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 patterns of insider trading driven by earnings announcement dates, or insiders timing their trades to evade prosecution.

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1 INTRODUCTION

Sir Arthur Conan Doyle made clear in his celebrated "Silver Blaze" mystery that some-
times 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 first study of the patterns
of insider trading preceding large movements in stock prices. Even though our entire
analysis is conducted at the individual stock level, it is convenient to first illustrate the
type of phenomena we study by means of a figure based on aggregate data. Figure 1
shows the sales and purchases done by corporate managers in the 12 months preceding,
respectively, the largest drop and the largest jump[1] in the monthly S&P 500 index dur-
ing the 1986-2005 period. It can be observed that aggregate sales by insiders peaked
ten months before the drop and then went down sharply before the drop occurred.
By way of contrast, aggregate purchases by insiders before the jump exhibit a very
different pattern: they remained low all year long and picked up only the month before
the jump. In the 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.

[Insert figure 1]

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 that most companies prohibit insiders from trading prior to an earning announce-
ment[2]. Thus, any insider who wishes to exploit private information related to poor

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[1]In the remainder of the paper we shall always 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 3.1.2 we provide
formal definitions of these variables.

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

company earnings has to trade significantly before the actual earnings announcement and, therefore, significantly before the crash. Another view is that insiders try to escape scrutiny from the SEC and that the SEC investigates any trade that takes place near the date at which the price movement occurred. A third alternative view is that insiders are forced to 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 six months[3]. In either case, 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 of the evidence on insider sales with the evidence on insider purchases. Why don't we observe a similar pattern of insider purchases prior to jumps? It is indeed the sharp asymmetry between sales before crashes and purchases before jumps that 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 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 some stocks as part of his compensation package but which he is not allowed to resell 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

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take-over deals.

[3]For an analysis of returns to insider trading based on the six months short swing rule, see Jeng et al. (2003).

[4]The short selling restrictions for individual investors in the US are fairly mild and stem mostly from the up-tick rule and from the extra cost for borrowing securities. On the other hand, the restrictions for corporate insiders are much more stringent. Section 16c of the Securities and Exchange Act prohibits US insiders to sell short their own stock. Furthermore, new regulations in the 1980's assure this requirement can not 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 mis-align shareholders and management interests.

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 only 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 are. 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 of 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 to a low likelihood of a crash (since in our model a crash occurs after the insiders have stopped trading) but insider sales in the far past should be associated to 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 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 dataset similar to the one used by Lakonishok and Lee (2001), covering the insider trading activity of companies traded on the NYSE, AMEX and NASDAQ

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during the 1986-2002 period. The empirical results provide strong support for both distinctive features of our theoretical 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 signals" portfolios is statistically insignificant. Jeng et al. (2003) estimate the returns to the insiders' own portfolio over a six-month window. They construct a "purchase portfolio" that holds all shares purchased by insiders over a six month period and a "sale portfolio" that holds all shares sold by insiders over a six-month period. They find that the purchase portfolio earns positive abnormal returns of 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 UK 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 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 insiders 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 that insider sales are very significantly associated with crashes, in a way both consistent with our theory and inconsistent with the hypothesis that insider sales are solely driven by liquidity needs.

The second branch of the literature 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 turns out useful to split this literature in two families, depending on whether crashes are associated with higher or lower uncertainty from the point of view of uninformed traders. In the first category we have, first, models that view crashes as bursting bubbles[5], all of which imply that a crash brings prices closer to fundamental values. Models based on rational herding[6] will deliver a similar prediction. Finally, in this category we also have a number of models that emphasize the role played by trading constraints, most notably Romer (1993), Cao et al. (2002) and Hong and Stein (2003), that predict that crashes reveal information as they are driven by initially sidelined informed investors going back into 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, on the contrary, by a sharp increase in uncertainty. Models belonging to the second family comprise work by Gennotte and Leland (1990), Barlevy and Veronesi (2003) and by Yuan (2005). Our model also belongs to this category with two differences relative to the existing literature. First, from a technical point of view, we eliminate some unnecessary ingredients of existing models, such as *ad-hoc* trading rules and borrowing or leverage constraints. Second, and more crucially, we let trading by informed investors to be observable by the rest of the market. This feature is important to bring the model

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[5]See for instance Allen et al. (1993), Allen and Gale (2000) Allen et al. (2003) and Hong et al. (2005)

[6]For instance, see Devenou and Welch (1996) for an early survey.

to the data since we wish to identify informed investors as insiders, whose trades are publicly observable in the US market.

Thus, 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 US markets in the past 20 years. We test whether a given class of informed investors, namely insiders, have been pulling in or out of the market prior to a crash. The results we obtain unambiguously supports the view of crashes associated with informed investors pulling out of the market. Indeed we find that both insiders trading volume and insiders 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 is obtained when there has been selling by insiders in the past but insiders have just pulled out of the market[7].

A closely related paper to our empirical analysis is the work by Chen et al. (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 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, Hong and Stein'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

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[7]A totally different test of the two hypotheses would consist in 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.

difference between our work and theirs is that we look not only at the impact of total trading volume on crashes but also at 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 2 we present a theoretical model of insider trading in the presence of trading constraints. Section 3 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 4 is dedicated to some concluding remarks.

2 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 on that information. They can also trade to hedge non-traded 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 us not being able to sell short 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 3 we test some of the predictions of this model.

2.1 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 in

substituting noise trading with rational trading driven by stochastic hedging needs[8]. 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 normally distributed random variables on Ω. We will omit the dependance on ω whenever it 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 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 on shares of a company. There is a per capita amount of $\overline{n}>0$ shares outstanding each of which offers a payoff given by the (normally distributed) random variable $f : \Omega \to \Re$,

$$f = \overline{f} + y + \epsilon$$

where y and ϵ are normally distributed random variables and $\overline{f}$ is a constant. There is a unit mass of traders in the economy. A fraction λ_I are "insiders" who have some private information which 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 $\overline{n}_I$ shares of the risky asset. The remaining fraction, $(1 - \lambda_I)$ of agents do not receive any private information and we will often refer to them as "uninformed" traders[9]. Each uninformed trader is endowed with $\overline{n}_U$ shares of the risky asset.

Agents also receive income $e_i : \Omega \to \Re$ at the end of the period. This income can

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

[9]Throughout this whole section 2 we denote insiders by I, uninformed traders by U, and generic traders by i.

either be interpreted as labor income or just income from holding assets which 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:

$$w_I = w_{0,I} + k_I x_I z + n_I(f - p) \tag{2.1}$$

$$w_U = w_{0,U} + n_U(f - p) \tag{2.2}$$

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

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

Before the market for assets 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 the insiders to trade on both sources of information[10]. Since uninformed traders do not hold any private information, the vector $s(\omega) = (y, x_I) \in \Sigma \subseteq \Re^m$ contains all private

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

information of the economy in state ω. Endowed with their private information, agents trade in a *Rational Expectations Equilibrium (REE)*[11]. 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:

$$n_I(y, x_I, p) = ArgMax E\left[U_I(w_I) \text{ s.t. } (2.1) \mid y, x_I, p\right]$$

$$n_U(p) = ArgMax E\left[U_U(w_U) \text{ s.t. } (2.2) \mid p\right]$$

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

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 0. All variances, except σ_ϵ^2, are set equal to 1. 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 2.3 we show that when insiders face trading constraints the REE price in this economy exhibit crashes. Before that, and for illustrative purposes, we compute the REE in the economy without trading constraints.

2.2   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

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[11]See Radner (1979)

wealth is normally distributed. Taking the first order conditions, we find that his demand for the risky asset is given by:

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

The equation above implies that equilibrium prices must reveal (to the uninformed traders) $\theta(y, x_I) \equiv y - a_I k_I \sigma_{\epsilon z} x_I$, which is normally distributed[12]. 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' future wealth is also normally distributed and his demand is given by:

$$n_U(p) = n_U(\theta) = \frac{E(f|\theta) - p - Cov(f, e_2|\theta)}{a_U Var(f|\theta)} = \frac{\theta(y, x_I) + (1 + m^2)(\overline{f} - p)}{a_U [m^2 + (1 + m^2)\sigma_\epsilon^2]}$$

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

The REE price is given by:

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

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

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

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.

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[12]In this economy, observing the trades of insiders does not add information compared to just observing equilibrium prices. This is unlike most models with noise trading where the entire equilibrium unravels if uninformed traders observe the trades of the insiders. This point is important when bringing the model to the data since insider trades are public information in US markets.

At equilibrium, agents' asset holdings are given by:

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

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

2.3 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 $\overline{n}$[13].

In the next proposition 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 that region, the portfolio constraint of the uninformed traders is binding, the portfolio constraint of the insider 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 that region, neither the portfolio constraint of the insiders nor the portfolio constraint of the uninformed traders are binding, and prices reveal θ to the market.

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[13]The case $\nu = 0$ corresponds to the standard no short-sales constraint.

- **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 that region, the portfolio constraint of the insider is binding, the portfolio constraint of the uninformed trader is not binding, and prices reveal θ to the market.

- **Region D** where the signal received by the insiders is so bad, or their hedging motive so weak that not only insiders would want to hold a number of shares below their minimum holding allowed but also a crash (i.e. a price discontinuity) occurs. In that region, the portfolio constraint of the insider is binding, the portfolio constraint of the uninformed trader is not binding, and prices do **not** reveal θ to the market. Expected returns are higher in Region D than in either of the other three regions.

More formally, we show in the Appendix the following result:

Theorem 1 *Let:*

- $\overline{\theta} \equiv \frac{a_I}{\lambda_I m^2}\left((1+m^2)\sigma_\epsilon^2\overline{n} - a_U\nu\left(\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}\right)\right)$

- $\underline{\theta} \equiv \frac{a_U}{(1-\lambda_I)m^2}\left(-((1+m^2)\sigma_\epsilon^2 + m^2)\overline{n} + a_I\nu\left(\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}\right)\right)$

- θ^* *defined as a real number no larger than the smallest root t^* of the equation:*

$$t + \frac{1}{\sqrt{1+m^2}}\frac{f\left(\frac{t+a_U\frac{\overline{n}-\lambda_I\nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)}{F\left(\frac{t+a_U\frac{\overline{n}-\lambda_I\nu}{1-\lambda_I}}{\sqrt{1+m^2}}\right)} + a_U(1+\sigma_\epsilon^2)\frac{\overline{n}-\lambda_I\nu}{1-\lambda_I} = \nu a_I\sigma_\epsilon^2 \qquad (2.3)$$

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. $\theta \geq \overline{\theta}$

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

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

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

$Prices:\ p_b(\theta) = \overline{f} + \theta\frac{\gamma\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}(1+\sigma_\epsilon^2)}{\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}} - \overline{n}\frac{\sigma_\epsilon^2\left((1+m^2)\sigma_\epsilon^2 + m^2\right)}{\gamma(1+m^2)\sigma_\epsilon^2 + \frac{\lambda_I m^2}{a_I}}$

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

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

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

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

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

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

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

Proof: (See Appendix)

In this economy equilibrium holdings are determined but equilibrium prices are indeterminate (multiplicity of equilibria)[14]. A typical equilibrium is illustrated in Figure 2. The key features of any equilibrium of the economy with trading constraints are the following:

1. Prices are discontinuous at the point $\theta = \theta^*$. In other words, a crash occurs between Regions C and D.

2. Insiders holdings are constant in Region C. This means that a crash is preceded by a region where 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 in the stock.

[14]The result of multiplicity of equilibria arising from trading constraints is not specific to our setting with asymmetric information. For instance, see Basak et al. (2006).

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.

[Insert figure 2]

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 why a crash occurs after insiders have stopped trading and what explains 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.

3 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

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[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.

in Section 2. 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.

3.1 Data, Variable Definitions and Methodology

3.1.1 The 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 this 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).

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 had 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 done by three groups of insiders[18]:

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[16]According to Section 16(a) of the Securities and Exchange Act, insiders are required to report their trades by the tenth day of the month that follows the trading month. Reporting requirements have tightened recently as the Sarabanes-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 Subsection 3.2.4, where earnings announcement data is necessary for testing our model against an alternative hypothesis.

[18]The "Management" group includes those transactions done 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

"Management", "Large Shareholders" and "Others". Our sample contains transactions done 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 dataset 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 insiders 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 involves more than the 20% of the number of shares outstanding are eliminated to avoid problematic records. After this cleansing process and after merging the insider trading dataset with the filtered CRSP dataset, 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 done by "Management", 185,096 done by "Large Shareholders" and 18,894 done by "Others".

3.1.2 Crash variables

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

1. In our model, insider trading matters because it is observable to market participants and these update their beliefs as insiders' trades, or lack of trades, are

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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. So our dataset misses some of the earlier observations but focuses on the later 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.

observed. In reality, given that our sample period is prior to the Sarabanes-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, the information about the insiders' 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 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.

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[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.

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 five years, or sixty months, of data. Finally, we define:

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

In other words, $ERCRASH_{i,t}$ takes the value 1 when the excess return of stock i in month t is more than 2 standard deviations away and below the average excess monthly return of that stock in the past 60 months, and takes the value 0 otherwise.

Our second baseline variable for a crash, $MMCRASH_{i,t}$, is constructed in a 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 sixty months window and $r_{f,t}$ is the risk-free rate. We then compute the 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

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[23]Robustness checks of the main regression are provided in subsection 3.2.3.

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.

[Insert figure 3]

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 $ERJUMP_{i,t}$, $MMJUMP_{i,t}$, $RAWJUMP_{i,t}$. Each of these three variables is defined in a totally symmetric fashion as their crash variables counterparts. For instance, we have:

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

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 in the case 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.

[Insert figure 4]

3.1.3 Independent variables

Independent variables fall in two categories: variables suggested by our model and variables suggested by the existing literature. Variables suggested by our model mostly consist in 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 of the day of the transaction. The main variables we use are: insider

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

sales, $INSSAL$, and insider purchases, $INSPURCH$. A first subscript, i, refers to the individual stock considered. The variable may then have one or two time subscripts. If there 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 $INSPURCH_{i,t-1,t-12}$ 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 1 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 90's than in the 80's. This observation suggests that findings regarding correlations between insider activity and crashes may be sensitive to the choice of sub-sample. In subsection 3.2.3 we address this issue.

[Insert table 1]

[Insert figure 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 thereafter note 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 investors. When interpreting our own

results we want to make sure that trading volume by insiders does not act as a proxy for TTV. Thus we 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 two years, $ER_{t-1,t-24}$ is likely to matter for two reasons. First, Lakonishok and Lee (2001) have shown 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].

3.1.4 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), and the logit and probit models. Each procedure has some defects: with the linear probability model, estimated probabilities may lie outside the [0,1] interval and disturbances are heteroskedastic. With logit and probit the interpretation of coefficients is less straightforward than with the linear probability model.

To the extent that our objective is not as much to get an estimate of the probability of a crash as to test whether or not insider trading patterns are correlated with crashes and jumps, we use the linear probability model in our main regressions. Since we know that using the linear probability model will give rise to heteroskedasticity and since we can also suspect problems of auto-correlation, we report significance of coefficients based on Newey-West standard errors. As a robustness test, we also estimate our leading regressions using logit and probit and report the results in subsection 3.2.3.

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

3.2 Empirical Results

3.2.1 Preliminary result: Sidelined investors vs. 'the dog that did not bark'

In the introduction we established a dichotomy in the literature that view crashes as a phenomenon that arises because of the existence of trading constraints. Models like 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, like Gennotte and Leland (1990), Barlevy and Veronesi (2003) and Yuan (2005), has the opposite 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 favors or not 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 insiders trading volume as the measure of insider trading activity. In particular we regress our measures of crashes on the past month trading volume by insiders $INSTV_{i,t-1}$ and the average monthly insiders trading volume in the past year, excluding the last month[26], $INSTV_{i,t-2,t-12}$. We also include the past two years cumulative excess returns $ER_{i,t-1,t-24}$ and the total trading volume (by both insiders and outsiders) of the past month $TTV_{i,t-1}$. Fixed month and firms effects are allowed for through mean-differencing.

Table 2 presents the results of the first two regressions. Column 1 presents the results for $ERCRASH_{i,t}$, where crashes are identified using simple excess returns, and Column 2 for $MMCRASH_{i,t}$, where the definition of crashes uses beta adjusted returns. The results provide a conclusive answer about the relationship between crashes and insiders activity. The coefficient of the past month insiders trading volume,

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

$INSTV_{i,t-1}$, has a negative sign (-0.039 for the $ERCRASH$ regression, -0.032 for the $MMCRASH$ regression) and is highly significant (Newey-West corrected standard errors around 0.01 in both cases). Furthermore, we find that the probability of a crash is positively correlated to the past year average insider trading volume, $INSTV_{i,t-2,t-12}$ (coefficients equal to 0.09 and 0.039 for the $ERCRASH$ and $MMCRASH$ regressions, respectively), although the coefficient is not significant for the case of crashes defined using the market model. Putting the two findings together establishes that a crash is most likely to occur when insiders have been trading in the past and have recently dropped out of the market and that it is least likely to occur when they have been out of the market in the past and have just recently gotten back in. These preliminary results thus support the general class of theories of crashes our model belongs to.

[Insert table 2]

Finally, the variables $ER_{i,t-1,t-24}$ and $TTV_{i,t-1}$ are also strongly significant and of the same sign as found in the existing literature, most notably Chen et al. (2001). The significance of the coefficients associated to these two coefficients is important not only as it confirms the findings of the existing literature using a different methodology, but also as it dispels any suspicion that our insider trading variables play the role of a proxy for total trading volume. Note indeed that the coefficient of the past month total trading volume, TTV_{t-1}, is positive (0.015) while the coefficient of the past month insider trading volume, $INSTV_{i,t-1}$, is negative (-0.039) and that both coefficients are significant at the 1% level. Actually, we find that past month 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 a 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.

3.2.2 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 2 is that a crash occurs in a region characterized by insiders being short-sale 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 far away sales 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 past month, $INSSAL_{i,t-1}$, and the average sales by insiders in the past year, $INSSAL_{i,t-2,t-12}$. We also include the past two years cumulative excess returns $ER_{i,t-1,t-24}$ and the total trading volume (by both insiders and outsiders) of the past month $TTV_{i,t-1}$. Fixed year and firms effects are allowed for through mean-differencing. Formulating regressions in this fashion presents three advantages:

1. Our model still has predictions for the sign of the coefficients. On the one hand, the sign of $INSSAL_{i,t-2,t-12}$ 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. On the other hand, the sign of $INSSAL_{i,t-1}$ 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 market model without constraints can also be tested. According to that hypothesis, the coefficient of $INSSAL_{i,t-2,t-12}$ should not be significant since it is a variable which was public information by month $t-1$ (taking the most conservative stance about when the trades were reported by insiders and the diffusion of information). The coefficient of $INSSAL_{i,t-1}$ should either be non significant or positive, again depending on the speed of reporting and of 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 of the insider sales variables should come up significant.

Table 3 contains the results of the regression of crashes on sales. As before, in the first column crashes are defined using simple excess returns while in the second column crashes are defined using the market model. In both regressions, the coefficients of both insider sales variables are statistically significant. The sign of the past month insider sales, $INSSAL_{i,t-1}$, is negative (-0.025 for $ERCRASH$ and -0,028 for $MMCRASH$), which means that high sales by insiders today reduce the chance of a crash in the next month. This finding can hardly be reconciled with a standard rational expectations model but is fully consistent with our "Dog that did not bark" theory. Similarly, the sign of the past year average sales by insiders variable, $INSSAL_{i,t-2,t-12}$, is positive (0.232 for $ERCRASH$, 0.127 for $MMCRASH$), which runs against the standard efficient market hypothesis that states that past news should not affect today's returns but yet is consistent with our hypothesis that crashes occur when the insiders holdings reach the point at which the trading constraint is binding.

[Insert table 3]

The strong statistical significance of the insiders sales variable is in sharp contrast with an important literature that has argued that insiders purchases, rather than sales, are the only insiders' transactions with an informational content and the source of profitable trading rules. Lakonishok and Lee (2001) examines insider trading activity of companies traded on the NYSE, AMEX and NASDAQ during the 1975-1995 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 six month period and a "sale portfolio" that holds all shares sold by insiders over a six month period. They find that the purchase portfolio earns positive abnormal returns

of 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 UK 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 from Table 3 with the findings of the existing literature on insider trading. It suggests indeed that 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 is the way to disentangle those two effects.

However, the empirical evidence reported in Table 3 is consistent with a few other possible explanations, apart from our model. One possible explanation is the fact 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 six months. A second possible explanation has to do with earning announcements. Indeed, many large drops in prices are due to companies failing to meet earnings expectations and we know that most companies prohibit insiders from trading prior to an earning announcement. Thus, our finding that crashes are preceded by a drop in selling by insiders could potentially be a pure artefact driven by calendar effects.

We shall go back to the earnings announcement explanation in subsection 3.2.4 where we test it explicitly against our model. However, testing the "no trading on short-

lived information" story against our model can easily be done at this stage. Indeed, another implication of our model is that while continuous sales by insiders followed by a period of no selling may drive a crash because of the short-sale constraint, continuous purchases followed by a period of no buying will not drive a jump. Indeed, the absence of a "ceiling" constraint explains that there is no jump in Region A. Thus, we should not expect insider purchases to become significant if we run the symmetric regressions for jumps. By way of contrast, the "no trading on short-lived information" story is perfectly symmetric: whether it is for avoiding prosecution by the SEC or because of the six months short swing rule, traders should abstain from trading on short-live positive information the same way as they do with negative information.

In Table 4 we present the results of regressions where we run $ERJUMP_{i,t}$ and $MMJUMP_{i,t}$ against the past month purchases by insiders $INSPURCH_{i,t-1}$ and the average purchases by insiders in the past year $INSPURCH_{i,t-2,t-12}$. As before, we include the past two years cumulative excess returns $ER_{i,t-1,t-24}$, total trading volume (by both insiders and outsiders) of the past month $TTV_{i,t-1}$ as well as year and firm dummies. We find that the coefficient of $INSPURCH_{i,t-2,t-12}$ is statistically insignificant (t statistic around 1.2)[27] and, most importantly, that the coefficient $INSPURCH_{i,t-1}$ is positive (0.087) and significant at the 5% level. In other words, we find that an increase in recent insider purchases raises the probability of a crash. Thus, we do not observe the same "dog that did not bark" effect for jumps as we did for crashes, rather the opposite. This finding is consistent with our theoretical model where such an asymmetry is imbedded. It is however not consistent with the "avoiding prosecution by the SEC" story and the "six months short swing rule" which treat sales and purchases in a perfectly symmetric way. 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 grip with the absence of similar patterns prior to jumps.

[Insert table 4]

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

3.2.3 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 sample period, estimation technique and definition of the variables, both dependant and independent.

As mentioned in Subsection 3.1.3, and illustrated in Figure 5, insider trading, as a fraction of market capitalization, has increased sharply in the mid 90's. This opens up the question of how robust our results are to the choice of sample period. We split our sample into two sub-samples, one covering the period 1986-1995 (low insider trading) and the other the period 1996-2002 (high insider trading) and run the base regressions on the two separate sub-samples. Table 5 reports the results for the leading regressions for each subperiod. As could be expected given the relative activities of insider trading in the two periods, results for the earlier period are less strong than for the later period. Nevertheless, results are supportive of our theory. For the 1986-1995 period, all insider trading variables in the crash regressions are of the right sign predicted by the theory (negative for $INSSAL_{i,t-1}$, positive for $INSSAL_{i,t-2,t-12}$) even though, to one exception, they lose significance. 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. As expected, results for the 1996-2002 period are strongly supportive of our theory: all insider trading variables are of the right sign and significant at the 1% level (to one exception, which is only significant at the 5% level).

[Insert table 5]

Our next sequence of checks deals with the estimation technique. For simplicity and ease of interpretation, we have so far estimated the base regressions using a linear probability model. In Tables 6 and 7 we report results of similar regressions using, respectively, a logit and a probit model[28] to specify the probability of a crash. The results of the regressions are quite encouraging. When crashes are defined using simple

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[28]Both sets of regressions include year dummy variables whose coefficients are not reported in the tables.

excess returns, all insider trading variables are of the right sign and significant, both with the logit and with the probit specifications. Also, as in all our regressions, the asymmetry between crashes and jumps is preserved. In particular, while in the crash regressions, the coefficient of $INSSAL_{i,t-1}$ is always negative (varying between -0.998 and -3.564 depending on the specifications) and significant at the 5% level, in the jump regressions the coefficient of $INSPURCH_{i,t-1}$ is positive (varying between 0.517 and 0.912).

When crashes are defined using a market model, results are less strong. The good news for our theory is that the "dog that did not bark" effect remains significant: under both specifications, higher insider sales in month $t-1$ lowers the probability of a crash in month t. Also, the asymmetry between crashes and jumps is again preserved. However, the "long term" insider sales variable ($INSSAL_{i,t-2,t-12}$) becomes totally insignificant (and of the wrong sign). A possible explanation for the comparatively weaker results using the market model than using simple excess returns is the instability of beta estimates over a 60-month window.

[Insert table 6]

[Insert table 7]

Our final robustness check concern the way we constructed our crash variables as well as our insider trading variables. We first check if the 1-year window for insiders activities preceding large price movements is critical for the results. In Table 8 we report the regression results for two alternative windows: six months and 24 months. In these regressions the near past variable remains as in the baseline regression (one month), but the far past variables goes back to months $t-6$ and $t-24$. The results are at least as strong as the ones in the baseline regressions: the coefficients have the right sign and (to one exception) are very strongly significant. The "dog that did not bark" effect is present for crashes (coefficient of $INSSAL_{i,t-1}$ negative and ranging from -0.024 to -0.03) and absent for jumps (coefficient of $INSPURCH_{i,t-1}$ positive and ranging from 0.086 to 0.088), as predicted by the theory.

[Insert Table 8]

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Finally, in Table 9 we report the results of the base regressions but using a definition of crashes and jumps based on raw returns, rather than returns in excess of the CRSP equally weighted market portfolio or the returns predicted by the market model. To the extent that our model is not a model of market-wide crashes, we expected the results of this regression to be considerably noisier than when adjustments for market changes are being 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 but the "short-term" variable is insignificant (and of the wrong sign).

[Insert table 9]

The overall picture we draw from these robustness tests is that the effects we identified in the previous section seem to be quite robust. In most of the alternate specifications we tried, both insider trading variables remained of the right sign and significant for the crash regressions. In some regressions, one of the variables stopped being significant but never two at the same time, nor did we observe a coefficient coming with the wrong sign and even mildly significant. Finally, the asymmetry between crash and jump regressions, which we argued earlier is one of our most striking findings remains present in all the alternative specifications.

3.2.4 Crashes and Earning Announcements

The last item we have so far left aside concerns the alternative interpretation of our results based on the possible coincidence of crash dates and earnings announcement dates. According to that hypothesis, there may be a large proportion of crashes that take place during months where an earning announcement takes place, because of the 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 earning 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 artefact 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 sub-sample with only observations (stock/month) where no earning announcement was made for that stock during that month. We then run the base regressions for that sub-sample. If our model is correct, then we should find the same results in the sub-sample without earning announcement dates since earning announcements play no role in our analysis. On the other hand, if the alternative hypothesis are correct then the "dog that did not bark" effect should disappear in that sub-sample.

The results, reported in Table 10, are unambiguous: all coefficients of insider trading variables for the crash regressions are significant at the 1% or at the 5% level and of the right sign predicted by the theory. By way of contrast, none of the insider trading variables are significant for the jump regressions, which confirms our earlier findings of the crash/jump asymmetry.

[Insert table 10]

To further confirm the interpretation of our results, we perform one last test: we run the base regressions on the sub-sample where 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 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 insider trading variables should stop being significant in the sub-sample. The results we report in Table 11 support that hypothesis: not only insider sales the month before stop being significant, which is expected given that there is very little insider trading around earning announcement dates, but average insider sales of the previous year stop being significant as well.

[Insert table 11]

4 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 insiders selling intensity preceding crashes (high in the far past and low in the near past) with no symmetric counterpart in the case of insiders purchases and jumps. Our empirical study shows that the evidence in the US markets is consistent with the predictions of the model. These results shed a new light on the informative role of insider sales.

We believe this paper sets the starting point in a new way of thinking about insider trading and crashes. As such, it leaves many questions unanswered and open lines for further research. First, notice that our theory is developed under the assumption of fully rational agents. Thus no arbitrage opportunity is left unexploited in the model. Nevertheless, 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 performing the same tests performed here across countries with different insider trading regulations. All these extensions are beyond the scope of the present paper and are left for future research.

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A Appendix

A.1 Proof of Theorem 1

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

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

since $\nu < N$.

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

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

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

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 $\overline{\theta} > \theta \geq \underline{\theta}$

Region C. For insiders, we have as before:

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

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:

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

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

Region D. We first need to show that t^* is well defined. First notice that the LHS of equation (2.3) 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 (2.3) when $t \to -\infty$ is equal to $-\infty$. Thus, equation (2.3) has at least one root and there exists t^* such that for any $t \leqslant t^*$:

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

For insiders, we have as before:

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

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

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

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:

$$p_c(\theta^*)-p^* = \frac{\theta^*}{1+m^2}+\frac{1}{1+m^2}\frac{a_U(\overline{n}-\lambda_I\nu)}{1-\lambda_I}+\frac{1}{\sqrt{1+m^2}}\frac{f\left(\frac{\theta^*}{\sqrt{1+m^2}}+\frac{1}{\sqrt{1+m^2}}\frac{a_U(\overline{n}-\lambda_I\nu)}{1-\lambda_I}\right)}{F\left(\frac{\theta^*}{\sqrt{1+m^2}}+\frac{1}{\sqrt{1+m^2}}\frac{a_U(\overline{n}-\lambda_I\nu)}{1-\lambda_I}\right)}$$

or,

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

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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:

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

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

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

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.

A.2   Figures
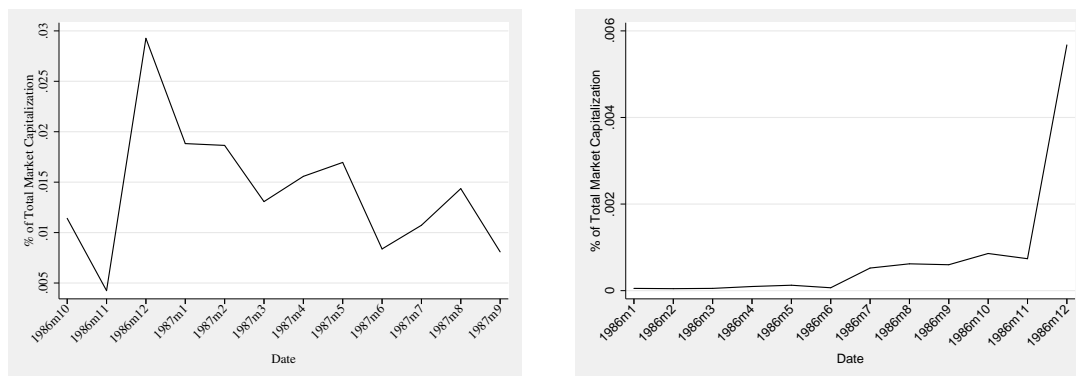
(a) *Managers sales before October, 1987 (Largest S&P 500 "drop" in period 1986-2002)*

(b) *Managers purchases before January, 1987 (Largest S&P 500 "jump" in period 1986-2002)*

Figure 1: **Managers transactions before large market movements.**

This 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 dataset, before the largest market movements in the S&P 500 during the 1986-2002 period. The data on insider transactions comes from Thomson Financial Data Filings dataset. 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. 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.
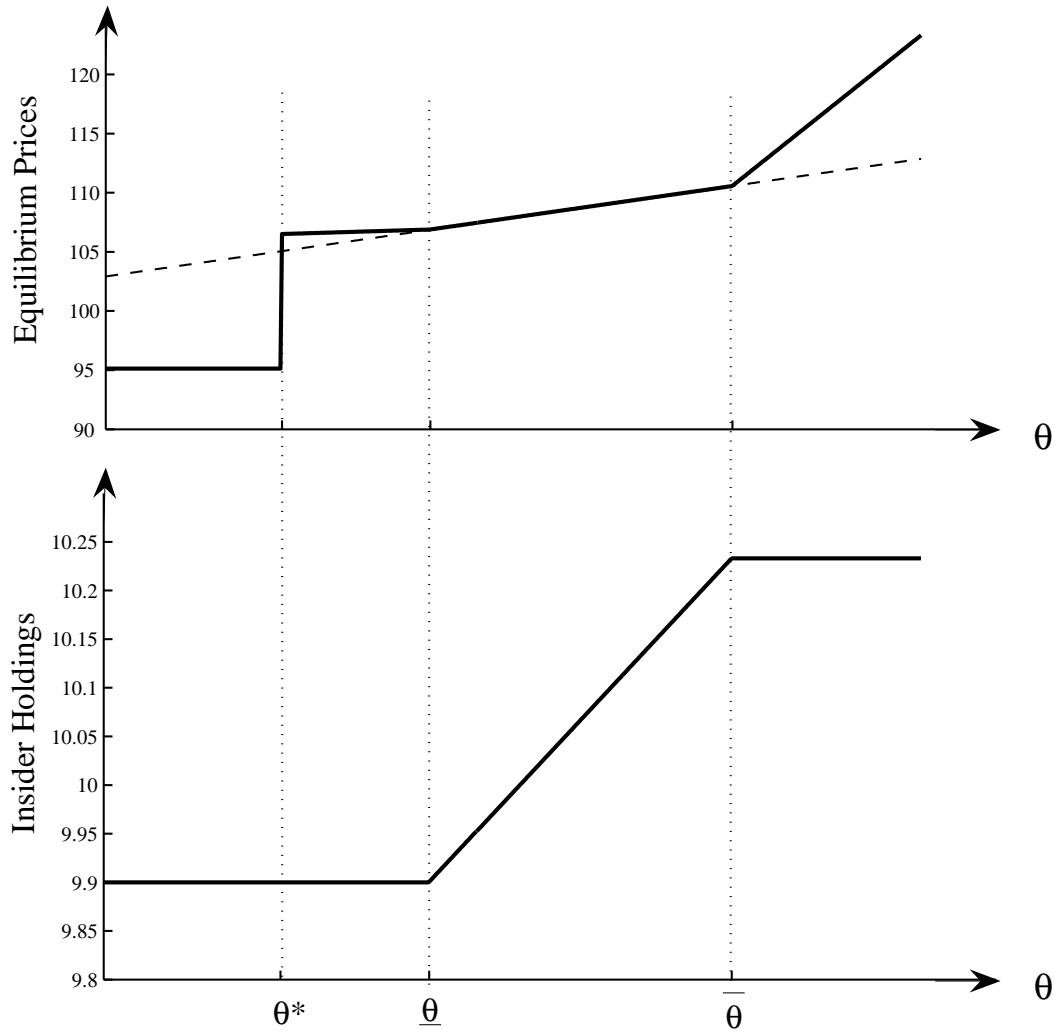
Figure 2: **Equilibrium prices and insider holdings.**

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: $a_I = 1$, $a_U = 0.4$, $\lambda_I = 0.3$, $\overline{n} = 10$, $\sigma_\epsilon^2 = 50$, $\nu = 9.90$, $\sigma_{\epsilon z}^2 = 1$, $k_I = 5$, and $\overline{f} = 300$.
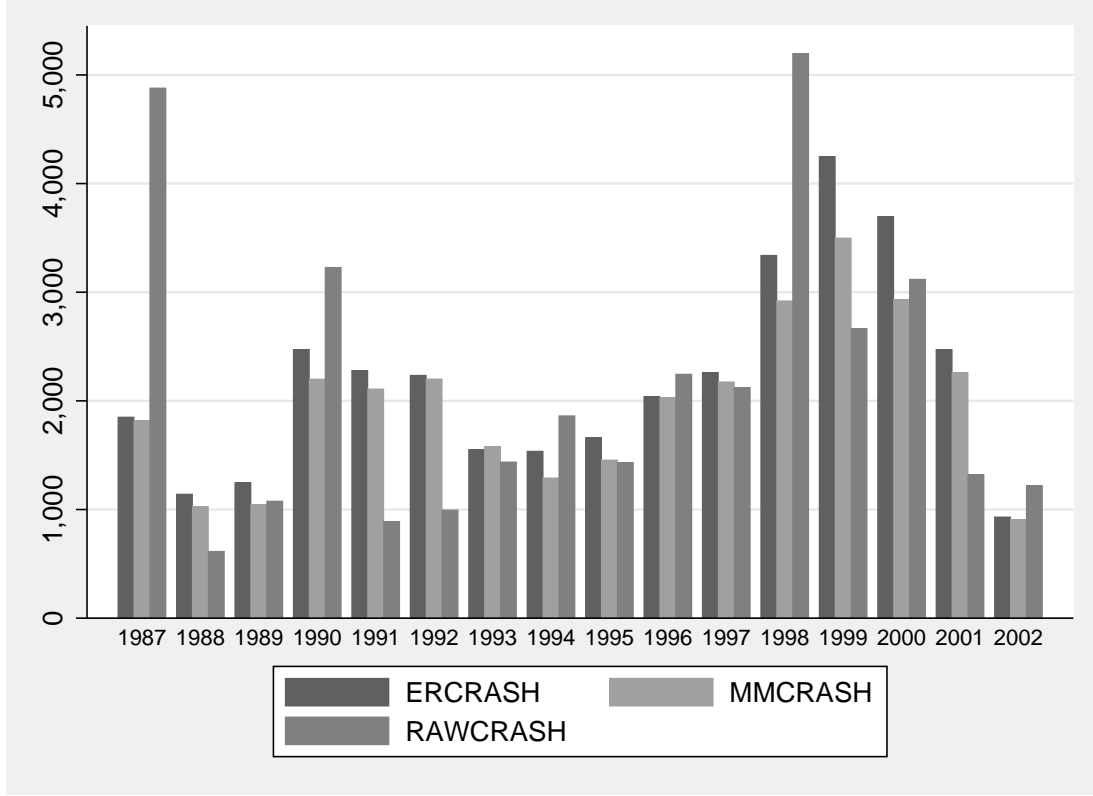
Figure 3: **Number of crashes over the sample period.**

The figure reports the evolution of the aggregate number of crashes for common stocks traded in NYSE, AMEX and Nasdaq that appear in CRSP dataset, 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:

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

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

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

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 sixty-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 five-year rolling window.

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 CRSP dataset, 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 sixty-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 five-year rolling window.
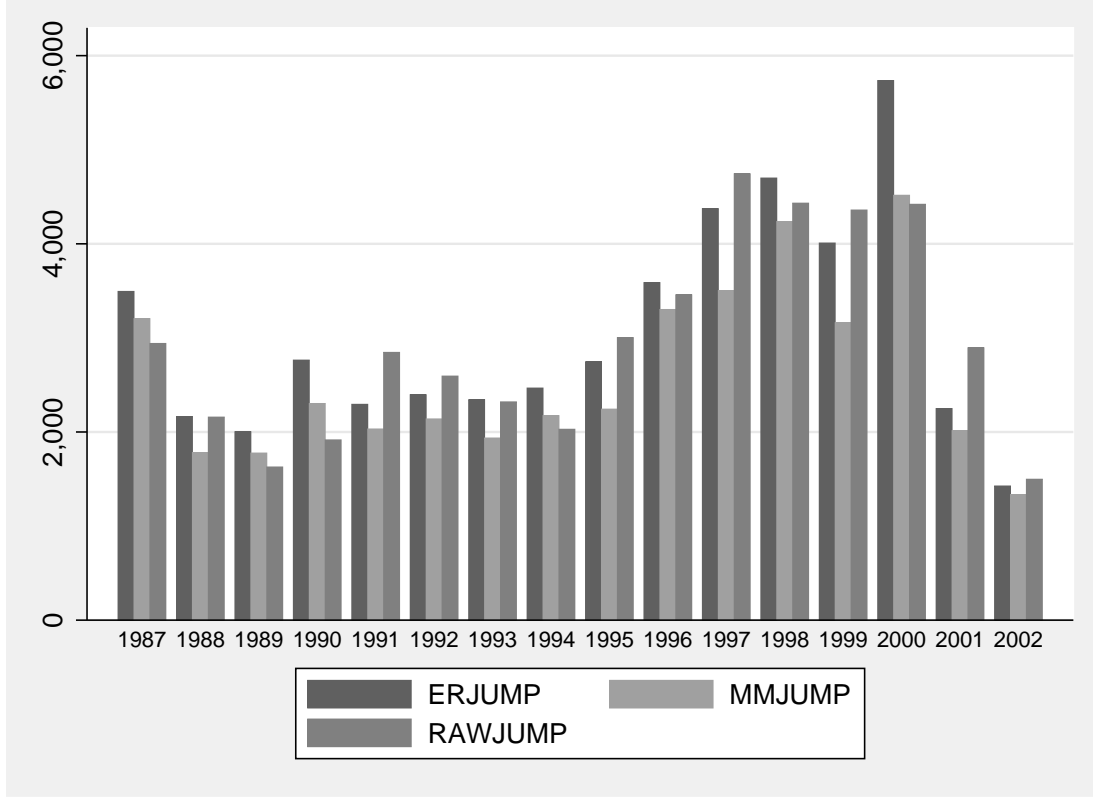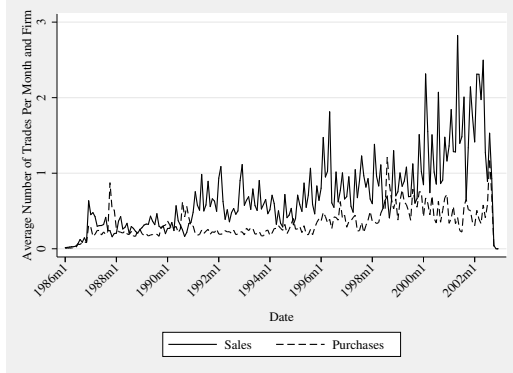
(a) *Insider transactions: average number of trades*
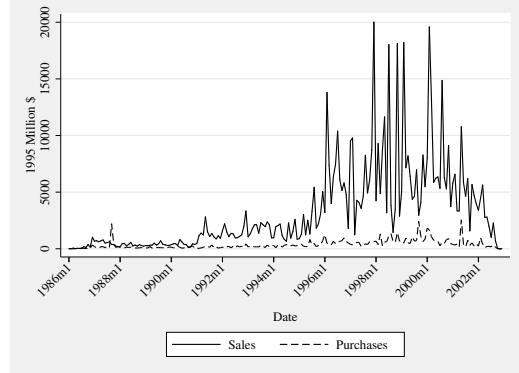
(b) *Insider transactions: total monthly dollar volume*
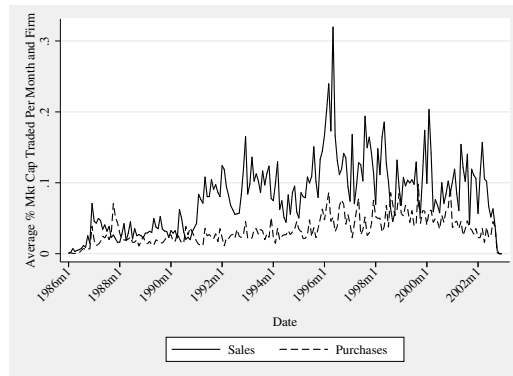
(c) *Insider transactions: average fraction of firm's market capitalization*

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; 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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.

A.3 Tables

Table 1: **Insider trading activity: summary statistics.**

| | | Large | | |
	Management	Shareholders	Others	Total
Purchases				
Fraction	0.483	0.052	0.013	0.501
# 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
# 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%

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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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.

Table 2: **Preliminary regression: insiders trading volume and crashes.**

	(1)	(2)
	ERCRASH	MMCRASH
$INSTV_{t-1}$	-0.039**	-0.032**
	(0.011)	(0.010)
$INSTV_{t-2,t-12}$	0.090+	0.039
	(0.053)	(0.047)
$ER_{t-1,t-24}$	0.001**	0.001**
	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.012**
	(0.002)	(0.002)
$TTV_{t-2,t-12}$	-0.002	0.012**
	(0.003)	(0.003)
Observations	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In columns 1 and 2 we report the results obtained in the following two preliminary regressions for crashes:

$$ERCRASH_{i,t} = \alpha_i + \gamma_t + \beta_1 INSTV_{i,t-1} + \beta_2 INSTV_{i,t-2,t-12} + \beta_3 ER_{i,t-1,t-24}$$
$$+ \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$
$$MMCRASH_{i,t} = \alpha_i + \gamma_t + \beta_1 INSTV_{i,t-1} + \beta_2 INSTV_{i,t-2,t-12} + \beta_3 ER_{i,t-1,t-24}$$
$$+ \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$

where i and t are indexes for the company and the calendar month, respectively. In the estimation we use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The dependent variables 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 sixty-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 five-year rolling window. Regarding the independent variables: $INSTV_{i,t-1}$ is the past month 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 past year (excluding the previous month), $TTV_{i,t-1}$ is the past month total trading volume in stock i, $TTV_{i,t-2,t-12}$ is the average total trading volume in stock i in the past year (excluding the previous month) and $ER_{i,t-1,t-24}$ is stock's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 3: **Leading regression: insider sales and crashes.**

	(1)	(2)
	ERCRASH	MMCRASH
$INSSAL_{t-1}$	-0.025+	-0.028*
	(0.013)	(0.011)
$INSSAL_{t-2,t-12}$	0.232**	0.127*
	(0.068)	(0.059)
$ER_{t-1,t-24}$	0.001**	0.001**
	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.012**
	(0.002)	(0.002)
$TTV_{t-2,t-12}$	-0.002	0.012**
	(0.003)	(0.003)
Observations	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In columns 1 and 2 we report the results obtained in the following two leading regressions for crashes:

$$ERCRASH_{i,t} = \alpha_i + \gamma_t + \beta_1 INSSAL_{i,t-1} + \beta_2 INSSAL_{i,t-2,t-12} + \beta_3 ER_{i,t-1,t-24}$$
$$+ \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$
$$MMCRASH_{i,t} = \alpha_i + \gamma_t + \beta_1 INSSAL_{i,t-1} + \beta_2 INSSAL_{i,t-2,t-12} + \beta_3 ER_{i,t-1,t-24}$$
$$+ \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$

where i and t are indexes for the company and the calendar month, respectively. In the estimation we use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The dependent variables 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 sixty-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 five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 4: **Leading regression: insider purchases and jumps.**

	(1)	(2)
	ERJUMP	MMJUMP
$INSPURCH_{t-1}$	0.087+	0.087*
	(0.044)	(0.043)
$INSPURCH_{t-2,t-12}$	0.162	0.171
	(0.140)	(0.130)
$ER_{t-1,t-24}$	-0.007**	-0.006**
	(0.001)	(0.000)
TTV_{t-1}	0.015**	0.010**
	(0.003)	(0.002)
$TTV_{t-2,t-12}$	-0.070**	-0.056**
	(0.004)	(0.004)
Observations	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In columns 1 and 2 we report the results obtained in the following two leading regressions for jumps:

$$ERJUMP_{i,t} = \alpha_i + \gamma_t + \beta_1 INSPURCH_{i,t-1} + \beta_2 INSPURCH_{i,t-2,t-12}$$
$$+\beta_3 ER_{i,t-1,t-24} + \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$
$$MMJUMP_{i,t} = \alpha_i + \gamma_t + \beta_1 INSPURCH_{i,t-1} + \beta_2 INSPURCH_{i,t-2,t-12}$$
$$+\beta_3 ER_{i,t-1,t-24} + \beta_4 TTV_{i,t-1} + \beta_5 TTV_{i,t-2,t-12} + \epsilon_{i,t}$$

where i and t are indexes for the company and the calendar month, respectively. In the estimation we use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The dependent variables are defined as:

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

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 sixty-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 five-year rolling window. Regarding the independent variables: $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 5: **Robustness check: subsample analysis.**

	Subsample 1986-1995				Subsample 1996-2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ERCRASH	MMCRASH	ERJUMP	MMJUMP	ERCRASH	MMCRASH	ERJUMP	MMJUMP
$INSSAL_{t-1}$	-0.009	-0.027			-0.034**	-0.030**		
	(0.051)	(0.049)			(0.012)	(0.010)		
$INSSAL_{t-2,t-12}$	0.308*	0.174			0.216**	0.148*		
	(0.140)	(0.135)			(0.075)	(0.064)		
$INSPURCH_{t-1}$			0.257*	0.293**			0.047	0.040
			(0.110)	(0.114)			(0.038)	(0.032)
$INSPURCH_{t-2,t-12}$			0.735**	0.434			0.009	0.061
			(0.267)	(0.269)			(0.168)	(0.166)
$ER_{t-1,t-24}$	0.001	0.001**	-0.011**	-0.010**	0.002**	0.002**	-0.006**	-0.005**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
TTV_{t-1}	0.020**	0.023**	0.015**	0.014**	0.009**	0.005**	0.008**	0.004+
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
$TTV_{t-2,t-12}$	0.033**	0.027**	-0.084**	-0.066**	-0.012**	0.002	-0.083**	-0.066**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.006)	(0.005)
Observations	408217	408217	408217	408217	381441	381441	381441	381441

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the equivalent to tables 3 and 4 (leading regressions for crashes and jumps, respectively) for the subsamples 1986-1995 (columns (1) to (4)) and 1996-2002 (columns (5) to (8)). As before, in the estimation we allow for fixed firm and year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-month rolling window and $r_{f,t}$ is the risk-free rate. $\bar{r}_{i,t}^k$ and $\sigma_{i,t}^k$, $k = ER, MM, 0$, denote the sample mean and standard deviation of the corresponding k variable and are computed using a five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

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Table 6: **Robustness checks: the logit model.**

	(1)	(2)	(3)	(4)
	ERCRASH	MMCRASH	ERJUMP	MMJUMP
$INSSAL_{t-1}$	-2.476*	-3.564*		
	(1.122)	(1.404)		
$INSSAL_{t-2,t-12}$	2.970+	-1.196		
	(1.523)	(1.916)		
$ER_{t-1,t-24}$	-0.010	-0.003	-0.280**	-0.265**
	(0.006)	(0.005)	(0.013)	(0.012)
TTV_{t-1}	0.234**	0.194**	0.367**	0.305**
	(0.040)	(0.034)	(0.045)	(0.039)
$TTV_{t-2,t-12}$	-0.619**	-0.002	-0.878**	-1.098**
	(0.072)	(0.059)	(0.080)	(0.081)
$INSPURCH_{t-1}$			0.811+	0.912*
			(0.433)	(0.442)
$INSPURCH_{t-2,t-12}$			0.439	1.920
			(2.388)	(2.477)
Observations	789658	789658	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the estimation of the logit version of our leading regressions for crashes and jumps. In the estimation we only allow for year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-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 five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 7: **Robustness checks: the probit model.**

	(1)	(2)	(3)	(4)
	ERCRASH	MMCRASH	ERJUMP	MMJUMP
$INSSAL_{t-1}$	-0.988*	-1.442*		
	(0.454)	(0.586)		
$INSSAL_{t-2,t-12}$	1.547*	-0.393		
	(0.680)	(0.806)		
$ER_{t-1,t-24}$	-0.006*	-0.002	-0.105**	-0.102**
	(0.003)	(0.002)	(0.009)	(0.006)
TTV_{t-1}	0.136**	0.111**	0.192**	0.162**
	(0.020)	(0.017)	(0.023)	(0.020)
$TTV_{t-2,t-12}$	-0.261**	0.000	-0.398**	-0.488**
	(0.032)	(0.027)	(0.038)	(0.038)
$INSPURCH_{t-1}$			0.517*	0.564*
			(0.263)	(0.269)
$INSPURCH_{t-2,t-12}$			0.610	1.091
			(1.067)	(1.129)
Observations	789658	789658	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the estimation of the probit version of our leading regressions for crashes and jumps. In the estimation we only allow for year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-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 five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 8: **Robustness check: window for past insider activity.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ERCRASH	MMCRASH	ERCRASH	MMCRASH	ERJUMP	MMJUMP	ERJUMP	MMJUMP
$INSSAL_{t-1}$	-0.024+	-0.030**	-0.026*	-0.030**				
	(0.013)	(0.011)	(0.013)	(0.011)				
$INSSAL_{t-2,t-6}$	0.120**	0.070						
	(0.046)	(0.044)						
$INSSAL_{t-2,t-24}$			0.400**	0.116				
			(0.111)	(0.086)				
$INSPURCH_{t-1}$					0.086+	0.086*	0.088*	0.087*
					(0.044)	(0.043)	(0.045)	(0.043)
$INSPURCH_{t-2,t-6}$					0.131	0.111		
					(0.080)	(0.081)		
$INSPURCH_{t-2,t-24}$							0.314+	0.136
							(0.191)	(0.186)
$ER_{t-1,t-24}$	0.001**	0.001**	0.001**	0.001**	-0.007**	-0.006**	-0.008**	-0.006**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
TTV_{t-1}	0.013**	0.013**	0.017**	0.014**	0.012**	0.008**	0.014**	0.010**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$TTV_{t-1,t-6}$	0.004	0.005*	-0.022**	-0.001	-0.040**	-0.033**	-0.112**	-0.092**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Observations	789658	789658	789658	789658	789658	789658	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the equivalent to tables 3 and 4 (the leading regressions for crashes and jumps, respectively) but using insiders purchases and sales in the last 6 months (columns (1), (2) and (5), (6)) and the last 24 months (columns (2), (4) and (7), (8)), rather than 12 months. As before, in the estimation we allow for fixed firm and year effects and use the Newey-West standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-month rolling window and $r_{f,t}$ is the risk-free rate. $\bar{r}^{k}_{i,t}$ and $\sigma^{k}_{i,t}$, $k = ER, MM$, 0, denote the sample mean and standard deviation of the corresponding k variable and are computed using a five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-k}$ is the average of the insiders sales in stock i during the period $t-k$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-k}$ is the average of the insiders purchases in stock i during the period $t-k$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 9: **Robustness checks: large raw returns.**

	(1)	(2)
	RAWCRASH	RAWJUMP
$INSSAL_{t-1}$	0.007	
	(0.017)	
$INSSAL_{t-2,t-12}$	0.343**	
	(0.070)	
$INSPURCH_{t-1}$		0.117*
		(0.054)
$INSPURCH_{t-2,t-12}$		0.117
		(0.146)
$ER_{t-1,t-24}$	0.001**	-0.006**
	(0.000)	(0.000)
TTV_{t-1}	0.011**	0.017**
	(0.002)	(0.003)
$TTV_{t-2,t-24}$	0.007*	-0.062**
	(0.003)	(0.004)
Observations	789658	789658

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the equivalent to tables 3 and 4 (leading regressions for crashes and jumps, respectively) but using a definition of crashes and jumps based on raw returns rather than returns in excess of the CRSP equally weighted market portfolio or the returns predicted by the market model. As before, in the estimation we allow for fixed firm and year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

In these expressions we have: $r_{i,t}$ 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 and are computed using a five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 10: **Leading regression when no earning announcements.**

	Not Earning Announcement			
	(1)	(2)	(3)	(4)
	EWCRASH	MMCRASH	EWJUMP	MMJUMP
$INSSAL_{t-1}$	-0.028*	-0.028**		
	(0.011)	(0.009)		
$INSSAL_{t-2,t-12}$	0.274**	0.156*		
	(0.086)	(0.072)		
$INSPURCH_{t-1}$			0.083	0.080
			(0.055)	(0.051)
$INSPURCH_{t-2,t-12}$			0.130	0.310
			(0.227)	(0.211)
$ER_{t-1,t-24}$	0.001**	0.001**	-0.006**	-0.005**
	(0.000)	(0.000)	(0.000)	(0.000)
TTV_{t-1}	0.015**	0.012**	0.015**	0.010**
	(0.002)	(0.002)	(0.003)	(0.002)
$TTV_{t-2,t-12}$	-0.005	0.009**	-0.066**	-0.050**
	(0.003)	(0.003)	(0.005)	(0.004)
Observations	463395	463395	463395	463395

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the results of the estimation of our leading regression for crashes and jumps when these do not take place in an earning announcement month. As before, in the estimation we allow for fixed firm and year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-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 five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.

Table 11: **Leading regression when earning announcements.**

	Earning Announcement			
	(1)	(2)	(3)	(4)
	ERCRASH	MMCRASH	ERJUMP	MMJUMP
$INSSAL_{t-1}$	0.005	-0.032		
	(0.043)	(0.039)		
$INSSAL_{t-2,t-12}$	0.099	0.039		
	(0.103)	(0.088)		
$INSPURCH_{t-1}$			0.118	0.079
			(0.078)	(0.074)
$INSPURCH_{t-2,t-12}$			0.324	0.050
			(0.213)	(0.176)
$ER_{t-1,t-24}$	0.002**	0.003**	-0.008**	-0.007**
	(0.000)	(0.000)	(0.001)	(0.001)
TTV_{t-1}	0.018**	0.017**	0.022**	0.019**
	(0.004)	(0.004)	(0.006)	(0.005)
$TTV_{t-2,t-12}$	-0.002	0.009+	-0.085**	-0.069**
	(0.005)	(0.005)	(0.008)	(0.007)
Observations	224993	224993	224993	224993

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

In this table we report the results of the estimation of our leading regressions for crashes and jumps when these do take place in an earning announcement month. As before, in the estimation we allow for fixed firm and year effects and use the *Newey-West* standard errors to control for *autocorrelation* and *heteroscedasticity*. The depended variables in the regressions are defined as follows:

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

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

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 sixty-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 five-year rolling window. Regarding the independent variables: $INSSAL_{i,t-1}$ are the past month insiders' sales in stock i, $INSSAL_{i,t-2,t-12}$ is the average of the insiders sales in stock i during the period $t-12$ to $t-2$, $INSPURCH_{i,t-1}$ are the past month insiders' purchases in stock i, $INSPURCH_{i,t-2,t-12}$ is the average of the insiders purchases in stock i during the period $t-12$ to $t-2$, $TTV_{i,t-1}$ is the past month 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's i cumulative excess return over the CRSP equally weighted market portfolio for the previous two 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 CRSP dataset; the data on insider transactions comes from Thomson Financial Data Filings dataset. 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 the 20% of the number of shares outstanding.