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**Order Imbalance Volatility, Persistence, and Liquidity :
A Replication and Extension**

par

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Résumé

Bogousslavsky and Collin-Dufresne (2023) montrent que la volatilité du déséquilibre des ordres à haute fréquence (HFOIV), l'écart-type intrajournalier des déséquilibres d'ordres à cinq minutes, prédit les fourchettes effectives et résout l'association positive volume-fourchettes pour les grandes capitalisations. Leur modèle suppose un flux d'ordres markovien, excluant tout rôle de la structure temporelle des déséquilibres au-delà de la volatilité. Or, le flux d'ordres intrajournalier présente une dépendance sérielle attribuable au fractionnement d'ordres institutionnels. Ce mémoire reproduit leur cadre dans un échantillon étendu et examine si la persistance du flux d'ordres fournit un pouvoir explicatif incrémental pour les fourchettes.

Nous introduisons l'autocorrélation du déséquilibre des ordres (OIAC), le coefficient AR(1) des déséquilibres d'ordres à cinq minutes, signés en actions, au sein de chaque journée, comme mesure de persistance intrajournalière. À partir d'un panel d'actions ordinaires cotées au NYSE, à l'AMEX et au NASDAQ de 2004 à 2024, construit à partir des données TAQ et CRSP, nous reproduisons et étendons le cadre de Bogousslavsky and Collin-Dufresne (2023) selon cette dimension.

La réplication confirme que le HFOIV prédit les fourchettes effectives et que le contrôle pour le HFOIV rétablit la relation négative volume-fourchettes; ces résultats se maintiennent sept ans au-delà de l'échantillon original. Le principal résultat nouveau est que l'OIAC présente un pouvoir explicatif incrémental significatif pour les fourchettes des grandes capitalisations : le coefficient dans la spécification conjointe est de $-0,05$, fortement significatif. Une augmentation d'un écart-type intra-titre de l'OIAC est associée à un rétrécissement des fourchettes d'environ un pour cent, un ordre de grandeur inférieur à l'effet du HFOIV mais statistiquement significatif. Le signe négatif est compatible avec un canal d'antisélection : un flux d'ordres prévisible reflète le fractionnement mécanique d'ordres institutionnels plutôt qu'une négociation informée, ce qui permet aux teneurs de marché d'intégrer un risque d'antisélection plus faible dans la fourchette.

Des tests auxiliaires renforcent cette interprétation : l'interaction HFOIV-OIAC est non significative, l'OIAC chute fortement lors des échéances de produits dérivés, et seule la persistance idiosyncrasique explique la relation avec les fourchettes. Pour les petites capitalisations, l'OIAC n'est pas significative, ce qui est cohérent avec des taux plus faibles d'exécution algorithmique. La prime de rendement HFOIV ne survit pas à l'extension au-delà de l'échantillon de BCD, et l'OIAC ne prédit pas les rendements en coupe transversale. Ces résultats établissent la persistance du flux d'ordres comme une dimension distincte de l'activité intrajournalière qui affecte le coût de la fourniture de liquidité.

Abstract

Bogousslavsky and Collin-Dufresne (2023) show that high-frequency order imbalance volatility (HFOIV), the within-day standard deviation of five-minute order imbalances, predicts effective spreads and resolves the positive volume-spread association for large stocks. Their model assumes Markov order flow, excluding any role for the temporal structure of imbalances beyond volatility. Intraday order flow, however, exhibits serial dependence driven by institutional order splitting. This thesis replicates their framework in an extended sample and tests whether order flow persistence provides incremental explanatory power for spreads.

We introduce order imbalance autocorrelation (OIAC), the AR(1) coefficient of five-minute signed share imbalances within each trading day, as a measure of intraday persistence. Using a panel of NYSE, AMEX, and NASDAQ common stocks from 2004 to 2024 constructed from TAQ and CRSP data, we replicate and extend the Bogousslavsky and Collin-Dufresne (2023) framework along this dimension.

The replication confirms that HFOIV predicts effective spreads and that controlling for HFOIV recovers the negative volume-spread relationship; these results hold seven years beyond the original sample. The main new finding is that OIAC carries significant incremental explanatory power for large-stock spreads: the coefficient in the joint specification is -0.05 , strongly significant. A within-stock standard deviation increase in OIAC is associated with approximately one percent narrower spreads, an order of magnitude smaller than the HFOIV effect but strongly significant. The negative sign is consistent with an adverse selection channel: predictable order flow reflects mechanical institutional order splitting rather than informed trading, allowing market makers to price lower adverse selection risk into the spread.

Auxiliary tests reinforce this interpretation: the HFOIV-OIAC interaction is insignificant, OIAC falls sharply on derivative expiration days, and only idiosyncratic persistence drives the spread relationship. For small stocks, OIAC is insignificant, consistent with lower algorithmic execution rates. The HFOIV return premium does not survive extension beyond the BCD sample, and OIAC does not predict cross-sectional returns. These results establish order flow persistence as a distinct dimension of intraday order flow that affects the cost of liquidity provision.

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List of Acronyms

BCD	Bogousslavsky and Collin-Dufresne (2023)
CRSP	Center for Research in Security Prices
I/B/E/S	Institutional Brokers' Estimate System
NBBO	National Best Bid and Offer
TAQ	Trade and Quote
WRDS	Wharton Research Data Services
HFT	High-Frequency Trading
AMEX	American Stock Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
EWMA	Exponentially Weighted Moving Average
HFOIV	High-Frequency Order Imbalance Volatility
ILLIQ	Illiquidity (Amihud measure)
OI	Order Imbalance
OIAC	Order Imbalance Autocorrelation
PIN	Probability of Informed Trading
TWAP	Time-Weighted Average Price
VWAP	Volume-Weighted Average Price

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Generative AI Declaration

I declare that I used Claude (Anthropic, claude.ai) throughout the preparation of this thesis for the following purposes: assisting in writing and debugging Python and SAS code, interpreting error messages, proofreading written text for typographical and grammatical errors, and formatting $\text{\LaTeX}$ files. The outputs were reviewed, revised, and integrated into my work at my own discretion.

1 Introduction

The bid-ask spread compensates liquidity providers for two fundamental risks: adverse selection (the cost of trading against better-informed counterparties) and inventory risk (the cost of holding unwanted positions while awaiting offsetting order flow) (Glosten & Milgrom, 1985; Stoll, 1978). Identifying which properties of order flow drive each component is central to the study of market microstructure. This thesis replicates the framework of Bogousslavsky and Collin-Dufresne (2023) and examines whether the temporal structure of intraday order flow (specifically its persistence) carries information about spreads beyond what its volatility captures.

Bogousslavsky and Collin-Dufresne (2023) introduce high-frequency order imbalance volatility (HFOIV), defined as the within-day standard deviation of five-minute order imbalances scaled by shares outstanding. Motivated by a continuous-time inventory model in which a risk-averse liquidity provider absorbs stochastic order flow, they show that HFOIV captures the magnitude of inventory shocks at intraday frequencies. Their central empirical finding is that HFOIV resolves the “volume puzzle”: the positive time-series association between trading volume and effective spreads observed for large stocks in their sample, which contradicts the classical prediction that higher volume reduces the cost of immediacy (Demsetz, 1968). Once HFOIV is controlled for, the volume-spread relationship becomes strongly negative across all size groups, consistent with the model’s two-channel prediction that volume and order imbalance volatility affect spreads through distinct mechanisms.

The BCD model, however, assumes a Markov structure for order flow: each inventory state transition is independent of previous transitions. Under this assumption, the temporal structure of order imbalances carries no information about spreads beyond what the transition intensities (which jointly determine volume and HFOIV) already capture. This assumption is not borne out empirically. Order flow exhibits substantial intraday serial dependence, driven primarily by the splitting of large institutional orders into sequences of smaller child orders executed incrementally across five-minute intervals (Lillo et al., 2005; Tóth et al., 2015). BCD themselves note that their order imbalance measure is “positively autocorrelated, consistent with order flow picking up order-splitting strategies of institutions,” and they identify the interaction between inventory risk and adverse selection as an

avenue for future work. Whether this persistence carries incremental information about spreads, or is fully subsumed by volatility, is the question this thesis addresses.

We introduce order imbalance autocorrelation (OIAC), defined as the AR(1) coefficient of five-minute signed share imbalances within each trading day, as a measure of order flow persistence. OIAC is conceptually distinct from HFOIV: two stocks can have identical order imbalance volatility but markedly different persistence, with different implications for liquidity provision. Two competing mechanisms generate opposite predictions for the sign of the OIAC coefficient in spread regressions. Under the inventory duration hypothesis, persistent one-sided flow extends the horizon over which market makers hold inventory, compounding position risk and widening spreads (building on Grossman and Miller, 1988). Under the adverse selection signalling hypothesis, predictable flow reflects order splitting (Tóth et al., 2015) that, to the extent it is mechanical rather than information-driven, allows market makers to reduce the adverse selection component of the spread (Glosten & Milgrom, 1985). The sign of the OIAC coefficient discriminates between these channels.

Using a panel of NYSE, AMEX, and NASDAQ common stocks from 2004 to 2024, constructed from TAQ intraday data and CRSP daily files, we replicate the main findings of Bogousslavsky and Collin-Dufresne (2023) and extend their framework along this new dimension. The analysis pursues three objectives: (i) replicate and validate the HFOIV-spread relationship in a sample that extends seven years beyond the original; (ii) test whether order imbalance persistence provides incremental explanatory power for spreads beyond HFOIV; and (iii) identify the economic channel through which persistence operates. The empirical strategy follows Bogousslavsky and Collin-Dufresne (2023) in estimating year-by-year panel regressions with stock fixed effects and double-clustered standard errors, supplemented by calendar-based identification tests, a systematic-idiosyncratic decomposition, and Fama–MacBeth cross-sectional return regressions.

The replication confirms the main findings of Bogousslavsky and Collin-Dufresne (2023): HFOIV is a strong predictor of effective spreads, and controlling for HFOIV recovers the negative volume-spread relationship predicted by Demsetz (1968). In the BCD sample period, HFOIV flips the turnover coefficient for large stocks from positive to negative; in the extended sample, the baseline volume-spread relationship is already weakly negative, and HFOIV strengthens it substantially.

The main new finding is that OIAC carries statistically significant incremental explanatory power for effective spreads among large stocks, with a negative and strongly significant coefficient in the joint specification with HFOIV. Higher persistence is associated with *narrower* spreads, consistent with the adverse selection signalling channel rather than inventory duration. The effect is economically modest relative to HFOIV (a within-stock standard deviation increase in OIAC narrows spreads by approximately one percent, versus roughly 27 percent for HFOIV) but is robust to first differencing and to the inclusion of an HFOIV-OIAC interaction term, which is statistically indistinguishable from zero, indicating that the two variables operate through independent channels. Calendar-based identification tests show that HFOIV increases on derivative expiration days (consistent with inventory risk) while OIAC decreases sharply (consistent with the disruption of institutional order-splitting patterns by hedging flows). A commonality decomposition reveals that the OIAC-spread relationship is driven entirely by idiosyncratic persistence rather than market-wide persistence, consistent with firm-specific order splitting rather than cross-broker herding. For small stocks, OIAC has no significant explanatory power, consistent with lower rates of algorithmic execution in less liquid names.

Regarding return predictability, the HFOIV premium documented by BCD for their sample period does not replicate in the extended sample (2004–2024), and OIAC does not predict cross-sectional returns in either sample period, suggesting that high-frequency order flow characteristics affect the cost of liquidity provision without commanding characteristic-based return premia in the current market environment.

The remainder of the thesis is organised as follows. Section 2 positions the research question within the market microstructure literature on inventory risk, adverse selection, and order flow persistence. Section 3 presents the BCD model, develops the testable hypotheses, and specifies the regression framework. Section 4 describes the TAQ, CRSP, and I/B/E/S datasets, variable construction, sample filters, and summary statistics. Section 5 reports and interprets the findings. Section 6 concludes with a discussion of contributions, limitations, and directions for future research.

2 Literature Review

2.1 The Evolution of Liquidity Theory

Liquidity remains one of the most elusive concepts in financial economics. Demsetz (1968) posed the question that launched the field: what does it cost to trade, and why does this cost vary? The bid-ask spread captures the price of immediacy, declining as trading activity increases through economies of scale. Yet liquidity is inherently multi-dimensional, comprising both a price dimension (spread) and a quantity dimension (depth). Liquidity providers actively manage risk by adjusting both dimensions simultaneously (Lee et al., 1993).

Two theoretical paradigms have shaped the study of transaction costs. The inventory paradigm explains spreads as compensation for the risk of holding unwanted positions; the adverse selection paradigm explains them as protection against traders with superior information. Determining the relative importance of each channel, and identifying the specific properties of order flow that drive spreads, is a central focus of the literature.

The following sections trace how these paradigms developed, how empirical methods evolved alongside increasingly granular data, and how the discovery that order flow has both variable volatility and persistent serial structure leads to the research question this thesis addresses.

2.2 Theoretical Foundations: Inventory Risk and Adverse Selection

The Inventory Paradigm

The inventory paradigm begins with a simple observation: buy and sell orders arrive asynchronously, forcing dealers to hold positions that deviate from their preferred portfolios. Garman (1976) provided the earliest formal treatment, modelling order flow as a stochastic process in which buy and sell orders arrive according to independent Poisson processes with rates depending on quoted prices. Garman demonstrated the “gambler’s ruin” problem: a dealer employing fixed bid-ask prices faces certain failure as inventory or cash eventually hits a zero boundary through random fluctuations.

Stoll (1978) asked what happens when the dealer is risk-averse. A risk-averse dealer demands compensation for bearing inventory, and this compensation appears as a spread. Stoll decomposes the spread into three components: holding costs (price risk from inventory), order-processing costs, and information costs. The holding cost depends on the dealer’s risk aversion, return variance, and position size. Subsequent work treated inventory as a state variable: optimal bid and ask prices are monotone decreasing in inventory, declining when the dealer holds excess stock to encourage buying and discourage selling (Amihud & Mendelson, 1980). Spreads are minimised at a preferred inventory position and widen as positions approach limits.

Ho and Stoll (1981) extended Stoll’s static framework to a dynamic programming setting, decomposing the spread into a risk-neutral component and a risk adjustment depending on transaction size, risk aversion, and return variance. When only asset prices are uncertain and order arrival is deterministic (“single-source uncertainty”), inventory affects the placement of the spread (the quote midpoint) but not its width. Even under competition among three or more dealers, inventory risk remains priced (Ho & Stoll, 1983). Together, these models establish that the equilibrium spread compensates a risk-averse dealer for inventory risk, widening with risk aversion, return variance, and position size.

When both order flow quantity and asset prices are uncertain (“dual uncertainty”), spread width itself becomes inventory-dependent (O’Hara & Oldfield, 1986). Dealers cannot control risk solely by shifting quotes; they must also widen them. This result established theoretically that the variance of order flow, not only the variance of returns, affects the width of the spread. The dynamic inventory model of Bogousslavsky and Collin-Dufresne (2023) (presented in Section 3) builds on this prediction.

Grossman and Miller (1988) formalised the supply-of-immediacy view: market makers absorb temporary order imbalances by taking inventory positions, bearing price risk until offsetting counterparties arrive. In their static three-period model, the equilibrium price discount demanded by intermediaries is increasing in the variance of the supply shock, establishing that the volatility of order imbalances determines the cost of immediacy. Because the model features a single supply shock, persistence is zero by construction.

Direct empirical support for inventory-based spread determination comes from a study of eleven years of NYSE specialist positions and revenues (Comerton-Forde et al., 2010).

Spreads widen when specialists hold extreme inventory positions or suffer trading losses, with the effects strongest at the tails of the inventory distribution, consistent with financing constraints that amplify inventory risk.

Adverse Selection Models

In contrast to inventory models, which explain spreads as compensation for position risk, adverse selection models explain spreads as protection against traders with superior information. Bagehot (1971) articulated the core intuition: market makers systematically lose to informed traders and must recoup these losses from uninformed traders through the spread. Glosten and Milgrom (1985) showed that a positive spread arises even without inventory or processing costs, purely from the information content of trades. Competitive market makers set the ask equal to the expected asset value conditional on a buy and the bid conditional on a sell; the spread exists because buys carry adverse news for the seller. Each trade triggers Bayesian updating, incorporating the information revealed by trading into prices.

Strategic behaviour introduces a second dimension. Kyle (1985) showed that an informed insider trades gradually to conceal her information, camouflaging informed orders within uninformed trading. Because the market maker cannot distinguish the two, prices respond to aggregate net order flow: the price impact coefficient λ measures this sensitivity. Market depth (the inverse of λ) increases with noise trading volume, because uninformed flow dilutes the market maker's signal extraction problem. Kyle's framework therefore predicts that more noise trading improves liquidity. This prediction is superficially similar to the Demsetz effect, but operates through a distinct channel. Whereas Demsetz's mechanism is indifferent to trader type (any volume reduces waiting costs), Kyle's result depends on the *composition* of order flow: uninformed trading dilutes the information signal, but additional informed trading worsens liquidity by raising λ .

These theoretical predictions require an empirical measure of information asymmetry. Easley et al. (1996) provide one through the probability of informed trading (PIN), estimated from a structural model of the trading process. They find that less-active stocks suffer not from too many informed traders but from too few uninformed ones: the unin-

formed arrival rate is so low that informed trading constitutes a larger fraction of total activity.

The inventory paradigm predicts that trade-driven price impact is transient (inventory mean-reverts); the adverse selection paradigm predicts that it is permanent (beliefs do not revert). Decomposing the spread into permanent and transitory components reveals that both are economically significant (Glosten & Harris, 1988). Neither paradigm alone explains spreads: dealers simultaneously bear inventory risk and face informed traders.

Implications for Order Imbalance

Order imbalance serves as a natural bridge between these paradigms. The level of order imbalance (the directional excess of buyer-initiated over seller-initiated trades) may signal private information (Kyle, 1985), or may represent the stochastic variation that dealers must absorb as inventory (Grossman & Miller, 1988). Chordia et al. (2002) document both channels empirically: order imbalances “sometimes signal private information, which should reduce liquidity at least temporarily and could also move the market price permanently,” while “even a random large order imbalance exacerbates the inventory problem faced by the market maker.” The volatility of order imbalance, which Bogousslavsky and Collin-Dufresne (2023) measure as High-Frequency Order Imbalance Volatility (HFOIV), captures the uncertainty in cumulative inventory accumulation, while the level captures directional information content. The equilibrium spread therefore depends on both the variance of returns (price risk per unit held) and the variance of order imbalances (inventory exposure), linking the theoretical predictions of both paradigms to observable properties of order flow.

2.3 The Persistence of Order Flow

The preceding section treats order imbalance volatility as a contemporaneous phenomenon. Yet order flow is not independent across intervals: it exhibits substantial serial dependence whose origins and consequences this section examines.

Why are order imbalances persistent? Aggregate daily order imbalances are highly autocorrelated (first-order autocorrelation of 0.54 for NYSE number-based imbalances), decaying slowly through at least five daily lags (Chordia et al., 2002), and this pattern

extends to individual stocks (Chordia & Subrahmanyam, 2004). The economic intuition centres on order splitting: optimal execution strategies fragment large “parent” orders into sequences of smaller “child” orders executed incrementally to minimise price impact.

Lillo et al. (2005) provide the theoretical mechanism: if institutional investors’ hidden order sizes are heavy-tailed, as they document empirically, the revealed order signs exhibit long-memory autocorrelation. Order splitting by large investors mechanically induces persistence in order flow, with significant autocorrelation at lags as long as two weeks.

Tóth et al. (2015) provide the most direct test distinguishing order splitting from herding. Using unique broker identification data, they decompose order flow autocorrelation into “same-agent” and “other-agent” components. Same-broker autocorrelation accounts for approximately 75% of total persistence at short lags, while cross-broker correlations are essentially zero or negative at longer lags. The negative cross-broker correlation reflects liquidity provision in response to persistent buying by individual brokers. On timescales of less than a few hours, persistence is overwhelmingly due to splitting rather than herding. This evidence confirms that intraday persistence arises primarily from the mechanical fragmentation of large orders rather than correlated trading decisions across investors. Given that intraday persistence is substantial and driven by order splitting, the question becomes whether this temporal structure carries implications for spreads beyond what the inventory volatility literature has captured.

2.4 The Interaction of Persistence and Volatility

Order Flow Predictability and Market Making

Autocorrelated imbalances create continuing price pressures: lagged daily order imbalance positively forecasts next-period returns (Chordia & Subrahmanyam, 2004). When controlling for contemporaneous imbalance, lagged imbalance becomes negatively related to returns. This sign reversal is the signature of the inventory paradigm: conditioning on current imbalance reveals that past imbalance created temporary price displacement that subsequently reverses, providing empirical confirmation of inventory stabilisation.

The implications of persistence for market makers are not settled by the existing literature. The long-memory order-splitting process documented by Lillo et al. (2005) suggests

that persistent order flow compounds inventory risk, as positions trend in one direction until the underlying splitting process completes, extending the horizon over which the market maker bears position risk. Yet predictable order flow may also reduce adverse selection costs: if market makers can anticipate the direction of future flow because it reflects mechanical splitting rather than new information, they can better distinguish informed from uninformed trading and adjust quotes accordingly. These two mechanisms pull in opposite directions, and the existing literature does not resolve which dominates.

Modern Market Making and Inventory Management

Direct evidence on how modern market makers manage persistent positions comes from a study of a high-frequency trader functioning as a market maker across Chi-X and Euronext (Menkveld, 2013). The trader earns profits on the bid-ask spread but incurs losses on inventory positions, consistent with the inventory-risk framework of Ho and Stoll (1981). The trader ends the day flat approximately 70% of the time, confirming that inventory management remains a central constraint on market-making profitability even when holding periods are measured in seconds (see also O’Hara, 2015).

Causal evidence on the inventory management channel comes from a colocation upgrade at NASDAQ OMX Stockholm used as a natural experiment (Brogaard et al., 2015). The resulting spread improvement is driven almost entirely by a 37% reduction in the realised spread component (inventory and processing costs), while the price impact component (adverse selection) is essentially unchanged. After upgrading, fast market makers maintain presence at the best quotes even when holding large inventories, consistent with relaxed inventory constraints. The convex relationship between inventories and subsequent spreads confirms that inventory costs remain the binding constraint on spread-setting for modern market makers.

Causal evidence on the adverse selection channel comes from the staggered introduction of NYSE’s autoquote system, used as an instrument for algorithmic trading (Hendershott et al., 2011). The resulting increase in algorithmic trading narrows effective spreads for large stocks, with 75–90% of the improvement attributable to reduced adverse selection rather than reduced realised spreads. For small stocks, the effect is insignificant; this size

dependence is consistent with algorithmic execution concentrating in liquid names.

If liquidity itself is persistent and this persistence is priced, then the characteristics of order flow that generate liquidity persistence may carry independent information. Investors demand compensation for bearing liquidity risk when high illiquidity today predicts high illiquidity next period (Acharya & Pedersen, 2005). Because order imbalances drive liquidity from the market maker’s perspective, the persistence of those imbalances may carry information about spreads beyond what volatility measures alone capture.

Before examining whether persistence carries incremental information, the asset-pricing evidence on illiquidity merits attention. Illiquidity itself is a priced characteristic: Amihud (2002) defines illiquidity as the average ratio of daily absolute return to dollar volume and shows that expected illiquidity positively predicts cross-sectional returns, with the effect concentrated among small stocks. Building on this illiquidity premium, order flow volatility is a priced return predictor in its own right: the level of order imbalance volatility positively predicts cross-sectional returns, and shocks to volatility negatively affect contemporaneous returns as adverse selection costs rise (Chordia et al., 2019). This measure (the monthly standard deviation of daily order imbalance) is conceptually aligned with HFOIV but operates at a lower frequency, suggesting that order flow volatility captures economically meaningful variation at multiple timescales.

2.5 Synthesis and the Research Gap

The preceding sections establish three empirical regularities relevant to the determination of bid-ask spreads. First, the inventory paradigm identifies order imbalance volatility as a primary determinant of inventory risk: more volatile order flow exposes liquidity providers to larger and less predictable position changes, widening the spread they demand as compensation (Grossman & Miller, 1988; O’Hara & Oldfield, 1986). Second, order flow is persistent at intraday frequencies, driven primarily by the splitting of large institutional orders rather than by correlated trading decisions across investors (Lillo et al., 2005; Tóth et al., 2015). Third, the implications of this persistence for market making are theoretically ambiguous: persistent flow may compound inventory risk by extending holding periods, or it may reduce adverse selection costs by signalling uninformed execution.

Bogousslavsky and Collin-Dufresne (2023) formalise the first of these regularities through a continuous-time inventory model in which the equilibrium spread arises as compensation for bearing order imbalance risk. Their model generates two testable predictions: controlling for order imbalance volatility, higher volume should reduce spreads (the Demsetz (1968) effect); and controlling for volume, higher order imbalance volatility should widen spreads (the inventory risk channel). These predictions, and the model that generates them, are presented in Section 3.

The model, however, assumes a Markov structure for order flow: each state transition is independent of previous transitions. Although the Markov chain produces autocorrelated inventory levels, the degree of autocorrelation is fully determined by the transition intensities that also determine order imbalance volatility. Once these intensities are controlled for, the temporal structure of imbalances carries no additional information. The persistence literature reviewed in Section 2.3 documents that this assumption is violated empirically, raising the question of whether persistence provides incremental explanatory power for spreads beyond what volatility captures.

While Bogousslavsky and Collin-Dufresne (2023) establish that high-frequency order imbalance volatility (HFOIV) drives the volume-spread relationship, and Chordia et al. (2019) confirm that order flow volatility is priced in returns, neither study examines whether the temporal structure of order flow provides additional explanatory power. Whether order imbalance persistence, measured as the first-order autocorrelation of five-minute share imbalances within each trading day (OIAC), explains residual variation in spreads after controlling for HFOIV remains untested. The literature reviewed above yields two competing predictions for the sign of this relationship. Under the inventory duration channel, persistent one-sided flow extends the horizon over which the market maker holds inventory and bears the associated price risk (Grossman & Miller, 1988), compounding position risk and widening spreads. Under the adverse selection signalling channel, predictable flow reflects algorithmic order splitting (Tóth et al., 2015) rather than new information, allowing market makers to reduce the adverse selection component of the spread (Glosten & Milgrom, 1985). These channels predict opposite signs for the relationship between persistence and spreads, and the sign that obtains empirically depends on which mechanism dominates. The next section formalises these predictions within the Bogous-

slavsky and Collin-Dufresne (2023) model and develops the regression specifications used to test them.

3 Empirical Strategy

The empirical framework for testing the roles of order imbalance volatility and persistence in determining stock liquidity proceeds in five steps. We begin by presenting the theoretical model of Bogousslavsky and Collin-Dufresne (2023), which provides the microfoundation for the HFOIV-spread relationship and generates the predictions that structure our regression specifications. We then derive the testable hypotheses, including the null prediction for order imbalance persistence that arises from the model’s Markov structure. The remainder of this section describes the regression specifications, estimation approach, identification strategy, and cross-sectional return tests.

3.1 Theoretical Framework

The literature review documented that order imbalance volatility is a primary determinant of inventory risk and that order flow persistence is substantial at intraday frequencies. Bogousslavsky and Collin-Dufresne (2023) formalise the first of these observations through a continuous-time equilibrium model in which a competitive liquidity provider absorbs stochastic order flow and prices the resulting inventory risk into the bid-ask spread. The model is relevant to our analysis for two reasons. First, it provides the microfoundation for the HFOIV-spread relationship documented empirically: the spread is not merely correlated with order imbalance volatility but arises as the equilibrium compensation for bearing inventory risk generated by that volatility. Second, by decomposing the forces that drive spreads into two independent channels (a volume channel and an order imbalance volatility channel), the model generates testable predictions that a single-parameter adverse selection framework cannot replicate. We summarise the model here, following Bogousslavsky and Collin-Dufresne (2023) closely.

Model Setup

The model features a single long-lived liquidity provider (LP) with constant absolute risk aversion (CARA) preferences,

$$u(c, t) = -e^{-\beta t - \alpha c_t},$$

where $\alpha > 0$ is the coefficient of absolute risk aversion and $\beta > 0$ is the discount rate. The LP invests at a constant risk-free rate r and trades a single risky asset. CARA utility is analytically convenient because it eliminates wealth effects: the LP's optimal quoting policy depends only on the current state of dividends and inventory, not on accumulated wealth. This stationarity permits closed-form characterisation of the equilibrium spread.

Order flow is modelled as the total supply of shares available to the LP, which switches among M discrete states according to a continuous-time Markov chain with transition intensities λ_{ij} . The LP holds the entire available supply in equilibrium; every supply shock is absorbed by the LP, so that inventory is determined by the Markov state. Dividends follow an Ornstein–Uhlenbeck process,

$$d\delta_t = \kappa_\delta(\bar{\delta}(N_t) - \delta_t) dt + \sigma_\delta dZ_t,$$

where δ_t is the dividend rate, κ_δ governs mean reversion, $\bar{\delta}(N_t)$ allows the long-run dividend level to depend on the supply state N_t , σ_δ is dividend volatility, and Z_t is a standard Brownian motion. Because dividends and supply are the only sources of uncertainty, the equilibrium price is a function of these two state variables alone.

Equilibrium and Price Decomposition

In equilibrium, the asset price decomposes into a fundamental value and an inventory risk premium:

$$S(\delta_t, N_t) = V(\delta_t, N_t) + s(N_t).$$

The first component, $V(\delta_t, N_t)$, is the risk-neutral present value of future dividends, which depends on both the current dividend rate and the supply state (through $\bar{\delta}$). The second component, $s(N_t)$, is the state-dependent inventory premium: a discount the LP demands for holding risky inventory. When the LP holds more shares, s is more negative (the price is lower), reflecting greater compensation for inventory risk. When inventory is zero, the premium vanishes.

To derive closed-form results, Bogousslavsky and Collin-Dufresne (2023) specialise to a symmetric three-state model ($M = 3$), with dividends independent of order flow, in which inventory takes values $\{-\hat{\theta}, 0, +\hat{\theta}\}$. The parameter $\hat{\theta}$ represents the size of each supply

shock. Transitions follow a birth-death chain governed by two intensities: λ_i , the rate at which imbalance-increasing trades arrive (moving inventory from zero to $\pm\hat{\theta}$), and λ_d , the rate at which offsetting trades arrive (returning inventory to zero). Because the LP absorbs all supply, order imbalance in this model equals the absolute value of inventory. The half-spread $\hat{s}$ measures the LP's per-share compensation for absorbing a trade of size $\hat{\theta}$. It is bounded:

$$0 \leq \hat{s} \leq \alpha\sigma^2, \quad \text{where } \sigma = \frac{\sigma_\delta}{r + \kappa_\delta}.$$

The trade size $\hat{\theta}$ does not appear in this bound; it enters the model through the volume and OIV expressions rather than the spread itself (Bogousslavsky & Collin-Dufresne, 2023, Appendix B). The upper bound obtains when $\lambda_d \rightarrow 0$: offsetting trades never arrive, the LP is a permanent buy-and-hold investor, and the spread equals the full risk-aversion-weighted variance of the discounted dividend stream. The lower bound obtains when $\lambda_d \rightarrow \infty$: offsetting trades arrive instantaneously, the LP bears no inventory risk, and the spread collapses to zero. Between these extremes, the spread increases monotonically as λ_d decreases, because slower offset arrival extends the period over which the LP bears price risk on accumulated inventory. When either risk aversion (α) or return variance (σ^2) is zero, the spread is zero regardless of λ_d , confirming that the model is purely an inventory risk mechanism.

Volume, Order Imbalance Volatility, and the Two Channels

The model generates closed-form expressions for trading volume and order imbalance volatility as functions of the two transition intensities:

$$\begin{aligned} \text{VOL} &= 4\hat{\theta} \left(\frac{1}{\lambda_i} + \frac{2}{\lambda_d} \right)^{-1}, \\ \text{OIV} &= \frac{\hat{\theta}}{2\lambda_d} \cdot \text{VOL}. \end{aligned}$$

Here OIV denotes the model's theoretical order imbalance volatility: the unconditional variance of the LP's inventory position. Its empirical counterpart, HFOIV, is the daily standard deviation of five-minute share imbalances scaled by shares outstanding, so the two objects differ in both units (variance versus standard deviation) and horizon (unconditional versus daily). Because the standard deviation is a monotone transformation of the variance,

the model’s prediction of a positive OIV-spread relationship extends directly to HFOIV. The volume expression is the expected number of shares traded per unit time in steady state; it is increasing in both λ_i (more frequent trade initiation) and λ_d (faster offsets). The OIV expression reveals the central theoretical result: OIV is proportional to volume, but the proportionality constant $\hat{\theta}/(2\lambda_d)$ depends on how quickly offsetting trades arrive. Two stocks with identical volume can have different order imbalance volatility if their offset rates differ.

This two-parameter structure generates two distinct comparative statics through which trading activity affects spreads.

The first channel corresponds to the classical volume-spread relationship identified by Demsetz (1968). Setting $\lambda_d = \lambda_i = \lambda$ and varying λ produces symmetric changes in trade arrival rates. Volume increases linearly in λ ($\text{VOL} = \frac{4}{3}\lambda\hat{\theta}$), while OIV remains constant ($\text{OIV} = \frac{2}{3}\hat{\theta}^2$). Higher λ means that offsetting trades arrive more rapidly, shortening the LP’s holding period and reducing inventory risk. The spread decreases monotonically: more frequent trading provides liquidity through faster inventory turnover (Stoll, 1978). This is the Demsetz (1968) economies-of-scale effect, in which greater volume reduces the cost of immediacy.

The second channel operates through order imbalance volatility while holding volume fixed. Holding the composite rate $(1/\lambda_i + 2/\lambda_d)$ constant (thereby fixing volume), a decrease in λ_d accompanied by an offsetting increase in λ_i shifts the composition of trading activity. Trades initiate more frequently (λ_i rises), but offsetting trades arrive more slowly (λ_d falls). From the OIV formula, this shift in composition raises order imbalance volatility because the $\hat{\theta}/(2\lambda_d)$ factor increases. The spread rises sharply because the LP holds each inventory position for longer before an offset arrives.

The interaction of these two channels explains why volume and spreads can be positively correlated in the cross-section, a pattern that contradicts classical predictions. One can change λ_i and λ_d to increase volume while simultaneously increasing spreads, provided the OIV effect dominates the Demsetz (1968) effect (Bogousslavsky & Collin-Dufresne, 2023). When HFOIV is included in spread regressions alongside volume, it absorbs the OIV channel, allowing the volume coefficient to recover its theoretically predicted negative sign. This decomposition motivates the central empirical test in Bogousslavsky and Collin-

Dufresne (2023) and forms the basis of our replication.

Contrast with Adverse Selection

The richer prediction structure of the inventory model becomes apparent when compared with the continuous-time adverse selection framework of Back (1992) and Kyle (1985). In the Kyle–Back model, price impact is σ_i/σ_u , where σ_i is the standard deviation of the informed trader’s private value and σ_u is the standard deviation of noise trading volume. A single parameter, σ_u , governs both volume and order imbalance volatility. Increasing noise trading raises volume and OIV simultaneously but *lowers* price impact because the market maker faces a more favourable signal-to-noise ratio.

Interpreting the Kyle–Back price impact as analogous to the bid-ask spread, this single-parameter structure prevents the framework from generating opposing effects of volume and OIV on spreads. Any change in σ_u moves volume and OIV in the same direction, and both changes reduce price impact. There is no mechanism through which higher OIV can widen spreads while higher volume narrows them, because both are driven by the same underlying parameter.

The Bogousslavsky and Collin-Dufresne (2023) model, by contrast, separates imbalance-increasing order arrival (λ_i) from offsetting order arrival (λ_d), giving two independent parameters that can move volume and OIV in opposite directions relative to spreads. This independence permits the model to rationalise the empirical finding that, conditional on OIV, volume reduces spreads, while conditional on volume, OIV increases them. The adverse selection framework predicts a negative volume-spread relationship unconditionally, and cannot account for the positive relationship observed among large stocks (Bogousslavsky & Collin-Dufresne, 2023) without invoking additional mechanisms. This theoretical distinction motivates the use of HFOIV as the primary explanatory variable in our spread regressions and suggests that inventory risk, rather than adverse selection, is the primary constraint on market maker pricing for the stocks and frequencies we study.

The two-channel structure of the model, combined with its Markov order flow assumption, provides the theoretical foundation for the hypotheses that follow. The key question is whether order flow persistence, which the model assumes away, carries additional infor-

mation about spreads once order imbalance volatility is controlled for.

3.2 Hypothesis Development

The model generates two predictions that structure the core specifications. First, the HFOIV coefficient should be positive: higher order imbalance volatility increases the inventory risk borne by liquidity providers, widening spreads. Second, controlling for HFOIV should recover the negative turnover-spread relationship predicted by Demsetz (1968): with inventory risk held constant, higher volume reflects faster arrival of offsetting trades, reducing the cost of immediacy.

The model is silent on order flow persistence. The Markov property implies that each state transition is independent of previous transitions: knowing the current inventory state is sufficient for predicting future states, regardless of how the LP arrived at that state. The Markov chain does produce positively autocorrelated inventory *levels* (if the LP is in state $+\hat{\theta}$, the probability of remaining there over a short interval is approximately $1 - \lambda_d dt$), but the degree of this autocorrelation is fully determined by λ_d , the same parameter that determines OIV.

In the model, the spread depends on four parameters: λ_i , λ_d , α , and σ . The regression controls for turnover (which, together with HFOIV, identifies the transition intensities λ_i and λ_d), realised volatility (which proxies for σ), and stock fixed effects (which absorb α). With all model-relevant parameters controlled for, HFOIV is a sufficient statistic for the inventory-risk properties of order flow. Persistence, measured as the autocorrelation of intraday order imbalances (OIAC), carries no *incremental* information about spreads beyond what HFOIV and the other regressors already capture. This yields the null hypothesis:

H_0 : *Markov Order Flow*

If the Markov structure is a sufficient description of order flow dynamics, OIAC should have no incremental explanatory power for spreads after controlling for HFOIV ($\beta_{OIAC} = 0$).

The persistence literature reviewed in Section 2.3 documents that order flow exhibits temporal dependence beyond what the Markov transition intensities imply, but the di-

rection of the effect on spreads is ambiguous. Two competing channels yield opposite predictions.

H₁: Inventory Duration

Persistent one-sided flow extends the horizon over which the market maker holds inventory and bears the associated price risk (Grossman & Miller, 1988). Under this channel, higher persistence compounds position risk and widens spreads ($\beta_{OIAC} > 0$). The interaction term (Equation 3.3) provides a further test: persistent *large* shocks should be costlier than persistent *small* shocks ($\beta_{\times} > 0$).

H₂: Adverse Selection Signalling

Predictable flow reflects algorithmic order splitting (Tóth et al., 2015) rather than new information, allowing market makers to reduce the adverse selection component of the spread (Glosten & Milgrom, 1985). Under this channel, higher persistence narrows spreads ($\beta_{OIAC} < 0$). The interaction term should be zero or negative ($\beta_{\times} \leq 0$), since predictability reduces adverse selection regardless of shock size.

H_1 is grounded in the inventory risk framework of the BCD model, while H_2 draws on the adverse selection framework of Glosten and Milgrom (1985). No single model jointly generates both predictions; the empirical test identifies the net effect of the two channels.

Both hypotheses carry auxiliary predictions for the decomposition and return tests developed below. If the adverse selection signalling channel (H_2) dominates, the effect should concentrate in idiosyncratic persistence (since order splitting is stock-specific) and in large-capitalisation stocks (where uninformed execution algorithms are most prevalent, owing to the deeper liquidity that these strategies require). If OIAC reduces adverse selection costs (a diversifiable friction), it should not command a systematic return premium, unlike HFOIV, which captures inventory risk exposure.

3.3 Panel Spread Regressions

We test whether HFOIV and OIAC explain effective spreads beyond turnover and realised volatility using a panel regression with stock fixed effects. The baseline levels specification

is

$$\log s_{i,t} = \alpha_i + \beta_\tau \log \tau_{i,t} + \beta_\sigma \log \sigma_{i,t} + \gamma' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \quad (3.1)$$

where $s_{i,t}$ is the percent effective spread, $\tau_{i,t}$ is intraday share turnover, $\sigma_{i,t}$ is realised volatility computed from five-minute midquote returns, and α_i denotes stock fixed effects. The control vector $\mathbf{Z}_{i,t}$ includes log lagged price, which controls for the mechanical relationship between tick size and spreads; log lagged market capitalisation, which absorbs residual size variation not captured by the quintile stratification; and day-of-week and month-of-year indicators, which account for well-documented calendar patterns in liquidity.

Specification (2) adds $\log HFOIV_{i,t}$, replicating the main test of Bogousslavsky and Collin-Dufresne (2023). Specification (3) adds $OIAC_{i,t}$ in place of $HFOIV$, to isolate its univariate relationship with spreads. Specification (4) includes both $\log HFOIV_{i,t}$ and $OIAC_{i,t}$ jointly; this is the key test of incremental explanatory power. $OIAC$ enters in levels because it can take negative values, so β_{OIAC} is a semi-elasticity. Since $OIAC$ is approximately bounded on $[-1, 1]$, economic magnitudes are best assessed using the within-stock standard deviation (0.15–0.19 for large stocks; Table 1). All other explanatory variables enter in logs, yielding standard elasticity interpretations.

To verify that results are not driven by time-invariant omitted stock characteristics, which are absorbed by the fixed effects, we also estimate a changes specification:

$$\Delta \log s_{i,t} = \alpha_i + \beta_{\Delta\tau} \Delta \log \tau_{i,t} + \beta_{\Delta\sigma} \Delta \log \sigma_{i,t} + \gamma' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \quad (3.2)$$

where Δ denotes the first difference from day $t - 1$ to t . Specifications (2)–(4) augment this baseline with $\Delta \log HFOIV_{i,t}$ and/or $\Delta OIAC_{i,t}$, paralleling the levels specifications. Changes in $OIAC$ are computed as a simple difference ($OIAC_{i,t} - OIAC_{i,t-1}$) rather than a log-difference, consistent with its levels treatment in Equation 3.1.

To test whether the effects of $HFOIV$ and $OIAC$ interact, a fifth specification augments Equation 3.1 with a centred interaction term:

$$\dots + \beta_\times (\log HFOIV_{i,t} - \overline{\log HFOIV}_{g,y}) \times (OIAC_{i,t} - \overline{OIAC}_{g,y}) + \dots \quad (3.3)$$

where $\bar{\cdot}_{g,y}$ denotes the mean within size quintile g and calendar year y . Centring ensures that the main-effect coefficients β_{HFOIV} and β_{OIAC} are interpretable at group-year means. A positive interaction would indicate that the effect of $HFOIV$ on spreads intensifies when

order flow is persistent, consistent with an inventory duration mechanism; a null interaction would suggest that volatility and persistence operate through independent channels.

Specification Strategy

Specifications (1)–(2) replicate the baseline and main test of Bogousslavsky and Collin-Dufresne (2023); specifications (3)–(5) constitute our extension, introducing OIAC into the BCD framework. If HFOIV captures inventory risk distinct from turnover, its inclusion in specification (2) should render the turnover coefficient more negative. If OIAC carries incremental information beyond HFOIV, the joint specification (4) is the key test: β_{OIAC} should be non-zero, with the sign discriminating between the inventory duration (H_1 : positive) and adverse selection signalling (H_2 : negative) channels.

Estimation

We estimate Equation 3.1 separately for each calendar year and report the median coefficient and median t -statistic across years. This approach alleviates non-stationarity in spread and turnover series, since each annual subsample is short enough that slow-moving trends are unlikely to contaminate the estimates (Bogousslavsky & Collin-Dufresne, 2023). The median provides a robust summary of 21 annual estimates, limiting the influence of outlier years; individual year-by-year coefficients and t -statistics are reported in the appendix and reveal how the relationships evolve over time. Regressions are estimated separately for small stocks (bottom size quintile) and large stocks (top quintile).

Standard errors are double-clustered by calendar date and stock (Cameron et al., 2011; Thompson, 2011):

$$\hat{V}_{DC} = \hat{V}_{\text{date}} + \hat{V}_{\text{stock}} - \hat{V}_{\text{White}},$$

where $\hat{V}_{\text{date}}$ and $\hat{V}_{\text{stock}}$ are the one-way clustered variance estimators and $\hat{V}_{\text{White}}$ is the heteroskedasticity-consistent (HC0) estimator. Negative diagonal elements of $\hat{V}_{DC}$ can arise mechanically when the two clustering dimensions overlap (see Cameron et al., 2011, Section 2.3). We set such elements to zero before computing t -statistics; this is a practical correction that prevents undefined standard errors but may modestly understate uncer-

tainty for the affected coefficients.¹

Because the year-by-year regressions (Tables 4, 5, and 8) estimate within a single calendar year, year fixed effects are absorbed by construction. The pooled panel regressions (Tables 6 and 7) include explicit year fixed effects alongside stock, day-of-week, and month indicators. Table 7 also serves as a conventional pooled-panel confirmation of the year-by-year spread results, using two-way clustering rather than year-by-year estimation. The Fama–MacBeth return regressions (Table 10) are cross-sectional by design and do not include year fixed effects.

Winsorisation

Effective spreads are winsorised at the 0.05th and 99.95th percentiles within each year for the panel regressions (Tables 4–8) and descriptive statistics (Tables 1–3 and Figures 1–3). In the Fama–MacBeth return regressions (Table 10), all explanatory variables are winsorised at the more aggressive 0.5th and 99.5th percentiles.² OIAC is not winsorised in the spread regressions because values outside $[-1, 1]$ carry economic information about non-stationary order flow (Section 4.2); in the Fama–MacBeth regressions, OIAC is winsorised along with all other explanatory variables at the 0.5th and 99.5th percentiles.

3.4 Identification and Decomposition Tests

The panel regressions in the previous section establish partial correlations between order flow measures and spreads. This section develops two complementary identification strategies to distinguish the economic channels through which these variables operate.

Calendar-Based Identification

To distinguish inventory-based from information-based channels, we exploit predictable calendar variation in order flow. If HFOIV captures inventory risk, it should increase on

¹The BCD replication code does not apply this correction, which may yield undefined t -statistics when the estimated variance is negative.

²The winsorisation levels stated in the published paper (0.05% for spread tables, 0.5% for Fama–MacBeth) are reversed in the Bogousslavsky and Collin-Dufresne (2023) replication code, which applies 0.5% to spread tables and 0.05% to Fama–MacBeth regressions. We follow the levels reported in the published paper.

days with large hedging flows (option expiration generates substantial uninformed directional order flow (Barclay et al., 2008)), but not necessarily around information events such as earnings announcements. Conversely, if HFOIV proxies for adverse selection, it should increase around earnings announcements, when informed trading intensifies. Table 6 regresses log HFOIV, log turnover, and OIAC on calendar event indicators (option expiration, end-of-quarter witching, beginning and end of month, Russell reconstitution, and earnings announcement window), controlling for size and price, with stock, day-of-week, month, and year fixed effects.

Mediation Test

If HFOIV mediates the effect of calendar events on spreads, adding it as a control should attenuate or eliminate the direct calendar coefficients. Table 7 implements this mediation test: specification (1) regresses log effective spreads on calendar indicators and controls, omitting order flow variables; specification (2) adds log HFOIV. The degree to which the calendar coefficients are attenuated measures how much of the calendar-spread relationship operates through inventory risk. Specifications (4) and (5) extend the mediation test to OIAC, alone and jointly with HFOIV.

Systematic and Idiosyncratic Decomposition

To distinguish between inventory risk driven by correlated order flow across stocks and stock-specific effects, we decompose each variable into common (systematic) and idiosyncratic components. The turnover, realised volatility, and HFOIV decompositions follow (Bogousslavsky & Collin-Dufresne, 2023); we extend the approach to OIAC.

Turnover. For each stock i , log turnover is regressed on the leave-one-out quintile mean (the equal-weighted average of log turnover for all other stocks in the same size quintile, excluding stock i) across all days in the sample. The common component $\tau_{i,t}^C$ is the fitted value (the stock’s loading on quintile-level turnover variation) and the idiosyncratic component $\tau_{i,t}^I$ is the residual. Both components are in the log-turnover scale.

Realised volatility and HFOIV. These variables are decomposed within each trading day using a variance decomposition based on the covariance of each stock’s five-minute values

with the leave-one-out quintile mean. The systematic variance is $\text{Cov}(X_{i,t,k}, X_{q,t,k})^2 / \text{Var}(X_{q,t,k})$, where summations are over intraday intervals k ; the idiosyncratic variance is the residual. Both components are converted to standard deviations and enter the regressions in logs.

OIAC. The systematic component is the AR(1) coefficient of the quintile-mean order imbalance series (identical for all stocks in a given quintile-day). The idiosyncratic component is the AR(1) of the residuals from regressing each stock’s intraday order imbalances on the quintile mean within the same day. Both components enter in levels.

The decomposed specification replaces each variable in Equation 3.1 with its common and idiosyncratic components. The baseline decomposition is

$$\begin{aligned} \log s_{i,t} = & \alpha_i + \beta_{\tau^C} \tau_{i,t}^C + \beta_{\tau^I} \tau_{i,t}^I + \beta_{\sigma^C} \log \sigma_{i,t}^C + \beta_{\sigma^I} \log \sigma_{i,t}^I \\ & + \gamma' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \end{aligned} \quad (3.4)$$

where superscripts C and I denote common and idiosyncratic components, and τ^C, τ^I are already in the log-turnover scale. Specification (2) adds decomposed HFOIV ($\log HFOIV_{i,t}^C$ and $\log HFOIV_{i,t}^I$). Specification (3) adds decomposed OIAC ($OIAC_{i,t}^C$ and $OIAC_{i,t}^I$) without HFOIV. Specification (4) includes all decomposed components. Under inventory risk models, both common and idiosyncratic HFOIV should be positively associated with spreads. A significant common component is particularly informative: market-wide order flow shocks cannot reflect firm-specific private information and are therefore difficult to reconcile with pure adverse selection (Bogousslavsky & Collin-Dufresne, 2023). Under the adverse selection interpretation of OIAC, idiosyncratic persistence should dominate, since order flow persistence is driven primarily by individual agents splitting large orders rather than by correlated trading across agents (Tóth et al., 2015).

3.5 Cross-Sectional Return Tests

If HFOIV represents priced liquidity risk, stocks with high HFOIV should earn higher subsequent returns after controlling for turnover (Bogousslavsky & Collin-Dufresne, 2023). We test this prediction using portfolio sorts and Fama–MacBeth cross-sectional regressions, and extend the analysis to OIAC.

Portfolio Sorts

At the end of each week, stocks are sorted into quintiles on turnover (average daily turnover over the previous 20 trading days) and then, within each turnover quintile, into quintiles on HFOIV or OIAC (both computed as exponentially weighted moving averages of daily values with a half-life of one day). Portfolios are value-weighted and rebalanced weekly. Quintile breakpoints are determined using NYSE stocks to prevent over-representation of small NASDAQ stocks.³ We estimate four-factor alphas from the regression

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_{p,t}, \quad (3.5)$$

where α_p is the abnormal return of portfolio p , MKT , SMB , HML , and UMD are the Fama–French three factors plus momentum, and standard errors are computed using the Newey and West (1987) estimator with one lag.

Fama–MacBeth Regressions

Each week, we run a weighted least squares (WLS) cross-sectional regression of next-week stock returns on lagged characteristics, using market capitalisation as the weight:

$$r_{i,t+1} = \alpha_t + \sum_k \beta_{k,t} X_{k,i,t} + \varepsilon_{i,t}, \quad (3.6)$$

where $X_{k,i,t}$ includes log HFOIV, log turnover, OIAC, and (in expanded specifications) log market equity, lagged weekly return, log ILLIQ, log realised volatility, log effective spread, log depth-to-volume, log Kyle’s lambda, log absolute order imbalance, log PIN, and log $\sigma(\text{OI}/\text{VOL})$. All explanatory variables except the lagged return and OIAC are in logs. Lagged characteristics are computed as exponentially weighted moving averages of daily values with a half-life of one day (Bogousslavsky & Collin-Dufresne, 2023). All explanatory variables are winsorised at the 0.5th and 99.5th percentiles. We report the time-series average coefficient $\bar{\beta}_k = T^{-1} \sum_t \hat{\beta}_{k,t}$ with Newey–West standard errors using one lag.

The main results use the full sample (2004–2024); the BCD replication period (2004–2017) is reported in the appendix to verify comparability with the original estimates. This

³The spread regression size quintiles (Section 3.3) use breakpoints computed over all sample stocks, matching Bogousslavsky and Collin-Dufresne (2023). The portfolio sorts use NYSE-only breakpoints, following the convention in asset pricing tests.

dual reporting allows us to assess the out-of-sample stability of the HFOIV return premium documented by Bogousslavsky and Collin-Dufresne (2023) and to evaluate whether OIAC carries return-predictive power.

The BCD model’s two-channel structure provides the microfoundation for the HFOIV-spread relationship, and its Markov assumption generates a testable null for order flow persistence: once HFOIV and the other regressors control for the model’s parameters, OIAC should add nothing. The competing hypotheses (that persistence widens spreads through prolonged inventory exposure under H_1 , or narrows them by signalling uninformed flow under H_2) yield opposite sign predictions and distinct interaction patterns that the five-specification design is built to discriminate. The calendar-based identification tests and systematic-idiosyncratic decompositions provide cross-validation, and the return tests assess whether these order flow characteristics carry systematic risk premia. The next section describes the data and variable construction used to implement these tests.

4 Data

4.1 Data Sources and Sample Construction

We construct a daily panel of liquidity, order flow, and return measures for NYSE, AMEX, and NASDAQ common stocks (CRSP share codes 10 and 11) from January 2004 to December 2024. Intraday data are from the NYSE Trade and Quote (TAQ) database, aggregated into five-minute intervals; daily stock characteristics and returns are from the Center for Research in Security Prices (CRSP); and earnings announcement dates are from I/B/E/S, linked to CRSP via the ICLINK procedure. All three databases are accessed through Wharton Research Data Services (WRDS). Trades are restricted to those executed during regular trading hours (9:30–16:00), with positive price and size, and are signed using the Lee and Ready (1991) algorithm. The national best bid and offer (NBBO) is reconstructed from TAQ NBBO and Consolidated Quotes files, following standard NBBO reconstruction procedures (Holden & Jacobsen, 2014). Quotes with non-standard condition codes are excluded, as are locked or crossed quotes. Liquidity measures (effective spreads, realised spreads, and price impact) follow the Interpolated Time methodology of Holden and Jacobsen (2014). Our sample begins in 2004 because TAQ intraday data with millisecond timestamps are available from September 2003, and the 100-prior-trading-day requirement excludes all observations before late January 2004. Relative to the 2002–2017 sample of Bogousslavsky and Collin-Dufresne (2023), our sample begins two years later but extends seven years further, to December 2024.

To be included in a given month, a stock must satisfy three conditions evaluated on its first trading day of that month: (i) a previous trading day’s closing price greater than \$5 and less than \$1,000, (ii) a trailing 250-day average market capitalisation exceeding \$100 million, and (iii) at least 100 days of prior trading history. The third filter is enforced implicitly through the rolling average calculation, which requires a minimum of 100 observations. These filters follow Bogousslavsky and Collin-Dufresne (2023)¹ and ensure

¹The replication code accompanying Bogousslavsky and Collin-Dufresne (2023) does not implement the price or market capitalisation screens described in their paper; the trading history requirement is enforced only implicitly through a rolling window minimum. These filters may have been applied in earlier data construction steps not included in the replication package. We implement all filters explicitly as described in their paper.

that the sample consists of actively traded securities for which intraday measures can be estimated reliably. We follow Bogousslavsky and Collin-Dufresne (2023) in excluding days with early market closures (e.g., the day after Thanksgiving and Christmas Eve). These shortened sessions yield fewer than the standard 78 five-minute intervals, which would distort both HFOIV and OIAC estimates. Stocks are linked from TAQ to CRSP using the WRDS TAQ-CRSP link table (TAQMCLINK); observations without a valid link are excluded. Appendix Table A1 reports the observation counts at each stage of the sample construction.

The final sample contains 13,567,823 stock-day observations covering 7,587 unique common stocks over 21 years. Observations with missing CRSP returns or no valid TAQ trades on a given day are excluded implicitly: derived variables (returns, spreads, intraday measures) propagate as missing values and are dropped from the relevant analyses. Effective regression sample sizes vary across specifications because each analysis drops observations with missing values for the variables it requires.

Figure 1 plots the number of unique common stocks in the sample each year, broken down by exchange. The sample peaks at approximately 3,500 stocks in 2007, falls sharply to roughly 2,700 following the 2008–2009 financial crisis, and never fully recovers: coverage stabilises near 2,800 through the 2010s as delistings and mergers outpace new listings. A brief rebound to approximately 3,350 stocks in 2021–2022 coincides with elevated IPO and SPAC activity before retreating to 2,799 stocks by 2024. Throughout the sample, NASDAQ accounts for the majority of stocks, while the AMEX share declines from 101 stocks in 2004 to 46 in 2024.

At the beginning of each month, stocks are sorted into size quintiles based on their trailing 250-day average market capitalisation, with breakpoints computed over all stocks in the sample. On average, each quintile contains approximately 700 stocks per year, ranging from 793 in the bottom quintile to 577 in the top quintile. Throughout the analysis, we refer to the bottom quintile as “small stocks” and the top quintile as “large stocks.” This size stratification is central to the empirical design because the volume-spread relationship and the role of order flow variables differ markedly across the size distribution (Bogousslavsky & Collin-Dufresne, 2023).

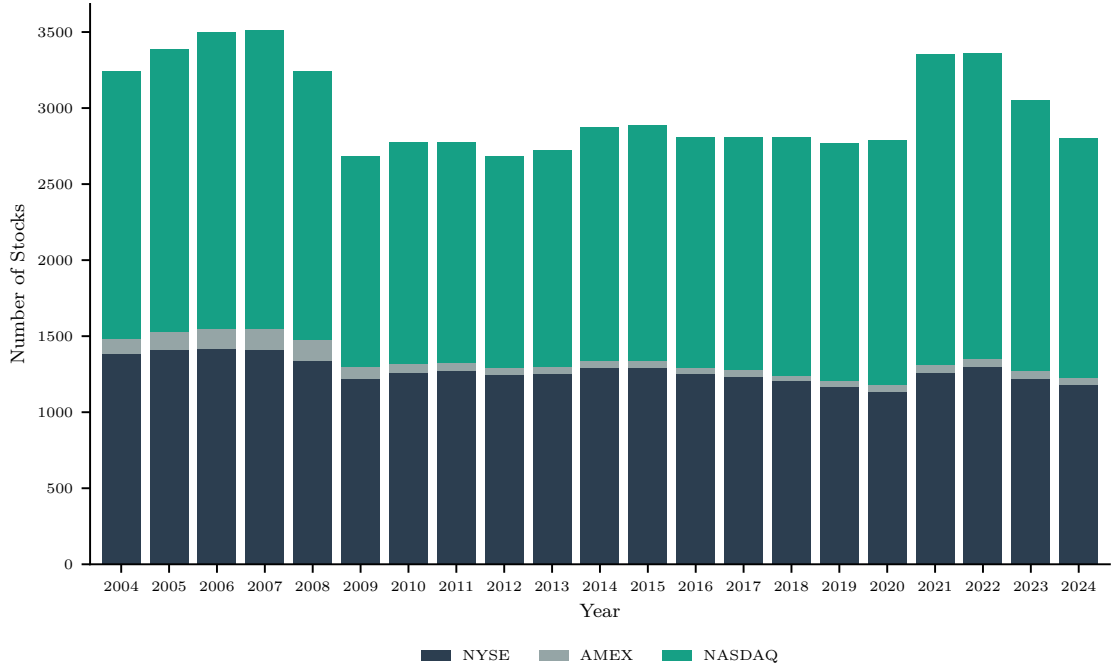


Figure 1
Sample Composition by Exchange

This figure plots the number of unique common stocks in the sample each year, broken down by exchange (NYSE, AMEX, and NASDAQ). The sample consists of NYSE, AMEX, and NASDAQ common stocks over 2004 to 2024. To be included in a given month, a stock is required to have a lagged closing price greater than \$5 and less than \$1,000, a trailing 250-day average market capitalisation greater than \$100 million, and at least 100 days of prior trading.

4.2 Variable Construction

This section defines the variables that appear in the regression analysis.

All intraday variables are computed from five-minute intervals within the regular trading session (9:30–16:00), yielding 78 intervals per full trading day (Bogousslavsky & Collin-Dufresne, 2023). The five-minute frequency offers sufficient granularity to capture intraday dynamics while avoiding the microstructure noise inherent in trade-by-trade data. A comparison of sampling frequencies from 65 minutes to five minutes confirms that five-minute intervals achieve the highest explanatory power for large-stock spreads (Bogousslavsky & Collin-Dufresne, 2023, Internet Appendix, Table XII).

Liquidity and Trading Activity

The *effective spread* ($s_{i,j}$) is the percent effective spread of trade j on stock i , defined as

$$s_{i,j} = 2 |\ln P_{i,j} - \ln M_{i,j}|,$$

where $P_{i,j}$ is the trade price and $M_{i,j}$ is the NBBO midpoint associated with the trade. The daily effective spread is the dollar-volume-weighted average of the effective spreads of all trades within the regular trading session. We use the effective spread as our primary measure of transaction costs because it reflects the cost actually paid by traders, including any price improvement relative to quoted spreads.

Turnover ($\tau_{i,t}$) is daily intraday share turnover, defined as total shares traded during the regular session (9:30–16:00) divided by total shares outstanding. *Realised volatility* ($\sigma_{i,t}$) is the square root of the sum of squared five-minute midquote log returns over the trading day (Andersen et al., 2001). For the first interval of each stock-day, the opening midquote return is computed relative to the volume-weighted average price (VWAP) of that interval (Bogousslavsky & Collin-Dufresne, 2023). We expand the data to the full 78-interval grid (one interval per five minutes from 9:30 to 15:55) to compute realised volatility, with missing returns set to zero for intervals with no trading activity. Turnover and realised volatility both enter the regressions in logs.

Order Imbalance Volatility

High-frequency order imbalance volatility (HFOIV) is the daily standard deviation of five-minute signed order imbalances expressed as a percentage of shares outstanding:

$$HFOIV_{i,t} = \text{Std} \left(\frac{B_{i,t,k} - S_{i,t,k}}{SHROUT_{i,t}} \times 100 \right), \quad k = 1, \dots, K_t,$$

where $B_{i,t,k}$ and $S_{i,t,k}$ are buyer- and seller-initiated shares in interval k (classified using the Lee–Ready algorithm (Lee & Ready, 1991)), $SHROUT_{i,t}$ is shares outstanding, and K_t is the number of intervals with at least one trade on day t . Trades at the midquote for which the tick test also yields a tie receive no directional classification and contribute zero to order imbalance. If a stock is not traded during a five-minute interval, that interval is excluded from the computation; this contrasts with the realised volatility calculation,

which fills missing returns with zero on the full 78-interval grid. The standard deviation uses $K_t - 1$ degrees of freedom (the centred estimator). HFOIV enters the regressions in logs.

HFOIV captures the dispersion of order flow within a trading day. A market maker who absorbs order imbalances across intervals accumulates end-of-day inventory whose variance scales with HFOIV. Higher HFOIV thus implies greater inventory risk and, in equilibrium, wider spreads (Bogousslavsky & Collin-Dufresne, 2023).

Absolute daily order imbalance ($|OI|_{i,t}$) is the absolute value of daily net signed share imbalance expressed as a percentage of shares outstanding. Unlike HFOIV, which captures intraday dispersion, $|OI|$ measures the directional magnitude of order flow over the full day.

Order Imbalance Autocorrelation

Bogousslavsky and Collin-Dufresne (2023) note that their measured order imbalance is “positively autocorrelated, consistent with order flow picking up order-splitting strategies of institutions” (see also Tóth et al., 2015). We formalise this observation by introducing order imbalance autocorrelation (OIAC), defined as the slope coefficient from an AR(1) regression of five-minute signed share imbalances within a trading day:

$$OI_{i,t,k} = \alpha_{i,t} + \rho_{i,t} OI_{i,t,k-1} + \varepsilon_{i,t,k}, \quad k = 2, \dots, K_t,$$

where $\rho_{i,t}$ is the OIAC coefficient and $OI_{i,t,k} = B_{i,t,k} - S_{i,t,k}$ is the signed share imbalance in interval k . The AR(1) coefficient is scale-invariant, so expressing order imbalance in shares or as a percentage of shares outstanding yields identical estimates. As with HFOIV, intervals with no trading activity are excluded. The regression is estimated by OLS with Newey and West (1987) standard errors using four lags (the Newey and West (1987) automatic lag selection rule gives $\lfloor 4(T/100)^{2/9} \rfloor = \lfloor 4(78/100)^{2/9} \rfloor = 3$; we use four as a conservative choice) to account for residual serial correlation within the trading day. A minimum of 20 valid five-minute intervals is required for estimation.²

²As a robustness check, we also estimate OIAC using a stricter threshold of 50 intervals (approximately four hours of trading). Results are qualitatively unchanged.

The AR(1) specification provides a parsimonious summary of within-day serial dependence. While the long-memory literature documents persistence structures that operate across days and weeks (Lillo & Farmer, 2004), these dynamics exceed the horizon of a single 78-interval trading session. Within such a short window, an AR(1) coefficient captures the dominant first-order dependence while remaining estimable with reasonable precision even for stocks with fewer active intervals. The 20-interval minimum ensures sufficient degrees of freedom for stable AR(1) estimation with HAC standard errors; 557,746 observations (4.1% of the full sample) fall below this threshold and lack OIAC estimates.

OIAC captures the persistence, or predictability, of intraday order flow. Positive OIAC indicates that buying (selling) pressure in one interval tends to be followed by buying (selling) pressure in the next, consistent with the order-splitting mechanism documented by Tóth et al. (2015).

OIAC is not log-transformed because it can take negative values (indicating mean-reverting order flow); its functional form in the regression specifications is discussed in Section 3.3. Although OIAC is conceptually bounded by $[-1, 1]$ for stationary processes, approximately 0.30% of stock-day observations (38,556 out of 13,010,077 with valid OIAC estimates) exhibit values outside this range. These outliers represent days with non-stationary (explosive) order flow patterns rather than estimation error: they cluster at 78 intervals (i.e., stock-days with complete trading day coverage) and are dispersed across stocks and calendar months. The treatment of OIAC outliers in each regression context is discussed in Section 3.3.

Additional Liquidity Measures

Several additional liquidity measures enter the Fama–MacBeth return regressions (Section 3.5) as controls. The Amihud illiquidity ratio ($ILLIQ_{i,t}$) is the average ratio of absolute daily return to dollar volume over the prior 250 trading days (minimum 100 observations). Kyle’s lambda ($\lambda_{i,t}$) is the slope coefficient from a regression of five-minute midquote returns on contemporaneous signed order flow within a trading day, measuring price impact per unit of order flow. Depth-to-volume ($Depth/VOL_{i,t}$) is the ratio of average quoted depth (shares available at the best bid and offer) to daily share volume. PIN is defined as

the absolute daily trade imbalance divided by the total number of trades, following the approximation of Aktas et al. (2007) as implemented by Bogousslavsky and Collin-Dufresne (2023). $\sigma(OI/VOL)_{i,t}$ is the standard deviation of daily signed share imbalance divided by share volume, computed over the prior 22 trading days (minimum 11 observations).

4.3 Summary Statistics

Time-Series and Cross-Sectional Properties

Figure 2 plots the daily cross-sectional median of the five main variables over the sample period. Effective spreads decline through the mid-2000s, consistent with the ongoing effects of decimalisation and the growth of electronic trading, and spike during the 2008–2009 financial crisis and early 2020 (COVID-19). Turnover and volatility co-move, with both rising during periods of market stress. HFOIV exhibits a persistent downward trend, while OIAC fluctuates near zero with no apparent trend, though its dispersion increases during crisis episodes. Both HFOIV and OIAC exhibit patterns suggestive of calendar effects: at similar frequency, HFOIV spikes and OIAC drops to near zero.

Figure 3 compares the cross-sectional distributions of HFOIV and OIAC for small and large stocks. HFOIV is right-skewed for both groups, with small stocks exhibiting substantially higher levels and wider dispersion, reflecting their lower liquidity and smaller order sizes. OIAC is approximately symmetric around zero for both size groups, consistent with order flow that is, on average, neither persistent nor mean-reverting. The similar distributional shapes across size groups suggest that OIAC captures a common microstructural phenomenon (order splitting) that is not mechanically driven by firm size.

Table 1 reports descriptive statistics for the main variables, separately for small and large stocks, for a selection of years spanning the sample. Effective spreads are substantially wider for small stocks: in 2004, the median spread is 51.65 bps for small stocks versus 6.87 bps for large stocks, a ratio of roughly 7.5-to-1. By 2024, the ratio is closer to 10-to-1. For large stocks, median spreads decline from 6.87 bps in 2004 to 4.43 bps in 2024, consistent with broad improvements in market quality over the sample period. Small-stock spreads show no comparable trend, fluctuating between 37 and 60 bps at the median across the sample, with a pronounced spike during the 2008–2009 crisis (median 59.13 bps, mean

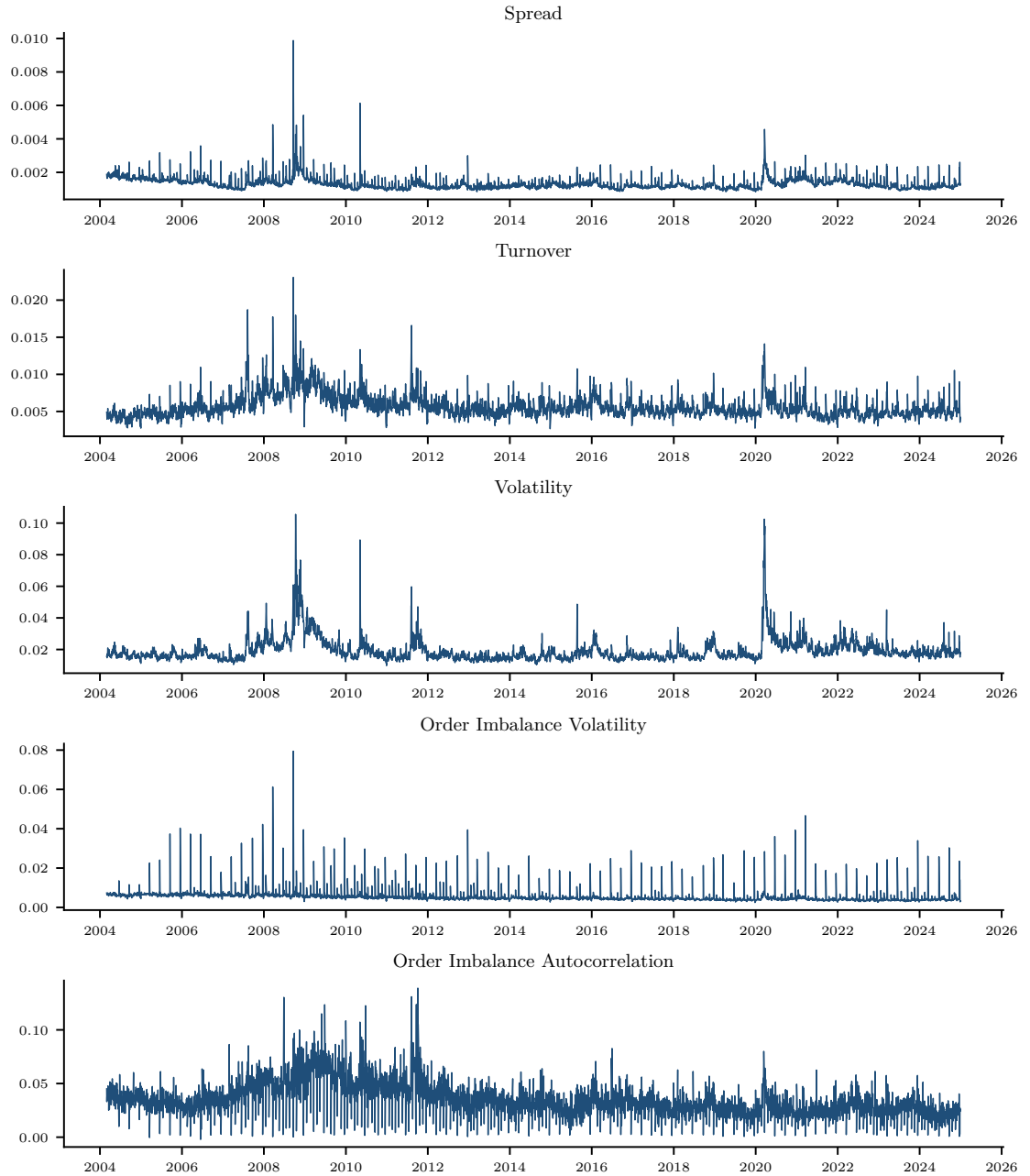


Figure 2
Spreads, Turnover, Volatility, Order Imbalance Volatility, and Order Imbalance Autocorrelation

This figure plots the daily cross-sectional median of effective spread, turnover, realised volatility, high-frequency order imbalance volatility (HFOIV), and order imbalance autocorrelation (OIA) over 2004 to 2024. Spread is the daily percent effective spread, turnover is daily intraday share turnover, volatility is realised volatility computed from five-minute midquote returns, HFOIV is the standard deviation of five-minute share imbalance scaled by total shares outstanding, and OIA is the first-order autocorrelation of five-minute share imbalance. The sample consists of NYSE, AMEX, and NASDAQ common stocks.

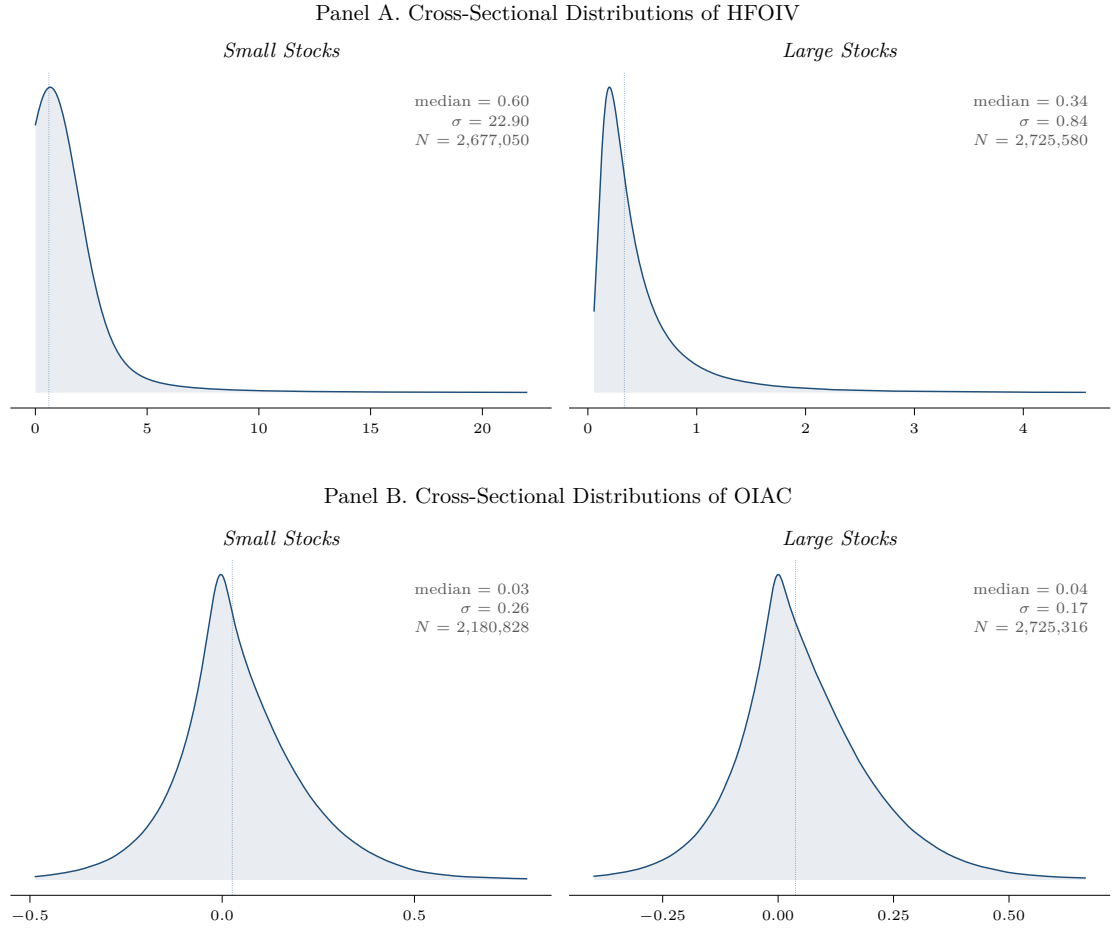


Figure 3
Cross-Sectional Distributions of HFOIV and OIAC by Size Group

This figure plots kernel density estimates of the cross-sectional distributions of high-frequency order imbalance volatility (HFOIV) and order imbalance autocorrelation (OIAC), separately for small and large stocks. Distributions are computed using the full sample (2004–2024) and trimmed at the 0.5th and 99.5th percentiles for display. Panel statistics report the median, standard deviation, and number of stock-day observations in each group.

117.58 bps).

HFOIV declines over the sample for both size groups. For large stocks, mean HFOIV falls from 0.62 bps in 2004 to 0.42 bps in 2024; for small stocks, from 1.54 bps to 1.14 bps. This trend is consistent with declining average order sizes as trading becomes more fragmented across venues (O’Hara, 2015).

OIAC is stable across years and similar in magnitude across size groups: mean OIAC is typically around 0.05 for both small and large stocks, with somewhat elevated values during crisis periods. The within-stock standard deviation, however, is substantial (0.21 for small stocks and 0.15 for large stocks in 2004), indicating that OIAC varies considerably from day to day within a given stock even though its cross-sectional average is near zero.

Table 2 presents mean effective spreads, turnover, and realised volatility within quintiles formed on HFOIV and OIAC separately. For large stocks, sorting by HFOIV reveals a monotonically increasing relationship with spreads: mean spreads rise from 4.89 bps in the low-HFOIV quintile to 7.45 bps in the high quintile, yielding a high-minus-low differential of 2.56 bps ($t = 12.88$). This confirms the positive association between HFOIV and transaction costs in Bogousslavsky and Collin-Dufresne (2023). Turnover also increases monotonically with HFOIV (from 0.41% to 1.96%), consistent with the mechanical link between trading activity and order flow dispersion.

For small stocks, the HFOIV sort produces a negative spread gradient: spreads fall from 94.88 bps in the low-HFOIV quintile to 62.49 bps in the high quintile ($H - L = -32.38$ bps, $t = -7.91$). This reversal reflects the strong correlation between HFOIV and turnover for small stocks (Table 3): the low-HFOIV quintile captures the least actively traded small stocks (turnover 0.19%), whose wide spreads are driven by low liquidity rather than low order flow risk. Once turnover is controlled for in the panel regressions, the HFOIV-spread relationship becomes positive for small stocks as well (Table 4).

The OIAC sort yields a weaker and less monotonic pattern. For large stocks, the high-minus-low spread differential is 0.08 bps ($t = 0.31$), statistically indistinguishable from zero. For small stocks, the differential is -14.12 bps ($t = -4.65$), again reflecting confounding variation in turnover rather than a direct OIAC effect. These univariate results suggest that OIAC’s role in spread determination, if present, operates through its interaction with other order flow variables rather than as a standalone predictor.

Table 1
Descriptive Statistics of Daily Variables for Stocks in the Bottom and Top Size Quintiles

This table reports descriptive statistics for daily variables for a selection of years. Spread is the percent effective spread (reported in basis points), turnover is intraday share turnover, volatility is realised volatility computed from five-minute midquote returns, HFOIV is high-frequency order imbalance volatility computed as the standard deviation of five-minute share imbalance scaled by total shares outstanding, and OIAC is the first-order autocorrelation of five-minute share imbalance. The within standard deviation (σ (within)) is computed as the standard deviation of each stock's deviations from its time-series mean. Spreads are winsorised at the 0.05% and 99.95% levels each year. At the beginning of each month, stocks are sorted into size quintiles based on their trailing 250-day average market capitalisation. The sample consists of NYSE, AMEX, and NASDAQ common stocks over 2004 to 2024. To be included in a given month, a stock is required to have a lagged price greater than \$5 and less than \$1,000, a trailing average market capitalisation greater than \$100 million, and at least 100 days of prior trading.

		2004	2006	2008	2010	2012	2014	2016	2018	2020	2022	2024
<i>Small Stocks</i>												
Spread [bps]	Mean	71.00	65.09	117.58	57.09	65.47	66.47	68.65	77.68	96.74	78.52	78.68
	Median	51.65	42.86	59.13	36.74	41.64	45.28	44.69	50.58	60.04	45.28	48.71
	σ (within)	50.64	51.19	131.24	60.86	59.89	57.25	60.70	65.31	87.76	77.43	64.51
Turnover [%]	Mean	0.52	0.54	0.52	0.59	0.45	0.58	0.52	0.71	1.13	0.68	0.81
	Median	0.19	0.20	0.23	0.28	0.21	0.25	0.26	0.27	0.31	0.15	0.29
	σ (within)	1.61	1.20	0.91	1.17	1.04	1.54	1.79	5.74	5.67	17.96	6.22
Volatility [%]	Mean	2.52	2.18	3.92	2.93	2.33	2.45	2.84	2.93	4.23	2.42	3.13
	Median	2.20	1.90	3.28	2.33	2.07	2.15	2.41	2.54	3.55	1.97	2.67
	σ (within)	1.53	1.27	2.95	8.91	1.20	1.36	1.64	1.68	2.91	1.86	1.70
HFOIV [bps]	Mean	1.54	1.51	1.47	1.12	1.04	1.05	0.98	1.12	1.52	2.20	1.14
	Median	0.83	0.78	0.66	0.63	0.56	0.57	0.54	0.56	0.59	0.46	0.48
	σ (within)	3.63	3.86	5.72	2.15	2.37	2.67	4.26	3.72	5.07	10.70	4.33
OIAC	Mean	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.05
	Median	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.02	0.02
	σ (within)	0.21	0.22	0.19	0.25	0.22	0.49	0.21	0.21	0.21	0.34	0.23
<i>N</i>		120,839	149,686	132,234	121,139	116,635	126,950	124,953	123,434	121,162	136,329	120,598
<i>Large Stocks</i>												
Spread [bps]	Mean	8.89	7.43	8.53	5.46	4.82	4.53	4.64	4.50	6.84	6.54	5.35
	Median	6.87	5.81	6.25	4.03	3.75	3.37	3.49	3.47	5.34	5.26	4.43
	σ (within)	10.88	7.73	15.91	17.03	4.91	4.80	4.68	4.75	5.40	5.14	4.19
Turnover [%]	Mean	0.72	0.84	1.52	1.20	0.97	0.81	0.86	0.80	0.91	0.91	0.69
	Median	0.47	0.57	1.09	0.88	0.71	0.60	0.64	0.59	0.59	0.57	0.48
	σ (within)	0.69	0.71	1.45	0.95	0.79	0.64	0.65	0.62	1.01	0.99	0.66
Volatility [%]	Mean	1.32	1.31	2.90	1.51	1.25	1.14	1.32	1.42	2.16	2.04	1.35
	Median	1.17	1.17	2.28	1.31	1.13	0.99	1.12	1.25	1.71	1.76	1.19
	σ (within)	0.67	0.47	1.93	2.69	0.43	0.47	0.60	0.59	1.51	0.77	0.50
HFOIV [bps]	Mean	0.62	0.67	0.74	0.63	0.55	0.49	0.46	0.42	0.49	0.46	0.42
	Median	0.41	0.42	0.46	0.41	0.35	0.31	0.31	0.28	0.31	0.29	0.27
	σ (within)	0.74	0.90	1.04	0.79	0.67	0.63	0.63	0.55	0.63	0.56	0.58
OIAC	Mean	0.05	0.05	0.08	0.07	0.06	0.05	0.06	0.05	0.05	0.05	0.04
	Median	0.04	0.03	0.06	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.02
	σ (within)	0.15	0.16	0.16	0.18	0.17	0.18	0.19	0.17	0.16	0.16	0.17
<i>N</i>		123,771	154,394	137,362	121,843	117,367	128,227	126,356	124,496	121,747	142,331	121,477

Table 2
Univariate Spread Sorts by HFOIV and OIAC Quintiles

This table reports equal-weighted cross-sectional means of effective spread (in basis points), turnover (%), and realised volatility (%) within quintiles formed on HFOIV or OIAC, separately for small and large stocks. Within each year and size group, stocks are independently sorted into quintiles by the sorting variable. Quintile means are first computed within each year and then averaged across the 21 sample years (2004–2024). The High–Low row reports the difference between the top and bottom quintiles; t -statistics test whether this difference is significantly different from zero across years. Spreads are winsorised at the 0.05% and 99.95% levels each year. Size quintiles are formed at the beginning of each month based on the trailing 250-day average market capitalisation. The sample consists of NYSE, AMEX, and NASDAQ common stocks.

<i>Panel A: Sorted by HFOIV</i>							
	Low HFOIV	2	3	4	High HFOIV	H–L	t
<i>Small Stocks</i>							
Spread [bps]	94.88	77.17	71.28	65.76	62.49	-32.38	-7.91
Turnover [%]	0.19	0.33	0.49	0.77	4.90	4.71	2.24
Volatility [%]	2.98	2.89	2.98	2.99	3.01	0.04	0.19
N	159	158	159	158	159		
<i>Large Stocks</i>							
Spread [bps]	4.89	5.31	5.87	6.55	7.45	2.56	12.88
Turnover [%]	0.41	0.59	0.77	1.04	1.96	1.55	17.37
Volatility [%]	1.21	1.34	1.48	1.69	2.04	0.83	11.00
N	116	115	115	115	116		
<i>Panel B: Sorted by OIAC</i>							
	Low OIAC	2	3	4	High OIAC	H–L	t
<i>Small Stocks</i>							
Spread [bps]	88.24	69.62	64.88	65.88	74.12	-14.12	-4.65
Turnover [%]	0.55	0.72	0.88	1.20	3.43	2.87	1.39
Volatility [%]	2.92	2.99	3.03	3.08	2.94	0.02	0.27
N	156	155	156	155	156		
<i>Large Stocks</i>							
Spread [bps]	6.15	5.82	5.95	5.93	6.22	0.08	0.31
Turnover [%]	0.99	0.92	0.93	0.90	1.04	0.05	0.99
Volatility [%]	1.49	1.51	1.55	1.55	1.66	0.17	2.95
N	116	115	115	115	116		

Table 3 reports average within-stock time-series correlations among the main variables. Three patterns stand out. First, HFOIV and OIAC are nearly orthogonal (correlation of 0.01 for small stocks and -0.02 for large stocks), confirming that order flow volatility and order flow persistence capture distinct dimensions of the intraday trading environment. This near-independence supports treating HFOIV and OIAC as complementary rather than competing explanatory variables in spread regressions.

Second, HFOIV is strongly positively correlated with turnover (0.82 for small stocks, 0.74 for large stocks) and with absolute order imbalance (0.62 and 0.48, respectively). These high correlations explain the confounded univariate sort results in Table 2 and motivate the multivariate panel regressions in the analysis that follows, which disentangle the independent contributions of HFOIV and turnover.

Third, the spread-turnover correlation differs in sign across size groups: -0.15 for small stocks and 0.16 for large stocks. This sign reversal reflects the tension between the negative cross-sectional association between volume and spreads first documented by Demsetz (1968) and the positive within-stock time-series association observed for large stocks, where high-turnover days tend to coincide with wider spreads. For small stocks, the negative within-stock correlation suggests that days of elevated trading activity are associated with improved liquidity, possibly because higher volume attracts competing liquidity providers. OIAC’s strongest correlation is with absolute order imbalance (0.08 for small, 0.07 for large), a natural association since persistent order flow requires non-trivial imbalance to begin with.

Two properties documented in this section are central to the empirical design. The near-orthogonality of HFOIV and OIAC (Table 3) permits their joint inclusion in spread regressions without multicollinearity concerns. The confounding role of turnover in univariate sorts (Table 2), particularly for small stocks, necessitates multivariate controls to isolate the independent contributions of each order flow measure. The next section presents the results of the regression specifications that exploit these properties.

Table 3
Correlations among Daily Variables for Stocks in the Bottom and Top Size Quintiles

This table reports correlations between the percent effective spread (s), intraday turnover (τ), realised volatility (σ), absolute daily order imbalance as a fraction of shares outstanding ($|OI|$), high-frequency order imbalance volatility ($HFOIV$), and order imbalance autocorrelation ($OIAC$). All variables except $OIAC$ are in logs. The table reports the cross-sectional average of individual stocks' within-stock time-series correlations. Size quintiles are formed at the beginning of each month based on the trailing 250-day average market capitalisation. Spreads are winsorised at the 0.05% and 99.95% levels each year. The sample consists of NYSE, AMEX, and NASDAQ common stocks over 2004 to 2024.

	Small Stocks					Large Stocks				
	τ	σ	$ OI $	$HFOIV$	$OIAC$	τ	σ	$ OI $	$HFOIV$	$OIAC$
s	-0.15	0.41	-0.04	0.01	-0.02	0.16	0.45	0.14	0.31	-0.02
τ		0.31	0.57	0.82	0.04		0.51	0.40	0.74	0.04
σ			0.10	0.22	0.01			0.15	0.27	0.04
$ OI $				0.62	0.08				0.48	0.07
$HFOIV$					0.01					-0.02

5 Results

Using the specifications developed in Section 3, we examine the relationship between order flow characteristics and stock liquidity. The analysis proceeds in three stages: spread regressions to establish the baseline relationship between order imbalance volatility, order imbalance persistence, and effective spreads (Section 5.1); calendar-based identification tests and systematic-idiosyncratic decompositions to distinguish inventory risk from adverse selection channels (Section 5.2); and cross-sectional return predictability to test whether order flow characteristics are priced as liquidity risk factors (Section 5.3).

5.1 Spread, Volume, and Volatility

This section establishes the baseline spread relationships in three steps: replication of the BCD turnover and HFOIV results (specifications 1–2), introduction of OIAC as a standalone and joint predictor (specifications 3–5), and an orthogonalisation test distinguishing HFOIV from absolute order imbalance (Table 5).

We begin by replicating the baseline spread regressions of Bogousslavsky and Collin-Dufresne (2023). Figure 4 presents the estimated elasticities from month-by-month panel regressions of log effective spreads on log turnover and log realised volatility, controlling for size and price. For large stocks, the turnover coefficient exhibits a sign reversal around 2013. In the early period (2004–2012), β_τ is positive (averaging +0.08), confirming the volume puzzle addressed by Bogousslavsky and Collin-Dufresne (2023): higher trading activity is associated with wider spreads, contrary to standard liquidity theory. However, this pattern inverts in the later period (2014–2024), where the coefficient averages -0.09 . The median coefficient across the full sample is -0.05 , marginally significant, reflecting the dominance of the later years. This inversion may reflect structural changes in market microstructure, including increased retail participation via commission-free platforms and the growth of passive investing; we return to the implications of this sign reversal for return predictability in Section 5.3.¹

¹The timing of this reversal (2013–2014) coincides with the dominance of high-frequency market making (Menkveld, 2013) and increased ETF activity. Quantifying the specific drivers is beyond the scope of this thesis.

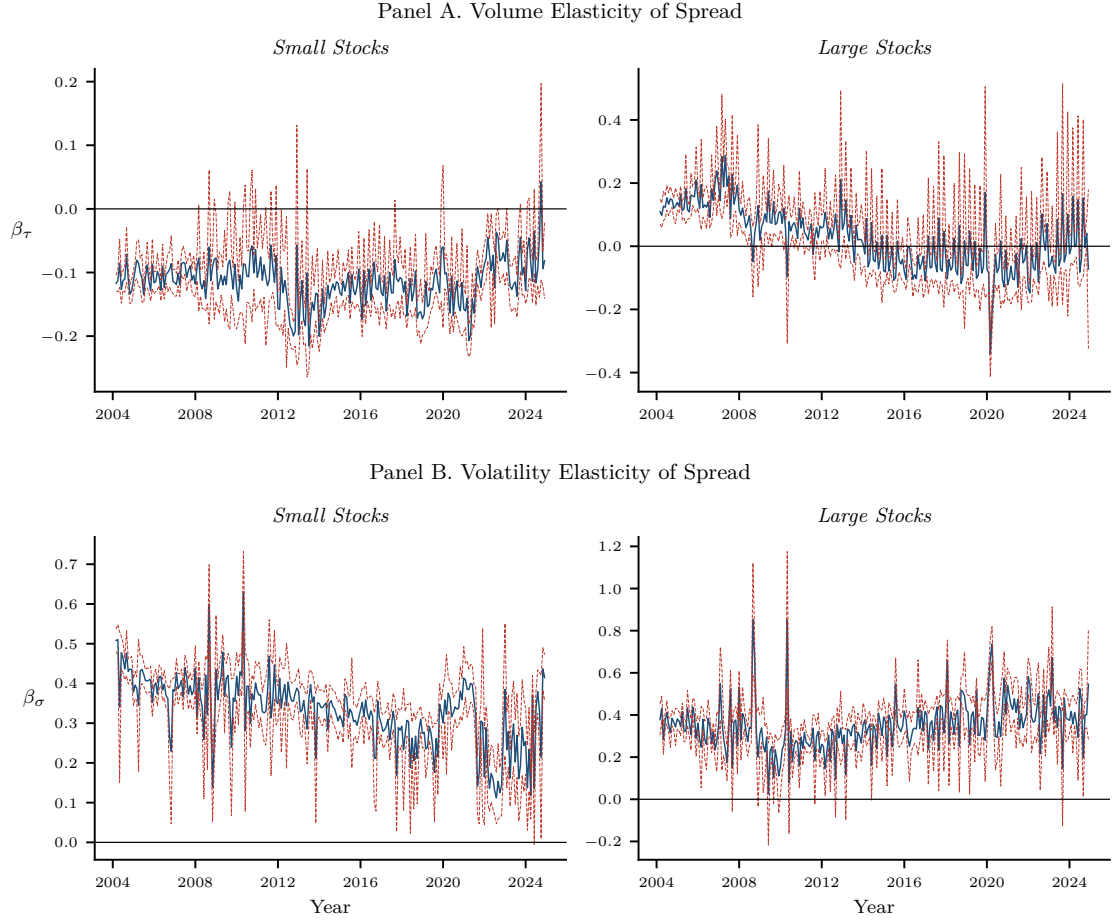


Figure 4
Effective Spread Regressed on Volume and Volatility across Size Quintiles

This figure plots elasticities estimated from the monthly panel regression $\log s_{i,t} = \alpha_i + \beta_\tau \log \tau_{i,t} + \beta_\sigma \log \sigma_{i,t} + \text{controls} + \varepsilon_{i,t}$ for stock i on day t , where $s_{i,t}$ is the percent effective spread, $\tau_{i,t}$ is daily intraday turnover, and $\sigma_{i,t}$ is realised volatility computed from five-minute midquote returns. Controls are log market capitalisation, log price, and day-of-week indicators. The regression includes stock fixed effects and is estimated on a month-by-month basis for stocks in a given size quintile. Effective spreads are winsorised at the 0.05% and 99.95% levels each month. Standard errors are double-clustered by date and stock. Dashed lines indicate 95% confidence intervals.

High-Frequency Order Imbalance Volatility

Bogousslavsky and Collin-Dufresne (2023) reconcile the puzzling positive spread-volume relationship by introducing high-frequency order imbalance volatility (HFOIV), defined as the within-day standard deviation of five-minute order imbalances scaled by shares outstanding. This measure captures the magnitude of inventory shocks faced by liquidity providers at a higher frequency than daily order imbalance. The economic intuition follows from inventory-based market-making models: when order flow exhibits high volatility at five-minute intervals, liquidity providers face greater uncertainty about the direction and magnitude of the next trade, requiring wider spreads to compensate for inventory risk (Amihud & Mendelson, 1980; Ho & Stoll, 1981, 1983).

Table 4 presents the baseline spread regressions, estimated using the year-by-year panel approach described in Section 3.3. Specification (1) reports results for the regression of log effective spreads on log turnover and log realised volatility (Equation 3.1 without the order flow terms). For large stocks, the baseline specification yields a median turnover coefficient of -0.05 , negative but only marginally significant. This contrasts with the BCD sample, where the baseline turnover coefficient was positive and significant at $+0.04$. The Demsetz effect, whereby higher volume reduces the cost of immediacy as offsetting counterparties arrive more quickly (Bogousslavsky & Collin-Dufresne, 2023; Demsetz, 1968), has thus inverted in the extended sample: by 2024, higher turnover is associated with narrower spreads even without controlling for HFOIV.²

Specification (2) adds log HFOIV. For large stocks, the turnover coefficient becomes strongly negative at -0.43 and the HFOIV coefficient is positive at 0.36 , both significant well beyond the one percent level. A one percent increase in HFOIV is associated with a 0.36 percent widening of effective spreads, holding turnover and volatility constant. For small stocks, the HFOIV coefficient is smaller at 0.25 , consistent with the weaker univariate relationship documented in Table 2.

The changes specification (Panel B) confirms that the relationship holds in first differences, mitigating concerns about omitted persistent stock characteristics. Adjusted

²This sign flip reflects the turnover coefficient reversal around 2013–2014 shown in Figure 4. Increased retail trading via commission-free platforms may have altered the information content of volume, making high-turnover stocks more liquid in the conventional sense.

R^2 increases from 15.36 percent to 32.25 percent for large stocks when HFOIV is added (Panel A), indicating substantial incremental explanatory power beyond turnover and return volatility. Appendix Tables A3–A7 report year-by-year coefficients for all five specifications, revealing substantial time variation in the relationship between order flow characteristics and spreads.

Intraday Order Imbalance Autocorrelation

As discussed in Section 3.3, two competing mechanisms predict different signs for the OIAC coefficient: inventory duration ($\beta_{OIAC} > 0$) and adverse selection signalling ($\beta_{OIAC} < 0$).

We introduce order imbalance autocorrelation (OIAC) as a measure of persistence, computed as the AR(1) coefficient from a regression of each five-minute imbalance on its one-period lag within a day.³ A value near zero indicates memoryless (i.i.d.) order flow; positive values indicate persistence; negative values indicate intraday mean reversion beyond what would arise mechanically from bid-ask bounce (largely mitigated by the five-minute aggregation).

Specification (3) of Table 4 introduces OIAC in the levels regression, omitting HFOIV. For large stocks, OIAC enters with a coefficient of -0.11 , strongly significant: higher persistence is associated with narrower spreads. This sign contradicts the hypothesis that persistent order flow widens spreads through prolonged inventory exposure.

Instead, the negative coefficient is consistent with a mechanism linking order splitting and adverse selection. Tóth et al. (2015) show that on short horizons, order flow persistence is overwhelmingly attributable to same-broker order splitting rather than cross-broker herding, with approximately 75 percent of the first-lag autocorrelation arising from same-member contributions. This is consistent with institutional execution algorithms that split large parent orders across intervals. In the model of Kyle (1985), informed traders trade gradually, exploiting the camouflage that noise trading volume provides; their order flow is positively autocorrelated, but hidden within aggregate noise. If the bulk of observed

³As described in Section 4.2, OIAC is estimated via OLS for each stock-day with at least 20 five-minute intervals, using Newey–West standard errors with four lags to account for serial correlation. Unlike HFOIV, OIAC is not log-transformed because it can take negative values (indicating mean reversion within the day). OIAC is not winsorised, as values outside $[-1, 1]$ reflect explosive order flow rather than measurement error; see Section 4.2 for details.

Table 4
Spread, Volume, Order Imbalance Volatility and Persistence

This table reports the median coefficient estimate and median t -statistic (in parentheses) across years. The following panel regression with stock fixed effects is estimated each year for small and large stocks separately. Panel A (levels): $\log s_{i,t} = \alpha_i + \beta_\tau \log \tau_{i,t} + \beta_\sigma \log \sigma_{i,t} + \beta_{HFOIV} \log HFOIV_{i,t} + \beta_{OIAC} OIAC_{i,t} + \text{controls} + \varepsilon_{i,t}$, where $s_{i,t}$ is the percent effective spread, $\tau_{i,t}$ is daily intraday turnover, $\sigma_{i,t}$ is realised volatility computed from five-minute midquote returns, $HFOIV_{i,t}$ is high-frequency order imbalance volatility, and $OIAC_{i,t}$ is order imbalance autocorrelation. Specification (5) adds an interaction term $\log HFOIV \times OIAC$, centred within quintile-year cells so that main effects are interpretable at group means. Panel B (changes): $\Delta \log s_{i,t} = \alpha_i + \beta_{\Delta\tau} \Delta \log \tau_{i,t} + \beta_{\Delta\sigma} \Delta \log \sigma_{i,t} + \beta_{\Delta HFOIV} \Delta \log HFOIV_{i,t} + \beta_{\Delta OIAC} \Delta OIAC_{i,t} + \text{controls} + \varepsilon_{i,t}$. Controls are log lagged market capitalisation, log lagged price, and day-of-week and month-of-year indicators. Effective spreads are winsorised at the 0.05% and 99.95% levels each year. t -statistics are based on standard errors double-clustered by date and stock.

	Small Stocks					Large Stocks				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Level Regressions</i>										
β_τ	-0.16 (-19.87)	-0.37 (-24.33)	-0.19 (-21.03)	-0.45 (-38.21)	-0.45 (-38.16)	-0.05 (-2.16)	-0.43 (-28.67)	-0.04 (-2.08)	-0.43 (-28.57)	-0.43 (-28.79)
β_σ	0.39 (18.39)	0.43 (20.34)	0.46 (32.01)	0.50 (39.32)	0.50 (39.31)	0.40 (20.40)	0.51 (35.42)	0.40 (20.58)	0.51 (35.50)	0.51 (35.51)
β_{HFOIV}		0.25 (13.63)		0.29 (19.45)	0.29 (19.45)		0.36 (22.27)		0.36 (22.22)	0.36 (22.41)
β_{OIAC}			-0.02 (-1.20)	0.00 (0.32)	-0.00 (-0.12)			-0.11 (-9.75)	-0.05 (-7.56)	-0.06 (-8.04)
$\beta_{HFOIV \times OIAC}$					0.00 (0.62)					-0.00 (-0.00)
Adj. R^2 (%)	20.62	26.04	25.41	32.95	32.96	15.36	32.25	15.51	32.27	32.27
N	122,437	122,418	104,237	104,237	104,237	124,496	124,496	124,496	124,496	124,496
<i>Panel B: Change Regressions</i>										
$\beta_{\Delta\tau}$	-0.08 (-11.01)	-0.29 (-18.91)	-0.08 (-6.76)	-0.37 (-31.40)		0.10 (2.81)	-0.38 (-29.17)	0.10 (2.88)	-0.38 (-29.11)	
$\beta_{\Delta\sigma}$	0.26 (13.06)	0.29 (13.61)	0.34 (21.53)	0.38 (35.11)		0.35 (16.32)	0.43 (30.02)	0.35 (16.35)	0.43 (30.05)	
$\beta_{\Delta HFOIV}$		0.23 (12.87)		0.27 (18.88)			0.35 (26.65)		0.35 (26.77)	
$\beta_{\Delta OIAC}$			-0.02 (-1.09)	-0.01 (-0.71)				-0.10 (-10.92)	-0.05 (-7.71)	
Adj. R^2 (%)	5.93	11.04	7.58	13.32		6.44	21.75	6.82	21.79	
N	122,063	122,027	98,137	98,137	124,490	124,490	124,490	124,490		

intraday persistence reflects mechanical order splitting rather than informed directional trading, a market maker can infer that the conditional probability of the marginal order being informed is lower, narrowing the spread (Glosten & Milgrom, 1985).⁴

Specification (4) includes both log HFOIV and OIAC jointly. The HFOIV coefficient is unchanged ($\beta_{\text{HFOIV}} = 0.36$ vs. 0.36 in specification 2), and OIAC remains negative and significant for large stocks at -0.05 , smaller in magnitude than the -0.11 in specification (3), which omits HFOIV. The unconditional correlation between HFOIV and OIAC is low (-0.02 for large stocks; Table 3), confirming that volatility and persistence capture distinct dimensions of order flow. The reduction in magnitude nevertheless arises because the two variables share some explanatory power for spreads conditional on the other regressors: adding HFOIV absorbs variation that OIAC partially captured when it was the sole order flow measure.

In economic terms, a one-standard-deviation within-stock increase in OIAC (0.15–0.19 depending on year; Table 1) is associated with a $0.05 \times 0.17 \times 100 \approx 0.85$ percent narrowing of effective spreads, statistically significant but economically modest relative to HFOIV. The analogous calculation for HFOIV yields $0.36 \times 0.66 \approx 0.24$ log-points, or approximately 27 percent spread widening, over 30 times larger.⁵ Accordingly, the incremental adjusted R^2 from adding OIAC is negligible (32.27 percent vs. 32.25 percent).

For small stocks, the median OIAC coefficient across years is not statistically significant ($\beta_{\text{OIAC}} = 0.00$, $t = 0.32$). Two features of the data help explain this null result. First, OIAC is substantially noisier for small stocks: the within-stock standard deviation ranges from 0.19 to 0.49 across years (Table 1), compared with 0.15 to 0.19 for large stocks, making the coefficient harder to estimate precisely. Second, the null median masks a sign reversal visible in the yearly estimates (Table A6, appendix): small-stock OIAC coefficients are weakly negative through 2013, transition to near zero in 2014–2016, and become consistently positive and significant from 2017 onward. The positive post-2017 coefficients are consistent with the inventory duration channel dominating for small stocks:

⁴The decomposition results below (Table 8) confirm that idiosyncratic OIAC drives the spread relationship while common OIAC is insignificant, indicating that order splitting is firm-specific rather than market-wide. Testing whether persistence-generating flow is uninformed directly would require broker-level order data; the inference rests on the equilibrium characterisation in Kyle (1985), where informed traders optimally exploit the anonymity of aggregate order flow.

⁵The value 0.66 is the mean within-stock standard deviation of log HFOIV for large stocks.

when persistent flow is more likely to reflect informed directional trading than mechanical order splitting, it compounds inventory risk and widens spreads. The opposing signs across size groups suggest that both channels are operative, with the balance depending on the composition of order flow in each segment. The median across all years washes out to zero as a consequence of this sign reversal. The size dependence of the stable large-stock result aligns with the order-splitting mechanism: institutional algorithmic execution concentrates in large, liquid stocks where deeper order books make algorithmic strategies feasible. In small stocks, the base rate of persistence-generating uninformed flow is lower, and higher information asymmetry means that even persistent flow carries a greater probability of being informed, weakening the signal.

Specification (5) adds an interaction term, $\log(\text{HFOIV}) \times \text{OIAC}$, centred within quintile-year cells so that main effects are interpretable at group means. The interaction coefficient is economically and statistically negligible for both size groups (large stocks: $\beta_{\times} = -0.00$, $t = -0.00$; small stocks: $\beta_{\times} = 0.00$, $t = 0.62$), indicating that the marginal effect of HFOIV on spreads does not depend on the level of persistence. This null interaction also weighs against the inventory duration hypothesis: if OIAC operated through prolonged inventory exposure, persistent *large* shocks should be more costly than persistent *small* shocks, producing a positive interaction coefficient. The null is consistent with the adverse selection interpretation, in which persistence functions as a signal of order flow composition independently of shock magnitude. The yearly estimates (Table A7, appendix) reveal more nuance: for small stocks, the interaction is statistically significant in 12 of 21 years but reverses sign around 2013 (positive before, negative after), paralleling the OIAC coefficient sign reversal noted above and washing out in the median. For large stocks, the interaction is significant in only five years with no consistent sign pattern.

Panel B of Table 4 confirms that these relationships hold in first differences. The OIAC coefficient for large stocks remains strongly negative in changes (-0.10 in specification (3) and -0.05 in specification (4), both significant at the one percent level), indicating that the spread-persistence relationship is not an artefact of time-invariant omitted variables.^{6,7}

⁶The interaction specification (5) is omitted from the changes regressions because the interpretation of changes in centred interaction terms is unclear.

⁷Because OIAC is an AR(1) coefficient, values outside $[-1, 1]$ indicate non-stationary order flow rather than data errors. Censoring OIAC at $[-1, 1]$ leaves all results qualitatively unchanged. Separately, replacing

Figure 5 plots the time variation in HFOIV and OIAC elasticities from month-by-month regressions. The HFOIV coefficient exhibits modest time variation, with a slight upward trend for large stocks post-2015, suggesting increased inventory risk during periods of elevated market volatility (particularly 2020–2021). This upward trend connects to the calendar-based findings in Section 5.2: as derivative markets have grown (e.g., Horenstein et al., 2025) and option expiration events have become more prominent sources of inventory shocks, the marginal contribution of HFOIV to spreads has increased. The OIAC semi-elasticity is more stable, remaining negative for large stocks throughout the sample, though moving closer to zero during crisis periods (2008–2009, early 2020). This stability supports the order-splitting interpretation: institutional execution algorithms are a structural feature of modern equity markets, and their contribution to intraday persistence does not vary materially with market conditions outside of crisis episodes.⁸

HFOIV versus Absolute Order Imbalance

Table 5 tests whether the intraday frequency of order flow variation adds explanatory power beyond the daily level. Absolute daily order imbalance ($|OI|$) is a widely used measure of order flow, but it cannot distinguish a day of offsetting trades arriving every few seconds from one with offsetting morning and afternoon imbalances. Both may produce similar daily $|OI|$, yet the latter generates higher HFOIV and greater inventory risk for liquidity providers (Bogousslavsky & Collin-Dufresne, 2023). We compare HFOIV to $|OI|$ and to orthogonalised versions of each variable constructed by regressing one on the other and taking residuals (Bogousslavsky & Collin-Dufresne, 2023). Specification (1) reproduces the HFOIV result from Table 4 for reference (coefficient of 0.36 for large stocks). Specification (2) replaces HFOIV with $|OI|$; the coefficient is positive at 0.04 but the adjusted R^2 falls substantially to 16.75 percent (from 32.25 percent), and the turnover coefficient reverts towards zero at -0.09 , indicating that $|OI|$ fails to resolve fully the volume puzzle.

OIAC computed with a 20-interval minimum with a 50-interval minimum (which mainly trims noisy small-stock days) also leaves all results qualitatively unchanged.

⁸Under normal conditions, persistent order flow is typically uninformed, reflecting institutional execution algorithms (e.g., VWAP or TWAP strategies) that split large parent orders across intervals. During crisis periods, however, market makers may be unable to distinguish algorithmic execution from informed directional trading, leading them to treat all persistent flow as potentially informed and widen spreads accordingly.

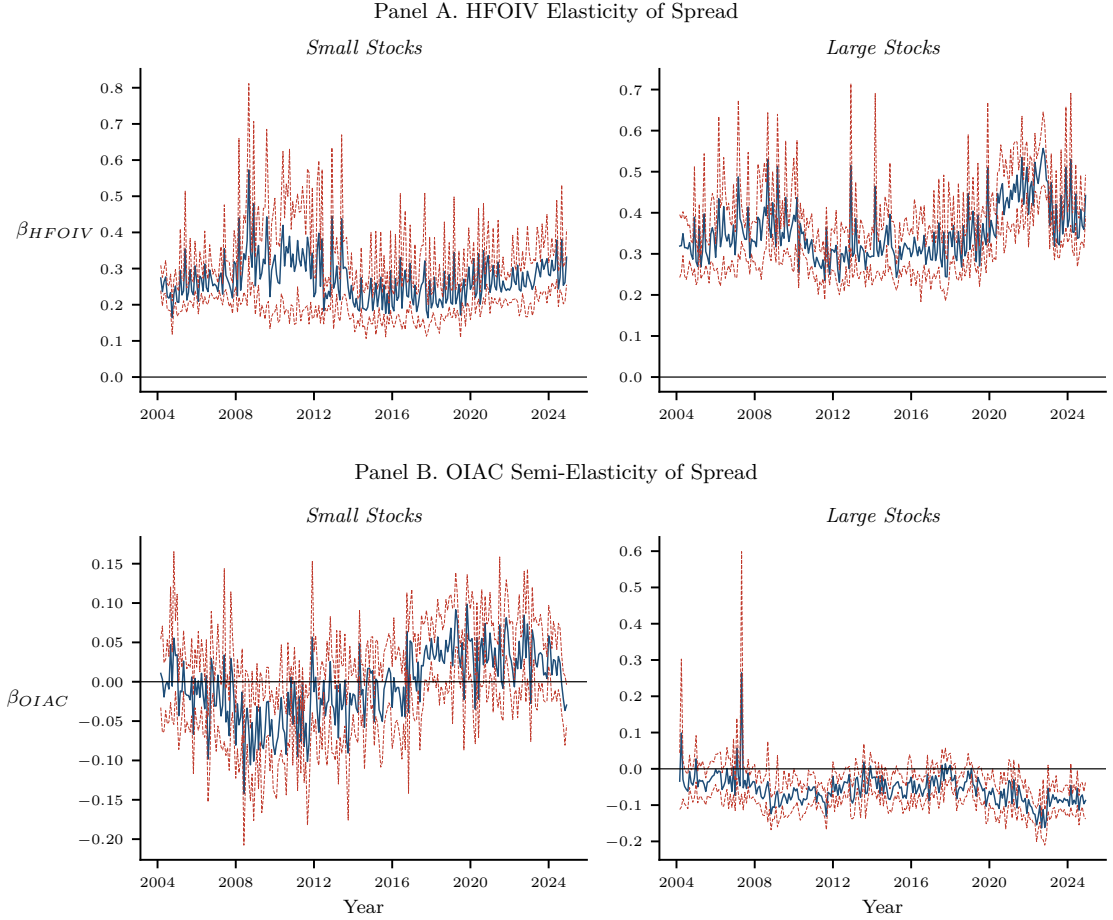


Figure 5

Order Imbalance Volatility and Autocorrelation Elasticities across Size Quintiles

This figure plots elasticities of the percent effective spread with respect to $HFOIV$ and $OIAC$, estimated from the monthly panel regression $\log s_{i,t} = \alpha_i + \beta_\tau \log \tau_{i,t} + \beta_\sigma \log \sigma_{i,t} + \beta_{HFOIV} \log HFOIV_{i,t} + \beta_{OIAC} OIAC_{i,t} + \text{controls} + \varepsilon_{i,t}$. Controls are log lagged market capitalisation, log lagged price, and day-of-week indicators. The regression includes stock fixed effects and is estimated on a month-by-month basis for stocks in a given size quintile. $OIAC$ enters in levels (semi-elasticity). Effective spreads are winsorised at the 0.05% and 99.95% levels each month. Standard errors are double-clustered by date and stock. Dashed lines indicate 95% confidence intervals.

Specification (3) uses residual HFOIV (after removing variation explained by $|OI|$); the coefficient retains strong explanatory power at 0.25, significant at the one percent level, and the R^2 increases to 24.00 percent. Specification (4) uses residual $|OI|$ (after removing HFOIV content); the coefficient is negative and small at -0.01 , indicating that once order flow volatility is accounted for, the residual level of daily imbalance does not independently widen spreads.

Table 5
Order Imbalance Volatility and Absolute Order Imbalance

This table reports the median coefficient estimate and median t -statistic (in parentheses) across years. The following panel regression with stock fixed effects is estimated each year for small and large stocks separately: $\log s_{i,t} = \alpha_i + \beta_\tau \log \tau_{i,t} + \beta_\sigma \log \sigma_{i,t} + \beta_v v_{i,t} + \text{controls} + \varepsilon_{i,t}$, where $v_{i,t}$ is one of: $\log HFOIV$ (specification 1), $\log |OI|$ (specification 2), residual $\log HFOIV$ orthogonalised with respect to $\log |OI|$ (specification 3), or residual $\log |OI|$ orthogonalised with respect to $\log HFOIV$ (specification 4). The orthogonalisation is performed on the logged variables for each stock over the full sample by regressing one on the other and a constant; the resulting residual enters the spread regression directly without further log transformation. Controls are log lagged market capitalisation, log lagged price, and day-of-week and month-of-year indicators. Effective spreads are winsorised at the 0.05% and 99.95% levels each year. t -statistics are based on standard errors double-clustered by date and stock.

	Small Stocks				Large Stocks			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β_τ	-0.37 (-24.33)	-0.21 (-31.42)	-0.21 (-29.09)	-0.16 (-20.69)	-0.43 (-28.67)	-0.09 (-5.50)	-0.23 (-20.44)	-0.04 (-2.14)
β_σ	0.43 (20.34)	0.40 (18.55)	0.40 (18.56)	0.39 (18.35)	0.51 (35.42)	0.41 (22.58)	0.45 (27.78)	0.40 (20.40)
β_{HFOIV}	0.25 (13.63)				0.36 (22.27)			
$\beta_{ OI }$		0.05 (13.76)				0.04 (7.44)		
$\beta_{HFOIV \perp OI }$			0.09 (9.98)				0.25 (15.81)	
$\beta_{ OI \perp HFOIV}$				-0.00 (-1.50)				-0.01 (-4.96)
Adj. R^2 (%)	26.04	22.42	21.98	21.16	32.25	16.75	24.00	15.37
N	122,418	122,402	122,277	122,277	124,496	124,495	124,495	124,495

These patterns are consistent with the interpretation that HFOIV captures inventory risk rather than merely proxying for the absolute level of imbalances. The higher adjusted R^2 from HFOIV compared to $|OI|$ (32.25 percent vs. 16.75 percent) indicates that the *volatility* of order flow matters more than its *level* for liquidity provision. This aligns with inventory-based models where market makers price spreads based on the uncertainty

of inventory shocks, not their average magnitude (Ho & Stoll, 1981, 1983). The strong performance of residual HFOIV (after removing $|OI|$ content) confirms that high-frequency dispersion contains incremental information beyond daily directional imbalances, consistent with the prediction that intraday inventory risk drives the observed spread patterns.

This section establishes that HFOIV and OIAC capture distinct dimensions of order flow: HFOIV measures the magnitude of inventory shocks (positively related to spreads), while OIAC captures the composition of order flow (negatively related to spreads for large stocks). Whether these two variables operate through independent channels is an empirical question that the calendar-based and decomposition tests in the next section address directly.

5.2 Characteristics of Order Imbalance and Liquidity

Having established that HFOIV and OIAC are associated with effective spreads, we implement the identification strategies described in Section 3.4 to distinguish inventory-based from information-based channels. Three tests follow: calendar-based determinants of order flow variables (Table 6), which test whether HFOIV responds to events associated with inventory risk; a mediation test for whether HFOIV transmits those calendar effects to spreads (Table 7); and a systematic-idiosyncratic decomposition (Table 8), which examines whether the spread relationship is driven by market-wide or firm-specific variation in order flow.

Determinants of Order Imbalance Volatility and Persistence

Table 6 regresses log HFOIV, OIAC, and log turnover on calendar event indicators, controlling for size, price, and stock fixed effects as well as day-of-week, month, and year fixed effects. Each dependent variable is estimated separately for small and large stocks.

HFOIV increases sharply on the third Friday of each month (regular monthly option expiration) and even more so on end-of-quarter option expiration days (quadruple witching days), consistent with prior findings (Bogousslavsky & Collin-Dufresne, 2023).⁹ For large

⁹Following the cessation of single-stock futures trading on OneChicago in 2020, these dates are technically “triple witching” days. We retain the BCD terminology for consistency and comparability, as the distinction affects only the final four years of our sample.

Table 6
Determinants of Order Imbalance Volatility, Turnover, and Order Imbalance Autocorrelation

This table reports coefficient estimates from panel regressions in which $\log HFOIV$, $\log \tau$ (turnover), and $OIAC$ are each regressed on a set of calendar event indicators and control variables, separately for small and large stocks. Calendar indicators include the third Friday of each month, the third Friday of end-of-quarter months (3rd Friday $\times$ EoQ), beginning-of-month (BoM) and end-of-month (EoM) indicators, Russell reconstitution dates, and indicators for the day before, of, and after an earnings announcement (EA-1, EA, EA+1). Controls are log lagged price and log lagged market capitalisation. The regression includes stock, day-of-week, calendar month, and year fixed effects. Standard errors are double-clustered by date and stock and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Small Stocks			Large Stocks		
	$\log HFOIV$	$OIAC$	$\log \text{Turnover}$	$\log HFOIV$	$OIAC$	$\log \text{Turnover}$
$\log \text{Turnover}$	0.739*** (0.004)	0.010*** (0.000)		0.900*** (0.005)	0.008*** (0.000)	
3rd Friday	0.174*** (0.018)	-0.015*** (0.001)	0.118*** (0.017)	0.459*** (0.024)	-0.028*** (0.001)	0.079*** (0.014)
3rd Friday $\times$ EoQ	0.428*** (0.039)	-0.006** (0.003)	0.454*** (0.040)	0.716*** (0.041)	-0.016*** (0.002)	0.250*** (0.024)
BoM	-0.037*** (0.005)	0.002 (0.001)	0.112*** (0.011)	-0.021*** (0.005)	-0.002* (0.001)	0.080*** (0.009)
EoM	-0.005 (0.005)	0.012*** (0.001)	0.060*** (0.010)	-0.014** (0.007)	0.012*** (0.001)	0.008 (0.012)
Russell	-0.030 (0.036)	0.133*** (0.023)	0.509*** (0.057)	-0.048 (0.065)	0.034*** (0.005)	0.080** (0.038)
EA-1	-0.008** (0.003)	0.002* (0.001)	0.028*** (0.007)	-0.051*** (0.003)	-0.001 (0.001)	0.207*** (0.005)
EA	-0.019*** (0.004)	0.002 (0.001)	0.391*** (0.011)	-0.089*** (0.004)	-0.002*** (0.001)	0.636*** (0.011)
EA+1	-0.031*** (0.004)	0.000 (0.001)	0.683*** (0.012)	-0.076*** (0.005)	-0.007*** (0.001)	0.660*** (0.012)
$\log \text{Price}$	0.230*** (0.017)	-0.003** (0.001)	0.218*** (0.042)	0.051*** (0.009)	0.005*** (0.001)	-0.032 (0.028)
$\log \text{Mkt. Cap.}$	-0.529*** (0.016)	0.005*** (0.001)	0.197*** (0.039)	-0.086*** (0.011)	-0.000 (0.001)	-0.321*** (0.029)
Calendar month/day FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	68.49	0.27	4.45	61.35	0.78	26.53
N	2,672,253	2,180,826	2,677,046	2,725,578	2,725,314	2,725,578

stocks, HFOIV increases by $e^{0.459} - 1 = 58$ percent on regular option expiration Fridays, controlling for turnover. On witching days, the combined effect is $e^{0.459+0.716} - 1 = 224$ percent (the interaction term contributes an additional multiplicative factor of $e^{0.716} - 1 = 105$ percent). Small stocks exhibit smaller but still economically meaningful increases (19 percent and 83 percent, respectively). These patterns support an inventory-based interpretation: derivative expiration generates large, directional, and largely informationless hedging flows (Barclay et al., 2008), creating substantial inventory risk for liquidity providers.

In contrast, HFOIV does not increase around earnings announcements. The coefficients on EA-1, EA, and EA+1 are all negative and statistically significant for both size groups. For large stocks, HFOIV decreases by 5 percent on EA-1, 8.5 percent on EA, and 7.3 percent on EA+1. Pre-earnings trading becomes more two-sided when analyst forecast dispersion is high (Sarkar & Schwartz, 2009); our finding of lower HFOIV around earnings days suggests a similar compositional shift in order flow, with belief heterogeneity generating offsetting trades that reduce the dispersion of intraday imbalances.

OIAC (column 5) exhibits the opposite pattern: it decreases sharply on option expiration days (large stocks: $\beta_{3rd\ Fri} = -0.028$, $\beta_{3rd\ Fri \times EoQ} = -0.016$; both significant at the 1 percent level). On quadruple witching days, the combined effect ($-0.028 - 0.016 = -0.044$) nearly eliminates the unconditional mean OIAC of approximately 0.05 for large stocks, implying that intraday order flow persistence effectively vanishes on these dates. This pattern is visually apparent in Figure 2, where the OIAC panel displays regular downward spikes to near zero at monthly intervals, while variation to the upside lacks any systematic structure. The collapse in persistence coincides with HFOIV more than tripling and turnover rising by 39 percent on the same days, consistent with derivative expiration generating large, directionally unpredictable hedging flows that do not persist across intervals. For small stocks, the effects are directionally identical but smaller (combined effect of -0.021), as expected given less active derivative markets for smaller stocks. OIAC increases on Russell reconstitution dates and end-of-month days. The positive coefficients on Russell reconstitution dates, particularly for small stocks (coefficient of 0.133, significant at the one percent level), may reflect the mechanical persistence induced by index-tracking trades executed over multiple intervals. Around earnings announcements, OIAC responds differently across size groups. For large stocks, persistence declines on

the announcement day ($\beta_{EA} = -0.002$, significant at 1 percent) and falls more sharply on the day after ($\beta_{EA+1} = -0.007$, significant at 1 percent), suggesting that the arrival of new information disrupts the gradual order-splitting patterns that generate persistence under normal conditions. For small stocks, the earnings-day coefficients are economically negligible, in line with less institutional order-splitting activity in smaller names.

These calendar patterns are consistent with an inventory risk interpretation of HFOIV and an order-splitting interpretation of OIAC: the two variables respond to distinct event types, reinforcing the conclusion from Table 4 that they capture independent dimensions of order flow.

The positive EoM coefficient on OIAC is consistent with the monthly payment cycle, in which institutional investors systematically sell liquid equity holdings before month-end to meet cash obligations, generating predictable selling pressure concentrated in large-capitalisation stocks (Etula et al., 2020). Figure 6 plots mean cross-sectional OIAC by event day around the last trading day of each month (T), separately for small and large stocks. For large stocks, OIAC rises gradually from T−8 to T, peaking on the last trading day, pointing to increasingly persistent order flow as institutional rebalancing intensifies towards month-end. For small stocks, the pattern differs: OIAC edges up around T−4 and remains slightly elevated before spiking on the last trading day, without the gradual build-up observed for large stocks. This size dependence aligns with the finding that the payment cycle is concentrated in large, liquid stocks (Etula et al., 2020) and our finding that the OIAC-spread relationship is concentrated in large stocks (Table 4).

Having established that HFOIV and OIAC respond to different calendar events, we next test whether HFOIV mediates the calendar-spread relationship, providing more direct evidence that inventory risk is the channel through which derivative expiration widens spreads.

Table 7 implements the mediation test described in Section 3.4. The baseline specification (1) regresses log spreads on calendar indicators and controls, omitting order flow variables. Spreads widen significantly on witching days for both small and large stocks (large stocks: $\beta_{3rd\ Fri} = 0.213$, $\beta_{3rd\ Fri \times EoQ} = 0.379$, both significant at 1 percent), with smaller and less consistent effects on beginning-of-month, end-of-month, and Russell dates. Adding log HFOIV in specification (2) reduces the witching-day coefficients substantially

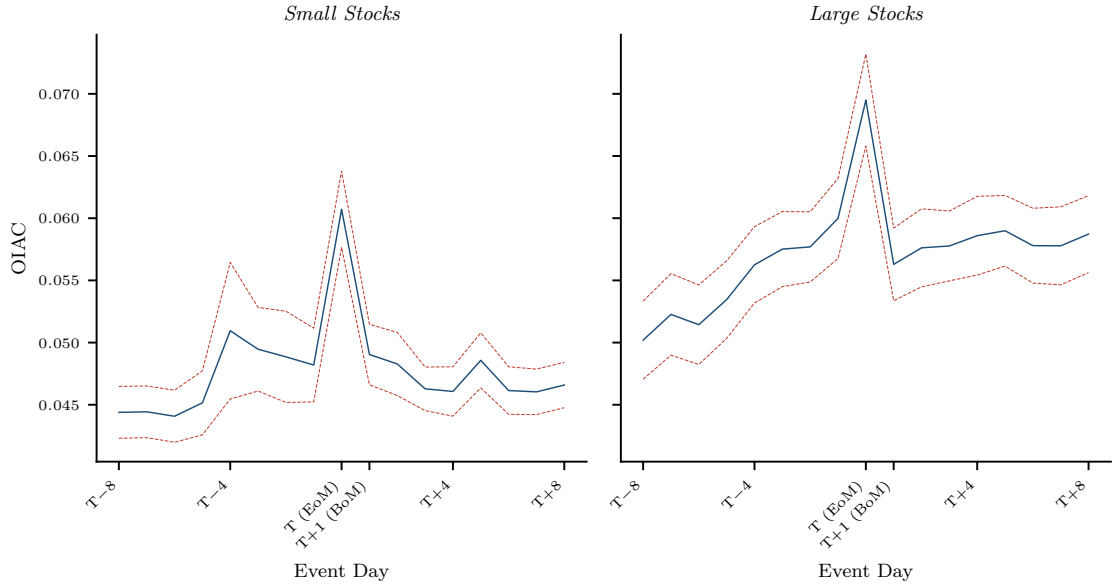


Figure 6
Mean OIAC around the Turn of the Month

This figure plots mean cross-sectional OIAC for each event day $T-8$ through $T+8$, where T is the last trading day of the month, separately for small and large stocks. Aggregation follows a Fama–MacBeth approach: for each month, we compute the cross-sectional mean OIAC within each size group on each event day, then average across months. Dashed lines indicate 95% confidence intervals based on Newey–West standard errors with one lag.

for large stocks (from 0.213 to 0.036 for regular option expiration, an 83 percent reduction; from 0.379 to 0.102 for quadruple witching days, a 73 percent reduction), indicating that HFOIV mediates most of the spread increase. Specification (4) introduces OIAC alone. For large stocks, the coefficient is -0.100 , with a t -statistic exceeding 33 in absolute value, reflecting the precision of the pooled estimator. This is comparable to the median of -0.11 from the year-by-year regressions without HFOIV (Table 4, specification 3), confirming that the pooled and year-by-year approaches yield similar estimates. Unlike HFOIV, adding OIAC does not absorb the calendar-spread relationship. Comparing specification (4) to the baseline, the witching-day coefficients for large stocks are virtually unchanged (regular option expiration: 0.210 vs. 0.213; witching days: 0.378 vs. 0.379). For small stocks, the witching-day coefficients are slightly larger in specification (4) than in the baseline (0.226 vs. 0.189 for regular option expiration; 0.350 vs. 0.289 for witching days), likely because controlling for OIAC, which drops sharply on expiration days (Table 6), reveals a larger direct calendar effect on spreads. In neither size group does OIAC mediate the

calendar-spread relationship, confirming that OIAC captures structural persistence from algorithmic order splitting rather than event-driven inventory shocks.

Specification (5) includes both OIAC and HFOIV jointly. For large stocks, both variables remain statistically significant with signs consistent with Table 4: HFOIV positive ($\beta_{\text{HFOIV}} = 0.392$), OIAC negative ($\beta_{\text{OIAC}} = -0.043$). As in Table 4, adding HFOIV reduces the OIAC coefficient in magnitude (from -0.100 to -0.043), reflecting shared explanatory power between the two order flow measures.

Table 7
Effective Spread, Calendar Effects, and Order Imbalance Volatility

This table reports coefficient estimates from panel regressions in which $\log s_{i,t}$ (percent effective spread) is regressed on order imbalance measures, calendar event indicators, and control variables, separately for small and large stocks. Order imbalance measures are $\log \text{HFOIV}$ (specification 2), $\log |\text{OI}|$ (specification 3), OIAC (specification 4), and $\log \text{HFOIV}$ jointly with OIAC (specification 5). Calendar indicators include the third Friday of each month, the third Friday of end-of-quarter months (3rd Friday $\times$ EoQ), beginning-of-month (BoM) and end-of-month (EoM) indicators, Russell reconstitution dates, and indicators for the day before, of, and after an earnings announcement (EA -1 , EA, EA $+1$). Controls are $\log \tau$ (turnover), $\log \sigma$ (realised volatility), $\log$ lagged price, and $\log$ lagged market capitalisation. The regression includes stock, day-of-week, calendar month, and year fixed effects. Effective spreads are winsorised at the 0.05% and 99.95% levels each year. Standard errors are double-clustered by date and stock and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Small Stocks					Large Stocks				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$\log \text{HFOIV}$		0.265*** (0.005)			0.330*** (0.003)		0.393*** (0.005)			0.392*** (0.005)
$\log \text{OI} $			0.064*** (0.001)					0.041*** (0.001)		
OIAC				0.008** (0.003)	0.023*** (0.002)				-0.100*** (0.003)	-0.043*** (0.003)
3rd Friday	0.189*** (0.017)	0.144*** (0.014)	0.181*** (0.017)	0.226*** (0.019)	0.163*** (0.014)	0.213*** (0.013)	0.036*** (0.009)	0.199*** (0.013)	0.210*** (0.013)	0.036*** (0.009)
3rd Friday $\times$ EoQ	0.289*** (0.035)	0.177*** (0.027)	0.262*** (0.033)	0.350*** (0.036)	0.191*** (0.026)	0.379*** (0.028)	0.102*** (0.020)	0.350*** (0.027)	0.378*** (0.028)	0.102*** (0.020)
BoM	0.003 (0.005)	0.011** (0.005)	0.004 (0.005)	0.000 (0.005)	0.010** (0.004)	0.006 (0.006)	0.010* (0.006)	0.006 (0.006)	0.006 (0.006)	0.010* (0.006)
EoM	-0.003 (0.005)	-0.002 (0.005)	-0.003 (0.005)	-0.005 (0.005)	-0.005 (0.005)	-0.015*** (0.006)	-0.009* (0.005)	-0.014** (0.006)	-0.014** (0.006)	-0.009* (0.005)
Russell	-0.014 (0.029)	-0.008 (0.022)	-0.014 (0.028)	0.004 (0.032)	0.006 (0.023)	-0.065** (0.032)	-0.044*** (0.014)	-0.061** (0.030)	-0.061* (0.032)	-0.043*** (0.014)
EA -1	0.014*** (0.003)	0.014*** (0.003)	0.015*** (0.003)	0.010*** (0.003)	0.009*** (0.003)	-0.012*** (0.003)	0.006** (0.003)	-0.009*** (0.003)	-0.012*** (0.003)	0.006** (0.002)
EA	0.097*** (0.004)	0.094*** (0.004)	0.098*** (0.004)	0.100*** (0.004)	0.096*** (0.004)	0.077*** (0.005)	0.089*** (0.004)	0.080*** (0.005)	0.077*** (0.005)	0.089*** (0.004)
EA $+1$	0.128*** (0.005)	0.126*** (0.004)	0.131*** (0.005)	0.137*** (0.005)	0.135*** (0.004)	0.038*** (0.005)	0.051*** (0.005)	0.039*** (0.005)	0.037*** (0.005)	0.051*** (0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month/day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	31.00	35.74	32.37	39.18	45.26	34.64	44.52	35.44	34.76	44.54
N	2,661,999	2,658,944	2,656,861	2,179,945	2,179,945	2,725,578	2,725,578	2,725,392	2,725,314	2,725,314

Decomposing Common and Idiosyncratic Effects

The calendar and mediation tests examine the *temporal* dimension of the HFOIV- and OIAC-spread relationship: when does it strengthen? The decomposition in Table 8 examines the *cross-sectional* dimension: is the spread relationship driven by market-wide or firm-specific variation and persistence in order flow? This distinction bears directly on whether the underlying mechanism is aggregate inventory pressure or stock-level order splitting.

We decompose each variable into common and idiosyncratic counterparts using the leave-one-out approach described in Section 3.4. For turnover and realised volatility, the decomposition is applied at the variance level and produces additive components; for OIAC, it is applied to the underlying order imbalance series, yielding separate AR(1) coefficients on the common and residual processes (see Section 3.4 for details). Table 8 reports the decomposed specification (Equation 3.4). Specification (1) includes turnover and volatility only. For large stocks, idiosyncratic turnover is negatively related to spreads at -0.07 , consistent with the interpretation that stock-specific volume reflects uninformed noise trading that facilitates inventory offloading. Common turnover carries a small positive coefficient of 0.16 , significant at the five percent level. Idiosyncratic volatility dominates common volatility in explaining spreads (0.37 vs. 0.02 , both significant), consistent with both adverse selection models, in which firm-specific information events widen spreads, and inventory models, in which stock-specific shocks are harder to diversify away.

Specification (2) adds HFOIV components. Both common and idiosyncratic HFOIV are positively related to spreads, with idiosyncratic HFOIV exhibiting a much larger coefficient for large stocks (0.30 vs. 0.04 for common HFOIV, both strongly significant). This suggests that both market-wide inventory shocks and stock-specific inventory shocks matter for liquidity provision, with the latter dominating. The relative magnitudes are consistent with inventory-based market-making models in which firm-specific order flow imbalances are more difficult to offload than systematic imbalances (which can be more easily diversified).

The positive coefficient on common HFOIV is consistent with the inventory interpretation emphasised by Bogousslavsky and Collin-Dufresne (2023): market-wide order flow shocks cannot reflect firm-specific information, so their association with wider spreads

Table 8
Effective Spread Regressed on Common and Idiosyncratic Components of Volume, Volatility, and Order Imbalance

This table reports the median coefficient estimate and median t -statistic (in parentheses) across years. The following panel regression with stock fixed effects is estimated each year for small and large stocks separately: $\log s_{i,t} = \alpha_i + \beta_{\tau,C}\tau_{i,t}^C + \beta_{\tau,I}\tau_{i,t}^I + \beta_{\sigma,C}\log \sigma_{i,t}^C + \beta_{\sigma,I}\log \sigma_{i,t}^I + \beta_{HFOIV,C}\log HFOIV_{i,t}^C + \beta_{HFOIV,I}\log HFOIV_{i,t}^I + \beta_{OIAC,C}OIAC_{i,t}^C + \beta_{OIAC,I}OIAC_{i,t}^I + \text{controls} + \varepsilon_{i,t}$, where superscripts C and I denote common (systematic) and idiosyncratic components. Turnover is decomposed via time-series regression of each stock's log turnover on the leave-one-out quintile mean. Realised volatility and HFOIV are decomposed within each day using a covariance-based variance partition against the quintile mean. OIAC is decomposed as the AR(1) of quintile-mean order imbalance (systematic) and the AR(1) of residuals from regressing each stock's intraday imbalance on the quintile mean (idiosyncratic). See Section 3.4 for details. Controls are log lagged market capitalisation, log lagged price, and day-of-week and month-of-year indicators. Effective spreads are winsorised at the 0.05% and 99.95% levels each year. t -statistics are based on standard errors double-clustered by date and stock.

	Small Stocks				Large Stocks			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\beta_{\tau C}$	-0.04 (-0.59)	-0.16 (-3.66)	-0.03 (-0.48)	-0.23 (-5.21)	0.16 (2.24)	-0.18 (-3.70)	0.16 (2.33)	-0.18 (-3.67)
$\beta_{\tau I}$	-0.17 (-22.86)	-0.28 (-28.26)	-0.20 (-22.97)	-0.40 (-36.76)	-0.07 (-3.52)	-0.39 (-26.70)	-0.07 (-3.57)	-0.38 (-26.53)
$\beta_{\sigma C}$	0.00 (0.88)	0.00 (0.31)	0.00 (1.33)	0.00 (1.94)	0.02 (4.49)	0.03 (7.07)	0.02 (4.37)	0.03 (6.77)
$\beta_{\sigma I}$	0.39 (18.22)	0.41 (24.29)	0.45 (30.03)	0.48 (34.90)	0.37 (19.98)	0.44 (26.06)	0.37 (20.38)	0.44 (25.94)
β_{HFOIV^C}		0.05 (9.61)		0.04 (6.40)		0.04 (5.41)		0.04 (5.42)
β_{HFOIV^I}		0.06 (7.56)		0.21 (19.08)		0.30 (25.45)		0.30 (25.12)
β_{OIAC^C}			-0.00 (-0.19)	0.01 (0.30)			0.01 (0.25)	0.02 (0.34)
β_{OIAC^I}			0.01 (0.64)	0.04 (3.47)			-0.10 (-7.01)	-0.04 (-3.75)
Adj. R^2 (%)	20.96	25.96	26.27	32.54	15.64	27.74	15.81	27.83
N	122,434	121,864	104,233	104,233	124,496	124,496	124,496	124,496

points to aggregate inventory pressure. The turnover decomposition provides a related insight. In the baseline specification without HFOIV (specification 1), common turnover is positively associated with spreads ($\beta_{\tau C} = 0.16$) while idiosyncratic turnover is negatively associated ($\beta_{\tau I} = -0.07$). This suggests that the volume puzzle identified in Table 4 is concentrated in the common component: market-wide volume surges coincide with wider spreads, while firm-specific volume narrows spreads through the Demsetz (1968) mechanism of attracting offsetting counterparties. Adding HFOIV (specification 2) flips the common turnover coefficient to -0.18 , indicating that once order flow volatility absorbs the inventory risk content of common volume, both turnover components are associated with narrower spreads.

Specification (3) introduces OIAC components without HFOIV. For large stocks, idiosyncratic OIAC is strongly negative at -0.10 while common OIAC is insignificant, indicating that stock-specific persistence rather than market-wide persistence drives the spread relationship. Specification (4) adds HFOIV components alongside OIAC. Idiosyncratic OIAC attenuates to -0.04 , significant at the one percent level, paralleling the pattern in Table 4 where the OIAC coefficient halves when HFOIV is added, while common OIAC remains insignificant. This pattern aligns with the finding that approximately 75% of the first-lag autocorrelation is attributable to same-broker order splitting rather than cross-broker herding (Tóth et al., 2015): just as same-broker splitting dominates cross-broker herding in their data, idiosyncratic persistence dominates common persistence in ours. The dominance of idiosyncratic OIAC is consistent with persistence reflecting institutional order execution strategies rather than market-wide information diffusion.

The calendar-based tests and commonality decompositions support an inventory-based interpretation of HFOIV: it increases on derivative expiration days (large hedging flows) but not around earnings announcements (informed trading), and idiosyncratic HFOIV dominates common HFOIV in explaining spreads. For OIAC, the evidence is consistent with a reduction in information asymmetry costs rather than inventory risk. The negative coefficient indicates that persistence *reduces* spreads, inconsistent with the inventory hypothesis that prolonged directional pressure widens them. The dominance of idiosyncratic persistence in Table 8 reinforces the order-splitting interpretation established above: if OIAC reflects institutional execution algorithms rather than informed directional trading,

market makers can infer a lower probability of adverse selection, narrowing spreads. Because the dependent variable in these regressions is the effective spread, which aggregates both adverse selection and inventory components, the analysis cannot definitively attribute the effect to a specific spread component; the interpretation rests on the sign, the decomposition, and the calendar patterns rather than a direct test of the price impact channel. The null interaction with HFOIV (Table 4, specification 5) reinforces the independence of this channel: OIAC operates as a signal of order flow composition regardless of shock magnitude.

Across these tests, four strands of evidence establish that HFOIV and OIAC capture independent dimensions of order flow. First, the two variables are nearly uncorrelated in the cross-section ($\rho = -0.02$ for large stocks; Table 3). Second, their interaction is economically and statistically negligible in the spread regressions (Table 4, specification 5), confirming that each variable’s marginal effect does not depend on the level of the other. Third, the two variables respond in opposite directions to derivative expiration events: HFOIV more than triples on witching days while OIAC falls to near zero (Table 6), indicating that hedging flows generate large but non-persistent inventory shocks. Fourth, the decomposition reveals different component structures: HFOIV operates through both common and idiosyncratic channels, while OIAC operates exclusively through the idiosyncratic channel (Table 8), consistent with persistence arising from firm-specific order splitting rather than market-wide information diffusion. This independence also has a directional dimension: HFOIV is symmetric, treating upward and downward imbalance shocks identically, while OIAC captures the serial dependence of signed order flow, distinguishing sustained buying pressure from sustained selling. The two variables together thus provide complementary characterisations of intraday order flow that neither captures individually.

5.3 Order Imbalance and Cross-Sectional Returns

The final set of tests examines whether order flow characteristics predict cross-sectional stock returns, providing evidence on whether HFOIV and OIAC carry characteristic-based return premia. We first use double-sorted portfolio tests (Tables 9a–9b) to assess whether high-HFOIV or high-OIAC stocks earn abnormal returns, then turn to Fama–MacBeth

regressions (Tables 10 and A34) for multivariate return predictability with a range of controls. Stocks with high HFOIV earn higher subsequent returns after controlling for turnover, consistent with the interpretation that high-HFOIV stocks bear greater inventory risk and thus command a liquidity premium (Bogousslavsky & Collin-Dufresne, 2023). We extend this analysis to OIAC and examine the stability of the return-predictability relationship in the extended sample period.

Portfolio Sorts

Tables 9a and 9b report four-factor alphas estimated from Equation 3.5 for portfolios formed via sequential double sorts on turnover and HFOIV (Table 9a) or turnover and OIAC (Table 9b). Panel A of each table sorts first by turnover, then by the order flow measure within each turnover quintile. Panel B reverses the sort order. Portfolios are value-weighted and rebalanced weekly. HFOIV and OIAC are measured as exponentially weighted moving averages of prior daily values with a half-life of one day, following Bogousslavsky and Collin-Dufresne (2023). Quintile breakpoints are determined using NYSE stocks to prevent the over-representation of small NASDAQ stocks from skewing breakpoint thresholds.

Table 9a replicates the Bogousslavsky and Collin-Dufresne (2023) finding that high-HFOIV stocks earn higher four-factor alphas than low-HFOIV stocks, suggesting a liquidity premium. The high-minus-low HFOIV spread is positive and significant for the lowest turnover quintile (Panel A: 0.10 percent per week, $t = 2.43$) and turnover quintiles 3–4 show weakly positive spreads (0.07 percent and 0.10 percent per week, respectively), though statistical significance is weaker in the extended sample than in the original BCD period, where HFOIV spreads are statistically significant in four of five turnover quintiles (Bogousslavsky & Collin-Dufresne, 2023). Panel B (sorting first by HFOIV) shows that the effect is concentrated in the highest HFOIV quintile, where high-turnover stocks underperform low-turnover stocks by 11 basis points per week ($t = -1.32$, not statistically significant). Table A33 in the appendix replicates these sorts over the 2004–2017 period; the HFOIV spread is positive and significant in three of five turnover quintiles, while the turnover spread is negative and significant in three of five HFOIV quintiles. These results

Table 9a
Order Imbalance Volatility, Turnover, and Stock Returns

This table reports four-factor alphas (in percent) of value-weighted portfolios formed each week by sequentially sorting stocks on turnover and *HFOIV*. Panel A sorts first by turnover, then by *HFOIV* within each turnover quintile. Panel B reverses the sort order. Turnover is the average daily turnover over the previous 20 trading days. *HFOIV* is an exponentially weighted moving average of prior high-frequency order imbalance volatility with a half-life of one day. Quintile breakpoints are based on NYSE stocks. To be included in a portfolio, a stock must have a price greater than \$5 at the end of the previous week. *t*-statistics are reported in parentheses and computed using Newey–West standard errors with one lag. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

<i>Panel A: Sort by Turnover, then HFOIV</i>						
	Low HFOIV	2	3	4	High HFOIV	H–L
Low Turnover	0.00 (0.09)	-0.03 (-0.94)	0.05 (1.55)	-0.03 (-0.85)	0.10*** (3.13)	0.10** (2.43)
2	0.03 (1.25)	0.04 (1.51)	-0.00 (-0.06)	0.02 (0.70)	0.02 (0.74)	-0.01 (-0.18)
3	-0.00 (-0.17)	0.01 (0.49)	0.03 (1.10)	0.04 (1.45)	0.06** (2.02)	0.07 (1.58)
4	-0.06* (-1.85)	-0.05 (-1.46)	-0.03 (-0.98)	0.00 (0.07)	0.03 (0.98)	0.10** (2.00)
High Turnover	-0.01 (-0.11)	-0.02 (-0.40)	0.03 (0.63)	-0.09 (-1.64)	0.01 (0.20)	0.02 (0.26)
<i>Panel B: Sort by HFOIV, then Turnover</i>						
	Low Turnover	2	3	4	High Turnover	H–L
Low HFOIV	-0.02 (-0.40)	0.01 (0.34)	0.01 (0.29)	0.01 (0.28)	-0.01 (-0.43)	0.00 (0.04)
2	0.02 (0.59)	-0.00 (-0.07)	0.01 (0.21)	-0.04 (-1.17)	-0.04 (-1.10)	-0.06 (-1.17)
3	0.00 (0.12)	0.04 (1.25)	0.03 (1.02)	0.01 (0.19)	-0.03 (-0.59)	-0.03 (-0.51)
4	0.07* (1.95)	-0.01 (-0.21)	-0.00 (-0.04)	-0.07* (-1.69)	-0.01 (-0.17)	-0.08 (-1.06)
High HFOIV	0.11*** (3.17)	0.02 (0.64)	-0.01 (-0.26)	0.01 (0.22)	0.00 (0.02)	-0.11 (-1.32)

closely track those of Bogousslavsky and Collin-Dufresne (2023) despite the shorter sample (2004 vs. 2002 start date).

Table 9b
Order Imbalance Autocorrelation, Turnover, and Stock Returns

This table reports four-factor alphas (in percent) of value-weighted portfolios formed each week by sequentially sorting stocks on turnover and *OIAC*. Panel A sorts first by turnover, then by *OIAC* within each turnover quintile. Panel B reverses the sort order. Turnover is the average daily turnover over the previous 20 trading days. *OIAC* is an exponentially weighted moving average of prior order imbalance autocorrelation with a half-life of one day. Quintile breakpoints are based on NYSE stocks. To be included in a portfolio, a stock must have a price greater than \$5 at the end of the previous week. *t*-statistics are reported in parentheses and computed using Newey–West standard errors with one lag. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

<i>Panel A: Sort by Turnover, then OIAC</i>						
	Low OIAC	2	3	4	High OIAC	H–L
Low Turnover	0.00 (0.11)	0.02 (0.78)	-0.02 (-0.57)	0.01 (0.17)	0.04 (1.16)	0.03 (0.73)
2	0.06* (1.86)	-0.01 (-0.35)	0.07** (2.20)	-0.00 (-0.14)	-0.05* (-1.74)	-0.11*** (-2.70)
3	-0.01 (-0.39)	0.01 (0.19)	0.02 (0.59)	0.05 (1.44)	0.01 (0.24)	0.02 (0.46)
4	-0.07* (-1.90)	-0.02 (-0.44)	-0.04 (-1.22)	-0.07* (-1.84)	-0.05 (-1.25)	0.02 (0.44)
High Turnover	0.01 (0.18)	0.00 (0.08)	-0.06 (-1.03)	0.02 (0.33)	-0.05 (-0.75)	-0.06 (-0.80)
<i>Panel B: Sort by OIAC, then Turnover</i>						
	Low Turnover	2	3	4	High Turnover	H–L
Low OIAC	-0.01 (-0.18)	0.06** (2.17)	-0.03 (-0.83)	-0.06* (-1.69)	-0.03 (-0.64)	-0.03 (-0.38)
2	0.01 (0.26)	0.01 (0.35)	0.01 (0.48)	-0.02 (-0.53)	0.03 (0.52)	0.02 (0.28)
3	-0.01 (-0.24)	0.04 (1.21)	0.03 (0.82)	-0.02 (-0.57)	-0.03 (-0.54)	-0.02 (-0.32)
4	0.03 (0.78)	-0.02 (-0.78)	0.05* (1.73)	-0.07* (-1.70)	-0.05 (-0.87)	-0.08 (-1.03)
High OIAC	0.04 (1.27)	-0.02 (-0.60)	-0.03 (-0.85)	-0.02 (-0.57)	-0.02 (-0.31)	-0.06 (-0.76)

Table 9b presents analogous sorts for *OIAC*. The alpha patterns are less pronounced than for *HFOIV*. Within turnover quintiles (Panel A), the high-minus-low *OIAC* spread is

negative for turnover quintile 2 (-0.11 percent per week, or roughly -5.7 percent annualised, $t = -2.70$) but near zero or slightly positive for other quintiles. Reversing the sort order (Panel B), there is no consistent pattern across OIAC quintiles, with high-minus-low turnover spreads ranging from -0.08 to $+0.02$ percent per week, none statistically significant. The absence of systematic return patterns for OIAC is consistent with the spread regressions: OIAC’s negative coefficient implies that predictable order flow reduces transaction costs for market makers, but this benefit is stock-specific and diversifiable rather than a source of systematic risk. Unlike HFOIV, which reflects the magnitude of inventory shocks that may require compensation, persistence in order flow helps liquidity providers anticipate and manage inventory without generating a return premium that investors would demand for bearing additional risk.

The weak return predictability for OIAC contrasts with the statistically significant spread relationship established in Section 5.1. This suggests that while OIAC affects transaction costs (spreads), it does not carry a characteristic-based return premium. Investors may not demand compensation for persistence-related liquidity provision because it is diversifiable across stocks or because persistence helps market makers *reduce* costs rather than increase risk. The latter interpretation aligns with the negative OIAC coefficient in the spread regressions: predictable order flow narrows spreads, benefiting both liquidity providers and liquidity demanders without generating a return premium.¹⁰

Fama–MacBeth Regressions

Table 10 presents the Fama–MacBeth cross-sectional regressions (Equation 3.6) of weekly returns on HFOIV, OIAC, turnover, and controls for the full sample period (2004–2024). Table A34 in the appendix reports the same regressions for the BCD replication period (2004–2017) for direct comparability with the original paper. Each week, we run a cross-sectional regression of next-week returns on lagged characteristics; the table reports the time-series average of the weekly coefficients along with Newey–West standard errors with one lag. Specification (1) is a univariate regression on log HFOIV as the sole explanatory

¹⁰These characteristic-based tests establish that OIAC does not predict cross-sectional returns. Whether OIAC represents a priced systematic risk exposure (in the covariance sense) would require constructing an OIAC-based factor and testing whether exposure to that factor earns a premium, which is beyond the scope of this thesis.

variable. The coefficient is positive at 0.048 but only significant at the 10 percent level ($t = 1.66$), consistent with the out-of-sample instability documented above. Specification (2) adds log turnover; the HFOIV coefficient drops to near zero at 0.006 and the turnover coefficient is positive at 0.052, neither statistically significant, in contrast to the negative turnover coefficient documented by BCD for their sample period.

Specification (3) introduces OIAC. In the specification with HFOIV and turnover, OIAC is negative at -0.045 but not statistically significant ($t = -0.51$). Specification (4) adds standard control variables (market equity, lagged return, ILLIQ, realised volatility, effective spread, depth, and Kyle’s lambda);¹¹ none of the liquidity variables exhibit strong statistical significance. Specification (5) adds additional order-imbalance-based controls ($|OI|$, PIN, and $\sigma(OI/VOL)$); results are qualitatively unchanged.¹²

The HFOIV return premium documented by Bogousslavsky and Collin-Dufresne (2023) does not replicate in the extended sample. In the BCD period (Table A34, appendix), HFOIV is significant across all five specifications, with coefficients ranging from 0.051 to 0.065, and the turnover coefficient is negative in specifications (2)–(4). In the full sample (2004–2024), however, HFOIV loses statistical significance as soon as turnover is included (specification 2) and remains insignificant in all subsequent specifications. Only lagged returns (r_{t-1}) retain significance in the full-sample regressions.¹³ Bogousslavsky and Collin-Dufresne (2023) themselves anticipate this possibility, noting that “[t]his evidence is of particular interest since many high-frequency liquidity and volatility measures do not appear to be priced (Lou & Shu, 2017)”. Our extended-sample results confirm that concern: HFOIV joins the set of high-frequency liquidity measures that affect transaction costs without commanding characteristic-based return premia. OIAC does not predict cross-sectional returns in either sample, reinforcing this conclusion.

¹¹The BCD replication code labels Kyle’s lambda as “log lambda” but does not apply a log transformation, using the variable in levels. Our code correctly log-transforms lambda (replacing non-positive values with missing). This difference primarily affects the lambda coefficient in specifications (4) and (5); the qualitative conclusions for HFOIV and OIAC are unchanged.

¹²An unreported bivariate specification including only HFOIV and OIAC (omitting turnover) yields qualitatively similar results, confirming that the lack of OIAC significance is not driven by multicollinearity with turnover.

¹³The lagged return enters in decimals while the dependent variable is in percent, following Bogousslavsky and Collin-Dufresne (2023). The coefficient of -1.08 in specification (4) implies that a 10 percentage point higher lagged return is associated with a 0.108 percentage point lower next-week return. BCD report comparable magnitudes (-1.69 and -1.62) in their specifications with controls.

Table 10
Fama–MacBeth Regressions of Weekly Returns on Liquidity Characteristics

This table reports results from value-weighted Fama–MacBeth regressions of weekly stock returns on liquidity characteristics. $HFOIV_{t-1}$ is an exponentially weighted moving average (EWMA) of prior high-frequency order imbalance volatility with a half-life of one day. τ_{t-1} is the average daily turnover over the previous month. $OIAC_{t-1}$ is order imbalance autocorrelation (in levels). ME_{t-1} is market capitalisation at the end of the previous week. $ILLIQ_{t-1}$ is the Amihud illiquidity ratio computed over the past 250 trading days (minimum 100 observations). σ_{t-1} is an EWMA of prior daily realised volatilities with a half-life of one day. ES_{t-1} is an EWMA of prior daily effective spreads with a half-life of one day. λ_{t-1} is an EWMA of prior daily Kyle’s lambda with a half-life of one day. $Depth/VOL_{t-1}$ is an EWMA of prior daily share depth over daily share volume with a half-life of one day. $|OI|_{t-1}$ is an EWMA of prior daily absolute share imbalance (as a fraction of shares outstanding) with a half-life of one day. PIN is the absolute daily trade imbalance over the total number of trades. $\sigma(OI/VOL)_{t-1}$ is the standard deviation of share imbalance divided by share volume, computed over the past 22 trading days (minimum 11 observations). All explanatory variables except the lagged return and $OIAC$ are in logs. All explanatory variables are winsorised at the 0.5% and 99.5% levels. The sample is restricted to stocks with a price greater than \$5 at the end of the previous week. The sample period is 2004 to 2024. Adjusted R^2 is the time-series average of the weekly cross-sectional R^2 s. $\bar{N}$ is the average number of stocks at each date. t -statistics are reported in parentheses and based on Newey–West standard errors with one lag. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)
$HFOIV_{t-1}$	0.048* (1.660)	0.006 (0.219)	0.006 (0.215)	0.022 (0.930)	0.032 (1.228)
$Turnover_{t-1}$		0.052 (1.214)	0.050 (1.128)	0.034 (0.757)	0.036 (0.824)
$OIAC_{t-1}$			-0.045 (-0.512)	-0.089 (-1.210)	-0.079 (-1.094)
ME_{t-1}				-0.004 (-0.084)	-0.005 (-0.125)
r_{t-1}				-1.084*** (-2.655)	-1.021** (-2.528)
$ILLIQ_{t-1}$				0.016 (0.436)	0.011 (0.290)
$RVol_{t-1}$				0.002 (0.024)	0.007 (0.092)
ES_{t-1}				-0.028 (-0.891)	-0.031 (-1.006)
$Depth/VOL_{t-1}$				-0.025 (-1.295)	-0.027 (-1.382)
λ_{t-1}				-0.018 (-1.121)	-0.019 (-1.171)
$ OI _{t-1}$					-0.013 (-0.722)
PIN_{t-1}					0.008 (0.489)
$\sigma(OI/VOL)_{t-1}$					0.015 (0.466)
Adj. R^2 (%)	2.28	4.24	4.61	12.51	13.45
$\bar{N}$	2,574	2,573	2,475	2,405	2,404

Taken together, the results confirm the core findings of Bogousslavsky and Collin-Dufresne (2023) regarding HFOIV and spreads, extend the analysis along a new dimension, and show that the return-predictability result does not replicate out of sample. HFOIV substantially strengthens the negative turnover-spread relationship, its effect is concentrated in idiosyncratic rather than systematic order flow, and it increases on derivative expiration days but not around earnings announcements, consistent with an inventory risk interpretation. Beyond replication, OIAC provides statistically significant incremental explanatory power for large-stock spreads, with a negative coefficient consistent with predictable order flow reducing transaction costs for liquidity providers. This effect is driven by idiosyncratic persistence (consistent with institutional order splitting) rather than market-wide herding, and it is economically modest relative to HFOIV. Neither HFOIV nor OIAC predicts cross-sectional returns in the extended sample, consistent with the broader finding that high-frequency liquidity measures affect transaction costs without commanding return premia (Lou & Shu, 2017).

6 Conclusion

This thesis examines whether the temporal structure of intraday order flow provides incremental information about stock liquidity beyond what order imbalance volatility captures. The BCD model assumes Markov order flow, under which persistence carries no information about spreads once volatility is controlled for. The order-splitting literature documents that this assumption is violated empirically (Lillo et al., 2005; Tóth et al., 2015), raising the question of whether persistence provides incremental explanatory power for effective spreads. The answer is affirmative for large stocks, where order imbalance autocorrelation is negatively and significantly associated with effective spreads after controlling for HFOIV, consistent with the adverse selection signalling channel. For small stocks, persistence carries no significant incremental information.

We replicate the main results of Bogousslavsky and Collin-Dufresne (2023) in a sample of NYSE, AMEX, and NASDAQ common stocks spanning 2004 to 2024, seven years beyond their original sample. The replication confirms that HFOIV is a strong predictor of effective spreads, that controlling for HFOIV recovers the negative volume-spread relationship predicted by Demsetz (1968), and that HFOIV responds to calendar events associated with inventory risk (derivative expiration) but not to information events (earnings announcements). Both the common and idiosyncratic components of HFOIV are positively associated with spreads, with the significant common component providing identification against pure adverse selection explanations.

The main contribution is the finding that order imbalance autocorrelation (OIAC), the first-order autocorrelation of five-minute share imbalances, carries incremental explanatory power for spreads among large stocks. The OIAC coefficient is negative and strongly significant, indicating that higher persistence is associated with narrower spreads. This sign contradicts the inventory duration hypothesis, under which persistent one-sided flow should widen spreads by extending the market maker’s inventory holding period. It is consistent with the adverse selection signalling hypothesis: predictable order flow reflects mechanical institutional order splitting rather than informed directional trading, consistent with market makers pricing lower adverse selection risk into the spread (Glosten & Milgrom, 1985). Several auxiliary tests reinforce this interpretation. The HFOIV-OIAC

interaction is null, indicating that the two variables operate through independent channels. Calendar-based tests show that OIAC collapses on derivative expiration days, when hedging flows disrupt the order-splitting patterns that generate persistence under normal conditions. The commonality decomposition reveals that idiosyncratic persistence drives the spread relationship while common persistence is insignificant, aligning with evidence that approximately 75 percent of intraday autocorrelation originates from same-broker order splitting (Tóth et al., 2015).

Two features of the results require qualification. First, OIAC is significant only for large stocks. This size dependence is consistent with the proposed mechanism: institutional algorithmic execution concentrates in large, liquid stocks where deeper order books make algorithmic strategies feasible. In small stocks, the base rate of persistence-generating uninformed flow is lower, and higher information asymmetry means that persistent flow is more likely to reflect informed trading, weakening the signal that would otherwise reduce adverse selection costs. Second, the HFOIV return premium documented by Bogousslavsky and Collin-Dufresne (2023) for the BCD sample period (replicated over 2004–2017) does not replicate in the extended sample (2004–2024), and OIAC does not predict cross-sectional returns in either period. These null return results are consistent with the broader finding that high-frequency liquidity and volatility measures do not appear to be priced (Bogousslavsky & Collin-Dufresne, 2023; Lou & Shu, 2017).

Several limitations should be acknowledged. The AR(1) specification for OIAC provides a parsimonious summary of within-day serial dependence, but richer models could capture persistence structures that the first-order coefficient misses. The minimum threshold of 20 five-minute intervals for OIAC estimation excludes 4.1 percent of the sample, disproportionately among illiquid small stocks, potentially understating OIAC’s role in that size group. Beyond OIAC measurement, the year-by-year median regression approach mitigates non-stationarity but does not identify why the HFOIV return premium disappears in the extended sample. Regarding identification, OIAC and effective spreads are measured contemporaneously within the same trading day, so the coefficients capture partial correlations rather than strictly causal effects; the calendar-based tests, which exploit exogenous variation in order flow characteristics, provide the most compelling evidence on the direction of causation. More broadly, the adverse selection signalling interpreta-

tion rests on indirect evidence (the negative sign, idiosyncratic dominance, and calendar response patterns) rather than direct identification of informed versus uninformed order flow, which would require broker-level data unavailable in TAQ. Finally, the 2004 sample start date, dictated by the availability of millisecond TAQ timestamps and the 100-day trailing window requirement, excludes the transition period immediately following decimalisation.

These limitations suggest several directions for future research. The interaction between inventory risk and adverse selection in the presence of persistent order flow remains largely unexplored in the literature; extending the BCD model to accommodate state-dependent transition intensities could generate predictions for the OIAC-spread relationship from first principles. The post-2017 weakening of the HFOIV return premium raises the broader question of whether structural changes in market microstructure have altered the pricing of inventory risk, a question that extends beyond the scope of this thesis. Broker-level data, as employed by Tóth et al. (2015), would permit direct decomposition of OIAC into informed and uninformed components, providing a sharper test of the adverse selection signalling channel and of the small-stock sign reversal documented after 2017. Finally, exploring alternative persistence measures, such as the Hurst exponent or fractional differencing parameters, could reveal whether long-memory properties of order flow carry information about spreads beyond the first-order autocorrelation that OIAC captures.

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Appendix

This appendix collects supplementary tables referenced in the main text. Table A1 documents the sample construction filters and their effect on the number of observations. Table A2 reports distributional statistics for OIAC by size quintile. The remaining tables report year-by-year coefficient estimates underlying the median coefficients in Tables 4, 5, and 8, allowing the reader to assess the temporal stability of each specification. Table A33 replicates the Table 9a portfolio sorts over the 2004–2017 period for comparison with Bogousslavsky and Collin-Dufresne (2023). Table A34 reports Fama–MacBeth return regressions estimated over the same replication period.

Table A1
Sample Construction

This table documents the sequential application of sample filters and their effect on the number of stock-day observations. The sample covers NYSE, AMEX, and NASDAQ common stocks (CRSP share codes 10 and 11) from September 2003 to December 2024.

	Stock-Days	Unique Stocks
Initial CRSP–TAQ merged sample (2003–2024)	26,941,937	14,481
Less:		
Non-common stocks (SHRCD $\neq$ 10, 11)	(6,183,579)	(4,524)
Non-NYSE/AMEX/NASDAQ exchanges	(8,789)	(6)
Early market closures	(166,773)	—
Lagged price outside \$5–\$1,000	(4,720,522)	(793)
Avg. market cap < \$100M or < 100 trading days	(2,294,451)	(1,571)
Final sample (2004–2024)	13,567,823	7,587

Table A2
Order Imbalance Autocorrelation Statistics by Size Quintile

This table reports distributional statistics for order imbalance autocorrelation (OIAC) by size quintile. OIAC is the AR(1) coefficient from a regression of five-minute signed share imbalances on their one-period lag within each trading day, estimated via OLS with Newey–West standard errors (four lags). Size quintiles are formed at the beginning of each month based on trailing 250-day average market capitalisation.

	2004	2006	2008	2010	2012	2014	2016	2018	2020	2022	2024
<i>Small Stocks</i>											
Mean	0.046	0.042	0.047	0.053	0.041	0.053	0.049	0.043	0.045	0.046	0.047
Median	0.031	0.025	0.030	0.032	0.023	0.030	0.029	0.023	0.024	0.021	0.021
σ	0.209	0.220	0.195	0.252	0.225	0.492	0.208	0.211	0.215	0.369	0.235
N	79,471	100,226	94,129	106,364	93,386	114,066	111,219	110,984	113,342	92,434	114,821
<i>Quintile 2</i>											
Mean	0.049	0.043	0.058	0.061	0.049	0.052	0.050	0.045	0.044	0.047	0.039
Median	0.035	0.026	0.040	0.040	0.030	0.031	0.028	0.024	0.023	0.023	0.017
σ	0.183	0.182	0.185	0.218	0.202	0.220	0.282	0.232	0.202	0.222	0.243
N	115,981	149,720	134,609	119,597	114,451	127,452	125,210	123,282	121,155	136,633	121,008
<i>Quintile 3</i>											
Mean	0.052	0.046	0.065	0.069	0.055	0.044	0.054	0.046	0.049	0.052	0.039
Median	0.038	0.030	0.047	0.046	0.034	0.026	0.030	0.025	0.026	0.027	0.017
σ	0.188	0.166	0.176	0.237	0.203	0.223	0.220	0.214	0.207	0.219	0.235
N	122,517	153,562	136,770	121,333	117,190	127,536	126,282	124,108	121,508	141,799	121,217
<i>Quintile 4</i>											
Mean	0.050	0.048	0.074	0.076	0.061	0.045	0.060	0.049	0.056	0.061	0.048
Median	0.037	0.032	0.057	0.055	0.042	0.028	0.038	0.028	0.034	0.035	0.024
σ	0.162	0.167	0.176	0.202	0.197	0.197	0.219	0.210	0.198	0.215	0.221
N	122,916	153,654	137,041	121,449	117,029	127,944	126,228	124,196	121,627	142,139	121,337
<i>Large Stocks</i>											
Mean	0.049	0.050	0.079	0.070	0.060	0.053	0.059	0.052	0.047	0.053	0.044
Median	0.038	0.035	0.064	0.053	0.043	0.036	0.039	0.033	0.028	0.032	0.024
σ	0.153	0.158	0.163	0.180	0.174	0.176	0.188	0.174	0.158	0.161	0.171
N	123,723	154,316	137,362	121,842	117,329	128,227	126,356	124,496	121,747	142,331	121,476

Table A3
Yearly Coefficients: Table 4 Level Spec (1) — Baseline

Year	Small Stocks		Large Stocks	
	β_τ	β_σ	β_τ	β_σ
2004	-0.144*** (0.005)	0.482*** (0.016)	0.105*** (0.008)	0.381*** (0.012)
2005	-0.137*** (0.005)	0.435*** (0.012)	0.110*** (0.009)	0.379*** (0.011)
2006	-0.141*** (0.007)	0.397*** (0.027)	0.109*** (0.010)	0.319*** (0.013)
2007	-0.129*** (0.004)	0.425*** (0.009)	0.143*** (0.013)	0.369*** (0.021)
2008	-0.142*** (0.010)	0.392*** (0.022)	0.022* (0.012)	0.487*** (0.031)
2009	-0.160*** (0.010)	0.405*** (0.022)	0.044*** (0.012)	0.259*** (0.019)
2010	-0.153*** (0.010)	0.490*** (0.029)	0.004 (0.027)	0.403*** (0.091)
2011	-0.154*** (0.009)	0.422*** (0.012)	0.002 (0.010)	0.329*** (0.016)
2012	-0.208*** (0.011)	0.444*** (0.013)	0.026* (0.015)	0.296*** (0.017)
2013	-0.203*** (0.010)	0.393*** (0.018)	-0.002 (0.013)	0.333*** (0.019)
2014	-0.188*** (0.006)	0.385*** (0.010)	-0.046*** (0.016)	0.368*** (0.016)
2015	-0.170*** (0.006)	0.376*** (0.013)	-0.091*** (0.012)	0.425*** (0.024)
2016	-0.176*** (0.008)	0.355*** (0.017)	-0.088*** (0.014)	0.390*** (0.021)
2017	-0.171*** (0.008)	0.330*** (0.019)	-0.076*** (0.017)	0.416*** (0.018)
2018	-0.179*** (0.008)	0.319*** (0.020)	-0.104*** (0.017)	0.497*** (0.022)
2019	-0.169*** (0.010)	0.320*** (0.020)	-0.066*** (0.022)	0.414*** (0.020)
2020	-0.176*** (0.009)	0.407*** (0.017)	-0.146*** (0.015)	0.572*** (0.023)
2021	-0.156*** (0.009)	0.348*** (0.024)	-0.113*** (0.015)	0.492*** (0.017)
2022	-0.094*** (0.006)	0.226*** (0.018)	-0.100*** (0.017)	0.501*** (0.024)
2023	-0.128*** (0.006)	0.349*** (0.023)	-0.074*** (0.025)	0.520*** (0.038)
2024	-0.134*** (0.011)	0.306*** (0.032)	-0.050** (0.023)	0.483*** (0.025)
Adj. $\bar{R}^2$ (%)	21.31		17.70	

Table A4
Yearly Coefficients: Table 4 Level Spec (2) — HFOIV

Year	Small Stocks			Large Stocks		
	β_τ	β_σ	β_{HFOIV}	β_τ	β_σ	β_{HFOIV}
2004	-0.254*** (0.015)	0.507*** (0.017)	0.134*** (0.017)	-0.274*** (0.015)	0.485*** (0.012)	0.333*** (0.014)
2005	-0.267*** (0.013)	0.463*** (0.013)	0.155*** (0.016)	-0.273*** (0.015)	0.490*** (0.011)	0.332*** (0.015)
2006	-0.291*** (0.014)	0.427*** (0.029)	0.179*** (0.014)	-0.317*** (0.018)	0.448*** (0.009)	0.364*** (0.018)
2007	-0.296*** (0.012)	0.462*** (0.010)	0.193*** (0.014)	-0.301*** (0.018)	0.516*** (0.018)	0.372*** (0.018)
2008	-0.364*** (0.019)	0.427*** (0.024)	0.264*** (0.027)	-0.428*** (0.020)	0.589*** (0.023)	0.408*** (0.018)
2009	-0.400*** (0.021)	0.459*** (0.025)	0.287*** (0.027)	-0.371*** (0.018)	0.397*** (0.012)	0.384*** (0.018)
2010	-0.407*** (0.018)	0.529*** (0.026)	0.319*** (0.026)	-0.386*** (0.031)	0.506*** (0.087)	0.363*** (0.016)
2011	-0.410*** (0.013)	0.477*** (0.010)	0.326*** (0.020)	-0.330*** (0.010)	0.423*** (0.011)	0.304*** (0.009)
2012	-0.429*** (0.013)	0.484*** (0.012)	0.291*** (0.023)	-0.338*** (0.021)	0.393*** (0.015)	0.321*** (0.024)
2013	-0.400*** (0.012)	0.428*** (0.019)	0.257*** (0.018)	-0.363*** (0.011)	0.426*** (0.016)	0.319*** (0.011)
2014	-0.361*** (0.010)	0.414*** (0.010)	0.212*** (0.011)	-0.440*** (0.018)	0.484*** (0.013)	0.346*** (0.021)
2015	-0.345*** (0.011)	0.401*** (0.014)	0.217*** (0.013)	-0.441*** (0.012)	0.515*** (0.019)	0.315*** (0.010)
2016	-0.383*** (0.014)	0.383*** (0.018)	0.255*** (0.017)	-0.446*** (0.014)	0.483*** (0.019)	0.325*** (0.012)
2017	-0.368*** (0.012)	0.348*** (0.020)	0.240*** (0.014)	-0.430*** (0.015)	0.510*** (0.012)	0.319*** (0.018)
2018	-0.356*** (0.015)	0.338*** (0.021)	0.210*** (0.017)	-0.487*** (0.015)	0.603*** (0.016)	0.352*** (0.017)
2019	-0.385*** (0.013)	0.342*** (0.020)	0.249*** (0.013)	-0.478*** (0.017)	0.514*** (0.013)	0.378*** (0.021)
2020	-0.406*** (0.014)	0.452*** (0.017)	0.272*** (0.014)	-0.574*** (0.014)	0.640*** (0.016)	0.425*** (0.014)
2021	-0.371*** (0.014)	0.378*** (0.027)	0.251*** (0.011)	-0.588*** (0.014)	0.570*** (0.013)	0.469*** (0.016)
2022	-0.334*** (0.017)	0.242*** (0.019)	0.270*** (0.019)	-0.608*** (0.013)	0.584*** (0.017)	0.506*** (0.013)
2023	-0.344*** (0.021)	0.378*** (0.025)	0.246*** (0.022)	-0.512*** (0.017)	0.589*** (0.033)	0.424*** (0.019)
2024	-0.396*** (0.022)	0.319*** (0.034)	0.290*** (0.023)	-0.484*** (0.019)	0.564*** (0.016)	0.416*** (0.020)
Adj. $\bar{R}^2$ (%)	26.21			31.82		

Table A5
Yearly Coefficients: Table 4 Level Spec (3) — OIAC

Year	Small Stocks			Large Stocks		
	β_τ	β_σ	β_{OIAC}	β_τ	β_σ	β_{OIAC}
2004	-0.100*** (0.004)	0.568*** (0.006)	-0.014 (0.012)	0.106*** (0.007)	0.382*** (0.012)	-0.066*** (0.016)
2005	-0.109*** (0.006)	0.532*** (0.006)	-0.030** (0.012)	0.112*** (0.009)	0.380*** (0.011)	-0.080*** (0.010)
2006	-0.120*** (0.006)	0.501*** (0.007)	-0.036** (0.017)	0.112*** (0.010)	0.319*** (0.013)	-0.082*** (0.014)
2007	-0.118*** (0.005)	0.497*** (0.007)	-0.048*** (0.018)	0.144*** (0.013)	0.370*** (0.021)	-0.125*** (0.027)
2008	-0.135*** (0.020)	0.603*** (0.016)	-0.110*** (0.016)	0.023** (0.011)	0.487*** (0.030)	-0.195*** (0.022)
2009	-0.157*** (0.014)	0.462*** (0.036)	-0.041 (0.031)	0.044*** (0.012)	0.259*** (0.019)	-0.171*** (0.017)
2010	-0.138*** (0.012)	0.510*** (0.032)	-0.057*** (0.019)	0.004 (0.027)	0.405*** (0.092)	-0.127*** (0.012)
2011	-0.138*** (0.011)	0.448*** (0.014)	-0.024 (0.021)	0.002 (0.010)	0.330*** (0.016)	-0.127*** (0.009)
2012	-0.187*** (0.015)	0.473*** (0.015)	-0.036** (0.017)	0.026* (0.015)	0.297*** (0.017)	-0.106*** (0.011)
2013	-0.208*** (0.013)	0.423*** (0.024)	-0.077*** (0.014)	-0.002 (0.013)	0.333*** (0.019)	-0.113*** (0.011)
2014	-0.203*** (0.007)	0.428*** (0.011)	0.015*** (0.006)	-0.045*** (0.016)	0.368*** (0.016)	-0.101*** (0.010)
2015	-0.188*** (0.007)	0.445*** (0.010)	-0.031*** (0.010)	-0.090*** (0.012)	0.425*** (0.024)	-0.083*** (0.009)
2016	-0.188*** (0.009)	0.416*** (0.011)	-0.021* (0.012)	-0.087*** (0.014)	0.389*** (0.021)	-0.087*** (0.008)
2017	-0.175*** (0.009)	0.355*** (0.025)	0.005 (0.009)	-0.076*** (0.017)	0.415*** (0.018)	-0.063*** (0.011)
2018	-0.221*** (0.009)	0.384*** (0.021)	0.047*** (0.009)	-0.102*** (0.017)	0.497*** (0.022)	-0.097*** (0.011)
2019	-0.228*** (0.010)	0.398*** (0.014)	0.040*** (0.009)	-0.065*** (0.022)	0.415*** (0.020)	-0.125*** (0.012)
2020	-0.231*** (0.009)	0.466*** (0.011)	0.022*** (0.009)	-0.145*** (0.015)	0.572*** (0.023)	-0.144*** (0.013)
2021	-0.232*** (0.008)	0.470*** (0.019)	0.026*** (0.008)	-0.111*** (0.015)	0.492*** (0.017)	-0.147*** (0.013)
2022	-0.197*** (0.009)	0.380*** (0.027)	0.019* (0.011)	-0.097*** (0.017)	0.500*** (0.024)	-0.206*** (0.015)
2023	-0.221*** (0.009)	0.462*** (0.017)	0.027*** (0.007)	-0.071*** (0.025)	0.518*** (0.038)	-0.112*** (0.013)
2024	-0.199*** (0.011)	0.455*** (0.027)	0.016** (0.008)	-0.048** (0.023)	0.482*** (0.025)	-0.122*** (0.010)
Adj. $\bar{R}^2$ (%)	26.17			17.95		

Table A6
Yearly Coefficients: Table 4 Level Spec (4) — HFOIV and OIAC

Year	Small Stocks				Large Stocks			
	β_τ	β_σ	β_{HFOIV}	β_{OIAC}	β_τ	β_σ	β_{HFOIV}	β_{OIAC}
2004	-0.330*** (0.006)	0.616*** (0.006)	0.256*** (0.007)	0.012 (0.010)	-0.272*** (0.015)	0.484*** (0.012)	0.331*** (0.014)	-0.026* (0.014)
2005	-0.360*** (0.009)	0.588*** (0.006)	0.280*** (0.013)	-0.000 (0.008)	-0.271*** (0.015)	0.490*** (0.011)	0.331*** (0.015)	-0.029*** (0.007)
2006	-0.385*** (0.007)	0.556*** (0.006)	0.292*** (0.009)	-0.007 (0.011)	-0.315*** (0.018)	0.448*** (0.009)	0.363*** (0.018)	-0.016* (0.009)
2007	-0.384*** (0.008)	0.555*** (0.007)	0.288*** (0.010)	-0.010 (0.014)	-0.301*** (0.018)	0.516*** (0.018)	0.372*** (0.018)	-0.009 (0.024)
2008	-0.493*** (0.019)	0.656*** (0.014)	0.392*** (0.033)	-0.056*** (0.011)	-0.424*** (0.020)	0.588*** (0.023)	0.405*** (0.018)	-0.063*** (0.010)
2009	-0.464*** (0.019)	0.516*** (0.039)	0.343*** (0.024)	-0.026 (0.020)	-0.368*** (0.018)	0.396*** (0.012)	0.381*** (0.018)	-0.083*** (0.009)
2010	-0.452*** (0.017)	0.552*** (0.029)	0.356*** (0.026)	-0.037*** (0.012)	-0.384*** (0.031)	0.507*** (0.087)	0.361*** (0.016)	-0.066*** (0.008)
2011	-0.449*** (0.016)	0.506*** (0.012)	0.354*** (0.023)	-0.018 (0.013)	-0.327*** (0.010)	0.423*** (0.011)	0.302*** (0.009)	-0.074*** (0.006)
2012	-0.471*** (0.018)	0.516*** (0.013)	0.323*** (0.029)	-0.010 (0.008)	-0.337*** (0.021)	0.393*** (0.015)	0.320*** (0.024)	-0.044*** (0.006)
2013	-0.475*** (0.014)	0.461*** (0.026)	0.302*** (0.021)	-0.032*** (0.012)	-0.361*** (0.011)	0.426*** (0.016)	0.318*** (0.011)	-0.044*** (0.008)
2014	-0.415*** (0.010)	0.458*** (0.011)	0.244*** (0.013)	0.015*** (0.003)	-0.438*** (0.018)	0.483*** (0.013)	0.345*** (0.021)	-0.044*** (0.006)
2015	-0.413*** (0.011)	0.477*** (0.009)	0.261*** (0.015)	-0.009 (0.009)	-0.440*** (0.012)	0.515*** (0.019)	0.314*** (0.010)	-0.053*** (0.007)
2016	-0.440*** (0.013)	0.449*** (0.009)	0.290*** (0.019)	0.003 (0.010)	-0.444*** (0.014)	0.482*** (0.019)	0.324*** (0.012)	-0.059*** (0.006)
2017	-0.400*** (0.013)	0.373*** (0.027)	0.259*** (0.016)	0.024*** (0.008)	-0.429*** (0.015)	0.509*** (0.012)	0.319*** (0.017)	-0.027*** (0.007)
2018	-0.451*** (0.012)	0.404*** (0.022)	0.266*** (0.013)	0.066*** (0.008)	-0.486*** (0.015)	0.603*** (0.016)	0.351*** (0.017)	-0.034*** (0.006)
2019	-0.476*** (0.011)	0.420*** (0.012)	0.281*** (0.015)	0.042*** (0.010)	-0.476*** (0.017)	0.514*** (0.013)	0.376*** (0.021)	-0.048*** (0.007)
2020	-0.508*** (0.010)	0.505*** (0.009)	0.315*** (0.015)	0.043*** (0.008)	-0.572*** (0.014)	0.640*** (0.016)	0.423*** (0.014)	-0.076*** (0.007)
2021	-0.481*** (0.011)	0.502*** (0.020)	0.291*** (0.011)	0.044*** (0.007)	-0.585*** (0.014)	0.570*** (0.013)	0.467*** (0.016)	-0.078*** (0.007)
2022	-0.467*** (0.015)	0.406*** (0.029)	0.304*** (0.012)	0.034** (0.014)	-0.603*** (0.013)	0.583*** (0.017)	0.504*** (0.013)	-0.126*** (0.008)
2023	-0.513*** (0.013)	0.489*** (0.019)	0.324*** (0.014)	0.036*** (0.008)	-0.509*** (0.017)	0.588*** (0.033)	0.423*** (0.019)	-0.085*** (0.006)
2024	-0.505*** (0.015)	0.469*** (0.027)	0.347*** (0.016)	0.022*** (0.008)	-0.481*** (0.019)	0.563*** (0.016)	0.415*** (0.020)	-0.091*** (0.006)
Adj. $\bar{R}^2$ (%)	32.72				31.88			

Table A7
Yearly Coefficients: Table 4 Level Spec (5) — Interaction

Year	Small Stocks					Large Stocks				
	β_τ	β_σ	β_{HFOIV}	β_{OIAIC}	$\beta_{HFOIV \times OIAIC}$	β_τ	β_σ	β_{HFOIV}	β_{OIAIC}	$\beta_{HFOIV \times OIAIC}$
2004	-0.330*** (0.006)	0.616*** (0.006)	0.256*** (0.007)	-0.001 (0.008)	0.020 (0.012)	-0.272*** (0.015)	0.484*** (0.012)	0.332*** (0.014)	-0.028* (0.014)	0.017* (0.010)
2005	-0.360*** (0.009)	0.587*** (0.006)	0.280*** (0.013)	-0.008 (0.007)	0.014* (0.008)	-0.271*** (0.015)	0.490*** (0.011)	0.331*** (0.015)	-0.031*** (0.007)	0.023** (0.010)
2006	-0.385*** (0.007)	0.556*** (0.006)	0.292*** (0.009)	-0.018** (0.007)	0.011 (0.008)	-0.316*** (0.018)	0.448*** (0.009)	0.364*** (0.018)	-0.021*** (0.008)	0.030*** (0.010)
2007	-0.384*** (0.008)	0.555*** (0.007)	0.288*** (0.010)	-0.036*** (0.008)	0.040*** (0.008)	-0.301*** (0.017)	0.516*** (0.018)	0.372*** (0.018)	-0.013 (0.023)	0.017 (0.018)
2008	-0.493*** (0.019)	0.656*** (0.014)	0.393*** (0.033)	-0.058*** (0.009)	0.009 (0.012)	-0.425*** (0.020)	0.588*** (0.023)	0.407*** (0.018)	-0.064*** (0.009)	0.033 (0.022)
2009	-0.463*** (0.019)	0.515*** (0.039)	0.343*** (0.024)	-0.054*** (0.008)	0.020*** (0.005)	-0.368*** (0.017)	0.396*** (0.012)	0.381*** (0.017)	-0.083*** (0.008)	-0.000 (0.011)
2010	-0.452*** (0.017)	0.552*** (0.029)	0.356*** (0.026)	-0.055*** (0.007)	0.016*** (0.003)	-0.384*** (0.032)	0.507*** (0.087)	0.361*** (0.015)	-0.065*** (0.007)	-0.009 (0.008)
2011	-0.449*** (0.016)	0.505*** (0.012)	0.353*** (0.022)	-0.058*** (0.011)	0.015*** (0.002)	-0.327*** (0.010)	0.423*** (0.011)	0.302*** (0.009)	-0.074*** (0.006)	0.001 (0.009)
2012	-0.471*** (0.018)	0.516*** (0.013)	0.323*** (0.029)	-0.012 (0.008)	0.002 (0.003)	-0.336*** (0.021)	0.393*** (0.015)	0.319*** (0.024)	-0.044*** (0.005)	-0.013 (0.013)
2013	-0.475*** (0.014)	0.461*** (0.026)	0.302*** (0.021)	-0.021** (0.008)	-0.024*** (0.008)	-0.361*** (0.011)	0.426*** (0.016)	0.318*** (0.011)	-0.043*** (0.008)	-0.003 (0.015)
2014	-0.414*** (0.010)	0.458*** (0.011)	0.243*** (0.013)	-0.009 (0.007)	0.007*** (0.002)	-0.438*** (0.018)	0.483*** (0.013)	0.345*** (0.021)	-0.043*** (0.006)	-0.013 (0.009)
2015	-0.413*** (0.011)	0.477*** (0.009)	0.260*** (0.015)	0.002 (0.008)	-0.018*** (0.004)	-0.440*** (0.012)	0.515*** (0.019)	0.315*** (0.010)	-0.055*** (0.006)	0.010 (0.014)
2016	-0.440*** (0.013)	0.449*** (0.009)	0.290*** (0.019)	0.005 (0.009)	-0.013 (0.022)	-0.444*** (0.014)	0.482*** (0.019)	0.324*** (0.012)	-0.057*** (0.006)	-0.009 (0.009)
2017	-0.400*** (0.013)	0.373*** (0.027)	0.259*** (0.016)	0.022*** (0.008)	0.004 (0.007)	-0.429*** (0.015)	0.509*** (0.012)	0.319*** (0.017)	-0.031*** (0.006)	0.023** (0.011)
2018	-0.451*** (0.012)	0.404*** (0.022)	0.266*** (0.013)	0.067*** (0.008)	-0.003 (0.007)	-0.486*** (0.015)	0.603*** (0.016)	0.351*** (0.017)	-0.034*** (0.006)	-0.004 (0.010)
2019	-0.476*** (0.011)	0.420*** (0.012)	0.282*** (0.015)	0.057*** (0.009)	-0.010** (0.005)	-0.476*** (0.017)	0.514*** (0.013)	0.376*** (0.020)	-0.046*** (0.007)	-0.022* (0.013)
2020	-0.508*** (0.010)	0.505*** (0.009)	0.315*** (0.015)	0.051*** (0.007)	-0.021*** (0.008)	-0.572*** (0.014)	0.641*** (0.016)	0.423*** (0.014)	-0.074*** (0.007)	-0.014 (0.011)
2021	-0.481*** (0.011)	0.502*** (0.020)	0.291*** (0.011)	0.044*** (0.008)	0.001 (0.003)	-0.585*** (0.014)	0.570*** (0.013)	0.468*** (0.016)	-0.079*** (0.007)	0.007 (0.015)
2022	-0.467*** (0.015)	0.406*** (0.029)	0.304*** (0.012)	0.039*** (0.010)	-0.006 (0.008)	-0.603*** (0.013)	0.583*** (0.017)	0.503*** (0.013)	-0.125*** (0.007)	-0.014 (0.012)
2023	-0.513*** (0.013)	0.489*** (0.019)	0.324*** (0.014)	0.046*** (0.007)	-0.009*** (0.003)	-0.509*** (0.017)	0.588*** (0.033)	0.423*** (0.019)	-0.086*** (0.006)	0.002 (0.010)
2024	-0.505*** (0.015)	0.469*** (0.027)	0.347*** (0.016)	0.022*** (0.007)	-0.013** (0.007)	-0.481*** (0.019)	0.563*** (0.016)	0.415*** (0.020)	-0.091*** (0.006)	-0.000 (0.011)
Adj. $\bar{R}^2$ (%)	32.74					31.89				

Table A8
Yearly Coefficients: Table 4 Change Spec (1) — Baseline

Year	Small Stocks		Large Stocks	
	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$
2004	-0.081*** (0.006)	0.376*** (0.020)	0.188*** (0.010)	0.355*** (0.012)
2005	-0.070*** (0.005)	0.342*** (0.014)	0.209*** (0.013)	0.344*** (0.013)
2006	-0.071*** (0.006)	0.301*** (0.023)	0.210*** (0.013)	0.288*** (0.014)
2007	-0.072*** (0.004)	0.340*** (0.010)	0.297*** (0.022)	0.298*** (0.021)
2008	-0.066*** (0.008)	0.263*** (0.021)	0.141*** (0.015)	0.406*** (0.032)
2009	-0.065*** (0.010)	0.306*** (0.024)	0.160*** (0.018)	0.202*** (0.021)
2010	-0.075*** (0.015)	0.411*** (0.043)	0.097*** (0.036)	0.394*** (0.097)
2011	-0.068*** (0.011)	0.312*** (0.013)	0.103*** (0.013)	0.252*** (0.014)
2012	-0.115*** (0.014)	0.299*** (0.013)	0.149*** (0.030)	0.202*** (0.018)
2013	-0.121*** (0.010)	0.266*** (0.020)	0.096*** (0.017)	0.269*** (0.016)
2014	-0.107*** (0.006)	0.264*** (0.010)	0.063*** (0.023)	0.293*** (0.017)
2015	-0.089*** (0.006)	0.255*** (0.013)	0.014 (0.017)	0.341*** (0.028)
2016	-0.089*** (0.008)	0.238*** (0.018)	-0.001 (0.016)	0.351*** (0.017)
2017	-0.086*** (0.009)	0.210*** (0.021)	0.034 (0.022)	0.334*** (0.018)
2018	-0.110*** (0.007)	0.190*** (0.018)	0.029 (0.025)	0.348*** (0.021)
2019	-0.092*** (0.008)	0.186*** (0.015)	0.043 (0.030)	0.357*** (0.017)
2020	-0.094*** (0.009)	0.268*** (0.018)	-0.007 (0.020)	0.410*** (0.025)
2021	-0.075*** (0.006)	0.180*** (0.020)	0.020 (0.023)	0.373*** (0.020)
2022	-0.058*** (0.007)	0.110*** (0.011)	0.064*** (0.025)	0.370*** (0.026)
2023	-0.075*** (0.008)	0.189*** (0.021)	0.061* (0.033)	0.398*** (0.039)
2024	-0.037*** (0.008)	0.160*** (0.019)	0.110*** (0.030)	0.369*** (0.030)
Adj. $\bar{R}^2$ (%)	6.43		7.33	

Table A9
Yearly Coefficients: Table 4 Change Spec (2) — HFOIV

Year	Small Stocks			Large Stocks		
	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta HFOIV}$	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta HFOIV}$
2004	-0.179*** (0.014)	0.396*** (0.021)	0.108*** (0.014)	-0.215*** (0.014)	0.443*** (0.012)	0.324*** (0.013)
2005	-0.184*** (0.013)	0.369*** (0.011)	0.119*** (0.014)	-0.215*** (0.013)	0.441*** (0.011)	0.326*** (0.013)
2006	-0.208*** (0.013)	0.331*** (0.021)	0.143*** (0.013)	-0.254*** (0.015)	0.407*** (0.010)	0.351*** (0.014)
2007	-0.231*** (0.012)	0.370*** (0.010)	0.165*** (0.013)	-0.214*** (0.019)	0.425*** (0.017)	0.360*** (0.016)
2008	-0.279*** (0.021)	0.290*** (0.023)	0.227*** (0.026)	-0.359*** (0.018)	0.507*** (0.026)	0.386*** (0.015)
2009	-0.298*** (0.022)	0.348*** (0.027)	0.244*** (0.024)	-0.336*** (0.016)	0.328*** (0.013)	0.386*** (0.014)
2010	-0.354*** (0.020)	0.450*** (0.041)	0.304*** (0.024)	-0.357*** (0.036)	0.487*** (0.092)	0.361*** (0.013)
2011	-0.349*** (0.012)	0.367*** (0.011)	0.308*** (0.017)	-0.255*** (0.010)	0.340*** (0.011)	0.285*** (0.009)
2012	-0.354*** (0.013)	0.343*** (0.011)	0.271*** (0.022)	-0.271*** (0.013)	0.301*** (0.013)	0.320*** (0.021)
2013	-0.339*** (0.013)	0.299*** (0.021)	0.243*** (0.016)	-0.315*** (0.010)	0.365*** (0.012)	0.314*** (0.010)
2014	-0.279*** (0.010)	0.283*** (0.010)	0.185*** (0.011)	-0.395*** (0.013)	0.388*** (0.011)	0.349*** (0.017)
2015	-0.261*** (0.011)	0.272*** (0.014)	0.187*** (0.012)	-0.386*** (0.012)	0.425*** (0.025)	0.308*** (0.010)
2016	-0.292*** (0.013)	0.258*** (0.019)	0.218*** (0.015)	-0.397*** (0.013)	0.427*** (0.013)	0.316*** (0.012)
2017	-0.281*** (0.011)	0.226*** (0.023)	0.209*** (0.012)	-0.381*** (0.012)	0.421*** (0.013)	0.322*** (0.015)
2018	-0.289*** (0.015)	0.203*** (0.018)	0.191*** (0.017)	-0.419*** (0.013)	0.457*** (0.013)	0.345*** (0.015)
2019	-0.301*** (0.011)	0.202*** (0.016)	0.219*** (0.011)	-0.431*** (0.011)	0.431*** (0.012)	0.371*** (0.017)
2020	-0.358*** (0.012)	0.296*** (0.019)	0.265*** (0.011)	-0.503*** (0.013)	0.493*** (0.018)	0.415*** (0.013)
2021	-0.306*** (0.010)	0.199*** (0.022)	0.243*** (0.009)	-0.547*** (0.012)	0.450*** (0.015)	0.480*** (0.014)
2022	-0.324*** (0.018)	0.117*** (0.012)	0.289*** (0.019)	-0.564*** (0.013)	0.442*** (0.018)	0.513*** (0.012)
2023	-0.326*** (0.025)	0.204*** (0.023)	0.272*** (0.024)	-0.451*** (0.016)	0.470*** (0.033)	0.421*** (0.016)
2024	-0.291*** (0.020)	0.171*** (0.020)	0.256*** (0.021)	-0.393*** (0.013)	0.435*** (0.017)	0.402*** (0.015)
Adj. $\bar{R}^2$ (%)	11.15			22.62		

Table A10
Yearly Coefficients: Table 4 Change Spec (3) — OIAC

Year	Small Stocks			Large Stocks		
	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta OIAC}$	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta OIAC}$
2004	-0.039*** (0.005)	0.510*** (0.006)	-0.013 (0.012)	0.190*** (0.010)	0.355*** (0.012)	-0.053*** (0.013)
2005	-0.028*** (0.008)	0.458*** (0.007)	-0.037** (0.015)	0.210*** (0.013)	0.346*** (0.013)	-0.070*** (0.009)
2006	-0.043*** (0.008)	0.432*** (0.007)	-0.045*** (0.011)	0.214*** (0.013)	0.289*** (0.014)	-0.077*** (0.012)
2007	-0.044*** (0.007)	0.428*** (0.007)	-0.040** (0.019)	0.297*** (0.022)	0.299*** (0.021)	-0.111*** (0.020)
2008	-0.025 (0.023)	0.494*** (0.016)	-0.118*** (0.015)	0.142*** (0.015)	0.404*** (0.033)	-0.182*** (0.016)
2009	-0.044** (0.019)	0.353*** (0.043)	-0.094*** (0.010)	0.160*** (0.018)	0.201*** (0.021)	-0.165*** (0.014)
2010	-0.054*** (0.020)	0.447*** (0.050)	-0.067*** (0.022)	0.098*** (0.036)	0.394*** (0.098)	-0.126*** (0.010)
2011	-0.040** (0.016)	0.340*** (0.016)	-0.023 (0.022)	0.103*** (0.013)	0.251*** (0.013)	-0.131*** (0.008)
2012	-0.077*** (0.022)	0.336*** (0.017)	-0.050*** (0.018)	0.151*** (0.030)	0.202*** (0.018)	-0.105*** (0.009)
2013	-0.108*** (0.016)	0.291*** (0.033)	-0.089*** (0.013)	0.097*** (0.017)	0.268*** (0.016)	-0.105*** (0.010)
2014	-0.116*** (0.008)	0.330*** (0.009)	0.013** (0.006)	0.065*** (0.022)	0.292*** (0.017)	-0.103*** (0.008)
2015	-0.096*** (0.009)	0.360*** (0.008)	-0.040*** (0.009)	0.016 (0.017)	0.341*** (0.028)	-0.069*** (0.009)
2016	-0.086*** (0.012)	0.331*** (0.008)	-0.035*** (0.011)	0.001 (0.016)	0.350*** (0.016)	-0.078*** (0.007)
2017	-0.074*** (0.013)	0.247*** (0.034)	0.005 (0.009)	0.035 (0.022)	0.333*** (0.018)	-0.059*** (0.010)
2018	-0.140*** (0.011)	0.270*** (0.026)	0.013* (0.008)	0.031 (0.025)	0.347*** (0.021)	-0.101*** (0.011)
2019	-0.133*** (0.012)	0.281*** (0.009)	0.028** (0.011)	0.045 (0.030)	0.357*** (0.017)	-0.105*** (0.010)
2020	-0.136*** (0.011)	0.343*** (0.010)	-0.003 (0.008)	-0.004 (0.020)	0.410*** (0.025)	-0.142*** (0.012)
2021	-0.119*** (0.007)	0.297*** (0.016)	0.017** (0.008)	0.023 (0.023)	0.372*** (0.020)	-0.151*** (0.013)
2022	-0.088*** (0.008)	0.226*** (0.022)	0.009 (0.008)	0.069*** (0.025)	0.368*** (0.026)	-0.197*** (0.013)
2023	-0.089*** (0.009)	0.244*** (0.018)	0.002 (0.011)	0.066** (0.033)	0.396*** (0.039)	-0.109*** (0.012)
2024	-0.054*** (0.012)	0.258*** (0.026)	-0.006 (0.007)	0.113*** (0.030)	0.368*** (0.030)	-0.109*** (0.009)
Adj. $\bar{R}^2$ (%)	9.22			7.64		

Table A11
Yearly Coefficients: Table 4 Change Spec (4) — HFOIV and OIAC

Year	Small Stocks				Large Stocks			
	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta HFOIV}$	$\beta_{\Delta OIAC}$	$\beta_{\Delta\tau}$	$\beta_{\Delta\sigma}$	$\beta_{\Delta HFOIV}$	$\beta_{\Delta OIAC}$
2004	-0.270*** (0.007)	0.552*** (0.006)	0.229*** (0.007)	0.005 (0.011)	-0.211*** (0.014)	0.443*** (0.012)	0.322*** (0.013)	-0.024* (0.012)
2005	-0.290*** (0.009)	0.506*** (0.006)	0.253*** (0.012)	-0.016 (0.011)	-0.214*** (0.013)	0.442*** (0.011)	0.326*** (0.013)	-0.028*** (0.008)
2006	-0.311*** (0.008)	0.481*** (0.007)	0.254*** (0.009)	-0.019** (0.009)	-0.251*** (0.015)	0.407*** (0.010)	0.350*** (0.014)	-0.022** (0.009)
2007	-0.332*** (0.008)	0.479*** (0.007)	0.268*** (0.010)	-0.010 (0.015)	-0.213*** (0.018)	0.424*** (0.017)	0.359*** (0.016)	-0.014 (0.020)
2008	-0.428*** (0.019)	0.548*** (0.014)	0.372*** (0.029)	-0.074*** (0.011)	-0.354*** (0.018)	0.505*** (0.026)	0.382*** (0.015)	-0.069*** (0.010)
2009	-0.379*** (0.019)	0.407*** (0.049)	0.316*** (0.019)	-0.071*** (0.008)	-0.331*** (0.015)	0.326*** (0.013)	0.382*** (0.014)	-0.087*** (0.008)
2010	-0.410*** (0.018)	0.491*** (0.046)	0.345*** (0.021)	-0.051*** (0.015)	-0.354*** (0.036)	0.487*** (0.092)	0.358*** (0.013)	-0.071*** (0.007)
2011	-0.391*** (0.014)	0.406*** (0.012)	0.339*** (0.019)	-0.019 (0.016)	-0.251*** (0.010)	0.339*** (0.011)	0.282*** (0.009)	-0.085*** (0.006)
2012	-0.393*** (0.016)	0.389*** (0.012)	0.305*** (0.027)	-0.027*** (0.010)	-0.268*** (0.013)	0.300*** (0.013)	0.318*** (0.021)	-0.049*** (0.006)
2013	-0.403*** (0.016)	0.333*** (0.036)	0.286*** (0.019)	-0.054*** (0.011)	-0.313*** (0.010)	0.365*** (0.012)	0.312*** (0.010)	-0.048*** (0.008)
2014	-0.339*** (0.010)	0.351*** (0.008)	0.220*** (0.012)	0.013*** (0.004)	-0.393*** (0.013)	0.387*** (0.011)	0.348*** (0.016)	-0.053*** (0.007)
2015	-0.330*** (0.011)	0.385*** (0.008)	0.227*** (0.014)	-0.022*** (0.008)	-0.384*** (0.012)	0.425*** (0.025)	0.307*** (0.009)	-0.047*** (0.008)
2016	-0.348*** (0.011)	0.357*** (0.007)	0.252*** (0.017)	-0.017* (0.010)	-0.395*** (0.013)	0.426*** (0.013)	0.316*** (0.011)	-0.060*** (0.007)
2017	-0.307*** (0.014)	0.266*** (0.037)	0.226*** (0.014)	0.016* (0.008)	-0.380*** (0.012)	0.421*** (0.013)	0.321*** (0.015)	-0.031*** (0.007)
2018	-0.374*** (0.011)	0.287*** (0.027)	0.232*** (0.012)	0.029*** (0.007)	-0.416*** (0.013)	0.456*** (0.013)	0.344*** (0.015)	-0.045*** (0.007)
2019	-0.388*** (0.008)	0.305*** (0.008)	0.249*** (0.013)	0.030*** (0.011)	-0.429*** (0.011)	0.430*** (0.012)	0.370*** (0.017)	-0.047*** (0.007)
2020	-0.434*** (0.009)	0.376*** (0.009)	0.291*** (0.013)	0.016** (0.007)	-0.499*** (0.013)	0.492*** (0.018)	0.413*** (0.013)	-0.079*** (0.008)
2021	-0.383*** (0.011)	0.324*** (0.017)	0.266*** (0.011)	0.029*** (0.007)	-0.543*** (0.012)	0.449*** (0.015)	0.479*** (0.014)	-0.080*** (0.008)
2022	-0.356*** (0.014)	0.247*** (0.025)	0.270*** (0.012)	0.023*** (0.008)	-0.558*** (0.013)	0.440*** (0.018)	0.510*** (0.012)	-0.120*** (0.007)
2023	-0.390*** (0.012)	0.268*** (0.020)	0.297*** (0.011)	0.010 (0.012)	-0.446*** (0.016)	0.468*** (0.033)	0.420*** (0.015)	-0.088*** (0.007)
2024	-0.356*** (0.013)	0.281*** (0.027)	0.296*** (0.013)	0.002 (0.007)	-0.389*** (0.013)	0.434*** (0.017)	0.401*** (0.015)	-0.088*** (0.007)
Adj. $\bar{R}^2$ (%)	15.89				22.72			

Table A12
Yearly Coefficients: Table 5 Spec (1) — HFOIV

Year	Small Stocks			Large Stocks		
	β_τ	β_σ	β_{HFOIV}	β_τ	β_σ	β_{HFOIV}
2004	-0.254*** (0.015)	0.507*** (0.017)	0.134*** (0.017)	-0.274*** (0.015)	0.485*** (0.012)	0.333*** (0.014)
2005	-0.267*** (0.013)	0.463*** (0.013)	0.155*** (0.016)	-0.273*** (0.015)	0.490*** (0.011)	0.332*** (0.015)
2006	-0.291*** (0.014)	0.427*** (0.029)	0.179*** (0.014)	-0.317*** (0.018)	0.448*** (0.009)	0.364*** (0.018)
2007	-0.296*** (0.012)	0.462*** (0.010)	0.193*** (0.014)	-0.301*** (0.018)	0.516*** (0.018)	0.372*** (0.018)
2008	-0.364*** (0.019)	0.427*** (0.024)	0.264*** (0.027)	-0.428*** (0.020)	0.589*** (0.023)	0.408*** (0.018)
2009	-0.400*** (0.021)	0.459*** (0.025)	0.287*** (0.027)	-0.371*** (0.018)	0.397*** (0.012)	0.384*** (0.018)
2010	-0.407*** (0.018)	0.529*** (0.026)	0.319*** (0.026)	-0.386*** (0.031)	0.506*** (0.087)	0.363*** (0.016)
2011	-0.410*** (0.013)	0.477*** (0.010)	0.326*** (0.020)	-0.330*** (0.010)	0.423*** (0.011)	0.304*** (0.009)
2012	-0.429*** (0.013)	0.484*** (0.012)	0.291*** (0.023)	-0.338*** (0.021)	0.393*** (0.015)	0.321*** (0.024)
2013	-0.400*** (0.012)	0.428*** (0.019)	0.257*** (0.018)	-0.363*** (0.011)	0.426*** (0.016)	0.319*** (0.011)
2014	-0.361*** (0.010)	0.414*** (0.010)	0.212*** (0.011)	-0.440*** (0.018)	0.484*** (0.013)	0.346*** (0.021)
2015	-0.345*** (0.011)	0.401*** (0.014)	0.217*** (0.013)	-0.441*** (0.012)	0.515*** (0.019)	0.315*** (0.010)
2016	-0.383*** (0.014)	0.383*** (0.018)	0.255*** (0.017)	-0.446*** (0.014)	0.483*** (0.019)	0.325*** (0.012)
2017	-0.368*** (0.012)	0.348*** (0.020)	0.240*** (0.014)	-0.430*** (0.015)	0.510*** (0.012)	0.319*** (0.018)
2018	-0.356*** (0.015)	0.338*** (0.021)	0.210*** (0.017)	-0.487*** (0.015)	0.603*** (0.016)	0.352*** (0.017)
2019	-0.385*** (0.013)	0.342*** (0.020)	0.249*** (0.013)	-0.478*** (0.017)	0.514*** (0.013)	0.378*** (0.021)
2020	-0.406*** (0.014)	0.452*** (0.017)	0.272*** (0.014)	-0.574*** (0.014)	0.640*** (0.016)	0.425*** (0.014)
2021	-0.371*** (0.014)	0.378*** (0.027)	0.251*** (0.011)	-0.588*** (0.014)	0.570*** (0.013)	0.469*** (0.016)
2022	-0.334*** (0.017)	0.242*** (0.019)	0.270*** (0.019)	-0.608*** (0.013)	0.584*** (0.017)	0.506*** (0.013)
2023	-0.344*** (0.021)	0.378*** (0.025)	0.246*** (0.022)	-0.512*** (0.017)	0.589*** (0.033)	0.424*** (0.019)
2024	-0.396*** (0.022)	0.319*** (0.034)	0.290*** (0.023)	-0.484*** (0.019)	0.564*** (0.016)	0.416*** (0.020)
Adj. $\bar{R}^2$ (%)	26.21			31.82		

Table A13
Yearly Coefficients: Table 5 Spec (2) — $|OI|$

Year	Small Stocks			Large Stocks		
	β_τ	β_σ	$\beta_{ OI }$	β_τ	β_σ	$\beta_{ OI }$
2004	-0.180*** (0.006)	0.490*** (0.016)	0.035*** (0.002)	0.095*** (0.007)	0.383*** (0.012)	0.008*** (0.002)
2005	-0.176*** (0.004)	0.442*** (0.012)	0.039*** (0.003)	0.088*** (0.007)	0.384*** (0.011)	0.019*** (0.003)
2006	-0.182*** (0.008)	0.406*** (0.028)	0.041*** (0.002)	0.073*** (0.007)	0.328*** (0.013)	0.030*** (0.004)
2007	-0.173*** (0.004)	0.438*** (0.008)	0.041*** (0.002)	0.094*** (0.009)	0.388*** (0.020)	0.041*** (0.005)
2008	-0.202*** (0.006)	0.410*** (0.022)	0.058*** (0.008)	-0.026** (0.010)	0.502*** (0.030)	0.042*** (0.006)
2009	-0.216*** (0.008)	0.418*** (0.023)	0.054*** (0.006)	0.002 (0.009)	0.275*** (0.017)	0.036*** (0.006)
2010	-0.204*** (0.007)	0.500*** (0.027)	0.050*** (0.006)	-0.036 (0.028)	0.414*** (0.090)	0.036*** (0.006)
2011	-0.206*** (0.006)	0.436*** (0.011)	0.051*** (0.006)	-0.031*** (0.008)	0.339*** (0.015)	0.028*** (0.003)
2012	-0.262*** (0.007)	0.457*** (0.013)	0.052*** (0.007)	-0.019** (0.009)	0.309*** (0.017)	0.037*** (0.006)
2013	-0.249*** (0.007)	0.404*** (0.018)	0.045*** (0.005)	-0.047*** (0.010)	0.346*** (0.019)	0.038*** (0.004)
2014	-0.222*** (0.006)	0.393*** (0.010)	0.034*** (0.003)	-0.094*** (0.011)	0.382*** (0.015)	0.041*** (0.005)
2015	-0.210*** (0.006)	0.383*** (0.013)	0.040*** (0.003)	-0.133*** (0.010)	0.436*** (0.023)	0.036*** (0.003)
2016	-0.221*** (0.007)	0.362*** (0.017)	0.046*** (0.004)	-0.131*** (0.012)	0.401*** (0.020)	0.037*** (0.004)
2017	-0.217*** (0.007)	0.338*** (0.019)	0.046*** (0.003)	-0.123*** (0.012)	0.429*** (0.016)	0.040*** (0.005)
2018	-0.228*** (0.008)	0.325*** (0.021)	0.048*** (0.003)	-0.155*** (0.011)	0.511*** (0.021)	0.045*** (0.006)
2019	-0.228*** (0.009)	0.328*** (0.020)	0.055*** (0.003)	-0.120*** (0.015)	0.429*** (0.018)	0.046*** (0.007)
2020	-0.237*** (0.008)	0.417*** (0.016)	0.056*** (0.004)	-0.195*** (0.012)	0.580*** (0.022)	0.046*** (0.005)
2021	-0.213*** (0.008)	0.363*** (0.025)	0.051*** (0.003)	-0.175*** (0.010)	0.505*** (0.016)	0.056*** (0.005)
2022	-0.207*** (0.008)	0.232*** (0.018)	0.117*** (0.006)	-0.165*** (0.012)	0.513*** (0.023)	0.058*** (0.005)
2023	-0.210*** (0.008)	0.359*** (0.023)	0.087*** (0.005)	-0.130*** (0.017)	0.533*** (0.037)	0.049*** (0.007)
2024	-0.199*** (0.010)	0.311*** (0.033)	0.058*** (0.004)	-0.110*** (0.020)	0.500*** (0.025)	0.051*** (0.007)
Adj. $\bar{R}^2$ (%)	22.53			18.91		

Table A14
Yearly Coefficients: Table 5 Spec (3) — $HFOIV^{\perp}|OI$

Year	Small Stocks			Large Stocks		
	β_{τ}	β_{σ}	$\beta_{HFOIV^{\perp} OI}$	β_{τ}	β_{σ}	$\beta_{HFOIV^{\perp} OI}$
2004	-0.181*** (0.006)	0.492*** (0.017)	0.079*** (0.009)	-0.057*** (0.009)	0.430*** (0.012)	0.205*** (0.011)
2005	-0.178*** (0.005)	0.444*** (0.012)	0.088*** (0.008)	-0.064*** (0.008)	0.433*** (0.010)	0.218*** (0.013)
2006	-0.183*** (0.008)	0.405*** (0.028)	0.095*** (0.007)	-0.099*** (0.010)	0.386*** (0.010)	0.253*** (0.016)
2007	-0.171*** (0.005)	0.435*** (0.008)	0.094*** (0.007)	-0.092*** (0.012)	0.443*** (0.018)	0.277*** (0.018)
2008	-0.196*** (0.008)	0.406*** (0.022)	0.137*** (0.017)	-0.201*** (0.016)	0.528*** (0.026)	0.286*** (0.021)
2009	-0.217*** (0.010)	0.414*** (0.022)	0.143*** (0.017)	-0.160*** (0.012)	0.321*** (0.014)	0.266*** (0.020)
2010	-0.228*** (0.007)	0.498*** (0.029)	0.179*** (0.017)	-0.188*** (0.026)	0.454*** (0.092)	0.251*** (0.016)
2011	-0.232*** (0.006)	0.434*** (0.011)	0.191*** (0.015)	-0.154*** (0.008)	0.370*** (0.012)	0.206*** (0.011)
2012	-0.275*** (0.007)	0.451*** (0.013)	0.174*** (0.017)	-0.149*** (0.010)	0.340*** (0.015)	0.219*** (0.022)
2013	-0.262*** (0.008)	0.399*** (0.018)	0.149*** (0.013)	-0.182*** (0.009)	0.377*** (0.017)	0.223*** (0.012)
2014	-0.232*** (0.006)	0.389*** (0.010)	0.102*** (0.008)	-0.234*** (0.010)	0.423*** (0.013)	0.233*** (0.019)
2015	-0.211*** (0.006)	0.381*** (0.013)	0.098*** (0.009)	-0.252*** (0.010)	0.467*** (0.022)	0.206*** (0.011)
2016	-0.227*** (0.008)	0.361*** (0.017)	0.118*** (0.012)	-0.256*** (0.012)	0.433*** (0.020)	0.215*** (0.012)
2017	-0.214*** (0.007)	0.331*** (0.019)	0.101*** (0.010)	-0.242*** (0.009)	0.458*** (0.014)	0.211*** (0.017)
2018	-0.207*** (0.009)	0.319*** (0.020)	0.064*** (0.009)	-0.284*** (0.010)	0.546*** (0.018)	0.233*** (0.019)
2019	-0.201*** (0.011)	0.320*** (0.020)	0.071*** (0.011)	-0.268*** (0.011)	0.460*** (0.015)	0.262*** (0.022)
2020	-0.209*** (0.010)	0.410*** (0.016)	0.082*** (0.011)	-0.345*** (0.011)	0.602*** (0.019)	0.279*** (0.016)
2021	-0.176*** (0.009)	0.353*** (0.025)	0.047*** (0.007)	-0.337*** (0.009)	0.524*** (0.014)	0.317*** (0.018)
2022	-0.094*** (0.006)	0.223*** (0.018)	-0.007 (0.006)	-0.339*** (0.010)	0.537*** (0.019)	0.343*** (0.016)
2023	-0.129*** (0.007)	0.353*** (0.023)	0.006 (0.008)	-0.272*** (0.012)	0.546*** (0.035)	0.274*** (0.024)
2024	-0.172*** (0.012)	0.304*** (0.032)	0.087*** (0.013)	-0.254*** (0.021)	0.512*** (0.020)	0.283*** (0.026)
Adj. $\bar{R}^2$ (%)	22.90			25.22		

Table A15
Yearly Coefficients: Table 5 Spec (4) — $|OI|^{\perp HFOIV}$

Year	Small Stocks			Large Stocks		
	β_{τ}	β_{σ}	$\beta_{ OI ^{\perp HFOIV}}$	β_{τ}	β_{σ}	$\beta_{ OI ^{\perp HFOIV}}$
2004	-0.146*** (0.005)	0.485*** (0.017)	-0.011*** (0.002)	0.108*** (0.008)	0.382*** (0.012)	-0.022*** (0.002)
2005	-0.138*** (0.005)	0.436*** (0.012)	-0.010*** (0.001)	0.114*** (0.009)	0.379*** (0.011)	-0.018*** (0.001)
2006	-0.142*** (0.007)	0.398*** (0.027)	-0.011*** (0.002)	0.112*** (0.010)	0.319*** (0.013)	-0.018*** (0.001)
2007	-0.132*** (0.004)	0.429*** (0.008)	-0.009*** (0.001)	0.145*** (0.013)	0.368*** (0.021)	-0.015*** (0.001)
2008	-0.144*** (0.010)	0.401*** (0.022)	-0.014*** (0.002)	0.024** (0.012)	0.485*** (0.031)	-0.012*** (0.001)
2009	-0.162*** (0.010)	0.406*** (0.022)	-0.011*** (0.001)	0.046*** (0.012)	0.257*** (0.019)	-0.011*** (0.001)
2010	-0.152*** (0.010)	0.490*** (0.029)	-0.010*** (0.002)	0.006 (0.028)	0.403*** (0.092)	-0.009*** (0.002)
2011	-0.152*** (0.009)	0.421*** (0.012)	-0.013*** (0.002)	0.004 (0.010)	0.328*** (0.016)	-0.009*** (0.001)
2012	-0.207*** (0.011)	0.442*** (0.013)	-0.009*** (0.002)	0.027* (0.015)	0.295*** (0.017)	-0.004*** (0.001)
2013	-0.202*** (0.010)	0.392*** (0.018)	-0.009*** (0.002)	-0.001 (0.013)	0.333*** (0.019)	-0.005*** (0.001)
2014	-0.188*** (0.006)	0.385*** (0.010)	-0.002 (0.001)	-0.045*** (0.016)	0.368*** (0.016)	-0.005*** (0.001)
2015	-0.172*** (0.006)	0.376*** (0.013)	0.002* (0.001)	-0.090*** (0.012)	0.425*** (0.024)	-0.004*** (0.001)
2016	-0.178*** (0.008)	0.355*** (0.017)	0.001 (0.002)	-0.088*** (0.014)	0.390*** (0.021)	-0.004*** (0.001)
2017	-0.173*** (0.008)	0.331*** (0.019)	0.006*** (0.001)	-0.076*** (0.017)	0.416*** (0.018)	-0.002* (0.001)
2018	-0.184*** (0.008)	0.319*** (0.020)	0.012*** (0.002)	-0.103*** (0.017)	0.497*** (0.022)	-0.003*** (0.001)
2019	-0.178*** (0.009)	0.321*** (0.020)	0.010*** (0.002)	-0.065*** (0.022)	0.414*** (0.020)	-0.007*** (0.001)
2020	-0.185*** (0.009)	0.406*** (0.016)	0.007*** (0.002)	-0.145*** (0.015)	0.571*** (0.023)	-0.006*** (0.001)
2021	-0.165*** (0.008)	0.354*** (0.025)	0.006*** (0.001)	-0.112*** (0.014)	0.492*** (0.017)	-0.005*** (0.001)
2022	-0.096*** (0.006)	0.223*** (0.018)	0.026*** (0.003)	-0.099*** (0.017)	0.501*** (0.024)	-0.006*** (0.001)
2023	-0.130*** (0.007)	0.353*** (0.023)	0.025*** (0.002)	-0.073*** (0.025)	0.520*** (0.038)	-0.003** (0.001)
2024	-0.144*** (0.011)	0.306*** (0.033)	0.012*** (0.002)	-0.049** (0.023)	0.482*** (0.025)	-0.004*** (0.002)
Adj. $\bar{R}^2$ (%)	21.67			17.76		

Table A16
Yearly Coefficients: Table 8 Level Spec (1) — Baseline (Small Stocks)

Year	Small Stocks			
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$
2004	-0.210*** (0.021)	-0.143*** (0.005)	0.003 (0.002)	0.480*** (0.017)
2005	-0.133*** (0.041)	-0.137*** (0.005)	0.005** (0.002)	0.429*** (0.012)
2006	-0.142*** (0.026)	-0.141*** (0.007)	0.001 (0.002)	0.397*** (0.027)
2007	-0.111*** (0.022)	-0.129*** (0.004)	0.010*** (0.001)	0.414*** (0.009)
2008	0.038 (0.068)	-0.148*** (0.008)	0.004 (0.003)	0.385*** (0.022)
2009	0.003 (0.070)	-0.170*** (0.009)	0.002 (0.003)	0.403*** (0.022)
2010	0.116* (0.064)	-0.171*** (0.008)	0.002 (0.004)	0.485*** (0.028)
2011	0.086 (0.059)	-0.171*** (0.007)	0.003 (0.003)	0.411*** (0.013)
2012	-0.046 (0.092)	-0.220*** (0.008)	-0.000 (0.004)	0.438*** (0.014)
2013	-0.014 (0.063)	-0.212*** (0.007)	0.015*** (0.003)	0.372*** (0.018)
2014	-0.041 (0.042)	-0.195*** (0.006)	-0.001 (0.002)	0.387*** (0.010)
2015	0.032 (0.053)	-0.175*** (0.006)	-0.003 (0.002)	0.379*** (0.013)
2016	-0.023 (0.050)	-0.183*** (0.007)	-0.009*** (0.002)	0.367*** (0.018)
2017	0.117* (0.070)	-0.177*** (0.007)	0.001 (0.003)	0.328*** (0.020)
2018	-0.036 (0.061)	-0.184*** (0.008)	-0.013*** (0.003)	0.334*** (0.020)
2019	-0.034 (0.061)	-0.172*** (0.010)	0.002 (0.002)	0.318*** (0.020)
2020	-0.108*** (0.027)	-0.180*** (0.009)	-0.003 (0.003)	0.411*** (0.017)
2021	-0.161*** (0.025)	-0.157*** (0.009)	0.006** (0.003)	0.341*** (0.024)
2022	-0.121*** (0.031)	-0.093*** (0.006)	0.020*** (0.004)	0.203*** (0.018)
2023	-0.126*** (0.034)	-0.128*** (0.007)	0.030*** (0.004)	0.315*** (0.023)
2024	-0.090* (0.050)	-0.136*** (0.011)	0.007** (0.003)	0.296*** (0.032)
Adj. $\bar{R}^2$ (%)	21.49			

Table A17
Yearly Coefficients: Table 8 Level Spec (1) — Baseline (Large Stocks)

Year	Large Stocks			
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$
2004	0.063 (0.046)	0.091*** (0.007)	0.011*** (0.003)	0.384*** (0.010)
2005	0.223*** (0.063)	0.090*** (0.007)	0.012*** (0.003)	0.366*** (0.011)
2006	0.251*** (0.065)	0.085*** (0.007)	0.003 (0.005)	0.312*** (0.011)
2007	0.311*** (0.050)	0.107*** (0.010)	0.012* (0.006)	0.339*** (0.017)
2008	0.167*** (0.046)	-0.038*** (0.012)	0.006 (0.008)	0.477*** (0.030)
2009	0.116** (0.054)	0.006 (0.009)	0.008 (0.008)	0.267*** (0.015)
2010	0.112* (0.058)	-0.050 (0.037)	0.001 (0.011)	0.406*** (0.099)
2011	0.096*** (0.030)	-0.030*** (0.010)	0.022*** (0.005)	0.298*** (0.013)
2012	0.285*** (0.107)	-0.018 (0.011)	0.007 (0.006)	0.281*** (0.015)
2013	0.144** (0.061)	-0.037*** (0.011)	0.012*** (0.004)	0.329*** (0.019)
2014	0.152** (0.068)	-0.081*** (0.012)	0.019*** (0.005)	0.337*** (0.015)
2015	0.119** (0.047)	-0.116*** (0.012)	0.030*** (0.005)	0.370*** (0.019)
2016	-0.003 (0.040)	-0.108*** (0.014)	0.024*** (0.005)	0.351*** (0.018)
2017	0.159* (0.081)	-0.095*** (0.013)	0.018*** (0.003)	0.370*** (0.018)
2018	0.283*** (0.082)	-0.128*** (0.013)	0.027*** (0.006)	0.396*** (0.017)
2019	0.220* (0.118)	-0.101*** (0.017)	0.027*** (0.004)	0.365*** (0.023)
2020	0.062 (0.047)	-0.180*** (0.013)	0.043*** (0.006)	0.508*** (0.021)
2021	0.186** (0.077)	-0.132*** (0.011)	0.028*** (0.004)	0.402*** (0.017)
2022	0.158** (0.072)	-0.136*** (0.014)	0.057*** (0.008)	0.381*** (0.022)
2023	0.271** (0.125)	-0.115*** (0.018)	0.032*** (0.004)	0.431*** (0.035)
2024	0.204 (0.126)	-0.073*** (0.021)	0.030*** (0.005)	0.405*** (0.040)
Adj. $\bar{R}^2$ (%)	18.04			

Table A18
Yearly Coefficients: Table 8 Level Spec (2) — HFOIV (Small Stocks)

Year	Small Stocks					
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{HFOIVC}	β_{HFOIVI}
2004	-0.244*** (0.019)	-0.180*** (0.005)	0.004** (0.002)	0.537*** (0.007)	0.036*** (0.003)	0.013*** (0.002)
2005	-0.176*** (0.037)	-0.174*** (0.006)	0.005** (0.002)	0.477*** (0.013)	0.046*** (0.005)	0.004** (0.002)
2006	-0.203*** (0.023)	-0.196*** (0.006)	0.001 (0.002)	0.463*** (0.014)	0.053*** (0.004)	0.012*** (0.002)
2007	-0.172*** (0.021)	-0.193*** (0.005)	0.009*** (0.001)	0.468*** (0.006)	0.059*** (0.004)	0.014*** (0.002)
2008	-0.078 (0.056)	-0.232*** (0.008)	0.001 (0.002)	0.487*** (0.020)	0.088*** (0.010)	0.014*** (0.003)
2009	-0.138*** (0.052)	-0.267*** (0.009)	0.000 (0.003)	0.452*** (0.025)	0.081*** (0.008)	0.031*** (0.005)
2010	-0.067 (0.044)	-0.278*** (0.012)	0.001 (0.003)	0.507*** (0.027)	0.080*** (0.009)	0.063*** (0.011)
2011	-0.096** (0.041)	-0.281*** (0.008)	0.000 (0.003)	0.440*** (0.011)	0.089*** (0.008)	0.063*** (0.009)
2012	-0.184** (0.074)	-0.317*** (0.009)	-0.000 (0.004)	0.462*** (0.012)	0.069*** (0.009)	0.071*** (0.009)
2013	-0.153*** (0.048)	-0.316*** (0.010)	0.012*** (0.003)	0.397*** (0.018)	0.068*** (0.007)	0.071*** (0.009)
2014	-0.153*** (0.030)	-0.293*** (0.010)	-0.001 (0.002)	0.410*** (0.010)	0.046*** (0.005)	0.072*** (0.009)
2015	-0.071* (0.040)	-0.255*** (0.008)	-0.005** (0.002)	0.403*** (0.013)	0.044*** (0.005)	0.048*** (0.006)
2016	-0.136*** (0.037)	-0.280*** (0.010)	-0.010*** (0.002)	0.399*** (0.016)	0.055*** (0.007)	0.057*** (0.008)
2017	-0.018 (0.053)	-0.284*** (0.011)	0.000 (0.002)	0.343*** (0.020)	0.047*** (0.005)	0.079*** (0.011)
2018	-0.160*** (0.047)	-0.294*** (0.012)	-0.013*** (0.002)	0.350*** (0.021)	0.037*** (0.005)	0.076*** (0.009)
2019	-0.146*** (0.048)	-0.303*** (0.012)	-0.000 (0.002)	0.356*** (0.015)	0.046*** (0.005)	0.070*** (0.008)
2020	-0.278*** (0.023)	-0.343*** (0.013)	-0.004* (0.002)	0.445*** (0.017)	0.054*** (0.005)	0.113*** (0.011)
2021	-0.288*** (0.023)	-0.304*** (0.013)	0.003 (0.002)	0.385*** (0.026)	0.045*** (0.004)	0.099*** (0.009)
2022	-0.228*** (0.025)	-0.203*** (0.008)	0.009*** (0.003)	0.235*** (0.020)	0.057*** (0.006)	0.037*** (0.004)
2023	-0.214*** (0.034)	-0.239*** (0.009)	0.016*** (0.003)	0.361*** (0.024)	0.047*** (0.006)	0.041*** (0.005)
2024	-0.247*** (0.041)	-0.296*** (0.017)	0.005* (0.003)	0.326*** (0.035)	0.063*** (0.006)	0.093*** (0.012)
Adj. $\bar{R}^2$ (%)			26.50			

Table A19
Yearly Coefficients: Table 8 Level Spec (2) — HFOIV (Large Stocks)

Year	Large Stocks					
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{HFOIVC}	β_{HFOIVI}
2004	-0.285*** (0.024)	-0.283*** (0.016)	0.017*** (0.003)	0.477*** (0.010)	0.010** (0.004)	0.316*** (0.012)
2005	-0.156*** (0.035)	-0.268*** (0.014)	0.018*** (0.003)	0.459*** (0.010)	0.018*** (0.005)	0.296*** (0.013)
2006	-0.134*** (0.045)	-0.304*** (0.016)	0.012*** (0.004)	0.418*** (0.008)	0.034*** (0.007)	0.307*** (0.013)
2007	-0.078** (0.035)	-0.295*** (0.012)	0.031*** (0.005)	0.438*** (0.013)	0.037*** (0.008)	0.313*** (0.011)
2008	-0.240*** (0.030)	-0.442*** (0.020)	0.037*** (0.005)	0.517*** (0.020)	0.038*** (0.006)	0.348*** (0.013)
2009	-0.207*** (0.032)	-0.346*** (0.013)	0.035*** (0.007)	0.314*** (0.012)	0.040*** (0.009)	0.308*** (0.012)
2010	-0.194*** (0.052)	-0.386*** (0.041)	0.020* (0.010)	0.446*** (0.097)	0.036*** (0.008)	0.294*** (0.012)
2011	-0.163*** (0.025)	-0.324*** (0.011)	0.042*** (0.005)	0.333*** (0.012)	0.025*** (0.005)	0.260*** (0.009)
2012	-0.044 (0.074)	-0.310*** (0.009)	0.020*** (0.005)	0.334*** (0.013)	0.034*** (0.007)	0.244*** (0.009)
2013	-0.179*** (0.052)	-0.352*** (0.013)	0.023*** (0.004)	0.389*** (0.017)	0.033*** (0.005)	0.263*** (0.011)
2014	-0.131** (0.055)	-0.383*** (0.014)	0.029*** (0.004)	0.397*** (0.014)	0.043*** (0.008)	0.241*** (0.012)
2015	-0.178*** (0.039)	-0.425*** (0.012)	0.040*** (0.005)	0.424*** (0.017)	0.030*** (0.005)	0.258*** (0.008)
2016	-0.280*** (0.034)	-0.413*** (0.011)	0.034*** (0.005)	0.406*** (0.017)	0.036*** (0.007)	0.254*** (0.010)
2017	-0.123* (0.066)	-0.372*** (0.014)	0.020*** (0.003)	0.433*** (0.016)	0.039*** (0.008)	0.227*** (0.012)
2018	-0.011 (0.067)	-0.437*** (0.012)	0.040*** (0.005)	0.451*** (0.015)	0.039*** (0.008)	0.265*** (0.011)
2019	-0.100 (0.098)	-0.413*** (0.017)	0.031*** (0.004)	0.418*** (0.020)	0.054*** (0.009)	0.256*** (0.014)
2020	-0.319*** (0.034)	-0.553*** (0.016)	0.055*** (0.005)	0.535*** (0.017)	0.063*** (0.006)	0.336*** (0.015)
2021	-0.293*** (0.044)	-0.575*** (0.015)	0.035*** (0.003)	0.476*** (0.013)	0.056*** (0.005)	0.404*** (0.016)
2022	-0.346*** (0.056)	-0.609*** (0.016)	0.071*** (0.008)	0.438*** (0.020)	0.052*** (0.007)	0.448*** (0.016)
2023	-0.109 (0.104)	-0.469*** (0.022)	0.038*** (0.004)	0.477*** (0.033)	0.054*** (0.008)	0.318*** (0.016)
2024	-0.244*** (0.092)	-0.454*** (0.028)	0.038*** (0.004)	0.469*** (0.030)	0.049*** (0.009)	0.337*** (0.017)
Adj. $\bar{R}^2$ (%)	28.29					

Table A20
Yearly Coefficients: Table 8 Level Spec (3) — OIAC (Small Stocks)

Year	Small Stocks					
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{OIAC^C}	β_{OIAC^I}
2004	-0.139*** (0.022)	-0.101*** (0.004)	0.006*** (0.002)	0.562*** (0.006)	-0.030** (0.012)	-0.029*** (0.010)
2005	-0.062 (0.057)	-0.110*** (0.006)	0.007*** (0.002)	0.524*** (0.007)	-0.035** (0.017)	-0.044*** (0.008)
2006	-0.101** (0.040)	-0.121*** (0.006)	0.001 (0.002)	0.502*** (0.007)	-0.042** (0.017)	-0.059*** (0.010)
2007	-0.119*** (0.026)	-0.119*** (0.005)	0.008*** (0.002)	0.489*** (0.007)	0.027 (0.022)	-0.079*** (0.011)
2008	0.086 (0.099)	-0.149*** (0.015)	0.005* (0.003)	0.590*** (0.014)	0.072 (0.077)	-0.048*** (0.018)
2009	0.089 (0.071)	-0.175*** (0.011)	0.004 (0.004)	0.459*** (0.036)	-0.191*** (0.055)	-0.030* (0.018)
2010	0.146** (0.067)	-0.159*** (0.010)	0.005 (0.004)	0.503*** (0.030)	-0.127*** (0.047)	0.012 (0.019)
2011	0.137** (0.065)	-0.159*** (0.008)	0.005 (0.004)	0.434*** (0.014)	-0.037 (0.040)	-0.027 (0.017)
2012	0.022 (0.103)	-0.204*** (0.010)	-0.001 (0.005)	0.467*** (0.015)	0.055 (0.057)	-0.010 (0.013)
2013	0.020 (0.075)	-0.221*** (0.010)	0.012*** (0.003)	0.406*** (0.024)	-0.037 (0.036)	-0.007 (0.017)
2014	-0.037 (0.047)	-0.213*** (0.006)	-0.002 (0.002)	0.431*** (0.011)	0.018 (0.019)	0.013 (0.015)
2015	0.051 (0.063)	-0.196*** (0.006)	-0.003 (0.003)	0.448*** (0.009)	-0.088*** (0.033)	0.002 (0.012)
2016	-0.015 (0.059)	-0.199*** (0.008)	-0.009*** (0.002)	0.429*** (0.012)	-0.018 (0.025)	0.019 (0.012)
2017	0.149* (0.077)	-0.184*** (0.008)	0.002 (0.003)	0.351*** (0.026)	0.003 (0.026)	0.036*** (0.014)
2018	-0.034 (0.071)	-0.230*** (0.008)	-0.014*** (0.003)	0.402*** (0.021)	-0.004 (0.018)	0.094*** (0.010)
2019	-0.016 (0.076)	-0.236*** (0.008)	-0.001 (0.002)	0.400*** (0.014)	0.001 (0.031)	0.033 (0.029)
2020	-0.148*** (0.034)	-0.238*** (0.009)	-0.004 (0.003)	0.472*** (0.011)	0.025 (0.026)	0.028 (0.030)
2021	-0.217*** (0.026)	-0.234*** (0.008)	0.004 (0.003)	0.457*** (0.020)	0.043* (0.026)	0.045*** (0.012)
2022	-0.251*** (0.025)	-0.199*** (0.009)	0.006** (0.002)	0.373*** (0.027)	0.040** (0.020)	0.066*** (0.012)
2023	-0.172*** (0.038)	-0.224*** (0.009)	0.010*** (0.002)	0.452*** (0.018)	0.037 (0.026)	0.048*** (0.014)
2024	-0.130** (0.052)	-0.203*** (0.011)	0.009*** (0.003)	0.443*** (0.026)	-0.054 (0.037)	0.060*** (0.018)
Adj. $\bar{R}^2$ (%)			26.51			

Table A21
Yearly Coefficients: Table 8 Level Spec (3) — OIAC (Large Stocks)

Year	Large Stocks					
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{OIAC^C}	β_{OIAC^I}
2004	0.063 (0.045)	0.092*** (0.007)	0.012*** (0.003)	0.384*** (0.010)	0.004 (0.042)	-0.011 (0.025)
2005	0.221*** (0.061)	0.091*** (0.007)	0.012*** (0.003)	0.366*** (0.011)	0.030 (0.051)	-0.056 (0.038)
2006	0.251*** (0.062)	0.086*** (0.007)	0.003 (0.005)	0.312*** (0.011)	-0.109* (0.066)	0.020 (0.041)
2007	0.313*** (0.049)	0.107*** (0.010)	0.011* (0.006)	0.342*** (0.016)	0.027 (0.094)	-0.135*** (0.045)
2008	0.174*** (0.044)	-0.037*** (0.012)	0.007 (0.009)	0.476*** (0.030)	-0.075 (0.123)	-0.179*** (0.031)
2009	0.120** (0.055)	0.006 (0.009)	0.009 (0.008)	0.266*** (0.015)	-0.072 (0.054)	-0.116*** (0.017)
2010	0.112* (0.059)	-0.050 (0.037)	0.001 (0.011)	0.407*** (0.099)	-0.006 (0.045)	-0.124*** (0.015)
2011	0.095*** (0.029)	-0.030*** (0.010)	0.023*** (0.005)	0.298*** (0.013)	0.025 (0.026)	-0.111*** (0.010)
2012	0.255*** (0.076)	-0.018* (0.011)	0.008 (0.006)	0.282*** (0.015)	0.108 (0.118)	-0.098*** (0.012)
2013	0.141** (0.059)	-0.037*** (0.011)	0.012*** (0.004)	0.328*** (0.019)	0.039 (0.049)	-0.103*** (0.011)
2014	0.135** (0.058)	-0.081*** (0.011)	0.020*** (0.005)	0.337*** (0.014)	0.169* (0.091)	-0.085*** (0.010)
2015	0.117*** (0.044)	-0.115*** (0.012)	0.030*** (0.005)	0.369*** (0.018)	0.065 (0.041)	-0.099*** (0.012)
2016	-0.002 (0.040)	-0.107*** (0.014)	0.024*** (0.005)	0.351*** (0.018)	-0.022 (0.045)	-0.063*** (0.012)
2017	0.160** (0.081)	-0.094*** (0.013)	0.018*** (0.003)	0.370*** (0.018)	-0.016 (0.032)	-0.041*** (0.012)
2018	0.254*** (0.067)	-0.128*** (0.013)	0.030*** (0.005)	0.399*** (0.017)	0.176** (0.083)	-0.075*** (0.012)
2019	0.221* (0.117)	-0.099*** (0.017)	0.027*** (0.004)	0.365*** (0.023)	0.010 (0.041)	-0.102*** (0.012)
2020	0.063 (0.046)	-0.180*** (0.013)	0.045*** (0.006)	0.510*** (0.020)	-0.059 (0.041)	-0.133*** (0.017)
2021	0.194*** (0.070)	-0.133*** (0.011)	0.028*** (0.004)	0.410*** (0.016)	-0.204*** (0.043)	-0.131*** (0.021)
2022	0.161** (0.070)	-0.133*** (0.014)	0.057*** (0.008)	0.381*** (0.022)	-0.057 (0.059)	-0.173*** (0.018)
2023	0.258** (0.117)	-0.112*** (0.018)	0.032*** (0.004)	0.429*** (0.035)	0.061 (0.071)	-0.099*** (0.013)
2024	0.184 (0.117)	-0.071*** (0.020)	0.032*** (0.005)	0.405*** (0.039)	0.140 (0.121)	-0.128*** (0.025)
Adj. $\bar{R}^2$ (%)			18.31			

Table A22
Yearly Coefficients: Table 8 Level Spec (4) — Full (Small Stocks)

Year	Small Stocks							
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{HFOIVC}	β_{HFOIVI}	β_{OIAC^C}	β_{OIAC^I}
2004	-0.324*** (0.021)	-0.325*** (0.007)	0.008*** (0.002)	0.607*** (0.006)	0.012*** (0.003)	0.239*** (0.008)	-0.002 (0.011)	0.014 (0.010)
2005	-0.232*** (0.053)	-0.319*** (0.011)	0.008*** (0.002)	0.568*** (0.007)	0.032*** (0.007)	0.208*** (0.013)	-0.016 (0.016)	-0.003 (0.008)
2006	-0.333*** (0.034)	-0.367*** (0.007)	0.004*** (0.002)	0.549*** (0.007)	0.029*** (0.004)	0.246*** (0.008)	-0.022 (0.015)	-0.005 (0.009)
2007	-0.334*** (0.025)	-0.360*** (0.006)	0.010*** (0.001)	0.538*** (0.007)	0.039*** (0.005)	0.227*** (0.007)	0.040** (0.019)	-0.019** (0.010)
2008	-0.151* (0.090)	-0.384*** (0.025)	0.006** (0.003)	0.620*** (0.012)	0.077*** (0.014)	0.197*** (0.026)	0.053 (0.064)	-0.008 (0.016)
2009	-0.139** (0.058)	-0.369*** (0.017)	0.006* (0.004)	0.490*** (0.038)	0.069*** (0.009)	0.165*** (0.017)	-0.177*** (0.045)	-0.011 (0.015)
2010	-0.100* (0.051)	-0.343*** (0.018)	0.004 (0.003)	0.529*** (0.029)	0.075*** (0.010)	0.146*** (0.020)	-0.113*** (0.041)	0.026* (0.014)
2011	-0.144*** (0.046)	-0.383*** (0.011)	0.006* (0.003)	0.472*** (0.012)	0.077*** (0.009)	0.193*** (0.015)	-0.051 (0.035)	0.012 (0.014)
2012	-0.194** (0.086)	-0.400*** (0.016)	0.000 (0.005)	0.496*** (0.014)	0.059*** (0.011)	0.180*** (0.018)	0.054 (0.049)	0.027** (0.013)
2013	-0.201*** (0.063)	-0.412*** (0.017)	0.010*** (0.003)	0.435*** (0.026)	0.063*** (0.009)	0.166*** (0.018)	-0.023 (0.032)	0.035** (0.014)
2014	-0.223*** (0.033)	-0.395*** (0.009)	0.000 (0.002)	0.454*** (0.011)	0.039*** (0.006)	0.178*** (0.009)	0.026 (0.018)	0.042*** (0.012)
2015	-0.153*** (0.045)	-0.393*** (0.009)	-0.002 (0.002)	0.474*** (0.008)	0.032*** (0.006)	0.201*** (0.011)	-0.066** (0.029)	0.037*** (0.011)
2016	-0.213*** (0.048)	-0.398*** (0.011)	-0.008*** (0.002)	0.453*** (0.011)	0.046*** (0.009)	0.192*** (0.013)	-0.020 (0.023)	0.049*** (0.011)
2017	-0.084 (0.056)	-0.384*** (0.011)	0.002 (0.002)	0.367*** (0.027)	0.034*** (0.006)	0.201*** (0.010)	0.007 (0.023)	0.073*** (0.012)
2018	-0.261*** (0.050)	-0.442*** (0.010)	-0.011*** (0.002)	0.417*** (0.021)	0.028*** (0.004)	0.221*** (0.008)	0.007 (0.015)	0.122*** (0.010)
2019	-0.263*** (0.050)	-0.473*** (0.009)	0.001 (0.002)	0.419*** (0.012)	0.028*** (0.005)	0.244*** (0.009)	0.009 (0.023)	0.081*** (0.022)
2020	-0.401*** (0.024)	-0.491*** (0.011)	-0.001 (0.002)	0.502*** (0.010)	0.042*** (0.006)	0.251*** (0.012)	0.029 (0.021)	0.081*** (0.017)
2021	-0.436*** (0.021)	-0.470*** (0.012)	0.005** (0.002)	0.483*** (0.022)	0.034*** (0.004)	0.244*** (0.009)	0.058*** (0.020)	0.083*** (0.011)
2022	-0.471*** (0.032)	-0.444*** (0.023)	0.007*** (0.002)	0.396*** (0.029)	0.024*** (0.005)	0.252*** (0.020)	0.052*** (0.018)	0.110*** (0.012)
2023	-0.428*** (0.033)	-0.503*** (0.012)	0.010*** (0.002)	0.477*** (0.019)	0.030*** (0.006)	0.281*** (0.010)	0.045** (0.022)	0.094*** (0.012)
2024	-0.397*** (0.042)	-0.473*** (0.014)	0.010*** (0.003)	0.453*** (0.026)	0.054*** (0.007)	0.259*** (0.011)	-0.050* (0.028)	0.074*** (0.014)
Adj. $\bar{R}^2$ (%)	31.92							

Table A23
Yearly Coefficients: Table 8 Level Spec (4) — Full (Large Stocks)

Year	Large Stocks							
	$\beta_{\tau C}$	$\beta_{\tau I}$	$\beta_{\sigma C}$	$\beta_{\sigma I}$	β_{HFOIVC}	β_{HFOIVI}	β_{OIACC}	β_{OIACI}
2004	-0.284*** (0.024)	-0.283*** (0.016)	0.017*** (0.003)	0.477*** (0.010)	0.010** (0.004)	0.316*** (0.012)	0.017 (0.034)	0.017 (0.018)
2005	-0.156*** (0.036)	-0.266*** (0.014)	0.019*** (0.003)	0.459*** (0.010)	0.017*** (0.005)	0.295*** (0.012)	0.012 (0.037)	-0.007 (0.020)
2006	-0.136*** (0.043)	-0.304*** (0.016)	0.011*** (0.004)	0.418*** (0.008)	0.033*** (0.006)	0.307*** (0.012)	-0.091* (0.050)	0.064** (0.030)
2007	-0.077** (0.034)	-0.295*** (0.012)	0.031*** (0.005)	0.438*** (0.013)	0.037*** (0.008)	0.312*** (0.010)	0.024 (0.070)	-0.007 (0.022)
2008	-0.234*** (0.030)	-0.439*** (0.021)	0.037*** (0.006)	0.517*** (0.020)	0.038*** (0.006)	0.345*** (0.013)	-0.045 (0.073)	-0.051*** (0.012)
2009	-0.204*** (0.032)	-0.344*** (0.014)	0.035*** (0.007)	0.313*** (0.012)	0.040*** (0.009)	0.306*** (0.012)	-0.065 (0.042)	-0.046*** (0.013)
2010	-0.192*** (0.053)	-0.384*** (0.041)	0.019* (0.010)	0.446*** (0.097)	0.036*** (0.008)	0.292*** (0.012)	0.020 (0.037)	-0.056*** (0.012)
2011	-0.163*** (0.025)	-0.322*** (0.011)	0.042*** (0.005)	0.333*** (0.012)	0.025*** (0.005)	0.258*** (0.009)	0.016 (0.023)	-0.041*** (0.008)
2012	-0.064 (0.051)	-0.308*** (0.009)	0.020*** (0.006)	0.333*** (0.013)	0.034*** (0.007)	0.242*** (0.008)	0.084 (0.100)	-0.037*** (0.009)
2013	-0.181*** (0.049)	-0.351*** (0.013)	0.023*** (0.004)	0.389*** (0.017)	0.033*** (0.005)	0.262*** (0.011)	0.035 (0.044)	-0.032*** (0.009)
2014	-0.144*** (0.049)	-0.382*** (0.014)	0.030*** (0.004)	0.397*** (0.014)	0.042*** (0.007)	0.241*** (0.012)	0.142* (0.075)	-0.029*** (0.008)
2015	-0.177*** (0.038)	-0.422*** (0.012)	0.040*** (0.005)	0.423*** (0.016)	0.029*** (0.005)	0.257*** (0.008)	0.032 (0.035)	-0.039*** (0.008)
2016	-0.279*** (0.034)	-0.412*** (0.011)	0.033*** (0.005)	0.405*** (0.017)	0.036*** (0.007)	0.254*** (0.010)	-0.025 (0.037)	-0.016 (0.010)
2017	-0.123* (0.066)	-0.372*** (0.014)	0.020*** (0.003)	0.433*** (0.016)	0.039*** (0.008)	0.227*** (0.012)	-0.014 (0.025)	0.000 (0.010)
2018	-0.033 (0.056)	-0.437*** (0.012)	0.042*** (0.005)	0.453*** (0.015)	0.037*** (0.007)	0.265*** (0.011)	0.139** (0.070)	0.001 (0.010)
2019	-0.096 (0.098)	-0.412*** (0.017)	0.031*** (0.004)	0.418*** (0.020)	0.054*** (0.009)	0.255*** (0.014)	-0.012 (0.032)	-0.034*** (0.009)
2020	-0.317*** (0.034)	-0.551*** (0.016)	0.056*** (0.005)	0.537*** (0.017)	0.063*** (0.006)	0.334*** (0.015)	-0.045 (0.034)	-0.058*** (0.013)
2021	-0.284*** (0.042)	-0.573*** (0.015)	0.034*** (0.003)	0.480*** (0.013)	0.055*** (0.005)	0.402*** (0.016)	-0.132*** (0.029)	-0.051*** (0.012)
2022	-0.341*** (0.056)	-0.606*** (0.016)	0.071*** (0.008)	0.437*** (0.020)	0.051*** (0.007)	0.445*** (0.016)	-0.025 (0.047)	-0.076*** (0.013)
2023	-0.129 (0.093)	-0.468*** (0.022)	0.038*** (0.004)	0.477*** (0.032)	0.053*** (0.008)	0.318*** (0.015)	0.086 (0.061)	-0.051*** (0.010)
2024	-0.260*** (0.082)	-0.453*** (0.027)	0.039*** (0.005)	0.469*** (0.028)	0.047*** (0.008)	0.337*** (0.017)	0.130 (0.100)	-0.072*** (0.017)
Adj. $\bar{R}^2$ (%)	28.39							

Table A24
Commonality Analysis: Change Regressions (Median Coefficients)

	Small Stocks				Large Stocks			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\beta_{\Delta\tau^C}$	0.10 (1.85)	-0.05 (-1.07)	0.17 (2.01)	-0.07 (-1.25)	0.43 (4.58)	-0.02 (-0.28)	0.44 (4.81)	-0.01 (-0.17)
$\beta_{\Delta\tau^I}$	-0.09 (-12.02)	-0.18 (-20.57)	-0.09 (-7.92)	-0.30 (-25.62)	0.03 (1.73)	-0.35 (-19.50)	0.03 (2.00)	-0.34 (-19.53)
$\beta_{\Delta\sigma^C}$	0.01 (3.95)	0.01 (3.28)	0.01 (3.70)	0.01 (3.60)	0.01 (3.29)	0.02 (5.07)	0.01 (3.34)	0.02 (5.15)
$\beta_{\Delta\sigma^I}$	0.25 (12.65)	0.28 (14.67)	0.32 (22.65)	0.35 (28.14)	0.29 (17.29)	0.35 (22.76)	0.29 (17.46)	0.35 (23.04)
$\beta_{\Delta HFOIV^C}$		0.05 (11.85)		0.04 (8.15)		0.03 (7.27)		0.03 (7.24)
$\beta_{\Delta HFOIV^I}$		0.05 (6.79)		0.17 (18.26)		0.29 (27.23)		0.29 (27.37)
$\beta_{\Delta OIAC^C}$			-0.00 (-0.02)	0.01 (0.32)			0.02 (0.50)	0.01 (0.57)
$\beta_{\Delta OIAC^I}$			-0.00 (-0.03)	0.02 (1.39)			-0.10 (-8.31)	-0.04 (-4.17)
Adj. R^2 (%)	5.94	9.93	8.02	12.41	7.39	17.22	7.90	17.45
N	122,061	120,747	98,134	98,134	124,490	124,490	124,490	124,490

Table A25
Yearly Coefficients: Table 8 Change Spec (1) — Baseline (Small Stocks)

Year	Small Stocks			
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$
2004	-0.127*** (0.029)	-0.080*** (0.006)	0.004** (0.002)	0.371*** (0.020)
2005	0.003 (0.041)	-0.070*** (0.005)	0.008*** (0.002)	0.331*** (0.013)
2006	-0.061** (0.030)	-0.071*** (0.006)	0.008*** (0.002)	0.291*** (0.023)
2007	-0.038 (0.027)	-0.072*** (0.004)	0.012*** (0.002)	0.325*** (0.010)
2008	0.197*** (0.070)	-0.071*** (0.007)	0.015*** (0.003)	0.242*** (0.020)
2009	0.212*** (0.057)	-0.079*** (0.008)	0.012*** (0.003)	0.290*** (0.023)
2010	0.296*** (0.062)	-0.102*** (0.012)	0.007** (0.003)	0.403*** (0.043)
2011	0.178*** (0.059)	-0.086*** (0.008)	0.013*** (0.003)	0.290*** (0.012)
2012	0.085 (0.095)	-0.128*** (0.009)	0.011*** (0.004)	0.277*** (0.012)
2013	0.097* (0.053)	-0.133*** (0.008)	0.013*** (0.003)	0.246*** (0.019)
2014	0.055 (0.041)	-0.112*** (0.006)	0.007*** (0.002)	0.252*** (0.009)
2015	0.147** (0.060)	-0.094*** (0.005)	0.004* (0.002)	0.249*** (0.012)
2016	0.182*** (0.062)	-0.097*** (0.007)	0.003* (0.002)	0.236*** (0.018)
2017	0.313*** (0.063)	-0.095*** (0.008)	0.006*** (0.002)	0.202*** (0.022)
2018	0.263*** (0.068)	-0.116*** (0.007)	0.002 (0.002)	0.186*** (0.017)
2019	0.130** (0.064)	-0.096*** (0.008)	0.011*** (0.002)	0.172*** (0.016)
2020	-0.017 (0.039)	-0.096*** (0.009)	0.006** (0.003)	0.260*** (0.019)
2021	0.082* (0.048)	-0.076*** (0.006)	0.010*** (0.002)	0.166*** (0.019)
2022	-0.107** (0.054)	-0.056*** (0.007)	0.021*** (0.004)	0.085*** (0.012)
2023	-0.134*** (0.050)	-0.073*** (0.008)	0.026*** (0.004)	0.160*** (0.021)
2024	0.117** (0.055)	-0.039*** (0.008)	0.009*** (0.002)	0.148*** (0.019)
Adj. $\bar{R}^2$ (%)	6.69			

Table A26
Yearly Coefficients: Table 8 Change Spec (1) — Baseline (Large Stocks)

Year	Large Stocks			
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$
2004	0.263*** (0.068)	0.171*** (0.008)	0.009*** (0.003)	0.348*** (0.011)
2005	0.385*** (0.083)	0.188*** (0.009)	0.012*** (0.003)	0.324*** (0.011)
2006	0.429*** (0.082)	0.184*** (0.010)	0.004 (0.005)	0.275*** (0.011)
2007	0.591*** (0.085)	0.256*** (0.015)	0.013** (0.005)	0.254*** (0.017)
2008	0.455*** (0.085)	0.072*** (0.014)	0.004 (0.009)	0.351*** (0.027)
2009	0.357*** (0.095)	0.116*** (0.012)	0.011 (0.008)	0.192*** (0.014)
2010	0.319*** (0.085)	0.034 (0.043)	0.006 (0.007)	0.379*** (0.100)
2011	0.223*** (0.045)	0.081*** (0.011)	0.026*** (0.004)	0.204*** (0.010)
2012	0.517*** (0.165)	0.091*** (0.015)	-0.002 (0.006)	0.196*** (0.015)
2013	0.291*** (0.071)	0.063*** (0.013)	0.013*** (0.004)	0.255*** (0.015)
2014	0.397*** (0.106)	0.018 (0.014)	0.015*** (0.005)	0.253*** (0.014)
2015	0.302*** (0.071)	-0.018 (0.014)	0.020*** (0.004)	0.287*** (0.022)
2016	0.230*** (0.071)	-0.032*** (0.012)	0.016*** (0.004)	0.308*** (0.013)
2017	0.487*** (0.126)	-0.002 (0.015)	0.010*** (0.002)	0.304*** (0.017)
2018	0.611*** (0.124)	-0.026* (0.014)	0.006 (0.004)	0.288*** (0.015)
2019	0.573*** (0.133)	-0.020 (0.016)	0.022*** (0.004)	0.292*** (0.017)
2020	0.427*** (0.075)	-0.078*** (0.015)	0.024*** (0.005)	0.345*** (0.020)
2021	0.582*** (0.108)	-0.015 (0.014)	0.018*** (0.004)	0.268*** (0.018)
2022	0.503*** (0.110)	0.027* (0.016)	0.049*** (0.008)	0.216*** (0.018)
2023	0.691*** (0.145)	-0.010 (0.020)	0.024*** (0.004)	0.341*** (0.036)
2024	0.656*** (0.135)	0.046** (0.020)	0.008** (0.003)	0.311*** (0.034)
Adj. $\bar{R}^2$ (%)		8.07		

Table A27
Yearly Coefficients: Table 8 Change Spec (2) — HFOIV (Small Stocks)

Year	Small Stocks					
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta HFOIV^C}$	$\beta_{\Delta HFOIV^I}$
2004	-0.174*** (0.025)	-0.117*** (0.005)	0.006*** (0.002)	0.449*** (0.007)	0.027*** (0.003)	0.013*** (0.003)
2005	-0.040 (0.038)	-0.106*** (0.005)	0.009*** (0.002)	0.398*** (0.011)	0.037*** (0.004)	0.004* (0.002)
2006	-0.129*** (0.029)	-0.131*** (0.005)	0.008*** (0.001)	0.387*** (0.006)	0.041*** (0.003)	0.012*** (0.002)
2007	-0.123*** (0.027)	-0.139*** (0.005)	0.011*** (0.001)	0.401*** (0.006)	0.052*** (0.003)	0.015*** (0.002)
2008	0.080 (0.063)	-0.150*** (0.009)	0.012*** (0.002)	0.357*** (0.024)	0.073*** (0.007)	0.015*** (0.003)
2009	0.045 (0.045)	-0.177*** (0.010)	0.009*** (0.003)	0.341*** (0.029)	0.067*** (0.006)	0.030*** (0.005)
2010	0.083* (0.046)	-0.208*** (0.015)	0.005* (0.003)	0.428*** (0.044)	0.073*** (0.006)	0.049*** (0.010)
2011	-0.011 (0.045)	-0.200*** (0.009)	0.010*** (0.003)	0.324*** (0.011)	0.080*** (0.006)	0.055*** (0.008)
2012	-0.060 (0.081)	-0.224*** (0.009)	0.010*** (0.004)	0.307*** (0.010)	0.062*** (0.007)	0.057*** (0.007)
2013	-0.047 (0.042)	-0.239*** (0.010)	0.010*** (0.003)	0.270*** (0.021)	0.062*** (0.005)	0.059*** (0.008)
2014	-0.069** (0.031)	-0.209*** (0.009)	0.006*** (0.002)	0.277*** (0.008)	0.041*** (0.004)	0.062*** (0.008)
2015	0.048 (0.048)	-0.166*** (0.008)	0.003 (0.002)	0.274*** (0.013)	0.038*** (0.004)	0.038*** (0.006)
2016	0.062 (0.050)	-0.182*** (0.010)	0.002 (0.002)	0.265*** (0.020)	0.046*** (0.005)	0.041*** (0.007)
2017	0.173*** (0.055)	-0.202*** (0.011)	0.005*** (0.002)	0.222*** (0.024)	0.040*** (0.004)	0.070*** (0.009)
2018	0.112** (0.054)	-0.232*** (0.011)	0.001 (0.002)	0.204*** (0.019)	0.034*** (0.004)	0.073*** (0.009)
2019	0.017 (0.051)	-0.221*** (0.010)	0.008*** (0.002)	0.206*** (0.013)	0.039*** (0.004)	0.063*** (0.008)
2020	-0.183*** (0.030)	-0.268*** (0.013)	0.004* (0.002)	0.289*** (0.019)	0.048*** (0.004)	0.106*** (0.011)
2021	-0.085** (0.034)	-0.225*** (0.010)	0.005*** (0.002)	0.205*** (0.022)	0.042*** (0.003)	0.095*** (0.008)
2022	-0.156*** (0.039)	-0.158*** (0.009)	0.012*** (0.003)	0.110*** (0.014)	0.056*** (0.004)	0.035*** (0.005)
2023	-0.182*** (0.039)	-0.178*** (0.009)	0.011*** (0.002)	0.178*** (0.018)	0.050*** (0.004)	0.045*** (0.007)
2024	-0.050 (0.042)	-0.183*** (0.013)	0.007*** (0.002)	0.183*** (0.021)	0.056*** (0.004)	0.078*** (0.012)
Adj. $\bar{R}^2$ (%)				10.98		

Table A28
Yearly Coefficients: Table 8 Change Spec (2) — HFOIV (Large Stocks)

Year	Large Stocks					
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta HFOIV^C}$	$\beta_{\Delta HFOIV^I}$
2004	-0.086** (0.043)	-0.225*** (0.014)	0.014*** (0.003)	0.426*** (0.010)	0.011*** (0.003)	0.306*** (0.010)
2005	-0.022 (0.046)	-0.197*** (0.014)	0.016*** (0.003)	0.403*** (0.011)	0.018*** (0.004)	0.286*** (0.011)
2006	0.041 (0.060)	-0.233*** (0.016)	0.008** (0.004)	0.370*** (0.009)	0.032*** (0.005)	0.292*** (0.011)
2007	0.140** (0.064)	-0.196*** (0.014)	0.022*** (0.005)	0.347*** (0.014)	0.030*** (0.005)	0.309*** (0.009)
2008	-0.016 (0.058)	-0.391*** (0.020)	0.022*** (0.006)	0.406*** (0.018)	0.036*** (0.004)	0.338*** (0.011)
2009	-0.049 (0.062)	-0.303*** (0.014)	0.023*** (0.007)	0.252*** (0.012)	0.038*** (0.006)	0.312*** (0.010)
2010	-0.017 (0.074)	-0.350*** (0.048)	0.015** (0.007)	0.423*** (0.098)	0.034*** (0.006)	0.293*** (0.011)
2011	-0.027 (0.038)	-0.237*** (0.011)	0.035*** (0.004)	0.242*** (0.010)	0.023*** (0.004)	0.247*** (0.008)
2012	0.167 (0.129)	-0.228*** (0.010)	0.007 (0.005)	0.245*** (0.013)	0.033*** (0.004)	0.239*** (0.009)
2013	-0.044 (0.060)	-0.287*** (0.015)	0.019*** (0.004)	0.317*** (0.014)	0.031*** (0.004)	0.259*** (0.010)
2014	0.068 (0.089)	-0.318*** (0.017)	0.020*** (0.004)	0.304*** (0.013)	0.041*** (0.005)	0.241*** (0.011)
2015	-0.033 (0.060)	-0.365*** (0.015)	0.024*** (0.004)	0.342*** (0.021)	0.025*** (0.004)	0.255*** (0.008)
2016	-0.059 (0.057)	-0.355*** (0.013)	0.020*** (0.003)	0.353*** (0.012)	0.033*** (0.005)	0.241*** (0.009)
2017	0.181* (0.103)	-0.304*** (0.016)	0.011*** (0.002)	0.357*** (0.015)	0.037*** (0.005)	0.220*** (0.011)
2018	0.265*** (0.096)	-0.367*** (0.013)	0.015*** (0.004)	0.342*** (0.013)	0.034*** (0.005)	0.262*** (0.009)
2019	0.238** (0.118)	-0.346*** (0.019)	0.023*** (0.003)	0.333*** (0.016)	0.047*** (0.005)	0.246*** (0.011)
2020	-0.017 (0.058)	-0.492*** (0.015)	0.032*** (0.004)	0.386*** (0.017)	0.057*** (0.004)	0.337*** (0.014)
2021	-0.029 (0.061)	-0.529*** (0.012)	0.019*** (0.003)	0.352*** (0.012)	0.055*** (0.004)	0.416*** (0.014)
2022	-0.136 (0.095)	-0.536*** (0.016)	0.053*** (0.007)	0.284*** (0.015)	0.048*** (0.005)	0.459*** (0.014)
2023	0.257** (0.124)	-0.391*** (0.026)	0.026*** (0.004)	0.378*** (0.034)	0.046*** (0.005)	0.315*** (0.014)
2024	0.082 (0.111)	-0.355*** (0.026)	0.014*** (0.003)	0.357*** (0.027)	0.044*** (0.005)	0.319*** (0.014)
Adj. $\bar{R}^2$ (%)	18.84					

Table A29
Yearly Coefficients: Table 8 Change Spec (3) — OIAC (Small Stocks)

Year	Small Stocks					
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta OIAC^C}$	$\beta_{\Delta OIAC^I}$
2004	-0.039 (0.035)	-0.039*** (0.005)	0.007*** (0.002)	0.502*** (0.006)	-0.031** (0.013)	-0.028*** (0.010)
2005	0.086 (0.060)	-0.030*** (0.008)	0.011*** (0.002)	0.443*** (0.007)	-0.000 (0.016)	-0.058*** (0.010)
2006	-0.017 (0.051)	-0.043*** (0.007)	0.009*** (0.002)	0.422*** (0.007)	-0.016 (0.015)	-0.067*** (0.010)
2007	-0.045 (0.038)	-0.044*** (0.007)	0.012*** (0.002)	0.414*** (0.008)	0.041* (0.021)	-0.075*** (0.011)
2008	0.357*** (0.107)	-0.044** (0.017)	0.016*** (0.003)	0.464*** (0.014)	0.052 (0.059)	-0.057*** (0.016)
2009	0.299*** (0.061)	-0.073*** (0.015)	0.012*** (0.004)	0.340*** (0.042)	-0.173*** (0.037)	-0.031** (0.013)
2010	0.348*** (0.068)	-0.090*** (0.016)	0.011*** (0.003)	0.439*** (0.048)	-0.109*** (0.036)	0.002 (0.016)
2011	0.256*** (0.069)	-0.066*** (0.011)	0.014*** (0.004)	0.317*** (0.014)	-0.038 (0.045)	-0.026* (0.016)
2012	0.173* (0.105)	-0.101*** (0.013)	0.009** (0.004)	0.317*** (0.016)	0.096* (0.055)	-0.029*** (0.012)
2013	0.173*** (0.063)	-0.127*** (0.012)	0.010*** (0.003)	0.276*** (0.032)	-0.071 (0.050)	-0.023* (0.014)
2014	0.060 (0.048)	-0.125*** (0.007)	0.009*** (0.002)	0.315*** (0.008)	0.035* (0.021)	0.004 (0.014)
2015	0.199*** (0.072)	-0.107*** (0.007)	0.006*** (0.002)	0.352*** (0.008)	-0.056** (0.025)	-0.013 (0.012)
2016	0.233*** (0.074)	-0.102*** (0.009)	0.005** (0.002)	0.328*** (0.009)	0.036 (0.029)	0.003 (0.012)
2017	0.373*** (0.067)	-0.090*** (0.011)	0.008*** (0.002)	0.238*** (0.034)	-0.006 (0.029)	0.033*** (0.012)
2018	0.313*** (0.080)	-0.152*** (0.009)	0.005** (0.002)	0.265*** (0.025)	0.005 (0.022)	0.049*** (0.010)
2019	0.180** (0.078)	-0.143*** (0.009)	0.009*** (0.002)	0.271*** (0.009)	-0.001 (0.036)	0.011 (0.021)
2020	-0.009 (0.044)	-0.144*** (0.010)	0.004* (0.003)	0.337*** (0.010)	0.031 (0.028)	-0.001 (0.023)
2021	0.044 (0.054)	-0.122*** (0.007)	0.007*** (0.002)	0.282*** (0.015)	0.053** (0.024)	0.028*** (0.010)
2022	-0.067** (0.027)	-0.088*** (0.008)	0.011*** (0.002)	0.210*** (0.022)	0.039* (0.020)	0.015 (0.012)
2023	-0.030 (0.047)	-0.090*** (0.009)	0.009*** (0.002)	0.233*** (0.018)	0.030 (0.025)	0.010 (0.012)
2024	0.116** (0.058)	-0.057*** (0.011)	0.010*** (0.002)	0.243*** (0.025)	-0.068** (0.027)	0.029** (0.015)
Adj. $\bar{R}^2$ (%)	9.66					

Table A30
Yearly Coefficients: Table 8 Change Spec (3) — OIAC (Large Stocks)

Year	Large Stocks					
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta OIAC^C}$	$\beta_{\Delta OIAC^I}$
2004	0.264*** (0.068)	0.173*** (0.008)	0.009*** (0.003)	0.348*** (0.011)	-0.024 (0.033)	0.000 (0.020)
2005	0.378*** (0.079)	0.190*** (0.009)	0.013*** (0.003)	0.325*** (0.012)	0.050 (0.044)	-0.052* (0.027)
2006	0.436*** (0.081)	0.186*** (0.009)	0.005 (0.004)	0.276*** (0.011)	-0.089 (0.064)	0.022 (0.029)
2007	0.582*** (0.082)	0.255*** (0.015)	0.014** (0.005)	0.256*** (0.017)	0.078 (0.075)	-0.120*** (0.028)
2008	0.458*** (0.084)	0.073*** (0.013)	0.004 (0.009)	0.350*** (0.026)	-0.012 (0.104)	-0.166*** (0.020)
2009	0.370*** (0.095)	0.116*** (0.012)	0.012 (0.008)	0.191*** (0.014)	-0.082 (0.062)	-0.106*** (0.013)
2010	0.319*** (0.085)	0.034 (0.043)	0.006 (0.007)	0.381*** (0.100)	-0.025 (0.042)	-0.123*** (0.013)
2011	0.218*** (0.045)	0.081*** (0.011)	0.027*** (0.004)	0.204*** (0.010)	0.038 (0.023)	-0.121*** (0.009)
2012	0.470*** (0.125)	0.091*** (0.014)	-0.002 (0.006)	0.197*** (0.014)	0.103 (0.085)	-0.099*** (0.010)
2013	0.287*** (0.066)	0.063*** (0.013)	0.013*** (0.004)	0.255*** (0.015)	0.030 (0.040)	-0.094*** (0.010)
2014	0.353*** (0.087)	0.018 (0.014)	0.015*** (0.005)	0.253*** (0.014)	0.169*** (0.064)	-0.086*** (0.010)
2015	0.275*** (0.065)	-0.016 (0.014)	0.020*** (0.004)	0.286*** (0.021)	0.088** (0.037)	-0.086*** (0.010)
2016	0.232*** (0.071)	-0.031** (0.012)	0.016*** (0.004)	0.308*** (0.013)	0.006 (0.038)	-0.054*** (0.011)
2017	0.488*** (0.126)	-0.001 (0.015)	0.010*** (0.002)	0.304*** (0.017)	0.021 (0.028)	-0.034*** (0.012)
2018	0.561*** (0.103)	-0.025* (0.013)	0.007* (0.004)	0.289*** (0.015)	0.189*** (0.054)	-0.079*** (0.011)
2019	0.573*** (0.132)	-0.019 (0.016)	0.022*** (0.004)	0.292*** (0.017)	0.018 (0.037)	-0.089*** (0.010)
2020	0.419*** (0.073)	-0.076*** (0.015)	0.025*** (0.005)	0.346*** (0.019)	-0.075** (0.038)	-0.143*** (0.015)
2021	0.603*** (0.101)	-0.014 (0.014)	0.017*** (0.004)	0.275*** (0.017)	-0.175*** (0.039)	-0.128*** (0.018)
2022	0.522*** (0.107)	0.031** (0.016)	0.048*** (0.008)	0.214*** (0.018)	-0.083* (0.050)	-0.162*** (0.015)
2023	0.688*** (0.141)	-0.004 (0.020)	0.025*** (0.004)	0.339*** (0.036)	0.013 (0.058)	-0.108*** (0.011)
2024	0.607*** (0.117)	0.048** (0.020)	0.010*** (0.004)	0.312*** (0.034)	0.132* (0.073)	-0.107*** (0.017)
Adj. $\bar{R}^2$ (%)			8.40			

Table A31
Yearly Coefficients: Table 8 Change Spec (4) — Full (Small Stocks)

Year	Small Stocks							
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta HFOIV^C}$	$\beta_{\Delta HFOIV^I}$	$\beta_{\Delta OIAC^C}$	$\beta_{\Delta OIAC^I}$
2004	-0.214*** (0.033)	-0.263*** (0.008)	0.007*** (0.002)	0.542*** (0.006)	0.012*** (0.003)	0.210*** (0.008)	-0.012 (0.012)	0.004 (0.010)
2005	-0.067 (0.054)	-0.233*** (0.013)	0.010*** (0.002)	0.480*** (0.008)	0.031*** (0.006)	0.173*** (0.012)	0.005 (0.015)	-0.027*** (0.010)
2006	-0.233*** (0.042)	-0.287*** (0.009)	0.008*** (0.001)	0.466*** (0.007)	0.026*** (0.003)	0.209*** (0.008)	-0.011 (0.013)	-0.025*** (0.009)
2007	-0.253*** (0.035)	-0.295*** (0.008)	0.011*** (0.001)	0.458*** (0.007)	0.035*** (0.004)	0.203*** (0.007)	0.044** (0.019)	-0.029*** (0.010)
2008	0.114 (0.100)	-0.266*** (0.028)	0.013*** (0.003)	0.494*** (0.013)	0.072*** (0.009)	0.151*** (0.021)	0.022 (0.051)	-0.032** (0.015)
2009	0.058 (0.052)	-0.252*** (0.022)	0.011*** (0.003)	0.368*** (0.046)	0.063*** (0.006)	0.122*** (0.015)	-0.170*** (0.032)	-0.021* (0.011)
2010	0.073 (0.056)	-0.267*** (0.024)	0.008*** (0.003)	0.465*** (0.048)	0.071*** (0.007)	0.114*** (0.017)	-0.103*** (0.031)	0.010 (0.014)
2011	-0.025 (0.054)	-0.299*** (0.014)	0.012*** (0.003)	0.359*** (0.013)	0.071*** (0.007)	0.171*** (0.013)	-0.041 (0.037)	0.005 (0.013)
2012	-0.039 (0.092)	-0.285*** (0.020)	0.008* (0.004)	0.348*** (0.015)	0.056*** (0.008)	0.139*** (0.016)	0.084* (0.048)	-0.001 (0.012)
2013	-0.045 (0.055)	-0.316*** (0.020)	0.008*** (0.003)	0.304*** (0.034)	0.057*** (0.006)	0.140*** (0.015)	-0.060 (0.045)	0.007 (0.012)
2014	-0.128*** (0.037)	-0.307*** (0.010)	0.008*** (0.002)	0.333*** (0.008)	0.038*** (0.004)	0.149*** (0.008)	0.037* (0.019)	0.026** (0.012)
2015	0.006 (0.054)	-0.299*** (0.010)	0.004** (0.002)	0.373*** (0.008)	0.031*** (0.005)	0.162*** (0.010)	-0.045** (0.022)	0.015 (0.011)
2016	0.034 (0.061)	-0.283*** (0.013)	0.004* (0.002)	0.347*** (0.008)	0.041*** (0.006)	0.143*** (0.011)	0.021 (0.026)	0.024** (0.011)
2017	0.137** (0.056)	-0.284*** (0.014)	0.007*** (0.002)	0.254*** (0.037)	0.032*** (0.004)	0.163*** (0.009)	-0.007 (0.027)	0.059*** (0.012)
2018	0.065 (0.059)	-0.359*** (0.010)	0.004** (0.002)	0.280*** (0.026)	0.028*** (0.003)	0.182*** (0.007)	0.006 (0.018)	0.074*** (0.009)
2019	-0.080 (0.056)	-0.381*** (0.008)	0.008*** (0.002)	0.294*** (0.008)	0.027*** (0.004)	0.210*** (0.008)	0.006 (0.027)	0.051*** (0.017)
2020	-0.273*** (0.032)	-0.406*** (0.012)	0.005** (0.002)	0.364*** (0.009)	0.040*** (0.004)	0.225*** (0.010)	0.027 (0.022)	0.045*** (0.016)
2021	-0.221*** (0.034)	-0.371*** (0.009)	0.006*** (0.002)	0.309*** (0.016)	0.032*** (0.003)	0.222*** (0.007)	0.057*** (0.020)	0.055*** (0.009)
2022	-0.300*** (0.026)	-0.341*** (0.013)	0.010*** (0.002)	0.232*** (0.024)	0.026*** (0.004)	0.230*** (0.009)	0.043** (0.018)	0.053*** (0.011)
2023	-0.301*** (0.039)	-0.372*** (0.011)	0.009*** (0.002)	0.255*** (0.020)	0.030*** (0.004)	0.251*** (0.008)	0.031 (0.020)	0.046*** (0.011)
2024	-0.141*** (0.046)	-0.306*** (0.014)	0.009*** (0.002)	0.259*** (0.026)	0.049*** (0.004)	0.205*** (0.009)	-0.059*** (0.021)	0.044*** (0.012)
Adj. $\bar{R}^2$ (%)	14.95							

Table A32
Yearly Coefficients: Table 8 Change Spec (4) — Full (Large Stocks)

Year	Large Stocks							
	$\beta_{\Delta\tau^C}$	$\beta_{\Delta\tau^I}$	$\beta_{\Delta\sigma^C}$	$\beta_{\Delta\sigma^I}$	$\beta_{\Delta HFOIV^C}$	$\beta_{\Delta HFOIV^I}$	$\beta_{\Delta OIACC}$	$\beta_{\Delta OIAC^I}$
2004	-0.085** (0.043)	-0.223*** (0.014)	0.014*** (0.003)	0.426*** (0.010)	0.011*** (0.003)	0.306*** (0.010)	-0.016 (0.028)	0.018 (0.016)
2005	-0.026 (0.045)	-0.197*** (0.014)	0.017*** (0.003)	0.404*** (0.011)	0.018*** (0.004)	0.285*** (0.010)	0.028 (0.033)	-0.012 (0.016)
2006	0.044 (0.059)	-0.232*** (0.016)	0.009** (0.004)	0.371*** (0.009)	0.031*** (0.004)	0.292*** (0.011)	-0.069 (0.052)	0.056*** (0.022)
2007	0.134** (0.061)	-0.195*** (0.013)	0.022*** (0.005)	0.348*** (0.014)	0.030*** (0.005)	0.307*** (0.008)	0.058 (0.061)	-0.013 (0.015)
2008	-0.010 (0.058)	-0.387*** (0.020)	0.022*** (0.006)	0.406*** (0.018)	0.036*** (0.004)	0.335*** (0.011)	-0.035 (0.063)	-0.055*** (0.010)
2009	-0.038 (0.061)	-0.300*** (0.014)	0.023*** (0.007)	0.251*** (0.012)	0.039*** (0.006)	0.309*** (0.011)	-0.077 (0.051)	-0.048*** (0.010)
2010	-0.012 (0.075)	-0.347*** (0.048)	0.015** (0.007)	0.423*** (0.098)	0.034*** (0.006)	0.291*** (0.011)	0.010 (0.033)	-0.064*** (0.010)
2011	-0.026 (0.038)	-0.233*** (0.011)	0.036*** (0.004)	0.241*** (0.010)	0.023*** (0.004)	0.244*** (0.008)	0.019 (0.020)	-0.059*** (0.008)
2012	0.132 (0.097)	-0.226*** (0.010)	0.007 (0.005)	0.245*** (0.013)	0.032*** (0.004)	0.236*** (0.008)	0.085 (0.074)	-0.045*** (0.008)
2013	-0.047 (0.055)	-0.286*** (0.014)	0.019*** (0.004)	0.317*** (0.014)	0.031*** (0.004)	0.258*** (0.010)	0.022 (0.035)	-0.036*** (0.009)
2014	0.032 (0.074)	-0.318*** (0.017)	0.020*** (0.004)	0.304*** (0.013)	0.039*** (0.005)	0.241*** (0.011)	0.152*** (0.056)	-0.036*** (0.009)
2015	-0.049 (0.057)	-0.362*** (0.014)	0.024*** (0.004)	0.341*** (0.020)	0.025*** (0.004)	0.253*** (0.008)	0.059* (0.033)	-0.035*** (0.008)
2016	-0.057 (0.057)	-0.354*** (0.013)	0.020*** (0.003)	0.353*** (0.012)	0.033*** (0.005)	0.241*** (0.009)	0.001 (0.032)	-0.016* (0.009)
2017	0.182* (0.103)	-0.304*** (0.016)	0.011*** (0.002)	0.357*** (0.015)	0.037*** (0.005)	0.220*** (0.011)	0.013 (0.023)	-0.001 (0.010)
2018	0.229*** (0.083)	-0.366*** (0.013)	0.015*** (0.003)	0.342*** (0.013)	0.031*** (0.005)	0.262*** (0.009)	0.154*** (0.044)	-0.012 (0.010)
2019	0.240** (0.118)	-0.344*** (0.019)	0.023*** (0.003)	0.333*** (0.016)	0.047*** (0.005)	0.245*** (0.011)	-0.003 (0.030)	-0.037*** (0.009)
2020	-0.019 (0.057)	-0.488*** (0.015)	0.033*** (0.004)	0.387*** (0.017)	0.056*** (0.004)	0.335*** (0.013)	-0.053* (0.031)	-0.074*** (0.012)
2021	-0.010 (0.059)	-0.526*** (0.012)	0.019*** (0.003)	0.355*** (0.012)	0.054*** (0.004)	0.414*** (0.014)	-0.114*** (0.028)	-0.055*** (0.012)
2022	-0.122 (0.092)	-0.531*** (0.015)	0.053*** (0.007)	0.283*** (0.015)	0.048*** (0.005)	0.456*** (0.014)	-0.045 (0.041)	-0.071*** (0.011)
2023	0.243** (0.117)	-0.388*** (0.025)	0.026*** (0.003)	0.378*** (0.034)	0.045*** (0.005)	0.315*** (0.013)	0.056 (0.052)	-0.063*** (0.009)
2024	0.039 (0.091)	-0.354*** (0.025)	0.016*** (0.003)	0.358*** (0.026)	0.042*** (0.005)	0.321*** (0.014)	0.133** (0.065)	-0.063*** (0.013)
Adj. $\bar{R}^2$ (%)	18.98							

Table A33
Order Imbalance Volatility, Turnover, and Stock Returns, 2004–2017

This table replicates Table 9a over the 2004–2017 period for comparison with Bogousslavsky and Collin-Dufresne (2023) Table VIII (2002–2017). Four-factor alphas (in percent per week) are reported for value-weighted portfolios formed each week by sequentially sorting stocks on turnover and *HFOIV*. Panel A sorts first by turnover, then by *HFOIV* within each turnover quintile. Panel B reverses the sort order. Turnover is the average daily turnover over the previous 20 trading days. *HFOIV* is an exponentially weighted moving average of prior high-frequency order imbalance volatility with a half-life of one day. Quintile breakpoints are based on NYSE stocks. To be included in a portfolio, a stock must have a price greater than \$5 at the end of the previous week. *t*-statistics are reported in parentheses and computed using Newey–West standard errors with one lag. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

<i>Panel A: Sort by Turnover, then HFOIV</i>						
	Low HFOIV	2	3	4	High HFOIV	H–L
Low Turnover	0.01 (0.34)	-0.01 (-0.29)	0.04 (1.05)	0.01 (0.22)	0.13*** (3.79)	0.12*** (2.65)
2	0.02 (0.72)	0.06** (2.03)	0.00 (0.07)	0.07** (2.05)	0.05 (1.61)	0.03 (0.80)
3	-0.02 (-0.71)	-0.00 (-0.12)	0.07** (2.15)	0.08** (2.56)	0.08** (2.44)	0.10** (2.17)
4	-0.07* (-1.94)	-0.05 (-1.19)	0.03 (0.77)	0.01 (0.40)	0.10*** (2.91)	0.17*** (3.45)
High Turnover	-0.05 (-0.98)	-0.06 (-0.97)	0.02 (0.37)	-0.11** (-1.99)	0.03 (0.49)	0.08 (1.13)
<i>Panel B: Sort by HFOIV, then Turnover</i>						
	Low Turnover	2	3	4	High Turnover	H–L
Low HFOIV	-0.01 (-0.14)	0.01 (0.29)	0.00 (0.09)	0.03 (0.99)	-0.06** (-1.99)	-0.06 (-0.99)
2	0.04 (1.11)	0.01 (0.33)	0.02 (0.64)	-0.04 (-1.32)	-0.04 (-1.01)	-0.08 (-1.43)
3	0.05 (1.37)	0.07** (2.01)	0.07** (2.39)	0.06* (1.72)	-0.07 (-1.55)	-0.12* (-1.93)
4	0.10*** (2.73)	0.02 (0.53)	0.05 (1.47)	-0.06 (-1.20)	-0.05 (-0.81)	-0.14** (-2.05)
High HFOIV	0.13*** (3.81)	0.08*** (2.66)	0.02 (0.45)	0.03 (0.69)	-0.02 (-0.23)	-0.15* (-1.73)

Table A34

Fama–MacBeth Regressions of Weekly Returns on Liquidity Characteristics, 2004–2017

This table reports results from value-weighted Fama–MacBeth regressions of weekly stock returns on liquidity characteristics. $HFOIV_{t-1}$ is an exponentially weighted moving average (EWMA) of prior high-frequency order imbalance volatility with a half-life of one day. τ_{t-1} is the average daily turnover over the previous month. $OIAC_{t-1}$ is order imbalance autocorrelation (in levels). ME_{t-1} is market capitalisation at the end of the previous week. $ILLIQ_{t-1}$ is the Amihud illiquidity ratio computed over the past 250 trading days (minimum 100 observations). σ_{t-1} is an EWMA of prior daily realised volatilities with a half-life of one day. ES_{t-1} is an EWMA of prior daily effective spreads with a half-life of one day. λ_{t-1} is an EWMA of prior daily Kyle’s lambda with a half-life of one day. $Depth/VOL_{t-1}$ is an EWMA of prior daily share depth over daily share volume with a half-life of one day. $|OI|_{t-1}$ is an EWMA of prior daily absolute share imbalance (as a fraction of shares outstanding) with a half-life of one day. PIN is the absolute daily trade imbalance over the total number of trades. $\sigma(OI/VOL)_{t-1}$ is the standard deviation of share imbalance divided by share volume, computed over the past 22 trading days (minimum 11 observations). All explanatory variables except the lagged return and $OIAC$ are in logs. All explanatory variables are winsorised at the 0.5% and 99.5% levels. The sample is restricted to stocks with a price greater than \$5 at the end of the previous week. The sample period is 2004 to 2017. $\bar{N}$ is the average number of stocks at each date. t -statistics are reported in parentheses and based on Newey–West standard errors with one lag. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)
$HFOIV_{t-1}$	0.053* (1.715)	0.056** (2.474)	0.055** (2.390)	0.051* (1.909)	0.065** (2.228)
$Turnover_{t-1}$		-0.016 (-0.370)	-0.018 (-0.412)	-0.006 (-0.125)	0.010 (0.207)
$OIAC_{t-1}$			-0.125 (-1.334)	-0.169** (-2.074)	-0.144* (-1.801)
ME_{t-1}				-0.004 (-0.086)	-0.004 (-0.090)
r_{t-1}				-1.784*** (-3.967)	-1.745*** (-3.920)
$ILLIQ_{t-1}$				0.019 (0.429)	0.011 (0.253)
$RVol_{t-1}$				-0.056 (-0.608)	-0.041 (-0.457)
ES_{t-1}				-0.004 (-0.131)	-0.013 (-0.393)
$Depth/VOL_{t-1}$				-0.019 (-0.782)	-0.020 (-0.834)
λ_{t-1}				-0.011 (-0.529)	-0.010 (-0.478)
$ OI _{t-1}$					-0.029 (-1.556)
PIN $_{t-1}$					0.008 (0.438)
$\sigma(OI/VOL)_{t-1}$					0.056 (1.509)
Adj. R^2 (%)	2.01	3.49	3.84	10.94	11.75
$\bar{N}$	2,595	2,594	2,480	2,409	2,409

