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The nexus of overnight trend and asset prices in China

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A B S T R A C T

Leveraging the systematic variations in investor clientele within a day, we validate an adapted version of the Hong and Stein (1999) model that addresses the consequences of slow information diffusion in China. The model predicts that overnight returns, rather than total returns, strongly forecast future returns, as informed overnight clientele underreact to value-relevant signals. Empirically, we establish a consistent overnight trend phenomenon: Firms with a strong overnight trend reliably outperform those with a weak overnight trend in the subsequent month. The phenomenon is more pronounced among stocks with higher levels of information asymmetry, valuation uncertainty, and relative mispricing. Furthermore, the overnight trend predicts positively firm fundamentals in the cross section.

1. Introduction

Understanding why financial markets exhibit or do not exhibit simple forms of predictability (*e.g.*, momentum and short-term reversal) is crucial to the finance profession, and much research has been directed to this issue (Jegadeesh and Titman, 1993, 1995; Rouwenhorst, 1998; among others). Recently, Chui et al. (2022) highlight clientele differences—the degree of noise traders relative to informed investors who underreact to value-relevant signals—in determining return predictability. Using the unique setting of China's segmented markets that features the *persistent* difference in investor clienteles, they document that short-term reversal prevails, but conventional momentum shrinks in the Chinese A-share market.

While the prevalence of short-term reversals represents a high inventory risk premia required to absorb the noise trading (Jegadeesh and Titman, 1995; Nagel, 2012), the "disappearance" of conventional momentum in the Chinese A-share market is less well understood. Intuitively, the presence of noise traders adds difficulties for active investors to uncover reliable value-relevant information from past prices, but this does not necessarily rule out return continuation, because underreaction to fundamental signals (*i.e.*, slow information diffusion) is a general behavioral symptom that prevails in financial markets. Therefore, it is worthwhile to search for non-conventional momentum signals that better capture slow information diffusion in "high resolutions".

This paper examines the *cyclical* asset prices between day and night to explore the consequences of slow information diffusion in the Chinese A-share market. The novelty of our approach is to rely on the *temporary* clientele difference within a day, rather than the *persistent* clientele difference in segmented markets as in Chui et al. (2022), to identify alternative, non-conventional momentum measures that better reflect future price trends in a setting with a high direct ownership by retail investors (noise traders). How asset

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prices evolve within a day provides us a novel perspective to examine the clientele effects on cross-sectional return predictability, and thus it has emerged as an active research area in recent years (Heston et al., 2010; Berkman et al., 2012; Lou et al., 2019; Hendershott et al., 2020; Bogousslavsky, 2021). The emerging consensus is that there exists a striking tug of war between intraday and overnight clienteles (*i.e.*, clientele effects): Stocks that persistently earn high returns over the night (during the day) tend to experience large losses during the day (over the night), as the two investor clienteles engage in a back-and-forth battle over different time of the day (Lou et al., 2019; Hendershott et al., 2020). By separating the past intraday and overnight return components, we extract the informative price signals that are powerful in predicting subsequent cross-sectional stock returns and firm fundamentals. More crucially, our results help pin down what types of active investors (in the sense of Hong and Stein 1999 and Chui et al. 2022) underreact to information and yield the overnight momentum phenomenon (rather than conventional momentum).[1]

We proceed with a theoretical framework to reconcile how the prevalence of underreaction (*i.e.*, slow information diffusion) and the "disappearance" of convention momentum (based on total returns) could co-exist in the Chinese stock market. Our approach builds on the premise that informed institutional clientele trade throughout the entire day but *dominate* in the pre-open auction over the night, while retail clientele in China tend to place their orders when the market is open during the day. This is in vast contrast to the US equity market, in which institutions (informed intraday clientele) dominate at the end of the day, while retail investors (naïve overnight clientele) tend to trade at the beginning of the day (Berkman et al., 2012; Lou et al., 2019). Our reasoning that overnight (intraday) clientele in China are mostly informed institutions (naïve retail investors) is motivated on empirical grounds: Liu et al. (2023) document a striking overnight-intraday disparity in terms of the reaction to earnings news, indicating that informed institutional investors tend to trade and reveal their private information in the pre-open auction. Gao et al. (2021) documents that intraday winners (*i.e.*, stocks that exhibits strong intraday momentum) tend to be speculative and lottery stocks that are highly demanded by retail investors during the day. Using daily institutional and retail trade data (*i.e.*, super-large trades *versus* small trades), we perform a set of validation tests and find consistent evidence that large institutions tend to trade during the overnight period as well as intraday period, while small retail investors concentrate their bets during the intraday period only (see **Section A1** of the appendix).[2] Moreover, the specific within-a-day clientele difference also help reconciles several stylized facts (puzzles) in China that differs markedly from the US and other developed markets.[3]

To illustrate the theoretical underpinnings, we adopt the Hong and Stein (1999) model that is tailored to the clientele differences in China. The model features slow information diffusion and heterogeneous investors—newswatchers *versus* outside investors. In the model, newswatchers are endowed with private information and can trade during both the pre-open call auction and the normal intraday periods, while outside investors only have access to stale information and trade only during the intraday periods. In equilibrium, the two types of investors act as counterparties to one another. As private information spreads slowly across newswatchers, the informed trading of newswatchers causes overnight returns to exhibit short-term continuation, consistent with the underreaction to information of Hong and Stein (1999).[4] The outside investors, who have no information advantage and enter the market during the intraday periods, perceive the opening price being "incorrect" and trade against these close-to-open price changes (*i.e.*, overnight returns) during the day. The opposite price movements between day and night (*i.e.*, a tug of war) lead to the negative predictability of intraday returns with overnight returns, and negative profits of the overnight trend strategy during the intraday periods. However, the total returns of the overnight trend strategy remain positive, since outside investors cannot completely offset the informed trading when the newswatchers are also active. Our model makes three major predictions: (1) Stocks with a strong overnight trend on average yield higher overnight returns but lower intraday returns in the near future than stocks with a weak overnight trend. (2) Stocks with a strong overnight trend on average yield higher future returns than stocks with a weak overnight trend. (3) Overnight trend has stronger forecasting power for cross-sectional returns than intraday trend. While the first prediction is in line with empirical findings in the prior work (Gao et al., 2021), the latter two theoretical predictions, to the best of our knowledge, are new to the literature. Collectively, they

[1] In recent years, there is a growing interest in understanding China's financial markets (Carpenter et al., 2021; Liu *et al.* 2019). Carpenter et al., 2021 highlight the importance of exploring China's stock market and its role in resources allocation for the world's second-largest economy. Liu *et al.* (2019) and Chui *et al.* (2022) stress that it is crucial to allow for the *unique* features in China to deepen our understanding of asset pricing theory. In particular, the heavy presence of noise traders (i.e., naïve retail investors) and their excessive trading offer a unique setting to explore the implications of clientele effects on asset pricing anomalies (Chui *et al.* 2022).

[2] We are highly indebted to the associate editor and an anonymous referee for suggesting us to perform validation tests to confirm that retail investors have relatively low participation in the overnight period (i.e., the pre-open auction) in our sample period (see **Section A1** of the appendix).

[3] First, conventional momentum does not prevail in the Chinese A-share market (see **Table A2** in the appendix), as the persistent tug of war between overnight and intraday clientele virtually eliminates the effectiveness of pursuing the conventional momentum strategy based on total returns (Gao *et al.* 2021). Second, average overnight return is significantly negative in the Chinese stock market (see **Table A2** in the appendix), the so-called overnight puzzle (Qiao & Dam 2020). Third, we document that prominent anomaly strategies (such as beta, idiosyncratic risk, lottery preference, turnover, and return volatility) that buys non-speculative stocks and sells speculative stocks earn their "premium" exclusively over the night (see **Figure A1** in the appendix). This echoes the recent findings that informed institutional investors trade and reveal their information over the night in China (Liu *et al.* 2023), as they tend to correct mispricing over the night (i.e., in the pre-open auction) when there are low noise trader risks—small retail investors are more likely to be "crowded out" under the pre-open auction mechanism than the continuous trading mechanism (Liu *et al.* 2023).

[4] It is reasonable to assume that informed institutions underreact to information. Empirical literature shows that institutions, similar to individuals, are also constrained by limited investor attention (a scarce and limited cognitive resource), which leads to slow information diffusion and underreaction to news (see Hirshleifer, Lim, and Teoh (2009) among many others). For example, Ben-Rephael *et al.* (2017) show that institutional investors may also underreact to information, but when they do pay attention, they alleviate the post-earnings announcement drift (PEAD).

highlight that it is the past overnight returns (rather than total returns) that are information revealing about subsequent price movements in China.

Empirically, to test the model predictions, we construct a novel firm-level **overnight trend** measure (OVNT), defined as the monthly overnight returns averaged over the past *J*-months, skipping the most recent month. To the extent that overnight clientele's "order flows" are informative, and this information is gradually incorporated into price processes, we would expect stocks with a strong (weak) past overnight trend are linked with positive (negative) price-related information and are expected to deliver high (low) stock returns in the subsequent periods. Consistent with the prediction, we document a strong **overnight trend phenomenon** in China: A zero-cost equal-weighted overnight trend strategy that buys stocks with strong overnight trend and sells stocks with weak overnight trend generates positive returns over the full sample period July 1996 to December 2018.[5] Risk-adjusted returns (alphas) of the overnight trend strategy with a 12-month lookback period range from 53 to 86 basis points (bps) per month under the evaluation of alternative factor models and are all significant at the 1 % level.

We also observe a number of salient empirical features associated with the overnight trend strategy: First, when we examine the risk-adjusted performance of the long and short legs separately, we find that the overnight trend effect stems mainly from the short leg. This strengthens the slow-information-diffusion explanation, because we would expect the negative information (represented by a low overnight trend) to be incorporated more slowly by the market—bad news travels slowly (Hong et al., 2000). Second, the overnight trend strategy experiences large gains over the night but suffers large drawdowns during the day. The strategy generates a positive alpha of 3.19 % per month over the night but incurs a loss of –2.59 % per month during the day when evaluated by the Fama and French (1993) three-factor model. After aggregating the daytime and overnight performances, the combined effect indicates the overnight clientele moves the asset price in the right direction with a three-factor alpha of 86 bps per month that is significant at the 1 % level. Third, the overnight trend strategy is quite stable over time. We split the full sample into two subsample periods with similar lengths. The superior performance of the overnight trend strategy is stable over both subsample periods and derives its profits mainly from the short leg.

In addition, we perform two empirical tests to validate the key model assumption that overnight clientele are better informed (with more privileged information or better valuation skills). In the first validate test, we perform the Fama-MacBeth predictive cross-sectional regression, in which we regress the quarterly firm fundamentals (such as return on equity, return on asset, and earnings to price ratio) on the lagged overnight trend measured prior to the reporting quarter while accounting for other factors. We document that the lagged overnight trend is a strong positive predictor of firm fundamentals in the cross section. It "identifies" stocks with either higher level or greater quarterly change of firm fundamentals. Moreover, this strong and incremental predictability is not subsumed by the conventional momentum measure (*i.e.*, past 12-month returns). In the second validation test, we focus on one salient informational event: earnings announcement. Using quintile portfolio sorted by lagged overnight trend, we show that stocks with relatively high (low) lagged overnight trend to have more positive (negative) earnings surprises in the subsequent quarter. Overall, these validation tests provide consistent evidence that the overnight clientele are indeed better informed, as their collective demand, manifested by lagged overnight trend, predicts positively the subsequent firm fundamentals in the cross section.

To further validate the slow-information-diffusion mechanism, we test two sets of additional implications regarding the overnight trend effect. First, we show that the relation between overnight trend and subsequent stock returns is stronger among small, growth, and less profitable stocks that are subjected to higher information asymmetry or valuation uncertainty. Second, we also show that the overnight trend phenomenon is stronger among relatively overpriced stocks that are influenced more by investor sentiment, lottery preference, and limits to arbitrage (Shleifer and Vishny, 1997; Baker and Wurgler, 2006; Pontiff, 2006; Bali et al., 2011). We argue that if overnight clientele are truly informed, they would act on mispriced securities to exploit their information advantage or better valuation skills (Akbas et al., 2015).

Next, we consider several alternative explanations, as one might argue that some of our empirical findings could arise for other reasons. We first test for the disagreement hypothesis and find that our proposed overnight trend measure is unlikely to be a pure disagreement measure reflecting a divergence of opinions. This is because if the overnight trend purely reflects the disagreement (between intraday and overnight clienteles), a similarly constructed intraday trend measure, which is highly (negatively) correlated with overnight trend, should also predict the subsequent returns in the cross section. However, contrary to the disagreement hypothesis, we find that intraday trend does not exhibit any return predictability power in the cross section. Second, we rule out the sentiment hypothesis, as we find the powerful PMO (pessimistic minus optimistic) sentiment factor in Liu et al. (2019) explains little, if any, time variation of our overnight trend strategy. Finally, we validate the non-marketability hypothesis that explains the overnight puzzle in China (*i.e.*, the unique $T + 1$ trading rule). By construction, overnight trend might mechanically capture the non-marketability features of a stock, such as illiquidity and volatility. We employ a wide range of firm characteristics that are linked with the non-marketability features and utilize the Hou and Loh (2016) decomposition approach to evaluate the marketability hypothesis. We find that none of the non-marketability-related firm characteristics can explain more than 40 % of the overnight trend phenomenon.

Finally, we perform additional analyses to shed more light on the overnight trend strategy. First, we find that the overnight trend strategy has a mid-level portfolio turnover, and its breakeven transaction costs exceed 2 % per month to zero out the (risk-adjusted)

[5] We focus on equal-weighted portfolios in our baseline analysis, because the overnight trend effect (i.e., slow-information diffusion), in theory, should be stronger among small and speculative stocks. These stocks are favored more by retail investors, and subject to more market frictions (i.e., limits to arbitrage), which leads to stronger underreaction to information. However, all our key empirical findings remain robust when we use value-weighted portfolios (see our later empirical analysis and robustness checks).

returns. Therefore, the strategy would remain profitable when implemented alongside transaction costs in practice. Second, we provide out-of-sample evidence with US stock data to demonstrate that our slow information diffusion explanation could be generalized to other markets. Of course, informed "order flows" in the US stem from intraday clientele (Lou et al., 2019). Therefore, we find a similarly constructed intraday trend strategy delivers positive risk-adjusted performance in the US. Third, we present a battery of robustness checks to alleviate the data snooping concern and to ensure that our documented overnight trend strategy in China is robust under alternative lookback periods, weighting scheme, factor models, etc.

The rest of the paper is organized as follows. Section 2 develops an illustrative model. Section 2 documents the data sources and key variable constructions, and Section 4 provides portfolio-level and firm-level evidence on the overnight trend phenomenon. Section 5 performs additional validation tests and rules out possible alternative explanations, and Section 6 conducts robustness tests. Section 7 concludes.

2. An illustrative model

The Chinese stock market is featured with a number of striking empirical puzzles: (1) Conventional momentum strategies do not generate profits (see Table A2 in the appendix); (2) overnight return is negative (see Table A2 in the appendix); and (3) prominent anomaly strategies (including beta and idiosyncratic volatility) that buys non-speculative stocks and sells speculative stocks earn their "premium" exclusively over the night (see **Fig. A1** in the appendix). As is explained in the **Introduction** section, these seemingly puzzling patterns echoes the recent findings that there exists a strong within-a-day clientele difference that eliminates the profitability of conventional momentum strategies based on total returns (Gao et al., 2021) and overnight clientele in China are mostly informed institutions who *dominate* the pre-open auction (Liu et al., 2023). In short, these "puzzling" empirical patterns serve as the motivation evidence for our key assumption in the theoretical model as proposed below.

Model setup. We develop a simplified version of the Hong and Stein (1999 henceforth **HS**) model featuring slow diffusion of information that generates the "momentum" effect based on overnight return signals. Our model follows closely **HS**. Specifically, agents trade two assets: a risky asset, of which the final payoff at time T is given by $D_T = D_0 + \Sigma_{j=0}^{T}\epsilon_j$, where $\epsilon_j \sim$ IID $N(0,\sigma^2)$, and a risk-free asset with a risk-free rate normalized to zero. There are two types of agents, newswatchers and outside investors, who maximize constant absolute risk aversion (CARA) utility functions and are boundedly rational in the sense that they cannot optimally learn information from prices. We follow these same assumptions about investors' behavior as in **HS**, except that the momentum traders in **HS** are replaced with "outside investors" with reasons to be discussed shortly.

The first type of agents are newswatchers, who buy and hold the risky asset until the terminal time T. They are divided into z equal-sized groups. Each group is endowed with a part of dividend innovations before the pre-open call auction every day, and the news moves slowly across newswatchers over the following z days. Specifically, dividend innovation ϵ_j is decomposed into z independent sub-innovations with equal variance, $\epsilon_j = \sum_{i=1}^{z}\epsilon_j^i$. At time t, newswatcher group i observes ϵ_{t+z-1}^i, for $i = 1,\ldots,z$. At $t+1$, group i observes ϵ_{t+z-1}^{i+1}, for $i = 1,\ldots,z-1$, and group z observes $\epsilon_{t+z-1}^1\ldots$. This information diffusion process continues until time $t+z-1$, at which point each group has observed all the z sub-innovations, and hence ϵ_{t+z-1} becomes completely public within the newswatchers.

The second type of agents are outside investors, who have no private information and make trades using outdated data. At time t, their belief about the final payoff is given by $N(D_s,\delta^2)$, where $D_s = D_0 + \Sigma_{j=0}^{s}\epsilon_j$ is the expected value of D_T conditional on stale information ϵ_s, $s \le t$.[6] The outside investors in our model represent a deviation from **HS**, who study the interaction between newswatchers and momentum traders, which leads to a unified theory of short-term underreaction and long-term overreaction. The *only difference* between the outside investors in our model and the momentum traders in **HS** lies in their beliefs.[7] This notable deviation is motivated by the following reasons: First, momentum in the traditional fashion does not exist in the Chinese A-share markets, suggesting that momentum traders (*e.g.*, those modelled in **HS**) do not make consistent profits in these markets. Second, our paper focuses on underreaction-related continuation phenomenon, which is caused by slow information diffusion among newswatchers alone in **HS**. For parsimony, we do not consider momentum traders who can produce richer price dynamics, such as long-term reversal and even non-stationarity in **HS**, depending on parameters. Third, our result of the overnight trend still holds even without outside investors; in this case, there would be no trade during the daytime (see our discussion of **Prediction 4** below). The investor heterogeneity studied in our model is also consistent with the empirical evidence documented in Lou et al. (2019) that overnight and intraday trades tend to be dominated by heterogeneous investor groups.

The second model departure from **HS** is that we assume that newswatchers participate in both the pre-open call auction and the normal intraday market opening periods, while outside investors trade only during the intraday periods (not in the pre-open call auction). In principle, newswatchers (*i.e.*, informed investors such as mutual funds and other professional investors) have more resources and are able to follow the market for a longer time span within a day. Moreover, a stylized negative overnight return in China generates strong economic incentive for informed investors, especially long-only mutual funds, to place partially their orders at the

[6] We focus on the case $s \le t$ in which the outside investors trade on stale information. If $s > t$, then the outside investors have access to advance information, relatively to newswathcers.

[7] While the outside investors update their expectations based on public information without learning, the momentum traders in **HS** form an extrapolative belief about price changes, which produces overreaction. Similar as the momentum traders in **HS**, the outside investors in our model are also boundedly rational and have a short horizon (one period). Our results still hold if the outside investors are long-term investors (as the newswatchers) by formulating their demands based on the buy-and-hold strategy.

beginning of the day to gain profits and enhance fund performance.[8] Of course, mutual funds and other institutional investors would also need to trade near the end of day, because the close price is the reference price used to determine the net asset value (NAV) of the funds (for subscription and redemption). Therefore, it is reasonable to assume that these newswatchers are active throughout the day. In comparison, it is possible that outside investors (naïve retail investors) only dominate in the intraday periods. Barclay and Hendershott (2003) document information asymmetry escalates during market closure and declines during the day as more information is revealed via trading. As a result, uninformed retail investors are reluctant to trade until the market re-opens, since they are less informed or are unable to infer the open price (in the pre-open auction). Due to the absence of uninformed trading in the pre-open call auction, informed traders dominate the pre-open call auction (overnight). Therefore, the open price reflects primarily the aggregate "order flows" from newswatchers. Apart from the above two departures, our model would be the same as the seminal work of **HS**.

It is worth noting that our model does not assume that uninformed investors trade against overnight informed traders but that the two types of investors have different beliefs. As shown shortly, in the market clearing conditions, uninformed investors are counterparties of informed investors.[9]

Equilibrium. The close price at day t, denoted by P_t^{close}, is determined by the trades between newswatchers and outside investors during the intraday periods. In equilibrium, the aggregate demand equals supply :[10]

$$\frac{D_t + \sum_{i=1}^{z-1}\frac{z-i}{z}\epsilon_{t+i} - P_t^{close}}{\theta^z} + \frac{D_s - P_t^{close}}{\theta^o} = Q,$$

where the two terms on the left-hand side of the equation are the total demand of newswatchers and outside investors, respectively, and Q is a positive net supply of the risky asset. In particular, θ^z is a constant, depending positively on newswatchers' risk aversion and the variance of ϵ, and the constant θ^o depends positively on outside investors' risk aversion and their perceived risk δ associated with the dividends, but negatively on the population fraction of the outside investors. Therefore, the close price of the risky asset at day t is given by

$$P_t^{close} = \frac{\theta^o D_t + \theta^z D_s}{\theta^z + \theta^o} + \frac{\theta^o}{\theta^z + \theta^o}\sum_{i=1}^{z-1}\frac{z-i}{z}\epsilon_{t+i} - \frac{\theta^z\theta^o}{\theta^z + \theta^o}Q. \tag{2.1}$$

The opening price at day t, denoted by P_t^{open}, is determined in pre-open call auction that is participated by newswatchers alone. Since the outside investors do not trade in the auction, their demand is unchanged over night, given by $\frac{D_{s-1} - P_{t-1}^{close}}{\theta^o}$. Thus, the net supply becomes $Q - \frac{D_{s-1} - P_{t-1}^{close}}{\theta^o}$. In equilibrium, we have

$$\frac{D_t + \sum_{i=1}^{z-1}\frac{z-i}{z}\epsilon_{t+i} - P_t^{open}}{\theta^z} = Q - \frac{D_{s-1} - P_{t-1}^{close}}{\theta^o}. \tag{2.2}$$

Thus, the opening price is given by

$$P_t^{open} = D_t + \sum_{i=1}^{z-1}\frac{z-i}{z}\epsilon_{t+i} - \theta^z Q + \frac{\theta^z}{\theta^o}\left(D_{s-1} - P_{t-1}^{close}\right). \tag{2.3}$$

Eq. (2.3) is the same as Eq. (1) in **HS** that describes the equilibrium price when the market is populated by only newswatchers, except that the net supply is different due to the presence of outside investors.

Model predictions. The overnight return during day t is given by

$$r_t^{overnight} = P_t^{open} - P_{t-1}^{close} = \frac{1}{z}\sum_{i=1}^{z}\epsilon_{t+i-1}. \tag{2.4}$$

It shows that overnight returns have positive serial correlations over short horizons with length less than z. The return continuation is due to the slow diffusion of information (*i.e.*, underreaction), consistent with **HS**. As a result, an overnight trend, defined as the cumulative overnight return over past J time periods:

$$r_t^{OVNT} = \sum_{j=1}^{J} r_{t-j+1}^{overnight}, \tag{2.5}$$

should positively predict future asset returns. For example, when $J \geq z$, we have

[8] Performance-based fund rating scheme (such as Morningstar ratings) motivates mutual funds to find ways to compete for better performance. A persistently low opening price relative to prior-day's close price (i.e., the negative overnight return) offers such an opportunity. It incentivizes informed institutional investors, including mutual funds, to optimize the timing of their buying orders over the night (i.e., during the pre-open auction), so that they could systematically buy at a lower price to increase the expected return and enhance fund performance, everything else equal.

[9] We are greatly indebted to the Associate Editor and an anonymous referee who emphasized this important point to us.

[10] That is, the price formula (5) in **HS**, who have normalized the coefficients θ^z and θ^o to one.

$$cov\left(r_t^{OVNT}, r_{t+1}^{overnight}\right) = \frac{z(z-1)}{2}\sigma^2 > 0$$

The overnight trend r_t^{OVNT} in (2.5) exhibits the highest forecasting power for a "lookback period" of $J = z$.

Note that one way to interpret our model is to consider it as a model of individual stock, the same modelling approach as **HS**. This approach, without directly modelling the dynamics of the cross-section of many stock returns, not only significantly simplifies the notations but also directly implies momentum in the cross-section. In this case, the "overnight momentum" arises in the form of residual momentum (according to CAPM, *e.g.*, Grundy and Martin, 2001; Li, 2021). In addition, our model also captures the case when stock overnight momentum is due to the time series overnight momentum of systematic returns (*e.g.*, He and Li, 2015; Ehsani and Linnainmaa, 2022). In this case the risky asset should be considered as the factor asset that exhibits momentum. However, our simple model does not take a stand on the specific correspondence of the overnight momentum in a factor structure (*i.e.*, the factors, betas, residuals, or the interaction of them) but focuses instead on the economic mechanism (slow diffusion of information). In any correspondence, our model predicts that the overnight trend (2.5) positively forecasts future asset returns. This prediction, as discussed above, directly implies a positive predictability of the overnight trend in the cross-section, which will be tested in Section 4.

Prediction 1. *Stocks with a strong overnight trend on average yield higher overnight returns in the near future than stocks with a weak overnight trend.*

Prediction 1 implies that an overnight trend strategy that explores the price trend over past overnight periods can generate positive profits during subsequent overnight periods.

Next, we examine the performance of the overnight trend strategy during the intraday periods. The intraday return during day t is given by

$$r_t^{intraday} = P_t^{close} - P_t^{open} = -\frac{\theta^z}{\theta^z + \theta^o}\left(\frac{1}{z}\sum_{i=1}^{z}\epsilon_{t+i-1} - \epsilon_s\right). \tag{2.6}$$

By Eqs. (2.4) and (2.6), the covariance between past overnight returns and future intraday returns, $cov\left(r_{t-j}^{overnight}, r_t^{intraday}\right)$, is negative when the outside investors trade on stale information, *i.e.*, $s < t$. For example, when $s \le t - z$ and $J \ge z$, we have

$$cov\left(r_t^{OVNT}, r_{t+1}^{intraday}\right) = -\frac{\theta^z}{\theta^z + \theta^o}\frac{z(z-1)}{2}\sigma^2 < 0.$$

Following the same discussions above, this negative predictability directly leads to the following model prediction.

Prediction 2. *Stocks with a strong overnight trend on average yield lower intraday returns in the near future than stocks with a weak overnight trend.*

Prediction 2 suggests that the overnight trend strategy generates negative returns during subsequent intraday periods, which will be tested in Section 4.

Intuitively, after good (bad) private information starts to spread across newswatchers, the outside investors who base their expectations on stale information believe the resultant opening price is overvalued (undervalued), and trade against these price changes during the intraday periods, lowering (increasing) the close price. These opposite price movements during the overnight and intraday periods lead to the negative predictability of overnight returns on (future) intraday returns stated in Prediction 2, as well as a day-and-night tug of war.

The daily return of risky asset at day t (the sum of overnight and intraday returns at day t) is given by

$$r_t = P_t^{close} - P_{t-1}^{close} = \frac{\theta^0}{\theta^z + \theta^o}\frac{1}{z}\sum_{i=1}^{z}\epsilon_{t+i-1} + \frac{\theta^z}{\theta^z + \theta^o}\epsilon_s. \tag{2.7}$$

By Eqs. (2.4) and (2.7), the correlation between past overnight returns and future daily returns $corr\left(r_{t-j}^{overnight}, r_t\right)$ is positive over short horizons. However, the correlation coefficients are lower than the autocorrelations of overnight returns, as indicated by the lower coefficients $\frac{\theta^0}{\theta^z+\theta^o}$ of the innovation terms in Eq. (2.7), since outside investors tend to negate the effect of the trading of newswatchers on price changes during overnight.

Prediction 3. *Stocks with a strong overnight trend on average yield higher future returns than stocks with a weak overnight trend. However, this outperformance of strong overnight trend stocks in terms of total returns (the sum of overnight returns and intraday returns) is weaker than that in terms of overnight returns.*

Prediction 3 suggests that the overnight trend strategy (based on past overnight returns) generates positive total returns in subsequent periods. Intuitively, outside investors cannot completely offset the informed trading when the newswatchers are also active. The prediction also suggests that the total returns are lower than the returns accrued only during the overnight periods.

Similarly, we can define an intraday trend $r_t^{INDT} = \sum_{j=1}^{J} r_{t-j+1}^{intraday}$.

Prediction 4. *Overnight trend has stronger forecasting power for cross-sectional returns than intraday trend.*

Compared to intraday returns, overnight returns have stronger predicting power and are easier to predict. This is reflected by their higher sensitivity to private information as shown in Eqs. (2.4) and (2.6). The intuition is the same as that for Prediction 3. The sensitivity to private information is further affected by the relative strength of the two groups of investors. Note that θ^o in Eq. (2.1) depends positively on outside investors' risk aversion and their perceived risk associated with the dividends and negatively on their population fraction. If the outside investors trade less aggressively due to higher risk aversion, higher perceived risk, or lower population fraction, reflected as a larger value of θ^o, then the intraday return in Eq. (2.6) becomes less sensitive to the private information and the overnight return in Eq. (2.4) becomes more sensitive to the private information. Intuitively, in an extreme case where the outside investors do not trade, the close price would be the same as the opening price and the private information is only reflected in the overnight returns. As a result, intraday returns become less predictable and overnight returns become more predictable (by either past intraday or overnight returns).

3. Data and variable construction

3.1. Data and data sources

Stock data are retrieved from Thomson Reuters Datastream, which includes all available A-shares listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange (*i.e.*, Mainboard, SME board, and ChiNext boards). Earnings announcements and analyst forecast data are retrieved from CSMAR. Following Liu et al. (2019), we adopt similar filtering rules to compile the dataset: First, we exclude stocks that have just become public within the past three months. Second, we filter out stocks that have consecutive zero returns over the past three months. This prevents our results from being influenced by stocks that are experiencing trading suspensions. Third, we exclude the bottom 30 % of stocks ranked by market capitalization at the end of the previous month. This ensures that our results are not driven by the smallest-cap stocks which are considered to have unique characteristics (Liu et al., 2019). After applying these filtering rules, we have in total 3332 unique stocks during the full sample period from July 1996 to December 2018. Following the convention in the literature (Han and Li, 2017; Liu et al., 2019), we use the one-year time-deposit rate, retrieved from WIND, as the proxy for the risk-free rate in China. US stock data over the same sample periods (used in the out-of-sample test) are retrieved from the CRSP/Compustat database via WRDS.

3.2. Variable construction

Daily intraday and overnight components of individual stock returns. Following the prior literature, we compute the daily intraday return component of stock i as the simple return from market open to market close over the same day s:

$$r_{i,s}^{intraday} = \frac{P_{i,s}^{close}}{P_{i,s}^{open}} - 1, \tag{3.1}$$

where $P_{i,s}^{open}$ and $P_{i,s}^{close}$ are the open price at 9:30AM and the close price at 3:00PM of the trading day in China (Gao et al., 2019; Gao et al., 2021; Liu et al., 2023). Similar to many markets, the open price, $P_{i,s}^{open}$, is determined by a pre-open auction (*i.e.*, between 9:15AM and 9:25AM). The overnight period spans from 3:00PM of the *prior* trading day to 9:30AM of the trading day, during which there is only the 10-min pre-open auction between 9:15AM and 9:25AM available for trading. The daily overnight return component is imputed from the daily stock return and the intraday return component:

$$r_{i,s}^{overnight} = \frac{1 + r_{i,s}}{1 + r_{i,s}^{intraday}} - 1, \tag{3.2}$$

where $r_{i,s}$ denotes the daily return on day s. The above definition ensures that all corporate events, such as dividend adjustments and share splits, accrue over the night (Lou et al., 2019; Bogousslavsky, 2021).

Monthly intraday and overnight components of individual stock returns. We accumulate intraday and overnight returns across days within the month to get the monthly measure of intraday and overnight return components:

$$r_{i,t}^{intraday} = \prod_{s=1}^{N_t} \left(1 + r_{i,s}^{intraday}\right) - 1, \tag{3.3}$$

and

$$r_{i,t}^{overnight} = \prod_{s=1}^{N_t} \left(1 + r_{i,s}^{overnight}\right) - 1, \tag{3.4}$$

where N_t denotes the number of trading days in month t. Eqs. (3.3) and (3.4) represent the cumulative returns that could be achieved, if an investor always holds the individual stocks during intraday and overnight periods within the month, respectively.

In addition, we also construct a number of firm characteristics, such as the log of market capitalization (lnME) and the log of book-to-market equity ratio (lnBTM). Details of the variable definitions are documented in **Table A1** in the appendix.

4. Overnight trend and asset prices

In this section we validate the intuitions developed in the illustrative model (in Section 2) that an overnight momentum strategy that based on past overnight price signals should have predictive power for subsequent (total) returns due to gradual information diffusion.

4.1. Overnight trend measure

To validate the **slow-information-diffusion** mechanism, we construct a novel firm-level overnight trend measure, which captures the collective demand of the informed overnight clientele.

Overnight trend. We define the overnight trend of the individual stock i, denoted as $OVNT_{i,t}$, as the monthly overnight return averaged over the past J months, skipping the most recent month.

$$OVNT_{i,t} = \frac{1}{J-1}\left[\prod_{j=2}^{J}\left(1 + r_{i,t-j}^{overnight}\right) - 1\right], \tag{4.1}$$

where J denotes the length of the lookback window (measured in months). Similarly, we denote $INDT$ as the intraday trend, which is defined similarly as the monthly intraday returns averaged over the past J months, skipping the most recent month. This novel measure (4.1) is consistent with the overnight trend (2.5) developed in Section 2, except that (4.1) uses percentage returns and (2.5) uses dollar returns that are consistent with the model setup of HS, and that (4.1) also skips the most recent returns to avoid microstructure issues that are not considered in our model.

4.2. Portfolio analysis

Overnight trend strategy. At the end of each month, we assign stocks (in ascending order) to decile portfolios based on their rolling J-month overnight trend. The top decile (D10) consists of stocks with the strongest overnight trend, while the bottom decile (D1) comprises those with the weakest overnight trend. Following Liu et al. (2019), we exclude the bottom 30 % of the smallest firms to ensure that our results are not driven by small caps. The portfolios are then held for one month before rebalancing, and equal-weighted excess returns are computed for our baseline analysis.[11] The self-financed overnight trend portfolio is formed by going long the top decile portfolio and short the bottom decile portfolio. In other words, our strong-minus-weak overnight trend strategy exploits the predictive information contents in the past overnight returns, because it mimics the expected order flows of the overnight clientele. Note the construction of the overnight trend utilizes information prior to the portfolio formation, so it avoids forward-looking bias and can be implemented in real time. Our overnight trend measure serves as a good proxy to capture the informative "order flow" (*i.e.*, demand) of the overnight clientele. Previous studies document that order flows of informed traders positively predict future stock returns (Easley et al., 2002; Yan and Zhang, 2009; Boulatov et al., 2013). Under this premise, we interpret a strong (weak) overnight trend as potentially reflecting positive (negative) price-related information.

Note our definition of the overnight trend strategy is similar to the convention used in forming the momentum strategy that skips the most recent month (*i.e.*, a one-month gap between the formation and holding periods) to mitigate the possible impacts due to the bid-ask spread or lead-lag effects (Jegadeesh, 1990; Lo and MacKinlay, 1990).[12]

Table 1 presents the average monthly performance of the overnight trend strategy (D10– D1) and its long (D10) and short (D1) legs, respectively. The first three columns exhibit the results based on a 12-month rolling overnight trend (*OVNT*), while the next six columns exhibit those of the 9- and 6-month rolling overnight trends. As reported in the first row of **Panel A** of the table, stocks with a strong past overnight trend (D10) tend to earn high subsequent returns whereas stocks with a weak past overnight trend (D1) tend to earn low subsequent returns. The overnight trend strategy is highly profitable, and the return spread between the D10 and D1 portfolios is both economically and statistically significant. For example, the 12-month OVNT strategy generates a monthly spread of 0.52 %, which is significant at the 1 % level (Newey-West t-statistic of 3.33). In comparison, the conventional 12-month (skipping the most recent month) momentum strategy only generates a moderate return of 23 bps per month over the same period (see **Table A2** in the appendix), which is consistent with prior findings that conventional momentum does not prevail in China's A-share market (Cakici et al., 2017; Liu et al., 2019; Chui et al., 2022).

While the evidence suggests the overnight trend strategy with alternative lookback periods is considerably profitable, it is possible that the profitability is due to the exposures to existing risk factors. Therefore, we also report the risk-adjusted returns (alphas) of the overnight trend strategies under alternative factor models including the CAPM, Fama-French three-factor (FF3), Fama-French five-factor (FF5), Fama-French six-factor (FF6), and the augmented seven-factor (FF7) models. Focusing on the alphas of the 12-month OVNT strategy, it is clear that its superior performance cannot be explained away by the conventional risk factors. Moreover, the risk-adjusted performance appears more salient to the unadjusted counterpart (*i.e.*, excess return), as the alphas of the 12-month OVNT strategy ranges from 53 bps to 85 bps per month, which are all significant at the 1 % level. Moving across the table, we find similar

[11] Our main results for the overnight trend strategy are robust under alternative portfolio formation techniques such as the market-cap weighting scheme. See Section 6.2 for a battery of robustness checks.

[12] The portfolio results on the overnight trend strategy are not affected by whether we skip the most recent month or not (omitted for brevity).

Table 1
Portfolios sorted on overnight trend, excluding the bottom 30 % smallest firms.

Panel A: Excess returns and risk-adjusted returns

	12-month OVNT			9-month OVNT			6-month OVNT		
	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1
Exret	0.31	0.83	0.52	0.36	0.93	0.57	0.41	0.74	0.33
	[0.43]	[1.17]	[3.33]	[0.50]	[1.30]	[4.17]	[0.55]	[1.05]	[2.07]
CAPM Alpha	–0.40	0.13	0.53	–0.36	0.23	0.59	–0.32	0.04	0.36
	[–1.81]	[0.80]	[3.49]	[–1.63]	[1.41]	[4.25]	[–1.48]	[0.24]	[2.35]
FF3 Alpha	–0.92	–0.05	0.86	–0.89	0.02	0.91	–0.79	–0.22	0.57
	[–5.75]	[–0.29]	[3.43]	[–5.25]	[0.13]	[3.46]	[–4.44]	[–1.26]	[2.38]
FF5 Alpha	–0.81	–0.04	0.77	–0.73	0.02	0.75	–0.65	–0.26	0.39
	[–5.68]	[–0.32]	[4.14]	[–5.33]	[0.19]	[4.67]	[–4.23]	[–1.97]	[2.20]
FF6 Alpha	–0.72	–0.06	0.66	–0.63	0.00	0.63	–0.56	–0.26	0.31
	[–5.71]	[–0.50]	[3.75]	[–4.73]	[0.04]	[3.64]	[–4.04]	[–1.96]	[1.67]
FF7 Alpha	–0.78	0.06	0.85	–0.68	0.11	0.79	–0.60	–0.17	0.43
	[–5.59]	[0.48]	[4.45]	[–4.97]	[0.86]	[4.64]	[–4.21]	[–1.16]	[2.33]

Panel B: The alpha and factor loadings under the augmented seven-factor model (FF7)

	12-month OVNT			9-month OVNT			6-month OVNT		
	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1
FF7 Alpha	–0.78	0.06	0.85	–0.68	0.11	0.79	–0.60	–0.17	0.43
	[–5.59]	[0.48]	[4.45]	[–4.97]	[0.86]	[4.64]	[–4.21]	[–1.16]	[2.33]
RMRF	1.00	1.03	0.02	1.01	1.02	0.01	1.02	1.01	–0.01
	[39.57]	[46.72]	[0.63]	[39.37]	[51.41]	[0.28]	[39.53]	[47.30]	[–0.42]
SMB	0.62	0.41	–0.20	0.59	0.44	–0.14	0.56	0.51	–0.05
	[8.16]	[5.63]	[–3.71]	[9.78]	[6.07]	[–2.33]	[9.57]	[6.47]	[–0.83]
HML	–0.15	–0.22	–0.07	–0.16	–0.20	–0.04	–0.19	–0.17	0.02
	[–2.74]	[–2.50]	[–0.67]	[–3.32]	[–2.52]	[–0.37]	[–4.14]	[–2.06]	[0.19]
RMW	–0.26	–0.19	0.07	–0.34	–0.20	0.14	–0.34	–0.14	0.20
	[–3.09]	[–1.26]	[0.51]	[–4.26]	[–1.46]	[0.84]	[–3.57]	[–1.07]	[1.23]
CMA	–0.13	–0.35	–0.23	–0.14	–0.40	–0.26	–0.20	–0.33	–0.13
	[–0.85]	[–3.05]	[–1.15]	[–0.95]	[–3.42]	[–1.28]	[–1.33]	[–2.51]	[–0.62]
MOM	0.24	–0.08	–0.33	0.26	–0.07	–0.32	0.21	–0.02	–0.23
	[4.01]	[–0.85]	[–2.52]	[4.16]	[–0.75]	[–2.56]	[3.07]	[–0.18]	[–1.78]
STREV	0.06	–0.13	–0.20	0.06	–0.11	–0.17	0.03	–0.09	–0.13
	[1.19]	[–2.24]	[–2.47]	[1.33]	[–1.97]	[–2.31]	[0.65]	[–1.40]	[–1.33]
Adj. R^2	0.94	0.92	0.30	0.94	0.92	0.28	0.94	0.92	0.16
Obs.	270	270	270	270	270	270	270	270	270

At the end of each month, stocks are assigned to the equal-weighted decile portfolios sorted in ascending order on their overnight trend, OVNT. OVNT is defined as the monthly overnight return averaged over the past J(=12,9,6) months, skipping the most recent month. Panel A reports the excess returns and risk-adjusted returns: Exret denotes the time-series average of the excess return of the decile portfolio (in percentages). Alpha is the intercept term in the regression of the CAPM model, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), and the augmented seven-factor model with the short-term reversal factors (FF7). Panel B reports the alpha and factor loadings under the augmented seven-factor model (FF7). Newey-West adjusted t-statistics with a lag length of 12 are reported in brackets below the coefficients. The sample period is between July 1996 and December 2018.

results for the 6- and 9-month OVNT strategies as well.

Interestingly, after adjusting for risk exposures, we observe that the alphas of the overnight trend strategy arise primarily from the short leg, as the returns of the D1 portfolio are highly negative on a risk-adjusted basis. For example, the FF3 alpha of the 12-month overnight trend strategy amounts to 0.86 % per month, with more than 100 % (0.92/0.86=107 %) of its profits coming from the short leg. In comparison, the FF3 alpha of the long leg is indistinguishable from zero (–5 bps per month). The fact that the overnight trend strategy profits mainly from the short leg only strengthens the slow-information-diffusion mechanism, because we would expect negative information (measured by a low overnight trend) to be disseminated more slowly in the market—bad news travels slowly (Hong et al., 2000). Moreover, since short-selling is more costly and there exists stringent short-sell constraints in China (and similar markets), most long-only investors compete to uncover undervalued stocks (rather than overvalued stocks). Therefore, it is not surprising that the predictive information content of the past overnight trend appears asymmetrically and is stronger for stocks in the short leg.

Panel B of the table reports the factor loadings of the overnight trend strategies with alternative lookback periods under the augmented seven-factor models, which include the market (RMRF), size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and short-term reversal (STREV) factors.[13] Evidently, the superior performance of the overnight trend strategy is not due to partially capturing the risk premium earned on these risk factors. In fact, the overnight trend strategy loads slightly negatively on several of these risk factors. After adjusting for common factors, the performance of the overnight trend strategy remains strong and robust.

4.3. Return decomposition of the overnight trend strategy

In this subsection, we decompose the holding period returns of the overnight trend strategy into its intraday component and overnight component, respectively. Lou et al. (2019) document that stocks that performed well during the day (over the night) continue to outperform in the same period in subsequent months but perform badly over the night (during the day) in subsequent months. They attribute the cross-period return reversal phenomenon to the persistent (offsetting) order flows from different clienteles between day and night. Our proposed overnight trend strategy relies on the relative (past) overnight performance of a stock in the cross section. Therefore, we would expect the overnight trend strategy to perform well over the night, but to suffer large drawdowns during the day in the holding period.

Table 2 confirms our notion. The first three columns report the average performance of the 12-month overnight trend strategy and its long and short legs during the day, while the next three columns report the overnight counterparts. The final three columns relate to their total holding period performance. Two salient features emerge from the table: First, the overnight trend strategy experiences dramatic daytime losses, as the intraday return component is highly negative. Focusing on the excess returns, the long leg underperforms the short leg by –2.85 % per month during the day. In stark contrast, the long leg outperforms the short leg by 3.14 % per month over the night. The tug of war is essentially robust to adjustments of risk exposure under alternative factor models. When aggregating the daytime and overnight returns, the total strategy returns remain positive since the overnight return component dominates.

Overall, results of the return decomposition are largely in line with the findings of Lou et al. (2019) that the "back and forth" between intraday and overnight clienteles largely reduces the profitability of cross-sectional strategies. Moreover, it provides empirical support that are in line with our model predictions that stocks with relatively high past overnight trend continue to deliver high (low) future overnight (intraday) returns in the cross section (see Predictions 1 and 2 in Section 2).

These results, along with the strong performance of portfolios formed on overnight trend as reported in Table 1, further suggest that stocks with a strong overnight trend yield higher future returns and that the overnight trend demonstrates stronger forecasting power than the intraday trend, confirming Predictions 3 and 4 in Section 2. We will provide more evidence on this in the next section.

4.4. Subsample analysis

Despite the superior performance of the overnight trend strategy over the full sample, one legitimate concern is whether the strategy is stable over time. In this section, we perform subsample analysis on the overnight trend strategy. Given our full sample spans from July 1996 to December 2018, we split it into two subsamples of approximately equal length (*circa* 11 years). The former subsample ranges from July 1996 to June 2006, while the latter spans from July 2006 to December 2018.

Table 3 presents the output of the subsample analysis. For brevity purposes, we report only the results of the overnight trend strategy with a 12-month lookback period. As it stands, the overnight trend strategy behaves quite stably over time: In both subsample periods, stocks with a strong overnight trend outperform stocks with a weak overnight trend in the subsequent month. The return differential between the two groups of stocks amounts to 44 and 58 bps in the former and latter subsample periods, respectively. The risk-adjusted returns range from 49 (56) to 98 (90) bps in the first (second) subsample period. In both subsample periods, we also find consistent evidence that the profitability of the strategy stems mainly from the short leg.

4.5. Firm-level evidence

While the portfolio analysis is simple and intuitive, it might be difficult to draw strong inferences because the aggregation to portfolio level might "overlook" important firm-level cross-sectional information, and it does not necessarily increase the precision of the coefficient estimates (Ang et al., 2020). To alleviate this concern, we perform the Fama and MacBeth (1973) cross-sectional regressions at the firm level, which controls for a number of well-known return determinants (such as size and value):

[13] The market factor is calculated as the value-weighted average of all eligible A-share stocks. The other risk factors are constructed in the same way as in Fama and French (2015) by using the 2 × 3 double-sorted portfolios, which are formed in July each year and held for 12 months. The size factor (SMB) is the arithmetic average of the three size factors generated in the 2 × 3 bivariate sorts for the value (HML), profitability (RMW), and investment (CMA) factors. Momentum (MOM) and short-term reversal (STREV) are also constructed using the 2 × 3 bivariate sorts, except that they are rebalanced monthly. The breakpoints for the size, value, profitability, investment, momentum, and reversal portfolios are determined solely by A-shares listed in the Main Board of the Shanghai Stock Exchange and Shenzhen Stock Exchange, which is similar to the NYSE criteria in the US.

Table 2
Intraday and overnight return decomposition of the overnight trend strategy.

12-month OVNT-sorted Decile Portfolios	Daytime			Overnight			Total		
	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1
Exret	4.10	1.25	–2.85	–3.45	–0.30	3.14	0.31	0.83	0.52
	[5.76]	[1.84]	[–12.07]	[–8.39]	[–0.67]	[17.04]	[0.43]	[1.17]	[3.33]
CAPM Alpha	3.62	0.78	–2.83	–3.68	–0.54	3.14	–0.40	0.13	0.53
	[7.53]	[1.73]	[–12.52]	[–9.60]	[–1.31]	[17.19]	[–1.81]	[0.80]	[3.49]
FF3 Alpha	3.24	0.69	–2.55	–3.82	–0.63	3.19	–0.92	–0.05	0.86
	[7.67]	[1.43]	[–10.57]	[–9.85]	[–1.50]	[16.03]	[–5.75]	[–0.29]	[3.43]
FF5 Alpha	3.16	0.61	–2.54	–3.66	–0.55	3.11	–0.81	–0.04	0.77
	[7.96]	[1.37]	[–12.10]	[–9.84]	[–1.29]	[17.24]	[–5.68]	[–0.32]	[4.14]
FF6 Alpha	3.20	0.55	–2.65	–3.62	–0.51	3.10	–0.72	–0.06	0.66
	[8.50]	[1.28]	[–12.33]	[–10.17]	[–1.23]	[17.07]	[–5.71]	[–0.50]	[3.75]
FF7 Alpha	2.95	0.52	–2.43	–3.45	–0.38	3.07	–0.78	0.06	0.85
	[7.95]	[1.16]	[–10.21]	[–9.74]	[–0.90]	[17.32]	[–5.59]	[0.48]	[4.45]

The table presents the decomposition results of the12-month overnight trend (OVNT) strategy and its long (D10) and short (D1) legs, respectively. Daytime, Overnight, and Total denote the portfolio performance of the intraday component, overnight component, and total portfolio returns, respectively. Exret denotes the time-series average of the excess return of the decile portfolio (in percentages). Alpha is the intercept term in the regression of the CAPM model, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), and the augmented seven-factor model with the short-term reversal factors (FF7). Newey-West adjusted *t*-statistics with a lag length of 12 are reported in brackets below the coefficients. The sample period is between July 1996 and December 2018.

Table 3
Subsample analysis: portfolios sorted on overnight trend, excluding the bottom 30 % smallest firms.

12-month OVNT-sorted Decile Portfolios	1996:07— 2006:06			2006:07— 201,812		
	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1
Exret	0.08	0.52	0.44	0.50	1.08	0.58
	[0.10]	[0.72]	[1.61]	[0.45]	[0.98]	[3.34]
CAPM Alpha	–0.55	–0.06	0.49	–0.27	0.29	0.56
	[–2.60]	[–0.41]	[1.90]	[–0.76]	[1.09]	[3.34]
FF3 Alpha	–0.86	0.12	0.98	–1.03	–0.27	0.76
	[–3.12]	[0.47]	[2.04]	[–8.39]	[–1.75]	[5.25]
FF5 Alpha	–0.76	0.03	0.79	–0.82	–0.07	0.75
	[–3.20]	[0.21]	[2.72]	[–6.55]	[–0.42]	[4.33]
FF6 Alpha	–0.64	–0.03	0.61	–0.78	–0.04	0.74
	[–3.41]	[–0.18]	[2.71]	[–6.56]	[–0.26]	[4.14]
FF7 Alpha	–0.69	0.04	0.73	–0.87	0.04	0.90
	[–4.10]	[0.27]	[3.46]	[–6.66]	[0.19]	[4.39]

At the end of each month, stocks are assigned to the equal-weighted decile portfolios sorted (in ascending orders) on their overnight trend, OVNT. OVNT is defined as the monthly overnight return averaged over the past 12 months, skipping the most recent month. Exret denotes the time-series average of the excess return of the decile portfolio (in percentages). Alpha is the intercept term in the regression of the CAPM model, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), and the augmented seven-factor model with the short-term reversal factors (FF7). Newey-West adjusted *t*-statistics with a lag length of 12 are reported in brackets below the coefficients. The first subsample period is between July 1996 and June 2006, while the second subsample is between July 2006 and December 2018.

$$Ret_i - RF = a + b_1 OVNT_i + CONTROLS + \varepsilon_i, \tag{4.2}$$

where *Ret* denotes the return of stock *i*, and *RF* the risk-free rate. *OVNT* is the past *J*-month overnight trend, skipping the most recent month. The control variables includes the log of market equity (*lnME*), the log of book-to-market equity (*lnBTM*), the ratio of operational profits and book equity (*OP*), the growth rate of the total assets (*INV*), the intermediate-term return momentum (RET^{MOM}), and the prior one-month return (RET^{STREV}) capturing the short-term return reversal. All explanatory variables in the equation are lagged values. Definitions of these firm characteristics are documented in **Table A1** in the appendix.

Table 4 presents the firm-level evidence. **Panel A** (**B** and **C**) uses the 12-month (9- and 6-month) overnight trend in the predictive regression. The results in the table are largely in line with the portfolio evidence: When used alone, overnight trend is a strong positive return predictor in the cross section, as the slope coefficient on *OVNT* amounts to 6.70 with a Fama-MacBeth *t*-statistic of 3 and a Newey-West *t*-statistic of 3.87. The predictive power of the overnight trend remains strong when we add a battery of return determinants into the regression model, such as firm size, book-to-market, operational profitability, asset growth (*i.e.*, investment), and past returns (Jegadeesh, 1990; Jegadeesh and Titman, 1993). The slope coefficient on *OVNT* amounts to 6.56, which is significant at the 1 % level.

Table 4
Fama-MacBeth regression at the firm level, excluding the bottom 30 % smallest firms.

	Const.	OVNT	lnME	lnBTM	OP	INV	RET^{MOM}	RET^{STREV}	$Adj.R^2$	Firms	Periods
	Panel A: 12-month OVNT										
Coef.	0.98	**6.70**							0.0060	1141	270
	(1.74)	**(3.00)**									
	[1.40]	**[3.87]**									
Coef.	1.67	**6.56**	–0.32	0.50	1.05	–0.02	0.08	–4.27	0.0845	1101	270
	(1.11)	**(3.57)**	(–2.56)	(2.61)	(2.03)	(–0.17)	(0.27)	(–5.15)			
	[0.84]	**[3.58]**	[–2.01]	[1.82]	[2.05]	[–0.19]	[0.20]	[–5.89]			
	Const.	**OVNT**	**lnME**	**lnBTM**	**OP**	**INV**	RET^{MOM}	RET^{STREV}	$Adj.R^2$	**Firms**	**Periods**
	Panel B: 9-month OVNT										
Coef.	0.99	**6.14**							0.0059	1141	270
	(1.74)	**(3.06)**									
	[1.41]	**[4.06]**									
Coef.	1.64	**5.61**	–0.31	0.50	1.09	–0.03	0.11	–4.27	0.0843	1101	270
	(1.09)	**(3.42)**	(–2.54)	(2.62)	(2.14)	(–0.25)	(0.37)	(–5.15)			
	[0.83]	**[3.48]**	[–2.00]	[1.85]	[2.13]	[–0.28]	[0.28]	[–5.91]			
Panel C: 6-month OVNT											
Coef.	1.02	**4.33**							0.0056	1149	270
	(1.80)	**(2.53)**									
	[1.45]	**[2.81]**									
Coef.	1.56	**4.15**	–0.31	0.52	1.17	–0.03	0.12	–4.28	0.0845	1101	270
	(1.04)	**(2.91)**	(–2.53)	(2.69)	(2.28)	(–0.28)	(0.39)	(–5.16)			
	[0.79]	**[2.80]**	[–1.98]	[1.89]	[2.21]	[–0.31]	[0.29]	[–5.93]			

This table reports the Fama-MacBeth cross-sectional regressions at the firm level. OVNT is the overnight trend defined as the monthly overnight return averaged over the past $J(=12,9,6)$ months, skipping the most recent month. lnME is the natural logarithm of firm's market capitalization measured at the end of the prior month. lnBTM is the natural logarithm of a firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. RET^{MOM} is the past 12-month cumulative return, skipping the most recent month. RET^{STREV} is the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5 % level. Coefficients of the time-series averages of the period-by-period cross-sectional regressions, are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey-West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2018.

Overall, when interpreting the firm-level and portfolio-level evidence jointly, it becomes clear that overnight trend is a strong positive return predictor in the cross section.

5. Inspecting the economic mechanisms

In this section, we perform additional analyses to validate the slow-information-diffusion explanation. In addition, we also explore several possible mechanisms for the return predictability of overnight trend in Section 4.

5.1. *Are overnight clientele more informed?*

Our slow-information-diffusion hypothesis of the overnight trend phenomenon builds on the key premise that overnight clientele are better informed—They either possess more privileged information or have better valuation skills to infer future firm fundamentals, which guides their informed trading. This implies that their collective demand, measured by past overnight trend, should be positively correlated with *subsequent* firm fundamentals in the cross section, even though we cannot observe the information set of the overnight clientele (as an empirical challenge). In other words, overnight trend should reflect overnight clientele's better anticipation of the future firm fundamentals in the cross section. To validate the above conjecture, we perform two sets of validation tests in the cross section:

In the first validation test, we examine the cross-sectional predictability of overnight trend on subsequent firm fundamentals at the quarterly level. Specifically, we perform the Fama-MacBeth cross-sectional predictive regressions, in which we regress the quarterly firm fundamentals on lagged overnight trend after controlling for other firm characteristics. The proxies of firm fundamentals include return on equity (ROE), return on asset (ROA), and earnings-to-price ratio (EP). We use both the level and the quarterly changes of these firm fundamentals as the dependent variables in our cross-sectional regression. The key variable of interest is the lagged 12-month overnight trend (skipping the most recent month) available at the end of the prior quarter. The control variables include the natural logarithm of firm's market capitalization, the natural logarithm of firm's book-to-market equity, the lagged 12-month cumulative return (skipping the most recent month), and the past one-month return. All explanatory variables are measured at the end of the quarter prior to the reporting quarter and are winsorized at the 0.5 and 99.5 % level. The quarterly sample spans from 2005 Q1 to 2018 Q4, as quarterly financial reports become mandatory in China only after 2004 (Liu et al., 2023).

Panel A of Table 5 presents the regression outcome when the dependent variables are the levels of ROE, ROA, and EP, respectively. As it stands, when used alone, lagged overnight trend is a strong positive predictor of the subsequent firm fundamentals in the cross section (see columns 1, 4, and 7). In comparison, the predictability of the conventional momentum (based on total returns) is fairly small in economic magnitude, though it also positively predicts the level of firm fundamentals in subsequent quarter (see columns 2, 5, and 8). More importantly, lagged overnight trend contains "unique" value-relevant information that is not captured by conventional return momentum and other firm characteristics, as it remains a strong positive predictor in the multi-variable regression when we control for a number of firm characteristics (see columns 3, 6, and 9). **Panel B** of the table presents a very similar picture, lagged overnight trend is a strong positive predictor of the quarterly changes in firm fundamentals in the cross section. This strong positive predictability remains fairly stable both in the single-variable regression and in the multi-variable regression when we include a number of firm characteristics, indicating that overnight clientele are able to identify the stocks with better changes in firm fundamentals in the cross section.

In our second validation test, we focus on one salient informational event: earnings announcement. If overnight clientele are better informed, we would expect their collective demand, measured by past overnight trend, to be positively correlated with *subsequent* earnings surprises in the cross section. Empirically, we validate the above notion using portfolio analysis. At the beginning of each quarter, all valid stocks (with earnings announcements within the quarter) are assigned to quintile portfolios based on their rankings of lagged OVNT in ascending order. We use two alternative measures of earnings surprises: standardized unexpected earnings (SUE) based on the difference in EPS between current quarter and the same quarter in the prior year, and standardized unexpected earnings (SUEAF) based on the difference of actual EPS and the median of analyst forecasts.[14]

Table 6 presents the average values of the earnings surprises for the quintile portfolios. There exists an approximately monotonic increasing pattern in average earnings surprises from the low-OVNT portfolio (Q1) to the high-OVNT portfolio (Q5). For example, for the 12-month OVNT sorted portfolios, the average difference in the standardized ranks of the quarterly SUE between the Q5 and Q1 portfolios amounts to 0.15, which is statistically significant at the 1 % level. This monotonic increasing pattern is robust for the two alternative earnings surprises measures and remains virtually intact across the OVNT measures with alternative lookback windows. In unreported analysis, we also test the average difference in the three-day cumulative abnormal returns (CAR) around the earnings announcements between the Q5 and Q1 portfolios and find very similar patterns. The three-day CAR of the Q5 portfolio is 25 (27 and 31) bps more than that of the Q1 portfolio sorted by the 12-month (9-month and 6-month) OVNT with a Newey-West *t*-statistic of 4.12 (4.24 and 4.28).

Overall, when interpreting the results in Tables 5 and 6 collectively, the key message of our validation tests is clear: Overnight trend, which measures the overnight clientele's collective trading behavior, predicts positively the *subsequent* firm fundamentals in the cross section. This lends strong support to our conjecture that overnight clientele are better informed or have better valuation skills, because they are better able to pick up the stocks with better firm fundamentals or the ones with greater changes in firm fundamentals.

5.2. *Further evidence on the slow information diffusion hypothesis*

5.2.1. *Interaction with information uncertainty*

Our slow-information-diffusion explanation posits that the collective trading behavior of the overnight clientele are mainly information-motivated and persistent over time. Thus, the overnight trend measure captures the predictive information content of asset prices implied by the (past) trading activities by the overnight clientele. If overnight clientele are indeed more informed, their information advantage or better valuation skills should be greater among firms with greater information uncertainty. Typically, these are small, growth and unprofitable firms (Zhang, 2006; Yan and Zhang, 2009). If the overnight trend proxies for informed trading, we would expect the overnight trend phenomenon to be more pronounced for stocks with higher information asymmetry (or valuation uncertainty).

To test this implication, we employ firm size (lnME), book-to-market ratio (lnBTM), operational profitability (OP), and earnings-to-price ratio (E/P) as our proxies for informational/valuation uncertainty (see **Table A1** in the appendix for definitions of the four proxies). To make the distinction between big and small firms, we generate a dummy variable that has a value of one if the lagged market capitalization of a firm lies within the top 30 % of all available firms, and zero otherwise. The dummy variables that distinguish between value/growth and profitable/unprofitable groups are classified in the same manner using lagged lnBTM, OP, and E/P, respectively.

Next, we re-estimate the Fama-MacBeth cross-sectional regression in Section 4.5 by including the dummy variable and its interaction with overnight trend (of the 12-month lookback period). The inclusion of the dummy term alleviates the concern due to omitted variables we do not observe. Our key interest lies in the slope coefficient on the interaction term. If the return predictability of overnight trend reflects informed trading by the overnight clientele, we would expect the interaction term to be highly negative (*i.e.*, the overnight trend effect is stronger for small, growth, and unprofitable firms than for large, value, and profitable firms).

[14] We are conservative to report the results based on the standardized ranks of both SUE and SUEAF. The standardization procedure helps mitigate of impact of outliers and ensures that the standardized ranks have a mean zero and its value varies from –1 to +1, which is more comparable across time. Our results remain robust (and are actually stronger) when we use the raw levels of SUE and SUEAF.

Table 5
Predictability of firm fundamentals.

Panel A: Dependent variables are ROE, ROA, and EP									
Dep. Var. =	**ROE**			**ROA**			**EP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OVNT	88.04		65.93	34.81		27.14	35.34		27.37
(FM t-stat)	(12.09)		(11.59)	(13.66)		(13.77)	(10.87)		(10.25)
[NW t-stat]	[6.19]		[7.20]	[7.62]		[10.50]	[5.28]		[4.87]
RET^{MOM}		6.59	6.03		3.40	3.11		0.83	0.64
(FM t-stat)		(7.82)	(8.43)		(7.31)	(7.73)		(2.75)	(2.93)
[NW t-stat]		[4.50]	[5.19]		[4.51]	[5.16]		[1.44]	[1.77]
Controls	N	N	Y	N	N	Y	N	N	Y
$Adj.R^2$	0.0225	0.0368	0.1178	0.0184	0.0458	0.1633	0.0382	0.0150	0.1695
Firms	1445	1445	1400	1419	1419	1371	1465	1465	1416
Periods	56	56	56	56	56	56	56	56	56
Panel B: Dependent variables are ΔROE, ΔROA, and ΔEP									
Dep. Var. =	**ΔROE**			**ΔROA**			**ΔEP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OVNT	16.68		14.49	6.57		5.08	4.07		3.46
(FM t-stat)	(3.01)		(2.97)	(3.33)		(4.10)	(3.40)		(2.62)
[NW t-stat]	[2.91]		[2.66]	[3.97]		[3.93]	[3.27]		[2.40]
RET^{MOM}		2.10	2.23		0.98	1.04		0.69	0.66
(FM t-stat)		(6.96)	(8.08)		(7.58)	(8.81)		(5.45)	(5.42)
[NW t-stat]		[5.95]	[6.41]		[8.41]	[8.30]		[4.54]	[4.76]
Controls	N	N	Y	N	N	Y	N	N	Y
adj. R2	0.0055	0.0120	0.0305	0.0060	0.0193	0.0369	0.0074	0.0130	0.0496
Firms	1444	1444	1399	1419	1419	1371	1464	1464	1416
Periods	56	56	56	56	56	56	56	56	56

The table presents the Fama-MacBeth cross-sectional predictive regressions on firm fundamentals at the quarterly level. In panel A (B), the dependent variables are return on equity (quarterly changes in return on equity) denoted as ROE (ΔROE) in columns 1–3, return on asset (quarterly changes in return on asset) denoted as ROA (ΔROA) in columns 4–6, and earnings to price ratio (quarterly changes in earnings to price ratio) denoted as EP (ΔEP) in columns 7–9, respectively. The independent variable of interest is the lagged 12-month overnight trend (OVNT), skipping the most recent month. RET^{MOM} is the lagged 12-month cumulative return, skipping the most recent month. Control variables include the natural logarithm of firm's market capitalization, the natural logarithm of firm's book-to-market equity, and the past one-month return. All explanatory variables are measured at the end of the quarter prior to the reporting quarter and are winsorized at the 0.5 and 99.5 % level. Fama-MacBeth t-statistics (in parentheses) and Newey-West adjusted t-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is from 2005 Q1 to 2018 Q4.

Table 7 presents the estimation results. The slope coefficient on overnight trend, OVNT, remains highly positive, reinforcing a (baseline) overnight trend phenomenon. Consistent with our hypothesis, all four coefficients on the interaction terms are negative, confirming that the overnight trend effect is more pronounced among small, growth, and unprofitable firms which are subject to higher informational asymmetry or valuation uncertainty. The evidence is stronger for the two conventional valuation measures: book-to-market ratio and earnings-to-price ratio. The interaction term in both cases is statistically significant at the 5 % or finer levels based on the one-sided test. In terms of economic significance, the overnight trend effect is more than doubled for growth firms compared with value firms. Specifically, for growth firms, a 1 % increase in the overnight trend leads to a 7.55 % increase in expected returns in the subsequent month. In contrast, for value firms, a 1 % increase in the overnight trend only increases subsequent expected returns by 2.74 % (7.55 % – 4.81 %). We observe a similar interaction effect for the profitability partition. The interaction with firm size, however, seems relatively weak, as it is not statistically significant.

In sum, results in Table 7 indicate that the overnight trend has stronger predictive power for small, growth, and less profitable firms. These results are consistent with the hypothesis that overnight trend, a proxy that captures informed trading by overnight clientele, offers more predictive informational content and is thus more "informative" for firms subject to higher information asymmetry or valuation uncertainty.

5.2.2. *Interaction with mispricing*

To gain deeper insights on the slow-information-diffusion mechanism, we analyse whether the overnight clientele (who possess an information advantage or better valuation skills) engage in arbitrage activities to profit from mispricing. In other words, we expect these investors to bet against the mispricing in the cross section (*i.e.*, uncover the relatively undervalued and overvalued stocks).

To test this channel, we examine whether the return predictability of overnight trend is greater for mispriced stocks that are largely affected by retail investors' demand and/or associated with greater limits-to-arbitrage. Prior studies document that mispricing is driven by retail investors' sentiment and overconfidence (Baker and Wurgler, 2006; Stambaugh et al., 2012; Han et al., 2020), lottery

Table 6
Overnight trend and subsequent earning surprises.

	12-month OVNT		9-month OVNT		6-month OVNT	
	SUE	SUEAF	SUE	SUEAF	SUE	SUEAF
Q1	–0.05	–0.12	–0.06	–0.13	–0.06	–0.13
	[–2.03]	[–7.77]	[–2.40]	[–9.50]	[–1.81]	[–4.97]
Q2	–0.03	–0.12	–0.05	–0.12	–0.07	–0.09
	[–1.33]	[–3.53]	[–4.78]	[–4.59]	[–5.27]	[–5.07]
Q3	–0.02	–0.07	0.01	–0.02	0.01	–0.03
	[–0.66]	[–1.65]	[0.68]	[–0.64]	[0.42]	[–0.75]
Q4	0.01	–0.03	0.01	–0.06	0.02	–0.03
	[0.17]	[–1.82]	[0.73]	[–2.06]	[1.05]	[–2.67]
Q5	0.11	0.10	0.12	0.10	0.13	0.08
	[7.80]	[4.95]	[7.03]	[3.81]	[8.31]	[3.75]
Q5 – Q1	0.15	0.22	0.18	0.24	0.19	0.21
	[4.76]	[10.01]	[4.75]	[12.26]	[4.48]	[9.90]

The table reports the average of earnings surprises over the quarter for the OVNT-sorted quintile portfolios. At the beginning of each quarter, stocks are assigned into quintile portfolios based on their rankings of *ex ante* OVNT. OVNT is the overnight trend defined as the monthly overnight return averaged over the past $J(=12,9,6)$ months, skipping the most recent month. The two earnings surprise measures are standardized unexpected earnings based on the EPS of the same quarter in the prior year (SUE), and alternative standardized unexpected earnings based on median analyst forecasts (SUEAF). Their definitions are available in Table A1 in the appendix. Newey-West adjusted t-statistics with a lag length of 12 are reported in brackets below the coefficients. The sample period is from 2005 Q1 to 2018 Q4.

demand (Kumar, 2009; Bali et al., 2011; Nartea et al., 2017), and limits to arbitrage (Shleifer and Vishny, 1997). For example, Doran et al. (2012) find that retail investors in China exhibit a strong gambling preference for lottery-type stocks. Given the presence of limits to arbitrage (*i.e.*, short-sale constraints), overpricing tends to be more prevalent, whereas underpricing is less likely to persist (since long-only investors compete to identify these undervalued assets). As a result, we expect that the overnight trend effect is more pronounced among mispriced stocks that are highly influenced by investor sentiment, lottery demand, and short-sales constraints.

To measure retail investor sentiment, we use turnover (TURN) in which a high turnover reflects a high sentiment of retail investors (Baker and Wurgler, 2006; Liu et al., 2019). It seems reasonable to assume that retail sentiment is correlated with trading volume, as more than 80 % of trading volume is contributed by retail investors in China. In addition, we employ the MAX5 measure in Bali et al. (2011) as a proxy for the lottery feature of a stock, and idiosyncratic volatility (IVOL) proposed by Ang et al. (2006) and return volatility (Sigma) as the proxies for limits to arbitrage (see **Table A1** in the appendix for definitions of the four proxies). We then construct dummy variables measuring the relative mispricing of a stock, which equal to 1 if the stock is in the top 30 % group sorted by TURN, MAX5, IVOL, and Sigma, respectively.

We re-estimate the Fama-MacBeth cross-sectional regression in Section 4.5 by including the dummy variable and its interaction with overnight trend (of a 12-month lookback period). Table 8 presents the estimation results. The regression results are consistent with our prediction: Overnight clientele seem to engage in arbitrage activity that corrects mispricing because their collective trading behaviour (measured by overnight trend) is stronger among mispriced stocks with high trading volume, lottery demand, and idiosyncratic volatility. The slope coefficient on the interaction term between OVNT and those mispricing measures are uniformly positive and significant at the 10 % level or above. In addition, the return predictability of overnight trend is more than doubled among speculative stocks. For example, among high-turnover stocks, a 1 % increase in overnight trend leads to an 8.01 % increase in expected returns in the subsequent month. In comparison, among low-turnover stocks, a 1 % increase in overnight trend only increases subsequent expected returns by 3.53 %.

To sum up, results in Table 8 indicate that overnight trend has stronger predictive power for mispriced stocks with high turnover, larger lottery preference, and stringent short-sales constraints. These results are consistent with the hypothesis that overnight trend, a proxy that captures informed trading by overnight clientele, offers more predictive informational content regarding mispricing correlation in the cross section.

5.3. Alternative explanations

Overnight trend could predict positively subsequent returns for reasons other than the slow-information-diffusion explanation. In this subsection, we consider a number of alternative explanations.

5.3.1. The disagreement hypothesis

One might argue that some of our findings could arise from disagreement between the intraday and overnight clienteles, and stocks that are highly demanded by intraday clientele tend to be the ones being sold heavily by overnight clientele, and *vice versa*.

The disagreement hypothesis, however, implies that whether we sorted on overnight trend or on intraday trend, we should observe the same "symmetrical" effect with a strong return spread in the cross section. In other words, the intraday trend measure should serve as a strong negative return predictor, because it also captures the disagreement between the two investor clienteles.

However, we find that intraday trend has no predictive power for subsequent stock returns. Table 9 performs the Fama-MacBeth

Table 7
Interaction with information uncertainty measures.

	Const.	OVNT	IND	OVNT×IND	lnME	lnBTM	OP	INV	RET^{MOM}	RET^{STREV}	$Adj.R^2$	Firms	Periods
lnME													
Coef.	1.57	**7.00**	–0.17	–1.10	–0.30	0.50	1.05	–0.02	0.08	–4.25	0.0857	1101	270
(FM t–stat)	(1.04)	**(3.90)**	(–1.52)	(–0.43)	(–2.30)	(2.61)	(2.01)	(–0.16)	(0.26)	(–5.13)			
[NW t–stat]	[0.80]	**[3.74]**	[–1.39]	[–0.39]	[–2.00]	[1.80]	[1.98]	[–0.19]	[0.19]	[–5.88]			
lnBTM													
Coef.	1.81	**7.55**	–0.00	**–4.81**	–0.31	0.45	1.00	–0.02	0.08	–4.26	0.0862	1101	270
(FM t–stat)	(1.25)	**(3.89)**	(–0.02)	**(–1.83)**	(–2.56)	(3.01)	(1.93)	(–0.19)	(0.28)	(–5.16)			
[NW t–stat]	[0.96]	**[4.00]**	[–0.03]	**[–2.36]**	[–2.01]	[2.03]	[1.97]	[–0.22]	[0.21]	[–5.83]			
OP													
Coef.	1.73	**7.68**	0.22	–3.71	–0.34	0.54	0.55	–0.07	0.05	–4.33	0.0866	1101	270
(FM t–stat)	(1.15)	**(4.17)**	(1.74)	(–1.43)	(–2.86)	(2.72)	(0.99)	(–0.66)	(0.17)	(–5.25)			
[NW t–stat]	[0.87]	**[4.42]**	[1.59]	[–1.55]	[–2.26]	[1.91]	[1.28]	[–0.74]	[0.13]	[–6.02]			
EP													
Coef.	2.13	**8.03**	0.23	**–6.05**	–0.36	0.44	0.68	–0.02	0.10	–4.27	0.0896	1101	270
(FM t–stat)	(1.48)	**(4.20)**	(1.77)	**(–2.38)**	(–2.99)	(2.34)	(1.51)	(–0.15)	(0.34)	(–5.18)			
[NW t–stat]	[1.11]	**[4.16]**	[1.98]	**[–1.98]**	[–2.35]	[1.67]	[1.45]	[–0.17]	[0.26]	[–5.90]			

This table reports the Fama-MacBeth cross-sectional regressions at the firm level. OVNT is the overnight trend defined as the monthly overnight return averaged over the past 12 months, skipping the most recent month. IND is the indicator variable which equals one if a stock is in the top 30 % group sorted by lnME, lnBTM, OP, and EP. OVNT×IND denotes the interaction term, designed to validate the hypothesis that the overnight trend effect is less prominent among the big, value, and profitable stocks. lnME is the natural logarithm of firm's market capitalization measured at the end of the prior month. lnBTM is the natural logarithm of a firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. RET^{MOM} is the past 12-month cumulative return, skipping the most recent month. RET^{STREV} is the past one-month return. EP is the earnings-to-price ratio. All explanatory variables are winsorized at the 0.5 and 99.5 % level. Coefficients of the time-series averages of the period-by-period cross-sectional regressions, are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey-West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2018.

Table 8
Interaction with mispricing measures.

	Const.	OVNT	IND	OVNT×IND	lnME	lnBTM	OP	INV	RET^{MOM}	RET^{STREV}	$Adj.R^2$	Firms	Periods
IVOL													
Coef.	2.29	**3.62**	–0.79	**4.60**	–0.35	0.44	0.89	–0.01	0.26	–2.72	0.0903	1101	270
(FM t–stat)	(1.53)	**(1.83)**	(–6.78)	**(2.02)**	(–2.87)	(2.28)	(1.75)	(–0.07)	(0.83)	(–3.14)			
[NW t–stat]	[1.16]	**[1.83]**	[–8.41]	**[2.58]**	[–2.25]	[1.63]	[1.85]	[–0.08]	[0.63]	[–3.56]			
MAX5													
Coef.	1.71	**4.24**	–0.30	**5.57**	–0.31	0.47	0.94	–0.02	0.13	–3.00	0.0918	1101	270
(FM t–stat)	(1.16)	**(2.19)**	(–1.86)	**(2.33)**	(–2.53)	(2.56)	(1.87)	(–0.22)	(0.45)	(–3.12)			
[NW t–stat]	[0.88]	**[2.13]**	[–1.92]	**[2.52]**	[–2.00]	[1.83]	[1.94]	[–0.24]	[0.33]	[–3.38]			
TURN													
Coef.	2.27	**3.53**	–0.44	**4.48**	–0.37	0.50	0.92	–0.03	0.18	–4.17	0.0902	1101	270
(FM t–stat)	(1.52)	**(1.74)**	(–3.69)	**(1.78)**	(–3.03)	(2.66)	(1.78)	(–0.25)	(0.57)	(–5.09)			
[NW t–stat]	[1.13]	**[1.76]**	[–3.85]	**[1.67]**	[–2.34]	[1.85]	[1.72]	[–0.27]	[0.42]	[–5.85]			
SIGMA													
Coef.	1.86	**4.44**	–0.29	**4.75**	–0.32	0.46	0.91	–0.02	0.15	–3.50	0.0927	1101	270
(FM t–stat)	(1.26)	**(2.30)**	(–1.85)	**(1.88)**	(–2.61)	(2.51)	(1.82)	(–0.21)	(0.50)	(–4.10)			
[NW t–stat]	[0.97]	**[2.14]**	[–1.87]	**[2.14]**	[–2.06]	[1.80]	[1.91]	[–0.24]	[0.38]	[–4.64]			

This table reports the Fama-MacBeth cross-sectional regressions at the firm level. OVNT is the overnight trend defined as the monthly overnight return averaged over the past 12 months, skipping the most recent month. IND is the indicator variable which equals one if a stock is in the top 30 % group sorted by idiosyncratic risk (IVOL), lottery preference (MAX5), investor sentiment (TURN), and return volatility (SIGMA). OVNT×IND denotes the interaction term, designed to validate the hypothesis that the overnight trend effect is more prominent among stocks with high sentiment, strong lottery preference, and stringent short-sales constraints. lnME is the natural logarithm of firm's market capitalization measured at the end of the prior month. lnBTM is the natural logarithm of a firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. RET^{MOM} is the past 12-month cumulative return, skipping the most recent month. RET^{STREV} is the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5 % level. Coefficients of the time-series averages of the period-by-period cross-sectional regressions are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey-West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2018.

cross-sectional regression with the overnight trend (OVNT) and intraday trend (INDT). When used alone, INDT does not predict subsequent stock returns at all. Although the slope coefficients on INDT are of a negative sign as expected, they are indistinguishable from zero. More strikingly, once we put OVNT and INDT together in the regression, the slope coefficient on OVNT continues to be significantly positive, indicating overnight trend contains incremental price-related information that is not captured by intraday trend.[15] The fact that the overnight trend has stronger predictable power than intraday trend is consistent with Predictions 3 and 4 in Section 2.

Overall, the results suggest that the overnight trend phenomenon is unlikely to be a disagreement effect because intraday trend is not priced in the cross section. Overnight trend seems to convey unique price-related information that is not captured by intraday trend (or disagreement).

5.3.2. *The sentiment hypothesis*

Another potential mechanism is investor sentiment. Berkman et al. (2012) document that the overnight return is related to retail investor sentiment in the US. Their argument is based on the premise that retail investors, who are mostly sentiment traders (Lee et al., 1991), tend to trade over the night, whereas institutions tend to trade aggressively during the day in the US stock market (Berkman et al., 2012; Lou et al., 2019). Aboody et al. (2018) examine this empirical prediction and confirm the suitability of using overnight return as a measure for firm-level sentiment.

However, we cast doubt on the sentiment-based explanation in China. First, unlike the US, the Chinese stock market is dominated by retail investors who contribute 80 % of total trading volume and tend to trade during the day, rather than over the night (Gao et al., 2021; Liu et al., 2023). Second, if overnight return captures investor sentiment, overnight trend should negatively predict future stocks returns, as the key prediction of sentiment-based theory is return reversal (Da et al., 2015). That is, high (low) sentiment induces overpricing (underpricing) of a stock, resulting in lower (higher) expected return in subsequent periods. However, Section 4 instead finds that the overnight trend positively forecasts subsequent returns which contrasts with the sentiment argument.

In addition, in Section 6.4 we use the Liu et al. (2019) four-factor model (CH4), which includes the sentiment factor, PMO (pessimist over optimistic), and find that the superior performance of the overnight trend strategy cannot be explained away by the sentiment-augmented factor model. Importantly, the factor loading on the PMO factor is virtually zero, implying that the sentiment-based explanation does not reconcile with our documented overnight trend phenomenon (see **Table I8** in the **Internet Appendix**).

5.3.3. *The non-marketability hypothesis*

Besides the Qiao and Dam (2020) price discount view of the overnight puzzle in China, Bai (2020) provides an alternative explanation on the overnight puzzle by linking it to the non-marketability theory in Longstaff (1995): The negative average overnight return (*i.e.*, price discount) reflects the value of the non-marketability option, because stocks cannot be re-sold until the next day (due to the $T+1$ trading rule). Under the non-marketability theory, the magnitude of the negative average overnight return varies in the cross section: Stocks that have a higher volatility or are more illiquid tend to have a larger overnight return discount.

While the above non-marketability hypothesis could explain why there exists a striking cross-sectional pattern in average overnight returns in China, it does not lead to any clear-cut predictions regarding expected stock returns in the subsequent period. In fact, if the stocks with more negative average overnight returns are considered riskier (or at least exhibit higher illiquidity or volatility risk), then we should expect these stocks to deliver higher subsequent expected returns from a rational perspective. Such projection, however, is in stark contrast to our documented overnight trend phenomenon, in which stocks with a weak overnight trend (*i.e.*, those impacted more by the non-marketability issue) delivers a lower return on average.

Of course, the potential mechanism(s) could be more complex than we projected. Given stocks with larger overnight reversal (*i.e.*, weak overnight trend) tend to be speculative stocks with higher volatility, some behavioural mechanisms (such as overconfidence) could lead to a positive relation between overnight trend and subsequent stock returns in the cross section. Such conjecture is also consistent with the empirical results in Section 4. This channel does not rely on the overnight clientele to be more informed but only requires that our overnight trend measure somehow captures the (relative) speculative nature of a stock in the cross section.

To alleviate this concern, we adopt the novel firm-level decomposition approach proposed in Hou and Loh (2016) to evaluate the competing explanations on the overnight trend phenomenon. This decomposition exercise proceeds in three stages: In the first stage, the univariate Fama-MacBeth cross-sectional regressions are performed by regressing the DGTW characteristics-adjusted returns on overnight trend to obtain the time series of its slope coefficients, $\widehat{\lambda}_t$. In the second stage, an orthogonalization regression is performed for each month to decompose overnight trend into two components: one that is explained by the (sole) candidate variable Z, the other that is the unexplained part (the intercept plus the residual term). That is, the overnight trend of an individual stock is the sum of the explained component and the unexplained component. We employ a comprehensive list of firm characteristics, including idiosyncratic volatility (IVOL), stock price (PRC), lottery preference (MAX5), Amihud illiquidity ratio (ILLIQ), systematic skewness (SSKEW), idiosyncratic skewness (ISSKEW), turnover ratio (TURN), and return volatility (SIGMA), which are known to reflect the relative speculative nature of individual stocks and also to be related to overnight trend. In the final stage, the average slope coefficient

[15] The above findings are robust when we control for other well-known firm characteristics such as firm size, value, profitability, investment, intermediate-term returns and etc. Moreover, at the portfolio level, the strategy that goes long stocks with weak intraday trend and short stocks with strong intraday trend does not generate any profits (unreported for brevity).

Table 9
Comparing overnight and intraday trends, excluding the bottom 30 % smallest firms.

	Const.	OVNT	INDT	Const.	OVNT	INDT	Const.	OVNT	INDT
	Panel A: 12-month OVNT and INDT			**Panel B: 9-month OVNT and INDT**			**Panel B: 6-month OVNT and INDT**		
Coef.	0.98	6.70		0.99	6.14		1.02	4.33	
	(1.74)	(3.00)		(1.74)	(3.06)		(1.80)	(2.53)	
	[1.40]	[3.87]		[1.41]	[4.06]		[1.45]	[2.81]	
Coef.	1.04		–0.98	1.02		–1.01	1.02		–1.51
	(1.83)		(–0.39)	(1.82)		(–0.46)	(1.81)		(–0.87)
	[1.39]		[–0.40]	[1.38]		[–0.48]	[1.34]		[–0.87]
Coef.	1.09	9.90	3.30	1.04	8.87	2.51	1.08	4.71	0.31
	(1.97)	(2.58)	(0.89)	(1.89)	(2.71)	(0.80)	(1.95)	(1.89)	(0.13)
	[1.52]	[2.32]	[0.80]	[1.43]	[2.70]	[0.77]	[1.43]	[1.98]	[0.13]

This table reports the Fama-MacBeth cross-sectional regressions at the firm level. OVNT and INDT are defined as the monthly overnight and intraday returns averaged over the past $J(=12,9,6)$ months, skipping the most recent month, respectively. All explanatory variables are winsorized at the 0.5 and 99.5 % level. Coefficients of the time-series averages of the period-by-period cross-sectional regressions are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey-West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2018.

Table 10
Horse race.

	IVOL	PRC	MAX5	ILLIQ	SSKEW	ISKEW	TURN	SIGMA
Panel A: Fama-MacBeth Cross-sectional Regression (Stage 1)								
Const.	0.05	0.03	0.03	0.02	0.02	0.02	0.02	0.03
FM t-stat.	(1.38)	(0.89)	(0.89)	(0.43)	(0.43)	(0.43)	(0.43)	(0.65)
NW t-stat.	[1.22]	[0.73]	[0.73]	[0.39]	[0.39]	[0.39]	[0.39]	[0.62]
OVNT	6.99	6.77	6.77	6.15	6.15	6.15	6.15	6.66
FM t-stat.	(4.45)	(4.32)	(4.32)	(3.93)	(3.93)	(3.93)	(3.93)	(3.93)
NW t-stat.	[4.93]	[4.58]	[4.58]	[4.49]	[4.49]	[4.49]	[4.49]	[4.00]
Obs.	270	270	270	270	270	270	270	270
Panel B: The Decomposition of the Slope Coefficient (Stage 3)								
Explained: Coef. $=\overline{\widehat{\lambda}(Z)_t^{Explained}}$, and Proportion $=\frac{\overline{\widehat{\lambda}(Z)_t^{Explained}}}{\overline{\widehat{\lambda}_t}}$								
coef.	2.34	0.22	0.92	0.63	0.26	–0.44	2.58	1.67
Proportion	33.44	3.23	13.53	10.27	4.18	–7.15	41.94	25.01
t-stat.	[4.20]	[0.77]	[2.47]	[1.54]	[0.92]	[–1.02]	[3.46]	[2.09]
Unexplained: Coef. $=\overline{\widehat{\lambda}_t^{Unexplained}}$, and Proportion $=\frac{\overline{\widehat{\lambda}_t^{Unexplained}}}{\overline{\widehat{\lambda}_t}}$								
coef.	4.65	6.56	5.86	5.52	5.90	6.59	3.57	4.99
Proportion	**66.56**	**96.77**	**86.47**	**89.73**	**95.82**	**107.15**	**58.06**	**74.99**
t-stat.	[8.37]	[22.95]	[15.80]	[13.44]	[21.05]	[15.23]	[4.80]	[6.25]
Total: Coef. $=\overline{\widehat{\lambda}(Z)_t^{Explained}}+\overline{\widehat{\lambda}_t^{Unexplained}}=\overline{\widehat{\lambda}_t}$, and Proportion $=\frac{\overline{\widehat{\lambda}(Z)_t^{Explained}}}{\overline{\widehat{\lambda}_t}}+\frac{\overline{\widehat{\lambda}_t^{Unexplained}}}{\overline{\widehat{\lambda}_t}}=100\ \%$								
coef.	6.99	6.77	6.77	6.15	6.15	6.15	6.15	6.66
Proportion	100	100	100	100	100	100	100	100

Panel A reports the firm-level Fama-MacBeth cross-sectional regressions. The DGTW characteristics-adjusted returns are regressed on overnight trend (OVNT), period by period, and the time-series average of the slope coefficients are reported in the first row, together with the Fama-MacBeth *t*-statistics (in parentheses) and the Newey-West *t*-statistics (in brackets). OVNT is defined as the monthly overnight return averaged over the past 12 months, skipping the most recent month. **Panel B** reports the final-stage of the firm-level Hou and Loh (2016) decomposition. **Explained** is the component of the slope coefficient explained by the candidate variable. **Unexplained** is the remaining component of the slope coefficient unrelated to the candidate variable. **Total** is the sum of the explained and unexplained components. The relative proportion of the explained and unexplained parts is also reported, together with their *t*-statistics in brackets. All candidate variables are defined in **Table A1** in the appendix, and are winsorized at the 0.5 and 99.5 % level. The sample period is between July 1996 and December 2018. The final-stage decomposition could be concisely expressed as follows: The slope coefficient decomposed into two parts: $\underbrace{\overline{\widehat{\lambda}_t}}_{Total}=\underbrace{\overline{\widehat{\lambda}(Z)_t^{Explained}}}_{Explained\ Coefficient}+\underbrace{\overline{\widehat{\lambda}_t^{Unexplained}}}_{Unexplained\ Coefficient}$. The relative proportions of the two components: $\underbrace{100\%}_{Total}=\underbrace{\frac{\overline{\widehat{\lambda}(Z)_t^{Explained}}}{\overline{\widehat{\lambda}_t}}}_{Explained\ Proportion}+\underbrace{\frac{\overline{\widehat{\lambda}_t^{Unexplained}}}{\overline{\widehat{\lambda}_t}}}_{Unexplained\ Proportion}$.

obtained in the first stage is further decomposed into two orthogonal components based on the property of linearity of covariance. That is, the explained and the unexplained coefficients (*i.e.*, $\overline{\widehat{\lambda}(Z)_t^{Explained}}$ and $\overline{\widehat{\lambda}_t^{Unexplained}}$) sum up to the time-series average of the slope coefficient $\overline{\widehat{\lambda}_t}$, making it easy to quantify the pure contribution of the candidate variable Z in explaining the positive OVNT-return relation. The above decomposition exercise is repeated for a number of candidate variables, providing a "horse race" to objectively compare the ability of each candidate variable in explaining the observed overnight trend phenomenon in China.

Table 10 quantifies the explanatory power of the candidate variables in explaining the overnight trend effect. The table indicates that the majority of the OVNT-return relation is not explained by the candidate variables. To be specific, among the candidate variables, only IVOL, ILLIQ, TURN, and SIGMA could explain 33.4 %, 10.3 %, 41.9 %, and 25 %, respectively, of the positive relation between the overnight trend and future stock returns. This is not surprising because our overnight trend variable is highly correlated with these firm characteristics by construction. However, a significant remaining portion (ranging from 67 % to 90 %) of the return predictability of overnight trend remains unexplained. This lends strong support to our conjecture that the overnight trend measure contains incremental price-related information that is not subsumed by the volatility/speculative characteristics that are related to the $T+1$ rule.

Overall, the "horse race" suggests that the non-marketability hypothesis is unlikely to be the main reason for our documented overnight trend phenomenon.

6. Further analysis and robustness checks

6.1. Transaction cost analysis

In this section, we perform the transaction cost analysis to better understand the features of the overnight trend strategy (in Section 4) from a practical perspective.

Panel A of Table 11 presents the annualized turnover ratio of the overnight trend strategy of alternative lookback periods over the full sample period. Following the classification of Novy-Marx and Velikov (2015), the zero-cost overnight trend strategy with a 12-month lookback period is a mid-turnover strategy, because its annualized portfolio turnover (316 %) is between one and five times per year. This also applies to the counterparts with 9-month and 6-month lookback periods (*i.e.*, 367 % and 453 %, respectively). Note the portfolio turnover progressively increases as the lookback period becomes shorter, suggesting the transaction costs would be lower for the overnight trend strategy with relatively longer ranking periods.

Panel B of the table provides a simple, back-of-the-envelope calculation of the transaction costs involved in implementing the investment strategy. We follow Grundy and Martin (2001) and Barroso and Santa-Clara (2015) to compute two types of the breakeven transaction costs: First, we compute the round-trip cut-off cost that renders the excess return of the strategy to be zero. Second, we compute similar costs that would zero out the various risk-factor adjusted returns of the strategy. Focusing on the overnight trend strategy with a 12-month ranking period, we find the breakeven transaction cost to be 2.11 % per month for the strategy to end up with zero excess returns accounting for the portfolio turnover. Similarly, the monthly breakeven transaction costs range from 215 to 337 bps per month to zero out the risk-adjusted returns of the strategy. In comparison, it is not surprising that the corresponding breakeven transaction costs are a bit lower for the overnight trend strategies with shorter lookback periods (9-month and 6-month), as these counterparts have a higher annualized portfolio turnover (see **Panel A**) and also lower mean risk-adjusted returns (see Table 1).

In sum, the transaction cost analysis provides strong evidence that the overnight trend strategy will remain profitable when transaction costs are considered, because it survives reasonable trading costs for practical implementation.[16]

6.2. Extensions and robustness checks

In this subsection, we provide a summary of extensions and robustness checks, and their main outcomes.

Out-of-sample evidence. We provide out-of-sample evidence with US stock data. The out-of-sample analysis serves two purposes. First, it alleviates the data snooping concern. Second, it helps demonstrate that our slow-information-diffusion explanation on the tug of war between day and night could be generalized to other market settings. Of course, the slow-information-diffusion hypothesis needs to be modified to fit the US context: Lou et al. (2019) document that all prominent anomalies (except for momentum) accrue their "premium" during the day in the US, and they link it to institutions who mainly trade during the day. Informed "order flows" stem from intraday clientele in the US, and therefore, we should observe an intraday trend phenomenon in the US. **Fig. A2** in the appendix visualizes the portfolio performance of the similarly constructed intraday trend phenomenon in the US. Stocks with a strong intraday trend outperform those with a weak intraday trend on a risk-adjusted basis. The intraday trend strategy delivers a positive risk-adjusted return when evaluated with the CAPM and Fama-French three-factor model.

Alternative weighting scheme. Our proposed overnight trend strategy is robust under alternative weighting schemes. We repeat the portfolio analysis with the value-weighted portfolios. The value-weighted 12-month overnight trend strategy continues to deliver an average excess return of 54 bps per month. The risk-adjusted returns range from 56 to 90 bps per month under alternative factor models, which are all significant at the 5 % or finer levels (see **Table A3** in the appendix).

[16] We are indebted to an anonymous referee, who points out the possible short-selling related costs and constraints in our context. Therefore, we alert the readers to exercise their own caution when interpreting the portfolio results of the transaction cost analysis for real-time implementation.

Table 11
Portfolio turnover and breakeven transaction costs.

OVNT-sorted Decile Portfolios									
	12-month OVNT			9-month OVNT			6-month OVNT		
	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1	D1 = Low	D10 = High	D10 – D1
Panel A: Annualized Portfolio Turnover (in %)									
Turnover	314	319	316	358	377	367	437	469	453
Panel B: Breakeven Transaction Costs (in bps)									
Excess Return	114	320	211	153	366	200	136	234	83
CAPM Alpha	–	32	215	–	102	207	–	27	92
FF3 Alpha	–	–	341	–	25	322	–	–	149
FF5 Alpha	–	–	308	–	24	268	–	–	99
FF6 Alpha	–	–	260	–	17	225	–	–	79
FF7 Alpha	–	30	337	–	51	280	–	–	113

Panel A reports the annualized portfolio turnover of the bottom (1) and top (10) decile portfolios and the long-and-short portfolio (10–1). The equal-weighted decile portfolios are sorted by overnight trend, OVNT (*i.e.*, the monthly overnight return averaged over the past $J(=12,9,6)$ months, skipping the most recent month). For a long-and-short portfolio, the turnover is averaged over the long and short sides. Panel B reports the breakeven transaction costs that would zero out the average excess returns and the risk-adjusted returns (*i.e.*, alphas) under the CAPM model, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), and the augmented seven-factor model (FF7). - indicates that the breakeven transaction cost is either below the threshold of 10 basis points (bps), or undefined as the pre-cost average (risk-adjusted) return is negative. The sample period is from July 1996 to December 2018.

Alternative lookback period. Although a 12-month lookback period seems the convention in momentum- or trend-based strategies, we are aware that an investor could set the lookback window with alternative lengths. In fact, an investor who adopts the overnight trend strategy with a lookback period ranging between 9 months and 15 months tends to achieve a fairly strong performance in terms of excess returns and risk-adjusted returns (see **Table A4** in the appendix for value-weighted portfolios, and also **Tables I4** and I5 for equally-weighted portfolios in the **Internet Appendix**).

Size-neutralized overnight trend strategies. Our key empirical finding that stocks with a high overnight trend outperform stocks with a low overnight trend is robust to the impact of firm size. Following Liu et al. (2019), we construct the size-neutralized version of the overnight trend strategy. To be specific, we first sort all stocks into 10 groups based on firm size. Second, we sort stocks, based on their overnight trend, into 10 subgroups within each size decile. Finally, the size-neutralized overnight trend sorted decile portfolios are formed by merging stocks in the same overnight trend decile across the first dimension (firm size). **Panel B** of **Table A4** in the appendix presents the risk-adjusted returns of the value-weighted size-neutralized version of the overnight trend strategies with alternative lookback periods. Again, we confirm that an investor who adopts the (size-neutralized) overnight trend strategy with a lookback period ranging between 9 months and 15 months tends to achieve a fairly strong performance during the sample period (see also **Tables I4** and I5 for equally-weighted portfolios in the **Internet Appendix**).

Alternative factor models. Our key finding that stocks with strong overnight trend outperform stocks with a weak overnight trend on a risk-adjusted basis is robust to alternative factor models, such as the recently proposed CH3 factor model in Liu et al. (2019). We do not rely on the Liu et al. (2019) three-factor model in our main analysis, simply because their factors are only available from 2000 onwards, which limits the sample period of our dataset. The zero-cost overnight trend strategy with a 12-month lookback period generates a CH3-adjusted return of 53 bps per month, which is significant at the 5 % level. Again, the superior performance of the overnight trend strategy stem mainly from the short leg: Stocks with the weakest overnight trend have an average CH3 alpha of negative 48 bps per month, which is significant at the 1 % level (see **Table I7** in the **Internet Appendix**).

Sentiment factor. We also test the overnight trend strategy with the sentiment-augmented CH4 model in Liu et al. (2019). The CH4 model includes a traded sentiment factor, PMO (pessimist over optimistic), which is more powerful than the CH3 model in explaining returns in the cross section. The results remain virtually unchanged, as the 12-month overnight trend strategy delivers a monthly risk-adjusted return of 50 bps, which is significant at the 5 % level. Interestingly, the factor loading on the PMO factor is virtually zero, indicating the overnight trend strategy is unlikely to be driven by investor sentiment (see **Table I8** in **Internet Appendix**).

Including the bottom 30 % smallest firms. In our baseline analysis, we exclude the bottom 30 % smallest cap firms to ensure that our key empirical results are not driven by these “different animals”. However, the overnight trend phenomenon is robust when we add back these small-cap stocks. We re-do the Fama-MacBeth regression with all the stocks and find very similar results that the lagged overnight trend is a reliable positive return determinant in the cross section, after accounting for other well-known firm characteristics. The slope coefficients on overnight trend with different lookback periods are all significant at the 1 % level (see **Table I9** in the **Internet Appendix**).

7. Conclusion

This paper shed light on why financial markets exhibit (or do not exhibit) simple forms of predictability such as momentum. Utilizing the day-and-night clientele difference in China, we validate the central prediction of a modified Hong and Stein (1999) model: Informed investors (*i.e.*, overnight clientele in our context) underreact to fundamental signals (*i.e.*, past overnight returns) due to slow information diffusion.

Empirically, we establish a strong link between the overnight trend and subsequent stock returns: Firms with a strong overnight trend reliably outperform firms with a weak overnight trend in the subsequent month. The overnight trend effect is stable over time and is more pronounced among stocks with higher information asymmetry, valuation uncertainty, and relative mispricing. More crucially, we document that the *ex-ante* overnight trend predicts positively subsequent-quarter firm fundamentals (such as ROE, ROA, EP, and earning announcements) in the cross section, which confirms the key premise in the theoretical model that overnight clientele are informed (*i.e.*, they possess more privileged information and/or have better valuation skills). We also rule out a number of alternative explanations by carefully executing a number of additional tests to show that none of these alternative explanations are (fully) compatible with the empirical patterns.

This paper deepens our understanding of how the interplay between the day-and-night investor clientele could reshape the cross-sectional return predictability based on past price signals. The key message of the paper is clear: underreaction to fundamental signals that generates return continuation (*i.e.*, slow information diffusion) is a pervasive behavioral symptom which prevails in various financial markets (including the setting with a heavy presence of noise traders in China). The presence of noise traders (only) adds difficulty to active investors in uncovering reliable fundamental signals from past prices. By separating the overnight returns from the total returns, we can extract the reliable informative price signals (that are less distorted by noise trading) in predicting subsequent cross-sectional stock returns, and pin down the type of active investors that are underreacting to information and generating the overnight momentum phenomenon. Our "high-frequency" evidence lends strong support to a broad class of behavioral models that momentum arises from informed investors underact to fundamentals.

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Supplementary materials

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