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Heterogeneous liquidity providers and night-minus-day return predictability

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ABSTRACT

We present and test a model to understand the puzzling fact that characteristics-sorted stock portfolios tend to earn opposite-signed overnight and intraday expected returns. Heterogeneous arbitrageurs – “fast” arbitrageurs with informational advantages and “slow” arbitrageurs with low inventory costs – compete to determine the price of liquidity. High information asymmetry around market open allows fast arbitrageurs to demand large price deviations for absorbing order imbalances, as cream-skimming risk discourages competition from slow arbitrageurs. Despite persistent order imbalances, these deviations attenuate when cream-skimming risk subsides, leading to opposite-signed overnight and intraday returns. Our model identifies novel determinants that empirically explain substantial variations in predictable overnight-minus-intraday returns.

1. Introduction

Recent research has documented that characteristics-sorted stock portfolios earn large, predictable, and opposite signed overnight and intraday returns. For example, Hendershott et al. (2020) report that if a stock’s market beta increases by 1, its average overnight returns increase by 14 basis points (bps) per day while its average intraday returns decrease by 15 bps per day. The resulting beta-sorted portfolio has an average “night-minus-day” return of 73% per annum.[1] These patterns are particularly puzzling because expected risk exposures, risk premia, and information flows are unlikely to flip signs between night and day.

Existing explanations have conjectured that these predictable night-minus-day returns reflect recurring price pressures caused by order flow shocks. However, if order flows alone are responsible for generating the return patterns, then alongside the recurring swings in prices, we should observe similarly recurring swings in order flows. Our first novel finding is that such order flow swings do not occur. Order imbalances near the market open are in the same direction as the predictable overnight returns, consistent with the prevailing explanations. Surprisingly, however, these imbalances *persist* throughout the rest of the day and thus are in the *opposite* direction of the predictable intraday return, deepening the night-minus-day return puzzle.

We offer an alternative explanation of night-minus-day return predictability. Our explanation emphasizes

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[1] The overnight return is measured from the previous close to today’s open, the intraday return is measured from today’s open to today’s close, and the night-minus-day return is the overnight return minus the intraday return. See Fig. 3 for the predictable night-minus-day return patterns in our sample period.

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heterogeneity among liquidity providers and decreasing information asymmetry throughout the trading day. We build a model featuring key elements from Glosten and Milgrom (1985) and Grossman and Miller (1988), similar to Hendershott and Menkveld (2014). Informed or sentiment-driven investors trade at the best bid or ask price posted by liquidity providers. The novelty of our model is that liquidity providers differ in their expertise. "Fast" arbitrageurs (e.g., designated or de facto market makers) invest in market making technology, which gives them an advantage in separating informed order flows from uninformed ones. "Slow" arbitrageurs (e.g., large asset managers) invest in risk bearing capacity, which gives them an advantage in having low inventory costs.[2]

Due to the difficulty of trading on information that arrives during the thinly traded overnight session, the amount of unpriced private information tends to be highest at market open (Madhavan et al., 1997; Barclay and Hendershott, 2003). During these times, fast arbitrageurs' information advantage allows them to "cream-skim" orders that are less likely to be informed. Their limited risk bearing capacity causes them to set asymmetric bid and ask quotes to control their inventory risk, causing mid-quote prices to deviate from fundamental values. Due to cream skimming risk, slow arbitrageurs cannot undercut fast arbitrageurs despite their greater risk bearing capacity. As informed investors' private information is revealed, cream skimming risk subsides, and slow arbitrageurs are able to undercut by providing cheaper liquidity, compressing price deviations later in the day. Thus, even with persistent order flows in the same direction throughout the day, we observe predictable overnight and intraday returns in opposite directions.

Our model thus resolves an open question in the literature: given that trading on night-minus-day return patterns is highly profitable at mid-quote or volume-weighted average prices, even among large and liquid stocks, why doesn't competition from lower-cost liquidity providers eliminate these patterns? Our model highlights that fast arbitrageurs' cream skimming prevents slow arbitrageurs' entry, and thus night-minus-day returns should arise only in a subset of assets where fast arbitrageurs can charge a high price of liquidity due to the cream skimming mechanism. Testing our conjectured mechanism is empirically challenging due to the strategic and proprietary nature of fast arbitrageurs' liquidity provision algorithms. Using both standard and unique data, we design several tests to overcome these empirical challenges.

Our first set of tests operates under the premise that cream skimming risk near the market open allows fast arbitrageurs to determine the price of liquidity for at least some stocks in the cross section. Thus, on average, the magnitude of predictable night-minus-day returns should increase in the amount of predictable, uninformed order flows absorbed by fast arbitrageurs near the market open and in fast arbitrageurs' required returns. We proxy for the former using retail order imbalances filled by market makers (hereafter, RM OI) as identified by the Boehmer et al. (2021) algorithm,[3] and we proxy for the latter using the measure proposed by Nagel (2012) as well as other market-level liquidity proxies. Supporting our model's predictions, we find that predictable RM OI near the market open (hereafter, Open RM OI) strongly predicts stocks' night-minus-day returns and this predictive relationship is increasing in fast arbitrageurs' required returns from liquidity provision.

Having established the existence of an average predictive relationship between Open RM OI and night-minus-day returns, we proceed to identify the subsets of stocks where this predictive relationship should be weaker according to the model because slow arbitrageurs can outcompete fast arbitrageurs and determine the price of liquidity throughout the day. To test this model prediction, we examine U.S. stocks that are dual listed in the European stock markets. These stocks have active overseas trading immediately prior to the U.S. market open, which should reduce unpriced private information and thus curtail the cream skimming risk for slow arbitrageurs around market open. Consistent with this prediction, we find European dual-listed stocks have lower bid-ask spreads at the U.S. open, and Open RM OI predicts night-minus-day returns less strongly among these stocks. Further corroborating our proposed mechanism, we find no such effects among stocks that are dual-listed in the Canadian stock markets, which open at the same time as the U.S. stock market. Finally, we use a unique dataset from the NASDAQ exchange on high-frequency trading firms' (HFT) trading to identify stocks where fast arbitrageurs provide less liquidity near the market open. Consistent with an interpretation that fast arbitrageurs have a smaller advantage among these stocks, we find that in this subset of stocks, Open RM OI predicts subsequent intraday returns less negatively.

To evaluate the economic relevance of our model, we use its predicted determinants to explain the night-minus-day returns of the characteristics-sorted portfolios studied in the literature. Using the 17 anomaly-sorted portfolios from Lou et al. (2019) (hereafter, LPS portfolios), we find that the sign and magnitude of the average portfolio night-minus-day returns can be explained by the corresponding average Open RM OI to a large extent, with a cross-sectional regression R^2 of 71%. Consistent with our model prediction, the cross-sectional regression slope is more positive when the required returns from liquidity provision are higher. Further corroborating the result, we show that the α's of the night-minus-day returns of these portfolios are mostly insignificant after accounting for the exposure to Nagel's liquidity provision factor.

In the last part of our analysis, given that anomaly portfolios are simultaneously associated with predictable night-minus-day returns and close-to-close returns, we ex-

[2] In the real world, market makers have expertise in detecting high-frequency patterns in order flows and privileged first looks at orders. Large asset managers have low inventory costs because their liquidity provision occurs during the process of implementing their optimal portfolio. See Section 2 for detailed discussions.

[3] Our inferences are robust to using Lee and Ready (1991) order imbalances. See Section 3.3 for further discussions.

plore whether these two types of return predictabilities share a common source (McLean and Pontiff, 2016; Bogousslavsky, 2021). We find that the expected Open RM OI conditioned on the 17 LPS characteristics strongly predicts night-minus-day returns but does not predict close-to-close returns. Furthermore, when we zoom into the surprising finding in Hendershott et al. (2020) that the slopes of the capital asset pricing model (CAPM) switch signs between night and day, we find that controlling for expected Open RM OI has little effect on the relation between CAPM beta and close-to-close returns but substantially reduces the positive (negative) relation between CAPM beta and overnight (intraday) returns. Both results suggest that anomaly portfolios generate large and predictable night-minus-day returns because anomaly characteristics predict liquidity demand – but such predictable liquidity demand does not appear to be the channel by which anomaly characteristics influence expected close-to-close returns.

1.1. Related literature

Our paper is motivated by the recent evidence that stock characteristics-sorted long-short portfolios have sizable overnight and intraday returns that are similar in magnitude but opposite in sign – a puzzling phenomenon that is unlikely to arise from underlying risk exposures (e.g., Berkman et al., 2012; Branch and Ma, 2012; Lou et al., 2019; Hendershott et al., 2020, and Bogousslavsky, 2021).

Existing explanations share a focus on liquidity demand. Hendershott et al. (2020) attribute the positive beta-overnight return relationship to a positive risk-return tradeoff and the negative beta-intraday return relationship to speculators' trading at market open; Berkman et al. (2012) attribute night-minus-day return predictability to retail trading demand; Lou et al. (2019) propose a more general explanation emphasizing opposing clientele trading demands both at the market open and market close; and Bogousslavsky (2021) argues that an overnight arbitraging constraint causes arbitrageurs to shed their holdings right before the market close, resulting in predictable returns of a mispricing portfolio in the last half-hour of the trading session.[4] The only existing study that provides a formal model for explaining night-minus-day returns is Lou et al. (2019). In their model, predictable night-minus-day returns arise due to exogenously specified opposing demands of investor clienteles at the open and close, which can be interpreted as predicting opposite signed order imbalances throughout a trading day.

We propose a complementary explanation that emphasizes heterogeneity in liquidity provision. As a result, our model allows for persistent order imbalances throughout the day, as observed in the data. Furthermore, we demonstrate both theoretically and empirically that while the uninformed order flows near the market open emphasized by the literature are important, their predictive power for night-minus-day returns depends on the identity of the marginal liquidity provider as well as fast arbitrageurs' required returns. These key determinants identified by our model explain substantial variations in the predictable night-minus-day returns. Our model also reconciles the contrasting assumptions made by Lou et al. (2019) and Bogousslavsky (2021). While both papers appeal to intraday variation in the availability of arbitraging capital, the former assumes an *arrival* of additional arbitraging capital at the market close whereas the latter assumes *withdrawal* of arbitraging capital due to an aversion to holding overnight positions. Our model suggests that both characterizations can be true if the former pertains to the behavior of slow arbitrageurs and the latter pertains to that of fast arbitrageurs.

[4] Relatedly, Bogousslavsky (2016) argues that the periodicity of half-hour intraday stock returns documented by Heston et al. (2010) is due to the infrequent rebalancing of liquidity providers, which can also be interpreted as a liquidity demand story.

2. A model of night-minus-day returns

2.1. Setup

We present a stylized but tractable model to transparently illustrate how the marginal liquidity provider might change throughout the trading day. Consider a two-period economy, $t = 0, 1, 2$, with J risky assets, a representative sentiment-driven trader, a representative informed trader, a competitive group of slow arbitrageurs, and a competitive group of fast arbitrageurs. We call $t = 0$ "yesterday's close," $t = 1$ "today's open" or "open," and $t = 2$ "today's close" or "close." We analyze a representative asset $j \in J$, with fundamental value $\tilde{v}$.

The common knowledge about $\tilde{v}$ at $t = 0$ is normalized to zero, i.e., $v_0 \equiv E_0[\tilde{v}] = 0$. At $t = 1$, informed traders obtain private information η about $\tilde{v}$, that is, $\tilde{v} = v_0 + \eta$, with $\eta \sim U[-n, n]$ drawn independently for each risky asset. At $t = 2$, all other market participants observe η. Our results do not require private information at close to be exactly zero, but they do rely on the assumption that private information is higher at open than at close.[5]

For each asset, one trader arrives at $t = 1$. She is either informed or sentiment-driven.[6] We denote the probability that the arriving trader is informed by π, with $\pi \sim U[0, 1]$ drawn independently for each risky asset. The trader trades at the best available bid or ask price, using a market order. If the trader is sentiment driven, the sign of her trade is unrelated to the price; she buys with probability $\lambda = \frac{1}{2}$ and sells otherwise. If the trader is informed, she optimizes by trading if and only if it would be profitable given her private information.

[5] Numerous microstructure models imply that information asymmetry declines on average over the trading day as private information acquired overnight is incorporated into prices via trading (e.g., Kyle, 1985; Glosten and Milgrom, 1985, and Easley and O'Hara, 1992). Empirically, both Madhavan et al. (1997) and Barclay and Hendershott (2003) confirm that information asymmetry decays over the trading day.

[6] We use "sentiment-driven trade" as a catch-all term for all non-fundamental-based, uninformed trades, which include liquidity-driven demand.

Conditional on trade, we take the expected trade size, and hence the expected order imbalance, as an exogenously given parameter in the model.[7] Specifically, let q_a (q_b) denote the expected quantity conditional on trade at the ask (bid), so that $q_a - q_b$ determines the expected order imbalance conditional on trade in the model.[8] Consistent with Berkman et al. (2012), night-minus-day returns in our model will be *predictable* only if order imbalances near the market open are predictable. Importantly, as we will show in this section, these imbalances are a necessary but not sufficient condition for night-minus-day returns to arise.

Our model features two types of liquidity providers with offsetting advantages. The *fast* type (i.e., designated or de facto market makers) has an information advantage in knowing the realization of π, whereas the *slow* type (i.e., large asset management firms) only knows the distribution of π but not its realization. However, the slow type has an advantage of lower inventory cost. Specifically, slow arbitrageurs are risk neutral and require zero expected profit to fill a trade, similar to the liquidity providers in Glosten and Milgrom (1985). Fast arbitrageurs only fill a trade if they expect to earn a required return $c_{\{a,b\}} = c' \times q_{\{a,b\}}$, where the constant c' is the required return per unit of inventory risk and $q_{\{a,b\}}$ is the trade size, similar to the liquidity providers in Grossman and Miller (1988). Consequently, fast arbitrageurs set bid and ask quotes asymmetrically around the expected fundamental value, resulting in mid-quotes that are too high (low) when fast arbitrageurs expect to absorb a positive (negative) liquidity demand, similar to Hendershott and Menkveld (2014).

Our characterization of fast arbitrageurs' information advantage is motivated by market makers' specialization in detecting high-frequency order flow patterns, including but not limited to the privileged first-look at retail order flows through payment for order flow arrangements.[9] Our assumption that slow arbitrageurs have a relatively lower inventory cost reflects the fact that large asset management firms' liquidity provision occurs when they use limit orders to achieve their optimal portfolio.[10] In contrast, market makers have a much smaller balance sheet, mostly rely on internal capital, and employ costly high-frequency trading technology, so their goal is to maximize profit with a minimal inventory position rather than earning the risk premium on their inventory position.[11]

2.2. Agents' optimization

We denote "slow" and "fast" arbitrageurs using the subscripts s and f, respectively. At each $t = 1, 2$, there is a round of trading. Both types of arbitrageurs post limit orders simultaneously and thus cannot learn from one another's quotes.[12] Any market participant may use marketable orders to trade with these limit orders. Both types of arbitrageurs, as well as informed traders, maximize their expected terminal wealth at $t = 2$.

At $t = 2$, η is observed by all participants including slow arbitrageurs, so fully competitive and risk neutral slow arbitrageurs set bid ($b_{s,t}$) and ask ($a_{s,t}$) prices to break even in equilibrium at $b_{s,2} = a_{s,2} = \tilde{v} = v_0 + \eta$, and slow arbitrageurs are the marginal investor at $t = 2$. Fast arbitrageurs continue to face inventory costs, so they optimize at $t = 2$ by using market orders to trade with slow arbitrageurs' limit orders and offload their inventory.[13]

At $t = 1$, agents' optimization problems are more subtle. Sentiment-driven traders buy with a probability $\lambda = \frac{1}{2}$ and sell otherwise. Informed traders optimize by choosing whether or not to trade with any extant limit orders at $t = 1$; they buy if and only if $\eta > a \in \{a_{f,1}, a_{s,1}\}$, or sell short if and only if $\eta < b \in \{b_{f,1}, b_{s,1}\}$. Their position's expected value per share, conditional on trading, is

$$\psi(\{a, b\}) \equiv \begin{cases} E(\eta|\eta > a) & \text{if long,} \\ -E(\eta|\eta < b) & \text{if short.} \end{cases} \tag{1}$$

When there is no ambiguity about the relevant ask and bid prices, we will drop the $\{a, b\}$ and simply refer to the expected value conditional on informed trades as ψ.

Recall that slow arbitrageurs know the distributions of π and η, but do not know the realization of either as of $t = 1$. They can form their expectation of π conditional on their posted quotes being best, which we denote $\tilde{\pi}$, with subscript a (ask) or b (bid) when needed to avoid ambiguity. Under this expectation, recalling that $v_0 \equiv 0$, they solve for bid and ask prices as follows

$$(1 - \tilde{\pi}_a)(\lambda)(a_{s,1}) + (\tilde{\pi}_a)(1 - \Phi_\eta(a_{s,1}))(a_{s,1} - \psi(a_{s,1})) = 0 \tag{2}$$

[7] The attention hypothesis put forward in Berkman et al. (2012) is one explanation of the predictable order imbalances. More broadly, achieving a better understanding of the specific underlying determinants of predictable demand at market open remains an interesting open question.

[8] We assume sentiment-driven and informed traders place orders of the same size such that the order size is not informative about the trader's type, which reflects the fact that informed traders routinely split their orders into smaller ones to mimic the size of retail orders.

[9] For example, as of 2021, Citadel Securities executed over 40% of all U.S.-listed retail volume. Citadel Securities likely has better knowledge regarding retail order flows than its competitors. See U.S. Congress, "Game Stopped? Who Wins and Loses When Short Sellers, Social Media, and Retail Investors Collide," hearings before the House Financial Services Committee, testimony of Kenneth Griffin, 117th Congress, Feb. 18, 2021.

[10] For example, Eduardo Repetto (Chief Investment Officer at Dimensional Fund Advisors) states, "We really like to act as a liquidity provider...In some sense we have an advantage over a market maker since we do not have inventory costs. We want to hold the securities that we buy for our portfolios." See Pichardo, Raquel. September 17, 2007. "Applied Scientist: Face to Face with DFA's Eduardo Repetto." Pensions & Investments, https://www.pionline.com/article/20070917/PRINT/70914035/applied-scientist-face-to-face-with-dfa-s-eduardo-repetto.

[11] "Fast" and "slow" characterize differences in information gathering and processing systems rather than trade execution speeds. Both market makers and large asset management companies have access to high speed trading systems either internally or via intermediaries, but they specialize in forming predictive signals over high and low frequencies, respectively.

[12] In practice, it is difficult for slow arbitrageurs to learn π because market makers can often use payment-for-order-flow arrangements to internalize orders at prices not immediately observable to slow arbitrageurs, and because which limit orders are posted by market makers is also unknown to slow arbitrageurs.

[13] Fast arbitrageurs who carry a positive (negative) inventory into $t = 2$ will have a reservation selling (or buying) price of $\tilde{v} - c_b$ (or $\tilde{v} + c_a$), and thus gladly trade with slow arbitrageurs using a market order at $\tilde{v}$. In the real world, fast arbitrageurs' overnight inventory costs are higher than their intraday inventory costs, so our use of c_a and c_b is a lower bound on fast arbitrageurs' incentives to offload their inventory to slow arbitrageurs.

$$(1-\tilde{\pi}_b)(\lambda)(-b_{s,1})+(\tilde{\pi}_b)(\Phi_\eta(b_{s,1}))(\psi(b_{s,1})-b_{s,1})=0 \tag{3}$$

where $\Phi_\eta(x)$ is the cumulative distribution function of η evaluated at x. In both equations, the first term (which is positive) represents the expected profits from trading against a sentiment-driven counterparty. The second term (which is negative) represents the expected losses from trading against an informed counterparty.

Conditional on a conjectured $\tilde{\pi}_a$, slow arbitrageurs solve (2) by setting an ask price which we denote by the function $s(\tilde{\pi}_a)$,[14]

$$a_{s,1}=s(\tilde{\pi}_a)=\frac{n\left(1-\sqrt{1-\tilde{\pi}_a^2}\right)}{\tilde{\pi}_a}, \tag{4}$$

The prices that solve Eqs. (2) and (3) are sustained in equilibrium only if slow arbitrageurs' expectation $\tilde{\pi}$ correctly reflects meeting an informed counterparty conditional on their quotes and fast arbitrageurs' quotes. Note that $\tilde{\pi}$ will generally *not* equal the unconditional expectation $E_0[\pi]$, because in some states of the world (specifically, those states with low realizations of π), fast arbitrageurs' limit orders will undercut slow arbitrageurs' orders, and hence slow arbitrageurs' orders will not be hit. Thus, slow arbitrageurs face an adversely selected subset of counterparties. In a world without fast arbitrageurs, $\tilde{\pi}$ equals its unconditional expectation, and the analysis reduces to Glosten and Milgrom (1985).

The fast arbitrageur's problem is simpler: they observe π and hence simply post prices $a_{f,1}, b_{f,1}$ which solve

$$(1-\pi)(\lambda)(a_{f,1}-c_a)+(\pi)(1-\Phi_\eta(a_{f,1}))\big(a_{f,1}-c_a-\psi(a)\big)=0, \tag{5}$$

$$(1-\pi)(\lambda)(-b_{f,1}-c_b)+(\pi)(\Phi_\eta(b_{f,1}))\big(\psi(b)-b_{f,1}-c_b\big)=0 \tag{6}$$

The solution is denoted by the function $f(\pi)$, where[15]

$$a_{f,1}=f(\pi)=\frac{\pi c_a+n-\sqrt{\pi^2c_a^2+n^2(1-\pi^2)}}{\pi}. \tag{7}$$

Thus, when c is nonzero, fast arbitrageurs post an ask price higher than (and bid price lower than) the conditional expected fundamental value.

Figure 1 visualizes this ask price curve for $n=5$ and $c'=1$. In the left panel, we plot the fast arbitrageur's ask price as a function of π for $q_a=1.5$, the bid price $b_{f,1}$ for $q_b=0.5$, and the associated mid-quote $m_{f,1}=\frac{a_{f,1}+b_{f,1}}{2}$. With $q_a>q_b$, we observe asymmetric ask and bid price curves, and the midpoint of ask and bid quotes deviates from the expected fundamental value (i.e., $m_{f,1}>E_0(\tilde{v})=0$). In the right panel, we compare the ask price curve to the expected fundamental value conditional on a trade occurring at the ask, $E_1(\tilde{v}|\text{trade})$. The difference between these two lines captures the post-trade price deviation conditional on a trade occurring at the ask price, as opposed to the pre-trade price deviation illustrated in the left panel. Both pre-trade and average post-trade price deviations are increasing in fast arbitrageurs' required returns from liquidity provision. As we will see below, these deviations give rise to night-minus-day returns because overnight returns reflect fast arbitrageurs' required returns from providing liquidity, while intraday returns reflect the correction of these deviations as slow arbitrageurs replace fast arbitrageurs in determining the price of liquidity.

However, given that fast arbitrageurs' $t=1$ quotes generate profits that cover their inventory costs, one may wonder why slow arbitrageurs with no capital constraints do not undercut fast arbitrageurs by posting a narrower bid-ask spread at open. As we demonstrate below, this is because the fast arbitrageur's superior information about π exposes the slow arbitrageur to adverse selection risk. The analyses of the bid prices are similar, so we focus on the ask prices to avoid duplication.

2.3. Adverse selection

Slow arbitrageurs face two types of adverse selection. First, informed traders have more precise information about the fundamental value. Second, fast arbitrageurs have an informational advantage in knowing π, enabling them to disproportionately fill the marketable orders from sentiment-driven traders. Thus, if a slow arbitrageur places limit orders at $t=1$, those orders will be predominantly filled when the counterparty is informed, as shown in the following Lemma.

Lemma 1 (Cream skimming risk). *Suppose a slow arbitrageur posts an ask price $a_{s,1}=s(\tilde{\pi})$. The ask price will be competitive if and only if*

$$\pi \geq f^{-1}(s(\tilde{\pi})), \tag{8}$$

where $f^{-1}(a)$ is the inverse of $f(\pi)$ as defined in Eq. (7).

Proof. See Appendix A. □

Our analysis will focus on this cream skimming adverse selection, because this interplay between fast and slow arbitrageurs determines the identity of the marginal liquidity provider, and hence the predictable night-minus-day return. Intuitively, suppose a slow arbitrageur posts a limit order, expecting that she meets an informed trader with probability $\tilde{\pi}$. If fast arbitrageurs observe a true π that is sufficiently low compared to $\tilde{\pi}$, they will post a narrower spread than slow arbitrageurs and fill these orders. That is, fast arbitrageurs will "cream-skim" orders when counterparties are most likely to be uninformed. Understanding this, slow arbitrageurs have to set a wider spread than they would have done in the absence of competition from fast arbitrageurs, which makes it difficult for them to undercut fast arbitrageurs' quotes despite their advantage in cost of capital.

Our proposed cream skimming mechanism is related to Hoffmann (2014), which explores the effects of fast traders' ability to update stale limit orders to prevent

[14] See Appendix A for brief discussion of this calculation. While we focus on ask prices in the main text, note the slow arbitrageur's expression for the bid price is similar: $b_{s,1}=\frac{-n\left(1-\sqrt{1-\tilde{\pi}_b^2}\right)}{\tilde{\pi}_b}$.

[15] Again, bid prices are similar: $b_{f,1}=\frac{-\pi c_b-n+\sqrt{\pi^2c_b^2+n^2(1-\pi^2)}}{\pi}$.

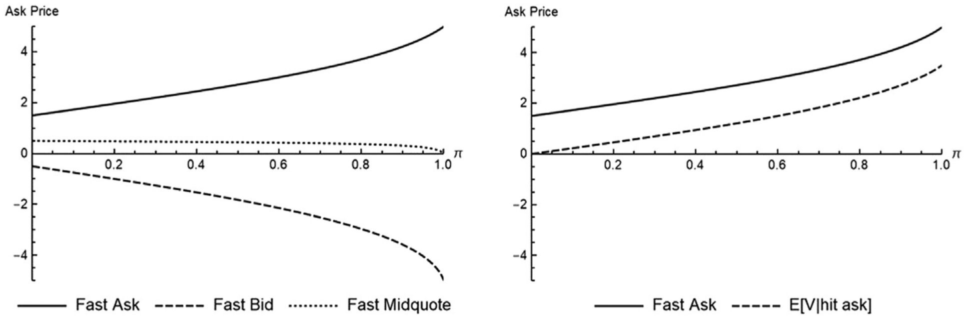

Fig. 1. Fast Arbitrageurs' Ask (Bid) Price Curve. This figure plots an example of our model's equilibrium ask price posted by fast arbitrageurs (solid line) in the presence of unpriced private information (described by parameters $n = 5$, $c_a = 1.5$, $c_b = 0.5$), along with bid and midquote prices (left panel) and the expected fundamental value conditional on a trade occurring at ask prices, $E_1[\tilde{v}|\text{trade}]$ (right panel). The x-axis gives the probability of meeting an informed trader, π. The unconditional expected value of the asset is zero, so that the difference between the dotted line and zero in the left panel corresponds to the positive deviation of the fast arbitrageur's midquote from the pre-trade fundamental value. In the right panel, the difference between the solid and dashed lines is the predictable price deviation conditional on a market buy, which is equal to fast arbitrageurs' required return, $c_a = c' \times q_a$.

them from being picked off by late-arriving (also dubbed "slow") traders. Similar to our results, he shows that slow traders post wider quotes than fast traders. However, his model focuses on bargaining power among monopolistic, sequentially-arriving, short-lived traders with heterogeneous speed, whereas our model features competitive fast and slow liquidity providers that coexist simultaneously in the market and endogenously become the marginal liquidity provider under different market conditions.

2.4. Equilibrium

Equilibrium in this economy is defined by the arbitrageurs' limit orders $a_{s,1}$ and $a_{f,1}$, such that, conditional on all agents' choices, both types of arbitrageurs correctly assess their counterparties' expected informedness. The following proposition characterizes slow arbitrageurs' ask prices in the presence of fast arbitrageurs.

Proposition 1 (Endogenous limited participation). *For any $\tilde{\pi}$, a slow arbitrageur is willing to price her limit order at $s(\tilde{\pi})$ if and only if*

$$\frac{f^{-1}(s(\tilde{\pi})) + 1}{2} \leq \tilde{\pi}. \tag{9}$$

As long as Eq. (9) is satisfied by some $\tilde{\pi} \in [0, 1]$, then the equilibrium $\tilde{\pi}$ will solve

$$f(2\tilde{\pi} - 1) = s(\tilde{\pi}). \tag{10}$$

For $\pi < \pi^* \equiv f^{-1}(s(\tilde{\pi}))$, slow arbitrageurs' quotes are inferior to fast arbitrageurs' quotes and thus fast arbitrageurs determine the price of liquidity at $t = 1$.

Proof. See Appendix A. □

Limited participation arises because slow arbitrageurs understand fast arbitrageurs' information advantage and hence form their equilibrium assessment of $\tilde{\pi}$ such that, given their ask price $s(\tilde{\pi})$, the average likelihood of meeting an informed counterparty is indeed $\tilde{\pi}$. Hence, their ask prices are above those of fast arbitrageurs in the region of $\pi < \pi^*$. In effect, slow arbitrageurs withdraw from setting the price of liquidity in this region despite their advantage of requiring a lower return from liquidity provision.

Fast arbitrageurs' information advantage increases in the amount of unpriced private information (n). We plot ask prices for fast and slow arbitrageurs for several values of n in Fig. 2. When the amount of unpriced private information is large (left panel, $n = 5$), fast arbitrageurs determine the price of liquidity for almost all assets ($\pi^* \approx 1$). With a moderate amount of unpriced private information (middle panel, $n = 3$), fast (slow) arbitrageurs determine the price of liquidity for assets with low (high) realizations of π. Lastly, when the amount of unpriced private information is small (right panel, $n = 0.75$), slow arbitrageurs determine the price of liquidity for all assets ($\pi^* = 0$). Thus, slow arbitrageurs end up being the marginal liquidity providers not just for stocks with little informed trading (small n), but also for stocks with lots of informed trading (high π).

For the assets where fast arbitrageurs determine the price of liquidity at the market open, the following Proposition characterizes the determinants of the price deviation and the resulting night-minus-day return.

Proposition 2 (Determinants of predictable night-minus-day returns). *For an asset with $\pi < \pi^*$, the price at market open ($t = 1$) is determined by fast arbitrageurs and thus deviates from expected fundamental values; the price at market close ($t = 2$) is determined by slow arbitrageurs and thus is equal to fundamental value. As a result, overnight returns and intraday returns will have opposite signs in expectation, generating expected night-minus-day returns that are increasing in c' and $(q_a - q_b)$.*

Proof. See Appendix A. □

Two types of variation in unpriced information are relevant. First, cross-sectionally, fast arbitrageurs are less likely to be the marginal liquidity provider for assets with less unpriced private information around market open (e.g., European dual-listed stocks, as we discuss in 4.3.1). Second, fast arbitrageurs are less likely to be the marginal liquidity provider at market close when intraday trading has re-

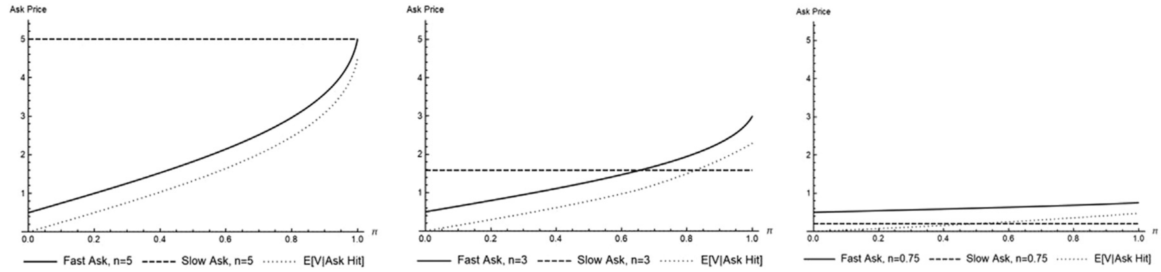

Fig. 2. Unpriced Private Information and the Marginal Liquidity Provider. This figure plots an example of our model's equilibrium ask prices for fast and slow arbitrageurs when unpriced private information is large (left panel, $n = 5$), moderate (middle panel, $n = 3$), and small (right panel, $n = 0.75$), for an asset with expected fundamental value $v_0 = 0$. Each panel also plots the expected fundamental value conditional on a trade executed at the best ask (dotted line). For all panels, the x-axis gives the probability of meeting an informed trader, π. In the left panel, at market open, for almost all π, the ask price of fast arbitrageurs with inventory cost $c_a = 0.5$ (solid line) undercuts the slow arbitrageur's ask price (dashed line). In the middle panel, with lower n, slow arbitrageurs' ask prices allow them to determine the price of liquidity where π is high, while fast arbitrageurs determine the price of liquidity where π is low. In the right panel, when unpriced private information is low, both slow and fast arbitrageurs post narrower quotes, but slow arbitrageurs' ask price (dashed line) falls below that of fast arbitrageurs. In all plots, over the regions where fast arbitrageurs determine the price of liquidity, the marginal ask prices exceed conditional fundamental values, and over the regions where slow arbitrageurs determine the price of liquidity, the marginal ask prices equal conditional fundamental values on average.

duced the unpriced private information.[16] For the subset of stocks where fast arbitrageurs determine the price of liquidity at market open, both pre-trade midquotes and prices of executed trades deviate from expected fundamental values, as illustrated in Fig. 1, leading to predictable night-minus-day returns that are increasing in fast arbitrageurs' inventory cost and in the expected order imbalance absorbed. For the subset of stocks where slow arbitrageurs determine the price of liquidity, midquotes and executed trade prices equal expected fundamental values and there is no predictable night-minus-day return.

2.5. Testable implications

Below we summarize testable predictions from the key economic forces characterized in the model.

Prediction 1. While predictable night-minus-day returns imply opposite movements in prices at market open and throughout the rest of the day, the associated order imbalances need not exhibit similar swings.

Proof. See Appendix A. □

Our model includes two key components: heterogeneous liquidity providers and variation in unpriced private information throughout the trading day. Both components are necessary for night-minus-day returns to occur in conjunction with persistent imbalances. Without heterogeneous liquidity providers, our model reduces to a standard price pressure story, in which persistent order imbalances cannot give rise to recurring swings in prices. Without variation in unpriced private information, the importance of each type of liquidity provider in setting the price would not vary throughout the trading day.

With these two components, order flows need not change sign throughout the day to generate price reversals. Fast arbitrageurs absorb order imbalances in the morning and then pass on the same imbalances to slow arbitrageurs near the market close. To the extent that fast arbitrageurs tend to enter positions passively and exit them actively, their exits generate order imbalances later in the day which are of the *same* sign as those at open. Unlike the open imbalances, these latter imbalances do not generate additional price pressure, because slow arbitrageurs have large amounts of capital to accommodate accumulated sentiment-driven demand and hold positions over longer horizons. As a result, while overnight returns are driven by market makers' inventory costs associated with absorbing order imbalances at open, intraday returns are driven by the increasing importance of slow arbitrageurs in setting the price of liquidity. Hence, the model can accommodate the negative correlation between overnight and intraday returns even when accompanied by order imbalances that have the same sign at open and at close.

Prediction 2. Cross-sectional differences in predictable night-minus-day stock returns align with cross-sectional differences in the predictable liquidity demand absorbed by fast arbitrageurs near market open, and the magnitude of this cross-sectional relationship increases in fast arbitrageurs' required returns from liquidity provision.

Proof. See Appendix A. □

The intuition for Prediction 2 is that, due to cream skimming risk, fast arbitrageurs are the marginal liquidity provider for selected assets around market open. The predictable night-minus-day returns are compensation for fast arbitrageurs' liquidity provision, and the magnitude increases in fast arbitrageurs' required returns. However, among the subset of assets where fast arbitrageurs do not determine the price of liquidity, the above patterns should be attenuated, as we discuss in the following prediction.

Prediction 3. Among stocks for which n is small and π is more positive, slow arbitrageurs are more likely to determine the price of liquidity; and thus among these stocks,

[16] Therefore, our model implications still hold when the assumption that private information is fully revealed at $t = 2$ is relaxed, as long as n at $t = 2$ is sufficiently small.

the relationship between fast arbitrageurs' liquidity provision and future returns will be attenuated.

Proof. See Appendix A. □

There are several illustrative cases to consider. For stocks with small n, the risk of providing liquidity to an informed counterparty is low. Crucially, both types of arbitrageurs know this, so slow arbitrageurs will typically be able to undercut fast arbitrageurs and determine the price of liquidity, as shown in Fig. 2 above. That is, as unpriced private information n becomes smaller, the threshold π^* (below which fast arbitrageurs undercut slow ones) approaches zero, so the importance of fast arbitrageurs' information advantage – the likelihood of fast arbitrageurs observing $\pi < \pi^*$ – shrinks.

For stocks with large n, if π is low, the risk of providing liquidity to an informed counterparty is again low. But only fast arbitrageurs know this, so slow arbitrageurs' quotes are inferior to fast arbitrageurs' among these stocks. As a result, among stocks with large n, slow arbitrageurs' quotes only bind if π is high (formally, with large n, equilibrium π^* is more positive, so $\pi > \pi^*$ only if π is high).

Aggregating over these cases, our model predicts that fast arbitrageurs will tend to be the marginal liquidity provider when n is large and the realization of π is low, while slow arbitrageurs will tend to be the marginal liquidity provider when n is small, or when n is large and π is high.[17] Prediction 3 is testable in two ways. First, the relationship between expected night-minus-day returns and expected liquidity provision of fast arbitrageurs should attenuate among stocks where n is predictably low at open. We investigate this aspect of Prediction 3 in Section 4.3.1. Second, π is privately observed by fast arbitrageurs, so by definition it is not predictable. However, we can still test Prediction 3 conditional on the realized liquidity provision of fast arbitrageurs. The idea is that fast arbitrageurs' choice to reduce their liquidity provision around market open is a signal that $\pi > \pi^*$ (either because of small n or large π), which implies they are less likely to determine the price of liquidity. Therefore, when fast arbitrageurs provide less liquidity, liquidity demand absorbed by fast arbitrageurs will predict future returns less strongly.

3. Data and measurement

3.1. Sample construction

We start by collecting data from the Center for Research in Security Prices (CRSP) database for all U.S. common stocks listed on the NYSE, AMEX, and NASDAQ stock exchanges. We then merge the CRSP data with the NYSE Trade and Quote (TAQ) database using the TAQ-CRSP link table provided by Wharton Research Data Services (WRDS). Our sample begins on January 4, 1993 due to the availability of TAQ data. See Section 1 of the Internet Appendix for a detailed description of the merge procedure. We impose the following data filters. First, like Hendershott et al. (2020), we drop stock days with an intraday return of over 1000% or when the open price is missing. Second, to mitigate microstructure issues and ensure that our results are not driven by small and illiquid stocks, we require the following for a stock to be included in the sample at the end of month t: (i) the stock's median daily trading volume in month t is greater than 1,000 shares, (ii) the stock has no more than one missing open price from CRSP in month t, and (iii) following Lou et al. (2019), stocks need to have a price above \$5 and a market capitalization above the NYSE bottom quintile at the end of month t. The night-minus-day return patterns are similar but larger in magnitude among microcap and low-priced stocks.

3.2. Measurement of overnight and intraday returns

We compute the intraday return ($r_{D,d}$) on day d as,

$$r_{D,d} = \frac{P_d^{close}}{P_d^{open}} - 1, \tag{11}$$

and the overnight return ($r_{N,d}$) from the close of day $d-1$ to the open of day d as,

$$r_{N,d} = \frac{1 + r_{\text{close-to-close},d}}{1 + r_{D,d}} - 1, \tag{12}$$

where $r_{\text{close-to-close},d}$ is the close-to-close return on day d. The daily night-minus-day return is then,

$$r_{NMD,d} = r_{N,d} - r_{D,d}. \tag{13}$$

Following Lou et al. (2019), our main specification of P_d^{open} is the volume-weighted average price between 9:30 am and 10:00 am. We also use the midquotes at 9:45 am and 10:00 am as alternative specifications of P_d^{open} in robustness tests, which are reported in Section 4 of the Internet Appendix. We compute $r_{\text{close-to-close},d}$ using the closing trade prices from TAQ as P_d^{close} and adjust for stock splits and dividends.[18]

3.3. Measurement of liquidity demand absorbed by fast arbitrageurs

Our model predicts that night-minus-day returns are driven by fast arbitrageurs' liquidity provision. Our empirical proxies for fast arbitrageurs' liquidity provision are the order imbalances computed based on the Lee and Ready (1991) algorithm and the Boehmer et al. (2021) (hereafter, BJZZ) algorithm. The advantage of the Lee-Ready algorithm is that it can classify all trades in the TAQ database as either buyer- or seller-

[17] In our model, fast arbitrageurs provide liquidity only if they are the marginal liquidity provider. In practice, for reasons outside the model (e.g., rebate arbitraging), fast arbitrageurs may still provide some liquidity even at times when slow arbitrageurs determine the price of liquidity.

[18] Hendershott et al. (2020) use the open price from CRSP, Berkman et al. (2012) use the first midquote after market open, and Bogousslavsky (2021) uses the midquote at 9:45 am. The night-minus-day return predictability is larger in magnitude when a price closer to the market open is used as P_d^{open} (see related discussions in Bogousslavsky (2021)).

initiated, so the resulting buy-minus-sell order imbalance is available starting in 1993.[19] However, in our model and in practice, fast arbitrageurs can be on the aggressive side of trades and other types of traders (e.g., slow arbitrageurs) can be on the passive side of trades, so the Lee-Ready order imbalance is at best a noisy measure of fast arbitrageurs' liquidity provision.[20]

BJZZ note that after the implementation of Regulation National Market System (Regulation NMS) in 2005, trades at non-midpoints with a subpenny price improvement are predominantly retail marketable orders filled by wholesalers and brokers. These orders are recorded in TAQ with exchange code "D", and the buy/sell direction of these trades can be identified by the magnitude of the subpenny price improvements. While the order imbalances captured by the BJZZ algorithm are commonly used as a proxy for retail trading demand,[21] the BJZZ order imbalances also reflect wholesalers' incentives to internalize these order flows (Barardehi et al., 2021). Thus, the BJZZ order imbalances map nicely onto our theoretical model – these trades are internalized by market makers likely because they have a lower probability of being informed. Furthermore, given that the BJZZ order imbalances are known to be filled by market makers (i.e., the fast arbitrageurs in our model), they are not contaminated by non market makers' liquidity provision. Therefore, we consider the BJZZ order imbalances to be a more accurate proxy for fast arbitrageurs' liquidity provision than the Lee-Ready order imbalances. The disadvantage of using the BJZZ order imbalance is its shorter sample period: following the convention in the WRDS data manual, we are only able to compute it in the post-October 2006 period when subpenny price improvements become more prevalent.

In our empirical analysis, we refer to the BJZZ order imbalances as the *retail* order imbalance absorbed by *market makers* (hereafter, RM OI), the Lee-Ready order imbalance as the total order imbalance (hereafter, OI), and the difference between OI and RM OI as Non-RM OI. We use RM OI as our main proxy for the liquidity provision by fast arbitrageurs and then use OI as the alternative proxy when conducting robustness tests over the full sample period. We scale order imbalance variables by daily trading volumes (both in number of shares) at the stock level and then compute value-weighted order imbalance ratios at the portfolio level. All our inferences remain qualitatively the same when we scale the order imbalances by the stock's total shares outstanding, which we report in Section 2 of our Internet Appendix.

4. Empirical results

4.1. Evaluating the existing price pressure hypothesis (Prediction 1)

Existing explanations for night-minus-day return predictability focus on the role of order flow shocks. Berkman et al. (2012) emphasize price pressures at market open, arguing that "attention-based retail trading causes prices to temporarily deviate from fundamental values at the open of the typical trading day." Other studies emphasize opposing price pressures that arise both at the market open and close, either from different clienteles as in Lou et al. (2019), where "[s]ome investors may prefer to trade at or near the morning open while others may prefer to trade during the rest of the day up to and including the market close"; or from the same clientele as in Hendershott et al. (2020), where "[a] speculator buys higher beta stocks at the open and reverses her position approaching the close".

If predictable order flow shocks solely determine the predictable night-minus-day returns of the characteristic-sorted portfolios studied in the literature, then the opposite-signed overnight and intraday returns of these portfolios should be associated with corresponding opposite-signed order flows near the market open and over the rest of the trading day.

We test this benchmark price pressure hypothesis using the 17 portfolios studied by Lou et al. (2019) (the "LPS portfolios"). These are anomaly-sorted long-short portfolios that are value-weighted and rebalanced monthly. As shown by Panel A of Fig. 3, these portfolios tend to have average r_N and r_D that are large in magnitude but opposite in sign. We summarize the common component of these portfolios' night-minus-day returns using the Bayesian stochastic discount factor (SDF) estimator proposed by Kozak et al. (2020). The resulting SDF implied night-minus-day mean-variance efficient (hereafter, NMD MVE) portfolio is a simple linear combination of the LPS portfolios.[22] The weights are constant over time and normalized by the sum of their absolute values so that the NMD MVE portfolio remains a zero-cost one-dollar long-short portfolio. For comparison, we also construct the corresponding SDF based on the close-to-close returns of the LPS portfolios (RET MVE). Table 1 reports the NMD MVE and RET MVE weights, which have opposite signs for 12 out of the 17 portfolios. We explore this difference more in Section 5.2.

Panel A of Fig. 3 shows that the NMD MVE portfolio has average overnight and intraday returns of 13% and −15% per annum, respectively. Panel B of Fig. 3 further shows that the average overnight and intraday returns of the NMD MVE portfolio have CAPM alphas of 12% and

[19] We thank Craig Holden and Stacey Jacobsen for making their SAS code used in Holden and Jacobsen (2014) available for performing the Lee and Ready algorithm. We thank Greg Eaton, Stacey Jacobsen, Zhengzi Li, and Vincent Bogousslavsky for helpful discussions of these SAS codes.

[20] Fast arbitrageurs are often on the active side of trades. In our model, fast arbitrageurs are on the passive side at $t = 1$, but on the active side at $t = 2$. Empirically, our data on high-frequency trading firms (more details in Section 4.3.2) show that these de facto market makers are on the passive (aggressive) side for 49% (51%) of the dollar trading volume when they trade with other types of traders.

[21] While the BJZZ order imbalance is not a perfect measure of retail order flows (e.g., it does not capture limit retail order flows), it has quickly become the standard proxy for retail order flows due to the lack of alternative measures that cover a broad panel of stocks.

[22] Kozak et al. (2020) show that their SDF coefficients are proportional to the weights of a $L2$-norm constrained MVE portfolio, which works better out of sample than the unconstrained MVE portfolio. Appendix B provides a detailed description of the NMD MVE portfolio construction.

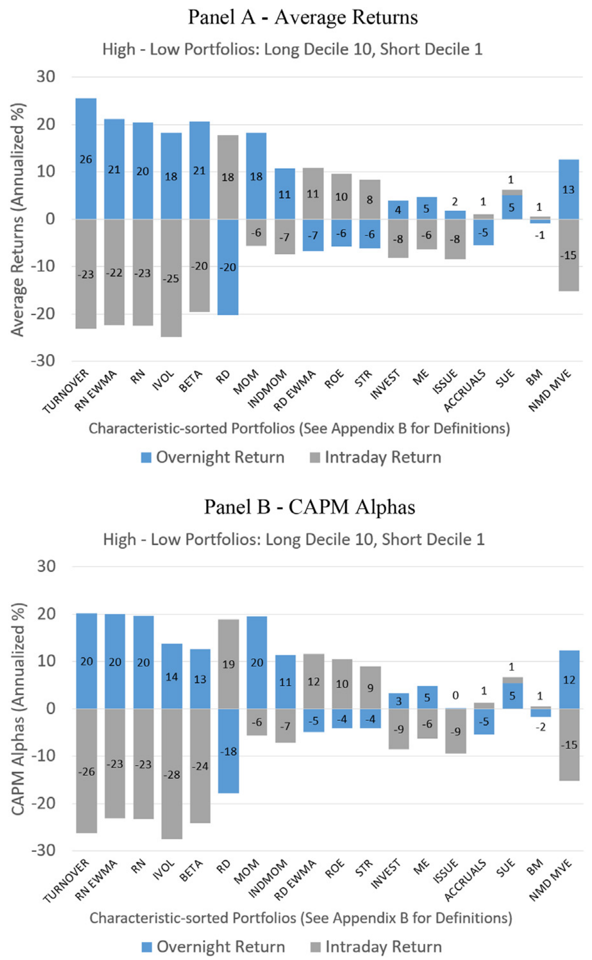

Fig. 3. Predictable Overnight and Intraday Returns. This figure plots the average overnight (r_N) and intraday (r_D) returns (Panel A) and CAPM alphas (Panel B) of the 17 high-minus-low Lou, Polk, and Skouras (2019, LPS) portfolios and the night-minus-day mean variance efficient (NMD MVE) portfolio in annualized percentage points. The portfolio returns are measured between February 1, 1995 and December 31, 2020.

−15%, respectively.[23] Hence, adjusting for market exposure accounts for only 1% per annum out of the 28% per annum predictable night-minus-day return. While we already exclude microcap stocks, we further demonstrate the robustness of this pattern by reporting the corresponding return patterns among S&P 500 stocks in Section 4 of our Internet Appendix. We find that the predictable night-minus-day returns remain economically large in the S&P 500 sample, with the NMD MVE portfolio earning overnight and intraday CAPM alphas of 11% and −13%, respectively.

To contrast the expected night-minus-day return pattern with the expected order imbalance pattern, we plot the average cumulative return of the NMD MVE portfolio over 30-minute intervals beginning at the previous day's market close and continuing until the current day's close in Fig. 4. We then plot the hypothetical order imbalances under the benchmark price pressure hypothesis in Panel A of Fig. 4, which depicts hypothetical order imbalances that follow the observed returns by being positive around the market open and negative over the rest of the day. Panel B presents the true average order imbalance of the NMD MVE portfolio in the data. We find that the true average OI is not only positive near the market open, but also remains positive throughout the rest of the day. That is, the order imbalance pattern does not mirror the price pattern.

We conduct formal tests of these order imbalance patterns in Table 2. Panel A tests the significance of the time-series mean of the order imbalance associated with the NMD MVE portfolio. If the stock characteristics used to form the portfolio do not predict order imbalances, then the mean order imbalance should be zero. Instead, we find that the average OI of the NMD MVE portfolio is positive and statistically significant at the 1% level for *each* of 13 half-hour trading intervals. In the subsequent rows, we separately examine RM OI and Non-RM OI in the post-October 2006 sample when such data are available. During this period, the average OI remains positive and statistically significant for all 13 half-hour trading intervals, albeit with smaller magnitudes across the board. The average RM OI and Non-RM OI are also all positive and statistically significant across the 13 half-hour trading intervals, with RM OI accounting for about one-fourth to one-third of the total order imbalance.

Panel B tests the significance of the autocorrelation between the order imbalances associated with the NMD MVE portfolio in the first half-hour interval (i.e., the market open) and those in each of the 12 remaining half-hour intervals. Specifically, we estimate a time-series predictive regression using daily data and conduct inference using Newey and West (1987) standard errors with 21 lags. Con-

Table 1
Mean-Variance Efficient Portfolio Weights. This table compares the night-minus-day mean-variance efficient (NMD MVE) and close-to-close mean-variance efficient (RET MVE) portfolios in terms of their mean-variance efficient loadings. We report the loadings in percentage points for each of the 17 high-minus-low Lou, Polk, and Skouras (2019, LPS) portfolios. The sample period is between February 1, 1995 and December 31, 2020.

Signal	NMD MVE Weights (%)	RET MVE Weights (%)
r_D	−10.49	−6.51
r_N	14.96	−4.39
r_D^{ewma}	−4.60	1.28
r_N^{ewma}	15.58	−4.24
BETA	3.02	−1.81
IVOL	6.46	−8.90
BM	7.21	−1.71
ISSUE	−3.00	−12.33
ACCRUALS	0.90	−6.20
INV	3.05	−10.52
ROE	−2.43	5.14
ME	9.68	−6.61
SUE	2.15	9.37
MOM	3.19	8.00
STR	−2.58	5.81
TURNOVER	6.56	6.02
INDMOM	4.14	−1.16

[23] We compute the CAPM alphas of these portfolios by regressing their r_N and r_D on the overnight and intraday returns of the market portfolio, respectively, to allow for different overnight and intraday market betas as well as the different overnight and intraday market excess returns (Cooper et al., 2008; Bondarenko and Muravyev, 2022, and Boyarchenko et al., 2022).

Table 2

The Predictable Order Imbalances of the NMD MVE Portfolio. This table presents the predictable order imbalance pattern of the night-minus-day mean-variance efficient (NMD MVE) portfolio across 30-minute trading intervals. Each column presents the ending point of a 30-minute trading interval during market trading hours, with the first (last) column ending at 10:00 AM (4:00 PM). Panel A reports the time series average of the order imbalances (in basis points per the daily trading volume in shares) and Panel B reports the autocorrelation coefficient between order imbalances in the first interval and those in each of the 12 remaining intervals. OI is order imbalances identified by the Lee and Ready (1991) algorithm, RM OI is the retail order imbalance absorbed by market makers identified by the Boehmer et al. (2021) algorithm, and Non-RM OI is the difference between the two. Order imbalances for the NMD MVE portfolio are computed by multiplying the value-weighted order imbalances for each of the 17 LPS long/short portfolios by their corresponding NMD MVE portfolio weight, and then summing the products. We report t-statistics in parentheses, computed based on Newey and West (1987) standard errors with 21 lags. In the first row for the full sample, OI is measured between February 1, 1995 and December 31, 2020. In the subsequent rows, OI, RM OI, and Non-RM OI are measured between October 1, 2006 and December 31, 2020.

Panel A - Average Predictable Order Imbalances

	10:00 AM	10:30 AM	11:00 AM	11:30 AM	12:00 AM	12:30 AM	1:00 PM	1:30 PM	2:00 PM	2:30 PM	3:00 PM	3:30 PM	4:00 PM
OI (Full Sample)	11.92	8.97	8.08	7.34	6.79	5.93	5.45	4.48	4.65	5.30	6.53	5.30	5.07
	(13.45)	(12.45)	(12.43)	(12.91)	(13.29)	(12.44)	(11.72)	(10.11)	(11.23)	(11.33)	(10.93)	(9.76)	(5.70)
OI	4.88	3.68	3.24	3.07	2.81	2.85	2.22	2.52	2.30	2.34	2.73	2.73	2.11
	(8.78)	(10.96)	(10.83)	(11.09)	(11.08)	(12.93)	(10.25)	(12.31)	(11.18)	(10.85)	(11.24)	(9.84)	(4.44)
RM OI	1.88	1.23	1.07	0.96	0.86	0.83	0.77	0.73	0.71	0.79	0.77	0.79	0.45
	(19.80)	(18.31)	(19.00)	(17.72)	(18.44)	(16.81)	(18.11)	(18.26)	(15.22)	(17.69)	(17.57)	(16.18)	(6.88)
Non-RM OI	3.00	2.45	2.17	2.11	1.95	2.02	1.45	1.79	1.59	1.55	1.94	1.94	1.66
	(5.66)	(7.43)	(7.52)	(7.90)	(8.00)	(9.72)	(6.92)	(8.94)	(7.81)	(7.51)	(8.26)	(7.17)	(3.53)

Panel B - Autocorrelation Coefficients

Predictive Coef	10:00 AM	10:30 AM	11:00 AM	11:30 AM	12:00 AM	12:30 AM	1:00 PM	1:30 PM	2:00 PM	2:30 PM	3:00 PM	3:30 PM	4:00 PM
OI (Full Sample)	1.00	0.20	0.13	0.11	0.09	0.08	0.07	0.04	0.06	0.07	0.08	0.07	0.11
		(9.82)	(8.65)	(8.84)	(6.99)	(7.08)	(6.30)	(4.17)	(7.46)	(6.19)	(6.97)	(4.90)	(5.77)
OI	1.00	0.10	0.06	0.05	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.05
		(4.66)	(5.28)	(4.47)	(2.78)	(1.71)	(1.67)	(2.27)	(2.78)	(2.01)	(2.51)	(1.55)	(3.22)
RM OI	1.00	0.24	0.16	0.12	0.10	0.10	0.08	0.06	0.06	0.06	0.06	0.08	0.05
		(14.23)	(11.73)	(9.13)	(8.35)	(8.66)	(6.97)	(6.15)	(4.38)	(5.08)	(4.87)	(5.54)	(2.43)
Non-RM OI	1.00	0.10	0.06	0.05	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.04
		(4.75)	(5.03)	(4.40)	(2.56)	(1.56)	(1.53)	(2.21)	(3.06)	(1.89)	(2.49)	(1.49)	(2.95)

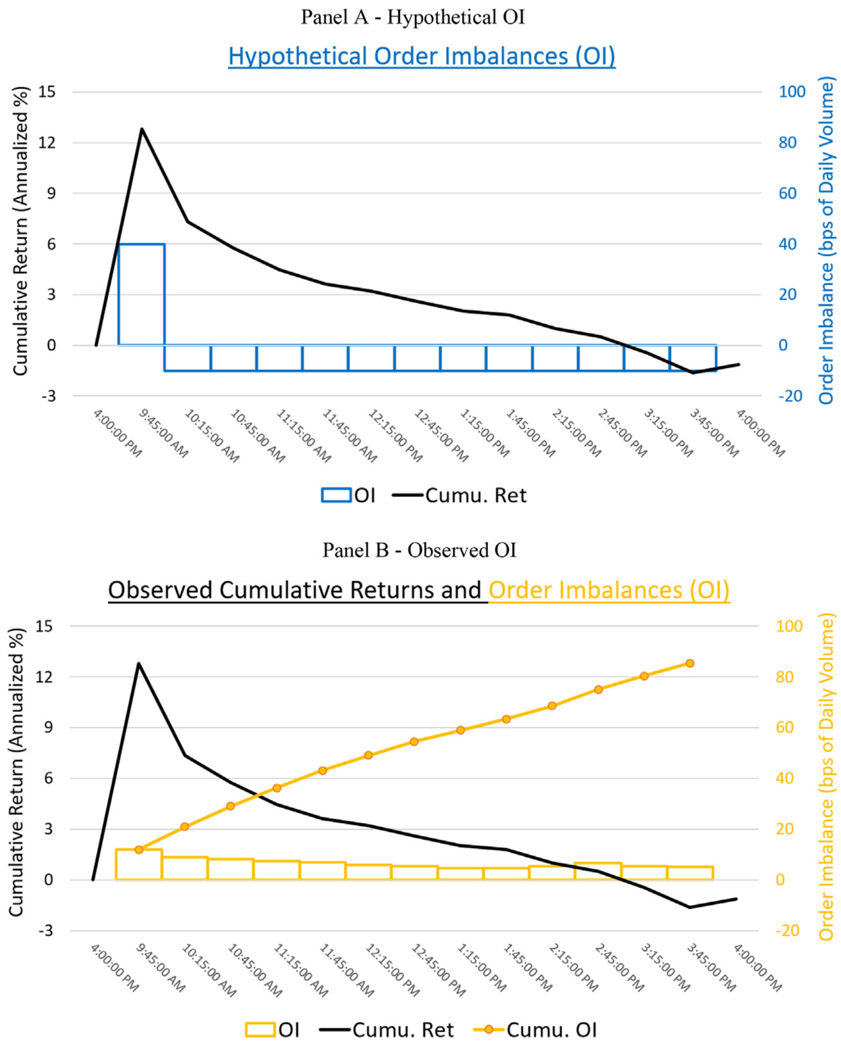

Fig. 4. Returns and Order Imbalances of the NMD MVE Portfolio. This figure plots the average cumulative returns and order imbalances of the night-minus-day mean variance efficient (NMD MVE) portfolio over 30-minute intervals of a trading day. Cumulative returns are computed from the previous day's close as $\frac{P_d^\tau}{P_{d-1}^{\text{close}}} - 1 = \frac{(1+r_{\text{close-to-close},d})}{(1+r_{\tau,d})} - 1$, where $1 + r_{\tau,d} = \frac{P_d^{\text{close}}}{P_d^\tau}$ and P_d^τ is the volume-weighted price in the 30-minute interval τ in day d. Both panels report the observed cumulative returns. Panel A presents the hypothetical order imbalance pattern under the benchmark price pressure hypothesis that order imbalances and returns are positively correlated. Panel B reports the average Lee and Ready (1991) order imbalances in the data. The sample period is between February 1, 1995 and December 31, 2020.

sistent across OI, RM OI, and Non-RM OI, the NMD MVE portfolio's order imbalances in the first half-hour positively predict its order imbalances in each of the remaining 12 half-hour intervals of the day, with 29 out of the 36 autocorrelations being significant at the 5% level.

Together, the above results suggest that the expected order imbalances associated with the NMD MVE portfolio are in the same direction throughout the trading day. Our results are related to Berkman et al. (2012)'s finding that stocks attracting retail investors' attention have more positive retail order imbalances at the market open and more positive night-minus-day returns. While Berkman et al. (2012)'s finding highlights the role of retail order imbalances in driving the night-minus-day returns, we show it cannot be the full explanation. Both RM OI and OI of the NMD MVE portfolio are not only positive near the market open, but also positive throughout the rest of the day. These patterns hence challenge the benchmark price pressure hypothesis: if the positive expected order imbalance near the market open causes the predictably positive r_N of the NMD MVE portfolio, why would its similarly positive expected order imbalances over the rest of the day cause a predictably *negative* r_D?

Our model provides a resolution to this puzzle. Fast arbitrageurs absorb the order imbalances in the morning and then pass on the same imbalances to slow arbitrageurs near the market close.[24] Slow arbitrageurs would be willing to accept lower compensation for absorbing the order

[24] For example, fast arbitrageurs fill a market buy order in the morning and then close their short position with a market buy order of their own near the market close. As a result, persistent order imbalances do not im-

imbalances, but they are deterred by cream skimming risk at open. As a result, overnight returns are driven by market makers' inventory costs associated with absorbing order imbalances at open, whereas intraday returns are driven by the increasing importance of slow arbitrageurs in setting the price of liquidity. Hence, our model generates opposite movements in prices at market open and over the rest of the day with persistent order imbalances throughout the day. To further evaluate our proposed mechanism, we now turn to testing the other predictions from our model.

4.2. Determinants of predictable night-minus-day returns (Prediction 2)

Prediction 2 states that predictable night-minus-day returns are driven by two factors: the predictable liquidity demand absorbed by fast arbitrageurs near market open and fast arbitrageurs' required returns from liquidity provision.

We first explore the effect of predictable liquidity demand absorbed by fast arbitrageurs near market open. Our main proxy for fast arbitrageurs' liquidity provision near market open is RM OI in the opening half-hour (Open RM OI). In order to capture the relationship described in Prediction 2 between expected night-minus-day returns and expected order imbalances absorbed by fast arbitrageurs, we run a two-stage least squares (2SLS) panel regression at the stock-day level with day fixed effects. Specifically, in the first stage we regress order imbalances on their one-day lagged values to generate expected order imbalances,[25] and in the second stage we regress stocks' night-minus-day returns on the instrumented order imbalances. The resulting 2SLS regression coefficient thus captures the relation between the expected night-minus-day returns and expected liquidity provision conditioned on the lagged order imbalances.

Panel A of Table 3 reports the 2SLS regression coefficients. Column (1) shows that the regression coefficient on instrumented Open RM OI is 1.18 and statistically significant, suggesting that a one basis point increase in stocks' expected Open RM OI (per daily trading volume) is associated with a 1.18 basis point increase in expected night-minus-day returns per day. These results are consistent with the prediction that expected liquidity demand absorbed by fast arbitrageurs near market open is an important driver of the predictable night-minus-day returns. Our results are also consistent with the findings in Berkman et al. (2012), although their interpretation emphasizes the role of retail trading demand whereas we emphasize the role of liquidity provision from fast arbitrageurs.

Next, we examine the role of fast arbitrageurs' required returns from liquidity provision. We use several proxies to measure these required returns. We first follow Nagel (2012) and use the daily reversal strategy return of Lehmann (1990) (henceforth, Daily Rev) to measure market makers' required returns from liquidity provision.[26] We then use the predictive model in Nagel (2012) to compute the expected returns from liquidity provision ($\widehat{\text{Daily Rev}}$). More details on the construction of Daily Rev and $\widehat{\text{Daily Rev}}$ are offered in Appendix B.

Building on the 2SLS regression from Column 1 of Panel A of Table 3, we add an indicator variable, High $\widehat{\text{Daily Rev}}$ (that is equal to one when $\widehat{\text{Daily Rev}}$ is above the sample median), and its interaction with instrumented Open RM OI, to test whether the relation between expected Open RM OI and expected night-minus-day returns is different when market makers' required returns are different. Column (2) in Panel A of Table 3 shows that the coefficient on the interaction is 0.64 and significant at the 1% level. A one basis point increase in expected Open RM OI is associated with a 0.89 (1.53) basis point increase in expected night-minus-day returns in low (high) $\widehat{\text{Daily Rev}}$ periods. Column (3) shows that the results are similar if we define High $\widehat{\text{Daily Rev}}$ using $\widehat{\text{Daily Rev}}$ computed over expanding estimation windows with no-look-ahead bias. Lastly, as Nagel (2012) discusses, required returns from liquidity provision can increase due to higher volatility or higher compensation per unit of risk. To examine the latter effect, we redefine the indicator variable High $\widehat{\text{Daily Rev}}$ using the conditional Sharpe Ratio of Daily Rev estimated following Eq. (25) of Nagel (2012). We find in Column (4) that the positive relation between instrumented Open RM OI and night-minus-day return is also significantly stronger when the conditional Sharpe Ratio of Daily Rev is high.

The recent literature has preferred to proxy for the required returns from liquidity provision using Daily Rev rather than bid-ask spreads because, as Nagel (2012) argues, the former is not affected by asymmetric information in a model with a representative market maker. However, in the presence of heterogeneous liquidity providers, Daily Rev can nevertheless be affected by asymmetric information. In particular, Daily Rev arises in our model when private information is not fully revealed at market close and fast arbitrageurs become the marginal liquidity provider for some proportion of stocks at market close. Because this proportion can increase in asymmetric information, Daily Rev can be positively associated with both c' and asymmetric information. Therefore, for robustness tests, we use alternative liquidity proxies that also are related to market makers' required returns to test Prediction 2.

In Panel B of Table 3, we replace $\widehat{\text{Daily Rev}}$ with expected spread, expected liquidity, and expected volatility at the market level. Our spread measure is the daily dollar-volume-weighted effective spread from TAQ, and our liq-

ply that the fast arbitrageurs will accumulate a large inventory position over time in our model.

[25] In Section 3 of the Internet Appendix, we report the first stage regression results to demonstrate the relevance of the instrument. The F-statistics are all well above 10, suggesting that our instruments are unlikely to be weak.

[26] Note that in our model, reversals occur entirely intraday. To generate predictable Daily Rev within our model (i.e., reversal over the subsequent day), we can relax the simplifying assumption of full information at market close. In this case, fast arbitrageurs will be the marginal liquidity provider for some stocks at market close, leading to incomplete intraday reversal and hence predictable Daily Rev. Alternatively, we can relax the assumption that slow arbitrageurs' required returns of liquidity provision are zero. In this case, we interpret Nagel's measure as the common component of required returns for fast and slow arbitrageurs.

Table 3

Predictable Order Imbalances and Night-minus-day Returns. This table examines the relation between expected night-minus-day (NMD) returns and expected order imbalances. In Panel A, we report daily two-stage least squares (2SLS) panel regressions of NMD returns on Open RM OI, which are instrumented (instru.) by their one-day lagged values. Open RM OI is the retail order imbalances absorbed by market makers in the first half-hour trading interval identified by the Boehmer et al. (2021) algorithm. Column (2) adds an interaction term with an indicator variable that is equal to one when Nagel (2012)'s measure of fast arbitrageurs' required returns (Daily Rev) is above the sample median. Columns (3) and (4) use two alternative proxies for the required returns (respectively, a construction of Nagel's measure that avoids look-ahead bias and the conditional Sharpe ratio of Nagel's measure). Panel B reports robustness results using aggregate expected spread, liquidity, and volatility as alternative proxies for the required returns. Panel C performs the analyses in Panel A using Lee and Ready (1991) order imbalance over a longer sample period. All models include Day fixed effects. We report t-statistics in parentheses based on robust standard errors two-way clustered by firm and day. Returns are in basis points per day and order imbalances are in basis points per daily trading volume. RM OI becomes available from October 1, 2006, OI from February 1, 1995, and Daily Rev, aggregate expected spread, liquidity, and volatility from January 1, 1998. The sample period ends December 31, 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A - RM OI

	$NMD_{i,t}$			
	(1)	(2)	(3)	(4)
Open RM $OI_{i,t}$ (instr.)	1.18***	0.89***	0.87***	0.82***
	(8.46)	(5.36)	(5.20)	(4.82)
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev}}_t$		0.64**		
		(2.23)		
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev}}_t^{\text{No Look Ahead}}$			0.68**	
			(2.38)	
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev SR}}_t$				0.74***
				(2.68)
Day Fixed Effects	Yes	Yes	Yes	Yes
N	6,184,322	6,184,322	6,184,322	6,184,322

Panel B - Alternative Liquidity Proxies

	$NMD_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Open RM $OI_{i,t}$ (instr.)	0.74***	0.67***	0.78***	0.84***	0.75***
	(3.79)	(3.43)	(4.56)	(4.75)	(4.74)
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Spread}}_t^{\text{ARIMA(5,1,0)}}$	0.85***				
	(3.02)				
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Spread}}_t^{\text{ARIMA(2,1,3)}}$		0.96***			
		(3.36)			
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Amihud}}_t^{\text{ARIMA(5,1,0)}}$			0.80***		
			(2.77)		
Open RM $OI_{i,t}$ (instr.) × High $\widehat{\text{Amihud}}_t^{\text{ARIMA(0,1,3)}}$				0.68**	
				(2.34)	
Open RM $OI_{i,t}$ (instr.) × High VIX_t					0.97***
					(3.31)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	6,184,322	6,184,322	6,184,322	6,184,322	6,184,322

Panel C - OI

	$NMD_{i,t}$			
	(1)	(2)	(3)	(4)
Open $OI_{i,t}$ (instr.)	0.15***	0.09***	0.09***	0.09***
	(18.15)	(11.65)	(11.43)	(11.39)
Open $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev}}_t$		0.11***		
		(6.66)		
Open $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev}}_t^{\text{No Look Ahead}}$			0.11***	
			(6.80)	
Open $OI_{i,t}$ (instr.) × High $\widehat{\text{Daily Rev SR}}_t$				0.11***
				(6.75)
Day Fixed Effects	Yes	Yes	Yes	Yes
N	12,190,348	10,689,613	10,689,613	10,689,613

uidity measure is the daily Amihud (2002) illiquidity measure. We winsorize these variables at the 1% level for each trading day and compute the cross-sectional mean to arrive at the market-level measure. We then compute the market-level expected spread (liquidity) using two ARIMA models selected under the Akaike information criterion.[27] Our expected volatility measure is VIX. Consistent with the results in Panel A, we find that the positive relation between instrumented Open RM OI and night-minus-day return is significantly stronger when expected spread, expected illiquidity, or expected volatility is high.

We conduct further robustness tests in Panel C of Table 3 by performing the analyses in Panel A using Lee-Ready OI over a longer sample period. We again find that expected Open OI is positively related to the expected night-minus-day returns and that this relation is stronger in high $\widehat{\text{Daily Rev}}$ periods. Consistent with our discussions in Section 3.3 that OI is a more noisy measure of fast arbitrageurs' liquidity provision, we find that the 2SLS regression coefficient on Open OI is much smaller at 0.15 (compared to that on Open RM OI of 1.18). For brevity, going forward, we report the results of robustness tests using Lee-Ready OI in Section 3 of the Internet Appendix.[28]

Taken together, our empirical tests in this section demonstrate a strong positive relation between expected night-minus-day returns and expected order imbalances absorbed by fast arbitrageurs, and this positive relation is stronger when the required returns of fast arbitrageurs are high.

4.3. Marginal liquidity providers (Prediction 3)

Our next set of tests examines our prediction that when fast arbitrageurs are less likely to determine the price of liquidity, order imbalances absorbed by fast arbitrageurs should cause smaller price deviations and less return predictability.

4.3.1. Dual listed stocks

As we discuss in Prediction 3, fast arbitrageurs are less likely to determine the price of liquidity when unpriced private information is small. To the extent that unpriced private information tends to be low for large-cap, liquid, and high institutional ownership stocks, Prediction 3 is consistent with existing evidence that these stocks exhibit weaker night-minus-day return predictability. But such evidence is also consistent with other types of limits to arbitrage being smaller among these stocks.

We thus conduct a sharper test of the cream skimming mechanism underlying Prediction 3 using dual-listed stocks. For most U.S. stocks, the accumulation of unpriced private information during the thinly traded overnight session leads to high information asymmetry at open. Yet, a small set of U.S. stocks are actively traded before the U.S. market open because they are dual-listed in the European stock markets. For these stocks, overnight information flow is incorporated into prices through overseas trading and thus the amount of unpriced information at the U.S. market open is likely to be relatively smaller. Thus, according to Prediction 3, slow arbitrageurs are more likely to be the marginal liquidity suppliers for these stocks at U.S. market open, which leads to a weaker relation between fast arbitrageurs' liquidity provision and price deviations.

To test this model implication, we identify U.S. stocks dual-listed in the European stock markets using Compustat Global (hereafter, European dual-listed stocks). We match these European dual-listed stocks to non-dual-listed U.S. stocks from the same industry with the closest market capitalization at the end of each month, which we refer to as the U.S. control sample.[29] We focus on the sample between October 2006 and December 2020, during which Open RM OI are available. The sample contains 84 European dual-listed stocks per day on average.

Similar to our earlier analysis, we run a 2SLS panel regression of daily night-minus-day returns on instrumented Open RM OI that includes day fixed effects to estimate the relationship between expected night-minus-day returns and expected liquidity provision. We conduct inference using t-statistics computed from two-way clustered standard errors at the firm and day levels. Columns (1) and (2) of Table 4 show the contrasting coefficients for the European dual-listed stocks and the U.S. control sample, respectively. While the 2SLS regression coefficient on instrumented Open RM OI is positive and significant in the U.S. control sample, similar to our earlier results based on the full cross-section of U.S. common stocks, the coefficient is insignificant among European dual-listed stocks. To test whether the relation between expected Open RM OI and the expected night-minus-day returns is different between these two groups, we combine the two samples and add a dual-listing indicator variable as well as its interaction with instrumented Open RM OI to the regression in Column (3). We find that the 2SLS coefficient on the interaction term is -0.12 ($t = -2.6$), which offers strong support for the prediction that the positive relation between Open RM OI and night-minus-day returns is weaker when overseas trading reduces unpriced private information at U.S. market open.[30]

[27] Our first ARIMA model is selected among ARIMA ($0 \le p \le 21, 0 \le d \le 2, q = 0$), where p, d, and q are the number of lags, differences, and moving averages, respectively. The selected model is ARIMA(5,1,0) for computing both the expected spread and the expected liquidity. Our second ARIMA model is selected among ARIMA ($0 \le p \le 21, 0 \le d \le 2, 0 \le q \le 21$). The selected model for computing the expected spread is ARIMA(2,1,3) and the selected model for computing the liquidity is ARIMA(0,1,3).

[28] Our 2SLS regression coefficients capture the relation between expected order imbalances and expected night-minus-day returns, which reflects market makers' inventory costs. These coefficients can be contrasted with Breen et al. (2002)'s evidence on the relation between realized order imbalances and realized returns, which additionally reflects the information content of the unexpected component of order imbalances. Consistent with this notion, our 2SLS regression coefficients are less positive than those reported by Breen et al. (2002).

[29] See Appendix B for more details on our dual-list sampling procedure.

[30] As an additional test, cream skimming risk should also be reduced when a fixed basket of stocks is traded. Consistent with this intuition, Section 4 of the Internet Appendix shows that expected Open RM OI is not significantly related to expected night-minus-day returns among exchange traded funds (ETFs). However, this ETF test may have low power relative to our stock-level test.

Table 4

Predictable Order Imbalances and Night-minus-day Returns Among Dual-listed Stocks. This table reports the results of two-stage least squares (2SLS) panel regressions of night-minus-day returns on RM OI at the market open (Open RM OI) instrumented (instru.) by its one-day lagged value among overseas dual-listed stocks. Day fixed effects are included. In Columns (1) and (4), we report the results using U.S. stocks that are dual-listed on European and Canadian exchanges, respectively. In Columns (2) and (5), we report the results in a control sample of market capitalization- and industry-matched non-dual-listed U.S. stocks. In Columns (3) and (6), we combine the dual-listed and control samples, and indicate dual-listed firms with Dual-list$_{i,t}$. We report t-statistics in parentheses based on robust standard errors two-way clustered by firm and day. Returns are in basis points per day and order imbalances are in basis points of daily trading volume. The sample period is between October 1, 2006 and December 31, 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Sample:	Europe DL	U.S. Control	Europe + U.S.	Canada DL	U.S. Control	Canada + U.S.
			NMD$_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)
Open RM OI$_{i,t}$ (instr.)	−0.02	0.09**	0.09**	0.04*	0.10**	0.09*
	(−1.12)	(2.22)	(2.26)	(1.70)	(2.23)	(1.95)
Open RM OI$_{i,t}$ (instr.) × Dual-list$_{i,t}$			−0.12***			−0.05
			(−2.64)			(−1.05)
Dual-list$_{i,t}$			−0.70			3.93**
			(−0.49)			(2.47)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	302,106	294,693	596,799	335,438	345,826	681,264

One potential concern is that our results above are not related to the cream-skimming mechanism but rather due to other confounding effects of being dual-listed. To address this concern, we present the same analysis using U.S. stocks dual-listed in Canadian stock markets (hereafter, Canadian dual-listed stocks). Because Canadian stock markets open at the same time as U.S. stock markets, Canadian dual-listed stocks would not have active trading prior to the U.S. market open. Consequently, our model predicts that the positive relation between Open RM OI and night-minus-day returns should not be weaker among Canadian dual-listed stocks. The results in Columns (4) through (6) of Table 4 support this model prediction. In particular, Column (6) shows that the regression coefficient on the interaction term between the Canadian dual-listing indicator and Open RM OI is insignificant at −0.05 ($t = -1.1$), which contrasts with the negative and significant coefficient on the corresponding European dual-listing interaction term in Column (3). These results together suggest that overseas trading immediately before U.S. market open, rather than dual-listing status in general, attenuates the relation between Open RM OI and night-minus-day returns.

Finally, we further verify the cream skimming mechanism by investigating bid-ask spreads. There are two reasons why spreads should be narrower for European dual-listed stocks at the US market open. First, microstructure models featuring asymmetric information (e.g. Glosten and Milgrom (1985)) predict a narrower bid-ask spread when unpriced private information is low. Second, our model predicts that slow arbitrageurs with low inventory costs are more likely to determine the price of liquidity when unpriced private information is low. Finding lower spreads among European dual-listed stocks would be consistent with either or both of these channels, but finding higher spreads would serve as disconfirmatory evidence for our proposed mechanism.

We follow Bogousslavsky and Collin-Dufresne (2022) in computing the log dollar-weighted effective spreads in the first 30 min of the market open. We regress the log spread on the dual-listing indicator controlling for commonly used determinants of the bid-ask spread and the day fixed effects in the combined sample of European dual-listed stocks and the U.S. control stocks. Control variables include turnover (i.e., the total daily trading volume divided by shares outstanding), volatility (i.e., the standard deviation of daily close-to-close returns in the previous month), 13F institutional ownership percentage at the previous quarter-end (from Thomson/Refinitiv), and the price and market capitalization as of the prior day.[31]

Columns (1) to (3) of Table 5 show that spreads are indeed smaller among European dual-listed stocks than the U.S. control sample with and without controls. After controlling for these commonly used determinants of bid-ask spreads, the regression coefficient on the dual-listing indicator remains negative and highly statistically significant. The magnitude of the regression coefficient is also relatively stable across the three specifications, ranging from −0.54 to −0.70, suggesting that the European dual-listed stocks on average have an effective bid-ask spread that is 42% to 50% lower near the market open. In contrast, Columns (4) to (6) show that the bid-ask spreads of Canadian dual-listed stocks are higher than the matched non-dual-listed stocks, although the difference is not statistically significant in the presence of control variables. These results are consistent with the notion that European dual-listed stocks have lower unpriced private information upon U.S. market open, thus further corroborating Prediction 3.

4.3.2. HFT liquidity provision

In this subsection, we provide an alternative test of Prediction 3 using direct data on the liquidity provision of high-frequency traders (HFT). As we explain in our discussions of Prediction 3, to the extent that fast arbitrageurs'

[31] Overseas trading prior to U.S. open reveals information and may cause the volatility of overnight (intraday) returns of European dual-listed stocks to be higher (lower) than that of the non-dual-listed stocks. Using the volatility of close-to-close returns avoids this issue. Since RM OI is not needed, we conduct the test over the full Daily TAQ sample period between September 10, 2003 and December 31, 2020.

Table 5
Bid-ask Spreads for Dual-listed Stocks. This table reports the panel regressions of the dollar-weighted effective spread in the first half-hour trading interval (Open Spread) on a dual-list indicator (Dual-list$_{i,t}$) as well as control variables (definitions in the main text). The sample contains dual-listed stocks and their capitalization- and industry-matched non-dual-listed U.S. stocks between September 10, 2003 and December 31, 2020, when the Daily TAQ files are available. The first (last) three columns focus on European (Canadian) dual-listed firms and the matched non-dual-listed U.S. stocks. Day fixed effects are included. All variables are log-transformed except for institutional ownership. We report t-statistics in parentheses based on robust standard errors two-way clustered by firm and day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	log(Open Spread)$_{i,t}$					
	European Dual-list			Canadian Dual-list		
	(1)	(2)	(3)	(4)	(5)	(6)
Dual-list$_{i,t}$	−0.54***	−0.70***	−0.59***	0.11*	−0.05	−0.03
	(−9.19)	(−12.62)	(−8.61)	(1.84)	(−0.85)	(−1.20)
log(Turnover)$_{i,t}$		−0.23***	−0.16***		−0.29***	−0.21***
		(−11.12)	(−10.41)		(−14.57)	(−16.90)
log(Volatility)$_{i,t-1}$		0.64***	0.38***		0.84***	0.31***
		(19.00)	(17.29)		(25.70)	(19.36)
Institutional Ownership$_{i,t-1}$			0.17*			−0.32***
			(1.95)			(−6.98)
log(Price)$_{i,t-1}$			−0.04			0.10***
			(−1.47)			(3.56)
log(Market Capitalization)$_{i,t-1}$			−0.33***			−0.43***
			(−18.61)			(−32.60)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	788,952	671,520	640,669	907,183	820,358	806,207
Adjusted R^2	0.14	0.27	0.46	0.07	0.20	0.50

choice to reduce their liquidity provision around market open is a signal of $\pi > \pi^*$ (i.e., of small n or of large π), liquidity demand absorbed by fast arbitrageurs should predict future returns less strongly when HFTs choose to provide less liquidity around market open.

We measure HFT activity using a unique dataset from the NASDAQ exchange on HFT liquidity provision. The database includes all trades that occur on the NASDAQ exchange (excluding the opening, closing, and intraday crosses) for 120 stocks between 2008 and 2009. The database includes a buy and sell indicator, which classifies trades into buyer initiated and seller initiated ones. Crucially, the database also provides information on whether a HFT is involved in a trade and whether the HFT is providing or seeking liquidity.[32] For each stock-day, we compute the HFT Liq Ratio as the ratio of the trading volume (in shares) for which HFTs are providing liquidity to the total trading volume on the NASDAQ exchange in each of the half-hour trading intervals. We focus on the HFT Liq Ratio in the first half hour when cream skimming activity is expected to be the highest (Open HFT Liq Ratio).[33] A lower realized Open HFT Liq Ratio indicates that fast arbitrageurs observe small n or large π near the market open and thus they choose to intermediate a smaller fraction of trades.

Since π is unpredictable in our model, instead of the 2SLS regression approach used in our earlier tests, we test how the predictive relation between realized Open RM OI and subsequent intraday returns varies with the realized Open HFT Liq Ratio. Specifically, we regress the intraday return (from the second half-hour trading interval to the close) on Open RM OI, Open HFT Liq Ratio, and their interaction term. The estimation result is presented below (day fixed effects are included, but not reported for brevity):

$$r^D_{it} = \underset{(t=1.58)}{0.10} \times \text{Open RM OI}_{it} \underset{(t=-0.95)}{-7.33} \times \text{Open HFT Liq Ratio}_{it}$$
$$\underset{(t=-2.24)}{-0.50} \times \text{Open HFT Liq Ratio}_{it} \times \text{Open RM OI}_{i,t} + \epsilon_{it}.$$

We find that the coefficient on the interaction term is negative and significant, with a t-statistic of −2.2 based on two-way standard errors clustered by firm and day. This result is consistent with the prediction that liquidity demand absorbed by fast arbitrageurs will predict future returns less strongly among stocks for which fast arbitrageurs choose to intermediate a smaller fraction of trades.

Overall, both of our tests in this section support Prediction 3 and the cream skimming mechanism in our model.

5. Explaining the night-minus-day returns of characteristics sorted portfolios

5.1. Explaining the night-minus-day returns of the 17 LPS portfolios

We next explore the ability of our model to explain the predictable night-minus-day returns of the 17 LPS characteristics sorted portfolios. In Panel A of Fig. 5, we plot the average night-minus-day return against the average Open RM OI for these portfolios. We find that the sign and magnitude of a portfolio's average Open RM OI tend to match

[32] See Brogaard et al. (2014) for a detailed data description. We thank Phil Mackintosh and Heinrich Lutjens at NASDAQ OMX for providing the data.

[33] Consistent with the notion that HFTs are more selective in choosing stocks for which to provide liquidity near the market open, Figure 6 of the Internet Appendix shows that the distribution of HFT Liq Ratio is more dispersed and the frequency of near-zero realized values is much higher for the first half-hour trading interval compared to the last half-hour trading interval.

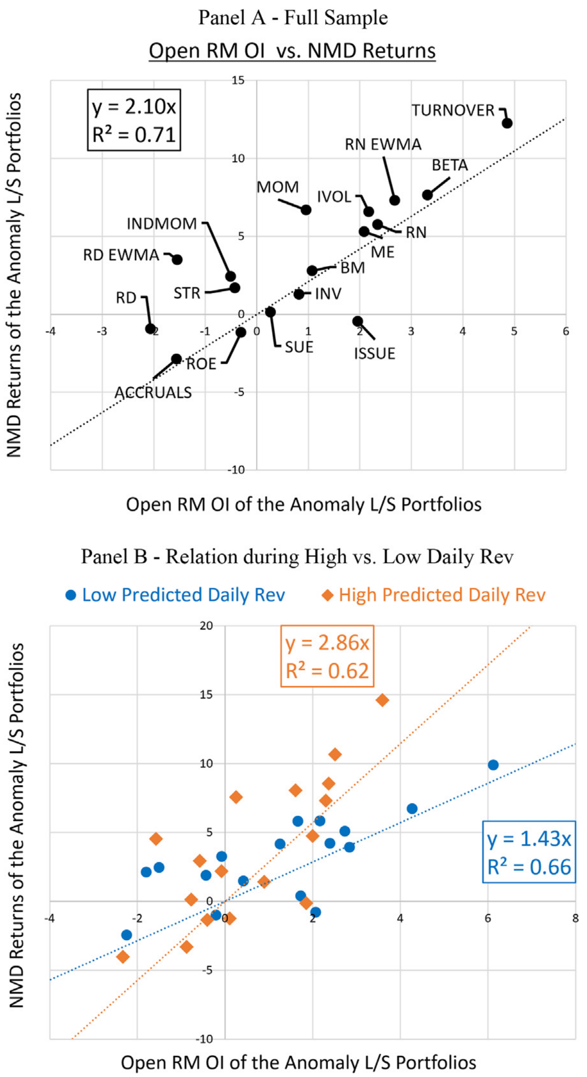

Fig. 5. Open RM OI and Night-minus-Day Returns of 17 LPS Portfolios. This figure plots the average night-minus-day (NMD) return against the average retail order imbalance absorbed by market makers in the first half-hour trading interval (Open RM OI) of the 17 high-minus-low Lou, Polk, and Skouras (2019, LPS) portfolios. In Panel A, we report the scatter plot and the regression line in the full sample period. In Panel B, we report the scatter plot and the regression line in periods with high and low required returns from liquidity provision, respectively. NMD returns are in annualized percentage points and Open RM OI is in basis points of daily trading volume. The sample period is between October 2006 and December 2020 when Open RM OI is available.

that of its average night-minus-day returns. Imposing the model prediction, we use a linear model without an intercept to fit the cross-sectional relation between average Open RM OI and average night-minus-day returns and find a cross-sectional R^2 of 71%.

The cross-sectional slope in Panel A of Fig. 5 can be interpreted as the average returns of fast arbitrageurs from providing liquidity at the open. Panel B of Fig. 5 further shows that this slope is positively correlated with our proxy for the expected returns from liquidity provision. Specifically, similar to the analysis in Section 4.2, we use $\widehat{\text{Daily Rev}}$ to define periods with high and low expected returns from liquidity provision. We find that the cross-sectional slope is twice as large in the high $\widehat{\text{Daily Rev}}$ period compared to the low $\widehat{\text{Daily Rev}}$ period. The cross-sectional R^2 is similar in magnitude between the two periods, at 62% and 66%, respectively.

In addition to the cross-sectional analysis above, we analyze the time-series relation between the returns from liquidity provision and night-minus-day returns in Table 6. For each of the 17 LPS portfolios and the NMD MVE portfolio, we regress their night-minus-day returns on contemporaneous Daily Rev. We use the monthly average in these regressions to allow for non-synchronization of daily returns. We interpret the intercept from this regression as an α because both the dependent and explanatory variables are excess returns. For ease of comparison, we also include the α^{CAPM} previously presented in Fig. 3. We find that accounting for exposure to Daily Rev results in an insignificant $\alpha^{\text{Daily Rev}}$ for 14 out of the 17 LPS anomaly portfolios, more than double the number of insignificant α^{CAPM}. In the last row, we focus on the NMD MVE portfolio that summarizes the cross-sectional night-minus-day return predictability across the 17 LPS portfolios. We find that Daily Rev largely explains this portfolio's average night-minus-day returns (25.7% per annum), leaving a statistically insignificant $\alpha^{\text{Daily Rev}}$ of 2.8% per annum ($t = 0.67$). Overall, our model's predicted determinants account for a substantial portion of the cross-sectional and time-series variability in the night-minus-day returns of the 17 LPS portfolios.

5.2. *A common cause of night-minus-day and close-to-close returns?*

The fact that the stock characteristics underlying the 17 LPS portfolios – many of which are known to determine the cross-section of close-to-close returns – generate predictable night-minus-day returns raises a tantalizing conjecture that expected close-to-close returns and night-minus-day returns might share the same common cause. Our analysis thus far has presented theory and evidence supporting the idea that when conditions allow for cream-skimming to occur at market open, night-minus-day returns are determined by Open RM OI and fast arbitrageurs' required returns to liquidity provision. Do these economic forces underlying night-minus-day returns also influence close-to-close returns?

5.2.1. *Predicted open RM OI*

We first explore whether the Open RM OI predicted by the 17 LPS stock characteristics is related to expected close-to-close returns. To test this prediction, we train a gradient boosted decision tree (GBDT) model using these 17 characteristics to predict Open RM OI over the following month. We choose a non-linear model because the recent literature has shown that a linear combination of stock characteristics does not sufficiently capture the variation in expected returns (Freyberger et al., 2020). We follow Gu et al. (2020) in using shallow trees with a maximum depth of 7 to reduce overfitting. We set the number of trees to be 2000, use five-fold cross validation to

Table 6

Explaining the Night-minus-day Returns of 17 LPS Portfolios. This table presents univariate regressions of the monthly average night-minus-day returns of the 17 high-minus-low Lou, Polk, and Skouras (2019, LPS) portfolios and the night-minus-day mean-variance efficient (NMD MVE) portfolio on either the market excess return (CAPM) or the Nagel (2012) short-term reversal strategy return (Daily Rev). We report t-statistics computed based on Newey and West (1987) standard errors with 12 lags in the parentheses next to the coefficients. The estimated intercept and coefficient from these time-series regressions are denoted by α and β, respectively. Returns are in annualized percentage points. The sample period is from January 1998 to December 2020 when Daily Rev is available.

Portfolio	α^{CAPM}	t-stat	$\alpha^{\text{Daily Rev}}$	t-stat	$\beta^{\text{Daily Rev}}$	t-stat
r_N^{ewma}	42.75	(4.69)	3.74	(0.58)	0.65	(3.91)
r_N	39.11	(3.65)	6.92	(1.05)	0.57	(3.28)
TURNOVER	39.06	(4.45)	10.93	(1.66)	0.59	(4.20)
IVOL	34.43	(2.90)	−8.58	(−1.18)	0.83	(3.99)
r_D	−30.89	(−2.44)	14.70	(1.41)	-0.82	(−3.29)
BETA	28.11	(3.31)	9.49	(1.20)	0.46	(3.18)
MOM	24.84	(4.16)	14.94	(1.33)	0.12	(0.52)
INDMOM	17.09	(3.32)	9.35	(1.39)	0.12	(0.84)
r_D^{ewma}	−15.44	(−1.66)	9.92	(1.43)	-0.46	(−2.77)
ROE	−12.97	(−1.90)	4.78	(0.78)	-0.35	(−2.78)
ME	11.32	(3.18)	26.19	(5.73)	-0.27	(−3.51)
INV	10.17	(2.17)	0.90	(0.19)	0.17	(2.64)
STR	−9.17	(−1.07)	18.44	(2.12)	-0.51	(−2.45)
ACCRUALS	−7.18	(−2.14)	−8.17	(−1.29)	0.02	(0.16)
ISSUE	6.52	(1.30)	−2.52	(-0.48)	0.18	(1.85)
SUE	3.75	(1.19)	5.72	(1.27)	-0.06	(-0.62)
BM	-0.25	(-0.05)	15.27	(2.48)	-0.24	(−1.79)
NMD MVE	25.73	(4.55)	2.76	(0.67)	0.39	(3.67)

Table 7

Explaining Close-to-close and Night-minus-day Returns using Predicted Open RM OI. This table presents Fama and MacBeth (1973) regressions of next month's average night-minus-day returns (NMD), close-to-close returns (RET), or RM OI in the first half-hour trading interval (Open RM OI) on the predicted Open RM OI based on stock-characteristics ($\widehat{\text{Open RM OI}}$) in the current month. The prediction model for Open RM OI is trained using data after January 2010 (see the main text for details). Columns (1) through (3) report the estimates based on the full sample period from February 1995 to December 2020 for NMD and RET and from October 2006 to December 2020 for RM OI. Columns (4) through (6) report the out-of-sample estimates based on the period before January 2010. We report t-statistics computed based on Newey and West (1987) standard errors with 12 lags in the parentheses. Returns are in basis points (bps) per day and the order imbalances are in basis points of daily trading volume. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Full Sample			Out-of-Sample		
	$\text{NMD}_{i,t}$	$\text{RET}_{i,t}$	Open RM $\text{OI}_{i,t}$	$\text{NMD}_{i,t}$	$\text{RET}_{i,t}$	Open RM $\text{OI}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Open RM OI}}_{i,t-1}$	5.83***	−0.22	1.42***	8.48***	−0.41	0.64***
	(5.90)	(−0.46)	(9.90)	(6.71)	(−0.54)	(7.77)
Constant	2.60	5.25***	0.10	4.26	4.56**	−0.10
	(1.19)	(3.73)	(0.95)	(1.25)	(2.17)	(−0.45)
N	602,124	602,124	294,171	373,387	373,387	65,467
Adjusted R^2	0.01	0.001	0.03	0.02	0.002	0.004

tune the learning rate, and fit the model using the data between January 2010 and December 2020. We then use the fitted GBDT model to generate predicted Open RM OI ($\widehat{\text{Open RM OI}}_t$) over the full sample period, so that the period prior to January 2010 is strictly out-of-sample.

In Table 7, we use $\widehat{\text{Open RM OI}}_{t-1}$ to predict night-minus-day returns, close-to-close returns, and Open RM OI in month t using a Fama and MacBeth (1973) regression. We find that $\widehat{\text{Open RM OI}}_t$ positively predicts next month's night-minus-day returns in Column (1) and Open RM OI in Column (3), with $t-$statistics equal to 5.9 and 9.9, respectively. In contrast, $\widehat{\text{Open RM OI}}_t$ predicts close-to-close returns with a negative but insignificant coefficient in Column (2), with a $t-$statistic of only −0.5. For robustness, we also conduct out-of-sample tests in the pre-January 2010 period in Columns (4) through (6) and similarly find that $\widehat{\text{Open RM OI}}_t$ positively and significantly predicts next month's night-minus-day returns and Open RM OI, but it does not significantly predict close-to-close returns. Overall, we fail to find evidence that expected Open RM OI is related to expected close-to-close returns.

Table 8
Explaining the Relation Between Beta and Night-minus-Day Returns. This table presents the post-formation CAPM beta (β^{CAPM}), average close-to-close returns (RET), overnight returns (r_N), and intraday returns (r_D), as well as their respective CAPM alphas (α) for both the univariate CAPM beta portfolios (Panel A) and bivariate CAPM beta portfolios (Panel B). The bivariate CAPM beta portfolios control for $\widehat{\text{Open RM}}$ OI and have similar average values of $\widehat{\text{Open RM}}$ OI across beta deciles. The sample period is between February 1, 1995 and December 31, 2020. We report t-statistics computed based on Newey and West (1987) standard errors with 21 lags in the parentheses under the coefficients. Returns are in annualized percentage points and expected Open RM OI is in basis points of daily trading volume.

Panel A - Univariate β^{CAPM} Portfolios

Decile	β^{CAPM}	RET	r_N	r_D	α^{CAPM}_{RET}	α^{CAPM}_{N}	α^{CAPM}_{D}
1	0.50	11.32	2.05	9.27	4.12	−3.13	7.41
	(17.47)	(4.96)	(1.34)	(4.91)	(2.50)	(−3.05)	(5.38)
2	0.66	11.53	3.20	8.24	2.77	−2.99	5.85
	(29.00)	(4.44)	(1.95)	(3.93)	(1.78)	(−3.34)	(4.63)
3	0.77	11.82	3.00	8.62	1.95	−4.01	5.89
	(30.69)	(4.04)	(1.47)	(3.65)	(1.23)	(−4.07)	(4.57)
4	0.86	11.82	4.15	7.48	1.11	−3.37	4.45
	(30.79)	(3.88)	(2.05)	(3.09)	(0.71)	(−3.82)	(3.52)
5	0.92	12.25	5.59	6.38	0.92	−2.32	3.08
	(47.62)	(3.58)	(2.64)	(2.41)	(0.58)	(−2.37)	(2.46)
6	1.02	12.31	5.17	6.88	0.00	−3.42	3.22
	(63.80)	(3.46)	(2.15)	(2.46)	(0.00)	(−3.67)	(2.86)
7	1.12	13.10	9.46	3.29	-0.23	0.30	-0.71
	(81.11)	(3.23)	(3.91)	(1.07)	(-0.16)	(0.34)	(-0.66)
8	1.24	12.34	10.10	1.73	−2.16	0.01	−2.73
	(51.95)	(2.69)	(3.53)	(0.50)	(−1.26)	(0.01)	(−2.11)
9	1.46	12.14	13.97	−2.47	−4.51	2.79	−7.77
	(40.37)	(2.34)	(4.55)	(-0.61)	(−2.13)	(2.03)	(−4.31)
10	1.79	13.56	22.74	−10.29	−6.37	9.48	−16.76
	(30.85)	(2.02)	(5.93)	(−2.02)	(−1.86)	(4.37)	(−5.67)
10 - 1	1.28	2.24	20.68	−19.56	−10.49	12.61	−24.16
	(15.26)	(0.37)	(6.41)	(−4.08)	(−2.31)	(4.33)	(−6.26)

Panel B - Bivariate β^{CAPM} Portfolios

Decile	β^{CAPM}	RET	r_N	r_D	α^{CAPM}_{RET}	α^{CAPM}_{N}	α^{CAPM}_{D}
1	0.56	11.37	3.02	8.33	3.58	−2.55	6.27
	(21.20)	(4.85)	(1.96)	(4.43)	(2.46)	(−2.81)	(5.27)
2	0.74	12.00	3.56	8.27	2.48	−3.13	5.62
	(33.81)	(4.37)	(1.98)	(3.91)	(1.99)	(−4.09)	(5.87)
3	0.82	11.65	3.21	8.26	1.34	−4.06	5.34
	(58.14)	(4.00)	(1.70)	(3.61)	(1.17)	(−6.20)	(5.89)
4	0.91	12.21	4.31	7.67	0.93	−3.51	4.43
	(52.05)	(3.75)	(2.02)	(3.06)	(0.79)	(−5.09)	(4.76)
5	0.98	12.75	4.51	7.94	0.81	−3.74	4.44
	(74.39)	(3.73)	(2.03)	(3.04)	(0.70)	(−5.55)	(5.11)
6	1.05	13.83	5.09	8.40	1.19	−3.63	4.66
	(85.84)	(3.78)	(2.20)	(2.98)	(1.05)	(−5.32)	(5.27)
7	1.13	12.92	4.92	7.67	-0.48	−4.24	3.62
	(79.67)	(3.27)	(1.96)	(2.53)	(-0.42)	(−5.93)	(3.84)
8	1.22	12.52	5.77	6.36	−1.76	−3.97	2.01
	(62.69)	(2.88)	(2.13)	(1.95)	(−1.39)	(−5.36)	(1.89)
9	1.33	13.99	6.60	6.85	−1.37	−3.74	2.11
	(58.14)	(2.97)	(2.29)	(1.94)	(-0.89)	(−4.16)	(1.57)
10	1.54	13.85	10.66	2.56	−3.62	-0.83	−3.00
	(48.60)	(2.40)	(3.16)	(0.59)	(−1.65)	(-0.66)	(−1.64)
10 - 1	0.98	2.49	7.63	−5.77	−7.19	1.71	−9.27
	(17.44)	(0.54)	(3.08)	(−1.63)	(−2.26)	(0.89)	(−3.64)

5.2.2. Alternative channels

The fact that expected Open RM OI conditioned on anomaly characteristics does not predict close-to-close returns indicates that these anomaly characteristics relate to Open RM OI differently from how they relate to expected close-to-close returns (e.g., via risk or mispricing). However, a common cause could still underlie the characteristics-sorted close-to-close and night-minus-day returns if the cross-sectional relation between these characteristics and night-minus-day returns operates through a channel other than expected Open RM OI. We explore this open-ended question by focusing on the opposite signed slopes of the capital asset pricing model (CAPM) between night and day, given its important implications for asset pricing theories (Hendershott et al., 2020).

Specifically, to isolate the variation in CAPM beta that is independent of expected Open RM OI, we perform 10-by-10 conditional double sorts first on $\widehat{\text{Open RM}}$ OI and then on CAPM beta at the end of each month t. For each of the resulting 100 portfolios, we calculate value-weighted close-to-close, overnight, and intraday returns in month $t+1$. Next, within each CAPM beta decile, we average across the 10 $\widehat{\text{Open RM}}$ OI portfolios to get the bivariate CAPM beta decile portfolios, which have similar values of $\widehat{\text{Open RM}}$ OI across the decile portfolios.

For context, Panel A of Table 8 first reports the univariate portfolio sort results based on CAPM beta. We observe a strongly positive (negative) monotonic relation between β^{CAPM} and overnight (intraday) returns. Specifically, if a stock's market beta increases by 1, its average overnight returns increase by 6.4 basis points (bps) per day, while its average intraday returns decrease by 6.1 bps per day, which is in line with the findings of Hendershott et al. (2020).[34] The univariate CAPM beta $10-1$ portfolio generates a significant -10.5% per annum close-to-close return CAPM alpha ($\alpha_{\text{RET}}^{\text{CAPM}}$), consistent with the well-known betting-against-beta effect (Frazzini and Pedersen, 2014). Its overnight return alpha (α_N^{CAPM}) is 12.6% per annum and its intraday return alpha (α_D^{CAPM}) is -24.2% per annum, a puzzling phenomenon highlighted by Hendershott et al. (2020).

In Panel B of Table 8, we report the results for the bivariate CAPM beta portfolios that control for $\widehat{\text{Open RM}}$ OI. We find there remains a strongly increasing post-formation CAPM beta across the ascending deciles of the bivariate CAPM beta portfolios, which results in a post-formation beta of 0.98 for the $10-1$ portfolio. The $10-1$ bivariate and univariate CAPM beta portfolios generate very similar average close-to-close returns (2.49% vs. 2.24% per annum). In contrast, the $10-1$ bivariate CAPM beta portfolio has a much smaller r_N and r_D at 7.6% and -5.8% per annum, respectively, compared to the 20.7% and -19.6% generated by its univariate counterpart. Noticeably, the $10-1$ bivariate CAPM beta portfolio has an insignificant α_N^{CAPM} that is 86% smaller compared to its univariate counterpart and a significant α_D^{CAPM} that is 62% smaller. For robustness, we again conduct an out-of-sample test in the pre-January 2010 period and find qualitatively similar results (see Section 4 of the Internet Appendix). Therefore, controlling for expected Open RM OI has little effect on the relation between CAPM beta and close-to-close returns, but it substantially reduces the positive beta-r_N relation and the negative beta-r_D relation.

[34] The magnitude of the beta-return relation is smaller here since we examine value-weighted portfolios and use the volume-weighted open price to compute returns.

Overall, our results in this section suggest that the channels that connect anomaly characteristics to night-minus-day returns are different from the channels that connect anomaly characteristics to expected close-to-close returns.

6. Conclusion

We develop a heterogeneous agent model to understand the predictability of night-minus-day returns. In our model, two different types of arbitrageurs with offsetting advantages endogenously determine the price of liquidity at different times of the day. At the market open, when unpriced private information is more plentiful, fast arbitrageurs' information advantages allow them to cream-skim and charge a high price for liquidity. As private information gets incorporated into prices throughout the trading day, slow arbitrageurs' advantages in bearing inventory risk become more important and they become the marginal liquidity provider, leading to predictable night-minus-day returns.

By providing the microfoundation that gives rise to the limited participation of these heterogeneous arbitrageurs, our model leads to novel testable predictions that are borne out in the data. First, we document that the order imbalances associated with the predictable night-minus-day returns persist throughout the trading day, which challenges the prevailing explanations that focus on liquidity demand but is consistent with our model. Second, we show that cross-sectional differences in predictable night-minus-day returns align with liquidity demand absorbed by fast arbitrageurs near market open, and this relationship increases in fast arbitrageurs' required returns from liquidity provision. Third, we validate our proposed cream-skimming mechanism by identifying two subsets of assets where fast arbitrageurs are unlikely to be able to determine the price of liquidity – specifically, European dual-listed stocks that have active overseas trading before the U.S. open and stocks where high frequency firms choose to intermediate a smaller fraction of trades. Among these assets, we show that the liquidity demand absorbed by fast arbitrageurs less strongly predicts future returns.

Our analysis demonstrates one novel channel by which the strategic interactions among arbitrageurs give rise to intraday variations in the identity of the marginal investor, providing new insights into the price formation process. These insights help explain substantial variations in the predictable night-minus-day returns of anomaly characteristics-sorted portfolios and, more broadly, highlight the complexity inherent in assessing the welfare implications of new technologies in market making: while improvements in high-frequency trading technology might lead the presence of HFTs to be associated with increasingly narrow spreads, these technologies may nevertheless make liquidity more costly overall.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We share the replication package at https://data.mendeley.com/datasets/9vnz5y9yzy.

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Appendix A

Solutions of (2) and (5)

Slow arbitrageurs' ask price solves Eq. (2). Given that η is uniformly distributed between $[-n, +n]$, $\Pr(\eta > a) = \frac{n-a}{2n}$, and $E[\eta|\eta > a] = \frac{n+a}{2}$, for $|a| \le n$. Thus, Eq. (2) becomes

$$(1-\tilde{\pi})\left(\frac{1}{2}\right)(a_{s,1}) + (\tilde{\pi})\left(\frac{n-a_{s,1}}{2\times n}\right)\left(a_{s,1} - \frac{n+a_{s,1}}{2}\right) = 0, \tag{A.1}$$

and has the solution given in the main text,

$$a_{s,1} = s(\tilde{\pi}) = \frac{n\left(1-\sqrt{1-\tilde{\pi}^2}\right)}{\tilde{\pi}}.$$

The fast arbitrageur's ask price solves Eq. (5) which, given the distributions of π and η, equates to

$$(1-\pi)\left(\frac{1}{2}\right)(a_{f,1}-c_a) + (\pi)\left(\frac{n-a_{f,1}}{2\times n}\right)\left(a_{f,1} - c_a - \frac{n+a_{f,1}}{2}\right) = 0, \tag{A.2}$$

and has the solution

$$a_{f,1} = f(\pi) = \frac{\pi c_a + n - \sqrt{\pi^2 c_a^2 + n^2(1-\pi^2)}}{\pi}.$$

Proof of Lemma 1

To begin, we define the inverse functions $f^{-1}(x)$ and $s^{-1}(x)$. Note that both $f(x)$ and $s(x)$ are monotonic for $x \in (0,1)$, so the inverses are well behaved on the range of f and s. To complete the definition of the inverses, we define

$$f^{-1}(a) = 0 \text{ if } a \le f(0),$$

and

$$f^{-1}(a) = 1 \text{ if } a \ge f(1).$$

We define $s^{-1}(a)$ in the same way, so that both inverses are well-defined for all a.

Next, consider x, y, such that $f(x) = s(y)$, and $x, y \in (0,1)$. In this case, by construction, both arbitrageurs' quotes are the same. Furthermore, $x = f^{-1}(s(y))$. To complete the proof, note that $\forall x' < x$, $f(x') < s(y)$. That is, for $\tilde{\pi} = y$, if the realization of π is below x, the fast arbitrageur's ask is lower than the slow arbitrageur's ask, and hence the slow arbitrageur's ask is not competitive.

Statement and Proof of Lemma 2

Lemma 2 (Slow arbitrageurs' profits). *The presence of fast arbitrageurs at $t = 1$ makes slow arbitrageurs unwilling to quote a narrow spread. Suppose a slow arbitrageur posts an ask price $a_{s,1}$ at $t = 1$. Relative to an economy with only slow arbitrageurs, the existence of competition from fast arbitrageurs reduces slow arbitrageurs' expected welfare by*

$$\int_0^{f^{-1}(a_{s,1})} V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi, \tag{A.3}$$

where $V_{s,1}$ is defined in Eq. (A.4) below, ϕ_π is the probability density function of π, and Eq. (A.3) is positive for all nonzero $f^{-1}(a_{s,1})$.

Proof. For a conjectured ask price $a_{s,1}$ and a realization π, slow arbitrageurs expect a filled order to be worth

$$V_{s,1}(a_{s,1},\pi) = (1-\pi)(\lambda)(a_{s,1}) + (\pi)(1-\Phi_\eta(a_{s,1}))(a_{s,1}-\psi(a)). \tag{A.4}$$

In the absence of fast arbitrageurs, slow arbitrageurs' valuation given the ask being hit is given by

$$E_0[V_{s,1}|\text{Fast absent}] = \int_0^{s^{-1}(a_{s,1})} V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi + \int_{s^{-1}(a_{s,1})}^1 V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi, \tag{A.5}$$

where the first term on the right hand side is positive, and the second term is negative. It follows from Lemma 1 that in the presence of fast arbitrageurs, this becomes

$$E_0[V_{s,1}|\text{Fast present}] = \int_{f^{-1}(a_{s,1})}^{s^{-1}(a_{s,1})} V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi + \int_{s^{-1}(a_{s,1})}^1 V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi. \tag{A.6}$$

The difference in these two expectations is

$$\int_0^{f^{-1}(a_{s,1})} V_{s,1}(a_{s,1},\pi)\phi_\pi d\pi, \tag{A.7}$$

as desired. $V_{s,1}$ is positive everywhere in the region $[0, f^{-1}(a_{s,1})]$ because $f^{-1}(a_{s,1}) \le s^{-1}(a_{s,1})$. This means that if slow arbitrageurs post $a_{s,1}$ that delivers zero profit in an economy without fast arbitrageurs, the same $a_{s,1}$ will result in expected losses when fast arbitrageurs are present. Given the potential for slow arbitrageurs to suffer a loss, their equilibrium quotes depend upon the extent to which fast arbitrageurs can cream-skim throughout the trading day. □

Proof of Proposition 1

Suppose both types of arbitrageurs appear in the market. The fast arbitrageur observes π, and prepares to post an ask price $f(x = \pi)$. The slow arbitrageur does not observe π, but she can make an estimate about the circumstances under which any given ask price $s(y)$ would be hit. Specifically, for any given y, she can solve for $\hat{x}$ such that $f(\hat{x}) = s(y)$, by calculating $\hat{x} = f^{-1}(s(y))$. Thus, if the slow arbitrageur posts an ask price of $s(y)$, she expects that the fast arbitrageur will undercut her if and only if they observe $\pi < \hat{x}$. She therefore concludes that with an ask price $s(y)$, she can capture the market for $\pi \in [\hat{x}, 1]$, but she will lose the market for $\pi \in [0, \hat{x})$.

Given that she wins the market in those states of the world where $\pi \in [\hat{x}, 1]$, it remains for her to calculate the circumstances under which it would be profitable to do so (i.e., to sell at a price $s(y)$ in the states of the world where $\pi \in [\hat{x}, 1]$). Note that π is distributed uniformly, so its conditional expectation is simply in the middle of the region $[\hat{x}, 1]$; she expects to meet an informed counterparty with probability $\frac{\hat{x}+1}{2}$. Her entry is (weakly) profitable if and only if

$$s\left(\frac{\hat{x}+1}{2}\right) \leq s(y), \tag{A.8}$$

i.e., the break-even ask price conditional on the expected informedness of her counterparty ($\tilde{\pi}$) given the states of the world in which her ask is hit is no higher than the actual ask price $s(y)$ that would win her that segment of the market. More specifically, following Lemma 1, it is profitable for a slow arbitrageur to post an ask price $s(y)$ if

$$s(y) \geq s\left(\frac{\hat{x}+1}{2}\right), \tag{A.9}$$

$$s(y) \geq s\left(\frac{f^{-1}(s(y))+1}{2}\right), \tag{A.10}$$

Rearranging to eliminate the inverse functions, the slow arbitrageur is willing to enter at an ask price $s(y)$ if and only if

$$y \geq \frac{f^{-1}(s(y))+1}{2}, \tag{A.11}$$

$$f(2y-1) \geq s(y). \tag{A.12}$$

Given competitive slow arbitrageurs, profits will be driven to zero and the above will hold with equality; i.e., if (9) holds for at least one $y \in [0, 1]$, then the equilibrium y will obey

$$f(2y-1) = s(y). \tag{A.13}$$

Note that segmentation will arise as long as $f(0) < s\left(\frac{1}{2}\right)$. This is because when $f(0) \geq s\left(\frac{1}{2}\right)$, slow arbitrageurs will be the marginal liquidity providers for all π. Given $f(0) = c$, $f(0) < s\left(\frac{1}{2}\right)$ implies $c < \frac{n - n\sqrt{1-0.5^2}}{0.5}$. Simplifying gives (A.14), the upper bound for c.

$$\bar{c} \equiv n \times (2 - \sqrt{3}). \tag{A.14}$$

If $c > \bar{c}$, fast arbitrageurs' cost of capital is too high for them to profitably provide liquidity, *even if* they observe $\pi = 0$. In this case, slow arbitrageurs are always the marginal liquidity provider.

At $t = 2$, slow arbitrageurs are fully informed, so they set the competitive risk-neutral bid and ask at $b_{s,2} = a_{s,2} = \tilde{v} = v_0 + \eta$. Fast arbitrageurs' reservation values will reflect any accumulated inventory from $t = 1$, so they will be willing to sell at a price above $\tilde{v} - c_b$ to offload their positive inventory and buy at price below $\tilde{v} + c_a$ to offload their negative inventory. Because fast arbitrageurs' reservation sales price is below slow arbitrageurs' bid, and fast arbitrageurs' reservation purchase price is above slow arbitrageurs' ask, fast arbitrageurs will take advantage of slow arbitrageurs' quotes to offload their inventory at $t = 2$, and exit the market. The ask and bid prices at $t = 2$ are pinned down by slow arbitrageurs' valuations rather than fast arbitrageurs' reservation value because fast arbitrageurs' demand for liquidity at $t = 2$ is finite (equal to their accumulated inventory over a trading day) whereas slow arbitrageurs' supply of liquidity is substantially larger (unlimited in the model).

Proof of Proposition 2

Note that when fast arbitrageurs determine the price of liquidity – i.e., when fast arbitrageurs are the marginal liquidity provider at both the ask and the bid – this entails $\pi \leq \text{Min}\{\pi_a^*, \pi_b^*\}$. Thus, the relationship between ask (bid) price and the fundamental values conditional on trades occurring at the ask (bid) price is given by

$$E_1[v_2|ask] = a - c' \times q_a, \tag{A.15}$$

and

$$E_1[v_2|bid] = b + c' \times q_b. \tag{A.16}$$

That is, the trade price deviates from post-trade expected fundamental values when fast arbitrageurs determine the price of liquidity. Next, considering pre-trade midquotes, the above can be rearranged to give

$$a = E_1[v_2|ask] + c' \times q_a, \tag{A.17}$$

$$b = E_1[v_2|bid] - c' \times q_b. \tag{A.18}$$

and thus

$$a + b = E_1[v_2|ask] + c' \times q_a + E_1[v_2|bid] - c' \times q_b. \tag{A.19}$$

Now suppose temporarily that (i) the expected fundamental value of the asset conditional on no trade is equal to its ex ante fundamental value; i.e., the absence of trade is uninformative, and (ii) trade at the ask is as likely as trade at the bid. By the law of iterated expectations,

$$v_0 = Pr(ask) \times E_1[v_2|ask] + Pr(bid) \times E_1[v_2|bid] + Pr(neither) \times E_1[v_2|neither], \tag{A.20}$$

and thus under the aforementioned (i) and (ii),

$$v_0 = \frac{E_1[v_2|ask] + E_1[v_2|bid].}{2}, \tag{A.21}$$

and hence

$$\frac{a+b}{2} - v_0 = \frac{1}{2}c'(q_a - q_b), \tag{A.22}$$

Lastly, note that, as we relax conditions (i) and (ii), because higher ask prices and lower bid prices will deter informed counterparties, the factor of proportionality will change, but the direction of the relationship will not change.

Thus, more generally, for an asset with $\pi < \pi^*$, the pre-trade price at market open, m_1, is given by the fast arbitrageur's midquote, and deviates from expected fundamental value,

$$E[(m_1 - v_0)|\pi] \sim c' \times (q_a - q_b). \tag{A.23}$$

The price at market close, m_2, is given by the slow arbitrageur's midquote, and does not deviate from fundamental value,

$$E[m_2] = E(v_2), \tag{A.24}$$

and $t = 2$ prices conditional on trade equal conditional expected values. Thus, averaging across all stocks, overnight returns $(m_1 - v_0)$ and intraday returns $(v_2 - m_1)$ will have opposite signs in expectation, generating night-minus-day returns that are (i) increasing in q_a, (ii) decreasing in q_b, and (iii) whose magnitude increases when c' increases.

Proof of Prediction 1

Propositions 1 and 2 establish that liquidity demand absorbed by fast arbitrageurs around market open will correlate positively with overnight returns. However, at market close, slow arbitrageurs determine the price of liquidity. Thus, intraday returns are given by the difference in fast and slow arbitrageurs' price of liquidity, which generates reversals irrespective of ongoing order imbalances.

Proof of Prediction 2

In the cross-section, the expected overnight returns increase in expected order imbalances at open (i.e., at $t = 1$) and in fast arbitrageurs' required returns, as shown by Eq. (A.23) of Proposition 2. Away from market open, once slow arbitrageurs become the marginal liquidity provider, order imbalances no longer exert any price pressure; persistent order imbalances will no longer increase price deviations, but rather price deviations will *decrease*. Therefore, predictable intraday returns are opposite to the overnight returns, generating predictable night-minus-day returns.

Proof of Prediction 3

The relationship between π and the identity of the marginal liquidity provider follows immediately from the result that slow arbitrageurs determine the price of liquidity when $\pi > \pi^*$. The relationship between n and the identity of the marginal liquidity provider follows from the equilibrium condition (10). Specifically, π^* that solves (10) is increasing in n, as shown by Fig. 2. To see why, recall that equilibrium requires, given some baseline $n = n_0$, the relationship $f(\pi_0^*; n_0) = s(\frac{\pi_0^*+1}{2}; n_0)$ to hold. Now consider a positive perturbation in n; $n_1 = n_0 + \epsilon$. To begin, suppose slow arbitrageurs conjecture $\pi^*_{n=n_1} = \pi_0^*$. At the original intersection point π_0^*, fast arbitrageurs expect to meet an informed counterparty with probability π_0^*, so their expected loss from trading against informed traders increases with the increased n and thus they have to raise their ask price, i.e., $f(\pi_0^*; n_1) = f(\pi_0^*; n_0) + \delta_f$. The slow arbitrageurs, who do not observe realized π, expect to meet an informed counterparty with probability $\frac{\pi_0^*+1}{2} > \pi_0^*$. Therefore, slow arbitrageurs' expected loss from trading against informed traders increases more with the increased n, and thus slow arbitrageurs raise their ask price by a larger amount, i.e., $s(\frac{\pi_0^*+1}{2}; n_1) = s(\frac{\pi_0^*+1}{2}; n_0) + \delta_s > f(\pi_0^*; n_1) = f(\pi_0^*; n_0) + \delta_f$. Thus, for $n = n_1$, at the original intersection point π_0^*, fast arbitrageurs' break-even ask price is lower than slow arbitrageurs' break-even ask price. If $f(\pi_0^*; n_1) < s(\frac{\pi_0^*+1}{2}; n_1)$, then slow arbitrageurs will trade with an informed counterparty with probability between $\pi = \pi^* > \pi_0^*$ and $\pi = 1$ and thus slow arbitrageurs have to increase their conjectured $\pi^*_{n=n_1}$. Therefore, as n decreases, slow arbitrageurs are more likely to determine the price of liquidity at market open (i.e., they determine the price of liquidity for a wider range of π).

Following Proposition 2, predictable night-minus-day returns arise when fast arbitrageurs determine the price of liquidity around market open. Therefore, predictable night-minus-day returns are smaller when slow arbitrageurs are more likely to determine the price of liquidity. With respect to the prediction, if fast arbitrageurs' liquidity provision occurs *only* when fast arbitrageurs determine the price of liquidity, predictable liquidity provision from *fast* arbitrageurs and predictable night-minus-day returns will shrink in tandem. However, as long as fast arbitrageurs at least occasionally provide liquidity for other reasons (e.g., as discussed in footnote 17 in the main text), the relationship between fast arbitrageurs' liquidity provision and the predictable night-minus-day returns will attenuate as fast arbitrageurs become less likely to determine the price of liquidity.

Appendix B

B1. Construction of the LPS portfolios

We use the 17 long-short portfolios from Lou et al. (2019) as our test assets. These portfolios are sorted on the following characteristics: the monthly cumulative overnight (r_N, RN) and intraday (r_D, RD) return, the exponentially-weighted moving average of the overnight (r_N^{ewma}, RN EWMA) and intraday (r_D^{ewma}, RD EWMA) return in months $t-1$ to $t-12$, idiosyncratic volatility (IVOL), turnover (TURNOVER), CAPM beta (BETA), month $t-1$ to month $t-11$ return momentum (MOM), month t short return reversal (STR), issuance (ISSUE), return on equity (ROE), investment (INV), industry momentum (INDMOM), accruals (ACCRUALS), book to market ratio (BM), post-earnings announcement drift (SUE), and market capitalization (ME).

Following Lou et al. (2019), we sort all stocks into decile portfolios based on an ascending ordering of each of these characteristics at the end of each month t. The long-short zero investment portfolio goes long the top decile portfolio and short the bottom decile portfolio. We then calculate the daily value-weighted close-to-close, overnight, and intraday portfolio returns realized in month $t+1$ with the prior day's market capitalization as the weights. The daily night-minus-day return of the long-short portfolio is the return on a trading strategy that goes long this portfolio overnight and shorts it intraday.

B2. Construction of NMD MVE and RET MVE

To parsimoniously summarize the night-minus-day and close-to-close return predictabilities associated with these 17 LPS portfolios, we construct their respective pricing factor using the Bayesian stochastic discount factor (SDF) estimator proposed by Kozak et al. (2020) (hereafter the KNS estimator). The KNS estimator of b in Eq. (B.1) resembles a ridge regression estimate with a L^2 norm penalty term,

$$\hat{b} = \left(\overline{\Gamma} + \gamma I\right)^{-1}\overline{\mu}, \tag{B.1}$$

where I is the identity matrix, $\overline{\Gamma}$ and $\overline{\mu}$ are the estimated return covariance matrix and the mean of the test asset returns, respectively, and γ is the hyperparameter associated with the L^2 penalty term. As Kozak et al. (2020) explain, this estimator shrinks the SDF coefficients of the naive estimator towards zero, with the shrinkage factor being stronger for the coefficients on the principal components with smaller variance.[35]

Our implementation of the KNS estimator is as follows. We denote the night-minus-day or close-to-close returns for the 17 LPS portfolios by F_t. With a time series of length T, we estimate the sample moments by,

$$\overline{\mu} = \frac{1}{T}\sum_{t=1}^{T} F_t \tag{B.2}$$

$$\overline{\Gamma} = \frac{1}{T}\sum_{t=1}^{T} (F_t - \overline{\mu})(F_t - \overline{\mu})'. \tag{B.3}$$

To choose the optimal γ, we follow Kozak et al. (2020) in using K-fold cross-validation (CV) with $K = 3$. We first equally divide our sample into three subsamples and then set a grid of potential values for γ. For a given γ value, we use $K-1$ subsamples to estimate the in-sample moments $\overline{\mu}_{IS}$ and $\overline{\Gamma}_{IS}$, according to Eqs. (B.2) and (B.3), and $\hat{b}_{IS} = \left(\overline{\Gamma}_{IS} + \gamma I\right)^{-1}\overline{\mu}_{IS}$. Then, using the withheld subsample, we compute the out-of-sample (OOS) moments, $\overline{\mu}_{OOS}$ and $\overline{\Gamma}_{OOS}$. Finally, we compute the out-of-sample R^2 as,

$$R^2_{OOS} = 1 - \frac{\left(\overline{\mu_{OOS}} - \overline{\Sigma}_{OOS}\hat{b}_{IS}\right)'\left(\overline{\mu_{OOS}} - \overline{\Sigma}_{OOS}\hat{b}_{IS}\right)}{\overline{\mu_{OOS}}'\,\overline{\mu_{OOS}}}.$$

We withhold each of the K subsamples, treat it as OOS data, and repeat the above procedure K times. The cross-validated R^2 is the average R^2_{OOS} across these K estimates for a given γ. Then, we select the optimal γ that maximizes the cross-validated R^2. With the optimal γ^*, we compute the SDF coefficient b^* using the full-sample moments according to Eqs. (B.1) – (B.3).

The mean-variance efficient portfolio implied by b^* is a one-dollar long and one-dollar short zero investment portfolio with the following weight on each LPS portfolio i,

$$w_i = \frac{b_i^*}{\sum_{i=1}^{17}\left|b_i^*\right|}. \tag{B.4}$$

When the test assets are the night-minus-day (close-to-close) returns of the 17 LPS portfolios, the above procedure delivers the NMD (RET) MVE portfolio. We note that the procedure uses full-sample information. We refer readers interested in the out-of-sample performance of the algorithm above to Kozak et al. (2020). In a companion paper (Lu and Qin, 2021), we also evaluate the OOS performance of the NMD MVE portfolio in pricing an expanded set of test assets.

B3. Computing portfolio-level order imbalances

We compute order imbalances as follows. First, we measure 30-minute order imbalances for stock i at time t as,

$$OI_{it} = \frac{\text{Buy}_{it} - \text{Sell}_{it}}{\text{Volume}_{it}},$$

where Buy_{it} and Sell_{it} are the orders that are classified as buys or sells according to either the Lee and Ready (1991) or the Boehmer et al. (2021) algorithms, and Volume_{it} is the daily trading volume in shares. Next, we compute the portfolio-level value-weighted order imbalances for the decile portfolios sorted on each of the 17 LPS characteristics as,

$$OI^c_{dt} = \sum_{i \in d} w^c_{it} OI_{it},$$

where w^c_{it} are the market capitalization weights for stock i belonging to the decile d portfolio sorted on the characteristic c at time t. Finally, we compute the order imbalance for the NMD MVE portfolio by applying the NMD MVE weight (w^{MVE}) on the order imbalances of the 17 LPS long-short portfolios ($OI^c_{LS,t}$),

$$OI^{\text{NMD}}_t = \sum_{c=1}^{17} w^{\text{MVE}} OI^c_{LS,t}.$$

B4. Construction of the daily rev predictive model

The daily reversal strategy return (Daily Rev) is the cross-sectional average of the returns of five long-short portfolios that weight stocks proportional to the negative of 1- to 5-day lagged daily market-adjusted returns, respectively. This strategy is rebalanced daily and hedged for time-varying market exposure following Eq. (18) of Nagel (2012). Following Nagel (2012), we replicate the Daily Rev strategy and use the daily returns of this reversal strategy beginning in 1998. From 1998 to 2020, the estimated predictive OLS model using daily data is $\widehat{\text{Daily Rev}}_t = -0.033 + 0.182 \times \text{VIX}_{t-5} - 0.515 \times R_{M,t-5} + 0.254 \times \text{Pre-Decimalization}_{t-5}$ following Eq. (19) and the variable definitions in Nagel (2012). We confirm that the VIX is the most important predictor. Our test results are robust to using VIX directly to capture the time-series variation in the expected returns from liquidity provision.

B5. Identifying dual-list stocks

We identify European dual-listed stocks with any of the following exchange codes (exchg) in Compustat Global that

[35] Among several alternatives that Kozak et al. (2020) explore, they state that this estimator is the natural starting point for applications of their approach if sparsity is not required.

also have the same GVKEY as a U.S.-traded stock. London Stock Exchange 194, NYSE Euronext Paris 286, NYSE Euronext Amsterdam 104, Germany XETRA 171, Swiss Exchange 151, Germany Deutsche Boerse AG 154, Sweden NASDAQ OMX Nordic 256, Italy Borsa Italiana Electronic Share Market 209, Norway Oslo Bors ASA 228, Spain Bolsa De Madrid 201, Denmark OMX Nordic Exchange Copenhagen AS 144, Finland NASDAQ OMX Helsinki Ltd 167, Belgium NYSE Euronext Brussels 132, BM and F Bovespa SA Bolsa De, Valores Mercadorias E Futuros 243. All of these stock exchanges have trading hours that overlap with the U.S. open. For Canadian dual-listed stocks, we use stocks with any of the following exchange codes (exchg) in Compustat Global that have the same GVKEY as a U.S.-traded stock: Toronto Stock Exchange Canada 7, TSX Venture Exchange Canada 9. When we match these dual-listed stocks by industry, we adopt the industry classification based on the GGROUP variable from Compustat Global, i.e., the leftmost 4 digits of Global Industry Classification Standard (GICS) code. Finally, we impose the data filters in Section 3.1 of the main paper on both the dual-listed and non-dual-listed U.S. stocks and then identify the market capitalization- and industry-matched pairs.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jfineco.2023.03.002

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