UNIVERSITY OF TURKU
Turku School of Economics

Overnight Returns and Intraday Reversals

Evidence from U.S. Equities

Accounting and Finance,
Department of Accounting and Finance
Master's thesis

Author:
Anton Vainio

Supervisor:
Prof. Luis Alvarez Esteban

25.5.2026
Turku

Student’s statement regarding the use of Artificial Intelligence (AI) for preparing and/or writing this thesis:

☐ **I have not used any AI-based tools.**

☒ **I have used AI-based tools**. Their use is documented in the Appendix. The AI tools were used in a way that complies with academic integrity guidelines.

The originality of this thesis has been checked in accordance with the University of Turku quality assurance system using the Turnitin Originality Check service.

Master's thesis

Subject: Finance
Author: Anton Vainio
Title: Overnight Returns and Intraday Reversals: Evidence from U.S. Equities
Supervisor: Prof. Luis Alvarez Esteban
Number of pages: 69 pages + appendices 3 pages
Date: 25.5.2026

Abstract

This thesis examines the relationship between overnight price gaps and subsequent intraday returns in the U.S. equity market. Using a large dataset of daily U.S. stock data from 2011 to 2024, the study tests whether overnight returns, measured from the previous closing price to the opening price, systematically predict the same-day intraday returns, measured from the opening to the closing price.

The primary finding is a robust and persistent overnight-to-intraday reversal: stocks that gap up significantly overnight tend to give back a measurable fraction of that gain during the subsequent trading session, and vice versa. Panel OLS regressions with day fixed effects and standard errors double-clustered by firm and trading day confirm that the reversal coefficient is negative and statistically significant across all fourteen years of the sample and across all specifications. The effect is present across the full overnight return distribution and is not driven by any single market regime or crisis period.

The study examines the structural drivers of the reversal using a series of interaction models. The reversal is strongest in small, illiquid stocks and intensifies during periods of elevated, market-wide uncertainty, as measured by the VIX. This is consistent with the limits-to-arbitrage framework. Once both are controlled for simultaneously, the liquidity channel dominates the behavioral size channel. Portfolio sorts confirm a perfectly monotonic inverse relationship between overnight return rank and mean intraday return.

A centile long-short strategy exploiting the reversal signal earns a substantial, statistically significant gross alpha, which is orthogonal to the Fama-French five-factor model. However, after estimating bid-ask spreads and trading commissions, the net alpha becomes clearly negative. This finding is consistent with the limits to arbitrage model. The reversal appears to be a structural feature of opening price formation in U.S. equity markets rather than an exploitable inefficiency.

Keywords: overnight returns, intraday returns, price reversal, market microstructure, behavioral finance, limits to arbitrage

Pro gradu -tutkielma

Oppiaine: Rahoitus
Tekijä: Anton Vainio
Otsikko: Yölliset tuotot ja päivänsisäiset käänteet: tarkastelussa Yhdysvaltojen osakemarkkinat
Ohjaaja: Prof. Luis Alvarez Esteban
Sivumäärä: 69 sivua + liitteet 3 sivua
Päivämäärä: 25.5.2026

Tiivistelmä

Tässä pro gradu -tutkielmassa tarkastellaan yön yli -hintamuutosten ja sitä seuraavan päivänsisäisen tuoton välistä yhteyttä Yhdysvaltain osakemarkkinoilla. Tutkimuksessa hyödynnetään laajaa päivittäistä osakekurssiaineistoa vuosilta 2011–2024. Tutkimuksessa selvitetään, ennustavatko yön yli -tuotot, jotka mitataan edellisen päivän päätöskurssin ja avaushinnan välisenä muutoksena, samana päivänä toteutuvia päivänsisäisiä tuottoja, jotka mitataan avaushinnan ja päätöskurssin väliltä.

Keskeinen löydös on vankka ja ajallisesti pysyvä käänteinen suhde yöllisten ja päivänsisäisten tuottojen välillä: osakkeet, joiden avaus on merkittävästi edellispäivän päätöskurssia korkeammalla, saavat tyypillisesti seuraavan kaupankäyntijakson aikana negatiivisia tuottoja, ja päinvastoin. Paneeli-OLS-regressiot vahvistavat, että suhde yöllisten ja päivänsisäisten tuottojen välillä on negatiivinen ja tilastollisesti merkitsevä koko otoksen läpi kaikissa spesifikaatioissa. Ilmiö esiintyy tuottojakauman kaikilla alueilla eikä selity yksittäisillä markkinasuhdanteilla tai kriisijaksoilla.

Käänteiden rakenteellisia taustatekijöitä tutkitaan interaktiomalleilla. Käänteet ovat voimakkaimpia pienissä ja epälikvideissä osakkeissa ja voimistuu markkinaepävarmuuden kasvaessa VIX-indeksillä mitattuna, mikä sopii yhteen arbitraasin rajoitteiden viitekehyksen kanssa. Likviditeetti selittää käänteen vaihtelua paremmin kuin yrityksen koon muuttuja, kun molemmat otetaan huomioon samanaikaisesti. Desiilisalkut vahvistavat täysin monotonisen käänteisen yhteyden yöllisten tuottojen ja keskimääräisen päivänsisäisen tuoton välillä.

Käännesignaaliin perustuvan yksinkertaisen kaupankäyntistrategian bruttotalpha on suuri ja tilastollisesti merkitsevä Fama–French-viisifaktorikorjauksen jälkeen. Kun arvioidut spread-kustannukset ja välityspalkkiot vähennetään, nettotalpha kääntyy selvästi negatiiviseksi. Myös tämä tulos on sopusoinnussa arbitraasin rajoitteiden mallin kanssa. Ilmiö säilyy markkinoilla juuri siksi, että sen hyödyntämiseen vaadittavat transaktiokustannukset riittävät estämään arbitraasin. Päivänsisäiset käänteet tuotoissa näyttävät olevan rakenteellinen piirre yhdysvaltalaisen osakemarkkinan hintamuodostuksessa pikemminkin kuin hyödynnettävissä oleva tehokkuuspoikkeama.

Avainsanat: yölliset tuotot, päivänsisäiset tuotot, markkinan mikrorakenne, behaviorismi, arbitraasin rajoitteet

TABLE OF CONTENTS

FIGURES

TABLES

1 Introduction

1.1 Background and motivation

Depending on the time of day, trading in contemporary financial markets can be separated into different periods. The primary period is the intraday trading session, also known as regular trading hours (RTH), which for US equities, lasts from 9:30 a.m. to 4:00 p.m. EST.

This main session is accompanied by periods of relatively limited trading. The after-hours session takes place immediately after the closure, and the pre-market session before the next day's opening. While these extended hours allow for some trading, they have fundamentally different characteristics: liquidity is a fraction of what it is during the regular session, bid-ask spreads are substantially greater, and participation is more limited (Barclay & Hendershott 2003). These sessions, in turn, revolve around the main overnight period, which for US equities runs from 8:00 p.m. to 4:00 a.m. EST. During this time, most trade is completely suspended.

Importantly, the flow of economically significant information continues even though the mechanism of continuous, liquid, and centralized trading is limited to the intraday RTH session. A pharmaceutical company might reveal the results of a crucial drug trial at 7:00 a.m. in the pre-market, a corporation might release its quarterly earnings report at precisely 4:30 p.m. to allow for digestion during the after-hours period, or a major geopolitical event could occur overnight.

The overnight period reflects a prolonged period of information accumulation during which prices do not change because no trade can take place. Any news, and the resulting shifts in investor attitude, cannot be gradually absorbed by market prices. Instead, the complete flood of information can only be consolidated after the markets reopen.

The overnight price gap, or the discrepancy between the official closing price of the previous day and the official opening price of the current day, is produced by this mechanism. A stock's price may gap up, opening 5%, 10%, or even 20% higher than where it closed, after a significant positive announcement. On the other hand, bad news can result in a big gap down. The market's initial collective effort to create a new, efficient equilibrium is represented by this opening price, which is usually established using an auction mechanism that combines pre-market orders and new market on open orders. Understanding these dynamics is crucial for determining whether the opening price is efficiently set or whether trading during the RTH session could result in predictable corrections or reversals of the overnight move.

One of the main topics of discussion in financial economics is the competition for stock market forecasting, which is where the study of these short-term dynamics fits in. According to the fundamental concept known as the Efficient Market Hypothesis (EMH), asset prices in an informationally efficient market already take into account all relevant information (Fama 1970). Under this framework, any new information is rapidly absorbed, making abnormal risk-adjusted returns unforecastable.

Since then, there have been ongoing empirical challenges to this hypothesis. Numerous studies have identified anomalies that imply the presence of abnormal returns. Research has found evidence of both intermediate-term price momentum (Jegadeesh & Titman, 1993) and long-term price reversals (De Bondt & Thaler, 1985). The former suggests that markets may underreact to information in the medium term, while the latter suggests that markets may overreact to long-term news. The strong predictive role of elements like business size and book-to-market value was recognized by Fama and French (1992). These results paved the way for a wave of studies that suggested historical data might actually be able to predict future returns.

However, there is still much disagreement on the evidence for general predictability, thus this argument is far from resolved. Significant counterarguments have been made by the pro-efficiency camp, casting doubt on the validity and interpretation of these anomalies. It is suggested that many patterns constitute reasonable compensation for aspects of systematic risk that are not captured, rather than free lunches (Fama & French, 2008). According to a study by Harvey et al. (2016), many published anomalies were probably statistical flukes and that the statistical threshold for finding a factor of expected returns should be far higher than the one that is typically used. Additionally, McLean and Pontiff (2016) presented strong evidence that most anomalies either completely vanish or become much weaker following their scholarly publication, which may be an ironic tribute to market efficiency. This implies that logical traders and arbitrageurs do take advantage of inefficiencies once they are discovered, leading to the pattern being arbitraged out. The market learns and adapts.

The return divergence between overnight and intraday returns is significant firstly because it serves as a test for the EMH but it also extends beyond just the search for abnormal returns. It tests the integrity of the opening call auction itself. If opening prices systematically overshoot their fundamental values due to pent-up retail attention or severe information asymmetry, it indicates a temporary misallocation of capital. For regulators, exchange operators, and institutional liquidity providers, studying these reversals provides critical insight into how well market infrastructure absorbs overnight shocks.

By focusing on patterns associated with the overnight period, this thesis addresses the ongoing debate. A growing body of research contends that stocks exhibit consistent trends throughout their trading cycle. For example, Kelly and Clark (2011) clearly discovered that the difference between trading and non-trading hours was substantial, with non-trading hours generating all of the market's gains throughout the study period.

This divergence was more recently illustrated by Lou et al. (2019), who showed a long-term cumulative return for the S&P 500 that trended flat to negative during the continuous intraday (open-to-close) session and strongly upward during the overnight (close-to-open) session. This implies that there are differences in how the pricing system functions between these two sessions. The existence of consistent return patterns across the daily trading cycle has been established by a large body of research, including studies like Bogousslavsky (2021) and Hendershott et al. (2020). The literature has also investigated the causes of these trends. Berkman et al. (2012) and Aboody et al. (2018) attribute these patterns to investor attentiveness, but questions about the patterns and their causes remain.

1.2 Objectives and purpose

This thesis's main purpose is to perform a thorough empirical analysis of stock returns in the U.S. equity market after notable overnight price gaps. This study intends to quantify the relationship between the information gathered in the overnight session and the price adjustment that takes place during the subsequent intraday session, building on the current literature between overnight and intraday return characteristics. The objective of this study is to answer the following research questions:

- Do overnight returns have statistically significant predictive power over subsequent same-day intraday returns in U.S. equities?

The test of the overnight-intraday phenomenon is the initial research question. It examines the empirical conclusions of research like Berkman et al. (2012) and Lou, et al. (2019), which showed a consistent inverse relationship between intraday (open-to-close) and overnight (close-to-open) returns.

- How do market-wide conditions and firm-specific characteristics moderate the strength and persistence of the intraday response?

The second question moves from what to why. It aims to explain the drivers of this phenomenon after determining the predictive relationship (if any) from the first research question. It examines Berkman et al. (2012)'s behavioral mispricing hypothesis, who argues that the negative relationship is driven by the attention of retail investors and should thus be stronger for stocks with specific, attention-grabbing characteristics. The goal of this question is to evaluate these drivers.

- Does the statistical predictability of overnight-to-intraday returns survive realistic transaction costs, and what does the answer imply about the nature of the anomaly?

The third question translates statistical predictability into economic significance and asks whether the reversal constitutes an exploitable market inefficiency or whether it is protected by trading frictions and costs.

To answer the research questions, this thesis defines and measures overnight and intraday returns for a diverse range of US equities across a prolonged time. It uses econometric tools, especially regression analysis, to separate the predictive capacity of the overnight gap from other market influences and random noise and quantifies the statistical relationship between overnight gaps and future intraday returns. Finally, it analyzes the empirical findings in light of the existing scientific research, adding to the academic literature by offering current evidence on this market phenomenon.

This thesis makes a threefold contribution to the existing literature. It provides updated evidence on the overnight-to-intraday reversal, using a 14-year sample of US equities that extends beyond the periods studied by Berkman et al. (2012), Lou et al. (2019) and Akbas et al. (2022). The thesis tests whether the reversal has persisted, weakened or disappeared in the most recent period. Secondly, the study uses a unique set of control variables, such as the VIX, dollar trading volume, Amihud illiquidity indicator and Corwin-Schultz spread estimator to test which variables best explain intraday reversal. The study also quantifies gross-to-net alpha decay under realistic transaction cost assumptions.

1.3 Structure of the thesis

Chapter 2 develops the theoretical foundation for empirical analysis. It covers the efficient market hypothesis and the joint hypothesis problem, introduces the time-varying risk premium approach as the most sophisticated rational alternative to behavioral explanations of return predictability, reviews the empirical challenges to the EMH, and develops the theories of market microstructure and behavioral finance that together motivate the specific hypotheses tested in the study.

Chapter 3 surveys the empirical literature on overnight and intraday predictability. It traces the foundational findings of Kelly and Clark (2011) and Lou et al. (2019), reviews the most recent empirical contributions through 2025, examines the microstructural and behavioral explanations for the documented patterns and looks into international evidence that suggests the importance of market rules in this phenomenon.

Chapter 4 describes the data and empirical methods in full. It documents sample construction, data cleaning and filtering procedures, variable definitions along with every empirical model this study uses and provides reasoning for the choices that are made.

Chapter 5 presents empirical results, proceeding from descriptive statistics and correlation analysis through diagnostic tests, main regression results, portfolio sorts, transaction cost analysis, asymmetry tests, and a wide range of stability checks.

Chapter 6 discusses the findings. It answers each research question, develops the theoretical interpretation of the results, engages with the behavioral versus rational debate, examines what the transaction cost findings reveal about market structure and proposes directions for future research.

2 Theoretical framework

2.1 Efficient market hypothesis

The efficient market hypothesis (EMH) is foundational to finance theory and provides the theoretical baseline against which virtually all empirical work on return predictability is measured. According to Fama (1965; 1970), a market is considered efficient if security prices fully reflect all available information at any given moment. The economic logic behind this idea is straightforward: if a subset of information could be used to generate predictable excess returns, rational, profit-seeking investors would immediately exploit it, driving prices to a point where the opportunity is no longer profitable. In a world with a sufficient number of rational investors, prices should always approximate their fundamental values, and no investor should be able to earn consistent excess returns.

The empirical literature was organized by Fama (1970) around three forms of market efficiency. These forms were distinguished by the information set assumed to be reflected in prices. Weak form efficiency assumes that prices incorporate all information contained in past trading data, including historical prices and volume. Thus, no strategy based on technical analysis or extrapolating past return patterns can generate abnormal profits. Semi-strong form efficiency extends this to all publicly available information, such as financial statements, analyst reports, macroeconomic indicators, and news. This implies that even diligent fundamental analysis cannot reliably identify mispriced securities once information enters the public domain. Strong form efficiency, the most demanding version, holds that prices reflect all information, including private information. This means that even market participants with access to nonpublic information could not outperform the market consistently.

This framework has guided decades of empirical research, but its apparent simplicity masks a fundamental logical challenge identified by Fama (1970): the joint hypothesis problem. Any empirical test of market efficiency tests two propositions: that the market is efficient and that the model used to define a "normal" risk-adjusted return is correct. A finding that a strategy earns positive average returns after adjusting for risk can be reinterpreted as evidence that the risk model is incomplete rather than as evidence that the market is inefficient. The true model of expected returns is unknown and unobservable, so no test of the EMH can be definitive (Fama, 1991). This dilemma represents the central interpretive challenge of studies on return predictability. Cochrane (2011) emphasizes this point in a broader survey of asset pricing, arguing that the recent increase in documented anomalies may indicate the inadequacy of current factor models as much as it suggests genuine market inefficiency.

The stochastic discount factor (SDF) approach is a framework for specifying what normal returns should look like. According to Cochrane (2009), all modern asset pricing theory can be derived from the fundamental pricing equation $p = E(mx)$, where p is the current asset price, x is the uncertain future payoff, and m is the SDF representing investors' marginal utility of wealth. The SDF is high in bad states of the world, recessions, financial crises, periods of low consumption, and low in good ones. An asset whose payoff covaries positively with m, meaning it pays off well precisely when investors are most desperate for wealth, commands a high price and a low expected return because it provides valuable insurance. On the other hand, an asset whose payoff negatively covaries with m, providing its highest returns when investors need them the least, must offer a risk premium to attract capital.

Cochrane (2011) builds on this logic to argue that return predictability is a rational byproduct of time-varying risk premiums rather than market mispricing. According to this view, predictability in returns, whether over time or across different trading sessions, reflects fluctuations in the price of risk. For example, returns may be higher during periods or sessions with significant illiquidity or the risk of large price fluctuations, such as the overnight period. Investors holding positions during these periods require a higher expected return to compensate for the risk.

The SDF model motivates the factor models used in empirical research. The most famous approach is the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), which uses aggregate market returns as a proxy for the SDF and predicts a linear relationship between market beta and expected returns. However, empirical research has shown that the CAPM is an incomplete representation of the cross-section of returns. Fama and French (1992) demonstrated that firm size and the ratio of book value to market value explain substantial cross-sectional variation in average returns that market beta cannot account for. This motivated the three-factor extension of Fama and French (1993). Further research identified additional sources of variation in returns related to profitability and investment policy. This led to the five-factor model of Fama and French (2015). Merton's (1973) intertemporal CAPM provides a theoretical justification for multi-factor models. In a world where investment opportunities vary over time, investors care about hedging against changes in the state of the economy. Assets that provide this hedge have lower expected returns.

Grossman and Stiglitz (1980) pose a theoretical challenge at the intersection of the EMH and the behavioral literature. They argue that perfectly informationally efficient markets are impossible in a strict sense. If prices always fully reflected all information, there would be no return on gathering and processing that information. Informed investors would earn only the risk-free rate after spending resources on information acquisition without receiving compensation. However, if informed investors earn no return on their information, they have no incentive to become informed, and prices would cease to be informative. This is, of course, a logical contradiction. Grossman and Stiglitz (1980) resolve this contradiction by positing an equilibrium in which prices are only partially informative. In this equilibrium, informed investors earn a return just sufficient to compensate for the cost of becoming informed. Residual uncertainty in prices is the mechanism by which this compensation is provided. According to this view, some degree of predictability in returns is a structural feature of markets where information is costly.

Samuelson (1973) offers a related perspective, proving formally that properly discounted asset prices must follow a martingale. However, he states that if a small number of investors have access to better information than others, they could earn abnormal returns. Therefore, the efficiency of real markets is an empirical question contingent on the strength of the competitive forces that enforce it, rather than a certainty.

There is extensive empirical evidence on market efficiency, but its interpretation is contested. Early tests largely supported the hypotheses of weak and semi-strong efficiency. Prices appeared to respond quickly and appropriately to earnings announcements, dividend changes, and other public events (Fama et al., 1969). However, subsequent decades produced a growing catalog of apparent anomalies. These were return patterns inconsistent with the predictions of standard models. De Bondt and Thaler (1985) documented long-term return reversals, which suggest overreaction to past performance. Jegadeesh and Titman (1993), on the other hand, documented medium-term momentum, suggesting underreaction. Rosenberg et al. (1985) and Fama and French (1992) documented the value premium. These and many other findings have been intensively debated. Schwert (2003) notes that anomalies often fade or vanish after publication, which is consistent with either arbitrage elimination or data snooping. Concern about data snooping, or the tendency to find spurious patterns by searching a large dataset for any correlation that clears a significance threshold, has emerged in the financial literature. Harvey et al. (2016) argue that the standard p-value threshold of five percent is far too permissive, given the number of hypotheses tested in the literature. On a broader scale, Hou et al. (2020) attempted to replicate hundreds of documented anomalies and found that the majority failed standard empirical controls, especially value-weighting and excluding microcap stocks. Their findings suggest that the documented efficiency failures in the literature are substantially overstated by methodological choices that amplify the influence of the smallest and least investable securities.

2.2 Market microstructure theory

2.2.1 Price discovery and information asymmetry

Market microstructure is the field of financial economics that focuses on the process by which latent investor demands are converted into realized transactions, prices, and quantities (Madhavan, 2000). Unlike asset pricing theory, which treats the trading mechanism as frictionless and considers the price an instantaneous reflection of all available information, market microstructure theory focuses on the mechanics of trading. This field of study examines how the rules, institutions, and strategic behavior of market participants influence the actual prices paid and the reasons behind systematic deviations from the theoretical ideal of a fully efficient, frictionless market (O'Hara, 1995).

The concept of the efficient price is also at the core of microstructure theory. This is the price that would prevail if all available information were immediately and without costs incorporated into the market. In practice, however, this efficient price is unobservable. Instead, observers see transaction prices, which are subject to a range of frictions and distortions. Hasbrouck (2007) models the efficient price as a random walk or martingale, meaning its changes are unpredictable based on currently available information. However, the transaction prices that investors pay are not martingales. These prices depend on the market's institutional structure, investor composition, and the information environment at the time of each trade.

Information asymmetry can cause transaction prices to deviate from the efficient price. In most real markets, some participants have private information about the true value of a security, such as the results of fundamental research, the ability to process public news more effectively, or access to order flow data, while others do not. Glosten and Milgrom's (1985) model examines this problem from the perspective of a market maker who must quote prices without knowing which counterparties are informed. Informed traders buy when the security is undervalued and sell when it is overvalued. Their order flow reveals information to the market maker, but this information is noisy and sequential; no single trade clearly reveals the informed trader's private signal. Consequently, the market maker engages in a Bayesian learning process, updating their estimate of the security's true value with each trade and adjusting the quoted price accordingly. Price discovery is a continuous process in which new information is incorporated into market prices trade by trade.

This has a direct implication for return dynamics. Since market makers can only learn from order flow sequentially, prices may take a considerable amount of time to converge to their new, full-information values after an informational event. During this period, transaction prices exhibit predictable patterns. Early trades in the direction of the information content generate subsequent trades in the same direction as the market gradually absorbs the signal. Therefore, the microstructure framework predicts that short-term return predictability is not necessarily evidence of market inefficiency in the behavioral sense. Instead, it may be the natural result of a rational, sequential price discovery process operating under information asymmetry (O'Hara, 1995).

2.2.2 The bid-ask spread

The bid-ask spread is the most visible manifestation of market microstructure frictions. It represents the difference between the price at which a market maker is willing to sell (the ask price) and the price at which they are willing to buy (the bid price). For any investor who buys and then sells right away, the spread is an immediate loss. It is a cost of doing business that must be overcome before a position starts making a profit. Therefore, understanding the sources of the spread is important when evaluating any trading strategy that relies on short-term price signals.

According to the microstructure literature, the bid-ask spread can be decomposed into three components (Stoll, 2000). The first component is the order processing cost, which covers the fixed operational expenses of running a market-making business, including technology, labor, and regulatory compliance. This component is relatively stable and unrelated to the information environment. The second is the inventory holding cost, which is basically what compensates the market maker for the risk of holding a position between trades that's not zero. A dealer who has sold a large quantity of a security is exposed to adverse price movements until they can rebalance their position. This cost increases with volatility and difficulty finding a counterparty. It motivates dealers to skew their quotes away from the midpoint to attract order flow that reduces their inventory risk (Ho & Stoll, 1981). The third component is the adverse selection cost, also called the information component. Since the market maker cannot distinguish between informed and uninformed traders, they must assume that some of their order flow comes from investors with superior information. By its very nature, trading with an informed investor is a losing proposition for the market maker. The market maker buys at the bid from someone who knows the security is overvalued, or sells at the ask to someone who knows it is undervalued. To break even, the market maker must widen the spread and recover these losses from trades with uninformed investors. Therefore, the spread is the price for providing immediacy in a market with private information (Glosten & Milgrom, 1985).

This leads to two important empirical patterns. First, spreads are wider for smaller, less liquid securities because thinner order flow makes it harder to determine the true value through trades. Thus, the adverse selection component is larger. Second, spreads are time-varying; they widen during periods of maximum informational uncertainty and narrow as uncertainty is resolved. The market open is the classic example of the former. The implications of this phenomenon for overnight-to-intraday dynamics are discussed further in Section 2.2.4.

2.2.3 Structure of the trading day

Modern equity markets are not open continuously. For U.S. equities, the primary trading session, or regular trading hours (RTH), runs from 9:30 a.m. to 4:00 p.m. Eastern Time. This session is marked by high liquidity, tight spreads, and continuous two-sided markets. This session is bookended by periods of limited but non-zero trading activity. The pre-market session runs from approximately 4:00 a.m. to 9:30 a.m., followed by the after-hours session from 4:00 p.m. to 8:00 p.m. During these extended hours, trading primarily occurs through electronic communication networks (ECNs) rather than the central exchange. These sessions have a fundamentally different character: participation is more restricted, trading volumes are a small fraction of those in the regular session, bid-ask spreads are substantially wider, and the price discovery process is less efficient (Barclay & Hendershott, 2003).

Despite their limited volume, extended-hours sessions are not economically irrelevant. Many corporate announcements, such as earnings releases, guidance updates, and regulatory filings, are timed to occur outside of regular trading hours. This allows investors time to process the information before normal trading resumes. These announcements generate significant price movements in the pre-market and after-hours sessions. Barclay and Hendershott (2003) studied NASDAQ stocks around the time ECNs were introduced and found that, although pre-market volume represents only a small fraction of regular-session volume, the price discovery efficiency of individual pre-market trades is remarkably high. Each pre-market trade incorporates more information than the typical regular-session trade. Consistent with the adverse selection framework, the pre-market primarily attracts informed participants, making each trade highly informative. The correspondingly high adverse selection costs account for the wider spreads observed outside regular hours.

Between the after-hours close (around 8:00 p.m.) and the pre-market open (around 4:00 a.m.), a significant period passes during which virtually no trading occurs. During this non-trading period, public and private information continues to arrive, geopolitical developments, foreign market movements, and macroeconomic releases from other time zones. However, this information cannot be continuously incorporated into prices through the normal order flow mechanism. The result is that informational pressure builds up during the overnight period and is released all at once at the market open each morning.

2.2.4 The market open

The transition from the non-trading overnight period to the regular trading session is one of the most significant moments in the daily life of an equity market. Most major exchanges, including the New York Stock Exchange and NASDAQ, use an opening call auction to manage this transition. This is distinct from the continuous double auction that governs the rest of the day (O'Hara, 1995). During the overnight period, investors submit market-on-open and limit-on-open orders that accumulate in a queue without executing. When the market opens, the exchange sets a single price that makes the most matches between orders, and all matching orders are executed at this price at the same time. Trading then immediately transitions to the continuous session.

The rationale behind the opening call auction is to aggregate information under uncertainty. Theoretically, call auctions are superior to continuous mechanisms for price discovery when there is a high degree of uncertainty about the asset's value because they allow order imbalances to be observed before execution. This gives the market time to aggregate dispersed information into a single clearing price (Madhavan, 2000). An overnight period without trading allows information to accumulate without the corrective feedback that continuous trading provides. This results in a aggregation problem for the opening auction.

The adverse selection environment at market open is therefore different from the rest of the trading day. Foster and Viswanathan (1990) modeled this phenomenon, demonstrating that the informational asymmetry between informed and uninformed traders is greatest at the start of a trading period following a non-trading interval. Informed participants have had the overnight period to process and act on private information without revealing it to the market. The longer the non-trading interval, the greater the informational advantage that accumulates. Market makers and liquidity providers are aware of this asymmetry at the open. In response, they widen their quoted spreads to protect against the elevated probability that their counterparties possess superior information. Barclay and Hendershott (2003) empirically documented this, confirming that bid-ask spreads are substantially higher around market open than during the rest of the trading day, and that this increase is directly related to the concentration of informed trading at that time.

This elevated level of adverse selection has led to a rational strategic response from uninformed traders. Since the terms of trade at the open are unfavorable and the adverse selection premium is higher than at any other point in the day, liquidity-motivated investors are incentivized to delay their participation until the informational asymmetry narrows as the session progresses (O'Hara, 1995). This strategic delay is self-reinforcing; the withdrawal of uninformed order flow at the open concentrates the remaining flow among informed participants, which further increases the adverse selection cost and widens spreads (Glosten & Milgrom, 1985). The result is a predictable intraday pattern in trading volume and bid-ask spreads. The open is characterized by concentrated, high-information trading and relatively wide spreads. This is followed by a gradual normalization as the session proceeds and another spike as the session closes (Foster & Viswanathan, 1990).

2.2.5 Inventory management

Market makers' inventory management provides another possible source of return predictability. Market makers are often required to provide continuous two-sided markets, meaning they must absorb order imbalances that would otherwise go unexecuted (Hasbrouck, 2007). After a period of sustained directional order flow, such as concentrated buying or selling at market open in response to an overnight gap, dealers may find themselves holding an inventory position that substantially deviates from their desired level (Madhavan, 2000).

Inventory control models pioneered by Stoll (1978) and Ho and Stoll (1981) demonstrate that a rational, risk-averse dealer will adjust both the bid and ask prices in response to an inventory imbalance to generate order flow that rebalances their position. A dealer with excess long inventory, perhaps due to absorbing heavy selling pressure at the open, lowers both prices relative to the efficient price. This makes it cheaper to buy from them and more expensive to sell to them. Buyers are attracted, and further selling is discouraged, gradually restoring the dealer's inventory to its target level. The price adjustment driven by inventory management is a temporary deviation from the efficient price. Once the dealer's inventory is rebalanced, the price returns to its fundamental value. Therefore, these inventory-driven price movements are inherently mean-reverting: a period of price decline due to dealer inventory adjustments will be followed by a partial price recovery once balance is restored (Hasbrouck, 2007).

In the context of overnight gaps, the inventory management mechanism provides an additional explanation for post-open price reversals that is independent of behavioral factors. When a large overnight gap generates heavy one-sided order flow at the open, dealers absorbing that flow accumulate an inventory position, which can then create predictable intraday price pressure in the opposite direction. Under this interpretation, the reversal is not a correction of irrational investor behavior, but rather a mechanical consequence of rational liquidity provision (Grossman & Miller, 1988; Ma et al., 2025). Market makers demand a liquidity premium for bearing the inventory risk associated with absorbing the opening shock, which naturally results in a price reversal once they eventually offload their excess inventory to newly arriving participants (Boyarchenko et al. 2023).

2.2.6 Return variance across trading periods

One of the most fundamental empirical findings in market microstructure theory is the relationship between trading activity and return variance. French and Roll (1986) demonstrated that stock return variances are significantly larger during trading hours than during equivalent non-trading periods. Specifically, returns measured from open to close are considerably more volatile than returns measured from close to the subsequent open, despite both intervals spanning a similar number of hours. Variance per unit of time is still far higher when trading is taking place.

There are several possible explanations for this asymmetry. One explanation is that trading itself generates price volatility through the price discovery process. The sequential revelation of private information via order flow produces price movements that would not occur if markets were closed. Another explanation is that public information is released more frequently during business hours because news releases, analyst reports, and macroeconomic announcements are concentrated during the trading day. French and Roll (1986) present evidence suggesting that the trading-induced component is substantial. This suggests that the price discovery process itself is a significant source of return variance.

For this thesis on overnight returns and opening price formation, this asymmetry has direct implications. The overnight period is characterized by lower return variance, not because less information arrives, but because the absence of continuous trading prevents the normal, trade-by-trade incorporation of that information into prices. When the market reopens and trading resumes, the accumulated overnight information is processed quickly, leading to increased volatility and the possibility of systematic price adjustments as the market absorbs the backlog of information through the auction and the initial minutes of continuous trading.

Taken together, the microstructure theories reviewed in this section explain why the market opening is a time of heightened microstructural complexity. The overnight non-trading period creates an information accumulation problem. The opening auction is an imperfect mechanism for resolving this problem. The transition to continuous trading generates predictable patterns in spreads, volume, and return dynamics as the market works through the effects.

2.3 Behavioral finance

2.3.1 Investor psychology and cognitive biases

The EMH rests on some assumptions: market participants process information rationally and rational arbitrageurs quickly eliminate any mispricing resulting from irrational behavior. However, the behavioral finance literature challenges both of these assumptions. Drawing on evidence from cognitive psychology, this field of finance literature argues that systematic and predictable departures from rationality are widespread among real investors and that structural market frictions prevent arbitrageurs from eliminating resulting price distortions. Together, these two arguments, irrational demand and limited arbitrage, provide an alternative framework for understanding why asset prices may persistently deviate from the values implied by more traditional models (Shleifer, 2000).

The roots of behavioral finance are in the contributions of Kahneman and Tversky (1979), whose prospect theory offers a descriptive model of decision-making under uncertainty that diverges systematically from the expected utility framework underlying standard finance theory. They demonstrated through a series of laboratory experiments that individuals evaluate outcomes relative to a reference point rather than in terms of final wealth levels. They also demonstrated that losses are perceived as more significant than equivalent gains, a phenomenon known as loss aversion. Furthermore, they showed that individuals apply non-linear probability weights, overweighing small probabilities and underweighting moderate and high ones. The authors contend that these deviations from rationality are not merely random fluctuations; rather, they are consistent and replicable patterns in human judgment that give rise to predictable biases in financial decision-making.

Overconfidence, the tendency of investors to overestimate the precision of their private information and the quality of their judgment relative to others, is among the most empirically consequential biases for financial markets. Daniel et al. (1998) developed a model in which investors place too much value on the accuracy of their private information and investing skills. This model generates both short-term momentum and long-term reversal. Overconfident investors push prices beyond fundamental values in the direction of their private signals, which attracts further momentum-driven buying until the public revelation of fundamentals eventually forces a correction. The model also predicts that overreaction should be strongest for assets about which public information is limited and private signals are ambiguous. This prediction is consistent with the idea that smaller, less-covered firms tend to exhibit stronger short-term return predictability.

Another important bias is conservatism. This concept was first documented in psychological literature by Edwards (1968) and then applied to financial markets by Barberis et al. (1998). Conservatism refers to the tendency to slowly update beliefs in response to new evidence, giving prior beliefs too much weight relative to new data. In a financial market context, conservatism predicts underreaction. When an unexpected news event occurs, investors adjust their expectations less than a fully rational investor would. This causes prices to gradually move toward their new equilibrium values over subsequent periods. This generates predictable price continuation in the direction of the initial news.

In contrast to conservatism, the representativeness heuristic is one of the central shortcuts in human probabilistic judgment, as identified by Tversky and Kahneman (1974). Representativeness is the tendency to judge the probability of an event based on how closely it resembles a typical example or stereotype rather than applying probability theory. In financial markets, this manifests as excessive extrapolation. Investors who observe a streak of positive earnings surprises or price increases judge the company to be a fundamentally strong performer. They then extrapolate that trend into the future, pushing prices above their fundamental values. De Bondt and Thaler (1985) attributed the representativeness heuristic as a driver of market overreaction and subsequent long-run reversals.

A third bias, applicable to the dynamics of overnight price formation, is investor attention. Due to the finite nature of the human attention span and the continuous arrival of information, one could argue that investors cannot process all available information equally. Barber and Odean (2008) provide empirical evidence showing that retail investors are net buyers of stocks that grab attention. These stocks are featured in the news, experience high trading volume, or show extreme returns. This occurs even when the attention-grabbing event carries no new fundamental information. Dramatic overnight events, earnings surprises, and price gap openings are precisely the circumstances most likely to attract the attention of retail investors and generate order flow driven by psychology rather than the rational processing of information. Hirshleifer and Teoh (2003) formalize the role of limited attention in price formation. They show that, when investors can only process a subset of available signals, prices are influenced by how information is presented rather than by its content alone. This is a departure from the rational information processing assumed by the EMH.

Investor sentiment, which is defined as the aggregate of subjective beliefs and emotions that influence market participants' expectations, provides another way through which psychology can affect prices. Baker and Wurgler (2006) created a composite sentiment index using several market-based indicators. They demonstrated that investor sentiment has predictable effects on the cross-section of stock returns. Stocks that are the most difficult to value and the hardest to arbitrage, such as small, young, volatile, unprofitable, and extreme-growth companies, are the most sensitive to swings in investor sentiment. High-sentiment periods are followed by lower returns for these stocks and low-sentiment periods are followed by higher returns. This is consistent with sentiment-driven mispricings that are subsequently corrected. This finding is directly relevant to the overnight-to-intraday context because these stocks are the most sensitive to sentiment fluctuations. Small, illiquid, high-volatility stocks are precisely those most likely to experience dramatic overnight price gaps driven by news events that occur outside of trading hours.

2.3.2 Limits to arbitrage

Although documenting that investors are subject to cognitive biases is necessary for explaining persistent price distortions, it is not sufficient. If rational arbitrageurs could quickly and cheaply exploit any resulting mispricing, then irrational demand would not affect prices in the long term. Therefore, an argument of behavioral finance is that real-world arbitrage is far more limited and costly than the frictionless version assumed by the EMH.

Shleifer and Vishny (1997) identify the limits of arbitrage in a model that captures the institutional structure of professional investment management. In their framework, arbitrageurs do not use their own capital but rather manage money on behalf of outside investors who cannot directly observe the quality of the arbitrage strategy. When an arbitrageur takes a position against a mispricing, like shorting an overvalued stock, and the mispricing worsens in the short term due to continued noise-trader buying, the arbitrageur's portfolio incurs mark-to-market losses. These losses may trigger fund withdrawals precisely when the position is most attractive on fundamental grounds. Facing this threat, rational, risk-averse arbitrageurs will preemptively limit their positions against the mispricing. The result is that noise trader risk constrains the mechanism that is supposed to enforce market efficiency. Noise trader risk is the risk that prices move further against a fundamentally correct position before ultimately converging. De Long et al. (1990) demonstrate this concept in a model of noise trader equilibrium. They show that the unpredictable nature of sentiment creates a systematic risk that rational arbitrageurs must be compensated to bear. This implies that arbitrageurs will not fully eliminate the positions of irrational investors, even in the long run.

In the textbook sense, pure arbitrage involves simultaneously buying and selling identical securities at different prices with no capital requirement or risk. However, this type of arbitrage is vanishingly rare in real markets. Most practical arbitrage involves taking positions in similar but not identical assets, which exposes the arbitrageur to basis risk, or the possibility that the spread between the overpriced asset and its substitute will widen rather than narrow (Shleifer, 2000). Short selling, a necessary component of strategies against overvalued assets, entails additional costs and constraints. Securities available for borrowing are not always obtainable at a low cost. Short squeezes can force premature liquidation, and in some jurisdictions and market segments, short selling is legally restricted (Shleifer, 2000). Pontiff (2006) empirically examines these holding costs and their consequences, showing that the magnitude of documented anomalies is systematically related to the cost of constructing and maintaining the arbitrage position. The largest and most persistent pricing anomalies are exhibited by assets for which arbitrage is most costly, those with high idiosyncratic volatility, limited borrow availability, or wide spreads.

Transaction costs introduce an additional layer of friction. Even when a mispricing is genuine and persistent, it may be unprofitable if the cost of the round-trip trade required to take advantage of it exceeds the gross spread. The bid-ask spread, commissions, and the market impact of trading all reduce the net return from any active strategy. These costs are highest for the very securities where behavioral distortions are most severe: small-cap, illiquid, and high-spread stocks. From this perspective, Malkiel (2003) argues that many apparent anomalies are irrelevant to investors in practice. They may exist in the data, but they cannot be profitably extracted once realistic trading costs are acknowledged.

2.3.3 The attention hypothesis

The behavioral tendencies described above have implications for the dynamics of opening price formation. The attention hypothesis, which was developed most notably in the context of overnight returns by Berkman et al. (2012), suggests a mechanism that links the psychology of retail investors to predictable intraday return patterns. The hypothesis proceeds in two steps.

First, individual investors, who are disproportionately subject to attention-driven buying, overconfidence, and sentiment effects, tend to execute their purchases at market open. This concentration of retail buying at the open is partly mechanical. Retail investors who process news in the evening and submit a market-on-open order will have that order executed at the opening auction. Barber and Odean (2008) found that retail investors are more likely to buy attention-grabbing stocks and that dramatic overnight events, such as earnings announcements, large price gaps, and news coverage, trigger attention-driven buying. Since these investors are net buyers based on attention rather than information, their collective demand at the open creates buying pressure that temporarily pushes opening prices of attention-grabbing stocks above their fundamental values.

Second, as the trading day progresses, the attention-driven demand dissipates. More patient and better-informed participants, such as institutional investors, market makers rebalancing inventory, and algorithmic traders, gradually correct the distortion by selling against the inflated opening price. This correction process generates predictable intraday price reversals. Stocks that gap up dramatically overnight due to salient events are subsequently sold back toward their fundamental values during the intraday session. The reversal is not instantaneous because arbitrage against retail-driven distortions faces the aforementioned limits, but it is systematic enough to produce a detectable statistical relationship between overnight and intraday returns. Berkman et al. (2012) provide direct empirical evidence of this mechanism. They show that the hidden cost of buying at the open, which is measured by the difference between the opening price and the subsequent intraday average, is greatest for stocks that attract the most retail attention. This is especially true following large overnight price gaps.

Lou et al. (2019) expanded this framework by testing whether the dominant investor type at different times during the trading day could explain the split between overnight and intraday returns at the market level. They demonstrate that, on average, stocks held predominantly by retail investors generate positive overnight returns and negative intraday returns, while stocks held predominantly by institutional investors show the opposite pattern. This finding aligns with the attention hypothesis: retail-dominated stocks are subject to greater retail buying pressure at the open, while institutionally dominated stocks benefit from institutional buying, which tends to occur during the continuous session rather than the opening auction. Therefore, the mechanism linking investor identity to return dynamics is not simply attention, but rather, the timing of order submission by different participant types.

It is worth noting that, in contrast to the microstructural theory discussed in Chapter 2.2.4, the behavioral attention hypothesis suggests a different reason for price reversals. According to the microstructural theory, heightened costs at the market open would result in uninformed traders buying stocks later in the day rather than at the open. However, this is in stark contrast to more recent empirical literature, such as that by Berkman et al. (2012), which showed that retail investors often buy attention-grabbing stocks at the open.

2.3.4 Behavioral finance versus market efficiency

The behavioral finance framework does not merely exist to disprove the EMH. Rather, it seeks to refine and complicate the EMH by specifying the conditions under which prices diverge from fundamental values and the mechanisms by which prices eventually return to those values. Because any test of market efficiency is simultaneously a test of the underlying asset pricing model (Fama, 1991), no anomaly can ever definitively falsify the EMH. Supporters can always argue that the apparent inefficiency reflects an incomplete model of risk. This joint hypothesis problem means the disagreement between behavioralists and efficient-market proponents is unlikely to be resolved by any single empirical study. However, before facing that issue, one must first ask whether apparent anomalies survive transaction costs, out-of-sample testing, and robustness checks that reduce the role of data snooping.

The critique of behavioral evidence is compelling. Schwert (2003) documents a systematic pattern in which anomalies tend to weaken or disappear after academic publication. This pattern is consistent with either rational arbitrage eliminating the opportunity or data snooping generating false positives that do not survive out-of-sample testing. Harvey et al. (2016) argue that the problems of multiple testing in empirical finance is so severe that the minimum threshold for claiming a new anomaly should be a t-statistic of three or higher, rather than two. Hou et al. (2020) demonstrate through large-scale replication that most documented anomalies fail even modest statistical hurdles when microcap effects and equal-weighting bias are controlled for.

Yet, the behavioral case still has many supporters. The systematic relationship between investor type and the split between overnight and intraday returns, as documented by Lou et al. (2019), is difficult to explain without considering differences in behavior between retail and institutional investors. Barber and Odean's (2008) finding that retail investors are net buyers of attention-grabbing stocks and suffer poor performance as a result is consistent with cognitive bias rather than rational risk-bearing. The sentiment index developed by Baker and Wurgler (2006) is able to predict variations in returns that withstand standard risk adjustments, especially for stocks where behavioral distortions are thought to be most significant.

A more balanced position is that behavioral and rational forces coexist in financial markets. Investor psychology generates systematic demand pressures that create predictable price patterns. However, competitive pressure from better-informed and better-capitalized participants constrains and partially corrects these distortions. The duration of mispricings depends on the size of the behavioral demand relative to the capacity and risk tolerance of the rational corrective forces. This balance varies across securities, market conditions, and time. This perspective aligns closely with the Grossman-Stiglitz (1980) framework discussed earlier. According to this framework, markets can exhibit predictable patterns in equilibrium because eliminating those patterns requires costly arbitrage, and behavioral frictions are an important component of that cost.

3 Empirical evidence

3.1 The overnight-intraday return divergence

Before examining the literature on the predictability of overnight and intraday returns, it is helpful to establish the empirical context from which it emerges. While the separation of daily stock returns into their overnight and intraday components is a methodological convenience, it also reflects a genuine economic boundary: the transition between two fundamentally different mechanisms of price formation.

The most striking fact in this body of literature is the asymmetric distribution of the equity risk premium across trading and non-trading hours. Kelly and Clark (2011) were among the first to document this pattern. They showed that essentially all of the cumulative market return over their sample period was generated during non-trading hours. Meanwhile, the intraday session contributed a flat-to-negative cumulative return. Bearing only the overnight risk would have earned a return comparable to buying and holding. In contrast, bearing only the intraday risk would have essentially earned nothing. This creates an immediate puzzle for standard risk-return models: If the risk premium compensates investors for bearing volatility, why is the compensation concentrated during periods when trading is suspended?

Lou et al. (2019) expanded on this observation with a broad empirical and theoretical approach in their tug-of-war study. By examining the broad CRSP universe of U.S. stocks from 1993 to 2013, they documented the diverging cumulative return paths of the overnight and intraday sessions and connected them to the behavior of distinct investor populations. They demonstrated that overnight and intraday returns differ unconditionally and also showed that the cross-sectional relationship between a stock's overnight return and its subsequent intraday return is systematically negative. Additionally, they proposed the behavioral mechanisms related to investor heterogeneity through which this cross-sectional predictability arises.

Hendershott et al. (2020) offer a perspective on overnight and intraday returns using asset pricing theory. They demonstrate that the relationship between market risk (beta) and returns flips depending on the time of day. Specifically, beta is positively related to returns overnight (earning a rational risk premium), whereas it is negatively related to returns during the trading day (earning a discount). Rather than framing this divide around information versus microstructural risk, they attribute these distinct characteristics to differing clienteles: the marginal day investor acts as a risk-loving speculator who overpays for high-beta stocks, while the marginal night investor acts as a rational, long-term investor who demands compensation for bearing market risk. Furthermore, their empirical analysis reveals that the implied risk-free rate differs significantly between night and day, which helps explain the failure of the traditional 24-hour CAPM.

Berkman et al. (2012) examined the behavioral dimension of the debate, focusing on the role of retail investor attention in generating opening price distortions. They predicted that the retail buying pressure driving the reversal would be strongest for attention-grabbing stocks. To test this, they utilized the stock's squared return and the actual net retail buying from the previous day as their primary empirical proxies for attention. The researchers confirmed this prediction empirically by showing that the negative overnight-to-intraday relationship is substantially stronger for such stocks. Aboody et al. (2018) built on this research by extending it to firm-specific investor sentiment. They demonstrated that overnight returns are correlated with subsequent intraday, sentiment-driven trading in a manner consistent with the behavioral attention mechanism.

3.2 Recent studies on intraday predictability

The tug-of-war approach of Lou et al. (2019) sparked a substantial body of follow-up literature, and the empirical evidence on overnight and intraday predictability has grown considerably richer in the years since. Akbas et al. (2022) developed a direct measure of tug-of-war intensity: the frequency with which individual stocks experience positive overnight returns followed by negative intraday reversals. They showed that this intensity measure predicts future cross-sectional returns. Stocks that have recently experienced a high frequency of reversals subsequently underperform. This is consistent with the interpretation that persistent reversals reflect overcorrection by aggressive institutional daytime traders pushing back against opening demand from retail investors. This finding adds a predictive dimension to the tug-of-war phenomenon; the reversal is not only a within-day pattern, but also a signal about future expected returns.

Barardehi et al. (2025) propose a theoretically different approach: using the overnight/intraday decomposition to distinguish between public and private information flows. They argue that the overnight session, during which trading is sparse and dominated by informed participants, reveals private information relatively more than the intraday session, which reflects the broader market's gradual incorporation of that information. This interpretation provides a rational, information-processing explanation for the reversal that supplements the behavioral attention narrative. Some portion of the overnight-to-intraday reversal may result from the correction of pricing errors between informed and uninformed participants rather than from the activity of noise traders at the open.

Wang (2024) developed the aggregate sentiment dimension, examining the sentiment-return relationship across different times of day using international data. His finding that the negative sentiment-return relationship is stronger intraday than overnight aligns with the tug-of-war approach. It is during the trading session that the return consequences of sentiment-driven opening moves are realized as the market corrects toward fundamental values. Glasserman et al. (2025) added a news-based dimension to their study. They attributed the difference between overnight and intraday returns to two main reasons. The difference in news topics reported intraday compared to overnight. They also reported that the market's response to the same news is more positive when they are reported overnight compared to intraday.

Ham et al. (2022) also focus on the effects of overnight events on daytime trading sessions. They examine how the content and nature of overnight news shape intraday return dynamics. Their analysis reveals that overnight returns play a key role in identifying investor overreactions caused by concentrated news announcements. This finding aligns with the overreaction hypothesis as well as the attention hypothesis of Barber and Odean (2008) and suggests that extreme overnight gaps, especially around earnings announcements, lead to predictable intraday reversals.

Aleti and Bollerslev (2025) offer a high-frequency characterization of systematic risk, estimating an intraday SDF. Using neural networks to analyze a variety of high-frequency factors, the researchers linked significant intraday changes in the SDF to real-time economic news topics from newswires. The researchers found that the importance of specific news topics, particularly those related to monetary policy and finance, varies over time. The SDF exhibits significantly higher volatility during periods of high economic uncertainty. Contrary to theories of slow-moving capital, the researchers found that markets typically absorb information from timed news announcements within 15 minutes. Their findings support the theory of a time-varying risk premium, showing that investors' demand for compensation for news-related risks shifts dynamically with fundamental economic shocks.

Many of the explanations on the relationship between overnight and intraday returns attribute their findings to news or investor heterogeneity. Kallinterakis and Karaa (2022) on the other found a strong relationship between feedback trading and the overnight to intraday return reversals. Feedback trading is the practice of buying or selling based on historical price movements. They found that the feedback trading of the previous intraday (overnight) sessions explains the returns of the next overnight (intraday) session.

According to Bogousslavsky (2021), cross-sectional variation in stock returns is heavily influenced by institutional constraints and overnight risks faced by arbitrageurs. Rather than a simple tug-of-war between clienteles, the study found that mispricing factors generally earned positive returns overnight and throughout the morning but performed poorly during the last 30 minutes of the trading day. Direct price pressure drives this pattern: capital-constrained arbitrageurs seek to avoid higher overnight margin requirements and lending fees by reducing their positions before the market closes. This systematic selling (or covering) causes overpriced stocks to outperform and underpriced stocks to underperform at the end of the day. This suggests that high-frequency limits to arbitrage prevent mispricing from fully correcting and can actually cause it to temporarily worsen.

Zhao et al. (2025) found that the relationship between overnight and intraday sessions is complex and bidirectional, involving nonlinear Granger causality rather than a simple one-period reversal. The study demonstrates that both returns and volatility in one period contain robust predictive information for the subsequent period by applying a multiscale analysis framework across multiple indices. Trading volume was identified as a vital transmission channel that amplifies these causal links. The authors traced the driving forces of this causality to particular time-frequency components and found that return causality depends on the specific market's structure, with return causality driven by different scales, such as high and medium frequencies in the S&P 500. This complexity enriches the tug-of-war metaphor, suggesting that session-to-session predictability is embedded in a richer dynamic in which investor sentiment and risk perceptions spread across multiple time scales.

3.3 Microstructure explanations for intraday predictability

The behavioral rationale for the overnight-to-intraday reversal, retail attention-driven purchasing at the start of the day, is persuasive but lacking. While it explains the origin of the opening price distortion, it does not fully account for why institutional arbitrageurs do not immediately eliminate it. Market microstructure theory attempts to address this issue by identifying the costs and constraints that restrict the speed of arbitrage correction at market open.

Barclay and Hendershott (2003) laid the empirical groundwork for this argument in their study of price discovery during extended trading hours. By examining NASDAQ stocks from March through December of 2000, they discovered that, although pre-market trading volume is a small fraction of regular session trading volume, each pre-market trade contains more information than any individual regular session trade because the ratio of informed to uninformed trading is highest at that time. However, due to the lack of trading liquidity, pre-market price discovery is less efficient, resulting in stock prices that are more volatile than during the day. Overall, trading costs and bid-ask spreads are significantly higher during extended hours. Therefore, any strategy that attempts to exploit opening price distortions must pay these elevated spreads, which substantially raises the bar for profitability.

According to Bogousslavsky (2021), intraday return patterns are heavily influenced by the end-of-day behavior of arbitrageurs who trade on mispricing. These arbitrageurs face elevated margin requirements and lending fees for positions held overnight. Thus, they are incentivized to reduce their exposure toward the end of each trading day to manage these costs and risks. Since arbitrageurs usually hold long positions in underpriced stocks and short positions in overpriced stocks, this end-of-day unwinding generates predictable selling pressure for underpriced stocks and buying pressure for overpriced stocks. Consequently, overpriced stocks outperform and underpriced stocks underperform in the final 30 minutes of the trading day, effectively reversing the mispricing corrections that occurred earlier.

Boyarchenko et al. (2023) apply the inventory risk argument to an international context. They found that the overnight drift in U.S. equity returns is heavily concentrated during the opening hours of European markets. They attribute this phenomenon to the correction of inventory imbalances generated at the close of the previous U.S. trading day. Since insufficient trading volume exists during Asian overnight hours to absorb the substantial order imbalances from the U.S. close, U.S. market makers must hold these positions until a surge of new market participants arrives at the European open. Market makers who absorb selling pressure at the U.S. close are compensated for bearing this extended overnight inventory risk through a positive expected return, which drives prices up when they offload their inventory to European traders. This cross-market evidence is interesting because it attributes the overnight drift to inventory management by intermediaries rather than to the behavior of retail investors. This suggests that the phenomenon has a rational institutional component independent of behavioral factors.

Gao et al. (2018) document another form of intraday predictability: intraday momentum. They show that the return during the first half-hour of trading predicts the return during the last half-hour of trading in the same direction. This intraday momentum appears contradictory to the overnight-to-intraday reversal because it operates through different mechanisms. They attribute this phenomenon to two distinct economic behaviors. First, it reflects the infrequent portfolio rebalancing of institutional investors. Due to slow-moving capital, some institutions rebalance near the open, while others delay their rebalancing trades until the close. This creates similar directional price pressure at both times. Second, it is driven by late-informed investors who slowly process early morning news and choose to execute their trades during the highly liquid last half-hour to avoid overnight risk. The coexistence of across-day reversal and within-day momentum in the same market reflects the complexity of intraday return dynamics.

Lu et al. (2023) examine the role of heterogeneous liquidity providers, specifically fast versus slow arbitrageurs. Their analysis shows that, at market open, fast arbitrageurs (e.g., market makers) exploit their informational advantage by "cream-skimming" uninformed order flows. They demand high price deviations to compensate for inventory risk. Although slow arbitrageurs (e.g., large asset managers) have lower inventory costs, they are deterred from competing at market open due to the risk of cream-skimming, causing opening prices to deviate from fundamental values. As information asymmetry subsides throughout the trading day, slow arbitrageurs can undercut fast agents and provide cheaper liquidity. This shift in marginal liquidity providers results in predictable opposite-signed overnight and intraday returns, even when order imbalances persist in the same direction throughout the day.

3.4 The role of market rules and international evidence

Evidence from markets with fundamentally different structures best illustrates how dependent overnight return patterns are on institutional trading rules. For instance, China's T+1 trading rule, which restricts investors from selling shares on the day of purchase, establishes an unparalleled asymmetric constraint in U.S. markets. According to Qiao and Dam (2020), this rule causes the inversion of China's overnight returns, which are consistently negative. This is in direct contrast to the pattern seen in the U.S. Specifically, the rule prevents buyers at market open from executing intraday reversal trades to take profits or stop losses on the same day. Conversely, traders who purchase shares just before the previous day's close face no such constraints and can sell at any time during the current day. Since buyers at the open are restricted, morning demand decreases, and they demand a price discount relative to yesterday's closing price at the opening bell. This suppresses the opening price, generating a negative overnight return. This T+1 discount gradually dissipates over the course of the day and is fully eliminated by the close. Thus, it simultaneously generates a positive daytime return. This inversion of the overnight-intraday relationship demonstrates that this phenomenon is a result of the specific trading rules that govern the market.

Lin et al. (2023) built upon this analysis by investigating whether traditional asset pricing anomalies in China follow the same pattern of being more prevalent overnight than during the intraday session as is observed in the U.S. However, they found mixed results rather than a complete inversion of this pattern. Unlike in the U.S., where anomalies are concentrated in the intraday session, Chinese anomalies are more evenly distributed between the overnight and intraday sessions. This overnight persistence is thought to be driven by Chinese market features. China's T+1 trading rule prevents daytime arbitrageurs from executing same-day trades to arbitrage away this overnight information immediately. Consequently, anomaly return premia become trapped and are more persistent during the overnight session. This contrasts with the pattern in the U.S., where unrestricted day trading can more quickly correct the overnight mispricing.

Ma et al. (2025) exemplify the susceptibility of these patterns to changes in trading regulations. They capitalized on the initiation of a nightly trading session in Chinese precious metals markets. Before this change, the first half-hour of the daytime session was the main predictor of subsequent intraday returns because domestic investors had to wait until the morning opening to respond to international price changes. However, after the introduction of night trading, this predictive power migrated to the first half-hour of the night session, enabling investors to promptly respond to global news. Furthermore, they document that these predictive patterns involve intraday reversals driven by liquidity oversupply from uninformed retail traders that actually precede intraday momentum. Following the regulatory change, the sequence shifted so that reversals now occur during the night session and momentum occurs during the early daytime session.

Hajiyev et al. (2024) examined the tug-of-war phenomenon in G7 stock markets to determine whether the predictability observed in U.S. stocks extends to other developed markets. Instead of finding a pervasive pattern of varying intensity, the authors discovered a clear geographic divide. The intensity of the daily tug-of-war strongly predicts future returns in North American markets but not in the other G7 countries. The authors attribute this difference to variations in retail participation and institutional regulations. European and Japanese markets have less retail noise trading and are subject to stricter short-selling constraints, limiting the ability of daytime institutional arbitrageurs to overcorrect prices. Furthermore, by analyzing the introduction of the Integrated Fee Model in Canada, which reduced the price impact of large institutional trades and subsequently eliminated the predictability of the tug-of-war, the authors determined that the magnitude of the reversal depends heavily on the regulatory environment and unrestricted capacity for daytime institutional overcorrection. These international comparisons are valuable for identifying how local market microstructures modulate the reversal and highlight that findings from the U.S. market cannot simply be transferred abroad.

3.5 Critiques of anomaly studies

The literature reviewed in the previous sections reveals a variety of predictable patterns in intraday and overnight returns. However, before drawing conclusions from this evidence, it is important to seriously consider the critiques leveled against anomaly studies in general, as the overnight-to-intraday reversal is not immune to these concerns.

The joint hypothesis problem, as discussed earlier, poses a fundamental challenge. The overnight-to-intraday reversal is an example of this problem. The predictable negative intraday return following a high overnight return could be caused by irrational opening price formation. It could also be caused by a rational difference in risk exposure between the overnight and intraday periods. Another possibility is time-varying risk premium that standard models fail to capture. Hendershott et al. (2020) address this possibility, documenting systematic differences in the market risk (CAPM beta) of overnight and intraday returns. However, whether the reversal coefficient reflects mispricing or a missing risk factor cannot be determined based on the data alone.

The data snooping problem is particularly relevant for studies that divide the trading day into multiple periods. However, the overnight-to-intraday reversal is somewhat shielded from this concern because the hypothesis was based on theory before examining the data. Berkman et al. (2012) extended the retail attention mechanism of Barber and Odean (2008) to provide clear ex ante predictions regarding price pressure at the open, while Lou et al. (2019) established the structural tug-of-war approach.

The microcap problem identified by Hou et al. (2020) is directly relevant to the methodology of this thesis, which employs a wide range of companies of different sizes. Their study concluded that many apparent anomalies stem from data on companies that are so small they may not be investable. Ince and Porter (2006) raise practical concerns about the quality of data from databases such as LSEG Datastream (formerly Thomson Datastream), which is especially significant since the data for this thesis was downloaded from that database.

The post-publication decay documented by McLean and Pontiff (2016) raises the question of whether the reversal identified in earlier studies persists during a more recent time period. Rolling coefficient analysis confirms that the reversal has been present and statistically significant every year from 2011 to 2024. The mild attenuation after 2021 is consistent with the idea that practitioners have incorporated this insight into their trading strategies. However, the phenomenon has not disappeared. This persistence, combined with the transaction cost analysis showing that the gross reversal cannot be exploited for profit, is consistent with the limits-to-arbitrage approach. According to this approach, anomalies that survive post-publication decay are typically those where the costs of exploitation are too high to attract sufficient arbitrage capital.

4 Data and methodology

4.1 Data sample and sources

The sample universe is constructed from the stocks that have been included in the Russell 3000 Index, a broad-market benchmark covering approximately 98 percent of the total market capitalization of all publicly traded U.S. stocks. The selection of the Russell 3000 over narrower alternatives, most notably the S&P 500, was deliberate. Since one of the analysis's goals is to examine how firm size moderates opening price dynamics, a sample restricted to large-cap stocks would prevent meaningful size analysis. The Russell 3000 provides a wide spectrum of market capitalizations, enabling a more thorough analysis of how firm-specific characteristics influence the relationship between overnight and intraday prices.

In any study of historical equity returns, a major risk is survivorship bias. This bias arises when the sample is restricted to firms that remained continuously listed throughout the observation period. This exclusion includes companies that were delisted, merged, or acquired. Brown et al. (1992) demonstrate that survivorship-biased samples systematically overestimate average returns and underestimate volatility. To address this issue, the sample was constructed using annual point-in-time constituent lists instead of the current index composition. The holdings of the Vanguard Russell 3000 ETF (ticker symbol VTHR) were obtained each December from 2011 through 2024. Any stock that appeared on at least one of the annual lists was kept in the sample for the relevant periods. Stocks removed from the ETF were not dropped from the panel if they remained tradable.

All market data were retrieved from the LSEG Datastream database. The observation period spans fourteen years, from January 1, 2011, to December 31, 2024, and includes meaningful market changes, such as the low-volatility bull market of the mid-2010s, the extreme volatility of the 2020 pandemic, and the inflationary period of the early 2020s. For each stock, the following data were retrieved: daily opening, high, low, and closing prices (OHLCV), daily market capitalization, and volume-weighted average price (VWAP). The CBOE Volatility Index (VIX) was included as a proxy for market-wide uncertainty and investor fear (Whaley, 2000).

The absence of directly quoted bid and ask prices in the dataset is one data limitation that shapes several methodological choices down the line. Since transaction costs cannot be measured directly, they will be estimated using the Corwin-Schultz (2012) high-low spread estimator from price data. The computation of this variable is detailed in chapter 4.3.2

4.2 Data cleaning and filtering

Large-scale financial databases are known to contain errors that can distort empirical results if left unaddressed. For this reason, the raw data underwent a multi-stage filtering procedure. Initially, the raw dataset comprised 12,807,087 observations.

The filtering steps are summarized in Tables 1 and 2. First, observations with missing values in any core field (price, volume, VWAP, or market capitalization) were removed. Second, observations with logical price inconsistencies were excluded. These inconsistencies included negative prices, daily high prices recorded below daily low prices, and non-positive market capitalization. Third, to reduce the influence of bid-ask bounce and microstructural noise disproportionately affecting very low-priced securities, penny stocks with an opening price below one dollar were removed. Fourth, we applied a minimum dollar volume threshold: observations where the product of daily share volume and VWAP fell below $50,000 were excluded, following the investability criterion of Hou et al. (2020). Fifth, observations on non-consecutive trading days were removed because overnight returns can only be computed meaningfully between adjacent trading days. Finally, observations where any of the three return components (overnight, intraday, or close-to-close) fell outside the range of −100% to +200% were removed, following the hard-filter methodology of Hendershott et al. (2020).

Table 1 Summary of data filtering criteria

This table summarises the filtering procedure applied to the raw LSEG Datastream extract of Russell 3000 constituents from 2011 to 2024. Each filter category specifies the applied restriction and its motivation.

Filter Category	Applied Restriction	Purpose
Minimum Price	Opening Price ≥ $1.00	Excludes penny stocks to reduce effect of bid-ask bounce and microstructural noise.
Liquidity	Volume × VWAP ≥ $50,000	Removes highly illiquid tickers.
Data Continuity	t - (t-1) = 1	Ensures overnight returns are calculated between consecutive trading days only.
Extreme Outliers	-100% ≤ R ≤ +200%	Eliminates extreme outliers and erroneous data points following Hendershott et al. (2020).

The hard-filter approach was chosen over simple winsorization, which was used as a robustness check. The study focuses on large overnight gaps, which are located in the tails of the overnight return distribution. Applying winsorization at a fixed percentile would attenuate or eliminate the observations most central to the research question. The applied bounds are hopefully wide enough to retain extreme overnight events, such as pharmaceutical announcements and earnings surprises, while removing observations that almost certainly reflect data errors rather than real price movements.

After filtering, the final dataset comprises 9,745,248 daily observations from 4,392 distinct companies spanning 3,521 trading days. There are several limitations of this dataset that are worth noting. As mentioned earlier, the spreads must be estimated. Additionally, a significant portion of the raw observations were discarded due to missing market capitalization or VWAP data. If the availability of data is systematically related to firm size or liquidity, the filtered dataset may underrepresent the smallest and least liquid stocks, even considering the applied filters. Finally, due to the large volume of data, manually verifying individual observations is not feasible, so the possibility of unnoticed data errors cannot be ruled out.

Table 2 Data filtering summary

This table reports the number of observations removed at each step of the data cleaning procedure. Initial observations refer to the raw LSEG Datastream extract before any filters are applied. The final observation count is the sample used in all subsequent empirical analyses.

Step / Description	Observations / Count
0. Total Raw Observations	12,807,087
1. Missing Core Fields (NaN)	1,849,756
2. Price Inconsistencies / Neg Market Cap	6,581
3. Penny Stocks (< $1.00)	123,886
4. Dollar Volume Filter (< $50k)	882,814
5. Observations Lost to Non-Consecutive Days	198,712
6. Hendershott Return Outliers (-100% to +200%)	90
Final observation count (N)	9,745,248
Total unique tickers	4,392
Total unique trading days	3,521

4.3 Hypotheses

Based on the theoretical frameworks developed in Chapter 2 and the empirical evidence reviewed in Chapter 3, the following specific, testable hypotheses guide the empirical analysis:

H1 (Reversal hypothesis): The coefficient on R_{ON} in a regression of R_{ID} on R_{ON} and controls is negative and statistically significant, indicating that overnight price gaps are systematically and partially reversed during the subsequent intraday session.

H2a (Size/attention hypothesis): In the full interaction model, the coefficient on Int_Size is positive when estimated without liquidity controls (i.e., the reversal weakens as firm size increases, consistent with the behavioral attention mechanism), but this relationship may change sign when liquidity is simultaneously controlled for, reflecting the empirical collinearity between size and liquidity.

H2b (Limits-to-arbitrage hypothesis): The coefficient on Int_VIX is negative, indicating that the reversal intensifies during periods of elevated market-wide uncertainty consistent with tighter arbitrage constraints.

H3 (Transaction cost hypothesis): After deducting estimated round-trip execution costs and trading commissions, the net alpha from a centile long-short strategy is negative. This suggests that the statistical predictability of H1 does not translate into an exploitable trading profit under this simple trading strategy.

4.4 Variable definitions

4.4.1 Primary return components

To quantitatively analyze the relationship between overnight price gaps and intraday performance, daily returns must be defined. In line with the conventions of market microstructure literature (e.g., Lou et al., 2019; Hendershott et al., 2020), this study defines the trading cycle as consisting of two distinct periods: the non-trading (overnight) session and the continuous trading (intraday) session.

The primary independent variable in this study is the overnight return R_{ON}, which serves as a proxy for the information accumulation and sentiment shifts that occur while the primary exchange is closed. For a given security i on trading day t, the overnight return is calculated as the arithmetic percentage change from the official closing price of the preceding trading day $(t-1)$ to the official opening price of the current day (t). Mathematically, this is expressed as follows:

$$R_{ON,i,t} = \frac{P_{open,i,t} - P_{close,i,t-1}}{P_{close,i,t-1}}$$

The dependent variable is the intraday return R_{ID}, which captures the price discovery process and potential reversal dynamics during the regular trading hours. It is defined as the arithmetic change from the market opening to the market close on the same day The same logic is used to define the close-to-close returns R_{C2C}:

$$R_{ID,i,t} = \frac{P_{close,i,t} - P_{open,i,t}}{P_{open,i,t}}$$

$$R_{C2C,i,t} = \frac{P_{close,i,t} - P_{close,i,t-1}}{P_{close,i,t-1}}$$

The main empirical tests in this study are done using arithmetic returns. This approach follows previous studies like Hendershott et al. (2020), Lou et al. (2019) and Akbas et al. (2022). To make sure that the choice of return definition does not drive the findings, the main regression model is re-estimated using log-transformed returns.

4.4.2 Control variables

Several control factors are integrated into the empirical models to mitigate the confounding effects of omitted variables or microstructural noise on the estimated relationship between R_{ON} and R_{ID}. These variables are selected based on their proven ability to explain the cross-section of expected returns and the limits of arbitrage.

Firm Size (Log_Size) is defined as the natural logarithm of total market capitalization at the start of the trading day. The logarithmic transformation reduces the right skew of the raw distribution, which spans several orders of magnitude across the Russell 3000. Firm size serves as a proxy for retail investor attention and institutional coverage. Smaller firms attract less analyst coverage and are more susceptible to noise-driven price distortions at market open (Berkman et al., 2012; Akbas et al., 2022).

$$Log\_Size_{i,t} = ln(Market\_Cap_{i,t})$$

Liquidity ($Log\_Dollarvolume$) is measured as the natural logarithm of the dollar trading volume, calculated as the product of the share volume and the VWAP (following the intuition of Amihud, 2002). A higher dollar volume is associated with narrower bid-ask spreads, more competitive market making, and faster, more efficient price discovery (Barclay & Hendershott, 2003). Because highly liquid stocks are less susceptible to speculative retail trading, these factors are expected to reduce the scope for opening price distortions to persist and dampen the magnitude of the subsequent reversal (Berkman et al., 2012; Akbas et al., 2022).

$$Log\_Dollarvolume_{i,t} = ln\left(Volume_{i,t} \times VWAP_{i,t}\right)$$

Market volatility (VIX) is the daily level of the CBOE Volatility Index. Under the limits-to-arbitrage framework, elevated uncertainty increases the inventory risk faced by market makers and tightens the capital and margin constraints of institutional arbitrageurs (Shleifer & Vishny, 1997; Brunnermeier & Pedersen, 2009). Consequently, a high VIX limits the risk-bearing capacity of liquidity providers, which is empirically expected to amplify opening price distortions and the subsequent return reversal (Boyarchenko, et al. 2023).

The Amihud illiquidity ratio ($Amihud$) measures the average daily price impact per unit of trading volume. Following Amihud (2002), it is calculated as the absolute daily close-to-close return divided by daily dollar volume. Because a single daily observation is highly noisy and calculating it on the prediction day introduces look-ahead bias, we measure illiquidity as a predetermined firm characteristic. Specifically, we calculate the Amihud ratio over the previous five-day window ending at day $t - 1$ (Gao et al., 2018). A higher value indicates greater adverse selection and inventory costs, reflecting stocks that are more susceptible to speculative retail trading. Because it is harder for daytime arbitrageurs to seamlessly correct mispricing in these stocks, high illiquidity is expected to amplify the magnitude of the subsequent intraday return reversal (Akbas et al., 2022). Specifically, for stock i on day t, the Amihud ratio is defined as:

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum_{d=t-W}^{t-1} \frac{\left|R_{C2C,i,d}\right|}{Dollar\_Volume_{i,d}} \times 10^6$$

where W is the lookback window of prior trading days (e.g., 5 days), $N_{i,t}$ is the number of valid trading days with non-zero volume.

Corwin-Schultz spread (CS_Spread) proxies the proportional bid-ask spread in the absence of directly quoted prices. The estimator exploits the insight that the ratio of the daily high to the daily low price over a two-day rolling window reflects both fundamental return volatility and the bid-ask spread, under the assumption that daily highs tend to occur at the ask price and daily lows at the bid (Corwin & Schultz, 2012). Let H and L denote the daily high and low prices, respectively. The key intermediate quantities are:

$$\beta = \sum_{j=0}^{1} \left[ln \left(\frac{H_{t-j}}{L_{t-j}} \right) \right]^2$$

$$\gamma = \left[ln \left(\frac{H_{t,t-1}}{L_{t,t-1}} \right) \right]^2$$

where $H_{t,t-1}$ and $L_{t,t-1}$ are the two-day high and low respectively. The spread estimate is:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$Spread\_CS = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}$$

Negative spread estimates are set to zero and the distribution is winsorized at the 99th percentile, which to limit the influence of data errors.

Mean-centering of moderating variables: To ensure that the main effect of R_{ON} in interaction models represents the reversal for a stock with average characteristics, and to reduce multicollinearity between the main effects and the interaction terms, all continuous moderating variables, $Log\_size, Log\_Dollarvolume, VIX, Amihud$ and $Spread\_CS$ are mean-centered at the full-sample mean prior to the construction of interaction terms, following Aiken and West (1991):

$$X_{i,t}^{c} = X_{i,t} - \bar{X}$$

The interaction terms used in the models take the following form:

$$Int\_Size_{i,t} = R_{ON,i,t} \times Log\_Size_{i,t}^{c}$$

$$Int\_VIX_{i,t} = R_{ON,i,t} \times VIX_{t}^{c}$$

$$Int\_Vol_{i,t} = R_{ON,i,t} \times Log\_Dollarvolume_{i,t}^{c}$$

$$Int\_Amihud_{i,t} = R_{ON,i,t} \times Amihud_{i,t}^{c}$$

The model uses interaction terms that allow the sensitivity of intraday returns to vary systematically according to firm-specific and market-wide characteristics. Rather than testing for direct effects, these interactions examine how the slope of the intraday-overnight return relationship changes in different contexts. The interaction with firm size tests the behavioral attention hypothesis. A positive coefficient indicates that reversals are weaker for larger firms, which is consistent with the idea that stocks with high institutional coverage experience less price distortion driven by retail investors at the open. Conversely, a negative interaction suggests that reversals are amplified in larger firms, indicating institutional herding or algorithmic mechanisms.

To test the limits-to-arbitrage framework, the model includes an interaction with the VIX. A negative coefficient on this term confirms that reversals intensify during market stress because of elevated uncertainty, wider spreads, and tighter capital constraints allow opening distortions to persist and correct more sharply subsequently.

Furthermore, the interaction with trading volume assesses the liquidity effect. A positive coefficient indicates that faster price discovery in liquid stocks dampens opening distortions, resulting in weaker reversals. Simultaneously estimating these interaction terms serves as a dominance test, identifying which moderating channel retains explanatory power once the others are controlled for. This distinguishes between behavioral, liquidity-based, and limits-to-arbitrage explanations.

4.5 Empirical models

4.5.1 Regression models

The primary estimation strategy employs Panel OLS with day fixed effects. The baseline panel specification is:

$$R_{ID,i,t} = \alpha_t + \beta_1 R_{ON,i,t} + \varepsilon_{i,t}$$

Where α_t is the day fixed effect absorbed via within-day demeaning. The baseline model is extended to include a set of control variables.

$$R_{ID,i,t} = \alpha_t + \beta_1 R_{ON,i,t} + \sum_{k=1}^{K} \beta_k X_{k,i,t}^{c} + \varepsilon_{i,t}$$

where $X_{k,i,t}$ is the vector of control variables, comprising of $Log\_size, Log\_Dollarvolume,$ the Amihud illiquidity ratio, and the Corwin-Schultz spread.

One challenge is cross-sectional correlation: on any given day, residuals across firms are likely correlated due to shared industry exposures or common factors not fully absorbed by the day fixed effect. An additional concern is serial correlation within firms over time. Standard OLS standard errors would be anticonservative in this setting. The model is therefore estimated with standard errors double-clustered at the firm and trading day level, as recommended by Petersen (2008). This allows for arbitrary correlation patterns among firms within the same session as well as persistence in firm-level residuals across time and provides the most conservative available assessment of statistical significance.

Beyond the baseline relationship, the study investigates the structural drivers of the reversal through a series of multivariate specifications incorporating interaction terms. The most advanced specification simultaneously tests all proposed moderators:

$$R_{ID,i,t} = \alpha_t + \beta_1 R_{ON,i,t} + \beta_2\left(Int\_Size_{i,t}\right) + \beta_3\left(Int\_VIX_{i,t}\right) + \beta_4\left(Int\_Vol_{i,t}\right) + \beta_5\left(Int\_Amihud_{i,t}\right) + \sum_{k=1}^{K} \beta_k X_{k,i,t}^{c} + \varepsilon_{i,t}$$

where the interaction terms $Int\_Size_{i,t}$, $Int\_VIX_{i,t}$, $Int\_Vol_{i,t}$ and $Int\_Amihud_{i,t}$ are as defined in section 4.3.2 above, and $X_{k,i,t}^{c}$ denotes the vector of mean-centered control variables ($Log\_size, Log\_Dollarvolume,$ the Amihud illiquidity ratio, and the Corwin-Schultz spread).

This full specification serves as a dominance test, determining which moderating variables retains explanatory power once the others are controlled for, and thereby distinguishing between the behavioral, limits-to-arbitrage, and liquidity-based explanations.

4.5.2 Risk-adjusted performance models

To determine if the returns generated by a reversal-based strategy constitute abnormal returns or are merely compensation for systematic risk, the study utilizes the Fama-French Five-Factor Model (2015). The daily returns of the Long-Short portfolios ($R_{p,t}$) are regressed against the five primary factors:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1\left(Mkt - R_f\right)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t$$

where α represents the daily abnormal return; $\left(Mkt - R_f\right)$ is the market risk premium; SMB (Small Minus Big) accounts for size risk; HML (High Minus Low) accounts for value risk; RMW (Robust Minus Weak) accounts for profitability risk; and CMA (Conservative Minus Aggressive) accounts for investment risk. A statistically significant positive α in this model would confirm that the overnight-intraday reversal anomaly represents a genuine pricing inefficiency unexplained by standard asset pricing models. These alpha tests are estimated using Newey-West corrected standard errors.

4.5.3 Portfolio sorts

Portfolio sorts complement the regression analysis on the relationship between R_{ON} and R_{ID}. The strategy is constructed daily based on the cross-sectional ranking of overnight returns. At each trading day t, all stocks in the cross-section are sorted by their realized $R_{ON,i,t}$ into $N = 100$ equally populated centile portfolios. The portfolio labelled P_1contains the one percent of stocks with the lowest overnight returns on day t (those that opened with the largest negative gaps relative to the previous close), and the portfolio labelled P_{100} contains the one percent of stocks with the highest overnight returns (the largest positive gaps). Under the reversal hypothesis H1, P_1 is expected to deliver positive mean intraday returns as the negative gap is partially corrected upward during the session, while P_{100} is expected to deliver negative mean intraday returns as the positive gap is partially corrected downward.

The daily gross return of the long-short strategy is defined as the difference between the equal-weighted mean intraday return of P_1 and that of P_{100}:

$$Gross_t = \bar{R}_{ID,P_1,t} - \bar{R}_{ID,P_{100},t}$$

where $\bar{R}_{ID,P_j,t}$ is the equal-weighted mean intraday return on day t of the j-th overnight return centile portfolio. The portfolios are reformed each day using only information observable at market open, so the strategy is fully implementable in real time.

4.5.4 Transaction cost estimation

The Corwin-Schultz spread estimator is applied to evaluate whether the statistical predictability of the overnight-to-intraday reversal translates into economically exploitable trading profits. The net daily strategy return is:

$$Net_t = Gross_t - Spread\_CS_{P1,t} - Spread\_CS_{P100,t} - Commission$$

The spread cost for each leg reflects the total cost of executing a round trip: entering a position by crossing half of the bid-ask spread at the open, and exiting by crossing the other half of the spread at the close. These two half-spread crossings sum to one full proportional spread per leg. When applied to both the long leg (P1) and the short leg (P100), the total spread cost per day equals the sum of the two estimated Corwin-Schultz spreads. Commission is modeled at 5 basis points per one-way trade, consistent with a low-cost institutional broker, for a total of 20 basis points per day across four one-way trades (two opens and two closes for the two legs). No borrow cost is assumed for the intraday short leg.

4.5.5 Robustness and stability

Several robustness checks are done to assess the sensitivity of the primary findings to methodological choices and specific sample conditions. First, the baseline panel OLS is re-estimated using winsorized returns at the first and ninety-ninth percentiles rather than the Hendershott hard filter to test whether the results are driven by extreme tail observations that the hard filter preserves. Second, the decile long-short strategy is constructed using value-weighted rather than equally weighted portfolio returns. This addresses the concern of Hou et al. (2020) that equally weighted results in large panels are disproportionately influenced by the smallest and least investable stocks. Third, the baseline regression is estimated separately for three market capitalization terciles—small, mid, and large cap—to determine if the phenomenon is more prevalent in smaller firms. Fourth, the year 2020 is excluded to confirm that the primary findings are not due to the spike in volatility caused by the onset of the pandemic. Finally, all primary specifications are re-estimated using logarithmic returns.

To test whether the market responds asymmetrically to positive versus negative overnight gaps, as predicted by the existence of short-selling constraints, an indicator variable D_{pos} is defined:

$$D_{pos,i,t} = \mathbb{1}\{R_{ON,i,t} > 0\}$$

The asymmetric regression model is then:

$$R_{(ID,i,t)} = \alpha_t + \beta_1\big(R_{(ON,i,t)} \cdot D_{(pos,i,t)}\big) + \beta_2\left(R_{(ON,i,t)} \cdot \big(1 - D_{(pos,i,t)}\big)\right) + \gamma' X_{i,t} + \varepsilon_{i,t}$$

Under the short-selling constraint hypothesis, correcting positive gaps requires short selling and should therefore produce a smaller reversal coefficient in absolute terms than correcting negative gaps. The temporal stability of the reversal is examined by estimating the following cross-sectional specification for each calendar year T:

$$R_{ID,i,t} = \gamma_{0,T} + \gamma_{1,T} R_{ON,i,t} + \epsilon_{i,t}, \quad \forall t \in Year_T$$

This decomposition tests whether the reversal is a persistent structural feature of U.S. equity market microstructure or concentrated in specific market regimes.

5 Empirical results

5.1 Descriptive statistics

The final dataset covers Russell 3000 constituents from 2011 to 2024 and contains nearly ten million daily observations across over four thousand unique companies and more than three thousand trading days. Table 3 presents the summary statistics.

The most notable feature of the data is the difference in average returns between the two trading sessions. The mean overnight return is positive, whereas the mean intraday return is negative. The findings of Lou et al. (2019) and Kelly and Clark (2011) are replicated by this unconditional asymmetry, positive returns accruing outside of regular trading hours, and flat-to-negative returns during the session itself. For this dataset, the risk premium appears to have been realized almost entirely outside of regular trading hours.

The two return series differ substantially in dispersion. Intraday returns are considerably more volatile than overnight returns. This is consistent with the microstructure literature's view that return variance is primarily driven by active trading and informed order flow, rather than by the mere passage of time.

Both series exhibit severe non-normality, with overnight returns showing particularly extreme fat tails, which could possibly be driven by event-driven gap events, such as earnings announcements, clinical trial results, and macroeconomic surprises, that occur outside trading hours. Market capitalization data reveals the wide cross-sectional range of the sample.

Market capitalization data reveals the wide range of firm sizes within the sample. The large gap between the median and mean firm size reflects the right skew of the size distribution; a relatively small number of large-cap firms pull the mean far above the typical observation. The Amihud illiquidity ratio and the Corwin-Schultz spread estimates both show substantial heterogeneity, confirming that liquidity varies enormously across the sample. This heterogeneity is important when interpreting the transaction cost analysis: the extreme-centile portfolios used in the strategy tests will disproportionately draw from the illiquid tail of the distribution.

Table 3 Descriptive statistics

This table reports summary statistics for the variables used in the empirical analysis. The sample consists of daily observations on Russell 3000 constituents from January 2011 to December 2024. R_{ON} denotes the overnight return (previous close to open), R_{ID} denotes the intraday return (open to close), and R_{C2C} denotes the close-to-close return, all expressed in percent. VIX is the daily level of the CBOE Volatility Index. Amihud is the five-day rolling Amihud illiquidity ratio ending at $t-1$, expressed in units of 10^6. $Spread\_CS$ is the proportional Corwin-Schultz spread estimate in percent.

Statistic	R_{ON} (%)	R_{ID} (%)	R_{C2C} (%)	$Mkt\ Cap$ ($M)	$Dollar\ Vol$ ($M)	VIX	$Amihud$	$Spread\_CS$ (%)
count	9,745,248	9,745,248	9,745,248	9,745,248	9,745,248	9,745,248	9,745,248	9,740,856
mean	0.07	-0.02	0.05	11,430	23.42	18.32	0.03	0.75
median	0.02	0.00	0.00	1,627	3.69	16.41	0.00	0.21
std	1.87	2.93	3.43	64,087	127.66	7.09	0.10	1.14
min	-93.08	-89.49	-93.30	0.01	0.05	9.14	0.00	0.00
max	197.01	197.18	199.73	3,915,300	68,862.98	82.69	6.82	5.85
skewness	7.46	1.60	2.73	25.54	54.46	2.51	6.84	2.19
kurtosis	693.63	59.46	118.31	921.57	11,895.96	12.01	99.79	5.33

The Pearson correlation matrix (Table 4) offers an initial test of the primary hypothesis in terms of direction. The correlation between overnight and intraday returns is negative. This offers initial evidence of a systematic reversal tendency: stocks that open above their previous close, on average, give back some of that gain during the trading day. The high correlation between market capitalization and dollar volume confirms that larger firms are substantially more liquid. This motivates their simultaneous inclusion as controls rather than treating them as interchangeable proxies.

Table 4 Pearson correlation matrix

This table reports the Pearson correlation coefficients between the return components as well as the control variables defined in chapter 4.4.

	R_{ON}	R_{ID}	R_{C2C}	$Mkt\ Cap$	$Dollar\ Vol$	VIX	$Amihud$	$Spread\_CS$
R_{ON}	1.0000							
R_{ID}	-0.0304	1.0000						
R_{C2C}	0.5091	0.8417	1.0000					
$Mkt\ Cap$	-0.0017	0.0032	0.0019	1.0000				
$Dollar\ Vol$	0.0077	0.0043	0.0080	0.7106	1.0000			
VIX	-0.0492	-0.0351	-0.0563	-0.0010	0.0213	1.0000		
$Amihud$	0.0387	-0.0051	0.0152	-0.0658	-0.0680	0.0773	1.0000	
$Spread\_CS$	0.0190	-0.0135	-0.0046	-0.0428	-0.0267	0.1336	0.1495	1.0000

5.2 Diagnostic tests of the regression model

Table 5 reports the results of five diagnostic tests conducted on the pooled OLS baseline specification. The results are consistent with what one would expect from a large financial panel with cross-sectionally correlated returns. There is not severe multicollinearity among the regressors. The residuals are strongly non-normal and heteroskedastic, which justifies robust inference throughout. Though residual autocorrelation is not severe, the Durbin-Watson statistic in a stacked panel captures both within-ticker serial correlation and artificial transitions between tickers and should not be overinterpreted as a precise quantification. Finally, the poolability test strongly rejects the null hypothesis that all day-specific intercepts are equal. This confirms that market-wide conditions vary significantly from day to day, affecting all stocks simultaneously. Thus, including day fixed effects is essential to isolating the firm-specific overnight signal from aggregate market noise.

Table 5 Regression diagnostic tests

This table reports five diagnostic tests conducted on the pooled OLS baseline specification. The Variance Inflation Factor (VIF) tests for multicollinearity among regressors. The Jarque-Bera test examines whether residuals are normally distributed. The Breusch-Pagan test detects heteroskedasticity in residuals. The Durbin-Watson statistic measures residual autocorrelation. The poolability F-test compares the pooled OLS specification against the day-fixed-effects specification, testing whether all day-specific intercepts are equal. Rejection of poolability motivates the inclusion of day fixed effects in all subsequent specifications.

Test	Statistic	p-value	Conclusion
Multicollinearity (VIF)	Max VIF: 4.56	N/A	No severe collinearity
Normality (Jarque-Bera)	9.29e+08	<0.001	Non-normal (fat tails)
Heteroskedasticity (Breusch-Pagan)	292,534.66	<0.001	Heteroskedastic. Use robust standard errors
Autocorrelation (Durbin-Watson)	1.9935	N/A	Slight positive autocorrelation
Poolability (F-Test)	482.57	<0.001	Use day fixed effects

5.3 Main regression results

Table 6 presents the primary regression results. The five specifications estimated, corresponding to Columns (1) through (5) of Table 6, proceed as follows: Column (1) is the univariate baseline containing only R_{ON} and day fixed effects. Column (2) adds the full set of microstructure controls without interactions; Column (3) adds the firm size interaction; Column (4) replaces the size interaction with the VIX interaction; Column (5) is the full model containing all four interaction terms simultaneously alongside the controls.

The coefficient on the overnight return is negative and statistically significant across all five specifications, providing support for the existence of the overnight-to-intraday reversal as stated in H1. However, several features of the results warrant careful interpretation before drawing conclusions.

Table 6 Main regression results

This table reports panel OLS estimates of the relationship between overnight returns and same-day intraday returns. The dependent variable is the intraday return R_{ID}. Column (1) is the univariate baseline; Column (2) adds a set of microstructure controls without interactions; Column (3) adds the firm size interaction; Column (4) replaces the size interaction with the VIX interaction; Column (5) is the full specification containing all four interaction terms simultaneously alongside the controls. All specifications include day fixed effects. Standard errors are double-clustered by firm and trading day following Petersen (2008). Sample period: 2011–2024. Significance levels: *, **, *** at 10%, 5%, and 1%.

Variable	(1)	(2)	(3)	(4)	(5)
R_{ON}	-0.0866***	-0.0867***	-0.0698***	-0.0767***	-0.1618***
	(-15.87)	(-15.93)	(-10.31)	(-17.80)	(-26.09)
Int_Size (c)			0.0117***		-0.0233***
			(5.44)		(-6.73)
Int_VIX (c)				-0.0037***	-0.0034***
				(-3.30)	(-3.35)
Int_Vol (c)					0.0542***
					(23.45)
Int_Amihud (c)					-0.0415**
					(-1.98)
Log_Size (c)		-0.0001	-0.0001	-0.0000	-0.0000
		(-0.59)	(-0.73)	(-0.55)	(0.21)
$Log\_Dollarvolume$ (c)		0.0005***	0.0005***	0.0005***	0.0004***
		(6.60)	(6.74)	(6.54)	(5.71)
$Amihud$ (c)		0.0045***	0.0047***	0.0045***	0.0057***
		(5.77)	(5.97)	(5.90)	(7.07)
CS_Spread (c)		-0.0362***	-0.0359***	-0.0361***	-0.0329***
		(-3.25)	(-3.23)	(-3.22)	(-2.93)
Observations	9,745,248	9,740,856	9,740,856	9,740,856	9,740,856
R^2 (Overall)	0.0029	0.0039	0.0041	0.0045	0.0097
R^2 (Within)	0.0001	0.0009	0.0015	-0.0023	-0.0002
F-statistic	28,441.83	7,584.26	6,727.07	7,311.01	10,572.34
Prob(F-stat)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

In the baseline (column 1), the estimate suggests that, on average, roughly one-twelfth of an overnight price movement is reversed during the subsequent intraday session after accounting for all market-wide variation through day fixed effects. However, before interpreting this as economically significant, it is important to consider what the within R-squared value indicates: even in the most fully specified model, the overnight return explains practically none of the cross-sectional variation in intraday returns, net of day fixed effects. While the reversal is systematic and repeatable, the overnight signal is just one of many forces that shape intraday prices on any given day. It captures only a small part of what determines the outcome. With nearly ten million observations, even a modest relationship can generate high t-statistics, the statistical significance of the results should be considered alongside this caveat.

When the full set of microstructure controls is added, the reversal coefficient remains stable. This is true when the Amihud illiquidity ratio and the Corwin-Schultz spread are included. This stability is significant because it indicates that the reversal is not merely a mechanical consequence of the bid-ask bounce or an indicator of illiquidity-driven price pressure. The effect persists after controlling for these channels. However, it is important to note that these controls rely on estimated rather than directly observed quantities, most notably the Corwin-Schultz spread, which is a daily high-low approximation rather than a true bid-ask measurement. Therefore, the precision of these controls should not be overstated.

The most extensive specification simultaneously estimates all four interaction terms. This reveals a more complex picture than the individual columns suggest. Liquidity is the most important moderator: more liquid stocks exhibit substantially weaker reversals, which is consistent with the view that liquid markets allow for faster and more complete price discovery at the open. Conversely, illiquid stocks show stronger reversals because their opening prices are susceptible to order imbalance distortions requiring subsequent intraday correction. Market-wide volatility also matters; the reversal intensifies during periods of elevated uncertainty. This is in line with the limits-to-arbitrage prediction, which states that stressed conditions constrain institutional correction capacity and widen the window for opening price distortions to persist.

The result regarding firm size is interesting. Examined in isolation, larger firm size dampens the reversal, which is consistent with the behavioral attention hypothesis. However, when liquidity is held constant in the full specification, the size interaction reverses sign. This reversal does not reflect instability; rather, it reflects the collinearity between size and liquidity, as documented in Table 4. Once the liquidity effect is identified separately, the residual size effect changes direction.

5.4 Portfolio sorts and strategy performance

The decile portfolios in Figure 1 confirm and extend the regression findings. As the deciles of overnight returns increase from lowest to highest, the average intraday returns move monotonically in the opposite direction. This negative relationship is evident throughout the entire distribution, not just in the tails, suggesting that it is a broad-based phenomenon rather than one confined to a few outlier observations. The Spearman rank correlation across deciles is perfect, indicating that the monotonic relationship holds without exception across every step of the overnight return distribution.

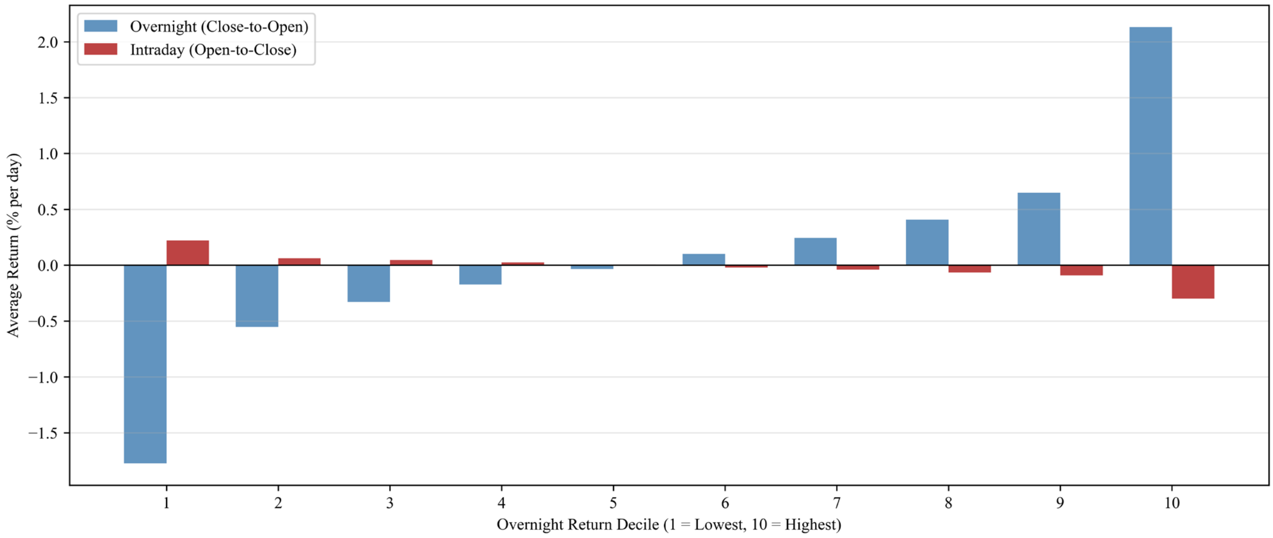

Figure 1 Average overnight and intraday returns by overnight return decile

This figure plots the average overnight return (close-to-open, blue bars) and average intraday return (open-to-close, red bars) within each decile of overnight returns, where decile 1 contains stocks with the lowest overnight returns and decile 10 contains stocks with the highest. The visually mirrored pattern illustrates the reversal directly: extreme overnight moves in either direction are followed by intraday returns of the opposite sign.

Table 7 reports the risk-adjusted alpha tests for the centile long-short strategy. The gross strategy, which involves going long on the lowest overnight return centile and shorting the highest centile without considering transaction costs, earns a substantial positive daily alpha against the Fama-French five-factor model. The factor coefficients apart from beta are all small and statistically insignificant; therefore, the gross strategy return appears largely orthogonal to standard systematic risk factors. According to a conventional asset pricing interpretation, this would categorize the reversal as an anomaly that cannot be explained by known risk premia.

The picture changes substantially once transaction costs are factored in. After incorporating the estimated Corwin-Schultz spread on both legs and a fixed daily commission, the net alpha becomes negative.

Table 7 Strategy alpha with Fama-French 5-Factor model

This table reports time-series regressions of daily long-short reversal strategy returns on the Fama-French five-factor model. The strategy is constructed by going long the lowest overnight return centile (P_1) and short the highest centile (P_{100}), equal-weighted within each leg and rebalanced daily. Gross returns ignore transaction costs. Net returns deduct the estimated round-trip Corwin-Schultz spread for both legs and 20 basis points of commissions per day across the four required one-way trades. Standard errors are Newey-West with 12 lags. Significance levels: *, **, *** at 10%, 5%, and 1%.

Factor	(1) Gross Strategy	(2) Net Strategy
Alpha (% per day)	1.5465***	-0.6564***
	(26.80)	(-12.58)
Market Beta	-0.2552*	-0.2658**
	(-1.87)	(-1.98)
SMB	0.0535	0.0354
	(0.60)	(0.43)
HML	-0.0856	-0.0445
	(-0.94)	(-0.52)
RMW	-0.0509	-0.0472
	(-0.40)	(-0.40)
CMA	0.0132	-0.0538
	(0.09)	(-0.40)
Adjusted R^2	0.0110	0.0127
F-statistic (factors)	0.76	0.93
Prob (F-statistic)	(0.5754)	(0.4578)
Observations	3,521	3,521
Spread cost	Excluded	Included
Commission (bps/day)	Excluded	20

5.5 Robustness

Figure 2 plots the rolling twelve-month reversal coefficient and its confidence interval. The coefficient remains negative throughout the entire sample period and never crosses zero. It deepens sharply during the spike in volatility caused by the onset of the pandemic, consistent with the finding of a VIX interaction, and has drifted gradually toward zero since approximately 2021. This slight fading is consistent with the post-publication decay documented for many financial anomalies (McLean & Pontiff, 2016). However, the effect remains statistically significant throughout.

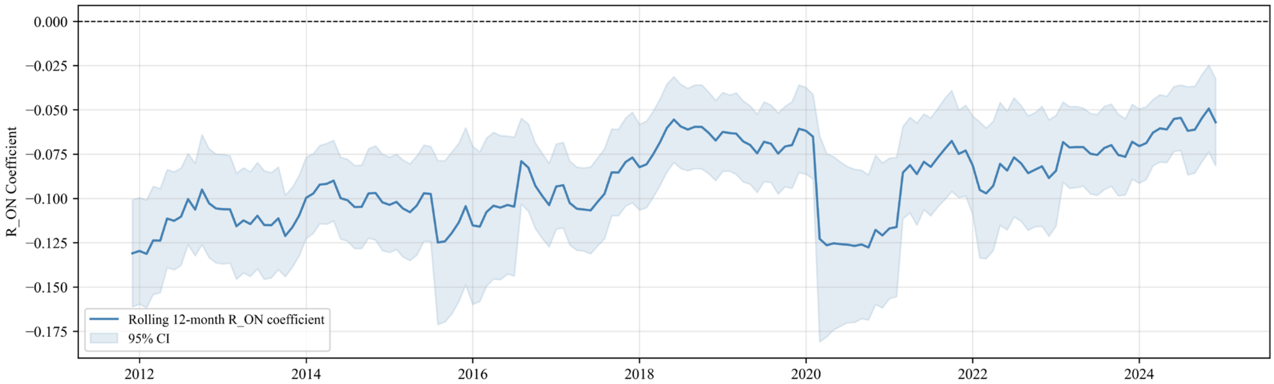

Figure 2 Rolling 12-month overnight-intraday reversal coefficient

This figure plots the baseline reversal coefficient estimated on a rolling 12-month window throughout the sample period, together with its 95% confidence interval. At each point on the time axis, the coefficient is estimated using the preceding twelve months of data.

The annual stability results clearly show that the overnight-to-intraday reversal is not concentrated in one market regime or crisis period. It has been present across fourteen consecutive years of varying volatility, interest rates, and market structures. While the period of the pandemic was extreme, it did not create the reversal; it merely amplified an existing effect.

Table 8 Annual stability of the reversal coefficient

This table reports the baseline reversal coefficient separately for each calendar year of the sample. The specification is the univariate baseline with day fixed effects. Standard errors are double-clustered by firm and trading day. Significance levels: *, **, *** at 10%, 5%, and 1%.

Year	Coefficient (R_{ON})	t-statistic	N
2011	-0.1310***	(-7.1059)	479,214
2012	-0.1056***	(-5.9019)	490,501
2013	-0.1097***	(-8.6651)	532,206
2014	-0.1022***	(-6.9124)	590,924
2015	-0.1044***	(-4.5383)	617,189
2016	-0.1038***	(-8.8888)	636,357
2017	-0.0769***	(-5.5330)	681,658
2018	-0.0673***	(-5.6917)	725,604
2019	-0.0607***	(-4.6696)	751,196
2020	-0.1209***	(-5.7444)	810,961
2021	-0.0730***	(-5.5841)	912,354
2022	-0.0885***	(-5.2285)	872,379
2023	-0.0680***	(-5.9309)	826,032
2024	-0.0570***	(-4.4509)	818,673

As shown in Table 9, the asymmetry test reveals that the reversal is stronger following positive overnight gaps than negative ones. Both types of gaps are significant, and the difference between them is statistically detectable. However, this finding contradicts the standard short-selling constraint hypothesis, which predicts that positive gaps, requiring short selling to correct, should be more difficult to reverse than negative ones. However, the data show the opposite. One possible explanation is that positive overnight gaps attract a more aggressive institutional response, including momentum-following algorithms and daytime traders who join and amplify the correction. In contrast, the correction of negative gaps proceeds more quietly. Another possibility is that the asymmetry reflects the structure of retail attention. Extreme positive news generates more retail buying at the open than extreme negative news generates retail selling. This creates a larger initial distortion on the positive side that subsequently corrects more forcefully.

Table 9 Regression analysis of asymmetric reversal dynamics

This table tests whether the market responds asymmetrically to positive versus negative overnight gaps. The reversal coefficient is estimated separately for positive and negative overnight returns. Specifications include day fixed effects and the full set of microstructure controls. Standard errors are double-clustered by firm and trading day. Significance levels: *, **, *** at 10%, 5%, and 1%.

Variable	(1) Symmetric	(2) Asymmetric	(3) Asymmetric + Controls
R_{ON}	-0.0860***		
	(-15.75)		
R_{ON} positive		-0.0953***	-0.0995***
		(-16.20)	(-17.45)
R_{ON} negative		-0.0719***	-0.0677***
		(-6.34)	(-5.82)
Control variables	No	No	Yes
Observations	9,740,856	9,740,856	9,740,856
R^2 (Within)	0.0001	0.0002	0.0010
Day Fixed Effects	Yes	Yes	Yes
Wald test: $\beta_{pos} = \beta_{neg}$		t = -2.46	t = -2.46
p-value (one-sided)		0.0069	0.0069

The remaining robustness checks yield results consistent with the main findings and highlight significant quantitative sensitivities. Using winsorization on returns instead of a hard outlier filter strengthens the reversal estimate. This clarifies that the overnight-intraday return phenomenon is not solely driven by statistical extremes; rather, the extremes actually weaken the effect in regression models.

Table 10 Winsorized vs hard-filter returns

This table reports the baseline reversal coefficient under two alternative outlier treatments. The hard-filter specification excludes observations outside the −100% to +200% return range. The winsorized specification retains the same sample but truncates returns at the 1st and 99th percentiles of each return variable. Both specifications use day fixed effects and double-clustered standard errors. Significance levels: *, **, *** at 10%, 5%, and 1%.

Specification	(1) Baseline (hard filter)	(2) Winsorized (P_1/P_{99})
R_{ON} coefficient	-0.0860***	-0.1625***
t-statistic	(-15.75)	(-25.93)
Observations	9,740,856	9,740,856
R^2 (within)	0.0001	-0.0013
Day FE	Yes	Yes

Using value-weighted rather than equal-weighted portfolio returns to construct the long-short strategy substantially reduces the estimated strategy return by roughly a factor of four, but the return remains statistically significant. While the anomaly is not purely a microcap phenomenon, it is concentrated in smaller, less liquid stocks. This is consistent with the attention hypothesis and the liquidity effect. However, it also means that a realistic implementation of any reversal-based strategy must consider that the stocks in which the effect is largest are precisely those in which trading is most costly and capacity is most constrained.

Table 11 Equal- vs value-weighted decile strategy

This table reports the gross daily return of the decile long-short reversal strategy under two weighting schemes. The equal-weighted scheme weights all stocks within a decile portfolio identically. The value-weighted scheme weights stocks by their market capitalization. Significance levels: *, **, *** at 10%, 5%, and 1%.

Weighting scheme	Equal-Weighted	Value-Weighted
Mean daily return	0.5062***	0.1193***
t-statistic	(31.89)	(6.26)
Observations	3,520	3,520
Strategy	Long D1 – Short D10	Long D1 – Short D10

The size-tercile analysis provides an overview of the size gradient. The reversal coefficient is nearly three times larger for small-cap stocks than for large-cap stocks; however, it remains statistically significant even among the largest firms in the sample. The persistence of the reversal among large-cap stocks, where retail participation is limited and institutional coverage is dense, suggests that the mechanism is not exclusively behavioral. Institutional herding, algorithmic order flow at the opening auction, or rational inventory management may contribute to this phenomenon across the size spectrum.

Table 12 Reversal coefficient by market cap tercile

This table reports the baseline panel OLS reversal coefficient estimated separately within each of three market capitalization terciles defined annually: small-cap (T1), mid-cap (T2), and large-cap (T3). The specification includes day fixed effects and double-clustered standard errors. Significance levels: *, **, *** at 10%, 5%, and 1%.

Size Group	Median Cap ($M)	R_{ON} coef	t-stat	N	R² (within)
Small	313	-0.1118***	(-20.26)	3,248,148	0.0016
Mid	1,628	-0.0455***	(-5.99)	3,245,720	-0.0006
Large	10,242	-0.0412***	(-4.75)	3,246,988	-0.0006

Excluding the COVID-19 year produces a coefficient nearly identical to the full-sample estimate, confirming that the pandemic's extreme volatility did not drive the results. That being said, the effect was clearly higher during 2020.

Table 13 Excluding COVID-19 year (2020)

This table reports the baseline reversal coefficient estimated on a sample that excludes the calendar year 2020. Specifications include day fixed effects and double-clustered standard errors. Significance levels: *, **, *** at 10%, 5%, and 1%.

Sample	R_{ON} coefficient	t-statistic	N	R² (within)
Full sample	-0.0860***	(-15.75)	9,740,856	0.0001
Excl. 2020	-0.0790***	(-16.81)	8,930,184	0.0012

Table 14 re-estimates the five main regression specifications using logarithmic rather than arithmetic returns. The results are nearly identical in sign and magnitude to those of the arithmetic return specifications in Table 6. The log-return baseline coefficient is nearly identical to the arithmetic return results. These results confirm that the choice of return definition does not influence the findings and that the reversal is a genuine feature of the data, not an artifact of the arithmetic return calculation.

Table 14 Panel OLS with logarithmic returns

This table reports the baseline panel OLS specification re-estimated using logarithmic rather than arithmetic returns. Log returns are defined as $ln(P_t/ P_{t-1})$ for each component. Day fixed effects and double-clustered standard errors are used throughout. Significance levels: *, **, *** at 10%, 5%, and 1%.

Variable	(1)	(2)	(3)	(4)	(5)
R_{ON}	-0.0800***	-0.0788***	-0.0701***	-0.0687***	-0.1643***
	(-13.75)	(-13.61)	(-9.53)	(-15.59)	(-25.79)
Int_Size (c)			0.0056**		-0.0340***
			(2.24)		(-9.87)
Int_VIX (c)				-0.0043***	-0.0037***
				(-4.20)	(-3.97)
Int_Vol (c)					0.0576***
					(23.39)
Int_Amihud (c)					-0.0713***
					(-3.47)
Log_Size (c)		0.0005***	0.0005***	0.0005***	0.0006***
		(5.76)	(5.71)	(5.75)	(6.33)
$Log\_Dollarvolume$ (c)		-0.0001	-0.0001	-0.0001	-0.0001
		(-0.82)	(-0.79)	(-0.82)	(-1.47)
$Amihud$ (c)		-0.0011	-0.0011	-0.0011	-0.0000
		(-1.44)	(-1.33)	(-1.34)	(-0.02)
CS_Spread (c)		-0.0353***	-0.0351***	-0.0316***	-0.0328***
		(-3.15)	(-3.14)	(-3.13)	(-2.91)
Observations	9,740,856	9,740,856	9,740,856	9,740,856	9,740,856
R^2 (Overall)	0.0026	0.0040	0.0041	0.0063	0.0101
R^2 (Within)	-0.0001	0.0005	0.0007	-0.0021	-0.0015
F-statistic	25,291.19	7,872.50	6,657.28	7,963.61	11,031.90
Prob(F-stat)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

Figure 3 illustrates the economic consequences of transaction costs in terms of cumulative returns and is perhaps the most intuitive representation of the limits to arbitrage. The gross cumulative return, depicted by the solid line, increases dramatically between 2011 and 2024. This trajectory reflects the consistency and persistence of the overnight-to-intraday reversal documented in the regression analysis. A strategy that mechanically exploits the signal earns substantial gross returns in virtually every year. Net returns immediately turn negative upon the application of transaction costs and trend at or below the initial level throughout the entire sample period. The visual gap between the gross and net trajectories is not a narrow borderline result that could be closed by slightly different cost assumptions. It is a chasm. The costs of trading the most extreme overnight shocks are so substantial and structurally tied to the illiquidity of stocks with the strongest signal that the strategy cannot generate positive net returns under any realistic implementation scenario. Thus, this figure provides the clearest possible answer to the third research question of this study. The reversal is not a free lunch that the market has inexplicably left on the table but rather a pattern whose exploitation is costly enough for it to sustain.

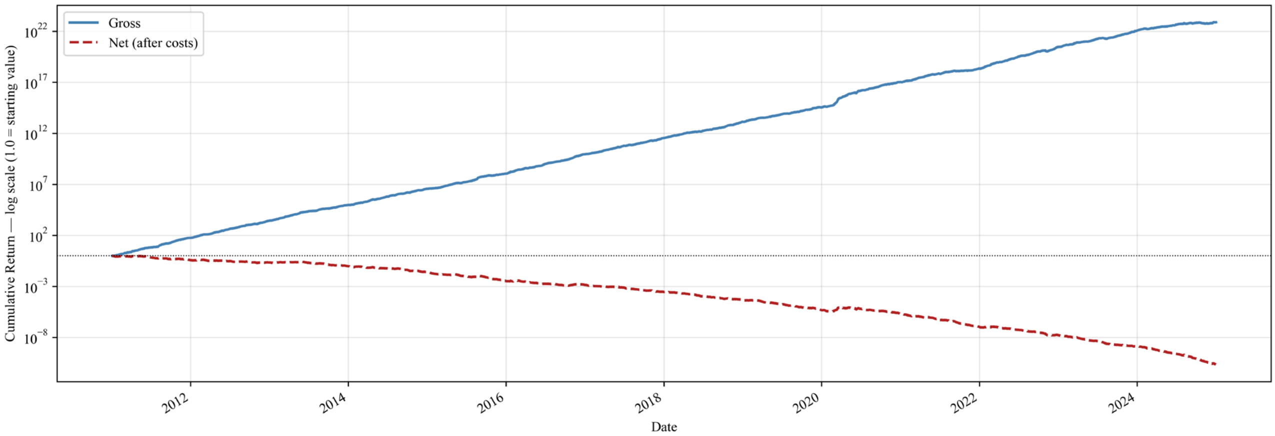

Figure 3 Cumulative returns of centile long-short strategy (2011–2024)

This figure plots the cumulative return of the daily long-short reversal strategy on a logarithmic scale. The strategy goes long for the lowest overnight return centile and short for the highest centile, equal-weighted, rebalanced daily. The blue solid line shows gross returns before any costs; the red dashed line shows net returns after deducting estimated Corwin-Schultz spreads and 20 basis points of daily commissions.

The overall quality of the data was also tested using the Akbas et al. (2022) replication presented in Appendix 2. The results show that the impact of the reversal pattern is also detectable at the monthly horizon on the same sample. The results are relatively consistent in size, magnitude, and significance with those of the original study. This was achieved despite using a data vendor that is not as highly regarded as that used in the original study.

6 Conclusions

This thesis set out to investigate what happens in the hours following the market open, a moment that is simultaneously mundane in its daily repetition and demanding in its informational requirements. Every morning, the opening call auction must resolve an overnight accumulation of news, sentiment shifts, and investor intentions into a single price. That price is then contested and partially corrected over the course of the trading day as more participants enter the market and the divergence between noise-driven opening flows and fundamental valuation narrows.

The main contribution of this study is the validation of this correction process using daily data from thousands of U.S. stocks from 2011 to 2024. The evidence assembled in this study establishes that the intraday reversal is systematic and, within the limits of the data, predictable. Stocks that open significantly above their prior close tend to give back a measurable fraction of that gain during the trading day; stocks that gap down tend to partially recover. The reversal is present across all fourteen years of the sample, across all market capitalization groups, and in both positive and negative overnight gap directions. It is not a statistical artifact of untraded microcap stocks, nor is it driven by the extreme volatility of any single market regime: it survives value-weighting, winsorization, COVID exclusion, and re-estimation with logarithmic returns.

The empirical tests provided answers to all three research questions. First, overnight returns have statistically significant predictive power over same-day intraday returns, and this relationship holds true across the entire distribution of overnight returns. Second, out of the used control variables, the reversal is most strongly moderated by firm-level liquidity, with more liquid stocks showing weaker reversals. While firm size also moderates the reversal when estimated in isolation, the size effect is largely subsumed by liquidity when both are tested jointly. The reversal additionally intensifies during high-VIX periods, when arbitrage may be more costly. Third, the statistical predictability does not survive realistic transaction costs under the assumptions of this study.

The results of this study lie at the intersection of the debate on market efficiency. The behavioral case for the reversal is compelling. It suggests that retail investors, driven by attention, concentrate their buying at market open after significant overnight events, causing opening prices to rise above their fundamental values, and is consistent with the observation that small-cap stocks exhibit larger reversals than large-cap stocks. However, according to the results of this study, the stronger reversal of the small-cap stocks may not come necessarily because of their smaller size, but because of their lower liquidity. Once liquidity is controlled for, the size coefficient flips sign. That implies the explanation that the reversal is result of liquidity-mediated friction.

The finding that the reversal intensifies during periods of high uncertainty is also consistent with behavioral amplification. When markets are stressed, retail sentiment is often most extreme, and institutional risk appetite is most constrained. This widens the window for opening price distortions to persist. Though difficult to interpret cleanly, the asymmetry between positive and negative gaps may also reflect the susceptibility of attention-driven retail buying at the open to positive overnight news.

However, the efficient markets position cannot be dismissed. Its most powerful argument is the joint hypothesis problem: The negative relationship between overnight and intraday returns could reflect a rational time-varying risk premium rather than mispricing. A market maker who sets the opening price assumes significant inventory risk, and the subsequent intraday return could be rational compensation for that risk rather than a correction of irrationality. This interpretation is supported by the finding that the reversal intensifies when volatility is high, which is precisely when one would expect a rational risk premium to be largest. The efficient markets view also receives indirect support from the temporal stability of the reversal. A pattern that has persisted for fourteen years, despite changes in market structures, trading technologies, and institutional compositions, is more consistent with a structural equilibrium feature than with an inefficiency that rational arbitrageurs have failed to notice.

The framework that unites these interpretations could be called efficient inefficiency: a competitive market in which the reversal is real, in that opening prices systematically differ from subsequent intraday values. However, it is not exploitable, as the costs of strategies needed to capture the reversal consume the gross profit. According to this view, the anomaly persists not because the market is failing but because the agents who could eliminate it require compensation for doing so. This compensation is embedded in the bid-ask spreads of the stocks where the effect is largest. Although the transaction cost evidence is consistent with this equilibrium, it cannot prove it. The use of a spread estimator means the study cannot rule out the possibility that a participant with low enough execution costs could exploit the signal profitably.

Ultimately, the data cannot clearly distinguish between behavioral mispricing, market frictions and a rational risk premium. The gross alpha is unrelated to the known Fama-French factors, making it difficult to explain with a purely rational model. However, the absence of a known risk factor does not prove irrationality. It may simply reflect the limitations of current asset pricing models in capturing the specific risks of the open market. This ambiguity is not a weakness of the study, it is an accurate reflection of the current state of the field.

Several natural extensions follow from the findings and limitations of this study. The most direct extension of this study would be to use trade-level TAQ data, with explicit bid and ask quotes, signed order flow, and trade-direction identification, to better test the behavioral and microstructural explanations that the daily-frequency data of this study cannot fully separate. Such data would allow the researcher to identify retail versus institutional order flow directly and to test whether the reversal is driven by the trader types predicted by the attention hypothesis or by the dealer-inventory response predicted by microstructure theory. Further research is also needed on the asymmetry between positive and negative opening gaps and why positive gaps appear to reverse more strongly than negative ones. Subsequent studies could also extend the alpha tests of this study to include more sophisticated trading strategies.

The gradual decay of the reversal coefficient since 2021 remains an open question. Future research could decompose this trend into its contributing factors, such as the normalization of post-pandemic retail activity, the repricing of arbitrage capital costs as interest rates increased, and the maturation of algorithmic trading during the opening auction. One way to address this question directly would be to measure the footprint of algorithmic participation in the opening call and test whether higher algorithmic involvement is associated with faster price discovery.

References

Aboody, D., Even-Tov, O., Lehavy, R., & Trueman, B. (2018). Overnight returns and firm-specific investor sentiment. Journal of Financial and Quantitative Analysis, 53(2), 803–830.

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage.

Akbas, F., Boehmer, E., Jiang, C., & Koch, P. D. (2022). Overnight returns, daytime reversals, and future stock returns. Journal of Financial Economics, 145(3), 874–896.

Aleti, S., & Bollerslev, T. (2025). Intraday market return predictability culled from the factor zoo. Management Science, 71(9), 7731–7751.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), 1645–1680.

Baltagi, B. H. (2008). Econometric analysis of panel data (Vol. 4, pp. 135-145). Chichester: John wiley & sons.

Barardehi, Y. H., Bogousslavsky, V., & Muravyev, D. (2026). What Drives Momentum and Reversal? Evidence from Day and Night Signals. The Review of Financial Studies.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The Review of Financial Studies, 21(2), 785–818.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics, 49(3), 307–343.

Barclay, M. J., & Hendershott, T. (2003). Price discovery and trading after hours. The Review of Financial Studies, 16(4), 1041–1073.

Berkman, H., Koch, P. D., Tuttle, L., & Zhang, Y. J. (2012). Paying attention: Overnight returns and the hidden cost of buying at the open. Journal of Financial and Quantitative Analysis, 47(4), 715–741.

Bogousslavsky, V. (2021). The cross-section of intraday and overnight returns. Journal of Financial Economics, 141(1), 172–194.

Boyarchenko, N., Larsen, L. S., & Whelan, P. (2023). The overnight drift. Federal Reserve Bank of New York Staff Reports, No. 917.

Brown, S. J., Goetzmann, W., Ibbotson, R. G., & Ross, S. A. (1992). Survivorship bias in performance studies. The Review of Financial Studies, 5(4), 553–580.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. The Review of Financial Studies, 22(6), 2201–2238.

Cochrane, J. H. (2009). Asset pricing (Rev. ed.). Princeton University Press.

Cochrane, J. H. (2011). Presidential address: Discount rates. The Journal of Finance, 66(4), 1047–1108.

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. The Journal of Finance, 67(2), 719–760.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. The Journal of Finance, 53(6), 1839–1885.

De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? The Journal of Finance, 40(3), 793–805.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 98(4), 703–738.

Edwards, W. (1968). Conservatism in human information processing. In B. Kleinmuntz (Ed.), Formal representation of human judgment (pp. 17–52). Wiley.

Fama, E. F. (1965). The behavior of stock-market prices. The Journal of Business, 38(1), 34–105.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. International economic review, 10(1), 1-21.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417.

Fama, E. F. (1991). Efficient capital markets: II. The Journal of Finance, 46(5), 1575–1617.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. The Journal of Finance, 47(2), 427–465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22.

Foster, F. D., & Viswanathan, S. (1990). A theory of the interday variations in volume, variance, and trading costs in securities markets. The Review of Financial Studies, 3(4), 593–624.

Gao, L., Han, Y., Li, S. Z., & Zhou, G. (2018). Market intraday momentum. Journal of Financial Economics, 129(2), 394–414.

Glasserman, P., Krstovski, K., Laliberte, P., & Mamaysky, H. (2025). Does Overnight News Explain Overnight Returns? https://doi.org/10.48550/arxiv.2507.04481

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics, 14(1), 71–100.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. The American Economic Review, 70(3), 393–408.

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. the Journal of Finance, 43(3), 617-633.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis.

Hajiyev, A., Keiber, K. L., & Luczak, A. (2024). Tug of war with noise traders? Evidence from the G7 stock markets. The Quarterly Review of Economics and Finance, 95, 234–243.

Ham, H., Ryu, D., & Webb, R. I. (2022). The effects of overnight events on daytime trading sessions. International Review of Financial Analysis, 83, Article 102228.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the cross-section of expected returns. The Review of Financial Studies, 29(1), 5–68.

Hasbrouck, J. (2007). Empirical market microstructure: The institutions, economics, and econometrics of securities trading. Oxford University Press.

Hendershott, T., Livdan, D., & Rösch, D. (2020). Asset pricing: A tale of night and day. Journal of Financial Economics, 138(3), 635–662.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics, 36(1–3), 337–386.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. The Review of Financial Studies, 33(5), 2019–2133.

Ince, O. S., & Porter, R. B. (2006). Individual equity return data from Thomson Datastream: Handle with care. Journal of Financial Research, 29(4), 463–479.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance, 48(1), 65–91.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–292.

Kallinterakis, V., & Karaa, R. (2022). From dusk till dawn (and vice versa): Overnight-versus-daytime reversals and feedback trading. International Review of Financial Analysis, 84, Article 102366.

Kelly, M. A., & Clark, S. P. (2011). Returns in trading versus non-trading hours: The difference is day and night. Journal of Asset Management, 12(2), 132–145.

Lin, C., Chang, H. W., & Chou, R. K. (2023). Overnight versus intraday returns of anomalies in China. Pacific-Basin Finance Journal, 79, Article 102028.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. The Journal of Finance, 20(4), 587–615.

Lo, A. W., & MacKinlay, A. C. (1990). Data-snooping biases in tests of financial asset pricing models. The Review of Financial Studies, 3(3), 431–467.

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. Journal of Financial Economics, 134(1), 194–213.

Lu, Z., Malliaris, S., & Qin, Z. (2023). Heterogeneous liquidity providers and night-minus-day return predictability. Journal of Financial Economics, 148(3), 175-200.

Ma, G., Bouri, E., Xu, Y., & Zhou, Z. I. (2025). The "night effect" of intraday trading: Evidence from Chinese gold and silver futures markets. Global Finance Journal, 64, Article 101084.

Madhavan, A. (2000). Market microstructure: A survey. Journal of Financial Markets, 3(3), 205–258.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. The Journal of Economic Perspectives, 17(1), 59–82.

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? The Journal of Finance, 71(1), 5–32.

Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. Journal of Monetary Economics, 15(2), 145–161.

Merton, R. C. (1973). An intertemporal capital asset pricing model. Econometrica, 41(5), 867–887.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

O'Hara, M. (1995). Market microstructure theory. Blackwell Publishing.

O'Hara, M. (2003). Presidential address: Liquidity and price discovery. The Journal of Finance, 58(4), 1335–1354.

Pedersen, L. H. (2015). Efficiently inefficient: How smart money invests and market prices are determined. Princeton University Press.

Petersen, M. A. (2008). Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies, 22(1), 435–480.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics, 42(1–2), 35–52.

Qiao, K., & Dam, L. (2020). The overnight return puzzle and the "T+1" trading rule in Chinese stock markets. Journal of Financial Markets, 50, Article 100534.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. Journal of Portfolio Management, 11(3), 9–16.

Russell. (2025). Russell 3000 index factsheet. FTSE Russell.

Samuelson, P. A. (1973). Proof that properly discounted present values of assets vibrate randomly. Bell Journal of Economics and Management Science, 4(2), 369–374.

Schwert, G. W. (2003). Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the economics of finance (Vol. 1B, pp. 939–974). Elsevier.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425–442.

Shleifer, A. (2000). Inefficient markets: An introduction to behavioral finance. Oxford University Press.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. The Journal of Finance, 52(1), 35–55.

Stoll, H. R. (2000). Friction. The Journal of Finance, 55(4), 1479–1514.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124–1131.

Vanguard. (2025). VTHR Russell 3000 ETF overview. <https://advisors.vanguard.com/investments/products/vthr/vanguard-russell-3000-etf#overview>, retrieved 20.10.2025.

Wang, W. (2024). Investor sentiment and stock market returns: A story of night and day. The European Journal of Finance, 30(13), 1437–1469.

Whaley, R. E. (2000). The investor fear gauge. Journal of portfolio management, 26(3), 12.

Wooldridge, J. M. (2016). Introductory econometrics a modern approach. South-Western cengage learning.

Zhao, X., Lv, M., Wen, X., & Xu, J. (2025). Intraday and Overnight Causality in Time and Frequency Domains: Evidence From Stock Returns and Volatility. International Journal of Finance & Economics.

Appendices

Appendix 1 Corwin-Schultz spread estimator figures

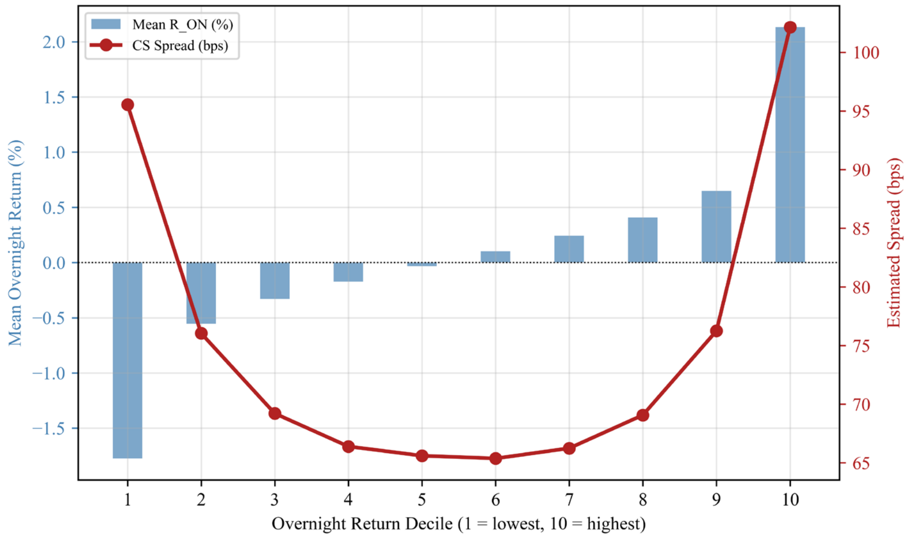

Figure 4 Corwin-Schultz spread vs overnight return by deciles

This figure illustrates the relationship between estimated bid-ask spreads and overnight return magnitude across portfolio groups. The panel plots mean overnight returns and mean Corwin-Schultz spread estimates across the ten overnight return deciles, demonstrating that spreads follow a U-shaped pattern, stocks with the most extreme overnight returns in either direction, both the lowest and highest deciles, carry the widest estimated spreads.

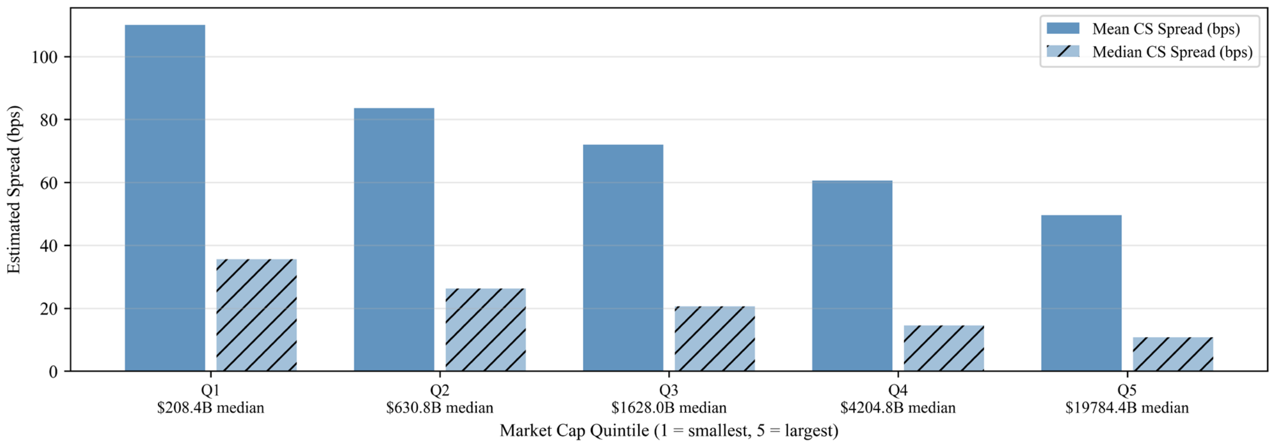

Figure 5 Corwin-Schultz spread by market cap quintile

This figure provides a plausibility check for the Corwin-Schultz spread estimator. It plots the mean and median estimated spreads across five market capitalization quintiles. These quintiles range from the smallest firms to the largest. The monotonically declining pattern, the spreads are widest for the smallest firms and narrowest for the largest, is consistent with the well-established empirical regularity that larger, more liquid stocks trade at narrower bid-ask spreads.

Appendix 2 The replication of Akbas et al. (2022)

Table 15 Abnormal negative daytime reversals and future returns

The replication serves two purposes within the context of this thesis. Firstly, it provides external validation that the LSEG Datastream sample used throughout this study captures the same overnight–intraday reversal dynamics documented in the published literature using CRSP and TAQ data. The close reproduction of the directional and magnitude results of Akbas et al. (2022) on this sample strengthens confidence in the daily-frequency results presented in the main text. Secondly, the replication extends the original study's sample period, which ended in 2018, by six years, reaching the same conclusions. This suggests that this phenomenon has not been a victim of post-publication decay.

This table reports Fama-MacBeth cross-sectional regression results replicating the analysis of Akbas et al. (2022, Journal of Financial Economics, Table 4, columns 1–3). The dependent variable is the stock return in month $t + 1$. The key independent variables are AB_NR (abnormal overnight return) and AB_PR (abnormal intraday return), which measure the deviation of each return component from its cross-sectional mean. Control variables added across the three columns include firm size, six-month past return, monthly turnover, return volatility, and the Amihud illiquidity ratio. Variables unavailable from LSEG Datastream daily files, book-to-market ratio (BM), gross profitability (GPA), analyst target price growth (ATGTH), and institutional ownership (IO), are omitted. Coefficients are time-series averages of monthly cross-sectional regression coefficients. Standard errors are Newey-West corrected with 12 monthly lags. Significance levels: *, **, *** at 10%, 5%, and 1%.

Variable	(1)	(2)	(3)
AB_NR	0.0142*	0.0124**	0.0109**
	(1.94)	(2.00)	(2.32)
AB_PR	-0.0211***	-0.0220***	-0.0198***
	(-4.28)	(-4.92)	(-6.53)
RET_CO_M	-0.0199**	-0.0181**	-0.0137*
	(-2.35)	(-2.18)	(-1.84)
RET_OC_M	0.0015	0.0053	0.0044
	(0.20)	(0.76)	(0.68)
SIZE		-0.0004	0.0004
		(-0.82)	(0.75)
RET_6M		0.0054**	0.0069***
		(1.98)	(2.93)
TURN_M			-0.5562***
			(-4.98)
STDRET_M			-0.1062
			(-1.29)
ILLIQ_M			0.0760***
			(7.43)

Appendix 3 Explanation of the use of AI

The artificial intelligence tools Claude by Anthropic and Gemini by Google were used to support writing this thesis across several phases. The tools were prompted in both Finnish and English.

In initial stages, AI assisted with creative thinking, helping to explore different topics, frame research questions, and determine the scope of the study. Once a topic was chosen, AI helped structure the initial chapters and subchapters and discuss the logical flow of the theoretical framework.

Furthermore, AI was prompted to help identify accurate keywords for searching high-quality references and to find related academic publications. AI was also asked to summarize academic references or explain the main findings of a paper in a concise manner.

AI assistance with this thesis includes discussing econometric design choices, interpreting empirical results, and rephrasing sentences or paragraphs. However, AI was never used solely to progress the writing process. Even when prompted to rephrase paragraphs or interpret results, the AI's output has been critically and carefully validated and modified before being incorporated into the thesis.

The most significant technical contribution of AI to this study was its assistance in generating and debugging Python scripts for the empirical research. This involved a large dataset with several stages of data cleaning and filtering; constructing return variables and microstructure controls; panel regression estimation; portfolio sort analysis; transaction cost estimation; and producing tables and figures.

Overall, the use of AI has been conducted in a manner that is in accordance with the academic writing guidelines of the University of Turku.