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The Dog That Did Not Bark: Insider Trading and Crashes

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ABSTRACT

This paper documents that at the individual stock level, insiders' sales peak many months before a large drop in the stock price, while insiders' purchases peak only the month before a large jump. We provide a theoretical explanation for this phenomenon based on trading constraints and asymmetric information. A key feature of our theory is that rational uninformed investors may react more strongly to the absence of insider sales than to their presence (the "dog that did not bark" effect). We test our hypothesis against competing stories, such as insiders timing their trades to evade prosecution.

SIR ARTHUR CONAN DOYLE MADE CLEAR in his celebrated "Silver Blaze" mystery that sometimes there is more to be learned from the absence of an action than from its presence. This insight turns out to be very relevant in the present, and first, study of the patterns of insider trading preceding large movements in stock prices. While our entire analysis is conducted at the individual stock level, it is convenient to illustrate the type of phenomena we study by means of a figure based on aggregate data. Figure 1 shows corporate managers' sales and purchases in the 12 months preceding, respectively, the largest drop and the largest jump in the monthly S&P 500 index during the 1986 to 2005 period.[1] It can be observed that aggregate sales by insiders peak 10 months before the drop and then decline sharply before the drop occurs. By way of contrast, aggregate purchases by insiders before the jump exhibit a very different pattern: They remain low all year long and pick up only the month before the jump. In this

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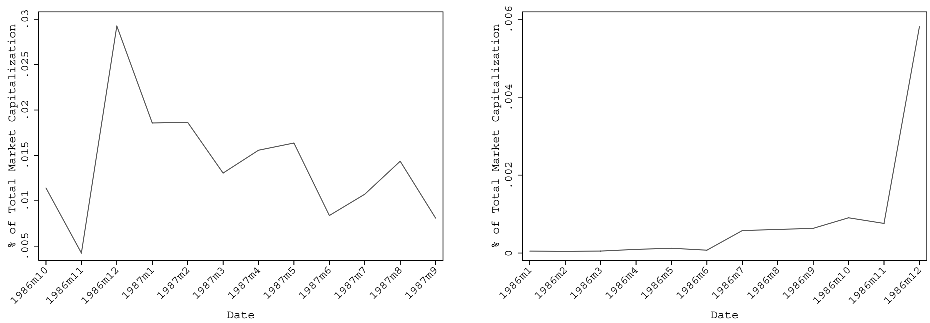
[1] In the remainder of the paper we use the word "jump" to refer to a "large" positive return and the words "drop" or "crash" to refer to a "large" negative return. In Section II.A.2, we provide formal definitions of these variables.



(a) Manager sales before October 1987 (Largest S&P 500 "drop" in the 1986-2002 period)

(b) Manager purchases before January 1987 (Largest S&P 500 "jump" in the 1986-2002 period)

Figure 1. Manager transactions before large market movements. The graphs show the evolution of managers' open market or private trades in common stocks traded in NYSE, Amex, and NASDAQ that appear in the CRSP data set, before the largest market movements in the S&P 500 during the 1986–2002 period. The data on insider transactions come from Thomson Financial Data Filings data set. We exclude stocks with a price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. We consider as *managers* the chairman, directors, CEOs, CFOs, officers, presidents, vice presidents, affiliate persons, members of committees, etc. *% of Total Market Capitalization* is defined as 100 times the value of all the managers trades during the month (number of shares traded times the transaction price or the closing price of the day if the transaction price is missing) divided by the total market value of our universe of firms at the beginning of the month.

paper, we look at individual stocks traded on the NYSE, Amex, and NASDAQ between 1986 and 2002 and find evidence of similar patterns of insider trading preceding large returns. The evidence is especially strong regarding insider sales, which runs against the mainstream view that insider sales are almost exclusively driven by the needs for liquidity and diversification.

Why would insiders sell many months before a large drop but stop selling soon before the event? There are many possible answers to this question. One view is that many large drops in prices are due to companies failing to meet earnings expectations and thus, because most companies prohibit insiders from trading prior to an earning announcement,[2] any insider who wishes to exploit private information related to poor company earnings has to trade significantly before the actual earnings announcement and hence significantly before the crash. Another view is that insiders try to escape scrutiny from the SEC coupled with the hypothesis that the SEC investigates trades that take place near the date at which a large price movement occurs. A third view is that insiders are forced to

[2] The Insider Trading and Securities Enforcement Act of 1988 makes top management responsible for insider trading by any employee. This regulation encourages companies to issue internal rules prohibiting all trading by insiders around major corporate events, such as earning announcements or takeover deals.

Table I

SEC Litigations

This table presents statistics on the number of SEC litigation releases concerning insider trading between September 20, 1995 and December 31, 2002. A litigation release is said to concern insider trading whenever it states that an insider benefited from a trade based on illegal material information. Each trade is classified either as "Trading on good news" or as "Trading on bad news" depending on the nature of the information used by the insider. If a release does not contain sufficient information to classify the trade, we look for the information in other releases about the same case. If a release mentions only insider trades in one category, the release is counted as one entry in that category. If the same release deals with multiple insider trades, some of which are based on good news and others based on bad news, we count the release twice, once in the "Trading on good news" category and once in the "Trading on bad news" category. Finally, in 10 instances we were not able to get sufficient information to classify the release in either category, in which case it is not counted in the table.

Year	Trading on Good News	% Good News	Trading on Bad News	% Bad News
1995	18	81.8%	4	18.2%
1996	43	65.2%	23	34.8%
1997	46	58.2%	33	41.8%
1998	51	66.2%	26	33.8%
1999	58	67.4%	28	32.6%
2000	56	66.7%	28	33.3%
2001	58	66.7%	29	33.3%
2002	66	69.5%	29	30.5%
Total	396	66.4%	200	33.6%

trade many months before the expected price drop because of the "short swing" rule of the 1934 Security Exchange Act that prohibits profit-taking by insiders for offsetting trades within 6 months.[3] In all these cases, insiders who wish to profit from their private information will optimally trade months before the date of the actual event.

It is hard, however, to reconcile any of these views with the evidence on insider purchases. For instance, the SEC prosecutes significantly more cases based on insider purchases than cases based on insider sales. Meulbroek (1992) reports that 87% of insider trading cases filed by the SEC during the 1980 to 1989 period concerned trades based on positive news. In Table I we report similar statistics for the period 1995 to 2002. These numbers suggest that if the "evading the SEC" hypothesis were really driving the pattern of insider sales prior to crashes, then we should see a similar pattern of insider purchases prior to jumps, which we do not.

Indeed, the sharp asymmetry between sales before crashes and purchases before jumps is hard to reconcile with any theory that treats both types of transactions symmetrically. In our view, these two types of transactions are not symmetric because of portfolio constraints faced by insiders when they trade on bad news. These constraints may arise for several reasons, such as short-selling

[3] For an analysis of returns to insider trading based on the 6-month short-swing rule, see Jeng, Metrick, and Zeckhauser (2003).

constraints,[4] the insider being a large shareholder who wishes to retain control of the company, or the insider being a manager who is granted stock as part of his compensation package that he is not allowed to sell before some period of time. In the first part of the paper we address this conjecture theoretically and show that the presence of such portfolio constraints can explain both the occurrence of crashes and the observed pattern of insider trading. We then test our model and compare its predictions with those of competing stories in the second part of the paper.

The model we use is a standard noisy rational expectations model à la Grossman and Stiglitz (1980) and Bhattacharya and Spiegel (1991), but where trading by informed traders (insiders in our setting) is restricted in that their stock holdings cannot go below a given floor. Whenever insiders are trading, information gets incorporated into prices and prices adjust continuously. However, once insiders' holdings reach the floor set by the constraint, insiders can no longer act on further bad news. Thus, uninformed traders can infer that insiders are in possession of bad news (as otherwise insiders would be buying the stock back) but not how bad the news really is. This results in a sharp change in outside investors' beliefs and perceived level of uncertainty. In particular, expected payoffs fall and uncertainty (risk) rises. The combination of the two effects leads to a discontinuity in the price process, that is, a crash. However, to the extent that the crash is driven by a drop in the informational content of prices and an increase in the risk premium required by uninformed investors, it is consistent with agents' rationality and with stock market efficiency.

This theory of crashes in asset prices exhibits two main distinctive features, which give rise to testable implications. The first feature is that compared to normal times, crashes occur after insiders' holdings have reached a floor and are preceded by an immediate period of low insider trading activity. Thus, insider sales in the immediate past should be associated with a low likelihood of a crash (since in our model a crash occurs after insiders have stopped trading) but insider sales in the far past should be associated with a high likelihood of a crash (since it brings insiders closer to the point where the "floor" constraint binds). The second feature is that a symmetric pattern of insider purchases, namely, a period of intense purchases followed by a period of relatively low activity, does not generate a jump in the stock price. This is because there is no "ceiling" constraint on insiders' holdings to mirror the "floor" constraint. We test our theory using a data set similar to the one used by Lakonishok and Lee (2001), covering the insider trading activity of companies traded on the NYSE, Amex, and NASDAQ during the 1986 to 2002 period. The empirical results provide strong support for both distinctive features of our theoretical

[4] The short-selling restrictions for individual investors in the U.S. are fairly mild and stem mostly from the uptick rule and from the extra cost of borrowing securities. Restrictions for corporate insiders are much more stringent. Section 16c of the Securities and Exchange Act prohibits U.S. insiders from selling short their own stock. Furthermore, new regulations in the 1980s assure this requirement cannot be evaded by creating a similar position by trading in derivatives. Allowing insiders to sell short would not be in the interest of shareholders as it would misalign shareholder and management interests.

model. The results are robust to splitting the sample and to the use of different estimation techniques, different measures of crashes, and different time periods for the insider trading variables.

Our work is related to two lines of research in finance: insider trading and stock market crashes. A key issue in the literature on insider trading is whether insiders earn abnormal returns on their portfolios. The answer provided by most recent empirical analysis is that stocks purchased by insiders earn positive abnormal returns but stocks sold by insiders do not exhibit negative abnormal returns. Lakonishok and Lee (2001) look at abnormal returns of portfolios based on the intensity of insider purchases and sales. After controlling for size, book to market, and momentum effects, they find a statistically and economically significant excess return of 4.82% for portfolios of stocks with a strong "purchase signal." By way of contrast, the excess return of strong "sell signal" portfolios is statistically insignificant. Jeng et al. (2003) estimate the returns to insiders' own portfolio over a 6-month window. They construct a "purchase portfolio" that holds all shares purchased by insiders over a 6-month period and a "sale portfolio" that holds all shares sold by insiders over a 6-month period. They find that the purchase portfolio earns positive abnormal returns on the order of 50 basis points per month while the sale portfolio earns no negative abnormal return. Friederich et al. (2002) and Fidrmuc, Goergen, and Renneboog (2006) provide evidence based on U.K. data suggestive of significantly smaller absolute price reaction to insider sales than to insider purchases. Thus, the consensus of the existing literature when interpreting these results is that "insider selling that is motivated by private information is dominated by portfolio rebalancing for diversification purposes" (Lakonishok and Lee (2001)).

In this paper, we provide new evidence regarding the informational content of insider sales. Our model provides an alternative interpretation of the empirical findings described above. Indeed, it suggests that the relation between expected returns and insider sales may be ambiguous even when insider sales are informationally driven. On the one hand, selling by insiders reveals bad news to the market and causes prices to go down. On the other hand, the absence of selling by insiders can reveal even worse news (the "dog that did not bark" effect) and thus cause prices to go down even more rapidly than if there had been moderate selling by insiders. In the empirical part of this paper we use insider sales and purchases to explain large returns (crashes and jumps) rather than returns per se, as in the existing literature on insider trading. We find a clear pattern of insider sales very significantly associated with crashes, which strongly suggests that insider sales are not solely driven by liquidity needs.

The second branch of the literature that our work is related to deals with stock market crashes. The past few years have seen an explosion of research providing insightful analysis of why and how crashes can occur. It is useful to split this literature into two families, depending on whether crashes are associated with higher or lower uncertainty from the point of view of uninformed traders. The first family views crashes as events that bring prices closer to fundamental values. It comprises models of bursting bubbles and models of rational herding.[5,6] It also comprises a number of models that emphasize the role played by trading constraints, most notably the models of Romer (1993), Cao, Coval, and Hirshleifer (2002), and Hong and Stein (2003), where crashes reveal information as initially sidelined informed investors get back in the market. Interestingly enough, trading constraints also play a crucial role in models belonging to the second family, where crashes are not driven by revelation of information, but, rather, by a sharp increase in uncertainty. Models belonging to the second family comprise work by Gennotte and Leland (1990), Barlevy and Veronesi (2003), and Yuan (2005, 2006).

Our model also belongs to the second family with two differences relative to the existing literature. First, from a technical point of view, we rely on a modeling strategy initially introduced by Bhattacharya and Spiegel (1991) that allows us to eliminate some unnecessary ingredients of existing models, such as ad-hoc trading rules and borrowing or leverage constraints, and to solve the model in closed form. Second, and more crucially, we allow trading by informed investors be observable (or inferred) by the rest of the market. This feature is important to bring the model to the data since we wish to identify informed investors as insiders, whose trades are publicly observable in the U.S. market.[7]

The above discussion suggests that a key variable for sorting among the many different views of crashes is whether crashes are associated with informed investors getting *in* the market and prices becoming more informative, or whether crashes are associated with informed investors getting *out* of the market and prices becoming less informative. Our empirical work allows us to shed some light on this issue in the context of the U.S. markets in the past 20 years. We test whether a given class of informed investors, namely, insiders, has been getting in or out of the market prior to a crash. The results we obtain unambiguously support the view of crashes associated with informed investors pulling out of the market. Indeed, we find that both insider trading volume and insider sales are negatively and significantly associated with the likelihood of a crash in the following month. We also find that these two variables are positively and significantly associated with the likelihood of a crash in the following year. In other words, the highest likelihood of a crash obtains when there has been insider selling in the past but insiders have just pulled out of the market.[8]

A closely related paper to our empirical analysis is the work by Chen, Hong, and Stein (2001). They look at the determinants of negative skewness in individual stock returns. They estimate negative skewness using daily returns and find that it is most pronounced in stocks where trading volume has recently

[5] See, for instance, Allen, Morris, and Postlewaite (1993), Allen and Gale (2000), and Hong, Scheinkman, and Xiong (2006).

[6] See Devenou and Welch (1996) for an early survey.

[7] Detailed insider trading information is easily and freely available, even for the least sophisticated investors, on websites such as finance.yahoo.com.

[8] A totally different test of the two hypotheses consists of looking at expected returns. If a crash is an event that makes prices more revealing, then the risk premium demanded by uninformed investors should go down after the crash. If a crash makes prices less revealing then the risk premium should go up.

gone up and in stocks with positive returns over the past 36 months. The first finding supports the view that more heterogeneity of beliefs is conducive to crashes, as emphasized in Hong and Stein (2003). The second finding is consistent with a number of models, most notably models with stochastic bubbles. Our results are an indication of the robustness of Chen et al.'s findings since we also find that both past returns and the change in total trading volume are positively associated with a higher likelihood of crashes. However, the main difference between our work and theirs is that we look at not only the impact of total trading volume on crashes but also the impact of *insider trading* on crashes, which allows us to test whether a well-defined group of investors with superior information gets into or out of the market before a crash.

The remainder of the paper is organized as follows. In Section I, we present a theoretical model of insider trading in the presence of trading constraints. Section II is dedicated to the empirical study. We first describe the data, define the variables, and explain the methodology. Then we empirically test the main predictions of the model. We also conduct additional tests supporting our model of insiders' behavior in the presence of trading constraints over competing stories. Finally, Section III presents some concluding remarks.

I. A Simple Model of Insider Trading and Crashes

In this section, we define a simple environment of insider trading. The model is simple but rich enough to identify some testable implications of insider trading activity on asset prices. In this framework "insiders" have access to private information on asset payoffs and can trade with uninformed traders on the basis of that information. They can also trade to hedge nontraded income risk. All agents have rational expectations and in equilibrium prices are partially revealing. In this simple setting we show that when insiders face some realistic trading constraints (such as not being able to short-sell shares of their companies) assets prices exhibit price discontinuities, or crashes. Furthermore, the model identifies a very specific pattern of insiders' stock holdings around those crashes. In Section II, we test some of the predictions of this model.

A. The Basic Assumptions

The following setting of asset trading is an extension of the Grossman and Stiglitz (1980) model. Following Bhattacharya and Spiegel (1991), one deviation consists of substituting noise trading with rational trading driven by stochastic hedging needs.[9] The main deviation, and our contribution, is to introduce a simple constraint on asset holdings.

More formally, there is an underlying probability space $(\Omega, \mathcal{F}, \mathbf{P})$, on which all random variables are defined. A state of nature is denoted by $\omega \in \Omega$. It is further assumed that all random variables belong to a linear space $\mathcal{N}$ of joint

[9] For instance, see Marin and Rahi (2000) for some of the implications of this source of trading on asset pricing and financial innovation.

normally distributed random variables on Ω. We omit the dependence on ω whenever doing so does not lead to confusion. The economy lasts for one period. At the beginning of the period agents trade in the asset market. At the end of the period all uncertainty is resolved and agents consume the only good in the economy whose price is normalized to one. There are two assets in the economy: a risk-free asset and a risky asset. The risk-free asset has a perfectly elastic supply and, without loss of generality, offers a rate of return equal to zero. The risky asset consists of shares of a company. There is a per capita amount of $\bar{n} > 0$ shares outstanding, each of which offers a payoff given by the (normally distributed) random variable $f : \Omega \rightarrow \Re$,

$$f = \bar{f} + y + \epsilon,$$

where y and ϵ are normally distributed random variables and $\bar{f}$ is a constant. There is a unit mass of traders in the economy. A fraction λ_I are "insiders" who have some private information that is statistically related to f. In particular, each insider is in a position that allows him to learn y, one of the components of the risky asset payoff. Each insider is endowed with $\bar{n}_I$ shares of the risky asset. The remaining $(1 - \lambda_I)$ agents do not receive any private information and we refer to them as "uninformed" traders.[10] Each uninformed trader is endowed with $\bar{n}_U$ shares of the risky asset.

Agents also receive income $e_i : \Omega \rightarrow \Re$ at the end of the period. This income can be interpreted as either labor income or income from holding assets that do not have a spot market for trading. For simplicity we assume only insiders receive this type of income. In particular,

$$e_I = k_I x_I z$$

$$e_U = 0,$$

where k_I is a constant, x_I is a standard normal random variable uncorrelated with all other random variables in the economy, and z a normal random variable statistically related to ϵ ($\sigma_{\epsilon z} = Cov(\epsilon, z) \neq 0$). Before trading, insiders also observe the realization of the random variable x_I.

Denoting by w_i the end-of-period wealth of agent i, by $w_{0,i}$ his initial wealth, by n_i the number of shares of the risky asset he holds after trading, and by p the price of the asset at time 0, we have

$$w_I = w_{0,I} + k_I x_I z + n_I(f - p) \tag{1}$$

$$w_U = w_{0,U} + n_U(f - p). \tag{2}$$

Agents maximize the expected utility of their end-of-period consumption (wealth) and behave competitively. In particular, each agent has a utility function $U_i : \Re \rightarrow \Re$, which exhibits constant absolute risk aversion:

[10] Throughout this section we denote insiders by I, uninformed traders by U, and generic traders by i.

$$U_i(w_i) = -\exp\{-a_i w_i\}.$$

Before the market for asset trading opens, agents receive their private information. Insiders are in possession of two important pieces of information, y and x_I. The first one, y, is relevant for assessing the true value of the asset in the future; the second, x_I, is a key determinant of the size of the agents' hedging needs. In our model we allow insiders to trade on both sources of information.[11] Since uninformed traders do not hold any private information, the vector $s(\omega) = (y(\omega), x_I(\omega)) \in \Sigma \subseteq \Re^2$ contains all private information of the economy in state ω. Endowed with their private information, agents trade in a *Rational Expectations Equilibrium* (REE).[12] In this equilibrium agents use both their private information and the information contained in equilibrium prices, $p \in \Re$, in the determination of their optimal asset holdings.

DEFINITION 1: *A REE is an equilibrium price function $p(s)$ and a set of optimal demand functions for insiders and uninformed traders $\{n_I(y, x_I, p), n_U(p)\}$ such that:*

1) *(measurability) $p : \Sigma \longrightarrow \Re$ is a (Borel) measurable function.*
2) *(optimality) $n_I(y, x_I, p)$ and $n_U(p)$ satisfy:*

$$n_I(y, x_I, p) = ArgMaxE[U_I(w_I)\ s.t.\ (1) \mid y, x_I, p]$$
$$n_U(p) = ArgMaxE[U_U(w_U)\ s.t.\ (2) \mid p].$$

3) *(clearing) $\lambda_I n_I(y, x_I, p) + (1 - \lambda_I) n_U(p) = \bar{n}$.*

For simplicity and without any bearing on the main results, we further assume that with the exception of $\sigma_{\epsilon z}$, all covariances and expectations of random variables are equal to zero. All variances, except σ_ϵ^2, are set equal to one. To summarize, the distributional assumptions on all the random variables are:

$$\begin{pmatrix} y \\ \epsilon \\ z \\ x_I \end{pmatrix} \longrightarrow \aleph \left\{ \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \sigma_\epsilon^2 & \sigma_{\epsilon z} & 0 \\ 0 & \sigma_{\epsilon z} & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \right\}.$$

In Section I.C, we show that when insiders face trading constraints the REE price in this economy exhibits crashes. For illustrative purposes, we first compute the REE in the economy without trading constraints.

[11] In most countries some of the y-driven trading is not allowed, but trading due to x_I is permitted. In the United States, all trading on y arising from so-called "material" information is not permitted and all insider trades must be reported to the SEC.

[12] See Radner (1979).

B. Equilibrium in the Economy without Trading Constraints

In the absence of trading constraints each agent solves a typical mean variance portfolio selection problem. Conditional on his information, the representative insider's future wealth is normally distributed. Taking the first-order conditions, we find that his demand for the risky asset is given by

$$n_I(y, x_I, p) = \frac{E(f \mid y, x_I, p) - p - \mathrm{Cov}(f, e_I \mid y, x_I, p)}{a_I \mathrm{Var}(f \mid y, x_I, p)} = \frac{\bar{f} + y - p - a_I k_I \sigma_{\epsilon z} x_I}{a_I \sigma_\epsilon^2}.$$

The equation above can be rewritten as

$$n_I(y, x_I, p) = \frac{\bar{f} - p + \theta(y, x_I)}{a_I \sigma_\epsilon^2},$$

where $\theta(y, x_I) \equiv y - a_I k_I \sigma_{\epsilon z} x_I$. The first term in $\theta(y, x_I)$ corresponds to trading driven by information on the stock fundamentals; the second term corresponds to the hedging demand of the insider and would not exist in an economy without nontraded income risk. The demand function of insiders implies that equilibrium prices must reveal (to the uninformed traders) $\theta(y, x_I)$, which is normally distributed. Hence, the demand function of the representative uninformed trader is identical to that of an agent with private signal $\theta(y, x_I)$. Thus, conditional on his signal and on the inferred information, each uninformed trader's future wealth is also normally distributed and his demand is given by

$$n_U(p) = n_U(\theta) = \frac{E(f \mid \theta) - p - \mathrm{Cov}(f, e_U \mid \theta)}{a_U \mathrm{Var}(f \mid \theta)} = \frac{\theta(y, x_I) + (1 + m^2)(\bar{f} - p)}{a_U\left[m^2 + (1 + m^2)\sigma_\epsilon^2\right]},$$

where $m \equiv a_I k_I \sigma_{\epsilon z}$.

The REE price is given by

$$P(y, x_I) = K_0 + K_1 \theta(y, x_I)$$

$$K_0 \equiv \bar{f} - \frac{\left[(1 + m^2)\sigma_\epsilon^2 + m^2\right]\sigma_\epsilon^2}{\gamma \sigma_\epsilon^2 (1 + m^2) + \dfrac{\lambda_I}{a_I} m^2} \bar{n}$$

$$K_1 \equiv \frac{\gamma \sigma_\epsilon^2 + \dfrac{\lambda_I}{a_I} m^2 \left(1 + \sigma_\epsilon^2\right)}{\gamma \sigma_\epsilon^2 (1 + m^2) + \dfrac{\lambda_I}{a_I} m^2},$$

where $\gamma \equiv \frac{\lambda_I}{a_I} + \frac{(1 - \lambda_I)}{a_U}$.

The equilibrium price is only partially revealing as it does not reveal y to the uninformed traders, but only a linear combination of y and x_I, the endowment shock of insiders.

In equilibrium, agents' asset holdings are given by

$$n_I = \frac{1}{a_I}\left(\frac{\left(\frac{1-\lambda_I}{a_U}\right)m^2\theta + \left((1+m^2)\sigma_\epsilon^2 + m^2\right)\bar{n}}{\gamma\sigma_\epsilon^2(1+m^2) + \frac{\lambda_I}{a_I}m^2}\right)$$

$$n_U = \frac{1}{a_U}\left(\frac{\sigma_\epsilon^2(1+m^2)\bar{n} - \frac{\lambda_I}{a_I}m^2\theta}{\gamma\sigma_\epsilon^2(1+m^2) + \frac{\lambda_I}{a_I}m^2}\right).$$

C. Equilibrium in the Economy with Trading Constraints

We now assume that the stock holdings of all agents, both insiders and uninformed traders, must satisfy the following portfolio constraint:

$$n_I \geq \nu$$
$$n_U \geq \nu,$$

where ν is a constant strictly smaller than $\bar{n}$.

A few remarks are in order about these constraints. First, notice that the case $\nu = 0$ corresponds to the standard no short-sales constraint. Note that we wish to allow for strictly positive floors so as to be able to map the model to the data on insider trading in the next section. Indeed, some classes of insiders (e.g., large shareholders) may face a tighter constraint on holdings than a simple short-sale constraint. Second, only the constraint faced by insiders drives the main results of the theoretical section of the paper. The reason we also introduce a constraint for uninformed investors is that it allows us to derive a side result that is helpful for a robustness check in the empirical section of the paper. Finally, given that we have only two types of investors and that the supply of the stock is fixed, agents are always able to infer in the equilibrium the other agent's holdings, and therefore whether their constraint is binding or not. Thus, our model is equivalent to a model in which holdings of investors are fully observable. Again, this feature of the model is important in order to bring the model to the data since insiders' trades and holdings are public information in the U.S. markets. It also has theoretical implications, which we discuss further at the end of the section.

In Theorem 1 we show that any equilibrium of the economy with portfolio constraints can be decomposed into four regions:

- Region A, where the signal received by the insiders is so good, or their hedging motive so strong, that they purchase all the shares that the uninformed traders can sell without violating the portfolio constraint. In this region, the portfolio constraint of the uninformed traders is binding, the portfolio constraint of the insiders is not binding, and prices reveal θ to the market.

- Region B, where the signal received by the insiders is good enough, or their hedging motive strong enough, that they demand a larger number of shares than the minimum holding allowed but not so good or so strong as to push the uninformed traders out of the market. In this region, neither the portfolio constraint of the insiders nor the portfolio constraint of the uninformed traders is binding, and prices reveal θ to the market.
- Region C, where the signal received by the insiders is bad enough, or their hedging motive weak enough, that they would want to hold a number of shares below their minimum holding allowed but not so bad or so weak as to cause a crash. In this region, the portfolio constraint of the insiders is binding, the portfolio constraint of the uninformed traders is not binding, and prices reveal θ to the market.[13]
- Region D, where the signal received by the insiders is so bad, or their hedging motive so weak, that insiders still would want to hold a number of shares below their minimum holding allowed, beside the large price correction. Uninformed traders revise their expectations downwards causing a crash (i.e., a price discontinuity). In this region, the portfolio constraint of the insiders is binding, the portfolio constraint of the uninformed traders is not binding, and prices do not reveal θ to the market. The fact that prices stop being informative in Region D explains why a crash occurs in this region: The expected value of y conditional on the information set of the uninformed investors goes down when moving from Region C to D. Furthermore, since uninformed investors are risk-averse, they demand a higher risk premium when there is added uncertainty about fundamentals.

More formally:

THEOREM 1: *Let*

- $\bar{\theta} \equiv \frac{a_I}{\lambda_I m^2}((1+m^2)\sigma_\epsilon^2 \bar{n} - a_U \nu(\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}))$
- $\underline{\theta} \equiv \frac{a_U}{(1-\lambda_I)m^2}(-((1+m^2)\sigma_\epsilon^2 + m^2)\bar{n} + a_I \nu(\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}))$
- θ^* *be defined as a real number no larger than the smallest root* t^* *of the equation*

$$t + \frac{1}{\sqrt{1+m^2}} \frac{f\left(\dfrac{t + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)}{F\left(\dfrac{t + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)} + a_U\left(1+\sigma_\epsilon^2\right)\frac{\bar{n} - \lambda_I \nu}{1-\lambda_I} = \nu a_I \sigma_\epsilon^2, \quad (3)$$

[13] A well-known drawback of the concept of REE is that it is silent about the exact mechanism through which information gets into prices. Prices may remain informative in Region C even though the equilibrium holdings of insiders are constant because of the latent demand from insiders who would step in if uninformed investors demand less of the stock and cause prices to fall.

where $f(.)$ and $F(.)$ are, respectively, the density and the CDF of the standard normal distribution. There exists a continuum of rational expectations equilibria to the economy with portfolio constraints, which are characterized as follows:

i) Region A: $\forall\theta$ *s.t.* $\theta \geq \bar{\theta}$,

$$\text{Prices: } p_a(\theta) = \bar{f} + \theta - \frac{a_I\sigma_\epsilon^2}{\lambda_I}(\bar{n} - (1-\lambda_I)\nu)$$

$$\text{Holdings: } n_I = \frac{\bar{n} - (1-\lambda_I)\nu}{\lambda_I}; n_U = \nu.$$

ii) Region B: $\forall\theta$ *s.t.* $\bar{\theta} > \theta \geq \underline{\theta}$,

$$\text{Prices: } p_b(\theta) = \bar{f} + \theta\frac{\gamma\sigma_\epsilon^2 + \dfrac{\lambda_I m^2}{a_I}(1+\sigma_\epsilon^2)}{\gamma(1+m^2)\sigma_\epsilon^2 + \dfrac{\lambda_I m^2}{a_I}} - \bar{n}\frac{\sigma_\epsilon^2\big((1+m^2)\sigma_\epsilon^2 + m^2\big)}{\gamma(1+m^2)\sigma_\epsilon^2 + \dfrac{\lambda_I m^2}{a_I}};$$

$$\text{Holdings: } n_I = \frac{1}{a_I}\left(\frac{\left(\dfrac{1-\lambda_I}{a_U}\right)m^2\theta + \big((1+m^2)\sigma_\epsilon^2 + m^2\big)\bar{n}}{\gamma\sigma_\epsilon^2(1+m^2) + \dfrac{\lambda_I}{a_I}m^2}\right);$$

$$n_U = \frac{1}{a_U}\left(\frac{\sigma_\epsilon^2(1+m^2)\bar{n} - \dfrac{\lambda_I}{a_I}m^2\theta}{\gamma\sigma_\epsilon^2(1+m^2) + \dfrac{\lambda_I}{a_I}m^2}\right).$$

iii) Region C: $\forall\theta$ *s.t.* $\underline{\theta} > \theta \geq \theta^*$,

$$\text{Prices: } p_c(\theta) = \bar{f} + \frac{\theta}{1+m^2} + \frac{(1+m^2)\sigma_\epsilon^2 + m^2}{(1-\lambda_I)(1+m^2)}(\lambda_I a_U\nu - a_U\bar{n})$$

$$\text{Holdings: } n_I = \nu; n_U = \frac{\bar{n} - \lambda_I\nu}{1-\lambda_I}.$$

iv) Region D: $\forall\theta$ *s.t.* $\theta < \theta^*$,

$$\text{Prices: } p_d(\theta) = p^* \equiv \bar{f} - \frac{1}{\sqrt{1+m^2}}\frac{f\left(\dfrac{\theta^* + a_U\dfrac{\bar{n}-\lambda_I\nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)}{F\left(\dfrac{\theta^* + a_U\dfrac{\bar{n}-\lambda_I\nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)} - a_U(1+\sigma_\epsilon^2)\frac{\bar{n}-\lambda_I\nu}{1-\lambda_I} < p_c(\theta^*)$$

$$\textit{Holdings}: n_I = \nu; n_U = \frac{\bar{n} - \lambda_I \nu}{1 - \lambda_I}.$$

Proof: See the Appendix.

First notice that Theorem 1 characterizes a continuum of equilibria, indexed by θ^*. Put differently, the cutoff point between Regions C and D is indeterminate in the economy, even though market-clearing conditions impose a minimum size of the C region, implicitly defined in equation (3). This multiplicity of equilibria should not come as a surprise: Basak et al. (2006) show that multiplicity of equilibria is to be expected in any standard model where trading constraints have been added.[14] Note, however, that equilibrium holdings are uniquely determined: The holdings of the insiders are uniquely determined because whenever insiders are in the market, uninformed investors can infer θ and the market-clearing price is unique; the holdings of the uninformed traders are uniquely determined because the holdings of the insiders are uniquely determined and there is a fixed supply of the stock. A typical equilibrium is illustrated in Figure 2. Any equilibrium of the economy with trading constraints exhibits the following key features:

1. Prices are discontinuous at the point $\theta = \theta^*$. In other words, a crash occurs between Regions C and D.
2. Insider holdings are constant in Region C. This means that a crash is preceded by a region in which insiders do not trade.
3. The trading constraint of insiders is binding in Regions C and D. In other words, for a crash to occur insiders need to have divested the stock.
4. Prices are continuous at the point $\theta = \bar{\theta}$. In other words, a jump does not occur when the trading constraint of uninformed investors is binding and insiders have purchased the maximum amount of stock possible.

These four features constitute the testable implications of our theory, which we investigate in the next section. Thus, it is useful to stress the intuition that underlies these features. As long as insiders can and do trade, their trades reveal the composite signal θ to the uninformed traders. To the extent that θ incorporates some information about the stock fundamentals, uninformed investors react to it and prices adjust proportionally to θ. However, once uninformed traders realize that insiders have reached their constraint and have stopped trading, they can no longer infer the exact value of θ but can only infer that θ lies below the threshold θ^*. Thus, from the point of view of uninformed traders, uncertainty about the stock fundamentals is larger when insiders are out of the market than when they are trading. Higher uncertainty combined with a downward revision of beliefs about the stock fundamentals is the reason a crash occurs after insiders have stopped trading and is what explains

[14] Even though Theorem 1 characterizes a continuum of equilibria, it leaves out some other possible equilibria. In particular, it is possible to construct equilibria with multiple crashes in the D region. We are grateful to the anonymous referee for pointing out the existence of these equilibria to us. However, such equilibria share the same four key features that we highlight in the next paragraph and that give rise to testable implications.

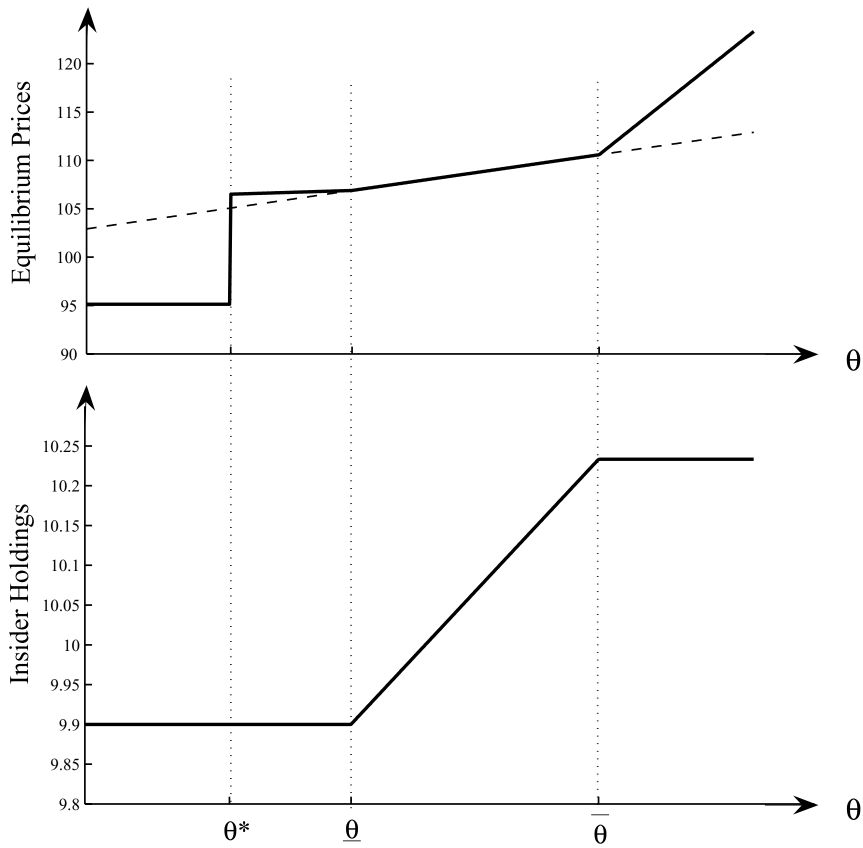


Figure 2. Equilibrium prices and insider holdings. This figure displays a parametric example of the equilibrium (prices and holdings) described in Theorem 1 resulting in a 10% crash. The parameter values are: $a_I = 1, a_U = 0.4, \lambda_I = 0.3, \bar{n} = 10, \sigma_\epsilon^2 = 50, \nu = 9.90, \sigma_{\epsilon z}^2 = 1, k_I = 5$, and $\bar{f} = 300$. The dashed line in the top panel corresponds to the equilibrium price in the economy without trading constraints.

features 1 to 3 of the equilibrium.[15] Note that the crash occurs only because the agents who are out of the market possess valuable information. No such discontinuity in the price process should be expected when the agents who are out of the market are the uninformed traders. This last observation gives rise to feature 4.

We end this section on a technical note. We pointed out earlier in the section that each type of investor can perfectly infer in equilibrium the holdings of the other type, and that our model is equivalent to a model in which trades are perfectly observable. This is unlike other models of asymmetric information with constraints where noise is added through the presence of noise traders, or

[15] Note that our theoretical model is static while the interpretation we provide is dynamic in nature. To make the argument fully rigorous, one would need to further extend the theoretical model to a setting where information gradually accrues over time through successive signals observed by insiders. Nevertheless, we trust that the current version of the model fulfils its role of providing guidance in the interpretation of the empirical evidence in the next section.

the assumption of a random net supply of the stock (e.g., Barlevy and Veronesi (2003) or Yuan (2005, 2006)). This seemingly minor change in the modeling strategy has deep implications. First, it makes the model easier to solve: We avoid having to conjecture an equilibrium price function, since the constraint status of insiders can be inferred directly given any equilibrium price. Second, it implies that the constraint of insiders is binding (which makes prices less informative) for low, rather than high, prices. This need not be the case in models with noise trading. For instance, in models such as that of Yuan (2006), high, rather than low, prices are the least informative.

Which type of model is more appropriate? In our view, this very much depends on the specific application at hand. In this paper, we are interested in looking at the asset pricing implications of insider trading. Since insider trading is public information in U.S. markets, it would not be appropriate to rely on a model where uncertainty about the presence or absence of informed investors plays a key role. However, corporate insiders are not the only type of informed investors in actual markets. Many informed investors, such as hedge funds, take great pains to hide their trades. Therefore, it would be inappropriate to use our setup for any application dealing with this type of trader. As such, we view our modeling strategy as complementary to the one used in the existing literature.

II. Empirical Study

In this section, we document a systematic pattern of insider trading preceding large drops in stock prices, which is consistent with the qualitative properties of the model in Section I. We test our model against competing stories such as patterns of insider trading driven by earnings announcement dates, or insiders timing their trades to evade prosecution. We argue that our results invalidate the mainstream view that insider sales are solely driven by liquidity needs.

A. Data, Variable Definitions, and Methodology

A.1. Data

Our tests require merging data from two different sources. The *Thomson Financial Insider Filings* (TFIF) database collects all insider trades reported to the SEC.[16] The CRSP database provides data on returns, total trading volume, and market capitalization. We use these data to identify crashes at the firm level. Our universe of securities includes all common stocks (with CRSP share code equal to 10 or 11) that trade on the NYSE, Amex, and NASDAQ markets from January 1985 to December 2002.[17] The procedures for selecting firms and cleaning the data are taken directly from Lakonishok and Lee (2001).

[16] According to Section 16(a) of the Securities and Exchange Act, insiders are required to report their trades by the 10th day of the month that follows the trading month. Reporting requirements have tightened recently as the Sarbanes-Oxley Act of 2002 requires reporting to the SEC within two business days following the insider's transaction date.

[17] In addition to CRSP and TFIF, we use the COMPUSTAT database for two sets of regressions in Section II.B.4, where earnings announcement data are necessary for testing our model against an alternative hypothesis.

Starting with the CRSP data, we exclude observations (firm/month record) for which we do not have the monthly returns. We also exclude stocks that have a price smaller than $2 at the beginning of the calendar year in order to avoid the measurement errors described in Conrad and Kaul (1993).

The TFIF database comprises transactions conducted by three groups of insiders[18]: "Management," "Large Shareholders," and "Others." Our sample contains transactions between January 1986 and December 2002.[19] We eliminate filings that do not match with CRSP data. This can happen because the security does not appear in the CRSP data set or because it is a non-common share. From the remaining filings, 889,473 correspond to open market or private sales (transaction code S), and 490,882 to open market or private purchases (transaction code P). The remaining records correspond to other types of transactions, in particular, grants and awards or exercise of derivatives, which we do not include in our sample.[20] We also exclude amended records, trades for which we do not have the insider's transaction price nor the closing price of the stock, and small transactions where less than 100 shares were traded. Finally, some filings in which the reported transaction price is not within 20% of the CRSP closing price on that day or that involve more than 20% of the number of shares outstanding are eliminated to avoid problematic records. After this filtering process and after merging the insider trading data set with the filtered CRSP data set, our sample contains 1,183,457 records. From those, 799,890 are sales and 383,567 are purchases, which are distributed as follows: 979,467 transactions by "Management," 185,096 by "Large Shareholders," and 18,894 by "Others."

A.2. Crash Variables

The first step in our empirical analysis consists of identifying crashes at the individual stock level. Both our model and the available data suggest a number of constraints at this stage:

1. In our model, insider trading matters because it is observable to, or inferred by, market participants who update their beliefs accordingly. In reality, given that our sample period is prior to the Sarbanes-Oxley Act of 2002, there can exist a gap of a few weeks between the date at which the trade takes place and the date at which it is reported. Furthermore, information about an insider's trade may actually become known to market participants at some point between these two dates. This would lead to a severe measurement problem if we were to conduct our analysis at a

[18] The "Management" group includes those transactions by the chairman, directors, CEOs, CFOs, officers, presidents, vice presidents, affiliates, members of committees, etc. The "Large Shareholders" group includes those equity holders (direct shareholders, indirect shareholders, and beneficial owners) who own more than 20% of shares and are not management. Finally, the transactions by the rest of insiders (for example, founders or former managers) are classified as "Others."

[19] The Lakonishok and Lee (2001) study covers the period 1975 to 1995. Thus, our data set misses some of the earlier observations but focuses on a more recent period where insider trading has been relatively more active.

[20] Note, however, that the sales of stocks acquired through the exercise of a derivative is counted as an open market or private sale (S) and is therefore included in our sample.

daily frequency. We thus choose to work instead at a monthly frequency. Furthermore, we take a conservative stance about the speed of reporting and revelation of information and assume that an insider trade made in month t becomes known to market participants in month $t+1$.

2. While insiders have private information about their own company, they do not necessarily have valuable information about the evolution of the entire market. Thus, if insider trading and crashes are related at the individual stock level, they must be for crashes driven by idiosyncratic shocks and not for crashes driven by market-wide corrections. Consequently, our measure of crashes at the individual stock level should correct for moves of the aggregate market.
3. Our theoretical model has sharp testable implications about the patterns of insider trading prior to a crash. However, it does not have similar implications regarding expected returns or conditional skewness.[21] The model does not provide restrictions about the size of the crash when a crash occurs either.[22] Thus, if we are to take our model seriously we must define a crash as a binary variable (either a crash occurred or it did not occur) and test whether patterns of insider trading can predict the *probability* of a crash. An important side benefit of using binary variables is that it makes it much less likely that our measures of crashes are driven by a few outliers.

Taking into account these restrictions, we construct our first baseline variable for a crash in stock i in month t, $ERCRASH_{i,t}$, as follows. We first compute the series of monthly excess returns for each stock, $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}$, where $r_{i,t}$ is the raw return of stock i in month t and $r_{m,t}$ the monthly return of the CRSP equally weighted market portfolio. Then, for each observation (stock/month), we compute the mean excess return, $\bar{r}_{i,t}^{ER}$, and the standard deviation of excess returns, $\sigma_{i,t}^{ER}$, over a rolling window of the past 5 years, or 60 months, of data. Finally, we define:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \le -2\sigma_{i,t}^{ER}; \\ 0, & \text{otherwise.} \end{cases}$$

In other words, $ERCRASH_{i,t}$ takes the value one when the excess return of stock i in month t is more than two standard deviations away and below the average excess monthly return of that stock in the past 60 months, and takes the value zero otherwise.

Our second baseline variable for a crash, $MMCRASH_{i,t}$, is constructed in similar fashion except that excess returns are adjusted for beta. That is, we define $r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, where $\beta_{i,t}$ is the beta of the stock estimated over a 60-month window and $r_{f,t}$ is the risk-free rate. We then compute the

[21] In particular, before a crash occurs, expected returns are the same no matter the pattern of insider trading.

[22] This is because of the multiplicity of equilibria in our model.

standard deviation of the residuals of the market regression, $\sigma_{i,t}^{MM}$. Finally, we formally define

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \leq -2\sigma_{i,t}^{MM}; \\ 0, & \text{otherwise.} \end{cases}$$

To check the robustness of our results with respect to our definition of crashes,[23] we also compute another measure of crashes, $RAWCRASH_{i,t}$, which is constructed in the same way as the other two measures of crashes but using raw returns instead of excess returns or residuals from the market model. As can be expected, the three measures of crashes are fairly close to one another. For instance, the median of the monthly threshold return for a crash to happen is −21.58%, −23.03%, and −21.78% for *ERCRASH*, *MMCRASH*, and *RAWCRASH*, respectively. Sample correlations range from 0.49 (between *RAWCRASH* and *MMCRASH*) to 0.71 (between *ERCRASH* and *MMCRASH*). Figure 3 represents the number of crashes per year over the 15 years of our sample according to each measure.[24] Note that according to all three measures, the post-1996 period has the largest number of crashes.

Finally, as we want to compare patterns of insider trading prior to crashes to patterns of insider trading prior to jumps, we construct the variables $ERJUMP_{i,t}$, $MMJUMP_{i,t}$, and $RAWJUMP_{i,t}$. Each of these three variables is defined in a symmetric fashion as their crash variable counterparts. For instance, we have

$$ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \geq 2\sigma_{i,t}^{ER}; \\ 0, & \text{otherwise.} \end{cases}$$

Figure 4 represents the number of jumps per year according to each measure. Our three measures of jumps are even more strongly and positively correlated with one another than our measures of crashes. Sample correlations now range from 0.7 (between *RAWJUMP* and *MMJUMP*) to 0.79 (between *ERJUMP* and *MMJUMP*). In percentage terms, we find that the median of the monthly threshold return for a jump to happen is 21.76%, 22.75%, and 24.32% for *ERJUMP*, *MMJUMP*, and *RAWJUMP*, respectively. We also observe a sharp increase in the number of jumps after 1996.

A.3. Independent Variables

Independent variables fall in two categories: variables suggested by our model and variables suggested by the existing literature. Variables suggested

[23] Robustness checks of the main regression are provided in Section B.5.

[24] Since we are using 1-year lagged insider trading variables as independent variables in our regressions and since our insider trading data start in January 1986, we look only at crashes from January 1987 onward.

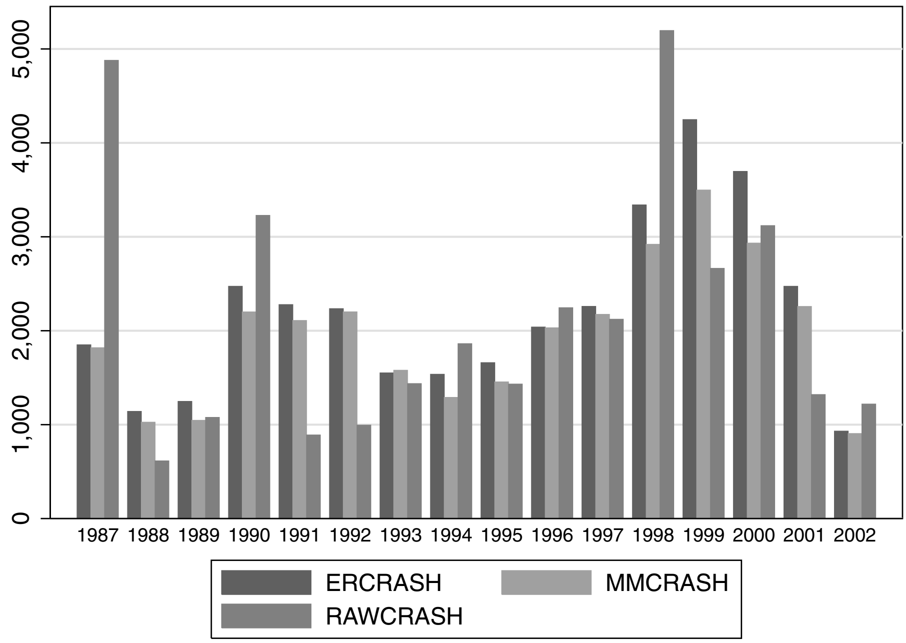


Figure 3. Number of crashes over the sample period. The figure reports the evolution of the aggregate number of crashes for common stocks traded in NYSE, Amex, and NASDAQ that appear in the CRSP data set, excluding stocks with a price smaller than $2 at the beginning of each calendar year. The figure is reported for the following alternative definitions of a crash:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \leq -2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise} \end{cases}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \leq -2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise} \end{cases}$$

$$RAWCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t} - \bar{r}_{i,t} \leq -2\sigma_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}$, $r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}$, $k = ER, MM, \emptyset$, denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window.

by our model mostly consist of different measures of insider trading. To homogenize the insider trading variables across stocks and across time, we normalize them by dividing the dollar value of each particular trade by the market capitalization of the stock, computed using the closing price on the day of the transaction. The main variables we use are insider sales, *INSSAL*, and insider purchases, *INSPUR*. A first subscript, i, refers to the individual stock considered. The variable may then have one or two time subscripts. If there

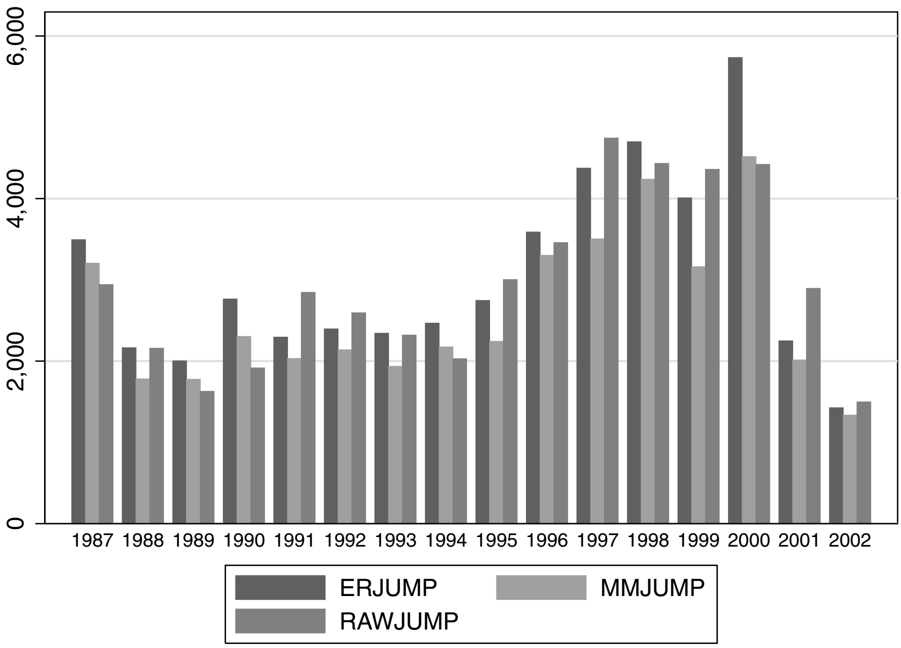


Figure 4. Number of jumps over the sample period. The figure reports the evolution of the aggregate number of jumps for common stocks traded in NYSE, Amex, and NASDAQ that appear in the CRSP data set, excluding stocks with a price smaller than \$2 at the beginning of each calendar year. The figure is reported for the following alternative definitions of a jump:

$$ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \geq 2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise} \end{cases}$$

$$MMJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \geq 2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise} \end{cases}$$

$$RAWJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t} - \bar{r}_{i,t} \geq 2\sigma_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}$, $r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}$, $k = ER, MM, \emptyset$, denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window.

is only one time subscript, then the variable refers to trades that took place during the corresponding month t. Thus, $INSSAL_{i,t}$ gives the total amount of insider sales on stock i during month t. If there are two time subscripts, then the variable refers to the monthly average between the two time subscripts. Thus, $INSPUR_{i,t-1,t-12}$ gives the average monthly amount of insider purchases on stock i between month $t-1$ and month $t-12$. Finally, we define insider trading volume, $INSTV$, as the sum of insider sales and insider purchases.

Table II

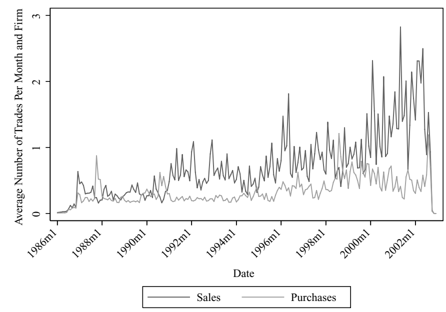
Insider Trading Activity: Summary Statistics

This table presents some summary statistics on aggregate insider trading activity. *Fraction* shows the average fraction of firms with at least one insider trade per year; *# of Trades* is the average number of sales or purchases per year and firm, and includes companies without any trading; *Tot Million $* is the average of the annual dollar value of insider trades per year expressed in terms of 1995 million dollars; *% Mkt Cap* is the ratio of the average of the value of insiders' trades per company and year to market capitalization in percentage terms, where market capitalization is computed using the closing price of the day of the trade. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions come from the Thomson Financial Data Filings data set. We exclude stocks with a price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than the 20% of the number of shares outstanding.

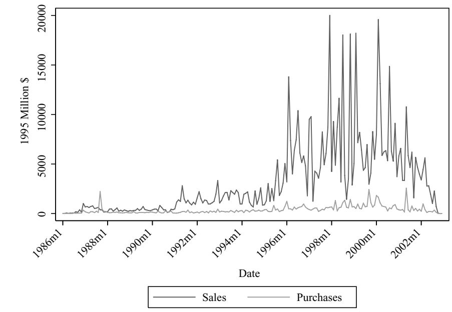
	Management	Large Shareholders	Others	Total
Purchases				
Fraction	0.483	0.052	0.013	0.501
Number of Trades	2.927	0.845	0.052	3.824
Tot Million $	$1,891	$2,482	$94	$4,467
% Mkt Cap	0.213%	0.168%	0.008%	0.388%
Sales				
Fraction	0.509	0.088	0.031	0.531
Number of Trades	6.838	1.000	0.136	7.975
Tot Million $	$24,045	$13,394	$783	$38,222
% Mkt Cap	0.561%	0.348%	0.023%	0.932%

Table II provides summary statistics on aggregate insider trading activity in our sample. We see from the table that every year one company out of two in our sample has at least one insider purchase and one company out of two has at least one insider sale. However, the average value of insider purchases is smaller than that of insider sales: On average, over all firms in our sample, insider purchases amount to 0.39% of their company's market capitalization every year while insider sales amount to 0.93%. These statistics are in line with those of Lakonishok and Lee (2001). Figure 5 represents the evolution of insider purchases and sales over time. An important point to note from Figure 5 is that insider transactions, and most notably insider sales, have been much larger in the 1990s than in the 1980s. This observation suggests that findings regarding correlations between insider activity and crashes may be sensitive to the choice of subsample. We address this issue in Section II.B.5.

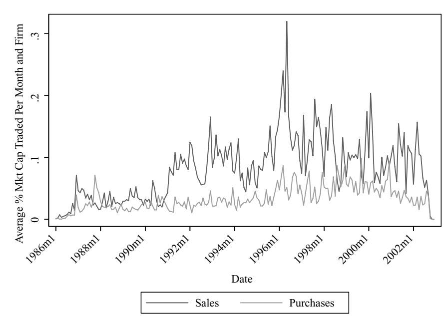
Independent variables suggested by the existing literature include trading volume and past returns. First, Chen et al. (2001) have shown that total trading volume (i.e., both by insiders and outsiders), which we hereafter denote as *TTV*, is a strong predictor of negative skewness, a concept very much related to crashes. Their interpretation of the results, consistent with the Hong and Stein (2003) model, is that *TTV* acts as a proxy for the dispersion of opinions across



(a) Insider transactions: average number of trades



(b) Insider transactions: total monthly dollar volume



(c) Insider transactions: average fraction of firm's market capitalization

Figure 5. Evolution of insider trading activity. These figures show the evolution over time of several measures of aggregate insider trading activity. Panel (a) plots the average number of sales and purchases per month and firm, and includes companies without any trading; panel (b) the total monthly dollar value of insider sales and purchases expressed in terms of 1995 million dollars; and panel (c) the average monthly fraction of insider sales and purchases to company market capitalization, where market capitalization is computed using the closing price of the day of the trade. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with a price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding.

investors. When interpreting our own results we want to make sure that trading volume by insiders does not act as a proxy for TTV. We therefore include TTV, at the same frequency as our insider trading variables, in all our regressions. Similarly, the cumulative excess return over the equally weighted market portfolio of the past 2 years, $ER_{t-1,t-24}$, is likely to matter for two reasons. First, Lakonishok and Lee (2001) show that insiders are contrarian investors. If valuable information about crashes is contained in insider trading, it is likely to be contained in the unexpected component of insider trading. Thus, to the extent that past returns predict insider trading, we want to include the variable in our regression. Another reason for including past returns is the finding by Chen et al. (2001) that past returns can predict negative skewness. Finally, our main regressions allow for firm and year effects.[25]

A.4. Estimation Procedure

The binary nature of our dependent variables raises some estimation concerns. There are three leading estimation procedures for regressions with a binary dependent variable: the linear probability model (OLS), the logit model, and the probit model. All three procedures normally yield consistent estimators.[26] However, our choice of the procedure to adopt is severely constrained by the fact that we are doing panel data estimation and that we wish to control for firm fixed effects. We know from the seminal work of Chamberlain (1980) that probit with fixed effects does not yield consistent estimators. Thus, OLS and logit remain. From the same reference, we know that consistency is not an issue for OLS. However, we know that using OLS with a binary dependent variable gives rise to problems of heteroskedasticity. We can also suspect problems of autocorrelation from the nature of our long-run independent variables. For this reason, the significance of the coefficients and p-values of OLS regressions need to be computed using Newey–West standard errors. As far as logit is concerned, we know that controlling for fixed effects using dummy variables would give rise to the same problem of inconsistent estimators as would probit. However, there exists a solution to this problem, as proposed by Chamberlain (1980): to use a conditional maximum likelihood estimator, which can be implemented with a standard conditional logit package. As a consequence of these considerations, we run each regression in the paper twice, once using OLS and once using conditional logit with fixed effects (CLFE), and always report both sets of results.

B. Empirical Results

B.1. Preliminary Result: Sidelined Investors versus the "Dog That Did Not Bark"

In the introduction we establish a dichotomy in the literature that views crashes as a phenomenon that arise because of the existence of trading constraints. Models like those of Romer (1993), Cao et al. (2002), and Hong and Stein (2003) share the property that crashes occur when previously sidelined informed investors get back into the market. Our model, as in Gennotte and Leland (1990), Barlevy and Veronesi (2003), and Yuan (2005), has the opposite

[25] An example of firm characteristics that may have an impact on crashes is size, as suggested by Chen et al. (2001).

[26] OLS is not only consistent but also unbiased in this context. For instance, see Wooldridge (2002, p. 454).

property: Crashes occur when informed investors get out of the market. Before testing specific implications of our model, we want to check more generally whether the data favor the type of models ours belongs to. Despite the wealth of theoretical models on crashes so far, to the best of our knowledge no attempt has been made to ask the data the simple question: Do informed investors get into or out of the market before a crash?

To answer this question we run regressions of our two baseline measures of crashes, $ERCRASH_{i,t}$ and $MMCRASH_{i,t}$, against insider trading volume as the measure of insider trading activity. In particular, we regress our measures of crashes on the previous month's trading volume by insiders, $INSTV_{i,t-1}$, and the average monthly insider trading volume in the past year, excluding the last month,[27] $INSTV_{i,t-2,t-12}$. We also include the previous 2 years' cumulative excess returns, $ER_{i,t-1,t-24}$, and the total trading volume (by both insiders and outsiders) of the previous month, $TTV_{i,t-1}$. In the OLS regressions, fixed year and firm effects are allowed through mean-differencing. A full set of year dummy variables is included in the conditional logit with fixed effects (CLFE) regressions. In both cases, we report the p-value of the coefficient in parentheses. Note, however, that one cannot compare the point estimates of the same regression using the two estimation techniques since one regression is linear while the other is not.

Table III presents the results of the preliminary regressions. The dependent variable for regressions in columns 1 and 2 is $ERCRASH_{i,t}$, which identifies crashes using simple excess returns. The regression in column 1 is estimated using OLS; the regression in column 2 using CLFE. Columns 3 and 4 present parallel results when the dependent variable is $MMCRASH_{i,t}$, which uses beta-adjusted returns. The results provide a conclusive answer about the relation between crashes and insider activity. Regardless of the definition of the crash and of the estimation procedure, the coefficient on the previous month's insider trading volume, $INSTV_{i,t-1}$, has a negative sign and is highly significant (p-values lower than 0.5%). Furthermore, we find that the probability of a crash is positively correlated with the previous year's average insider trading volume, $INSTV_{i,t-2,t-12}$, although the coefficient is significant only in one regression. The two findings together establish that a crash is most likely to occur when insiders have been trading in the past and have recently dropped out of the market. These preliminary results thus support the general class of theories of crashes that our model belongs to.[28]

Finally, the variables $ER_{i,t-1,t-24}$ and $TTV_{i,t-1}$ are also strongly significant and of the same sign as in the existing literature, most notably, in Chen et al. (2001). The significance of these two coefficients is important not only because it confirms the findings of the existing literature using a different methodology, but also because it dispels any suspicion that our insider trading variables

[27] The choice of a 1-year window is arbitrary. However, results based on a different choice of horizon are qualitatively similar to the ones presented here.

[28] These results hold only at the individual stock level. The same regressions ran at the aggregate level yield large p-values for all coefficients.

Table III

Preliminary Regression: Insiders Trading Volume and Crashes

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{ER}_{i,t} - \bar{r}^{ER}_{i,t} \le -2\sigma^{ER}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{MM}_{i,t} - \bar{r}^{MM}_{i,t} \le -2\sigma^{MM}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r^{ER}_{i,t} \equiv r_{i,t} - r_{m,t}$, $r^{MM}_{i,t} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}^{k}_{i,t}$ and $\sigma^{k}_{i,t}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSTV_{i,t-1}$ is the previous month's trading volume by insiders in stock i, $INSTV_{i,t-2,t-12}$ is the average trading volume by insiders in stock i in the previous year (excluding the previous month), $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i in the previous year (excluding the previous month), and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, *p*-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH
Estimation Technique:	OLS	CLFE	OLS	CLFE
INSTV_{t-1}	−0.039**	−3.166**	−0.032**	−2.725**
	(0.000)	(0.001)	(0.002)	(0.005)
$\text{INSTV}_{t-2,t-12}$	0.090+	1.251	0.039	0.315
	(0.088)	(0.452)	(0.406)	(0.862)
$\text{ER}_{t-1,t-24}$	0.001**	0.071**	0.001**	0.056**
	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.390**	0.012**	0.294**
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TTV}_{t-2,t-12}$	−0.002	0.272*	0.012**	0.788**
	(0.508)	(0.029)	(0.000)	(0.000)

play the role of a proxy for total trading volume. Indeed, the coefficient on the previous month's total trading volume, $TTV_{i,t-1}$, is always positive while the coefficient on the previous month's insider trading volume, $INSTV_{i,t-1}$, is always negative and both coefficients are always very highly significant. Further, we find that the previous month's total trading volume is significant at the 1% level in all regressions performed in this paper. This suggests that both the channel emphasized in Chen et al. (high total trading volume signals an increase in the heterogeneity of beliefs, which raises the likelihood of a crash) and the one we emphasize here (the "dog that did not bark": low trading volume by insiders raises uncertainty and the likelihood of a crash) play separate and complementary roles in explaining crashes at the individual stock level.[29]

B.2. Baseline Regression: Insider Sales and Crashes

In this section, we directly test the empirical implications of our theory of asset crashes. The main implication of the model in Section I is that a crash occurs in a region characterized by insiders being short-sales constrained. In order for this to occur insiders must have sold shares in the past. So, the main prediction of the model is that sales by insiders in the recent past must be negatively correlated with the probability of a crash while sales in the distant past must be positively correlated.

To test this hypothesis we regress our measures of crashes, $ERCRASH_{i,t}$ and $MMCRASH_{i,t}$, against sales by insiders in the previous month, $INSSAL_{i,t-1}$, and the average sales by insiders in the previous year, $INSSAL_{i,t-2,t-12}$. We also include the previous 2 years' cumulative excess returns, $ER_{i,t-1,t-24}$, and the total trading volume (by both insiders and outsiders) of the previous month, $TTV_{i,t-1}$. Fixed effects are accounted for as before. Thus, the only difference with the preliminary regressions in the previous section is that we now look at the impact of insider sales (*INSSAL*) on crashes, while the preliminary regressions deal with the impact of insider trading volume (*INSTV*), that is, of the *sum* of insider sales and insider purchases, on crashes. Isolating the impact of insider sales presents three advantages:

1. Our model has strong predictions about the sign on the coefficients. The sign on $INSSAL_{i,t-2,t-12}$ should be positive since, ceteris paribus, more sales by insiders in the past bring them closer to the point where the constraint is binding and increases the probability of a crash. The sign on $INSSAL_{i,t-1}$ should be negative since a crash is supposed to occur after insiders have stopped trading.
2. The alternative hypothesis provided by a standard static efficient markets model without constraints can also be tested. According to that hypothesis, the coefficient on $INSSAL_{i,t-2,t-12}$ should not be significant since it is a variable that was public information by month $t-1$. The coefficient on $INSSAL_{i,t-1}$ should either be nonsignificant or positive, depending on the speed of reporting and diffusion of information.
3. These regressions allow us to test whether the market believes that valuable information is contained in insider sales. Indeed, if it were not the case, as suggested by the existing literature on insider trading, then none of the coefficients on the insider sales variables should come up significant.

[29] This interpretation is confirmed by evidence from experimental markets (e.g., Smith, Suchanek, and Williams (1988)) where common knowledge of the structure of payoffs leads to a negative correlation between total trading volume and crashes.

Table IV

Insider Sales and Crashes

OLS regressions account for firm and year fixed effects through mean-differencing. P-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{ER}_{i,t} - \bar{r}^{ER}_{i,t} \leq -2\sigma^{ER}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{MM}_{i,t} - \bar{r}^{MM}_{i,t} \leq -2\sigma^{MM}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r^{ER}_{i,t} \equiv r_{i,t} - r_{m,t}$, $r^{MM}_{i,t} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}^{k}_{i,t}$ and $\sigma^{k}_{i,t}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insider sales in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than \$2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, p-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH
Estimation Technique:	OLS	CLFE	OLS	CLFE
INSSAL_{t-1}	-0.025^{+}	-1.687^{+}	-0.028^{*}	-2.456^{*}
	(0.052)	(0.092)	(0.013)	(0.037)
$\text{INSSAL}_{t-2,t-12}$	0.232^{**}	5.606^{**}	0.127^{*}	3.700^{+}
	(0.001)	(0.001)	(0.031)	(0.053)
$\text{ER}_{t-1,t-24}$	0.001^{**}	0.070^{**}	0.001^{**}	0.055^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015^{**}	0.380^{**}	0.012^{**}	0.290^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TTV}_{t-2,t-12}$	-0.002	0.265^{*}	0.012^{**}	0.780^{**}
	(0.407)	(0.033)	(0.000)	(0.000)

Table IV contains the results of the regression of crashes on sales. As before, in the first two columns crashes are defined using simple excess returns, while in columns 3 and 4 crashes are defined using the market model. In all regressions, the coefficients on both insider sales variables are statistically significant. The sign on the previous month's insider sales, $INSSAL_{i,t-1}$, is negative, which means that high sales by insiders today reduce the chance of a crash in the next month. It is also significant in all four regressions, with p-values ranging from 1% to 9%. This finding can hardly be reconciled with a standard rational expectations model but is consistent with our "dog that did not bark" theory. Similarly, the sign on the previous year's average sales by insiders variable, $INSSAL_{i,t-2,t-12}$, is positive and significant (p-values ranging from 0.1% to 5%), which runs against the standard efficient markets hypothesis that states that past news should not affect today's returns. Yet, it is consistent with our hypothesis that crashes occur when insider holdings reach the point at which the trading constraint is binding.

The strong statistical significance of the insider sales variable is also in sharp contrast to an important literature that argues insider purchases, rather than sales, are the only insider transactions with informational content and the source of profitable trading rules. Lakonishok and Lee (2001) examine insider trading activity of companies traded on the NYSE, Amex, and NASDAQ during the 1975 to 1995 period. They find that after controlling for size, book to market, and momentum effects, being long in a portfolio composed of stocks heavily purchased by insiders earns an annual excess return of 4.82% while being short in a portfolio composed of stocks heavily sold by insiders does not seem to earn any significant excess return. Jeng et al. (2003) construct a "purchase portfolio" that holds all shares purchased by insiders over a 6-month period and a "sale portfolio" that holds all shares sold by insiders over a 6-month period. They find that the purchase portfolio earns positive abnormal returns on the order of 50 basis points per month while the sale portfolio earns no negative abnormal return. Friederich et al. (2002) and Fidrmuc et al. (2006) provide evidence based on U.K. data suggestive of significantly smaller absolute price reaction to insider sales than to insider purchases. Thus, the consensus of the existing literature is that "insider selling that is motivated by private information is dominated by portfolio rebalancing for diversification purposes" (Lakonishok and Lee (2001)).

Our model provides some guidance on how to reconcile the evidence in Table IV with the findings of the existing literature on insider trading. It suggests that, indeed, the relation between returns and insider sales may be ambiguous even when insider sales contain information. On the one hand, high sales by insiders signal worse news to uninformed investors than moderate sales. On the other hand, no sales at all by insiders may signal even worse news than high sales if the insiders have already hit their trading constraint. Looking at the sequence of trades by insiders as we do in this paper allows us to disentangle these two effects. Our findings suggest that insider sales are not solely driven by liquidity needs.

However, the empirical evidence reported in Table IV is consistent with a few other possible explanations, apart from that of our model. One possible explanation is that insiders are unlikely to trade on sensitive short-lived information. This is because insiders trading on information want to escape scrutiny from the SEC and the SEC is likely to investigate any trade by insiders that took place a few days before a crash. The absence of trading on short-lived information could also arise because of the "short swing" rule of the 1934 Security Exchange Act that prohibits profit-taking by insiders for offsetting trades within 6 months. A second possible explanation has to do with earnings announcements. Indeed, many large price drops are due to companies failing to meet earnings expectations and we know that most companies prohibit insiders from trading prior to an earnings announcement. Thus, our finding that crashes are preceded by a drop in selling by insiders could be a pure artifact driven by calendar effects. We test our model against these competing stories in the next two subsections.

B.3. The Dog That Did Not Bark versus Evading the SEC

To test our explanation of the evidence of insider sales preceding crashes against the "evading the SEC" story, we rely on extra predictions provided by each hypothesis. First notice that in our model continuous sales by insiders followed by a period of no selling may drive a crash because of the short-sales constraint, but continuous purchases followed by a period of no buying do not drive a jump. Thus, if the pattern of insider trading prior to crashes is best explained by our story, then one should not expect a symmetric pattern for purchases prior to jumps. By way of contrast, the "evading the SEC" story is symmetric to the following extent: If the SEC prosecutes insider trading based on positive news at least as much as it prosecutes insider trading based on negative news, then insiders who wish to avoid being prosecuted by the SEC should abstain from trading on short-lived positive information the same way they do with negative information.

To what extent does the SEC prosecute trading based on positive news? Table I in the introduction provides some evidence that we collect from the SEC website. The SEC posts on its webpage any news related to filed cases (litigation releases). Currently, all litigation releases since September 20, 1995 are freely available on the SEC website. We check all releases that overlap with the sample period of the data we use in this paper, which represent a total of more than 3,000 items over a period of 7 1/4 years.[30] For each release, we establish whether the release is related to an insider trading case and whether the information used by the insider to trade corresponds to positive news (e.g., a forthcoming takeover) or negative news (e.g., earnings below expectations). In most cases, the release contains information about both the type of information and the exact trade by the insider, which allows us to classify it in the right category. In some cases, we need to check other releases concerning the same case to obtain the required information. Sometimes the same litigation release concerns multiple cases of insider trading, some of which are based on positive news and others on negative news. In such instances, we count the release twice, once in the "Trading on good news" category and once in the "Trading on bad news" category. Finally, for 10 releases (out of 600) we are unable to

[30] Litigation releases are not classified by type of offence. Only 20% of the releases concern insider trading, directly or indirectly.

determine either the nature of the information used by the insider or the type of trade. In these cases the release is not counted in any of the categories.

The main lesson to be drawn from Table I is that two-thirds of the litigation releases concern insider trading based on positive news. This number is to be compared with a similar statistic provided by Meulbroek (1992) for earlier data: She finds that 87% of insider trading cases filed by the SEC between 1980 and 1989 concerned trading on positive news. The difference between Meulbroek's number and ours can be explained in different ways. The most obvious explanation is the fact that we are looking at different sample periods. Another possible explanation is that her unit of measurement is the number of cases while ours is the number of news releases. Finally, we count as "insider trading on bad news" a number of releases where insider trading was only a side item of the release. A typical example is a news release about an accounting fraud, where it is indicated that the defendant benefited from the fraud through insider trading. In any case, whether one accepts Moelboek's estimate of 87% of insider trading cases prosecuted by the SEC dealing with trading on positive news, or whether one prefers our more conservative estimate of two-thirds, the bottom line is that the SEC prosecutes insider trading on good news at least as much as it prosecutes insider trading on bad news.[31] This evidence is robust enough to conclude that, unlike our hypothesis, the "evading the SEC" hypothesis predicts the same pattern for insider purchases before jumps and for insider sales before crashes. Thus, we have a clean test to distinguish our story from the "evading the SEC story."

In Table V we present the results of regressions where we run $ERJUMP_{i,t}$ and $MMJUMP_{i,t}$ against the previous month's purchases by insiders, $INSPUR_{i,t-1}$, and the average purchases by insiders in the previous year, $INSPUR_{i,t-2,t-12}$. As before, we include the past 2 years' cumulative excess returns, $ER_{i,t-1,t-24}$, the total trading volume (by both insiders and outsiders) of the previous month, $TTV_{i,t-1}$, and account for year and firm fixed effects. We find that the coefficient on $INSPUR_{i,t-2,t-12}$ is statistically insignificant: The lowest p-value of the coefficient in the four regressions is 18.9%.[32] Most importantly, we find that the coefficient on $INSPUR_{i,t-1}$ is positive and most of the time significant at the 5% level. In other words, we find that an increase in recent insider purchases raises the probability of a jump. Thus, we do not observe the same "dog that did not bark" effect for jumps as we do for crashes, but rather the opposite. This finding is consistent with our theoretical model where such an asymmetry is imbedded. It is not consistent, however, with the "avoiding prosecution by the SEC" story. It is also not consistent with the "6-month short-swing rule," which also treats

[31] An even starker picture arises if we normalize the number of prosecutions of insider trading on good news by the total number of insider purchases, and the number of prosecutions of insider trading on bad news by the total number of insider sales. Table II in Section II.A.3 shows that, indeed, there are twice as many insider sales as there are insider purchases. The average value of an insider sale is also larger than the average value of an insider purchase.

[32] The lack of significance of the coefficient associated with $INSPUR_{i,t-2,t-12}$ is not driven by multicolinearity considerations as the correlation between $INSPUR_{i,t-2,t-12}$ and $INSPUR_{i,t-1}$ is just 0.01.

Table V

Insider Purchases and Jumps

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables are defined as:

$$ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \geq 2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases}$$

$$MMJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \geq 2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}$, $r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSPUR_{i,t-1}$ are the previous month's insider purchases in stock i, $INSPUR_{i,t-2,t-12}$ is the average of the insider purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, AMEX, and Nasdaq markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than \$2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, *p*-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ERJUMP	ERJUMP	MMJUMP	MMJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE
$INSPUR_{t-1}$	0.087^{+}	0.899^{+}	0.087*	1.067*
	(0.050)	(0.063)	(0.044)	(0.029)
$INSPUR_{t-2,t-12}$	0.162	2.059	0.171	2.672
	(0.248)	(0.453)	(0.189)	(0.368)
$ER_{t-1,t-24}$	−0.007**	−0.322**	−0.006**	−0.314**
	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.200**	0.010**	0.174**
	(0.000)	(0.000)	(0.000)	(0.000)
$TTV_{t-2,t-12}$	−0.070**	−2.204**	−0.056**	−2.011**
	(0.000)	(0.000)	(0.000)	(0.000)

sales and purchases in a symmetric fashion. The main message of this section is that any theoretical model trying to explain the patterns of insider trading prior to crashes also has to come to grips with the absence of similar patterns prior to jumps.

B.4. The Dog That Did Not Bark versus Earnings Announcements

We now test our story against the earnings announcement hypothesis as explanations of the patterns of insider trading prior to crashes. According to the earnings announcement hypothesis, a large proportion of crashes may take place during months in which an earnings announcement takes place, because of earnings failing to meet the market's expectations. To the extent that insiders are prevented from trading their own company's stock for a few weeks prior to the earnings announcement, it is natural to see crashes associated with low trading by insiders the previous month. Thus, if the alternative hypothesis is correct, the correlation between crashes and insider trading is a pure artifact driven by calendar effects, and the absence of trading by insiders contains no valuable information for outsiders.

In order to test our hypothesis against this alternative hypothesis, we merge our data set with information from COMPUSTAT regarding earnings announcements. We eliminate all observations for which we do not have data regarding earnings announcement dates for that stock and that year. We then construct a subsample with only observations (stock/month) where no earnings announcement was made for that stock during that month. We then run the base regressions for this subsample. If our model is correct, we should find the same results in the subsample without earnings announcement dates since earnings announcements play no role in our analysis. On the other hand, if the alternative hypothesis is correct then the "dog that did not bark" effect should disappear in this subsample.

The results, reported in Table VI, are unambiguous. The OLS crash regressions (regressions 1 and 3) offer an especially good fit, with all coefficients of the sign predicted by the theory and with p-values far below 5%. The CLFE regressions (2 and 4) also obtain coefficients of the sign predicted by the theory but with higher p-values. Nevertheless, most coefficients remain significant. By way of contrast, none of the insider purchase variables are significant at the 5% level for any of the four jump regressions. Furthermore, the point estimates of $INSPUR_{i,t-1}$ are all positive, which confirms our earlier findings of the crash/jump asymmetry.

To further confirm the interpretation of our results, we perform another test. Specifically, we run the base regressions on the subsample in which all observations correspond to a month where an earning announcement took place. To the extent that insider trading is strongly regulated for most firms around these periods, both in terms of purchases and in terms of sales, uninformed traders should not be able to draw any inference, either positive or negative, from the pattern of insider trading around those dates. Thus, if our theory that the pattern of insider trading around crashes is driven by informational considerations is correct, then the insider trading variables should stop being significant in this subsample. The results we report in Table VII support this hypothesis: Not only do the previous month's insider sales stop being significant, which is expected given that there is very little insider trading around earnings announcement dates, but the previous year's average insider sales stop being significant as well.

Table VI

No Earning Announcements

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{ER}_{i,t} - \bar{r}^{ER}_{i,t} \leq -2\sigma^{ER}_{i,t} \\ 0, & \text{otherwise,} \end{cases} \qquad ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r^{ER}_{i,t} - \bar{r}^{ER}_{i,t} \geq 2\sigma^{ER}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r^{MM}_{i,t} - \bar{r}^{MM}_{i,t} \leq -2\sigma^{MM}_{i,t} \\ 0, & \text{otherwise,} \end{cases} \qquad MMJUMP_{i,t} = \begin{cases} 1, & \text{if } r^{MM}_{i,t} - \bar{r}^{MM}_{i,t} \geq 2\sigma^{MM}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r^{ER}_{i,t} \equiv r_{i,t} - r_{m,t}, r^{MM}_{i,t} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t})), r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}^{k}_{i,t}$ and $\sigma^{k}_{i,t}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insider sales in stock i during the period $t-12$ to $t-2$, $INSPUR_{i,t-1}$ are the previous month's insider purchases in stock i, $INSPUR_{i,t-2,t-12}$ is the average of the insider purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set, where we dropped all observations corresponding to months where an earnings announcement took place for that stock; the data on insider transactions comes from the Thomson Financial Data Filings data set, and the data on earning announcements from COMPUSTAT. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, p-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH	ERJUMP	ERJUMP	MMJUMP	MMJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
$INSSAL_{t-1}$	-0.028^{*}	-2.142	-0.028^{**}	-2.973^{+}				
	(0.013)	(0.129)	(0.003)	(0.065)				

$\text{INSSAL}_{t-2,t-12}$	0.274**	7.571**	0.156*	5.051*				
	(0.001)	(0.001)	(0.030)	(0.038)				
INSPUR_{t-1}					0.083	0.750	0.080	1.004+
					(0.135)	(0.165)	(0.119)	(0.071)
$\text{INSPUR}_{t-2,t-12}$					0.130	0.879	0.310	5.319
					(0.566)	(0.805)	(0.140)	(0.136)
$\text{ER}_{t-1,t-24}$	0.001**	0.068**	0.001**	0.066**	−0.006**	−0.276**	−0.005**	−0.283**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.514**	0.012**	0.422**	0.015**	0.233**	0.010**	0.215**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TTV}_{t-2,t-12}$	−0.005	0.157	0.009**	0.835**	−0.066**	−2.390**	−0.050**	−2.174**
	(0.128)	(0.359)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table VII

Earning Announcements

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \leq -2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases} \qquad ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \geq 2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \leq -2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise,} \end{cases} \qquad MMJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \geq 2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}, r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t})), r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}$, $k = ER, MM$, denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insider sales in stock i during the period $t-12$ to $t-2, INSPUR_{i,t-1}$ are the previous month's insider purchases in stock i, $INSPUR_{i,t-2,t-12}$ is the average of the insider purchases in stock i during the period $t-12$ to $t-2, TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set, where we dropped all observations corresponding to months where an earnings announcement did not take place for that stock; the data on insider transactions comes from the Thomson Financial Data Filings data set, and the data on earning announcements from COMPUSTAT. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, p-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH	ERJUMP	ERJUMP	MMJUMP	MMJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
INSSAL_{t-1}	0.005	−0.066	−0.032	−1.857				
	(0.906)	(0.963)	(0.406)	(0.349)				

$INSSAL_{t-2,t-12}$	0.099	0.989	0.039	0.872				
	(0.338)	(0.750)	(0.658)	(0.795)				
$INSPUR_{t-1}$					0.118	1.840	0.079	1.699
					(0.131)	(0.313)	(0.291)	(0.414)
$INSPUR_{t-2,t-12}$					0.324	9.181	0.050	−2.236
					(0.128)	(0.147)	(0.777)	(0.753)
$ER_{t-1,t-24}$	0.002**	0.117**	0.003**	0.066**	−0.008**	−0.322**	−0.007**	−0.295**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.018**	0.519**	0.017**	0.479**	0.022**	0.349**	0.019**	0.472**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$TTV_{t-2,t-12}$	−0.002	0.148	0.009+	0.441*	−0.085**	−2.248**	−0.069**	−2.140**
	(0.718)	(0.488)	(0.091)	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)

B.5. Other Robustness Checks

We now proceed to check the robustness of our base regressions. We want to check the robustness of our results with respect to the sample period and the definition of the variables, both dependent and independent.

As mentioned in Section II.A.3, and illustrated in Figure 5, insider trading as a fraction of market capitalization has increased sharply in the mid-1990s. This raises the question of how robust our results are to the choice of sample period. We split our sample into two subsamples, one covering the period 1986 to 1995 (low insider trading) and the other the period 1996 to 2002 (high insider trading) and run the base regressions on the two separate subsamples.

Tables VIII and IX report the results for the leading regressions for crashes and jumps, respectively, for each subperiod. For the 1986 to 1995 period, all insider trading variables in the crash regressions are of the sign predicted by the theory (negative for $INSSAL_{i,t-1}$, positive for $INSSAL_{i,t-2,t-12}$), except for one variable in one of the four regressions ($INSSAL_{i,t-2,t-12}$ in regression 4) that is highly insignificant (p-value equal to 82%). Also, the asymmetry between crashes and jumps is preserved: High insider sales in the previous month lower the probability of a crash while high insider purchases raise the probability of a jump. However, p-values are all very high. Results for the 1996 to 2002 period are much stronger: All insider trading variables are of the predicted sign and significant. As before, the OLS regressions offer a slightly better fit than CLFE, with p-values around or below 2%.

Two explanations are possible for the weaker results in the earlier subsample. First, insider trading activity picked up after the mid 1990s. It is therefore not surprising to find "more action" in the later subsample. The second explanation is related to the nature of our model. Our theory relies on uninformed traders being able to observe, or infer, trades by insiders. This assumption fits the current situation in U.S. markets: Even very unsophisticated investors can now get free access to insider trading data, for instance on such popular websites as finance.yahoo.com. This was much less true in the 1980s/early-1990s, where it can be argued that many investors lacked easy or cheap access to such data. This observation, and the evidence of the subsample analysis, suggest that our model fits better with the current trading environment.

Our next robustness check concerns the way we construct our crash variables as well as our insider trading variables. We first check if the 1-year window for insider activities preceding large price movements is critical for the results. In Tables X and XI we report the regression results for two alternative windows: 6 and 24 months. In these regressions the near past variable remains as in the baseline regression (1 month), but the far past variables go back to months $t-6$ and $t-24$, respectively. The results are as strong as those in the baseline regressions: The coefficients have the right sign and are strongly significant most of the time. The "dog that did not bark" effect is present for crashes (negative coefficient on $INSSAL_{i,t-1}$) and absent for jumps (positive coefficient on $INSPUR_{i,t-1}$), as predicted by the theory.

Finally, in Table XII we report the results of the base regressions using a definition of crashes and jumps based on raw returns, rather than returns in

Table VIII
Robustness Check: Subsample Analysis for Crashes

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \leq -2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases} \qquad MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \leq -2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}, r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t})), r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}, k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_i, t-2, t-12$, is the average of the insider sales in stock i during the priod $t = 12$ to $t-2$, $T\ TV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, p-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	Subsample 1986–1995				Subsample 1996–2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH	ERCRASH	ERCRASH	MMCRASH	MMCRASH
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
INSSAL_{t-1}	−0.009	−0.715	−0.027	−1.579	−0.034**	−2.076	−0.030**	−3.014+
	(0.867)	(0.654)	(0.577)	(0.387)	(0.005)	(0.104)	(0.002)	(0.051)
$\text{INSSAL}_{t-2,t-12}$	0.308*	2.616	0.174	−1.297	0.216**	7.420**	0.148*	6.491**
	(0.028)	(0.633)	(0.197)	(0.820)	(0.004)	(0.000)	(0.021)	(0.005)
$\text{ER}_{t-1,t-24}$	0.001	0.078**	0.001**	0.106**	0.002**	0.108**	0.002**	0.082**
	(0.102)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.020**	0.492**	0.023**	0.653**	0.009**	0.364**	0.005**	0.181**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.006)
$\text{TTV}_{t-2,t-12}$	0.033**	1.141**	0.027**	1.256**	−0.012**	0.217	0.002	0.657**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.197)	(0.549)	(0.000)

Table IX

Robustness Check: Subsample Analysis for Jumps

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r^{ER}_{i,t} - \bar{r}^{ER}_{i,t} \geq 2\sigma^{ER}_{i,t} \\ 0, & \text{otherwise,} \end{cases} \qquad MMJUMP_{i,t} = \begin{cases} 1, & \text{if } r^{MM}_{i,t} - \bar{r}^{MM}_{i,t} \geq 2\sigma^{MM}_{i,t} \\ 0, & \text{otherwise,} \end{cases}$$

where $r^{ER}_{i,t} \equiv r_{i,t} - r_{m,t}, r^{MM}_{i,t} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}^{k}_{i,t}$ and $\sigma^{k}_{i,t}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSPUR_{i,t-1}$ are the previous month's insider purchases in stock i, $INSPUR_{i,t-2,t-12}$ is the average of the insider purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, *p*-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	Subsample 1986–1995				Subsample 1996–2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERJUMP	ERJUMP	MMJUMP	MMJUMP	ERJUMP	ERJUMP	MMJUMP	MMJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
$INSPUR_{t-1}$	0.257*	3.407*	0.293**	4.113**	0.047	0.592	0.040	0.634
	(0.019)	(0.015)	(0.010)	(0.003)	(0.213)	(0.281)	(0.212)	(0.310)
$INSPUR_{t-2,t-12}$	0.735**	15.906*	0.434	10.007	0.009	0.538	0.061	1.481
	(0.006)	(0.033)	(0.106)	(0.208)	(0.959)	(0.863)	(0.711)	(0.659)
$ER_{t-1,t-24}$	−0.011**	−0.451**	−0.010**	−0.433**	−0.006**	−0.288**	−0.005**	−0.278**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.170	0.014**	0.224*	0.008**	0.153**	0.004+	0.103*
	(0.001)	(0.120)	(0.001)	(0.050)	(0.002)	(0.000)	(0.059)	(0.039)
$TTV_{t-2,t-12}$	−0.084**	−2.929**	−0.066**	−2.569**	−0.083**	−2.269**	−0.066**	−2.080**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table X

Robustness Check: Window for Past Insider Sales

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \leq -2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases} \qquad MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \bar{r}_{i,t}^{MM} \leq -2\sigma_{i,t}^{MM} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}, r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, $r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}$, $k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_{i,t-2,t-k}$ is the average of the insider sales in stock i during the period $t-k$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, *p*-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERCRASH	ERCRASH	MMCRASH	MMCRASH	ERCRASH	ERCRASH	MMCRASH	MMCRASH
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
INSSAL_{t-1}	-0.024^{+}	-1.681^{+}	-0.030^{**}	-2.620^{*}	-0.022^{+}	-1.622	-0.029^{*}	-2.595^{*}
	(0.060)	(0.092)	(0.009)	(0.028)	(0.086)	(0.105)	(0.011)	(0.029)
$\text{INSSAL}_{t-2,t-6}$	0.120^{**}	2.397^{*}	0.070	1.618				
	(0.010)	(0.031)	(0.113)	(0.203)				
$\text{INSSAL}_{t-2,t-24}$					0.336^{**}	10.984^{**}	0.096	6.208^{*}
					(0.002)	(0.000)	(0.261)	(0.036)
$\text{ER}_{t-1,t-24}$	0.001^{**}	0.069^{**}	0.001^{**}	0.058^{**}	0.001^{**}	0.068^{**}	0.001^{**}	0.058^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.013^{**}	0.352^{**}	0.013^{**}	0.324^{**}	0.013^{**}	0.351^{**}	0.013^{**}	0.324^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TTV}_{t-2,t-6}$	0.004	0.338^{**}	0.005^{*}	0.291^{**}	0.004	0.326^{**}	0.005^{*}	0.285^{**}
	(0.105)	(0.001)	(0.020)	(0.002)	(0.129)	(0.001)	(0.018)	(0.003)

Table XI

Robustness Check: Window for Past Insider Purchases

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \le -2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases} \qquad ERJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \bar{r}_{i,t}^{ER} \ge 2\sigma_{i,t}^{ER} \\ 0, & \text{otherwise,} \end{cases}$$

where $r_{i,t}^{ER} \equiv r_{i,t} - r_{m,t}, r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t})), r_{i,t}$ is the raw return of stock i in month t, $r_{m,t}$ is the monthly return of the CRSP equally weighted market portfolio, $\beta_{i,t}$ is the beta of the stock estimated over a 60-month rolling window, and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^{k}$ and $\sigma_{i,t}^{k}, k = ER, MM$ denote the sample mean and standard deviation of the corresponding k variable and are computed using a 5-year rolling window. Regarding the independent variables: $INSPUR_{i,t-1}$ are the previous month's insider purchases in stock i, $INSPUR_{i,t-2,t-k}$ is the average of the insider purchases in stock i during the period $t-k$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and NASDAQ markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than $2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, *p*-values are reported in parentheses. The plus sign denotes significance at the 10% level. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ERJUMP	ERJUMP	MMJUMP	MMJUMP	ERJUMP	ERJUMP	MMJUMP	MMJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE	OLS	CLFE	OLS	CLFE
INSPUR_{t-1}	0.086^{+}	0.904^{+}	0.086^{*}	1.075^{*}	0.087^{+}	0.899^{+}	0.087^{*}	1.030^{*}
	(0.053)	(0.063)	(0.046)	(0.030)	(0.051)	(0.063)	(0.045)	(0.034)
$\text{INSPUR}_{t-2,t-6}$	0.131	1.785	0.111	1.972				
	(0.103)	(0.246)	(0.167)	(0.262)				
$\text{INSPUR}_{t-2,t-24}$					0.281	6.105	0.109	2.570
					(0.140)	(0.171)	(0.557)	(0.601)
$\text{ER}_{t-1,t-24}$	-0.007^{**}	-0.326^{**}	-0.006^{**}	-0.317^{**}	-0.007^{**}	-0.326^{**}	-0.006^{**}	-0.318^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.012^{**}	0.180^{**}	0.008^{**}	0.155^{**}	0.012^{**}	0.180^{**}	0.008^{**}	0.154^{**}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
$\text{TTV}_{t-2,t-6}$	-0.040^{**}	-1.230^{**}	-0.033^{**}	-1.169^{**}	-0.040^{**}	-1.227^{**}	-0.033^{**}	-1.167^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table XII

Large Raw Returns

OLS regressions account for firm and year fixed effects through mean-differencing. *P*-values are computed using Newey–West standard errors to control for autocorrelation and heteroskedasticity. CLFE regressions are estimated using conditional logit with (firm) fixed effects and include a full set of year dummy variables. The dependent variables in the regressions are defined as:

$$RAWCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t} - \bar{r}_{i,t} \leq -2\sigma_{i,t} \\ 0, & \text{otherwise,} \end{cases} \qquad RAWJUMP_{i,t} = \begin{cases} 1, & \text{if } r_{i,t} - \bar{r}_{i,t} \geq 2\sigma_{i,t} \\ 0, & \text{otherwise.} \end{cases}$$

In these expressions, $r_{i,t}$ is the raw return of stock i in month t, $\bar{r}_{i,t}$ and $\sigma_{i,t}$ denote the sample means and standard deviations of the raw return, respectively, and are computed using a 5-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the previous month's insider sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insider sales in stock i during the period $t-12$ to $t-2$, $INSPUR_{i,t-1}$ are the previous month insider purchases in stock i, $INSPUR_{i,t-2,t-12}$ is the average of the insider purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the previous month's total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i during the period $t-12$ to $t-2$, and $ER_{i,t-1,t-24}$ is stock i's cumulative excess return over the CRSP equally weighted market portfolio for the previous 2 years. The sample consists of insiders' open market or private sales and purchases from 1986 to 2002 in common stocks traded in NYSE, Amex, and Nasdaq markets that appear in the CRSP data set; the data on insider transactions comes from the Thomson Financial Data Filings data set. We exclude stocks with price smaller than \$2 at the beginning of each calendar year, amended insider trading records, transactions involving less than 100 shares, and filings in which the reported transaction price was not within 20% of the CRSP closing price on that day, or that involved more than 20% of the number of shares outstanding. For each regression, p-values are reported in parentheses. One and two asterisks (*,**) denote significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	RAWCRASH	RAWCRASH	RAWJUMP	RAWJUMP
Estimation Technique:	OLS	CLFE	OLS	CLFE
INSSAL_{t-1}	0.007	0.195		
	(0.704)	(0.770)		
$\text{INSSAL}_{t-2,t-12}$	0.343**	9.576**		
	(0.000)	(0.000)		
INSPUR_{t-1}			0.117*	1.040*
			(0.031)	(0.028)
$\text{INSPUR}_{t-2,t-12}$			0.117	−0.102
			(0.423)	(0.972)
$\text{ER}_{t-1,t-24}$	0.001**	0.048**	−0.006**	−0.269**
	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.011**	0.253**	0.017**	0.208**
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TTV}_{t-2,t-12}$	0.007*	0.658**	−0.062**	−2.029**
	(0.015)	(0.000)	(0.000)	(0.000)

excess of the CRSP equally weighted market portfolio or of the returns predicted by the market model. To the extent that our model is not a model of marketwide crashes, we expect the results of this regression to be more noisy than when adjustments for market changes are made. The results are consistent with our expectations: The "long-term" insider trading variable remains of the right sign and significant at the 1% level in both crash regressions but the "short-term" variable is insignificant (and of the wrong sign).

The overall picture we draw from these robustness tests is that the effects we identify in the leading regressions seem to be quite robust. In most of the alternate specifications, both insider trading variables remain of the right sign and significant for the crash regressions. In some regressions, one of the variables stops being significant but we never observe a coefficient with the wrong sign and even mildly significant. Finally, the asymmetry between the crash and the jump regressions, which we argue earlier is one of our most striking findings, remains present in all the alternative specifications.

III. Concluding Remarks

Insider trading and crashes in asset prices are among the finance concepts that have historically attracted the largest amount of attention, both in the academic arena and among practitioners. In this paper we introduce a theoretical framework that relates them in a novel fashion. The model we develop in this framework points at a clear pattern of insider selling intensity preceding crashes (high in the far past and low in the near past) with no symmetric counterpart in the case of insider purchases and jumps. Our empirical study shows that the evidence in the U.S. markets is consistent with the predictions of the model. These results shed new light on the informative role of insider sales.

We believe this paper presents a starting point in a new way of thinking about insider trading and crashes. As such, it leaves many questions unanswered and in turn opens lines for further research. First, notice that our theory is developed under the assumption of fully rational agents. This implies no arbitrage opportunity is left unexploited in the model. We could certainly obtain the "dog that did not bark" effect in models where some form of irrationality prevails. Therefore, the issue of the existence of profitable trading strategies based on the pattern of insider sales remains an open issue to be settled empirically. In particular, one could look at the profitability of stock or option trading strategies based on the sequence of insider sales as suggested by the model. Second, from an international perspective, it would be interesting to conduct the same tests performed here across countries with different insider trading regulations. These extensions are beyond the scope of the present paper and are left for future research.

Appendix: Proofs

Proof of Theorem 1: We proceed on a region-by-region basis.

i) Region A. From the study of the unconstrained economy, we have that the demand of the representative insider is given by

$$n_I(y, x_I, p) = \text{Max}\left(\frac{\bar{f} + \theta - p}{a_I \sigma_\epsilon^2}; \nu\right) = \text{Max}\left(\frac{\bar{n} - (1 - \lambda_I)\nu}{\lambda_I}; \nu\right)$$
$$= \frac{\bar{n} - (1 - \lambda_I)\nu}{\lambda_I}$$

since $\nu < \bar{n}$.

It can easily be checked that any price $p \geqslant p(\bar{\theta})$ corresponds to one and only one θ. Thus, prices reveal θ in Region A and, as seen in the study of the unconstrained economy, the demand of the uninformed traders is given by

$$n_U(p) = \text{Max}\left(\frac{(1 + m^2)(\bar{f} - p) + \theta}{a_U((1 + m^2)\sigma_\epsilon^2 + m^2)}; \nu\right)$$
$$= \text{Max}\left(\frac{-m^2\theta + \dfrac{(1 + m^2)\sigma_\epsilon^2 a_I}{\lambda_I}(\bar{n} - (1 - \lambda_I)\nu)}{a_U\big((1 + m^2)\sigma_\epsilon^2 + m^2\big)}; \nu\right) = \nu \text{ if } \theta \geq \bar{\theta}.$$

Thus, the market-clearing condition is satisfied in Region A.

ii) Region B. The derivation of equilibrium prices and equilibrium holdings in this region is identical to that of the equilibrium of the economy without portfolio constraints. The restriction that equilibrium holdings need to be larger than ν for both types of agents provides the condition $\bar{\theta} > \theta \geq \underline{\theta}$.

iii) Region C. For insiders, we have as before

$$n_I(y, x_I, p) = \text{Max}\left(\frac{\bar{f} + \theta - p}{a_I \sigma_\epsilon^2}; \nu\right)$$
$$= \text{Max}\left(\frac{(1 - \lambda_I)m^2\theta + \big[(1 + m^2)\sigma_\epsilon^2 + m^2\big](a_U\bar{n} - \lambda_I a_U \nu)}{a_I \sigma_\epsilon^2(1 - \lambda_I)(1 + m^2)}; \nu\right)$$
$$= \nu \text{ if } \theta \leqslant \underline{\theta}.$$

It can easily be checked that any price p such that $p(\underline{\theta}) \geqslant p \geqslant p(\theta^*)$ corresponds to one and only one θ. Thus, prices reveal θ in Region C and, from the study of the unconstrained economy, the demand of the uninformed trader is given by

$$n_U(p) = \text{Max}\left(\frac{(1 + m^2)(\bar{f} - p) + \theta}{a_U\big((1 + m^2)\sigma_\epsilon^2 + m^2\big)}; \nu\right) = \text{Max}\left(\frac{\bar{n} - \lambda_I \nu}{1 - \lambda_I}; \nu\right) = \frac{\bar{n} - \lambda_I \nu}{1 - \lambda_I}$$

since $\nu < N$. Thus, the market-clearing condition is satisfied in Region C.

iv) Region D. We first need to show that t^* is well defined. First notice that the LHS of equation (3) is a continuous function of t and that its limit when $t \to +\infty$ is equal to $+\infty$. Applying L'Hospital rule twice, one can show that the limit of the LHS of equation (3) when $t \to -\infty$ is equal to

$-\infty$. Thus, equation (3) has at least one root and there exists t^* such that for any $t \leqslant t^*$,

$$t + \frac{1}{\sqrt{1+m^2}} \frac{f\left(\dfrac{t + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)}{F\left(\dfrac{t + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)} + a_U(1+\sigma_\epsilon^2)\frac{\bar{n} - \lambda_I \nu}{1-\lambda_I} \leqslant \nu a_I \sigma_\epsilon^2.$$

For insiders, we have as before

$$n_I(y, x_I, p) = \operatorname{Max}\left(\frac{\bar{f} + \theta - P}{a_I \sigma_\epsilon^2}; \nu\right) = \nu.$$

The last expression follows from the fact that $\theta^* \leqslant t^*$ implies

$$\frac{\bar{f} + \theta - P}{a_I \sigma_\epsilon^2} = \frac{1}{a_I \sigma_\epsilon^2}\left(\theta + \frac{1}{\sqrt{1+m^2}} \frac{f\left(\dfrac{\theta^* + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)}{F\left(\dfrac{\theta^* + a_U \dfrac{\bar{n} - \lambda_I \nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)} + a_U\big(1+\sigma_\epsilon^2\big)\frac{\bar{n} - \lambda_I \nu}{1-\lambda_I}\right) < \nu.$$

Notice that the equilibrium price is constant in Region D and different from the equilibrium price in any of the other three regions. Indeed, it is easy to show that it is strictly smaller. Using the expressions in Theorem 1, we have

$$\begin{aligned} p_c(\theta^*) - p^* = {} & \frac{\theta^*}{1+m^2} + \frac{1}{1+m^2}\frac{a_U(\bar{n} - \lambda_I \nu)}{1-\lambda_I} \\ & + \frac{1}{\sqrt{1+m^2}} \frac{f\left(\dfrac{\theta^*}{\sqrt{1+m^2}} + \dfrac{1}{\sqrt{1+m^2}}\dfrac{a_U(\bar{n} - \lambda_I \nu)}{1-\lambda_I}\right)}{F\left(\dfrac{\theta^*}{\sqrt{1+m^2}} + \dfrac{1}{\sqrt{1+m^2}}\dfrac{a_U(\bar{n} - \lambda_I \nu)}{1-\lambda_I}\right)}, \end{aligned}$$

or

$$p_c(\theta^*) - p^* = \frac{1}{\sqrt{1+m^2}}\left(x + \frac{f(x)}{F(x)}\right),$$

where, $x \equiv \frac{\theta^*}{\sqrt{1+m^2}} + \frac{1}{\sqrt{1+m^2}}\frac{a_U(\bar{n}-\lambda_I \nu)}{1-\lambda_I}$.

Since $f(\cdot)$ and $F(\cdot)$ are the density and the CDF of the normal distribution, respectively, it is immediate that $x + \frac{f(x)}{F(x)} > 0$, since $x \int_{-\infty}^{x} e^{-\frac{1}{2}t^2} dt > \int_{-\infty}^{x} t e^{-\frac{1}{2}t^2} dt = -e^{-\frac{1}{2}x^2}$. This proves that $p_c(\theta^*) > p^*$.

Therefore, observing the equilibrium price of Region D, $P(\theta) = p^*$ is equivalent to observing that $\theta < \theta^*$. Thus, the expected utility of an uninformed agent who observes the equilibrium price in Region D can be written as follows:

$$
\begin{aligned}
&E\left[U(w_U) \mid P = p^*\right] \\
&= -E\left[e^{-a_U n_U(\bar{f}+y+\epsilon-P)} \mid \theta < \theta^*\right] \\
&= -\frac{1}{Pr(\theta \le \theta^*)} \int_{-\infty}^{\theta^*} E\left[e^{-a_U n_U(\bar{f}+y+\epsilon-P)} \mid \theta\right] f(\theta)\, d\theta \\
&= -\frac{e^{-a_U n_U(\bar{f}-P)\}}}{Pr(\theta \le \theta^*)} \int_{-\infty}^{\theta^*} \exp\left(-a_U n_U E(y \mid \theta) + \frac{1}{2} a_U^2 n_U^2 \left(\mathrm{Var}(y \mid \theta) + \sigma_\epsilon^2\right)\right) f(\theta)\, d\theta \\
&= -\frac{e^{-a_U n_U(\bar{f}-P) + \frac{1}{2} a_U^2 n_U^2 \left(\frac{m^2}{1+m^2} + \sigma_\epsilon^2\right)}}{Pr(\theta \le \theta^*)} \int_{-\infty}^{\theta^*} \exp\left(-a_U n_U \frac{\theta}{1+m^2}\right) f(\theta)\, d\theta \\
&= -\frac{e^{-a_U n_U(\bar{f}-P) + \frac{1}{2} a_U^2 n_U^2 (1+\sigma_\epsilon^2)}}{Pr(\theta \le \theta^*)} F\left(\frac{\theta^* + a_U n_U}{\sqrt{1+m^2}}\right).
\end{aligned}
$$

Taking the first-order-conditions and dividing left and right by $a_U F(\frac{\theta^* + a_U n_U}{\sqrt{1+m^2}})$, we find that the demand of the uninformed trader, n_U, must satisfy the following condition:

$$
\frac{1}{\sqrt{1+m^2}} \frac{f\left(\dfrac{\theta^* + a_U n_U}{\sqrt{1+m^2}}\right)}{F\left(\dfrac{\theta^* + a_U n_U}{\sqrt{1+m^2}}\right)} + P - \bar{f} + a_U\left(1 + \sigma_\epsilon^2\right) n_U = 0.
$$

It is straightforward to check that the equilibrium prices and holdings given in the theorem for Region D satisfy both the above equation (optimality) and market clearing.

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