Purchase	Probit Regression			Tobit Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ABSVI-Information)	-1.246*		-1.267	-28.117		-29.516
	(0.7345)		(0.8347)	(55.5102)		(55.5357)
Log(ABSVI-Sentiment)		-0.063**	-0.065**		-3.901**	-3.951**
		(0.0303)	(0.0303)		(1.8672)	(1.8688)

		-				
Constant	-0.409***	0.391***	-0.410***	-61.015***	-60.618***	-61.106***
	(0.1074)	(0.1072)	(0.1074)	(13.6674)	(13.6366)	(13.6683)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	43,144	43,144	43,144	43,144	43,144	43,144
Pseudo R^2	0.0273	0.0286	0.0292	0.0090	0.0095	0.0096

Table 20: Opportunistic Trading, ABSVI, and Future 1-month Stock Returns

This table shows the relationships of opportunistic trading, ABSVI, and future 1-month stock returns. We separate the sample into the net sales and net purchase subsamples, and we independently create quintiles based on the ABSVI and net sales and net purchase positions of each individual firm.

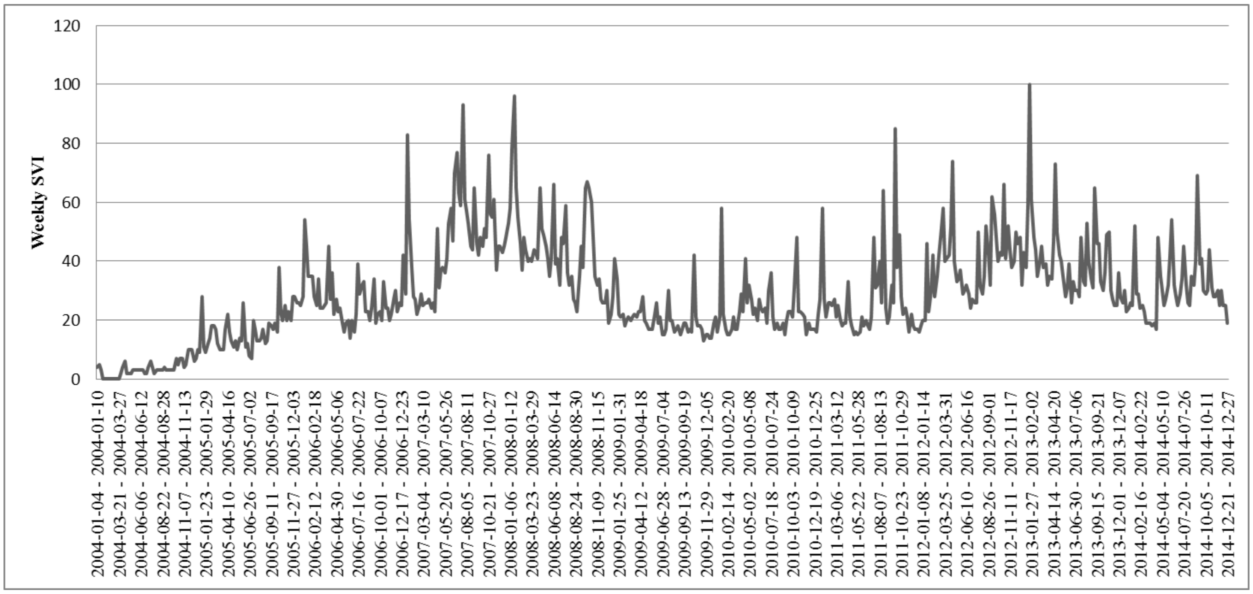
Net Sales\ABSVI	1 (Low)	2	3	4	5 (High)
1 (High)	1.871%	1.537%	1.347%	1.242%	0.878%
2	1.526%	1.323%	1.301%	0.968%	0.859%
3	1.416%	1.255%	1.054%	1.187%	0.746%
4	1.213%	1.125%	0.930%	0.954%	0.706%
5 (Low)	1.112%	1.129%	1.307%	0.952%	0.641%
Net Purchase\ABSVI	1 (Low)	2	3	4	5 (High)
1 (High)	3.625%	3.266%	3.356%	2.728%	1.756%
2	2.601%	2.924%	3.270%	2.102%	1.715%
3	2.568%	2.330%	2.172%	1.363%	1.600%
4	1.923%	1.948%	1.542%	1.311%	1.011%
5 (Low)	1.696%	1.284%	1.142%	1.604%	1.179%

Table 21: Portfolio Returns on SVI-based Trading Strategies

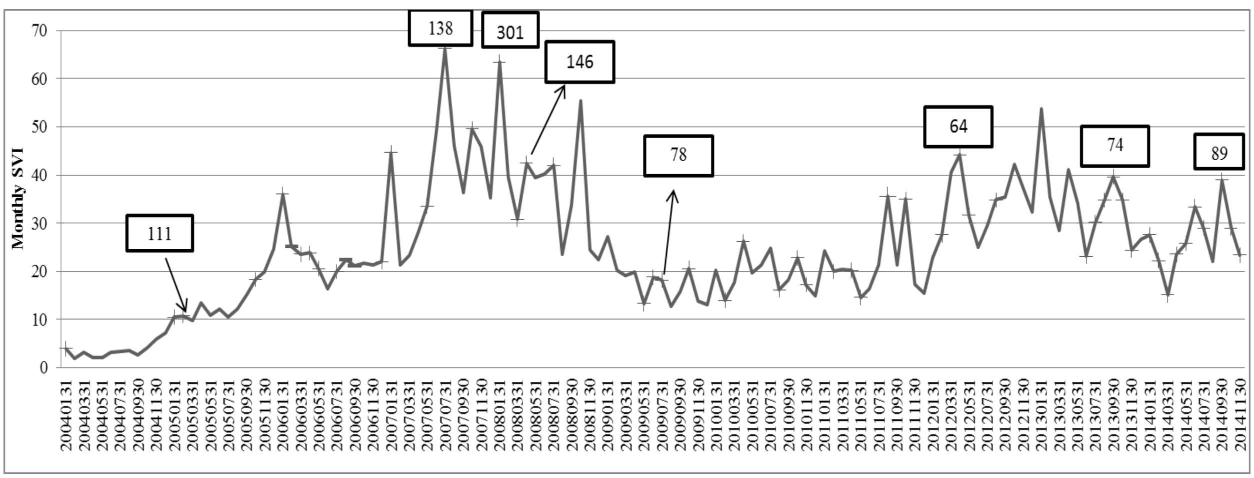
This table shows the returns of buy and sale portfolios that follow the ABSVI from 2004-2014. We first classify the sample into the positive or negative Log(ABSVI) and then create sub-groups of buy and sell portfolio samples based on the net sale or purchase positions. For example, if a firm in month t has a net sales position and encounters a positive Log(ABSVI) in month t, we group this firm into a Positive Log(ABSVI) Sells portfolio. At the end of month t+1, we rebalance the portfolio based on new firms' net positions and ABSVI. We report below the monthly percentage return on both buy and sell equally weighted as well as value weighted portfolios. Panel A presents the results of equal-weighted portfolios and Panel B shows those of value-weighted portfolios. Standard errors at the portfolio level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Positive Log(ABSVI) Buys	Negative Log (ABSVI) Buys	L/S Buys	Positive Log(ABSVI) Sells	Negative Log(ABSVI) Sells	L/S Sells	Negative Log(ABSVI) Buys-Positive Log(ABSVI) Sells
			Panel A: Equal-Weighted				
Average Returns %	0.667	2.261	-1.594	-0.021	2.315	-2.335	2.281
Standard dev.	6.1646	5.8811	3.7997	5.4006	5.2111	3.7997	3.6811
CAPM Alpha	0.448	2.043***	-1.594***	-0.299	2.073***	-2.371***	2.341***
	(0.5469)	(0.5197)	(0.3373)	(0.4731)	(0.4565)	(0.2656)	(0.3250)
Fama-French Alpha	0.428	2.032***	-1.604***	-0.317	2.056***	-2.373***	2.349***
	(0.5393)	(0.5206)	(0.3353)	(0.4646)	(0.4503)	(0.2662)	(0.3234)
Carhart Alpha	0.455	2.064***	-1.610***	-0.269	2.081***	-2.350***	2.334***
	(0.5410)	(0.5214)	(0.3377)	(0.4618)	(0.4514)	(0.2656)	(0.3245)
5-factor Alpha	0.581	2.144***	-1.562***	-0.180	2.139***	-2.319***	2.323***
	(0.5387)	(0.5239)	(0.3391)	(0.4621)	(0.4542)	(0.2675)	(0.3280)
			Panel B: Value-Weighted				

Average Return %	0.670	1.395	-0.725	0.292	1.427	-1.135	1.103
Standard dev.	6.1397	5.5957	4.9426	4.7540	4.6496	3.1868	4.3025
CAPM Alpha	0.468	1.182**	-0.713	-0.005	1.175***	-1.168	1.177***
	(0.5442)	(0.4958)	(0.4385)	(0.4121)	(0.4055)	(0.2822)	(0.3796)
Fama-French Alpha	0.458	1.166**	-0.708	-0.012	1.162***	-1.174***	1.177***
	(0.5453)	(0.4908)	(0.4391)	(0.4036)	(0.4028)	(0.2805)	(0.3826)
Table 21 (Continued)							
Carhart Alpha	0.477	1.204**	-0.727	0.019	1.189***	-1.172***	1.188***
	(0.5477)	(0.4902)	(0.4411)	(0.4037)	(0.4031)	(0.2821)	(0.3845)
5-factor Alpha	0.5440	1.256**	-0.712	0.059	1.177***	-1.138***	1.197***
	(0.5515)	(0.4941)	(0.4459)	(0.4070)	(0.4076)	(0.2841)	(0.3887)



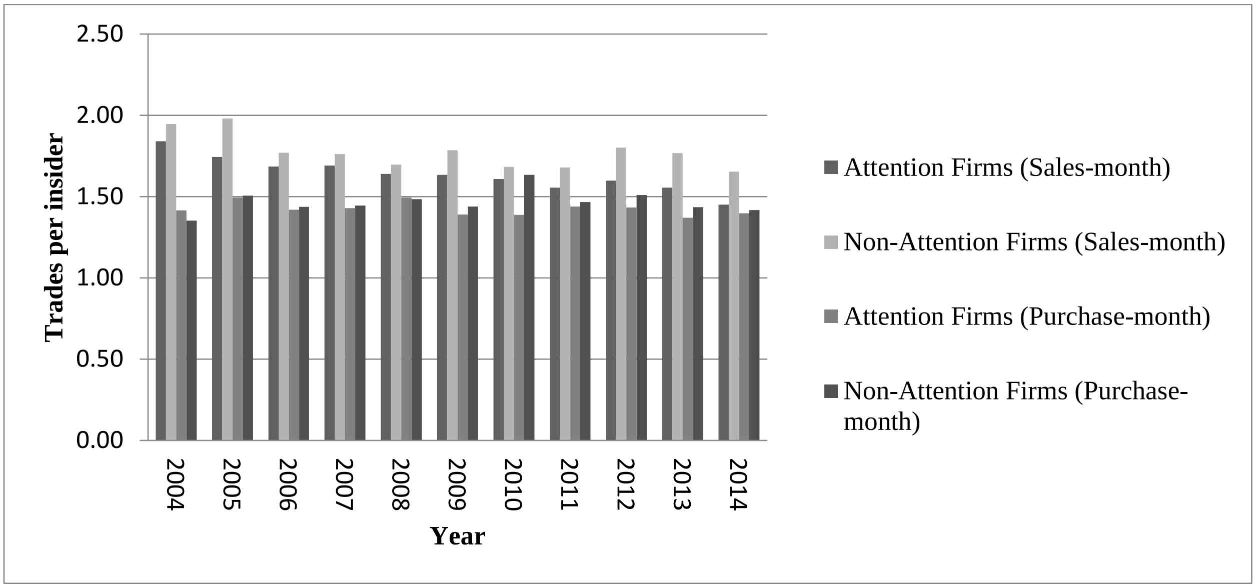
Panel A: Weekly Google Trends for Apple Inc. (AAPL)



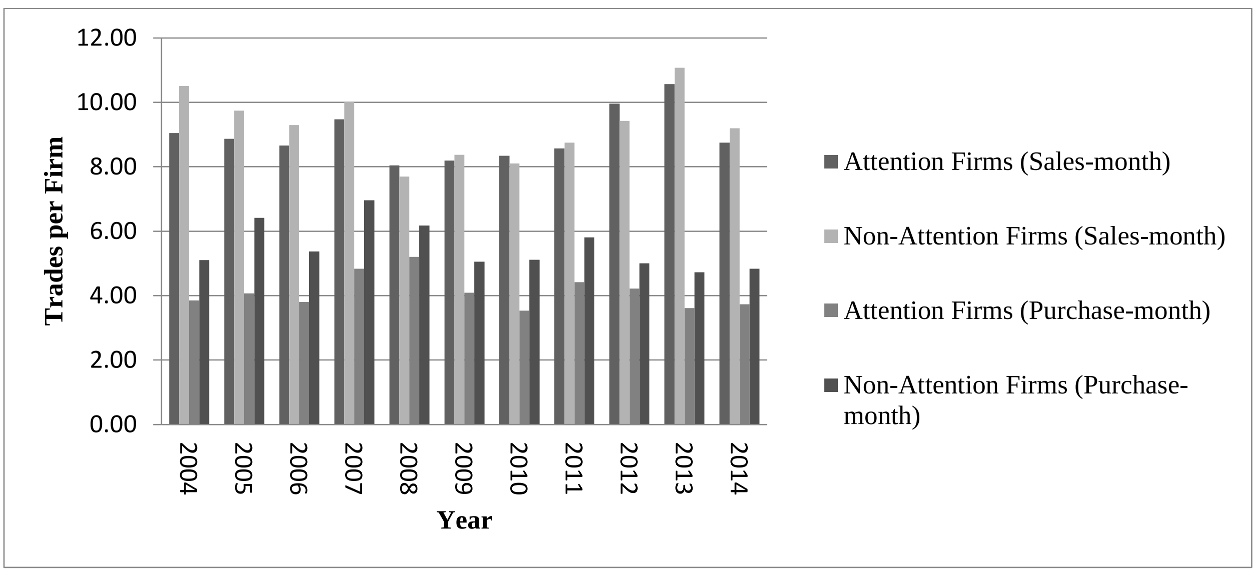
Panel B: Monthly SVI and Insiders trading Patterns of Apple Inc. (AAPL)

Figure 1: Google Trends Search Index and Insider Trading

Figure 1 illustrates Google Trends search index and insider trading. Panel A displays the graphical output of Google Trends search index on Apple Inc. (ticker: AAPL). The graph plots a weekly aggregate search frequency (SVI) on "AAPL." The SVI measures the weekly search volume on "AAPL" scaled by the highest searching volume on the chart. Panel B displays insider trading patterns as related to the monthly SVI. The "+" ("-") sign refers to a net insider sale (purchase) month. Panel B only presents a trading volume greater than 50 (in thousands) shares and the number in each box is rounded to the nearest thousands.



Panel A: Number of Trades per Insider (Firm-month)



Panel B: Number of Trades per firms (Firm-month)

Figure 2: Number of Trades per Insider and per Month