



SCHOOL OF ECONOMICS AND MANAGEMENT

Analyst Coverage, Blockholder Monitoring, and the Informativeness of Insider Purchases

An Empirical Study of the Swedish Equity Market 2018-2024

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Abstract

This thesis investigates how analyst coverage and blockholder ownership shape the informativeness of insider purchases in a market characterized by concentrated ownership, dispersed analyst coverage, and high retail participation. While prior research has established a negative relationship between analyst coverage and insider purchase abnormal returns in the U.S., whether this relationship generalizes to markets with different institutional features remains an open question. Using a sample of insider purchase events on the Swedish equity market (Nasdaq Stockholm and First North) between 2018 and 2024, we conduct an event study and cross-sectional OLS regression analysis. Consistent with the investor recognition channel of Merton (1987), the results confirm that insider purchases are followed by significant positive abnormal returns, and that analyst coverage amplifies rather than dampens this effect in a market with high retail participation. We also find no robust evidence that blockholder ownership moderates the relationship between analyst coverage and insider purchases abnormal returns. These findings suggest that the effect of analyst coverage and blockholder on insider purchase informativeness is institutionally contingent and that in markets where retail investors form a meaningful share of the trading base, analyst coverage shapes informativeness through audience size rather than through the reduction of information asymmetry.

Keywords: Insider purchases, abnormal returns, analyst coverage, investor recognition, blockholder ownership

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Additionally, we truly hope that this thesis will be an interesting read, make a meaningful contribution to the research field and that it can inspire future research in the area.

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1. Introduction

1.1 Background

When corporate insiders, who are commonly defined as officers, directors, and large shareholders buy or sell shares in their own companies, they are required to disclose these transactions to regulatory authorities. These disclosure requirements are governed by frameworks such as the EU Market Abuse Regulation (Regulation 596/2014, art. 19) in Europe or SEC Rule 10b-5 (1934) in the U.S. The intent behind requirements such as MAR is to level the informational playing field by making insider transactions publicly observable, where the regulators aim to ensure that the signals embedded in these trades are available to all market participants. Yet, if markets are semi-strong efficient, as proposed by Fama's (1970) efficient market hypothesis (EMH), these disclosures should be rapidly incorporated into prices, leaving no opportunity for outside investors to profit from mimicking them.

Previous research, however, tells a different story. Lakonishok and Lee (2001) documented that U.S. firms with material insider purchases outperformed their benchmarks by 3.5% over the following twelve months. Seyhun (1988) demonstrates that overall insider purchasing is positively correlated with market returns, which suggests that insiders possess timing ability at both the firm and market-wide level. More recently, Cohen et al. (2012) distinguished between routine and opportunistic insider trades. The authors provide evidence that only opportunistic trades, which are those not following predictable patterns, generated abnormal returns of 82 basis points per month, where routine trades showed no predictive pattern. These findings suggest that insiders have superior information about the company's fundamentals and that the market is slow to incorporate the signals behind these transactions, which constitutes a direct challenge to the semi-strong market efficiency (Cohen et al. 2012; Lakonishok & Lee, 2001).

An important insight from the literature is that the informativeness of insider trades depends on the firm's information environment, meaning the quantity and quality of publicly available information about the firm, which in turn determines the degree of information asymmetry

between insiders and outside investors (Frankel & Li, 2004). Information asymmetry, first proposed by Akerlof (1970), is a situation where one party in a transaction has more or superior information than the other. This was later applied to financial markets by Kyle (1985). Corporate insiders naturally possess private knowledge about a firm's performance and prospects, which could give them an advantage over public investors (Seyhun, 1986). However, the extent of this advantage can vary depending on how much information is already publicly available about the firm (Frankel & Li, 2004).

There are multiple factors that shape a firm's information environment and thus the degree of information asymmetry. For example firm size: smaller firms receive less attention from market participants and are generally considered less efficiently priced, leading to more informative insider purchases (Lakonishok & Lee, 2001; Seyhun, 1986). Another example is liquidity, where insider trades have greater price impact in less-liquid stocks, where wider bid-ask spreads indicate higher information asymmetry (Degryse et al. 2014). Additionally, abnormal returns following insider trades vary with country-level shareholder protection and enforcement of insider trading regulations (Aussenegg et al. 2018; Fidrmuc et al. 2013). However, size, liquidity, and shareholder protection are structural characteristics rather than mechanisms that actively reduce the informational gap between insiders and outsiders. The literature identifies two such mechanisms: analyst coverage, which reduces asymmetry by generating, processing and spreading firm-specific information (Frankel & Li, 2004; Marcus & Wallace, 1997) and blockholder monitoring, which constrains insiders' ability to exploit private knowledge through direct oversight of management (Fidrmuc et al. 2006).

Sell-side analysts are key information intermediaries in capital markets: they collect, process and spread information about firms, reducing the information gap between insiders and outside investors, demonstrated by Frankel and Li (2004), who showed that firms with greater analyst coverage have less frequent insider purchases and less profitable ones. Wu (2019) established the causal nature of this relationship by looking at brokerage firm closures, which led to sharp increases in insiders' abnormal returns as analyst coverage declines. However, analyst coverage is not only an information production channel, covered firms also tend to attract larger institutional investor bases (O'Brien & Bhushan, 1990) and greater retail attention (Barber & Odean, 2008).

Since disclosed insider purchases need an audience to move the share price, the same coverage that reduces post transaction asymmetry may also amplify the speed and magnitude of the market reaction once the signal is released. Therefore, while the U.S. evidence establishes that lower analyst coverage leads to higher abnormal returns following insider purchases, the conditions under which this relationship holds remain an empirical question. In markets where analyst coverage primarily expands the audience capable of pricing a disclosed signal rather than substituting for the information it contains, the relationship may operate in the opposite direction.

The second such mechanism, that actively affects the amount of information released to the public, is blockholder ownership. Unlike analysts, who affect the information environment by making firm-specific information publicly available (Frankel & Li, 2004; Wu, 2019), blockholders reduce it through direct oversight of management, which constrains insider's ability to exploit private knowledge before it reaches the market (Fidrmuc et al. 2006). Fidrmuc et al. (2006) distinguish between active and passive owners, finding that the market reaction to insider trades is weaker in firms with active blockholders, suggesting that monitoring by these owners partially closes the information gap before the trade occurs. In their UK setting, active blockholders included families and corporations whose engaged monitoring produced this effect.

1.2 Problematization

If markets are semi-strong efficient, disclosed insider transactions should not leave opportunities for outside investors to earn abnormal returns (Clarke et al. 2001; Fama, 1970). However, decades of evidence consistently demonstrate that legal insiders can identify mispriced securities, generating returns that outperform market benchmarks (Finnerty, 1976; Jaffe, 1974; Lakonishok & Lee, 2001; Lorie & Niederhoffer, 1968). This presents a fundamental puzzle: insider filings are publicly available to all market participants, yet the market consistently underreacts to the information they contain.

The literature points to information asymmetry as the key explanation for this puzzle. Studies show that insiders can exploit private knowledge about firm fundamentals that is not yet reflected in prices, and that the market underreacts to these disclosed signals (Cohen et al. 2012; Lakonishok & Lee, 2001; Seyhun, 1986). Similarly, previous research also establishes that Sell-side financial

analysts work as intermediaries of information, and by their way of acquiring information and communicating it through recommendations, reduced information asymmetry between insiders and outsiders (Brennan & Subrahmanyam, 1995; Frankel and Li, 2004; Roulstone, 2003; Wu, 2019). However, because the number of analysts varies across firms, the degree to which the market underreacts also varies. This means that firms with little or no analyst coverage have a wider information gap, which would imply that when an insider purchases shares, the signal contains relatively more new information. However, whether this signal translates into larger measured abnormal returns may depend on whether the market reaches a large enough audience that can react to it. In low-coverage firms, fewer investors are positioned to detect, evaluate and act on the disclosure, which may slow or mute the price adjustment compared to firms with higher analyst coverage (Merton, 1987). The net effect of analyst coverage on insider purchase informativeness therefore depends on which mechanism dominates.

While Wu (2019) and Frankel and Li (2004) establish a relationship in the U.S., demonstrating that analyst coverage reduces information asymmetry between corporate insiders and the public, whether this moderating effect on insider trade informativeness extends to international markets remains an open question. This is particularly relevant given that the role of analysts differs across markets. Azevedo and Müller (2024) found that a released analyst recommendation led to higher abnormal returns in international markets, as opposed to the U.S, suggesting that analysts play a more substantive role in price discovery outside the U.S. The U.S. market is also characterised by dispersed ownership (OECD, 2025b), a high share of institutional investors (OECD, 2025b), and higher analyst coverage, averaging 76% of firms compared to an international average of 55% (Azevedo & Müller, 2024). These features make it an unrepresentative setting from which to generalise conclusions about the moderating effect of analyst coverage on insider informativeness.

A meaningful test of whether the mechanism generalises therefore requires a market that differs from the U.S. along these dimensions. First, ownership should be more concentrated. This introduces a structurally present alternative monitoring channel through blockholder oversight that may complement or substitute for the role of analyst coverage in bridging the information gap between insiders and outsiders (Fidrmuc et al. 2006; Maug, 1998). Second, analyst coverage variation across firms within a single regulatory framework provides a clean identification

strategy. This within-market approach eliminates the confounding differences in regulation, enforcement, and disclosure that typically complicate cross-country comparisons. The European post-2018 setting is particularly suited to this requirement. MiFID II unbundling of research fees from execution costs reduced analyst coverage across European markets by roughly 10-15% (Lang et al. 2024), widening the gap between covered and uncovered firms. Third, retail investor participation should be meaningfully present. The U.S. evidence supporting that lower coverage leads to higher insider purchase abnormal returns (Frankel & Li, 2004; Wu, 2019) was established in a market dominated by institutional investors (OECD, 2025b) who are better capable to independently detect and evaluate disclosed insider signals even in the absence of analyst coverage (Ke & Petroni, 2004). In markets with high retail investor participation, this assumption may not hold.

Retail investors typically rely on public information and visible signals rather than proprietary research (Wei et al. 2017), and evidence suggests that their attention concentrates on firms that are covered by analysts (Barber & Odean, 2008). Therefore, in a market where retail investors form a meaningful share of the trading base, analyst coverage may not only reduce the information advantage of insiders, it might rather determine whether an audience exists to price a disclosed signal at all. Under the investor recognition framework of Merton (1987), covered firms attract a larger and more attentive investor base. This means that a disclosed insider purchase is more likely to be detected, evaluated, and acted upon in covered firms than in uncovered ones. Under these conditions, the relationship may reverse from the U.S. literature established by Frankel and Li (2004) and Wu (2019), with covered firms experiencing larger abnormal returns following insider trades than uncovered ones.

Testing the analyst coverage mechanism in a market that satisfies all of these criteria provides a direct test of whether the U.S. findings hold, or reverse, in a different institutional setting. It also enables an examination of whether blockholder monitoring, as a competing mechanism through which information asymmetry is reduced, substitutes or complements for the role of analyst coverage in moderating insider purchase informativeness. This question cannot be meaningfully addressed in a dispersed ownership setting where blockholders are more absent as a monitoring force.

1.3 Aims and Objectives

This thesis aims to investigate how analyst coverage affects the informativeness of insider purchases in a market characterised by concentrated ownership and high retail investor participation, and whether the direction follows the logic of Merton (1987). A secondary aim is to examine whether concentrated blockholder ownership serves as an alternative mechanism that substitutes for or complements the role of analyst coverage in explaining abnormal returns of insider purchases. The thesis tests whether the investor recognition channel, drawing on the logic of Merton (1987), dominates in the Swedish setting and produces the opposite relationship from the information production channel established in the U.S. by Frankel and Li (2004) and Wu (2019). Under the production channel, lower coverage should produce higher abnormal returns following insider purchases, as insiders in less covered firms hold a wider informational advantage that is released to the market upon disclosure. The recognition channel predicts the opposite. Higher coverage should produce higher abnormal returns, because covered firms attract a larger audience capable of detecting and acting on a disclosed insider signal. The central research question guiding this thesis is therefore:

How does the information environment, specifically analyst coverage and ownership structure, affect the informativeness of insider purchases?

To address this question, the thesis is structured as follows. First, it reviews the existing literature on market efficiency, insider trading, and the role of analyst coverage and ownership structure in shaping the information environment, from which three hypotheses are derived. Second, it conducts an empirical analysis using an event study methodology applied to insider purchase transactions between 2018 and 2024, which measures abnormal returns across firms with different levels of analyst coverage and ownership concentration. Third, the findings are interpreted in relation to existing theories and the stated hypotheses to assess whether the analyst coverage mechanism in the U.S. differs from a market characterized by blockholder ownership, dispersion in analyst coverage, and a higher degree of retail investors.

1.4 Delimitation

This study is delimited to the Swedish equity markets from 2018 to 2024. The 2018 start date ensures the sample operates entirely within the post-MAR (2016) and MiFID II (2018) regulatory framework. Furthermore, the dataset includes both currently listed and delisted firms to mitigate survivorship bias.

1.5 Outline of the Thesis

Chapter 2 presents a review of the relevant literature on market efficiency, insider trading, and the role of analyst coverage and ownership structure in shaping the information environment, establishing the theoretical foundation from which the three hypotheses are derived. Chapter 3 outlines the research design and methodological approach, including data sources, sample construction, variable definitions and considerations of validity, reliability and limitations. Chapter 4 reports the empirical results, drawing on an event study of insider purchases and cross sectional regression analyses of the cumulative abnormal returns. Chapter 5 discusses these findings, interpreting them in light of the literature and institutional features. Chapter 6 concludes the thesis by summarising the research contributions, highlighting practical implications and proposing topics for future research.

2. Literature review

2.1 The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) (Fama, 1970) serves as a baseline for evaluating information asymmetry in financial markets. The strong and semi-strong forms of market efficiency are directly testable through insider trading (Finnerty, 1976; Jaffe, 1974; Lorie & Niederhoffer, 1968). If markets were semi-strong efficient, outside investors could not profit by mimicking disclosed insider trades, since the disclosure, under those circumstances, would immediately be incorporated into prices (Clarke et al., 2001; Malkiel, 2003). Furthermore, because strong-form efficiency assumes prices reflect even non-public, private knowledge, the documented ability of corporate insiders to systematically generate abnormal returns (Lakonishok & Lee, 2001; Seyhun, 1986) acts as a clear proxy for market inefficiency. The consistent rejection of both predictions, reviewed in the next section, motivates this thesis. The literature often attributes these deviations in efficiency to information asymmetry, which is the possibility that not all market participants have equal access to valuable information, even when that information is technically public. This thesis pursues that explanation.

2.2 Insider trading and market efficiency

There are two types of insider trading, legal and illegal. Illegal insider trading occurs when someone trades a financial instrument based on inside information, which is information that is not yet public, and would likely affect the price if it were made public (Regulation 596/2014, arts. 7 & 14). Conversely, legal insider trading is when individuals in a managerial position, such as CEOs, board members, and senior executives, as well as their closely associated individuals, buy or sell shares in their own company based on their general conviction, not on specific inside information (Regulation 596/2014, art. 19).

A substantial body of empirical evidence rejects both the strong and semi strong forms in the insider trading setting (Finnerty, 1976; Jaffe, 1974; Lakonishok & Lee, 2001). Lakonishok and Lee (2001) showed purchases are more informative than sales, as sales are frequently driven by liquidity needs or diversification rather than negative firm-specific information, with the effect

largest in small cap stocks. Jeng et al. (2003) found insider transactions outperformed the market by about 6% per year. Cohen et al. (2012) further showed that filtering out routine trades isolate the truly informative ones, with opportunistic purchases yielding 82 basis points per month. Taken together, the informativeness of insider purchases depends on the nature of the trade, firm characteristics and the information environment in which it occurs.

These studies have all been based on the U.S stock market, but the effects are not limited to this market. Fidrmuc et al. (2006) found significant abnormal returns following insider trades in the UK, with the effect being even stronger than the U.S, likely due to faster reporting requirements. Fidrmuc et al. (2013) extended this across 15 European countries and the U.S., showing that the market reaction to insider trades varies with country level shareholder protection, controlling for the effects of the Market Abuse Directive that came in 2003. Aussenegg et al. (2018) examined seven EU countries after the implementation of the Market Abuse Directive and found that the price impact of insider transactions is strongest in countries with weaker public enforcement.

The international evidence reviewed above establishes that insider purchases generate abnormal returns across a range of regulatory regimes, but also that the magnitude of the effect varies with institutional features. The EU introduced the Market Abuse Regulation (MAR) to eliminate these gaps by strengthening and harmonizing public enforcement across the European market (Lombardo & Mucciarelli, 2019). Whether this effect persists under the tightened disclosure requirements of the post 2018 European framework, particularly MAR's three business day reporting mandate, is itself a meaningful empirical question (Regulation 596/2014, art. 19). Before examining the moderating role of the information environment, this thesis must first confirm whether the underlying effect holds in the post MAR/MiFID II setting. Consistent with the international evidence, the hypothesis is stated directionally.

H1: Insider purchases are followed by positive abnormal returns.

2.3 Information environment and insider trading informativeness

The literature attributes the predictive power of insider purchases to the degree of information asymmetry surrounding the firm (Frankel & Li, 2004). This thesis focuses on two mechanisms that

have been shown to actively reduce the information gap: analyst coverage and blockholder monitoring. The following subsections review each in turn.

2.3.1 The role of analyst coverage

One strand of the literature emphasizes analyst coverage as an information production channel that directly reduces information asymmetry between insiders and outside investors. Frankel and Li (2004) empirically established this mechanism, showing that firms with greater analyst coverage experience less frequent and less profitable insider purchases, a finding later reinforced by Wu (2019). Taken together, this strand of the literature treats analyst coverage as a substitute for the private information embedded in insider trades which means that when coverage is high, less of the firm's fundamental information remains undisclosed, leaving insiders with a smaller informational advantage to exploit. Under this view, abnormal returns following insider purchases should be larger in firms with low analyst coverage, since the disclosure releases more previously unpriced information into the market.

A second strand of the literature, however, suggests that analyst coverage may not only reduce asymmetry but also shape who is positioned to react once a trade becomes public information. Under the investor recognition framework of Merton (1987), assets are only priced by investors who are aware of them, and the size of a firm's recognized investor base directly influences how new information is incorporated into prices. Analyst coverage has been identified as one of the key channels through which investor recognition expands (Lehavy & Sloan, 2008) and is positively associated with institutional ownership (O'Brien & Bhushan, 1990). Under this view, covered firms have a larger and more attentive base of market participants that are ready to act on insider purchases. Uncovered firms, by contrast, may have a smaller audience capable of acting on the disclosure, which can slow or mute the measured price adjustment even when the underlying informational content of the trade is larger.

The two strands of the literature generate opposing predictions of how analyst coverage moderates insider purchase informativeness. The information production channel predicts that less covered firms produce larger abnormal returns and the investor recognition channel predicts the opposite.

Which channel dominates is an empirical question and the answer depends on the institutional setting in which the test is conducted.

Thus, the role of analysts in price discovery is seemingly not uniform across markets, indicating that the institutional setting determines which channel dominates (Azevedo & Müller, 2024).

Azevedo and Müller (2024), examined 45 countries from 1994 to 2019 and documented that analyst recommendations are followed by highly significant abnormal returns in international markets, in contrast to U.S evidence where the same recommendations obtain no comparable reaction. Their finding that analysts contribute to price discovery rather than substitute for it abroad suggests that the information production channel established in the U.S literature may not generalize to other institutional settings, and that the relative weight of the two channels depends on characteristics of the market in question.

The investor recognition channel gains more importance in markets where the audience capable of pricing a disclosed signal is small. Two structural features amplify this effect. First, analyst coverage is positively associated with firm size (Bhushan, 1989), meaning that in markets with a high share of small and mid-cap firms, a meaningful portion of listed companies have few or no analysts following them. Second, the composition of the trading base matters as much as its size. Institutional investors are well equipped to independently detect and evaluate disclosed insider signals even in the absence of analyst coverage (Ke & Petroni, 2004), which means that in institutionally dominated markets, uncovered firms still have an audience capable of reacting to the signal. Retail investors, by contrast, typically rely on public information and visible signals rather than proprietary research (Wei et al. 2017), and their attention concentrates on firms that are already publicly visible (Barber & Odean, 2008). By applying this logic, markets where retail investors form a meaningful share of the trading base, the audience capable of reacting to an insider purchase in an uncovered firm is considerably smaller. Analyst coverage therefore takes on the additional role of determining whether such an audience exists at all. As established in Section 1.2, the reduction in analyst coverage following MiFID II affected low coverage firms more (Lang et al. 2024), increasing the gap in investor recognition. Consistent with the investor recognition logic developed above, the second hypothesis is stated directionally:

H2: The predictive power of insider purchases is stronger among firms with high analyst coverage than among firms with low analyst coverage.

2.3.2 Ownership structure as an alternative information mechanism

One strand of the literature treats concentrated ownership as a mechanism that actively reduces the informational distance between corporate insiders and outside investors. Drawing on the theoretical foundations of Maug (1998) and Fidrmuc et al. (2006) argue that large blockholders have a unique incentive to monitor management directly, and that this internal oversight reduces the information gap by improving transparency for the wider shareholder base. They distinguish between active and passive owners, with active blockholders, which are those engaged in direct monitoring of management, being more effective at reducing the asymmetry between management and the market. In the UK setting, this category typically includes corporations and families with significant ownership stakes. Consistent with this, Fidrmuc et al. (2006) document that the market reaction to insider trades is weaker in firms with active blockholders, indicating that part of the informational content of insider trades has already been incorporated into prices through monitoring before the trade occurs.

This raises the question of how blockholder monitoring interacts with the analyst coverage mechanism developed in section 2.3.1. The two mechanisms operate through different channels. In firms with a concentrated blockholder, monitoring may close part of the information gap before the insider trades, so the disclosure carries a smaller informational signal. In firms with dispersed ownership, no such monitoring takes place in advance, so the insider purchasing signal carries more residual content for analyst coverage to amplify.

Extending this logic to the interaction with analyst coverage generates the third hypothesis. Under the recognition channel framing developed in H2, where analyst coverage amplifies insider purchase signals through audience size, the amplifying effect should be stronger in firms where blockholder monitoring has not already partially closed the information gap, and weaker in firms where it has. Hence, the third hypothesis is stated directionally:

H3: The amplifying effect of analyst coverage on insider purchase informativeness is stronger in firms with dispersed ownership than in firms with a concentrated blockholder.

3. Methodology

This chapter outlines the methodological approach used to examine how analyst coverage and ownership structure moderate the informativeness of insider purchases. It begins with a description of the quantitative research design and what literature has been used to ground the hypotheses. This is followed by the presentation of the data collection process and sample construction, which includes sources, filtering criteria, and event definition. Two main empirical methods are used. First, an event study methodology is employed, which estimates the cumulative abnormal returns (CAR's) following insider purchases. The CAR's are used to directly test whether insiders can earn abnormal returns on the Swedish equity market (H1). Second, a cross-sectional OLS regression is applied to the individual event-level CARs and examines if analyst coverage and blockholder ownership moderate the magnitude of the informativeness of insider purchases (H2 and H3), along with robustness checks. The methodology chapter concludes with a discussion of validity and reliability and the study's limitations.

3.1 Research Approach and Design

This thesis adopts a deductive research approach, formulating hypotheses based on established theoretical frameworks (Bell & Bryman, 2022). Specifically, the research questions are derived from the Efficient Market Hypothesis (EMH) and from two competing theoretical channels through which the information environment shapes the price reaction to insider purchases: the information production channel (Frankel & Li, 2004; Wu, 2019) and the investor recognition channel (Lehavy & Sloan, 2008; Merton, 1987). This approach is appropriate given that the underlying mechanisms of insider trading are well-documented in a particular market, this thesis contributes to the literature by testing the mechanisms in a setting characterized by concentrated ownership, dispersed analyst coverage, and high retail participation.

To examine the relationship between the information environment and stock returns, a quantitative research design is employed. The analysis utilizes a two-stage methodology. First, an event study is conducted to isolate the market reaction to insider purchase disclosures, following the standards established by MacKinlay (1997). Second, a cross-sectional regression analysis is performed,

similar to Lakonishok and Lee (2001), to determine how analyst coverage and ownership structure affect these returns.

3.1.1 Empirical Setting

Section 1.2 outlined three criteria a market should satisfy to provide a meaningful test of whether the analyst coverage mechanism documented in the U.S literature generalises to other institutional settings: concentrated ownership, within market variation in analyst coverage under a unified regulatory framework, and a high degree of retail investor participation. The Swedish equity market is selected as the setting for this investigation because it satisfies all three. Sweden is treated here as a test setting rather than as the object of the study in itself.

The first criterion is satisfied through Sweden's relatively more concentrated ownership structure, where control is typically exercised through dual class share structures and arrangements that separate voting power from capital commitment (La Porta et al. 1999; OECD, 2025a), in contrast to the dispersed ownership model typical of U.S listed firms (OECD, 2025b).

The second criterion is satisfied by the breadth of the Swedish listing landscape. Sweden has the highest number of publicly listed companies in the European Union, reaching 953 by 2024 end, driven largely by smaller firms listings on growth segments such as Nasdaq First North, which now hosts nearly two thirds of all listed Swedish companies (OECD, 2025a). The result is a wide spectrum of analyst coverage operating within the unified post-2018 regulatory framework (MAR and MiFID II) discussed previously.

The third criterion is satisfied by Sweden's high retail investor participation, the highest in Northwestern Europe at approximately 30% of trading volume on Nasdaq First North Gross Market and 12% across the overall market (OECD, 2025a).

3.2 Literature Search Strategy and Journal Selection

To ensure the credibility and relevance of the literature review, a systematic search strategy was employed across several academic databases, including JSTOR, ScienceDirect, Google Scholar, and the LUBsearch portal. The primary selection prioritized peer-reviewed articles from leading publications, such as *The Journal of Finance*, *Accounting research journal*, and *The Quarterly Journal of Economics*. These sources establish the theoretical bedrock of the study. Beyond peer-

reviewed publications, the search has included reputable working papers. International working papers, such as Wu (2019), were included to ensure that the most current research and theoretical developments were considered. To maintain methodological integrity, a clear hierarchy has been applied during the selection process. Peer-reviewed studies serve as the primary source for hypothesis formulation, while non-peer-reviewed studies are utilized to also contextualize findings. A large focus was placed on finding articles that relates to topics such as abnormal returns of insider tradings, factors influencing the market reaction of insider purchases, and the informative environment of the stock market. The search was conducted through the utilization of specific keywords, such as “insider purchases”, “abnormal returns”, “analyst coverage”, and “ownership structure”, to identify relevant studies.

3.3 Data Collection and Sample Construction

3.3.1 Bloomberg Terminal, Factset and Finansinspektionens database

This study utilizes secondary data from the Bloomberg terminal, FactSet and Holdings, along with primary data from Finansinspektionen. Bloomberg is used to extract analyst coverage data utilizing the Equity Screening (EQS) function and the Excel Add-in to retrieve historical data. The FactSet excel add-in has been used for financial data such as market capitalization, daily return data, and ownership. Moreover, Modular Finance ownership database Holdings has been used to complement ownership data from FactSet in cases where both A and B shares exist. This distinction is critical to isolate the difference between capital contribution and voting rights, in line with La Porta et al. (1999), and Cronqvist and Nilsson (2003). Swedish listed firms frequently employ dual-class share structures in which A-shares carry superior voting rights while B-shares are more widely held and actively traded (OECD, 2025a).

Insider transaction data was extracted from Finansinspektionen’s public database on insider transactions on the Swedish market (Finansinspektionen, 2026), the same database individuals directly report their insider transactions and where they first appear. Utilizing this primary source ensures the publication dates used for events are consistent with when the market first received the signal.

3.3.2 Sample Universe and Period

This study analyzes listed companies on the Nasdaq Stockholm Main Market as well as the Nasdaq First North Growth Market during the period 2018–2024 (stock returns 2017.06.15-2025.01.30). Both active and delisted firms are included to avoid survivorship bias (Frankel & Li, 2004; Lakonishok & Lee, 2001; Shumway, 1997). The selection of January 1, 2018, as the start date ensures the entire sample falls under a unified regulatory regime. As outlined in Section 1.4, restricting the sample to this period incorporates the structural market shifts introduced by MAR (2016) and MiFID II (2018) regarding disclosure requirements and analyst coverage, thereby ensuring institutional consistency across the dataset. Furthermore, the 2018–2024 timeframe provides a robust sample size while allowing for data collection across both pre- and post-pandemic market environments.

3.3.3 Sample Filtering and Cleaning

Raw insider transaction data is sourced from Finansinspektionen. To ensure the sample captures genuine informational signals, it is restricted exclusively to open-market purchases, resulting in 60 775 transactions. The decision to exclude insider selling is supported by Lakonishok and Lee (2001), Jeng et al. (2003) and Fidrmuc et al. (2006), who demonstrate that insider sales lack predictive power as they are primarily motivated by non-informational factors, such as personal liquidity needs, tax planning, or portfolio diversification. Furthermore, following Fidrmuc et al. (2006), non-discretionary "noise" transactions, such as option exercises, gifts, and transfers, are filtered out since these transactions are determined by pre-commitments rather than an insider's actual assessment of current firm value. Focusing exclusively on open-market purchases ensures that the estimated abnormal returns are driven by private information, offering a direct test of the information asymmetry hypothesis.

To ensure the sample contains economically meaningful trades, a minimum transaction threshold of 200,000 SEK is applied. This serves two primary purposes. First, empirical evidence suggests that larger purchases carry stronger informational signals (Fidrmuc et al. 2006; Jeng et al. 2003; Lakonishok & Lee 2001). Specifically, Lakonishok and Lee (2001) found that abnormal returns increase with transaction size, as larger trades represent larger personal financial commitments. In

contrast, small transactions are often motivated by non-informational factors like portfolio rebalancing, which introduces noise. Second, this threshold roughly aligns with the regulatory logic of MAR Article 19 of Regulation 596/2014, which exempts Swedish transactions below a cumulative EUR 20,000 annually due to a lack of materiality. This requirement reduced the sample to 19 969 transactions.

3.4 Data and variables

Variable	Definition	Period
OS_TOP_HLDR_PCTOS (Factset)	Binary variable equal to one if the largest individual shareholder holds 10% or more of total outstanding shares	2018.01.01-2024.12.31
P_TOTAL_RETURN (Factset)	Daily total stock return inc. dividends for each sample firm.	2017.06.15-2025.01.30
P_MARKET_VAL_SEC (Factset)	Raw market capitalisation, then logarithmic MCAP	2018.01.01-2024.12.31
TOT_ANALYST_REC (Bloomberg)	Nr. of unique analysts issuing recommendations for the firm on the event day	2018.01.01-2024.12.31
PX_TO_BOOK_RATIO (Factset)	Market to book ratio	2018.01.01-2024.12.31

3.4.1 Return data and market benchmark

Stock return data is defined as daily total returns, which includes dividends and is collected for each sample firm. The OMX Stockholm Gross Index (OMXSGI) is used as the market benchmark for all firms in the sample. OMXSGI captures all shares listed on Nasdaq Stockholm with dividends reinvested and serves as a broad proxy for the Swedish equity market (Nasdaq, n.d.a).

Although First North Growth Market firms are technically listed on a separate multilateral trading facility with slightly different listing requirements (Nasdaq, n.d.b), applying a single, broad market benchmark across both segments aligns with event-study methodologies in insider trading literature (Aussenegg et al. 2018; Fidrmuc et al. 2006). Furthermore, both marketplaces are subject to the same insider transaction reporting obligations under MAR, ensuring comparability (Regulation 596/2014, art. 19).

3.4.2 Independent variables

Analyst coverage is operationalized as a binary variable to classify firms as covered or uncovered, equaling one if the firm has five or more recommendations recorded on the publication day, and zero otherwise. This threshold follows Wu (2019), who defines low coverage at the same cutoff on the basis that the marginal effect of an analyst is concentrated among firms with few analysts. This means that when a firm moves from three to two analysts it experiences a meaningful change in its information environment, while moving from twenty five to twenty four does not.

While Wu's threshold is motivated by the information production channel, the same cutoff is consistent with the investor recognition channel that motivates H2. Under Merton (1987) and Lehavy and Sloan (2008), what matters for the price reaction to a disclosed signal is the size of the audience capable of detecting and acting on it. Firms with one or two analysts still have a thin investor base and the recognized audience only becomes meaningful once a handful of analysts follow the firm. As established in section 3.3.1 based on La Porta et al. (1999) and Cronqvist and Nilsson (2003), for firms with dual-class structures, this data is extracted from the B-share ticker to reflect the primary informational environment.

This study operationalizes blockholder ownership as a binary variable equaling one if a single shareholder holds 10% or more of total shares outstanding at the time of the publication date, and zero otherwise. This binary threshold follows Fidrmuc et al. (2006), who argue that significant blockholders signal governance regimes characterized by active monitoring. The selection of a 10% threshold is consistent with foundational research in insider trading and blockholder behavior (Lakonishok & Lee, 2001; Edmans, 2014). This regulatory logic extends to the Swedish market, where a 10% holding is considered a "qualified owner" with the legal authority to refuse discharge from liability for the board, call for extraordinary general meetings, or request special audits

(Finansinspektionen, 2025). As established in 3.3.1 firms with dual class share structures this study utilizes A-share ownership for blockholder classification (Cronqvist & Nilsson, 2003; La Porta et al. 1999). By prioritizing voting power, the classification ensures the variable reflects the shareholder's actual capacity for intervention within the firm.

3.4.3 Control Variables

To account for cross-sectional variations in expected stock returns that are not captured by the market model, the analysis includes firm size, the book-to-market (B/M) ratio, and momentum as control variables.

Following Fama and French (1992, 1993), firm size and the B/M ratio are included as they proxy for fundamental economic risks. Firm size controls for both the negative relationship between market capitalisation and expected returns as well as the broader information environment. Smaller firms tend to exhibit higher information asymmetry, which can inflate the informativeness of an insider trade (Lakonishok & Lee, 2001). Similarly, the B/M ratio is included to control for the value premium. High B/M ratios often indicate relative economic distress or undervaluation whereas low ratios typically reflect persistent profitability (Fama & French, 1992). Methodologically, consistent with Frankel and Li (2004), both firm size (market capitalization) and the B/M ratio are natural log-transformed ($\ln$) to mitigate the impact of outliers and normalize their inherently skewed distributions.

Furthermore, a momentum variable is used to control for the tendency of stock prices to follow recent performance trends. Building on the foundational work of Jegadeesh and Titman (1993) and Carhart (1997), empirical evidence demonstrates that short-term past winners tend to continue overperforming, while past losers continue to underperform. Because insiders are frequently contrarian investors who tend to purchase shares following periods of poor stock performance (Lakonishok & Lee, 2001), controlling for momentum is essential.

Natural Log Market capitalization:

$$SIZE_i = \ln(CUR_MKT_CAP_{i,t-1})$$

Book-to-market:

$$BM_i = \ln \left(\frac{BS_TOT_EQUITY_{i, \text{last FY}}}{CUR_MKT_CAP_{i,t-30}} \right)$$

Momentum:

$$MOM_i = \sum_{\tau=-200}^{-30} R_{i,\tau}$$

Where:

$CUR_MKT_CAP_{i,t-30}$: Market capitalization on the day prior to the buffer period (day $t - 30$)

$BS_TOT_EQUITY_{i,t-1}$: Total book value of equity for the most recent fiscal year

$R_{i,\tau}$: Daily stock return from day -200 to day -30 relative to the event transaction date

3.5 Event Study Methodology

To investigate whether insider purchases are followed by abnormal returns on the Swedish stock market (H1), this study employs an event study methodology. The event study is a standard approach in the insider trading literature for isolating the stock price impact of a specific corporate event, in this case, the public disclosure of an insider purchase, from broader market movements (Seyhun, 1986). Similar to previous literature, abnormal returns are estimated and cumulated into a cumulative abnormal return (CAR) (MacKinlay, 1997), which is used as a proxy for the extent to which the insider's trade transfers information that is not yet reflected in the stock price (Lakonishok & Lee, 2001; Seyhun, 1986). The CARs are then tested for statistical significance relative to zero using a cross-sectional t-test, in accordance with Boehmer et al. (1991).

3.5.1 Estimation and Event Window

The estimation window spans 170 trading days, from day -200 to day -30 relative to the publication date, during this period, the stock's normal return relationship with the market is estimated using the market model (MacKinlay, 1997). While MacKinlay (1997) does not provide a fixed estimation length, the choice reflects a trade-off between two competing considerations. First, the window must contain enough observations to estimate the market model parameters with sufficient precision as short windows produce unstable alpha and beta estimates. Second, the window should not extend so far into the past that the estimated parameters reflect a fundamentally different risk profile of the firm than that prevailing at the time of the event (MacKinlay 1997). A window of 170 trading days thus falls in the range used in comparable studies on insider trading, which typically have windows between 100 and 250 trading days (Fidrmuc et al. 2006; Fidrmuc et al. 2013; Seyhun, 1986), and provides sufficient parameter estimates while remaining recent enough to reflect each firm's characteristics at the time.

A 30 day trading day buffer is imposed between the end of the estimation window and the publication date. This buffer serves to ensure that the estimation period is uncontaminated by pre announcement price movements, such as declines that may have prompted a contrarian insider purchase (Lakonishok & Lee, 2001), as well as any information leakage between the transaction and the publication date. This clean window requirement serves two purposes: (1) it ensures that the estimation period provides uncontaminated normal return parameters, and (2) it ensures that the cumulative abnormal return (CAR) over the event window reflects a single informational episode rather than a sequence of overlapping purchases (Wu, 2019; Fidrmuc et al., 2013).

The event window spans day 0 to day +30, where day 0 is the publication date of the insider transaction Finansinspektionen's register. The 30-day horizon captures the market's gradual adjustment to insider purchases, as theory suggests investors initially underreact to the disclosure signal (Cohen et al., 2012; Lakonishok & Lee, 2001; Seyhun, 1986). Capturing this drift requires a window long enough to observe the post announcement price adjustment, not only the immediate announcement day reaction. The choice is consistent with prior insider trading event studies (Fidrmuc et al. 2006; Jeng et al. 2003), and Lakonishok and Lee (2001) who found that a large portion of the abnormal return following insider purchases accumulates within the first month of

disclosure. After applying the estimation window, event window, and clean window requirements described above on the 19 969 transactions left after the filtering criteria in section 3.3.3, the final H1 sample consists of 1 824 events over 993 unique securities.

3.5.2 Normal Return Estimation

In line with existing literature on event studies (MacKinlay, 1997) and for similar studies conducted on insider purchases (Fidrmuc et al. 2006; Lakonishok & Lee, 2001; Seyhun, 1986) expected returns are estimated using the market model. This methodology is normal in event study literature as it reduces abnormal return variance by filtering market-wide fluctuations following established practices from MacKinlay (1997).

$$R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \varepsilon_{i,t}$$

Where:

$R_{i,t}$: The actual return on stock i on day t

$R_{m,t}$: The return on the market portfolio (OMXSIG index) on day t

α_i : The intercept parameter, representing the stock's average baseline return.

β_i : The slope coefficient, representing the sensitivity of stock i to market movements

$\varepsilon_{i,t}$: The zero-mean disturbance term that represents the abnormal return not explained by the market

3.5.3 Abnormal Return Calculation

For each day in the event window, the abnormal return is calculated as the difference between the stock's actual return and its expected return as estimated by the market model MacKinlay (1997).

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i \times R_{m,t})$$

Where:

$AR_{i,t}$: the abnormal return for stock i on day t

$R_{i,t}$: the actual observed return

$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}$: the expected return derived from the market model parameters estimated during the estimation window

These daily abnormal returns are then cumulated over the event window to produce the cumulative abnormal return for each event (MacKinlay, 1997). The CAR captures the total informational impact of the insider purchase over the 30 trading days following its disclosure.

$$CAR_i(0, +30) = \sum_{t=0}^{30} AR_{i,t}$$

3.5.4 Statistical Significance Testing

Individual CARs are averaged into the Cumulative Average Abnormal Return (CAAR) to assess overall market reaction (Aussenegg et al., 2018; Fidrmuc et al., 2006, 2013). As the primary metric for testing H1, CAAR represents the average informational value of insider purchases on the Swedish market.

To test whether the CAAR is significantly different from zero, consistent with the thesis first hypothesis, a standard cross-sectional t-test is employed (Boehmer et al., 1991). The t-statistic is calculated as the mean CAR divided by the standard error of the CARs across events.

$$t_{CAAR} = \frac{\overline{CAR}}{\hat{\sigma}_{\overline{CAR}}/\sqrt{N}}$$

$$\overline{CAR} = \frac{1}{N} \sum_{i=1}^N CAR_i$$

$$\hat{\sigma}_{\overline{CAR}} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (CAR_i - \overline{CAR})^2}$$

Where:

N : Total number of events (insider transactions) in the sample.

CAR_i : Cumulative Abnormal Return for firm i over the event window.

$\overline{CAR}$: Cumulative Average Abnormal Return (CAAR) across the entire sample.

$\hat{\sigma}_{\overline{CAR}}$: Cross-sectional standard deviation of the individual CAR_i values

Additionally, the Boehmer et al. (1991) standardised cross-sectional test is considered as a robustness check, which is consistent with similar studies on insider trading (Aussenegg et al., 2018). By standardizing each CAR by the stock's estimation-period standard deviation, it accounts for event-induced increases in variance that can otherwise inflate standard t-statistics (Boehmer et al. 1991).

$$SCAR_i = \frac{CAR_i}{\sigma_i}$$

$$t_{BMP} = \frac{\overline{SCAR} \cdot \sqrt{N}}{\sqrt{\frac{1}{N-1} \sum_{i=1}^N (SCAR_i - \overline{SCAR})^2}}$$

Where:

σ_i : Standard deviation of returns for firm i , calculated during the pre-event estimation period.

$SCAR_i$: Standardized Cumulative Abnormal Return for firm i , used for the BMP test.

$\overline{SCAR}$: The sample mean of the standardized cumulative abnormal returns.

t_{CAAR} : The t-statistic for the standard cross-sectional significance test.

t_{BMP} : The t-statistic for the Boehmer, Musumeci, and Poulsen (1991) robustness check.

3.6 Cross-Sectional Regression Analysis

While H1 requires only return data and a market benchmark, meaning all 1 824 events can be included regardless of share class, the regression analysis requires six firm-specific variables that are defined only for the primary trading share. A-share events are excluded because analyst coverage, market capitalization, and price-based characteristics are only meaningfully captured via the primary trading B-shares; consequently, evaluating H2 and H3 on A-share transactions would introduce conceptual inconsistencies (Cronqvist & Nilsson, 2003; La Porta et al. 1999). Further, firms with negative book-to-market (B/M) are excluded following Lakonishok and Lee (2001) to permit log transformation which restricts the final regression sample to 1,246 events across 660 unique securities.

Having established the CARs from the event study in section 3.5, this section examines what drives their cross-sectional variation. While the aggregated CARs test whether insider purchases are informative on average in the Swedish equity market (H1), the individual, event-level CARs constitute the dependent variable for the cross sectional OLS regressions used to test H2 and H3.

Prior to conducting the regression analysis, the data undergoes a final cleaning process to address potential outliers. Following Fidrmuc et al. (2013), all continuous variables are winsorized at the 1st and 99th percentiles. This includes the individual CARs, consistent with Wu (2019), as well as momentum, and the log-transformed control variables.

Consistent with the methodologies of (Lakonishok & Lee, 2001; MacKinlay, 1997; Seyhun, 1986), and following Frankel and Li's (2004) approach of regressing firm level characteristics against measures of inside trading informativeness, these individual CARs are regressed against the independent variables analyst coverage and blockholder ownership, as defined in section 3.4.2, alongside a set of firm level control variables introduced in the same section. To test whether analyst coverage amplifies the informativeness of insider purchases (H2), the baseline regression is estimated:

$$CAR_i = \alpha + \beta_1 Covered_i + \beta_2 SIZE_i + \beta_3 BM_i + \beta_4 MOM_i + \epsilon_i$$

Where:

CAR_i : The Cumulative Abnormal Return for event i over the window $(0, +30)$.

$Covered_i$: is a binary variable equal to one if the firm has 5 or more analysts covering the firm at the time of the event and zero otherwise.

$\beta_2 SIZE_i$ $\beta_3 BM_i$ $\beta_4 MOM_i$: are the control variables defined in section 3.4.3.

ϵ_i : Is the error term

The coefficient β_1 is the key parameter for testing H2. A positive and significant β_1 would indicate that insider purchases in covered firms produce larger abnormal returns than in less covered firms.

To test H3, which predicts that the moderating effect of analyst coverage is stronger in firms with dispersed ownership than in firms with a concentrated blockholder, an interaction term is introduced in an extended regression.

$$CAR_i = \alpha + \beta_1 Covered_i + \beta_2 Blockholder_i + \beta_3 (Covered_i \times Blockholder_i) + \beta_4 SIZE_i + \beta_5 BM_i + \beta_6 MOM_i + \epsilon_i$$

Where:

$Blockholder_i$: a binary variable equal to one if the firm has a single shareholder holding 10% or more of total shares outstanding at the time of the event, and zero otherwise.

$\beta_3 (Covered_i \times Blockholder_i)$: the interaction term captures whether the analyst coverage effect differs depending on ownership structure

The coefficient β_3 on the interaction term is the key parameter for testing H3. Here, β_1 captures the effect of being covered in firms without a blockholder. For firms with a blockholder, the total effect of analyst coverage is $\beta_1 + \beta_3$. A negative and significant β_3 would support H3, indicating that blockholder monitoring partially substitutes for the absence of analyst coverage. An insignificant β_3 would suggest the two mechanisms operate independently.

A single firm may experience multiple insider purchases over the sample period. Because these separate trades occur within the same corporate environment, their data points are not entirely independent; they share unobserved firm-specific characteristics. If the regression model treats

every trade as a completely independent event, it could result in overconfident standard errors and falsely significant p-values. To correct for this, the standard errors in the regressions are clustered at the firm level (Cameron & Miller, 2015; Petersen, 2009). This ensures the model accounts for the repeated appearance of the same firm and produces reliable statistical significance.

3.7 Robustness check

To ensure that the empirical findings are not sensitive to specific modeling choices, parameter assumptions, or outlier effects, several robustness tests are conducted. These tests evaluate the stability of the results across alternative CAR windows, variable definitions, and statistical estimation techniques. While the primary analysis uses a (0, +30) window to capture abnormal returns, the regressions are re-estimated over shorter (0, +5), (0, +10), and (0, +20) day intervals. Adopting an approach of looking at multiple event horizons similar to Lakonishok and Lee (2001) and Fidrmuc et al. (2013), this analysis determines whether the effects of analyst coverage remain consistent or are concentrated in the immediate post-announcement period.

Covered dummy is based on a threshold of ≥ 5 analysts. To ensure the results are not dependent on this specific cutoff, H2 is re-estimated using alternative coverage definitions: ≥ 1 analyst, ≥ 3 analysts, and ≥ 10 analysts. This sensitivity analysis determines if the "recognition channel" requires a minimum number of analyst coverage to affect the price reaction to insider purchases, following robustness checks performed by Wu (2019).

While the primary analysis defines a blockholder at the 10% ownership level (Lakonishok & Lee, 2001), to ensure the findings are not restricted to this baseline definition, we will utilize alternative thresholds of 15%, 20%, and 25% to test the sensitivity of Hypothesis 3. This approach aligns with literature that monitoring incentives change continuously with ownership size (Edmans, 2014).

3.8 Validity and Reliability

Validity refers to the degree to which a research measurement accurately captures the theoretical concept it is designed to evaluate (Bell & Bryman, 2022). In this study, measurement validity (also named construct validity) is addressed by using analyst coverage as a proxy for the firm's information environment, a relationship grounded in both the information production channel

(Frankel & Li, 2004), and the investor recognition channel (Lehavy & Sloan, 2008; Merton, 1987). Face validity: which concerns whether an indicator "on the face of it" appears to reflect the content of the concept is established by following variable definitions used in previous insider trading literature (Frankel & Li, 2004), such as the number of analysts covering the stock, size of the company and insider purchase limitations.

Internal validity is rather concerned with the issue of causality and whether the researcher can be "confident that this apparent causal relationship is genuine and not produced by something else" (Bell & Bryman, 2022). To safeguard against "spurious relationships", where an observed association is actually driven by something else, this study incorporates control variables such as natural log-transformed Market Capitalization and Book-to-Market ratio. When controlling for these factors, the analysis takes into account that the informativeness of an insider purchase is not merely capturing the documented relationship between insider purchases' effect on small vs large firms (Lakonishok & Lee, 2001). Furthermore, the event study methodology supports internal validity by creating a time-ordered sequence; isolating the public announcement before measuring the market reaction helps establish the direction of influence. However, because this study relies on cross-sectional OLS regressions rather than a natural experiment, it cannot completely rule out endogeneity. Therefore, while the research design minimizes spurious relationships, the results should be interpreted as strong correlational evidence rather than strict causal proof.

Reliability refers to the consistency and stability of measures, as well as the extent to which the results of a study are replicable (Bell & Bryman, 2022). This study utilizes secondary data from financial databases, specifically Bloomberg, Factset, and Holdings, where the variables are constructed and documented in Sections 3.3, 3.4 and 3.5. All data is retrieved through automated tools, which minimizes the potential for human error and ensures consistent data extraction (Bell & Bryman, 2022). Furthermore, subjective interpretations are minimized as the study does not rely on survey-based methods, which reduces the risk of reactive effects and strengthens the overall reliability of the analysis (Bell & Bryman, 2022).

3.9 Limitations

A primary limitation of this study is the extent to which the results can be generalized outside the Swedish equity market. While factors such as high retail participation and concentrated ownership make Sweden an interesting testing ground, national regulatory differences may complicate broader generalizability. Although Sweden shares a broader legal framework within insider trading with its neighbors (Lombardo & Mucciarelli, 2019), country-level variations in local enforcement strictness can affect domestic outcomes, as these distinct institutional dynamics partially dictate how markets react to insider trading (Aussenegg et al. 2018; Fidrmuc et al. 2013).

A second set of limitations relates to the study's data collection and sample filtering constraints. To guarantee clear estimation parameters (MacKinlay, 1997) and prevent overlapping informational signals (Lakonishok & Lee, 2001), the study utilizes a strict clean window that excludes events with other meaningful insider purchases within 200 days before or 30 days after publication. While this leads to a robust final sample of 1824 isolated events, it inherently reduces representativeness among larger, more actively traded firms. Furthermore, applying a uniform 200,000 SEK transaction threshold, while grounded in literature suggesting that larger purchases are more informational (Fidrmuc et al. 2006; Jeng et al. 2003; Lakonishok & Lee, 2001), it remains a judgment call that may exclude smaller, genuinely informative trades.

Third, specific methodological choices present inherent trade-offs. Operationalizing analyst coverage and blockholder ownership strictly as binary dummy variables simplifies cross-sectional interpretation and is theoretically supported by Wu (2019) and Fidrmuc et al. (2006), respectively, but it results in a loss of granular information that might obscure non-linear relationships. Additionally, using a broad market index (OMXSGI) assumes uniform market sensitivities across multi-segment studies (Aussenegg et al. 2018; Fidrmuc et al. 2013). Because First North firms are typically smaller and less liquid, relying solely on a broad benchmark risk introducing a "size effect" bias that may misestimate expected returns for smaller firms (Fidrmuc et al. 2013). Consistent with seminal methodology (Fidrmuc et al. 2013; Jeng et al. 2003; Lakonishok & Lee, 2001), the regressions also lack a direct market liquidity control variable, such as the bid-ask spread, although Wu (2019) notes insiders in liquid firms generally trade more aggressively.

Lastly, an evident limitation relates to the correlation between analyst coverage and firm size (Bhushan, 1989). Because smaller firms receive less investor attention and are thereby often less efficiently priced (Lakonishok & Lee, 2001; Seyhun, 1986), the two variables overlap when explaining the information environment. Although the cross-sectional OLS regressions control for size (Frankel & Li, 2004), it remains challenging to fully isolate their respective impacts. Consequently, the analyst coverage coefficient may partly reflect size-related differences in information asymmetry rather than the pure effect of the information production or investor recognition channels.

4. Result

4.1 Descriptive Statistics

The following section presents the descriptive statistics for the main variables used in the analysis: CARs across event windows, analyst coverage, blockholder ownership, and the control variables. The final sample consists of 1824 insider purchase events drawn from 993 unique Swedish listed securities over the 2018-2024 period, after applying the filtering criteria described in Section 3.3.3. Consistent with the methodology, for H1, testing only abnormal returns, the full sample of 1824 was used. For H2 and H3, which test the CARs from B-shares and ordinary shares only, the sample was reduced to 1246 events (660 unique securities).

Table 1: Descriptive statistics - CAR's H1 event study sample (winsorized 1%/99%)

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
CAR (0, +5)	1824	2.133	0.896	9.850	-19.816	40.407	1.194	6.071
CAR (0, +10)	1824	1.863	0.597	12.307	-30.611	47.809	0.875	5.701
CAR (0, +20)	1824	1.911	0.645	15.747	-34.565	64.248	0.926	5.779
CAR (0, +30)	1824	1.844	0.563	19.553	-47.645	76.778	0.778	5.583

Note: The (0,+30) window is the main specification.

Table 1 shows the descriptive statistics for the dependent variable. The mean cumulative abnormal return is 1.84% at the main CAR (0,+30) window. This differs slightly across windows, where the CAR (0, +5) window shows the highest abnormal returns at 2.13%, suggesting that the majority of the market reaction occurs within the first trading week, which is consistent with previous literature (Fidrmuc et al. 2006). The standard deviation is high across all event windows, ranging from 9.85 to 19.5 from CAR (0,+5) and CAR (0,+30) respectively, which indicates that abnormal returns vary across events though the average is consistently positive. This dispersion is consistent with similar previous empirical studies on CARs of insider transactions (Fidrmuc et al. 2006).

Breaking down the CAR data by the median, these figures are notably lower than the mean across the four horizons (0.896 versus 2.133 at (0,+5); 0.563 versus 1.844 at (0,+30)). This implies that the abnormal return distribution is somewhat skewed by a smaller number of events with larger positive outcomes, which increases the mean. Similarly, observing the skewness statistic, the

values are moderately positive across all CAR distributions ranging from 0.778 (0,+30) to 1.194 at (0,+5), which confirms a right-skew implied by the mean-median gap. The kurtosis values across the CAR window ranges from 5.583 to 6.071, which signals that extreme outcomes occur more frequently than a normal distribution would predict. This pattern reflects the heterogeneity in insider trading informativeness, which is documented in prior literature (Fidrmuc et al. 2006; Jeng et al. 2003).

Table 2: Descriptive Statistics - CARs for H2/H3 regressions (winsorized 1%/99%)

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
CAR (0, +5)	1246	2.133	0.809	10.005	-19.816	40.407	1.120	5.668
CAR (0, +10)	1246	1.587	0.503	12.160	-30.611	47.809	0.811	5.393
CAR (0, +20)	1246	1.681	0.118	15.717	-34.565	64.248	0.874	5.501
CAR (0, +30)	1246	1.303	0.423	19.302	-47.645	76.778	0.760	5.696

Note: Sample restricted to B-share and Ordinary single-class events. The (0,+30) window is the main specification.

As the number of events used to test Hypothesis 2 and 3 differs, Table 2 showcases the CARs for different windows for the sample used here. The difference in N, which is here 1246 events, is attributed to that only B and ordinary shares are tested and firms with negative Book-to-Market values are dropped entirely, consistent with the methodology outlined in 3.6. The descriptives are similar to table 1, which suggest that the distributional properties of the smaller sample mirror the full sample. Given this similarity, the interpretation offered for Table 1 applies broadly to Table 2.

Table 3: Descriptive statistics - H2/H3 regression sample

	n	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Covered (≥ 5)	1246	0.134	0.000	0.34	0.00	1.00	2.148	5.616
Blockholder ($\geq 10\%$)	1246	0.775	1.000	0.41	0.00	1.00	-1.319	2.740
ln(MCap)	1246	6.674	6.358	2.12	2.40	12.44	0.394	2.708
ln(BM)	1246	-1.030	-0.945	1.01	-3.72	1.33	-0.338	2.791
Momentum	1246	4.623	-1.197	46.64	-81.25	181.02	1.205	5.284

Note: Covered = 1 if the firm has 5 or more analysts on the event date. Blockholder = 1 if a single shareholder holds at least 10% of outstanding shares.

Table 3 shows the descriptive statistics for the continuous and control variables used in the cross-sectional regression for both H2 and H3. The “Covered” dummy variable has a mean of 0.134, indicating that 13.4% of events are classified as covered by five or more analysts, confirming that

the majority of firms in the sample operate with little or no analyst coverage. The Blockholder dummy variable has a mean of 0.775 and a median of 1, indicating that approximately 77.5% of events have a blockholder present. Regarding the control variables, $\ln(\text{MCap})$ is slightly right-skewed at 0.394 due to the presence of a larger firm at the tail of the distribution. This is reasonable considering that the sample is dominated by small and mid-cap firms. $\ln(\text{BM})$ has a negative mean of -1.03, which shows that the typical firm in the sample trades at a slight premium to its book value. The variable is similarly to $\ln(\text{Mcap})$ slightly skewed, however, negatively at -0.339, which means that a small number of firms with particularly low book-to-market ratios are pulling the left tail of the distribution downward. The momentum variable shows a high standard deviation of 46.6 and a right-skewed distribution, reflecting the context in which insider purchases typically occur, consistent with the findings of Lakonishok and Lee (2001).

Table 4: Correlation matrix - regression sample

	CAR (0, 30+)	Covered (≥ 5)	Blockholder ($\geq 10\%$)	$\ln(\text{MCap})$	$\ln(\text{BM})$	Momentum
CAR (0, 30+)	—					
Covered (≥ 5)	0.00219	—				
Blockholder ($\geq 10\%$)	-0.0658*	0.105***	—			
$\ln(\text{MCap})$	-0.124***	0.601***	0.165***	—		
$\ln(\text{BM})$	0.137***	0.0242	0.000869	-0.104***	—	
Momentum	-0.360***	0.0377	0.0314	0.240***	-0.332***	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ indicates statistical significance based on two-tailed t-test.

Table 4 describes the Pearson correlation matrix for the regression variables. The dependent variable CAR (0,+30) is negatively correlated with $\ln(\text{MCAP})$, -0.124 ($p < 0.01$). This is consistent with prior evidence that insider purchases generate larger abnormal returns in smaller firms (Lakonishok & Lee, 2001; Seyhun, 1986). The CAR (0, +30) is also negatively correlated with momentum, -0.360 ($p < 0.001$), which is similarly in line with findings by Lakonishok and Lee (2001). Among the independent variables, a moderate correlation is found between Covered and $\ln(\text{MCap})$ of 0.601 ($p < 0.001$), which reflects that larger firms attract more analyst coverage, consistent with Bhushan (1989). To assess whether this correlation induces multicollinearity, variance inflation factors (VIFs) were calculated. VIFs remain low for both Covered at 1.60 and

ln(MCap) at 1.70, below the conventional rule of 10 (Hair et al., 1995), which indicates no multicollinearity concern.

Table 5: Descriptive Statistics - Coverage dummy frequencies

	Count	Proportion
Covered (≥ 1 analyst)	475	0.381
Covered (≥ 3 analysts)	266	0.213
Covered (≥ 5 analysts)	167	0.134
Covered (≥ 10 analysts)	63	0.051

Note: The Covered (≥ 5 analysts) are used in the main specification

Table 5 presents the distribution of the covered dummy variables across the four analyst thresholds used in the main analysis and the robustness check. As seen in the distribution table, the majority of firms in the sample are uncovered regardless of the threshold applied, which is consistent with the Swedish market structure outlined in Section 1.2. At the main specification threshold of ≥ 5 analysts, 167 events (13.4%) are classified as covered, and 1,079 as uncovered. Even at the lowest threshold of ≥ 1 analyst, only 475 (38.1%) of events are covered, which reinforces that uncovered firms dominate the sample. Importantly, all coverage groups contain well above 30 observations standard, which satisfy the minimum threshold for reliable statistical inference under the Central Limit Theorem (Bell & Bryman, 2022).

Table 6: Descriptive Statistics - Joint distribution of Covered (≥ 5 analysts) and Blockholder across ownership thresholds

	C0_BH0	C0_BH1	C1_BH0	C1_BH1
BH $\geq 10\%$	261	818	19	148
BH $\geq 15\%$	431	648	55	112
BH $\geq 20\%$	564	515	68	99
BH $\geq 25\%$	683	396	82	85

Note: Each row corresponds to a different blockholder ownership threshold. Columns show counts in each cell where: C0/BH0 = not covered and no blockholder; C0/BH1 = not covered with blockholder; C1/BH0 = covered without blockholder; C1/BH1 = covered with blockholder. Main specifications: Covered ≥ 5 analysts, Blockholder $\geq 10\%$.

Table 6 shows the joint distribution of the covered dummy (≥ 5 analysts) and the blockholder dummy across four ownership thresholds, which is used to examine the interaction effect in H3. At the main specification of BH $\geq 10\%$, the largest cell is uncovered firms with a blockholder at

818 events, while covered firms without a blockholder account for 19 events. This means that the majority of firms have a blockholder, and those firms tend to have analyst coverage, meaning the two variables cluster together rather than vary independently. This clustering represents a constraint on the precision of the H3 test, as the number of firms that are covered but lack a blockholder falls below the threshold of 30 observations, which is insufficient for a reliable statistical test on the interaction effect (Bell & Bryman, 2022). At higher blockholder thresholds the cell counts become more balanced, for example at $BH \geq 25\%$ 82 covered firms are classified as lacking a blockholder, which provides a more evenly distributed sample across cells. This distributional imbalance and its resolution at higher thresholds, motivates the robustness checks presented in Section 4.3.4.

4.2 Event Study Results (Hypothesis 1)

Table 7: Significance tests of CAARs across event windows

	N	CAAR	t_stat	p_std	BMP_t	p_BMP
(0,+5)	1824	2.133	9.247	0.000	8.727	0.000
(0,+10)	1824	1.863	6.463	0.000	6.471	0.000
(0,+20)	1824	1.911	5.183	0.000	5.249	0.000
(0,+30)	1824	1.844	4.028	0.000	4.721	0.000

Note: Main specification (0, +30)

Table 7 reports the cumulative average abnormal returns (CAARs) across the four event windows alongside the cross-sectional t-test (MacKinlay, 1997) and the Boehmer et. al (1991) BMP test. Across all four windows, the CAARs are positive and statistically significant at a 5% level under both tests. The (0,+30) window produces CAARs of 1.84%, with t-statistic of 4.028 under a standard t-test. The other CAARs across windows produces similar patterns, with the (0,+5) window at the highest CAAR of 2.133% with a t-statistic of 9.247 under the standard t-test, which indicates that the majority of the market reaction to a disclosed insider purchased is realized within the first trading week. Similarly, when controlling for event-induced increases in variance through the BMP-test, all CAARs show significance at a 5% level across all event windows. The results of both the t-test and extended BMP test indicate that insider purchases on the Swedish equity market are followed by economically and statistically significant positive abnormal returns after the transaction has been publicly disclosed, therefore H1 is supported.

4.3 Regression Results (Hypothesis 2 & 3)

4.3.1 Main results

Table 8: Cross-sectional regressions of CAR (0,+30)

	Baseline (H2)	Interaction (H3)
Covered (≥ 5 analysts)	3.512** (2.200)	-2.663 (-1.021)
ln(MCap)	-0.715** (-2.181)	-0.599* (-1.820)
ln(BM)	0.285 (0.510)	0.300 (0.544)
Momentum	-0.140*** (-9.950)	-0.141*** (-10.078)
Blockholder ($\geq 10\%$)	-	-2.871** (-2.017)
Covered # Blockholder	-	6.896*** (2.661)
Constant	6.548*** (2.731)	8.029*** (3.171)
Observations	1246	1246
R-squared	0.134	0.138
Adj. R-squared	0.131	0.134
F-statistic	30.66***	21.48***

Note: *t* statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8 presents the cross-sectional regression results for both hypothesis 2 and 3. Column 1 presents the baseline regression for testing H2, where CAR (0,+30) is regressed on the covered analyst dummy and control variables. The coefficient on the variable “covered” is positive at 3.51% and statistically significant at the 5% level ($t = 2.2$). This indicates that insider purchases in covered firms generate CARs at 3.5 percentage points higher than those in uncovered firms over the 30-days window after the insider transaction. This finding is in line with the predicted investor recognition channel, where analysts coverage increases the audience capable of detecting and pricing a disclosed insider signal (Lehavy & Sloan, 2008; Merton, 1987). The positive and significant coefficient therefore supports Hypothesis 2.

Regarding the control variables, $\ln(\text{MCap})$ carries a coefficient of -0.715, which is significant at the 5% level ($t = -2.181$). This is in line with the previous evidence that insider purchases generate larger abnormal returns in smaller firms (Lakonishok & Lee 2001; Seyhun, 1986). The coefficient on $\ln(\text{BM})$ is 0.285 and insignificant ($t = 0.510$), which means that the value premium does not significantly shape the cross-sectional variation in CARs. The momentum variable has a coefficient of -0.140 ($t = -9.950$), and is highly significant both at a 5% and 1% significance level. This indicates that insider purchases that have prior poor stock performance tend to generate larger abnormal returns, consistent with previous study by Lakonishok and Lee (2001), where insiders tend to buy following price declines, and the market subsequently corrects the undervaluation. The baseline regression model has an R^2 of 0.134 and an adjusted R^2 of 0.131, meaning 13% of the variation in CARs is explained by the model, which is consistent with similar studies on the explanation of the abnormal returns on insider purchases where R^2 values are typically low (Aussenegg et al. 2018; Fidrmuc et al. 2006). The model has an F-statistic of 30.66 and is significant at the 1% level, which reinforces that the model captures a statistical relationship with CARs rather than a spurious one.

Column 2 introduces the Blockholder dummy variable and the Covered # Blockholder interaction term to test Hypothesis 3. The interaction term is positive at 6.896 and significant at the 1% level ($t = 2.661$), which is the opposite to the direction predicted by H3. However, as documented in Table 5, only 19 events in the sample are covered without a blockholder, which limits the precision of this test as the interaction effect is identified from very limited variation. Table 11 addresses this limitation by re-estimating the model at higher blockholder thresholds (15%, 20%, 25%), where the sample distribution becomes more balanced. The control variables remain consistent with the baseline regression, with $\ln(\text{MCap})$ and momentum significant at -0.599 and -0.141 respectively. The R^2 increases marginally to 0.138 and adjusted R^2 to 0.134, which indicates limited additional explanatory power. Given the directional contradiction and the robustness tests discussed in Section 4.3.4, H3 is rejected.

4.3.2 Robustness across event windows

Table 9: H2 robustness - Effect of analyst coverage on CAR across event windows

	(0,+5)	(0,+10)	(0,+20)	(0,+30)
Covered (≥ 5)	0.549 (0.702)	1.018 (1.077)	2.294* (1.864)	3.512** (2.200)
ln(MCap)	-0.544*** (-3.289)	-0.413** (-1.982)	-0.559** (-2.067)	-0.715** (-2.181)
ln(BM)	-0.275 (-0.866)	-0.497 (-1.257)	-0.294 (-0.629)	0.285 (0.510)
Momentum	-0.029*** (-3.708)	-0.057*** (-6.052)	-0.093*** (-7.405)	-0.140*** (-9.950)
Constant	5.543*** (4.639)	3.962*** (2.634)	5.235*** (2.608)	6.548*** (2.731)
Observations	1246	1246	1246	1246
R-squared	0.034	0.054	0.086	0.134
Adj. R-squared	0.031	0.051	0.083	0.131
F-statistic	9.30***	12.44***	18.18***	30.66***

Note: statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9 shows the robustness check of the baseline H2 regression across shorter event windows. It reveals that the Covered coefficient 0.549 and 1.018 is insignificant at the (0,+5) and (0,+10) windows respectively. The Covered variable 2.294 becomes marginally significant at (0,+20) a 10% level, and at 3.512 it reaches full significance at the 5% level at the (0,+30) window. This indicates a temporal pattern, where the coverage effect is absent in the immediate post-disclosure period and emerges over several weeks. The adjusted R-squared increases steadily from 0.031 at (0,+5) to 0.131 at (0,+30), which shows that the model's explanatory power accumulates as the event window lengthens and the market reaction unfolds. This gradual buildup suggests that coverage expands the audience capable of detecting and acting on the signal, consistent with the logic of Merton (1987), and hence in further support of Hypothesis 2.

4.3.3 Robustness across coverage threshold

Table 10: H2 robustness - Coverage threshold sensitivity (CAR 0,+30)

	≥ 1	≥ 3	≥ 5	≥ 10
Covered	1.410 (0.984)	2.585* (1.723)	3.512** (2.200)	1.776 (1.109)
ln(MCap)	-0.604* (-1.660)	-0.713** (-1.988)	-0.715** (-2.181)	-0.449 (-1.536)
ln(BM)	0.283 (0.504)	0.278 (0.494)	0.285 (0.510)	0.341 (0.611)
Momentum	-0.141*** (-10.049)	-0.141*** (-10.053)	-0.140*** (-9.950)	-0.142*** (-10.063)
Constant	5.742** (2.404)	6.445*** (2.587)	6.548*** (2.731)	5.219** (2.290)
Observations	1246	1246	1246	1246
R-squared	0.132	0.133	0.134	0.132
Adj. R-squared	0.130	0.131	0.131	0.129
F-statistic	30.62***	30.74***	30.66***	30.55***

Note: statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10 presents the re-estimated baseline H2 regression using alternative coverage thresholds. The coverage effect is insignificant at ≥ 1 analyst, becomes marginally significant at ≥ 3 , peaks at ≥ 5 with the strongest and most significant coefficient of 3.512 ($p = 0.028$), and weakens again at ≥ 10 . This means H2 is supported at the ≥ 3 and ≥ 5 threshold, which is consistent with the logic that as coverage grows, so does the institutional and retail attention that can price the signal (Barber & Odean, 2008; O'Brien & Bhushan, 1990). Under this logic, the marginal recognition gained from additional coverage after a certain point is negligible, which explains why ≥ 10 loses significance.

4.3.4 Robustness across blockholder thresholds

Table 11: H3 Robustness - Coverage # Blockholder interaction across blockholder thresholds (CAR 0,+30)

	$\geq 10\%$	$\geq 15\%$	$\geq 20\%$	$\geq 25\%$
Covered (≥ 5)	-2.663 (-1.021)	1.140 (0.539)	2.056 (0.937)	2.921 (1.416)
Blockholder	-2.871** (-2.017)	-0.968 (-0.801)	-0.105 (-0.096)	0.021 (0.019)
Covered # Blockholder	6.896*** (2.661)	3.435 (1.542)	2.488 (1.063)	1.178 (0.510)
ln(MCap)	-0.599* (-1.820)	-0.680** (-2.056)	-0.717** (-2.180)	-0.718** (-2.173)
ln(BM)	0.300 (0.544)	0.306 (0.545)	0.274 (0.487)	0.283 (0.503)
Momentum	-0.141*** (-10.078)	-0.140*** (-9.980)	-0.140*** (-9.999)	-0.140*** (-9.952)
Constant	8.029*** (3.171)	6.931*** (2.818)	6.596*** (2.701)	6.556*** (2.718)
Observations	1246	1246	1246	1246
R-squared	0.138	0.135	0.135	0.134
Adj. R-squared	0.134	0.131	0.130	0.130
F-statistic	21.41***	20.65***	21.26***	20.47***

Note: statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11 shows the H3 interaction model across four blockholder thresholds (10%, 15%, 20%, 25%) to address the sample imbalance documented in Table 5. At the main 10% threshold, only 19 events are classified as covered without a blockholder, which limits the precision of the interaction test. Higher thresholds produce more balanced cell counts, which enables a more robust assessment of whether the positive interaction observed at 10% reflects a genuine effect. The interaction term is only significant at the main $BH \geq 10\%$ specification and disappears at higher threshold. The sign of the interaction remains consistently positive across all thresholds, from 6.896 at ($\geq 10\%$) to 1.178 at ($\geq 25\%$), confirming the rejection of H3.

4.4 Summary of Hypothesis

Table 12: Summary of hypotheses and findings

Hypothesis	Predicted Relationship	Result
<i>H1</i>	Insider purchases generate positive cumulative abnormal returns.	Supported
<i>H2</i>	Analyst coverage strengthens the informativeness of insider purchases (covered firms exhibit larger CARs).	Supported
<i>H3</i>	The amplifying effect of analyst coverage is stronger in firms with dispersed ownership than in firms with a concentrated blockholder.	Rejected

5. Discussion

5.1 Section 1 (H1): Insiders Still Win

Consistent with our first hypothesis, insider purchases on the Swedish equity market generate significant abnormal returns following public disclosure, a finding that constitutes a direct challenge to the semi-strong form of the EMH in this setting (Fama, 1970). The CAAR of 1,84% over the 30-day window is statistically significant at the 0,1% level and the result is robust across all alternative event windows tested. The CAAR peaks within the first five days, reaching 2,13%, before retracting slightly over the remainder of the 30 day window, likely due to investors taking profit from the initial increase.

This result is in line with the well-documented insider trading puzzle from the U.S. literature (Cohen et al. 2012; Lakonishok & Lee, 2001; Seyhun, 1986) and replicates across European markets (Aussenegg et al. 2018; Fidrmuc et al. 2006). The persistence of these abnormal returns is notable given that MAR (Regulation 596/2014, art. 19) was specifically designed to level the playing field by mandating rapid disclosure of insider transactions. If markets were semi-strong efficient, the publication itself should be incorporated into prices immediately, leaving no opportunity for outside investors to profit from mimicking the trade (Malkiel, 2003). The empirical results, however, contradict this theoretical assumption. Outside investors who acted on the public disclosure would, on average, earn a meaningful abnormal return over the following month.

Documenting this puzzle in the institutional context adds an additional dimension to the existing literature. Looking at the 2003 Market Abuse Directive (MAD), Aussenegg et al. (2018) found that the price impact of insider transactions is strongest in countries with weaker public enforcement. The EU introduced the Market Abuse Regulation (MAR) to eliminate these gaps by strengthening and harmonizing public enforcement across the European market (Lombardo & Mucciarelli, 2019). Yet, abnormal returns can still be found after these stricter enforcement measures were made. This highlights the role of information asymmetry as discussed in section 2.1: even though MAR have further tightened disclosure requirements for insider trades, they do not remove the insider's underlying informational advantage. Because market participants cannot

perfectly interpret the true value of the trade right away, the market cannot perfectly price the signal on day one.

However, this baseline average masks cross-sectional variation between firms. Some firms experience a much stronger and longer developing price reaction than others. Sections 5.2 and 5.3 will explore the specific firm-level variables that drive the magnitude of this reaction across different companies.

5.2 Section 2 (H2) : Coverage as Audience, not Substitute

The empirical results support Hypothesis 2, suggesting that analyst coverage amplifies, rather than dampens, the informativeness of insider purchases in the Swedish market. The covered analyst dummy carries a coefficient of +3,51 percentage points ($p = 0,028$) over the 30 day window. Covered firms produce consistently larger abnormal returns following insider purchases than their uncovered counterparts. This finding stands in contrast to the U.S. based evidence presented by Frankel and Li (2004) and Wu (2019). In their U.S. setting, the information production channel dominates: analyst coverage acts as a substitute for private insider knowledge, reducing information asymmetry and dampening the market reaction to insider trading.

The results instead support the investor recognition channel introduced in Section 2.3.1 (Lehavy & Sloan, 2008; Merton, 1987). Rather than evaluating how much "unknown" information the insider trade reveals, the critical factor in this context is whether there is a sufficient audience to price that signal. This is consistent with the international perspective of Azevedo and Müller (2024), who find that outside the U.S., analysts actively contribute to price discovery rather than merely substituting for private information. Covered firms benefit from a broader and more attentive base of market participants, ranging from institutional investors (O'Brien & Bhushan, 1990) to the retail attention that concentrates on publicly visible firms (Barber & Odean, 2008).

The temporal pattern of the coverage effect empirically supports this mechanism. The covered coefficient is small and insignificant at the (0, +5) and (0, +10) windows, becomes marginally significant ($p = 0,063$) at (0, +20), and reaches statistical significance ($p = 0,028$) at (0, +30). This is a slow, building effect rather than an immediate one. If the production channel were operating, meaning coverage were substituting for insider information content, the effect should be most

visible at the announcement, when the disclosed signal is at its informationally richest. Instead, the effect emerges only as the market has time to process the signal, exactly as the recognition channel predicts. This delayed price discovery is consistent with Merton (1987) and Barber and Odeon (2008), who argue that limited investor recognition and constrained attention prevent information from being instantaneously priced. The thin audience in less covered firms both delays the price adjustment and limits the potential arbitrageurs who would naturally correct it.

Given the high retail participation in the Swedish market, this audience mechanism is particularly important. Retail investors typically rely on public information and visible signals rather than proprietary research (Wei et al. 2017). Analyst coverage therefore takes on the crucial role of determining whether a disclosed signal reaches an audience capable of reacting to it at all. The post-MiFID II reduction in coverage (Lang, Pinto & Sul, 2024) is significant in this context, as it likely pushes marginal firms below the necessary "audience threshold," slowing down price discovery.

The robustness checks across analyst coverage thresholds illustrate this audience-building mechanism in detail. Defining covered firms as having at least 1 analyst produces a coefficient of +1,41 ($p = 0,325$, insignificant). Moving the threshold to ≥ 3 analysts strengthens the effect to +2,56 ($p = 0,085$); ≥ 5 yields 3,51 ($p = 0,028$); and ≥ 10 weakens to +1,78 ($p = 0,267$). The pattern increases in magnitude up to ≥ 5 analysts and then weakens. While the existing literature reviewed in Chapter 2 does not explicitly define this specific threshold, the pattern is a logical extension of the investor recognition channel (Merton, 1987). A single analyst does not form a meaningful market-wide audience. However, as coverage grows, so does the institutional and retail attention that can price the signal (Barber & Odean, 2008; O'Brien & Bhushan, 1990). Once the audience reaches adequate size, the marginal investor recognition gained from additional coverage becomes negligible, which explains the weakening of the effect above ≥ 5 analysts.

This coverage effect must be contextualized alongside the well-documented small-firm premium (Lakonishok & Lee, 2001; Seyhun, 1986). Coverage and size are correlated ($r = 0.61$ in the regression sample). However, the inverse U-pattern across the threshold sweep is inconsistent with size being the sole driver of the result, as a pure size effect would arguably produce a more linear trend across thresholds. The coverage coefficient remains robust when controlling for market

capitalization, suggesting that the recognition channel operates alongside, not in isolation from, the size effect.

Ultimately, these findings suggest that the mechanism proposed by Frankel and Li (2004) is institutional rather than universal. In markets with structural features similar to Sweden, analyst coverage acts as an essential audience-builder, changing how insider signals are absorbed by the market.

5.3 Section 3 (H3): Blockholders do not Substitute for Analyst Coverage in Sweden

Regarding Hypothesis 3, the study's empirical test shows that the predicted substitution effect between blockholders and analysts, which builds upon the combination of the predicted investor recognition channel (Barber & Odeon, 2008; Merton, 1987; O'Brien & Bhushan, 1990) and the blockholder monitoring evidence of Maug (1998) and Fidrmuc et al. (2006), does not translate to the Swedish market. The interaction terms between Covered and Blockholder runs contrary to the predicted direction across all thresholds tested (e.g. 6.90, $p = 0.008$ at the main 10% threshold). The Swedish setting was selected precisely because its concentrated ownership structure satisfies the precondition for the substitution mechanism to be testable. The fact that the prediction does not hold here therefore carries informational content about the mechanism itself rather than about the suitability of the test.

When applying the 10% ownership threshold to capture the monitoring mechanism, it led to only 19 events for the covered without blockholder cell. This distributional feature of the sample, which was not predictable from prior literature, constrains the precision of the main specification. The previous literature establishes Sweden's high ownership concentration (La Porta et al. 1999; OECD, 2025a), but the degree to which analyst coverage and blockholder presence cluster together, which is not as present in the studies from U.K. and U.S., emerges from the data rather than from prior theoretical or descriptive evidence. When expanding the blockholder threshold to 25%, which increases the subsample to 82 events classified as covered but without a blockholder, it creates a more balanced test. Across all these specifications, the interaction effect is either

wrong-signed or statistically indistinguishable from zero, all which are not in support of the prediction substitution effect of the third hypothesis.

Hypothesis 3 was formulated based on the theoretical frameworks of Maug (1998) and Fidrmuc et al. (2006), which suggest that blockholders could act as a substitute for analyst coverage by public monitoring management. However, the rejection of this prediction across the robustness checks suggest that the substitution mechanism could depend on features of the blockholder, which the existing literature has not yet isolated. The Maug (1998) and Fidrmuc et al. (2006) frameworks treat active blockholders as a relatively homogeneous category, but Swedish ownership is dominated by families and holding companies (Henrekson & Jakobsson, 2012), who may instead exercise control through mostly private channels rather than the public monitoring which the substitution mechanism is built upon. Whether this suggested explanation is the reason for the result here is a question for future research. What the study establishes is that the substitution prediction does not generalize to a market with concentrated ownership of this type.

Taken together, the supported prediction of H1 and H2, and the directional contradiction of H3, point to a broader conclusion: the moderating mechanisms governing insider trading informativeness are institutional, not universal. The information production channel established by Frankel and Li (2004) and Wu (2019) does not appear to dominate in this setting, where the investor recognition mechanism dominates instead. Similarly, the failure of the blockholder substitution effect suggests that in markets characterized by family-controlled blockholders, which is common across many European economies, the substitution dynamics may not hold.

6. Concluding remarks

6.1 Research contribution

This study contributes to the literature on insider trading informativeness by demonstrating that the moderating role of analyst coverage depends on the composition of the investor base in which it operates. Where retail investors form a meaningful share of the trading base, analyst coverage determines whether an audience capable of pricing a disclosed insider signal exists at all. Drawing on the investor recognition channel of Merton (1987) and Lehavy and Sloan (2008), this study predicted that covered firms would produce larger abnormal returns following insider purchases than uncovered ones, a prediction the data supported. This advances the literature beyond the information production channel established by Frankel and Li (2004) and Wu (2019), which predicts the opposite relationship. Those studies provided a relationship for their mechanism but were conducted in a market dominated by institutional investors, where the conditions needed to identify a competing channel were absent. The contribution is therefore one of both contradiction and contextualisation. The two channels generate opposing predictions, and the market's composition determines which one dominates.

A secondary contribution concerns the role of blockholder ownership. The H3 prediction extended the logic of Fidrmuc et al. (2006): if blockholder oversight partially closes the information gap before insider trades become public, the amplifying effect of analyst coverage through increasing the investor recognition should be smaller in firms with concentrated blockholder than in firms with dispersed. However, the data does not support this prediction. Across all robustness checks, the interaction between coverage and blockholder presence is wrong signed, and the prediction is unsupported regardless of the choice of cutoff. The assumption that blockholder monitoring produces public information that reaches the broader market may not hold in a setting where blockholders are predominantly families, foundations and holding companies (Henrekson & Jakobsson, 2012) who may exercise control through private rather than public channels. Blockholder identity therefore emerges as a possible boundary condition for when the substitution prediction holds. Both the H2 and H3 findings ultimately trace to the same source: the U.S. derived

theoretical channels were developed in a market whose institutional features do not characterise other settings, and when those features change, the mechanisms they support change with them.

6.2 Practical Implications

The findings carry implications for regulators, retail investors, and listed firms active in markets with structural similarities to the Swedish setting.

For regulators, the results reveal a tension between two major EU reforms. MAR operates on the premise that mandatory disclosure is sufficient to level the informational playing field between insiders and outside investors. This study suggests that premise is incomplete: disclosed insider signals generate abnormal returns because the audience capable of pricing it is too thin in low-coverage firms. MiFID II's documented reduction in analyst coverage among smaller firms (Lang et al. 2024) may therefore have weakened precisely the channel that translates MAR's transparency mandate into rapid price discovery. Policymakers evaluating the consequences of MiFID II should consider whether the coverage reduction it produced has impaired price discovery in the firms disclosure requirements were designed to protect.

For retail investors, the findings offer an actionable signal for portfolio construction. Insider purchases in analyst covered firms generate cumulative abnormal returns higher than those in uncovered firms over the 30 day window following disclosure. A retail investor filtering disclosed insider purchases from the Finansinspektionen register and restricting attention to firms with meaningful analyst coverage would therefore have been better positioned to exploit post announcement drift than simply acting on all disclosed transactions. The concentration of returns within the first five trading days further suggests that speed of reaction matters, and that investors monitoring disclosures directly rather than through secondary sources capture a meaningfully larger share of the signal. Taken together, the results point toward a simple screening method: prioritise insider purchases in covered firms, act early, and treat low coverage stocks with greater skepticism.

For listed firms and their management teams, the findings suggest analyst coverage is a strategic asset. The investor recognition channel implies that an insider purchase in a covered firm transmits a stronger and more complete signal to the market than the identical trade in an uncovered firm. A

manager who buys shares to credibly communicate conviction about the firm's prospects therefore achieves substantially less price discovery if the firm lacks an audience capable of processing and acting on the signal. This has implications for how smaller listed firms should think about investing in investor relations and analyst outreach. Securing a handful of analyst recommendations appears to improve the market's ability to incorporate publicly disclosed information into prices. For firms on growth segments such as First North, where many firms lack any analyst coverage, this suggests that the decision to invest in visibility could affect how the firm's stock responds to disclosed insider activity.

6.3 Future Research

Three directions follow from the findings of this study.

First, the central result motivates replication in other European markets that share Sweden's structural features but differ along specific dimensions. Markets with concentrated ownership but lower retail participation (such as Germany) (OECD, 2025b), or with high retail participation but more uniform analyst coverage, would allow future research to identify which structural feature acts as the primary driver in determining whether the recognition channel dominates. The findings here strongly suggest retail participation is the active mechanism, but a single-country study cannot fully isolate it.

Second, the failure of H3 to find support underscores the need for a closer examination of how different types of blockholders affect insider purchase informativeness. Fidrmuc et al. (2006) distinguished between active and passive owners and found varying effects across categories. The Swedish ownership landscape, with its prominent role for families, foundations, and holding companies, would benefit from an analysis that disaggregates blockholder identity rather than treating concentrated ownership as a single homogeneous category. This could test whether the absence of substitution documented in Sweden is specific to the Nordic family and foundation structure or whether it generalises to other settings where institutional blockholders are not the dominant ownership type.

Third, the temporal pattern of the H2 result, where the coverage effect builds over weeks rather than days, highlights the need for a more detailed study of post-disclosure price discovery

dynamics. A high-frequency analysis of trading volume and order flow following insider purchase disclosures, segmented by coverage level, could directly test whether the slow build in covered firms reflects the gradual entry of retail and institutional investors as predicted by the recognition channel, or whether other mechanisms (such as delayed analyst response or sentiment effects) contribute to the pattern. This would move the literature beyond establishing that the recognition channel operates, toward understanding how it operates in real time.

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Appendix

Appendix A: Authorship Statement

This thesis was written, with equal contribution, by Fredrik Lyrvall, Emil Sköldberg, and Fredrik Sölveld. The authors take collective and full responsibility for the content of this thesis and have all approved the submission of the final version.

Appendix B: AI Usage Statement

In writing this thesis, the authors used Artificial Intelligence (AI), specifically Claude AI, in the following three ways. First, AI was used to find synonyms in order to ensure a varied language. Second, AI was used to rephrase sentences in order to improve the clarity and readability of the text. Third, AI was used to support the authors in carrying out the methodological framework in the statistical software STATA. Examples and prompts of these three use cases are provided below.

Example 1: Finding synonyms for specific words to avoid repetition:

- “Can you find synonyms for the word consistent”

Example 2: Rephrasing and enhancing clarity of sentences

- “Can you give a list of suggestions on how to improve the clarity and readability of the following sentence: In markets where retail investors form a meaningful share of the trading base, the audience capable of reacting to an insider purchase in an uncovered firm is considerably smaller, and analyst coverage therefore takes on the additional role of determining whether such an audience exists at all. “

Example 3: When supporting in carrying out statistical analysis in STATA

- “Give me a step-by-step instruction on how we can perform a OLS cross-sectional regression analysis in STATA”

Or

- “How do we run an interaction term between two variables in a OLS cross-sectional regression in STATA”

Give me a step-by-step instruction on how we can perform a OLS cross-sectional regression analysis in STATA

To perform a cross-sectional OLS regression in Stata, here is a step-by-step example assuming your data is in the correct format:

```
stata

* STEP 1: Import your dataset
import excel "yourdata.xlsx", sheet("Sheet1") firstrow clear

* STEP 2: Drop rows with missing values in required variables
drop if missing(depvar, indepvar1, indepvar2, indepvar3)

* STEP 3: Log-transform skewed variables if needed (optional)
gen log_depvar = log(depvar) if depvar > 0

* STEP 4: Run OLS regression with clustered standard errors
regress depvar indepvar1 indepvar2 indepvar3, cluster(firm_id)

* STEP 5: Export results to Word
ssc install outreg2, replace
outreg2 using results.doc, replace word
```

Appendix C: Stata Output

Event Study Results STATA Output

```
. * H1: Event study significance tests (full sample, N = 1,824)
```

```
.
```

```
. use "output/full_sample_v3.dta", clear
```

```
.
```

```
. ttest CAR_0_5_w == 0
```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
CAR_~5_w	1,824	2.132631	.2306295	9.849798	1.680306	2.584957

```
mean = mean(CAR_0_5_w) t = 9.2470
H0: mean = 0 Degrees of freedom = 1823
```

```
Ha: mean < 0 Ha: mean != 0 Ha: mean > 0
Pr(T < t) = 1.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 0.0000
```

```
. ttest SCAR_0_5 == 0
```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
SCAR_0_5	1,824	.2560203	.0293356	1.252873	.1984854	.3135552

```
mean = mean(SCAR_0_5) t = 8.7273
H0: mean = 0 Degrees of freedom = 1823
```

```
Ha: mean < 0 Ha: mean != 0 Ha: mean > 0
Pr(T < t) = 1.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 0.0000
```

```
. ttest CAR_0_10_w == 0
```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
CAR~10_w	1,824	1.862541	.2881707	12.30729	1.297361	2.42772

```
mean = mean(CAR_0_10_w)          t = 6.4633
H0: mean = 0                      Degrees of freedom = 1823
```

```
Ha: mean < 0                      Ha: mean != 0                      Ha: mean > 0
Pr(T < t) = 1.0000                Pr(|T| > |t|) = 0.0000                Pr(T > t) = 0.0000
```

```
. ttest SCAR_0_10 == 0
```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
SCAR_~10	1,824	.1698723	.0262517	1.121164	.1183858	.2213588

```
mean = mean(SCAR_0_10)          t = 6.4709
H0: mean = 0                      Degrees of freedom = 1823
```

```
Ha: mean < 0                      Ha: mean != 0                      Ha: mean > 0
Pr(T < t) = 1.0000                Pr(|T| > |t|) = 0.0000                Pr(T > t) = 0.0000
```

```
.
. ttest CAR_0_20_w == 0
```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
CAR~20_w	1,824	1.910898	.3687137	15.74714	1.187752	2.634043

```

mean = mean(CAR_0_20_w)
H0: mean = 0
t = 5.1826
Degrees of freedom = 1823

```

```

Ha: mean < 0
Pr(T < t) = 1.0000
Ha: mean != 0
Pr(|T| > |t|) = 0.0000
Ha: mean > 0
Pr(T > t) = 0.0000

```

```

. ttest SCAR_0_20 == 0

```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
SCAR_~20	1,824	.133535	.0254378	1.086404	.0836447	.1834252

```

mean = mean(SCAR_0_20)
H0: mean = 0
t = 5.2495
Degrees of freedom = 1823

```

```

Ha: mean < 0
Pr(T < t) = 1.0000
Ha: mean != 0
Pr(|T| > |t|) = 0.0000
Ha: mean > 0
Pr(T > t) = 0.0000

```

```

.
. ttest CAR_0_30_w == 0

```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
CAR~30_w	1,824	1.844325	.4578257	19.55297	.9464068	2.742243

```

mean = mean(CAR_0_30_w)
H0: mean = 0
t = 4.0284
Degrees of freedom = 1823

```

```

Ha: mean < 0
Pr(T < t) = 1.0000
Ha: mean != 0
Pr(|T| > |t|) = 0.0001
Ha: mean > 0
Pr(T > t) = 0.0000

```

```

. ttest SCAR_0_30 == 0

```

One-sample t test

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
SCAR_~30	1,824	.1203402	.0254922	1.08873	.0703431	.1703372

```

mean = mean(SCAR_0_30)
H0: mean = 0
t = 4.7207
Degrees of freedom = 1823

```

```

Ha: mean < 0
Pr(T < t) = 1.0000
Ha: mean != 0
Pr(|T| > |t|) = 0.0000
Ha: mean > 0
Pr(T > t) = 0.0000

```

Cross-Sectional Regression STATA Output

```
. * Regression sample (N = 1,246 events, 660 firms)
.
. keep if voting_group_v2 == "B_or_Ordinary"
(139 observations deleted)

. drop if missing(CAR_0_30_w, covered, ln_mcap_w, ln_BM_w, momentum_w, blockholder)
(439 observations deleted)

. egen isin_id = group(isin)
```

```
. * H2: Baseline regression on CAR(0,+30)
.
. regress CAR_0_30_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression              Number of obs   =      1,246
                              F(4, 659)         =      30.66
                              Prob > F          =      0.0000
                              R-squared         =      0.1341
                              Root MSE      =      17.99
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
covered	3.511907	1.596034	2.20	0.028	.3779826	6.645832
ln_mcap_w	-.7153809	.3279443	-2.18	0.030	-1.359323	-.0714392
ln_BM_w	.2850487	.5593222	0.51	0.610	-.8132197	1.383317
momentum_w	-.1402316	.0140942	-9.95	0.000	-.1679066	-.1125567
_cons	6.548331	2.397985	2.73	0.006	1.839719	11.25694

```
.
.
. * H3: Interaction regression on CAR(0,+30)
.
. regress CAR_0_30_w covered blockholder c.covered#c.blockholder ///
> ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression              Number of obs   =      1,246
                              F(6, 659)         =      21.48
                              Prob > F          =      0.0000
                              R-squared         =      0.1381
                              Root MSE      =      17.963
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
covered	-2.663327	2.609127	-1.02	0.308	-7.786531	2.459877
blockholder	-2.870909	1.423335	-2.02	0.044	-5.665728	-.0760897
c.covered#c.blockholder	6.895768	2.591501	2.66	0.008	1.807174	11.98436
ln_mcap_w	-.5994859	.3293437	-1.82	0.069	-1.246175	.0472037
ln_BM_w	.3004114	.5525018	0.54	0.587	-.7844646	1.385287
momentum_w	-.1410338	.0139935	-10.08	0.000	-.1685111	-.1135565
_cons	8.028752	2.531842	3.17	0.002	3.057301	13.0002

```
.
.
```

Robustness STATA Output

```
.
. * Robustness: H2 across event windows
.
. regress CAR_0_5_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression                Number of obs    =      1,246
                                F(4, 659)         =      9.30
                                Prob > F           =      0.0000
                                R-squared           =      0.0342
                                Root MSE         =      9.8482
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_5_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	.548507	.7812871	0.70	0.483	-.9856051	2.082619
ln_mcap_w	-.5444254	.1655143	-3.29	0.001	-.8694245	-.2194264
ln_BM_w	-.2748377	.3175348	-0.87	0.387	-.8983396	.3486643
momentum_w	-.0288861	.0077909	-3.71	0.000	-.0441841	-.0135881
_cons	5.54298	1.194861	4.64	0.000	3.196786	7.889173

```
. regress CAR_0_10_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression                Number of obs    =      1,246
                                F(4, 659)         =     12.44
                                Prob > F           =      0.0000
                                R-squared           =      0.0539
                                Root MSE         =     11.847
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_10_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	1.017531	.9447169	1.08	0.282	-.837487	2.872549
ln_mcap_w	-.4133249	.208574	-1.98	0.048	-.8228745	-.0037753
ln_BM_w	-.4965978	.3951701	-1.26	0.209	-1.272542	.2793464
momentum_w	-.0572147	.0094539	-6.05	0.000	-.0757781	-.0386514
_cons	3.96177	1.504198	2.63	0.009	1.008172	6.915368

```
. regress CAR_0_20_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

Linear regression	Number of obs	=	1,246
	F(4, 659)	=	18.18
	Prob > F	=	0.0000
	R-squared	=	0.0858
	Root MSE	=	15.053

(Std. err. adjusted for **660** clusters in **isin_id**)

CAR_0_20_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	2.294098	1.230692	1.86	0.063	-.1224516	4.710648
ln_mcap_w	-.5593712	.2705545	-2.07	0.039	-1.090624	-.0281183
ln_BM_w	-.2944439	.4678347	-0.63	0.529	-1.21307	.6241825
momentum_w	-.093242	.0125918	-7.40	0.000	-.1179668	-.0685171
_cons	5.23461	2.006824	2.61	0.009	1.29407	9.175151

```
. regress CAR_0_30_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

Linear regression	Number of obs	=	1,246
	F(4, 659)	=	30.66
	Prob > F	=	0.0000
	R-squared	=	0.1341
	Root MSE	=	17.99

(Std. err. adjusted for **660** clusters in **isin_id**)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	3.511907	1.596034	2.20	0.028	.3779826	6.645832
ln_mcap_w	-.7153809	.3279443	-2.18	0.030	-1.359323	-.0714392
ln_BM_w	.2850487	.5593222	0.51	0.610	-.8132197	1.383317
momentum_w	-.1402316	.0140942	-9.95	0.000	-.1679066	-.1125567
_cons	6.548331	2.397985	2.73	0.006	1.839719	11.25694

.

```

.
. * Robustness: H2 across coverage thresholds
.
. gen covered_1 = (n_analysts >= 1)

. gen covered_3 = (n_analysts >= 3)

. gen covered_10 = (n_analysts >= 10)

.
. regress CAR_0_30_w covered_1 ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)

```

```

Linear regression              Number of obs   =      1,246
                              F(4, 659)        =      30.62
                              Prob > F         =      0.0000
                              R-squared         =      0.1323
                              Root MSE      =      18.009

```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered_1	1.410146	1.433658	0.98	0.326	-1.404943	4.225235
ln_mcap_w	-.6040353	.3637736	-1.66	0.097	-1.31833	.1102597
ln_BM_w	.2833046	.5620814	0.50	0.614	-.8203818	1.386991
momentum_w	-.1414732	.0140783	-10.05	0.000	-.1691168	-.1138296
_cons	5.742308	2.388281	2.40	0.016	1.05275	10.43187

```

. regress CAR_0_30_w covered_3 ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)

```

```

Linear regression              Number of obs   =      1,246
                              F(4, 659)        =      30.74
                              Prob > F         =      0.0000
                              R-squared         =      0.1333
                              Root MSE      =      17.999

```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered_3	2.585016	1.500317	1.72	0.085	-.3609611	5.530993
ln_mcap_w	-.7125967	.3585008	-1.99	0.047	-1.416538	-.0086552
ln_BM_w	.2778313	.5624954	0.49	0.622	-.826668	1.382331
momentum_w	-.1410767	.0140331	-10.05	0.000	-.1686318	-.1135216
_cons	6.445064	2.491022	2.59	0.010	1.553767	11.33636

```

. regress CAR_0_30_w covered ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)

```

```

Linear regression              Number of obs   =      1,246
                              F(4, 659)        =      30.66
                              Prob > F         =      0.0000
                              R-squared         =      0.1341
                              Root MSE      =      17.99

```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	3.511907	1.596034	2.20	0.028	.3779826	6.645832
ln_mcap_w	-.7153809	.3279443	-2.18	0.030	-1.359323	-.0714392
ln_BM_w	.2850487	.5593222	0.51	0.610	-.8132197	1.383317
momentum_w	-.1402316	.0140942	-9.95	0.000	-.1679066	-.1125567
_cons	6.548331	2.397985	2.73	0.006	1.839719	11.25694

```
. regress CAR_0_30_w covered_10 ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression               Number of obs   =       1,246
                                F(4, 659)         =       30.55
                                Prob > F           =       0.0000
                                R-squared           =       0.1320
                                Root MSE        =       18.012
```

(Std. err. adjusted for **660** clusters in **isin_id**)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered_10	1.775672	1.601761	1.11	0.268	-1.369498	4.920842
ln_mcap_w	-.4492669	.2925166	-1.54	0.125	-1.023644	.1251099
ln_BM_w	.3408535	.5577577	0.61	0.541	-.754343	1.43605
momentum_w	-.1419989	.0141111	-10.06	0.000	-.1697071	-.1142908
_cons	5.218919	2.279387	2.29	0.022	.743182	9.694657

```

.
. * Robustness: H3 across blockholder thresholds
.
. gen bh_15 = (blockholder_pct_paired >= 15)

. gen bh_20 = (blockholder_pct_paired >= 20)

. gen bh_25 = (blockholder_pct_paired >= 25)

.
. regress CAR_0_30_w covered blockholder c.covered#c.blockholder ///
> ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)

```

```

Linear regression                                Number of obs    =      1,246
                                                F(6, 659)         =      21.48
                                                Prob > F           =      0.0000
                                                R-squared          =      0.1381
                                                Root MSE          =      17.963

```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	-2.663327	2.609127	-1.02	0.308	-7.786531	2.459877
blockholder	-2.870909	1.423335	-2.02	0.044	-5.665728	-.0760897
c.covered#c.blockholder	6.895768	2.591501	2.66	0.008	1.807174	11.98436
ln_mcap_w	-.5994859	.3293437	-1.82	0.069	-1.246175	.0472037
ln_BM_w	.3004114	.5525018	0.54	0.587	-.7844646	1.385287
momentum_w	-.1410338	.0139935	-10.08	0.000	-.1685111	-.1135565
_cons	8.028752	2.531842	3.17	0.002	3.057301	13.0002

```

. regress CAR_0_30_w covered bh_15 c.covered#c.bh_15 ///
> ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)

```

```

Linear regression                                Number of obs    =      1,246
                                                F(6, 659)         =      20.65
                                                Prob > F           =      0.0000
                                                R-squared          =      0.1351
                                                Root MSE          =      17.994

```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	1.140242	2.115537	0.54	0.590	-3.013764	5.294249
bh_15	-.9679595	1.207926	-0.80	0.423	-3.339807	1.403888
c.covered#c.bh_15	3.435436	2.227461	1.54	0.123	-.9383405	7.809213
ln_mcap_w	-.6795716	.3304579	-2.06	0.040	-1.328449	-.0306943
ln_BM_w	.3061655	.5613401	0.55	0.586	-.7960653	1.408396
momentum_w	-.1403035	.0140578	-9.98	0.000	-.167907	-.1127
_cons	6.930907	2.459355	2.82	0.005	2.101791	11.76002

```
. regress CAR_0_30_w covered bh_20 c.covered#c.bh_20 ///
> ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression      Number of obs   =      1,246
                      F(6, 659)       =      21.26
                      Prob > F        =      0.0000
                      R-squared       =      0.1346
                      Root MSE     =      17.999
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	2.056028	2.195285	0.94	0.349	-2.254568	6.366624
bh_20	-.1054199	1.102509	-0.10	0.924	-2.270273	2.059433
c.covered#c.bh_20	2.488471	2.340344	1.06	0.288	-2.10696	7.083902
ln_mcap_w	-.7167533	.3287464	-2.18	0.030	-1.36227	-.0712366
ln_BM_w	.2739199	.5628452	0.49	0.627	-.8312661	1.379106
momentum_w	-.1404624	.014047	-10.00	0.000	-.1680447	-.1128801
_cons	6.596455	2.441982	2.70	0.007	1.801452	11.39146

```
. regress CAR_0_30_w covered bh_25 c.covered#c.bh_25 ///
> ln_mcap_w ln_BM_w momentum_w, vce(cluster isin_id)
```

```
Linear regression      Number of obs   =      1,246
                      F(6, 659)       =      20.47
                      Prob > F        =      0.0000
                      R-squared       =      0.1343
                      Root MSE     =      18.003
```

(Std. err. adjusted for 660 clusters in isin_id)

CAR_0_30_w	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
covered	2.920861	2.062261	1.42	0.157	-1.128533	6.970255
bh_25	.0213174	1.139184	0.02	0.985	-2.21555	2.258185
c.covered#c.bh_25	1.177723	2.307239	0.51	0.610	-3.352704	5.708149
ln_mcap_w	-.7182583	.3305292	-2.17	0.030	-1.367276	-.0692411
ln_BM_w	.2829391	.5623554	0.50	0.615	-.8212853	1.387164
momentum_w	-.1403228	.0141007	-9.95	0.000	-.1680105	-.1126352
_cons	6.55643	2.412423	2.72	0.007	1.819468	11.29339

```
.
end of do-file
```