A One-factor Model for Expected Night-minus-day Stock Returns*

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Abstract

We propose a one-factor model for expected night-minus-day (NMD) returns and use it to examine the economic forces underlying NMD return predictabilities. Our model successfully prices a large set of NMD portfolios with a cross-sectional R^2 around 80%. Consistent with the absence of near-arbitrage opportunities, the pricing factor has substantial exposure to the dominant common risks in the NMD return space. Finally, we link the pricing factor to retail order imbalances at the market open and the required returns from liquidity provision. Our findings point to a pricing equilibrium in which liquidity providers require compensation for accommodating sentiment-driven demand.

Keywords: Night-minus-day returns, liquidity provision, limits-to-arbitrage, retail trading

JEL Classifications: G12, G14, G23

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Stock return predictability is a subject of intense interest for finance practitioners and academics. Recent research documents more than a dozen characteristics that predict the cross-section of night-minus-day (NMD) stock returns, defined as the difference between a stock's overnight and intraday returns (e.g., Berkman, Koch, Tuttle, and Zhang (2012), Lou, Polk, and Skouras (2019), and Hendershott, Livdan, and Rösch (2020)). Moreover, the predictive power of these stock characteristics for NMD returns cannot be explained by standard factor models, e.g., Fama and French (2015); Hou, Xue, and Zhang (2015); Stambaugh and Yuan (2017); Daniel, Hirshleifer, and Sun (2020). As a first step towards understanding the pricing of these expected NMD returns, we propose a parsimonious one-factor model that summarizes the cross-sectional variation in expected NMD returns. We then use our proposed NMD pricing factor to examine the economic forces underlying these NMD return predictabilities.

To achieve our first objective of developing a factor model for explaining NMD returns, we start by spanning the NMD return space using the 17 long-short anomaly portfolios from Lou, Polk, and Skouras (2019) (hereafter, the LPS portfolios). Lou, Polk, and Skouras (2019) conduct the most comprehensive study of the cross-section of NMD returns in the literature and find that these 17 portfolios generate substantial spreads in NMD returns.[1] We then utilize two approaches to construct the NMD pricing factor.[2] First, we estimate the stochastic discount factor (SDF) in the NMD return space using the method proposed by Kozak, Nagel, and Santosh (2020) and use the resulting SDF (hereafter, NMD SDF) as our first specification of the pricing factor. Second, in the spirit of Stambaugh and Yuan

[1]Other research in this literature includes Hendershott, Livdan, and Rösch (2020), Berkman, Koch, Tuttle, and Zhang (2012), and Bogousslavsky (2021). The 17 anomaly characteristics examined in Lou, Polk, and Skouras (2019) is representative of the set of NMD return predictors examined by this literature.

[2]We focus on one-factor rather than multi-factor models in this paper chiefly due to a desire to avoid overfitting.

(2017), we combine the predictive information for NMD returns from all 17 characteristics into a composite score (CS). Following the long-time standard approach of constructing characteristic-based factors, we construct a long-short portfolio sorted on CS and use the NMD return of this portfolio (hereafter, NMD CS) as an alternative specification of the pricing factor.[3] The virtue of NMD CS is that it requires only information available at the time of its construction. These two specifications represent two distinct methodologies in a large and growing literature on factor modeling: the first specification imposes the asset pricing restriction linking expected NMD returns to NMD return covariance, whereas the second specification does not. Our use of these two specifications is to ensure that our key takeaways are robust to reasonable variations in methodology.

Next, we examine the ability of a one-factor model based on NMD SDF or NMD CS to explain the cross-section of NMD returns. We find that our one-factor model captures most of the cross-sectional variation in the average NMD returns of the 17 LPS portfolios, with a cross-sectional R^2 of 94% (84%) for the model based on NMD SDF (NMD CS). In contrast, the corresponding cross-sectional R^2 of the standard factor models used in the anomaly literature range from 6% to 11%. To further validate the pricing performance of our proposed NMD pricing factor, we conduct an out-of-sample test by augmenting the set of test assets with 80 long-short portfolios sorted on the anomaly characteristics examined in Green, Hand, and Zhang (2017) but not in Lou, Polk, and Skouras (2019). These additional long-short portfolios introduce independent cross-sectional and time-series return variations relative to the LPS portfolios, resulting in a more stringent pricing test (Lewellen, Nagel, and Shanken (2010)). Using the same one-factor model, we find that NMD SDF (NMD CS) still captures much of the cross-sectional variation in average NMD returns in this augmented set of 97 long-short portfolios, achieving a cross-sectional R^2 of 79% (78%).

[3] The long-short portfolio sorted on CS can also be interpreted as an approximation of the SDF if all stocks equally contribute to the NMD return covariance matrix. See Section 2 for more detailed discussions.

After demonstrating the good empirical performance of our proposed NMD pricing factor, our second objective is to use it to understand the economic sources of NMD return predictabilities. Our first set of tests focus on the relation between the NMD pricing factor and the common risk factors in the NMD return space. These tests are motivated by the insight in Kozak, Nagel, and Santosh (2018) that, given substantial cross-sectional variation in expected returns, either the return space should have a weak factor structure or the SDF should load heavily on the first few PCs. Since this prediction is predicated on the absence of near-arbitrage opportunities, if we find the opposite in the data, i.e., there is a strong factor structure but small SDF loadings on the common risk factors, then either near-arbitrage opportunities exist temporarily in the sample or NMD return predictabilities are a statistical fluke.

We find that the NMD returns of the 17 LPS portfolios have a strong factor structure, with the first three PCs explaining a majority of the total NMD return variance. Then, consistent with the prediction in Kozak, Nagel, and Santosh (2018), we find that both NMD SDF and NMD CS have statistically significant and economically large exposures to the first two PCs in the NMD return space. These first two PCs together explain 65% and 64% of the variation in NMD SDF and NMD CS, respectively, and a factor model based on the first two PCs explains 76% of the cross-sectional variation in the average NMD returns of 17 LPS portfolios. Therefore, to earn the return to the NMD pricing factor (i.e., a proxy for the mean-variance efficient NMD portfolio), one has to take on the common risk in the NMD return space. In addition, our results do not support a data mining or publication bias explanation because there is no reason to expect a data-mined NMD pricing factor (with a spuriously high in-sample Sharpe ratio) to have significant exposures to common risk factors.

Next, we conduct direct tests to link the NMD pricing factor to sentiment-driven demand and the required compensation for arbitrageurs to accommodate such demands.[4] Related

[4] As highlighted by Kozak, Nagel, and Santosh (2018), the existence of a common factor model can reflect

to the former, existing studies such as Berkman, Koch, Tuttle, and Zhang (2012) and Lou, Polk, and Skouras (2019) have studied the role of sentiment-driven demand in driving NMD return predictabilities. Complementing these studies, we provide new evidence on the timing and identity of the sentiment-driven demand. We find that the sentiment-driven demand underlying NMD return predictabilities is more likely to occur at the market open than at the market close. Then, using a comprehensive dataset on retail order imbalances, we find that this sentiment-driven demand is predominantly from retail investors.

Related to the role of the required compensation for arbitrageurs, we put forth a liquidity provision hypothesis that market makers are the marginal arbitrageurs who exploit NMD return predictabilities by accommodating the associated sentiment-driven demand. Our liquidity provision hypothesis is motivated by two key observations. First, exploiting NMD return predictabilities requires high-turnover trading strategies, which are not profitable if the implementation involves paying the bid-ask spreads. Second, given our finding that NMD return predictabilities are related to sentiment-driven demand from retail investors, exploiting NMD return predictabilities means trading against (i.e., accommodating) such sentiment-driven demand. For these two reasons, we consider market makers to be the only plausible arbitrageur of NMD return predictabilities, which as a sector does not pay the bid-ask spread and is uniquely positioned to provide liquidity to retail order imbalances.

Under this liquidity provision hypothesis, when market makers demand higher required returns from liquidity provision, as their risk-bearing capacity is low or their risk aversion is high, they would also demand a higher return to trade against NMD return predictabilities. To test this prediction, we measure the required returns from liquidity provision using the empirical proxy proposed by Nagel (2012). Specifically, Nagel (2012)'s liquidity provision factor is the return of a short-term reversal strategy sorted on 1 to 5-day lagged daily returns. We find that both NMD SDF and NMD CS load positively and statistically significantly on

both of these economic forces.

the liquidity provision factor. Furthermore, more than 80% of their average NMD returns are explained by exposure to the liquidity provision factor, resulting in insignificant alphas. These findings are consistent with our hypothesis that market makers are the marginal arbitrageur of NMD return predictabilities. Finally, when we jointly use our proxies for sentiment-driven demand and the required returns from liquidity provision in a regression, we find that the NMD pricing factor significantly loads on both proxies. Therefore, the magnitude of the NMD return predictabilities appears to be affected by time variation in both the strength of the sentiment-driven demand and the willingness of liquidity providers to accommodate such demand.

Our paper builds on an existing literature that documents a large number of predictors for NMD returns (e.g., Berkman et al. (2012), Lou, Polk, and Skouras (2019), Hendershott, Livdan, and Rösch (2020)), and Bogousslavsky (2021).[5] As a key step towards a common explanation for these NMD return predictabilities, we contribute to the literature by being the first to propose a parsimonious factor model for explaining the cross-section of expected NMD returns. We also show that the NMD return space has a strong factor structure and that our proposed NMD pricing factor is tied to the common risk in NMD returns. As a result, it is unlikely that NMD return predictabilities are entirely due to data mining or publication bias. Finally, we document new evidence linking the NMD pricing factor to both sentiment-driven demand and the required returns from liquidity provision.

The remainder of this paper is organized as follows. Section 1 describes our data, measurements of the overnight and intraday returns, and the construction of test assets. Section 2 constructs the NMD pricing factor and examines its pricing performance. Sections 3 and 4 investigate the economic sources of the NMD pricing factor. We conclude in Section 5.

[5]Heston, Korajczyk, and Sadka (2010); Bogousslavsky (2021) also document predictability in the cross-section of half-hour returns.

1. Data and Measurement

1.1. Sample Construction

We start by collecting data from the Center for Research in Security Prices (CRSP) database for all U.S. common stocks listed on the NYSE, AMEX, and NASDAQ stock exchanges. Because we are interested in overnight and intraday stock returns, we require the daily open price from CRSP, which is available starting on June 15, 1992. We then merge the CRSP data with the NYSE Trade and Quote (TAQ) database using the TAQ-CRSP link table provided by Wharton Research Data Services (WRDS). Since TAQ data starts on January 4, 1993, our analyses requiring TAQ data are conducted over the period between 1993 and 2020. See Data Appendix Subsections 6.2 and 6.3 for a more detailed description of the TAQ data and the procedure used to merge the TAQ data with the CRSP data.

We impose the following data filters. First, like Hendershott, Livdan, and Rösch (2020), we drop stock days with an intraday return over 1000% or when the open price is missing. Second, to mitigate the microstructure issues and ensure that results are not driven by small and illiquid stocks, we require the following for a stock to be included in the portfolios formed at the end of month t: (i) the median daily trading volume in month t is greater than 1,000 shares, (ii) the stock has no more than one missing open price from CRSP in month t, and (iii) following Lou, Polk, and Skouras (2019), stocks need to have a price above \$5 and a market capitalization above the NYSE bottom quintile at the end of month t. Since all our portfolio returns are value-weighted, our results are robust to removing the low price filter and the microcap filter.

1.2. Measurement of NMD Returns

We follow Lou, Polk, and Skouras (2019) and compute the intraday return ($r_{D,d}$) on day d as,

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

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

$$r_{N,d} = \frac{1 + r_{\text{close-to-close},d}}{1 + r_{D,d}} - 1, \tag{2}$$

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

$$r_{NMD,d} = r_{N,d} - r_{D,d}. \tag{3}$$

Both P_d^{close} in Eq. (1) and $r_{\text{close-to-close},d}$ in Eq. (2) are sourced from CRSP, following the convention in the literature. Our main specification of P_d^{open} is the open price from CRSP, similar to Hendershott, Livdan, and Rösch (2020), so that researchers who do not have access to TAQ data can still replicate our results.

The pricing performance of our proposed one-factor model and the other key takeaways from this article are robust to using the specifications of P_d^{open} from Berkman et al. (2012), Bogousslavsky (2021), or Lou, Polk, and Skouras (2019) based on TAQ data. Berkman et al. (2012) use the first midquote, Bogousslavsky (2021) use the midquote at 9:45 am, and Lou, Polk, and Skouras (2019) use the volume-weighted average price between 9:30 am and 10:00 am. Our Online Appendix reports all our results using Lou, Polk, and Skouras (2019)'s specification of P_d^{open}, which alleviates the concern that our results based on the CRSP open price are driven by microstructure noise or bid-ask bounce. Moreover, in our Online appendix, we confirm that all our results remain robust when we restrict the sample to stocks with market capitalizations above the NYSE median breakpoint.

1.3. Construction of the Test Assets

Our main set of test assets consists of the long-short portfolios sorted on the 17 anomaly characteristics examined by Lou, Polk, and Skouras (2019). We use the NMD returns of these 17 LPS portfolios to span the payoff space.[6] In our out-of-sample (OOS) test, we augment these 17 LPS portfolios with the long-short portfolios sorted on additional 80 anomaly characteristics from Green, Hand, and Zhang (2017) that are not examined by Lou, Polk, and Skouras (2019).[7]

To construct these long-short portfolios, following Lou, Polk, and Skouras (2019), we sort all stocks into decile portfolios based on an ascending ordering of each of these signals at the end of each month t. The long-short zero investment portfolio goes long the top decile portfolio and short the bottom decile portfolio. We then calculate the daily value-weighted overnight and intraday portfolio returns realized in month $t+1$ with the prior day's market capitalization as the weights. The daily NMD returns of the long-short portfolio is the return on a trading strategy that goes long this portfolio overnight and short it intraday. Since our focus is on the ability of a factor model for explaining the deviations from the CAPM model, we adjust all portfolio returns by subtracting the CAPM beta times the corresponding market excess returns, respectively.[8] In all subsequent analysis, NMD returns refer to market-adjusted NMD returns.

Table 1 reports the time-series mean of the overnight, intraday, and NMD returns for

[6]See Data Appendix Subsection 6.1 for detailed descriptions on the construction of these signals.

[7]Among these additional characteristics from Green, Hand, and Zhang (2017), we exclude the small number of binary ones that do not work for forming our decile portfolios. We thank Green, Hand, and Zhang (2017) for providing the SAS code used to generate these characteristics.

[8]We estimate the CAPM beta by regressing the daily close-to-close returns of the long-short portfolio on daily market excess returns in the full sample. Our results are robust to using the CAPM betas estimated in rolling estimation windows. Following Heston, Korajczyk, and Sadka (2010), we assume the risk-free rate is earned overnight. So, the market-adjusted intraday return is the portfolio intraday return minus the CAPM beta times the market intraday return, whereas the market-adjusted overnight return is the portfolio overnight return in excess of the risk-free rate minus the CAPM beta times the market overnight return in excess of the risk-free rate.

these long-short portfolios. We observe that most of these portfolios earn overnight and intraday returns that are opposite in sign but similar in magnitude, resulting in average unadjusted NMD returns ranging from −26.0% to 69.6% per year. Adjusting for exposures to the market factor explains very little of the average NMD returns because, unlike the close-to-close returns of these portfolios, the NMD returns of these portfolios typically have negligible exposure to the market factor. As a result, 13 out of the 17 portfolios have statistically significant market-adjusted NMD returns at the 1% level. Furthermore, the large cross-sectional variation in average NMD returns cannot be explained by risk adjustments under the five-factor model of Fama and French (2016) (FF5), the four-factor model of Hou, Xue, and Zhang (2015) (HXZ4), the four-factor model of Stambaugh and Yuan (2017) (SY4), or the three-factor model of Daniel, Hirshleifer, and Sun (2020) (DHS3).[9] Our results are largely consistent with the corresponding findings reported in Lou, Polk, and Skouras (2019) that are based on data up to the end of 2013 with the risk adjustment based on the CAPM and the Fama and French (1993) three-factor model. We now turn to our proposed one-factor model.

2. A One-factor Model for the Cross-section of Expected NMD Returns

In this section, we develop a one-factor model to summarize cross-section of NMD returns. We focus on one-factor models in this paper chiefly to avoid overfitting. Specifically, using a one-factor model with the factor premium set equal to the time-series mean of the factor returns results in only one degree of freedom (i.e., the exposure to the proposed factor) in the pricing tests. Our preference for a parsimonious model is consistent with the long empirical

[9] We obtain the factor returns for these models from these authors' websites. We thank Ken French, Lu Zhang, Robert Stambaugh, and Lin Sun for posting their data online. All factors are available for our sample period except for the SY4 factors, which are available up to the end of 2016.

asset pricing literature that tries to explain the cross-section of close-to-close returns with a small number of factors. Future research can seek to improve upon our proposed one-factor model by adding more factors.

2.1. Construction of the NMD Pricing Factor

We first lay out the motivation and the methodology for constructing our proposed NMD pricing factor. Consider an economy with N test assets. Denote the vector of the NMD excess returns for these assets by $R = (R_1, ..., R_N)$ and the covariance matrix of these NMD returns by Γ. Define $\mu \equiv E(R)$. In the payoff space formed by any linear combination of NMD returns, the law of one price implies the existence of a stochastic discount factor (SDF) as follows (Hansen and Jagannathan (1991)),

$$\mathrm{SDF} = 1 - b' (R - \mu), \tag{4}$$

where the SDF coefficients are the weights of the mean-variance efficient portfolio (i.e., $b = \Gamma^{-1}\mu$). A naive approach for estimating b is to plug in the sample counterparts of μ and Γ, but it is well known that this naive estimator performs poorly out-of-sample due to the uncertainty in the estimated means and covariance matrix of the returns.

Therefore, a large and growing literature since the seminal work of Fama and French (1993) has alternatively used three general approaches to construct pricing factors. One approach is to construct factors based on behavioral and rational asset pricing theories (Fama and French (2015); Hou, Xue, and Zhang (2015); Daniel, Hirshleifer, and Sun (2020)). So far however, the theory for explaining NMD return predictabilities is lacking. Thus, one of our goals in developing a parsimonious one-factor model is to inform future research on building such a theory. A second approach imposes the asset pricing restriction that links expected returns to return covariances in order to extract pricing factors from portfolio returns. The

Kozak, Nagel, and Santosh (2020) estimator that we use in our first specification of the NMD pricing factor is representative of this approach.[10] Finally, a third and widely-used approach in the anomaly literature is to use returns of characteristic-sorted portfolios as factors without imposing structural constraints. Our second specification of the NMD pricing factor is more in line with this approach. Our use of these two specifications is intended to ensure that our key takeaways are robust to reasonable variations in methodology.

2.1.1. The First Specification of the NMD Pricing Factor

We use the Bayesian SDF estimator proposed by in Kozak, Nagel, and Santosh (2020) (hereafter KNS estimator) to construct the first specification of the NMD pricing factor. With an economically motivated prior, the KNS estimator of b in Eq. (4) resembles a ridge regression estimate with a L^2 norm penalty term,

$$\hat{b} = \left(\overline{\Gamma} + \gamma I\right)^{-1} \overline{\mu}, \tag{5}$$

where I is the identity matrix, $\overline{\Gamma}$ and $\overline{\mu}$ are the estimated return covariance matrix and the average returns of the test assets, respectively, and γ is the hyperparameter associated with the L^2 penalty term. As Kozak, Nagel, and Santosh (2020) explain, this estimator shrinks the SDF coefficients of the naive estimator towards zero, with the shrinkage factor being stronger for the coefficients on the principal components with smaller variance.[11]

Our implementation of the KNS estimator is as follows. We denote the NMD returns for the 17 LPS portfolios by F_t. With a time series of length T, we estimate the sample

[10] See Kozak, Nagel, and Santosh (2020) for a discussion of this literature. Our results are also robust to using the approach proposed by Lettau and Pelger (2020).

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

moments by,

$$\overline{\mu} = \frac{1}{T}\sum_{t=1}^{T} F_t \tag{6}$$

$$\overline{\Gamma} = \frac{1}{T}\sum_{t=1}^{T} \left(F_t - \overline{\mu}\right)\left(F_t - \overline{\mu}\right)' \tag{7}$$

To choose the optimal γ, we follow Kozak, Nagel, and Santosh (2020) in using K-fold cross-validation (CV) with $K = 3$. We first equally divide our sample into three subsamples and then set a grid of potential values for γ. For a given γ value, we use $K - 1$ subsamples to estimate the in-sample moments $\overline{\mu}_{IS}$ and $\overline{\Gamma}_{IS}$, according to Eqs. (6) and (7), and $\hat{b}_{IS} = \left(\overline{\Gamma}_{IS} + \gamma I\right)^{-1} \overline{\mu}_{IS}$. Then, using the withheld subsample, we compute the OOS moments, $\overline{\mu}_{OOS}$ and $\overline{\Gamma}_{OOS}$. Finally, we compute the out-of-sample R^2 as,

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

We withhold each of the K subsamples, treat it as OOS data, and repeat the above procedure K times. The cross-validated R^2 is the average R^2_{OOS} across these K estimates for a given γ. Then, we select the optimal γ that maximizes the cross-validated R^2. With the optimal γ, we compute the SDF coefficient b^* using the full-sample moments according to Eqs. (5) – (7). Finally, we use b^* to construct the one-dollar long and one-dollar short zero investment portfolio as the NMD pricing factor. This pricing factor is then the linear combination of the 17 LPS long-short portfolios with the following weight on each portfolio i,

$$w_i = \frac{b_i^*}{\sum_{i=1}^{17} |b_i^*|}. \tag{8}$$

We use the NMD returns of this long-short portfolio as our first specification of the NMD pricing factor (NMD SDF). We note that the construction of NMD SDF uses full-sample information. Kozak, Nagel, and Santosh (2020) also conduct a pure OOS test, in which they withhold part of the data when estimating the optimal b^* and show that the resulting SDF estimator performs well in the withheld sample. Since our sample period is shorter than that in Kozak, Nagel, and Santosh (2020), we instead evaluate OOS performance by expanding the set of test assets in our cross-sectional pricing test. Furthermore, our second specification of the pricing factor requires only information available at the time of its construction.

2.1.2. The Second Specification of the NMD Pricing Factor

To construct our second specification of the pricing factor, we first combine all 17 LPS characteristics into a composite predictive signal of a stock's NMD return. This procedure is similar in spirit to Stambaugh and Yuan (2017), who construct a composite mispricing score based on 11 anomaly characteristics. Instead of equally weighting each characteristic, we follow Lewellen (2015) and use a Fama and MacBeth (1973) regression approach to let the data indicate how much weight to put on individual characteristics. Specifically, at the end of each month t, we run a multivariate cross-sectional regression of the NMD return on lagged characteristics as follows,

$$\mathrm{NMD}_{i,t} = \alpha + \beta_t^{'} \times x_{i,t-1} + \epsilon_{i,t},\ i = 1, ..., N, \tag{9}$$

where $\mathrm{NMD}_{i,t}$ is the average of daily NMD returns before the CAPM adjustment for firm i in month t, and $x_{i,t-1}$ is the vector of the 17 LPS characteristics for firm i in month $t-1$. Similar to Freyberger, Neuhierl, and Weber (2020) and Kozak, Nagel, and Santosh (2020), we minimize the influence of extreme values by normalizing the cross-sectional rank of a characteristic, $c_{i,t}^s$, as

$$x_{i,t}^s = \frac{\mathrm{rank}(c_{i,t}^s) - \overline{\mathrm{rank}(c_{i,t}^s)}}{n_t + 1}, \tag{10}$$

where n_t is the number of stocks in month t.[12] We then construct the composite signal for firm i in month t using 12-month moving averages of β_t (i.e., $\beta_{t,MA} = \frac{1}{12}\sum_{L=0}^{11}\beta_{t-L}$) and $x_{i,t}$:

$$CS_{i,t} = \beta_{t,MA}^{'} \times x_{i,t}. \tag{11}$$

Similar to the construction of the 17 LPS portfolios, we then construct a one-dollar long-short zero-investment portfolio sorted on CS. We use the NMD returns on this long-short portfolio as our second specification of the NMD pricing factor (NMD CS). The portfolio weights of NMD CS can be interpreted as a proxy for b in Eq. (4) under the assumption that CS is proportional to μ and all stocks equally contribute to Γ.

2.2. Pricing Performance of Factor Models

We start by reporting the summary statistics for NMD SDF and NMD CS. We first note that NMD SDF and NMD CS have a daily Pearson correlation of 0.81, which is consistent with the notion that both are proxies for the SDF. Next, Table 2 shows that NMD SDF and NMD CS have average returns of 44.9% and 94.7% per annum (p.a.) and annualized Sharpe ratios of 5.0 and 4.4, respectively. In comparison, as shown in Figure 1, the Sharpe ratios of the 17 individual LPS portfolios range from 0.1 to 3.4. These results again support the notion that NMD SDF and NMD CS are proxies for the SDF, which is the maximum Sharpe ratio portfolio in the payoff space. Finally, we observe that NMD SDF and NMD CS have a modest skewness of 0.20 and -0.17, a large kurtosis of 31.5 and 20.4, and a small first-order autocorrelation of 0.07 and 0.05, respectively.

To examine the pricing performance of various factor models, we run a time-series regression of the daily NMD returns of the 17 LPS portfolios on factors to determine factor exposures and alphas. Column (1) of Panel A of Table 3 shows that the cross-sectional mean

[12] We use the average rank if there is a tie in the characteristic value across stocks. If a characteristic value is missing, we use zero to fill it in.

of the absolute alpha relative to the CAPM, FF5, HXZ4, SY4, and DHS3 models are 31.4%, 29.5%, 30.3%, 33.8%, and 29.8% p.a., respectively. In contrast, the cross-sectional mean of the absolute alpha relative to a one-factor model based on NMD SDF (NMD CS) is much smaller, at 7.3% (12.4%) p.a. Similarly, Column (2) shows that the cross-sectional mean of the absolute $t-$statistic under the CAPM, FF5, HXZ4, SY4, and DHS3 factor models are all above 6, whereas the corresponding value for a one-factor model based on NMD SDF (NMD CS) is only 1.26 (2.06).

Following Kozak, Nagel, and Santosh (2020), we use cross-sectional R^2 as the main measure of the relative pricing performance across the competing factor models. Specifically, we define

$$R^{2,\mathrm{XS}} = 1 - \frac{\left(\overline{\mu} - \beta' \overline{F}\right)' \left(\overline{\mu} - \beta' \overline{F}\right)}{\overline{\mu}' \overline{\mu}}, \tag{12}$$

where $\overline{\mu}$ is the vector of the sample means of each test asset's NMD return, β is the matrix of the factor loadings from a time series regression of test asset's NMD return on the factor(s), and $\overline{F}$ is the vector of the sample mean of each factor.

Column (3) of Panel A of Table 3 reports that the cross-sectional R^2 of the CAPM is zero because all NMD returns are market-adjusted. The cross-sectional R^2s of the other standard factor models range from 6% to 11%. In contrast, a one-factor model based on NMD SDF (NMD CS) achieves a substantially higher cross-sectional R^2 of 94% (84%). In Panel A of Figure 2, we plot the average NMD returns against the predicted NMD returns by these factor models. For the CAPM, we observe a vertical line because the CAPM has no explanatory power for the (market-adjusted) NMD returns. Using the other standard factor models does not change the vertical pattern by much. In comparison, using the predicted NMD returns under our one-factor model based on either NMD SDF or NMD CS results in a much better alignment along the 45 degree line. These results demonstrate that our proposed one-factor model provides a good summary of the cross-section of the NMD returns spanned by the 17 LPS portfolios.

2.3. Out-of-sample Test with an Expanded Set of Test Assets

To further validate the pricing performance of our proposed NMD pricing factor, we conduct an OOS test by augmenting the test asset set with the long-short portfolios sorted on 80 anomaly characteristics that are examined in Green, Hand, and Zhang (2017) but not by Lou, Polk, and Skouras (2019). Since Lou, Polk, and Skouras (2019) do not pick their set of 17 anomaly characteristics based on the ability to predict NMD returns,[13] these additional anomaly characteristics may also predict NMD returns. In untabulated results, we find that 58 out of these additional 80 long-short portfolios have an average NMD return that is significantly different from zero at the 5% level. Therefore, conducting this test not only examines the OOS fit of the factor models but also results in a more stringent pricing hurdle by introducing independent cross-sectional and time-series variation in NMD returns relative to that of the LPS portfolios (Lewellen, Nagel, and Shanken (2010)).

Panel B of Table 3 reports the pricing results for this cross-section of 97 test assets. We find that the cross-sectional mean of the absolute CAPM alpha is 19.4% p.a., and the corresponding mean absolute $t-$statistic is 4.5. Both numbers are lower in this expanded set than in the 17 LPS portfolios because 22 out of the additional 80 portfolios do not have statistically significant average NMD returns. Similar to the results based on the LPS portfolios, we find that the alphas and the associated $t-$statistics based on our proposed one-factor model are much smaller in magnitude than those based on the standard factor models. To see the improved distributions of the $t-$statistic under our proposed model, Figure 3 plots the empirical distribution of the $t-$statistic for alphas under the different factor models.

[13] Lou, Polk, and Skouras (2019) state that they choose to examine these 17 anomaly characteristics because they are related to popular trading strategies.

We observe that adjusting NMD returns using standard factor models results in $t-$statistics that are far larger in magnitude than predicted by the null hypothesis. In contrast, adjusting NMD returns using our one-factor model results in an empirical distribution of the $t-$statistic that is much closer to a standard central $t-$distribution. Similarly, Panel B of Table 3 shows that while the cross-sectional R^2s under the standard factor models range from 14% to 19%, our one-factor model based on NMD SDF (NMD CS) achieves a much higher cross-sectional R^2 of 79% (78%). The large improvement in the pricing performance of our one-factor model relative to the standard factors models in this expanded set of test assets is also illustrated in Panel B of Figure 2.

3. Relation between the NMD Pricing Factors and the NMD Common Risk Factors

After establishing that the NMD pricing factor summarizes the cross-section of expected NMD returns, we move to use it to understand the economic forces underlying NMD return predictabilities. We start by exploring the relation between the NMD pricing factor and the common risk factors in the NMD return space.

Our test is motivated by the prediction that, given large cross-sectional spreads in expected return, either the return space has a weak factor structure or the SDF loads heavily on the first few dominant principal components (see, Kozak, Nagel, and Santosh (2018)).[14] To characterize the factor structure of the NMD return space, we perform a principal component analysis (PCA) of the NMD returns of the 17 LPS portfolios.[15] In Table 4, we find that the NMD return space exhibits a strong factor structure. The first five principal components

[14]Kozak, Nagel, and Santosh (2018) argue that given a large cross-sectional spreads in expected return and a strong factor structure, expected returns should align with the dominant sources of return variance as otherwise extremely high Sharpe ratio (near-arbitrage) opportunities would exist.

[15]Following Kozak, Nagel, and Santosh (2020), we center but do not scale the returns when performing the PCA.

(PCs) explain 26%, 22%, 13%, 7% and 6% of the total variance of the 17 LPS portfolios, respectively, and the first three PCs together explain a majority (61%) of the total variance.

Given this strong factor structure, we turn to testing whether our NMD pricing factor aligns with the first few dominant PCs. Columns (1) through (3) of Table 5 show the results of regressing the NMD pricing factor on progressively more PCs. We find that NMD SDF loads strongly on the first two PCs, with the first PC explaining 47% of its variance and the second PC explaining an additional 18% of its variance. Adding the third PC increases the adjusted R^2 by a modest 4 percentage points. Columns (4) through (6) of Table 5 show that NMD CS loads even more heavily on the first PC, with the first PC explaining 58% of its variance. Adding the second PC increases the adjusted R^2 by another 6 percentage points, whereas adding the third PC increases the adjusted R^2 by less than a percentage point. Consistent with this tight time-series relation between our NMD pricing factor and the dominant PCs, we also find that a factor model using the first two PCs achieves a cross-sectional R^2 of 76% when explaining the 17 LPS portfolios (see, Panel A of Table 3 and Figure 2).[16]

Therefore, our time-series and cross-sectional results are consistent with the economic equilibrium modeled in Kozak, Nagel, and Santosh (2018), in which near-arbitrage opportunities do not exist. Our test results can also be interpreted as being inconsistent with explanations based on the data mining or publication bias, since they do not predict the NMD pricing factor to load heavily on the common risk factors in the NMD return space.

[16] We note that, despite having one more degree of freedom, the two-factor model based on the first two PCs does not outperform our one-factor model based on NMD SDF or NMD CS in terms of cross-sectional R^2.

4. Sentiment-driven Demand and Required Returns from Liquidity Provision

Our finding that an NMD pricing factor loads heavily on common risk factors can be consistent with both sentiment-driven asset pricing models and risk-based asset pricing models, as shown by Kozak, Nagel, and Santosh (2018). Therefore, we conduct direct tests from both perspectives to link the NMD pricing factor to sentiment-driven demand and the compensation required by arbitrageurs to accommodate such demand in this section.

4.1. Sentiment-driven Demand

4.1.1. Timing of Sentiment-driven Demand

Lou, Polk, and Skouras (2019) attribute the NMD return predictabilities documented in their study to a tug-of-war between the opposing trading demand of clienteles who prefer to trade at the market open and close, respectively.[17] This notion of "tug-of-war" provides a good starting point for understanding how sentiment-driven demand can give rise to NMD return predictabilities. Specifically, as we show in Figure 4, our composite signal CS predicts (market-adjusted) NMD returns for up to 60 months after portfolio formation. At the same time, CS does not predict (market-adjusted) close-to-close returns.[18] This joint pattern of CS strongly predicting NMD returns and weakly predicting close-to-close returns have two possible tug-of-war explanations: one (the other) is that the sentiment-driven demand that gives rise to the predictive power of CS for NMD returns occurs repeatedly at

[17]Lou, Polk, and Skouras (2019) state "... as the primary focus in our analysis, some investors may prefer to trade at or near the morning open while others may prefer to trade during the rest of the day up to and including the market close." Relatedly, Berkman et al. (2012) attribute the NMD return predictabilities documented in their study to retail trading near the market open.

[18]Our results are similar to those documented in Figure 2 of Lou, Polk, and Skouras (2019), with the difference being we use our composite signal whereas they separately use 2 out of the 17 LPS stock characteristics as the predictor.

the market open (close) and its price impact is attenuated by the trading demand of the opposing clientele during the rest of the day, generating strong NMD return predictability and relatively weak close-to-close return predictability. Understanding whether the recurring mispricing concentrates at the market open or close is a key step toward characterizing the sentiment-driven demand underlying NMD return predictabilities.

We design a test to distinguish between these two explanations. In the first explanation, the deviations from the CAPM are the largest at the market open, and they decline during the rest of the trading day. Therefore, using prices progressively later in the morning as P^{open} in Eqs. (1) and (2) to compute r_N and r_D should lead to progressively weaker NMD return predictability. In the second scenario, the deviations from the CAPM are the largest at the market close and thus using prices earlier than 4:00 pm as P^{close} to compute r_N and r_D should result in weaker NMD return predictability. Figure 5 illustrates these two competing hypotheses.[19]

To implement this test, we divide the trading day into 13 half-hour trading intervals, with the first one starting at 9:30 am and the last one ending at 4:00 pm. Then, we recompute r_N and r_D using the following four alternative specifications of P^{open}: the first midquote after 9:30 am, 10:00 am, 10:30 am, and 11:00 am; and the following four alternative specifications of P^{close}: the last midquote before 4:00 pm, 3:30 pm, 3:00 pm, and 2:30 pm. We compute these midquotes as the average of the national best bid and offer from TAQ data.[20]

Panel A of Table 6 reports the average NMD SDF and NMD CS based on these alternative specifications of P^{open} or P^{close}. Columns "9:30 am" to "11:00 am" show a consistent pattern for both NMD SDF and NMD CS: the average NMD pricing factor decreases substantially when we use midquotes progressively later in the morning as P^{open} to compute r_D

[19] We assume the price is equal to the fundamental value at the market close (open) to simplify the exposition, but such an assumption is not necessary for our test.

[20] We set the first (last) midquote to be missing if it happens after (before) midday. We drop days with late openings or early closings. See Section 6.2 of the Appendix for detailed description of the data.

and r_N. For example, the average NMD SDF (NMD CS) is 48.7%, 16.6%, 10.4%, and 7.5% p.a. (106.6%, 36.5%, 20.9% and 17.8% p.a.) when using the first midquote after 9:30 am, 10:00 am, 10:30 am, and 11:00 am as P^{open}, respectively. This declining pattern supports the explanation that NMD return predictabilities are due to the price impact of sentiment-driven demand at the market open, which is in turn attenuated by opposing clientele demand throughout the rest of the day.

In sharp contrast, Columns "2:30 pm" to "4:00 pm" show that using midquotes earlier in the afternoon as P_d^{close} to compute r_D and r_N has relatively minor effects on the resulting average returns of the NMD pricing factor. The average NMD SDF (NMD CS) is 46.0%, 47.7%, 50.2%, and 48.8% p.a. (106.1%, 108.6%, 113.7%, and 109.9% p.a.) when using the last midquote before 2:30 pm, 3:00 pm, 3:30 pm, and 4:00 pm as P^{close}, respectively. Thus, these results are inconsistent with the explanation that NMD return predictabilities arise from sentiment-driven demand at the market close. Overall, our results in Panel A of Table 6 indicate that sentiment-driven demand underlying NMD return predictabilities is more likely to occur at the market open than at the market close.

4.1.2. Identity of Sentiment-driven Demand

We next test whether the sentiment-driven demand at the market open that gives rise to NMD return predictabilities comes from retail or institutional trading. Accurately deciphering traders' identities on both sides of a transaction is an empirical challenge due to data limitations. We tackle this challenge by using the new method proposed in Boehmer et al. (2020) to identify retail order flows. The Boehmer et al. (2020) algorithm identifies retail purchase and sales by noting that trades at non-midpoints with a subpenny price improvement after the implementation of Regulation National Market System (Regulation NMS) are almost always marketable retail orders. These orders are recorded in TAQ with exchange code "D", and the buy/sell direction of the trade can be identified by the magnitude of the subpenny price improvements.[21] We apply the Boehmer et al. (2020) algorithm in the post-October 2007 period when Regulation NMS is fully implemented. We use the retail marketable order imbalances identified by the Boehmer et al. (2020) algorithm to proxy for retail trading demand. We then use the buy-minus-sell total order imbalances identified by the Lee and Ready (1991) algorithm as a proxy for the total trading demand. The difference between the total and retail order imbalances is our proxy for the non-retail trading demand.

We use the following procedure to measure the order imbalances associated with the NMD pricing factor. We first measure order imbalances at the stock level for each of the 13 half-hour trading intervals,

$$
\begin{aligned}
\mathrm{OI}_{i,d,\tau} &= \frac{D_{\mathrm{buy},i,d,\tau} - D_{\mathrm{sell},i,d,\tau}}{\mathrm{MCAP}_{i,d-1}} \\
\mathrm{ROI}_{i,d,\tau} &= \frac{D^{\mathrm{retail}}_{\mathrm{buy},i,d,\tau} - D^{\mathrm{retail}}_{\mathrm{sell},i,d,\tau}}{\mathrm{MCAP}_{i,d-1}},
\end{aligned}
$$

where $D_{\mathrm{buy},i,d,\tau}$ and $D_{\mathrm{sell},i,d,\tau}$ ($D^{\mathrm{retail}}_{\mathrm{buy},i,d,\tau}$ and $D^{\mathrm{retail}}_{\mathrm{sell},i,d,\tau}$) are the dollar values of the buy and sell orders identified by the Lee and Ready (1991) (Boehmer et al. (2020)) algorithm for stock i, day d, and the 30-minute interval τ. We scale them by the lagged market value of the stock, $\mathrm{MCAP}_{i,d-1}$, to account for the size effect. Denote the weights of the long-short portfolio of NMD SDF (NMD CS) on stock i and day d by $w_{i,d}$. We then compute the order imbalances underlying the NMD pricing factor as,

$$
\begin{aligned}
\mathrm{OI}_{d,\tau} &= \frac{\sum_{i=1}^{n_{d,\tau}} w_{i,d} \times \mathrm{OI}_{i,d,\tau} \times I\left(\mathrm{OI}_{i,d,\tau}\right)}{\sum_{i=1}^{n_{d,\tau}} w_{i,d} \times I\left(\mathrm{OI}_{i,d,\tau}\right)} \\
\mathrm{ROI}_{d,\tau} &= \frac{\sum_{i=1}^{n_{d,\tau}} w_{i,d} \times \mathrm{ROI}_{i,d,\tau} \times I\left(\mathrm{ROI}_{i,d,\tau}\right)}{\sum_{i=1}^{n_{d,\tau}} w_{i,d} \times I\left(\mathrm{ROI}_{i,d,\tau}\right)},
\end{aligned}
$$

where $I(\cdot)$ is an indicator function that equals one when $\mathrm{OI}_{i,d,\tau}$ ($\mathrm{ROI}_{i,d,\tau}$) is non-missing

[21] The Boehmer et al. (2020) algorithm results in a substantial improvement in the coverage of retail order flows over other existing approaches. We refer interested readers to the related discussions in their study.

and zero otherwise. We annualize these order imbalance numbers by multiplying them by 13 times 252, so that they are in annualized percentage points (relative to market capitalization).

Panel B of Table 6 reports the order imbalances for NMD SDF and NMD CS, respectively. Since our analysis in the previous subsection suggests that the sentiment-driven demand underlying the NMD return predictabilities occurs at the market open, we focus on order imbalances in the first 30-minute interval. We observe that for both NMD pricing factors, the average total order imbalances (OI) between 9:30 am and 10:00 am are positive and highly significant at the 1% level. Therefore, at the market open, traders more aggressively buy stocks in the long end of the NMD pricing factor portfolio than stocks in the short end. This evidence is consistent with the explanation that sentiment-driven demand induces overvaluation of stocks in the long end (relative to those in the short end) of the portfolio at the market open, leading to positive overnight and negative intraday returns on the NMD pricing factor.

When we decompose OI into the retail order imbalance (ROI) and the non-retail order imbalance (OI-ROI), we find that the significant positive OI in the first 30-minute interval is almost entirely from the ROI component. In the first 30-minute interval, OI is 1.41% while the ROI is 1.12% for NMD SDF, which results in an OI-ROI of 0.29% that is not statistically significant. For NMD SDF, OI is 2.99% while ROI is 3.01%, which implies a OI-ROI of -0.02% that is again not statistically significant. Therefore, the sentiment-driven demand associated with the NMD pricing factor mostly comes from the retail trading demand. Over the remaining 30-minute trading intervals, we do not find strong evidence indicating that retail or non-retail investors are trading aggressively in the opposite direction of the OI in the first 30-minute interval. Combined with our evidence in Section 4.1.1 that the deviation from the CAPM declines throughout the day, our findings suggest that the price impact of sentiment-driven trading demand at the market open is likely to be offset by non-marketable orders in the opposite direction during the rest of the trading day.

Our results are related to the findings in Berkman et al. (2012) and Lou, Polk, and Skouras (2019). Berkman et al. (2012) find evidence that stocks with high past squared returns have more positive retail order imbalances at the market open for 100 NASDAQ stocks between 1997 and 2001. Our results are complementary because our new data on retail order imbalances cover more than 3,000 NYSE and NASDAQ stocks between 2007 and 2020. We also examine NMD returns associated with a broader set of predictors, enabling us to draw more general conclusions. Lou, Polk, and Skouras (2019) use small and large trades as a proxy for retail and institutional trades, respectively. They find that small trades occur more frequently at the market open, whereas large trades occur more frequently at the market close. Since they do not classify trades into buyer- versus seller- initiated trades, their evidence is less direct than ours based on order imbalances. Their analysis also ends in 2001 when institutional investors began to adopt trading strategies that split large parent orders into sequences of smaller child orders. Overall, our results provide new evidence suggesting that sentiment-driven demand at the market open is the source of the NMD return predictabilities and that the sentiment-driven demand is from retail investors but not non-retail investors.

4.2. Liquidity Provision Hypothesis

To link NMD return predictability to the compensation required by arbitrageurs, we first discuss the types of traders who can exploit this kind of predictability. We start by noting that implementing a NMD trading strategy involves two round-trip transactions per day by i) going long on the long-short portfolio of the NMD pricing factor at the market close and then closing this position at the next market open to earn the positive overnight return and ii) going short on the same long-short portfolio at the market open and then closing this position at the market close to benefit from the negative intraday return. If traders implement such a NMD trading strategy via market orders (i.e., buying stocks at the ask price and selling stocks at the bid price), then they would incur the bid-ask spread as a trading cost for each round-trip transaction. Transaction cost estimates from the existing literature, such as Novy-Marx and Velikov (2016), suggest that the trading cost would dwarf the excess returns on the NMD pricing factor. Thus, NMD return predictabilities are not likely to be tradable for arbitrageurs who need to pay transaction costs.

However, as we show in the Online Appendix, the NMD trading strategy remains highly profitable if traders can execute their morning orders at the volume-weighted transaction price in the first 30-minute trading interval and their afternoon orders at the closing transaction price. Doing so consistently is feasible for the fastest traders, that is, the de-facto market makers that have high-speed market access and state-of-art trading infrastructure, but it is almost impossible for all other types of traders. Moreover, our previous findings indicate that NMD return predictabilities are related to excess marketable retail order imbalances at the market open. In the U.S. markets, broker-dealer firms often have a first look at order flow and thus can execute most marketable equity orders before these orders hit the exchange through internalization or purchased order flow agreements. Thus, market makers can very plausibly take on the other side of these underlying retail order imbalances. In doing so and by unloading these positions gradually through the rest of the trading day, market makers would profit from NMD return predictabilities while earning rather than paying the bid-ask spread.[22]

Therefore, we put forward a liquidity provision hypothesis that market makers are the marginal arbitrageurs who exploit NMD return predictabilities by accommodating the associated sentiment-driven demand. This liquidity provision hypothesis is also consistent with our previous finding suggesting that the price impact of sentiment-driven trading demand at

[22]For example, Citadel Securities currently executes approximately 47% of all U.S.-listed retail volume. It is straightforward for Citadel Securities to implement NMD trading strategies and earn the bid-ask spread by accommodating the predictable retail order imbalances underlying the NMD pricing factor portfolio at the market open.

the market open is likely offset by non-marketable orders in the opposite direction during the rest of the trading day. Under this hypothesis, when market makers demand higher required returns from liquidity provision, as their risk-bearing capacity is low or their risk aversion is high, they would demand a higher return to trade against NMD return predictabilities. As a result, we expect the NMD pricing factor to be positively correlated with the required returns from liquidity provision.

To formally test this hypothesis, we follow Nagel (2012) and use the returns on the Lehmann (1990) short-term reversal strategy as a proxy for the required returns from liquidity provision.[23] Nagel (2012) motivates his measure by constructing a model in which investors trade for liquidity and informational reasons as in Kyle (1985), and risk-averse market makers charge a price for providing liquidity as in Grossman and Miller (1988). His model demonstrates that a short-term reversal strategy isolates the returns from liquidity provision from the asymmetric information effect because the latter increases the bid-ask spread but does not cause negative serial correlations in returns. He also carefully discusses why he chooses the Lehmann (1990) specification of the short-term reversal strategy as the preferred approximation of the returns earned by a hypothetical representative liquidity supplier. Given these arguments, we refer to Nagel (2012)'s reversal strategy return sorted on the 1 to 5-day lagged daily returns as the liquidity provision factor (denoted as LIQ) and explore its relation with the NMD pricing factor. Following Nagel (2012), we construct LIQ starting in January 1998.

In Columns (1) and (2) of Table 7, we regress the NMD pricing factor on LIQ. We use the monthly average of daily returns as a proxy for the conditional expected returns. We find that both NMD SDF and NMD CS load positively on LIQ, with a Newey and West (1987) $t-$statistics of 5.5 and 5.7, respectively. The economic magnitudes of these regression

[23]We replicate the reversal strategy return following the procedure in Nagel (2012) for the 1998 to 2020 sample period.

coefficients are large: a one percentage point increase in the return from liquidity provision is associated with a 0.65 (1.30) percentage point increase in NMD SDF (NMD CS). This strong time-series correlation also manifests in substantial regression R^2s of 36% and 28% for NMD SDF and NMD CS, respectively.

To visualize these time-series correlations, Figure 6 plots the six-month moving averages of the NMD strategy returns against that of LIQ. We observe two consistent patterns for NMD SDF and NMD CS. First, the NMD pricing factor and LIQ covary positively and strongly, with a secular decline over time. This is consistent with the notion that the profits of both strategies are driven down by increased competition among market makers over time. Second, the NMD pricing factor and LIQ simultaneously spike during the 2000 dot-com crash, the 2009 financial crisis, and the 2020 COVID-19 stock market crash, when liquidity providers have more constrained risk-bearing capacities and higher risk aversions. The COVID-19 stock market crash episode serves as an out-of-sample test relative to the sample period studied by Nagel (2012). The simultaneous large increases in LIQ and the NMD pricing factor around the COVID-19 stock market crash not only support Nagel's argument that the returns from liquidity provision spike during periods of financial market turmoil, but also our hypothesis that NMD return predictabilities are positively related to the required returns from liquidity provision.

This single-factor model based on LIQ also explains most of the average returns on the NMD pricing factor. Because both the left- and right-hand-side variables in the time-series regressions are returns, we can still interpret the regression intercepts as alphas, that is, the average returns unexplained by exposure to LIQ. We find that adjusting for exposure to LIQ results in alphas that are more than 80% smaller than the raw returns. Moreover, the alphas are no longer significant, with $t-$statistics of 1.1 and 1.5 for NMD SDF and NMD CS, respectively. This finding that exposure to LIQ accounts for almost all of the average return of the NMD pricing factor offers an economic explanation of our previous finding that a one-factor model captures most of the cross-sectional variation in expected NMD returns.

As a placebo test, in Columns (3) and (4) of Table 7, we replace LIQ with the short-term reversal factor from Ken French's website (hereafter, FF REV), which is a lower frequency reversal strategy based on the past 21-day return. Given that the half-life of market makers' inventory imbalances is typically shorter than a week, FF REV is unlikely to capture the returns from liquidity provision accurately. Consistent with this intuition, and in sharp contrast with LIQ, we find that neither NMD SDF nor NMD CS significantly load on FF REV. Moreover, both regressions have near zero adjusted R^2. Overall, our results offer strong support for the hypothesis that the NMD pricing factor premium is related to the required returns from liquidity provision

4.3. Sentiment-driven Demand vs. Required Returns from Liquidity Provision

Finally, we explore the relative importance of sentiment-driven demand and the required returns from liquidity provision in driving the time-series variation in the magnitude of the NMD return predictability. In limits-of-arbitrage models, sentiment-driven demand and the required risk compensation for arbitrageurs are tightly connected through the market clearing condition in equilibrium. Stronger sentiment-driven trading demand means arbitrageurs have to take on larger positions to accommodate the demand, which leads to higher required compensation. If time-varying sentiment is the sole source of time variation in the economy, then the price impact of sentiment-driven demand is perfectly correlated with the required returns from liquidity provision. On the other hand, if the willingness of arbitrageurs to accommodate sentiment-driven demand (e.g., due to their risk aversion) also varies over time, then sentiment-driven demand and the required returns from liquidity provision can have independent explanatory power for deviations from the CAPM.

To conduct these tests, we continue to use LIQ to measure the required returns from liquidity provision. Given our findings in Subsection 4.1, we use the OI of the NMD pricing factor in the first 30-minute trading interval as our proxy for sentiment-driven demand. In the period after October 2007 when ROI is available, we also use the first 30-minute ROI of the NMD pricing factor as an alternative proxy for sentiment-driven demand. We scale all explanatory variables by their respective standard deviations to facilitate the interpretation of the economic magnitudes of the regression coefficients. Finally, we also include a pre-decimalization dummy that is equal to one before April 2001 to account for the potential effects brought about by the introduction of decimalization.

In Panel A of Table 8, Columns (1), (3), (5), and (7) first examine whether there is a positive time-series correlation between the NMD pricing factor and our proxies for sentiment-driven demand, without including LIQ. Columns (1) and (3) show that both NMD SDF and NMD CS load significantly and positively on OI in the full sample period, with $t-$statistics of 3.5 and 2.9, respectively. Next, Columns (5) and (7) report the results using ROI in the post-October 2007 period. Similarly, we find that both NMD SDF and NMD CS have positive and significant loadings on ROI, with $t-$statistics of 2.5 and 1.7, respectively. These results show that sentiment-driven demand is positively related to the NMD return predictability, which is consistent with the prediction of a limits-of-arbitrage model.

When we add LIQ to these regressions, we find that the regression coefficients on measures of sentiment-driven demand and the required returns from liquidity provision are both positive and statistically significant at the 5% level. In Columns (2) and (4), a one standard deviation change in LIQ is associated with a 16.3 (35.0) percentage point p.a. change in NMD SDF (NMD CS), whereas a one standard deviation change in OI is associated with a 12.8 (24.4) percentage point p.a. change in NMD SDF (NMD CS). Columns (6) and (8) show that in the post-October 2007 period, required returns from liquidity provision are more important than the sentiment-driven demand in driving NMD SDF (NMD CS).

A one standard deviation change in LIQ is associated with a 16.3 (42.0) percentage point p.a. change in NMD SDF (NMD CS), whereas a one standard deviation change in ROI is associated with a 4.9 (12.1) percentage point p.a. change in NMD SDF (NMD CS).

These results indicate that the magnitude of the NMD return predictability is affected by time variation in both the strength of the underlying sentiment-driven demand and the required returns from liquidity provision. We note that the required returns from liquidity provision can also increase in equilibrium when arbitrageurs take large offsetting positions to accommodate stronger sentiment-driven demand. Thus, we conduct a sharper test by using the conditional Sharpe ratio of LIQ (i.e. the required returns per unit of risk) as a proxy for the time-varying willingness for arbitrageurs to provide liquidity (see, Nagel (2012)). To implement this test, we estimate forecasts of the one-day ahead volatility of daily LIQ by fitting a GARCH (1,1) model and use the forecasted volatility to scale LIQ. Panel B of Table 8 shows that both NMD SDF and NMD CS have a positive and significant loading on the volatility-scaled LIQ after controlling for our proxies for sentiment-driven demand. This result indicates that the time variation in arbitrageurs' willingness to provide liquidity also affects the NMD pricing factor.

Overall, our results are consistent with the pricing equilibrium in limits-of-arbitrage models, in which arbitrageurs require compensation for accommodating sentiment-driven demand. Our findings characterize the identity of these two forces and their relative importance in driving NMD return predictability. The sentiment-driven demand that gives rise to NMD return predictabilities is related to excess retail demand at the market open. The marginal arbitrageurs of NMD return predictabilities are likely to be the market making sector. Our findings also indicate that the magnitude of the NMD return predictabilities is determined by the strength of the sentiment-driven demand and the willingness of liquidity providers to accommodate such demand.

5. Conclusion

We propose a one-factor model that summarizes the predictive information in a large number of stock characteristics for the cross-section of night-minus-day (NMD) stock returns. We construct the NMD pricing factor using a covariance-based SDF approach as in Kozak, Nagel, and Santosh (2020) and a characteristic-based approach similar to Stambaugh and Yuan (2017). Across the two specifications, we find that the NMD pricing factor prices the average NMD returns of the 17 long-short portfolios examined by Lou, Polk, and Skouras (2019) with a cross-sectional R^2 above 84%. When the test asset set is augmented by long-short portfolios sorted on 80 additional anomaly characteristics that are not examined in Lou, Polk, and Skouras (2019), our proposed one-factor model still works well in this out-of-sample test with a cross-sectional R^2 above 78%.

Using the NMD pricing factor as a parsimonious summary of NMD return predictability, we subsequently explore its underlying economic forces. First, consistent with the absence of near-arbitrage opportunities, we find that the NMD pricing factor has substantial exposures to the dominant common risk factors within the NMD return space. Second, we find evidence pointing to a limits-of-arbitrage equilibrium in which arbitrageurs require compensation for accommodating sentiment-driven demand. We link the sentiment-driven demand that gives rise to NMD return predictabilities to retail order imbalances at the market open and the marginal arbitrageurs of NMD return predictabilities to market makers. Finally, we find that the magnitude of the NMD return predictabilities is affected by time variation in both the strength of the sentiment-driven demand and the willingness of liquidity providers to accommodate such demand. Future research can build on our analysis to further understand how the interplay between retail trading demand and liquidity provision affects NMD return predictability and, more broadly, market efficiency.

References

Berkman, H., Koch, P. D., Tuttle, L., and Zhang, Y. J. 2012. Paying Attention: Overnight Returns and the Hidden Cost of Buying at the Open. The Journal of Financial and Quantitative Analysis, 47(4), 715–741. ISSN 0022-1090. Publisher: Cambridge University Press.

Boehmer, E., Jones, C. M., Zhang, X., and Zhang, X. Tracking Retail Investor Activity. SSRN Scholarly Paper ID 2822105, Social Science Research Network, Rochester, NY, 2020. doi:10.2139/ssrn.2822105.

Bogousslavsky, V. 2021. The cross-section of intraday and overnight returns. Journal of Financial Economics. ISSN 0304-405X. doi:10.1016/j.jfineco.2020.07.020.

Daniel, K., Hirshleifer, D., and Sun, L. 2020. Short- and Long-Horizon Behavioral Factors. The Review of Financial Studies, 33(4), 1673–1736. ISSN 0893-9454. doi:10.1093/rfs/hhz069.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56. ISSN 0304-405X. doi:10.1016/0304-405X(93)90023-5.

Fama, E. F. and French, K. R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22. ISSN 0304405X. doi:10.1016/j.jfineco.2014.10.010.

Fama, E. F. and French, K. R. 2016. Dissecting Anomalies with a Five-Factor Model. Review of Financial Studies, 29(1), 69–103. ISSN 0893-9454, 1465-7368. doi:10.1093/rfs/hhv043.

Fama, E. F. and MacBeth, J. D. 1973. Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy, 81(3), 607–636.

Freyberger, J., Neuhierl, A., and Weber, M. 2020. Dissecting Characteristics Nonparametrically. The Review of Financial Studies, 33(5), 2326–2377. ISSN 0893-9454. doi: 10.1093/rfs/hhz123. Publisher: Oxford Academic.

Green, J., Hand, J. R. M., and Zhang, X. F. 2017. The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns. The Review of Financial Studies, 30(12), 4389–4436. ISSN 0893-9454. doi:10.1093/rfs/hhx019.

Grossman, S. J. and Miller, M. H. 1988. Liquidity and Market Structure. The Journal of Finance, 43(3), 617–633. ISSN 1540-6261. doi:https://doi.org/10.1111/j.1540-6261.1988.tb04594.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1988.tb04594.x.

Hansen, L. P. and Jagannathan, R. 1991. Implications of Security Market Data for Models of Dynamic Economies. Journal of Political Economy, 99(2), 225–262. ISSN 0022-3808. doi:10.2307/2937680.

Hendershott, T., Livdan, D., and Rösch, D. 2020. Asset pricing: A tale of night and day. Journal of Financial Economics, 138(3), 635–662. ISSN 0304405X. doi:10.1016/j.jfineco.2020.06.006.

Heston, S. L., Korajczyk, R. A., and Sadka, R. 2010. Intraday Patterns in the Cross-section of Stock Returns. The Journal of Finance, 65(4), 1369–1407. ISSN 1540-6261. doi:https://doi.org/10.1111/j.1540-6261.2010.01573.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2010.01573.x.

Hou, K., Xue, C., and Zhang, L. 2015. Digesting anomalies: an investment approach. Review of Financial Studies, 28(3), 650–705. ISSN 0893-9454. doi:10.1093/rfs/hhu068.

Kozak, S., Nagel, S., and Santosh, S. 2018. Interpreting Factor Models: Interpreting Factor Models. The Journal of Finance, 73(3), 1183–1223. ISSN 00221082. doi:10.1111/jofi.12612.

Kozak, S., Nagel, S., and Santosh, S. 2020. Shrinking the cross-section. Journal of Financial Economics, 135(2), 271–292. ISSN 0304-405X. doi:10.1016/j.jfineco.2019.06.008.

Kyle, A. S. 1985. Continuous Auctions and Insider Trading. Econometrica, 53(6), 1315. ISSN 00129682. doi:10.2307/1913210.

Lee, C. M. C. and Ready, M. J. 1991. Inferring Trade Direction from Intraday Data. The Journal of Finance, 46(2), 733–746. ISSN 1540-6261. doi:https://doi.org/10.1111/j.1540-6261.1991.tb02683.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1991.tb02683.x.

Lehmann, B. N. 1990. Fads, Martingales, and Market Efficiency. The Quarterly Journal of Economics, 105(1), 1–28. ISSN 0033-5533. doi:10.2307/2937816. Publisher: Oxford University Press.

Lettau, M. and Pelger, M. 2020. Factors That Fit the Time Series and Cross-Section of Stock Returns. The Review of Financial Studies, 33(5), 2274–2325. ISSN 0893-9454. doi:10.1093/rfs/hhaa020.

Lewellen, J. 2015. The Cross-section of Expected Stock Returns. Critical Finance Review, 4(1), 1–44. ISSN 2164-5744, 2164-5760. doi:10.1561/104.00000024.

Lewellen, J., Nagel, S., and Shanken, J. 2010. A skeptical appraisal of asset pricing tests. Journal of Financial Economics, 96(2), 175–194. ISSN 0304-405X. doi:10.1016/j.jfineco.2009.09.001.

Lou, D., Polk, C., and Skouras, S. 2019. A tug of war: Overnight versus intraday expected returns. Journal of Financial Economics, 134(1), 192–213. ISSN 0304-405X. doi:10.1016/j.jfineco.2019.03.011.

Nagel, S. 2012. Evaporating Liquidity. Review of Financial Studies, 25(7), 2005–2039. ISSN 0893-9454, 1465-7368. doi:10.1093/rfs/hhs066.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703. ISSN 00129682.

Novy-Marx, R. and Velikov, M. 2016. A Taxonomy of Anomalies and Their Trading Costs. Review of Financial Studies, 29(1), 104–147. ISSN 0893-9454, 1465-7368. doi:10.1093/rfs/hhv063.

Stambaugh, R. F. and Yuan, Y. 2017. Mispricing Factors. The Review of Financial Studies, 30(4), 1270–1315. ISSN 0893-9454. doi:10.1093/rfs/hhw107.

Figure 1: Ordered Sharpe Ratios

This figure plots the annualized Sharpe ratio of NMD SDF, NMD CS, and that of the 17 LPS portfolios. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

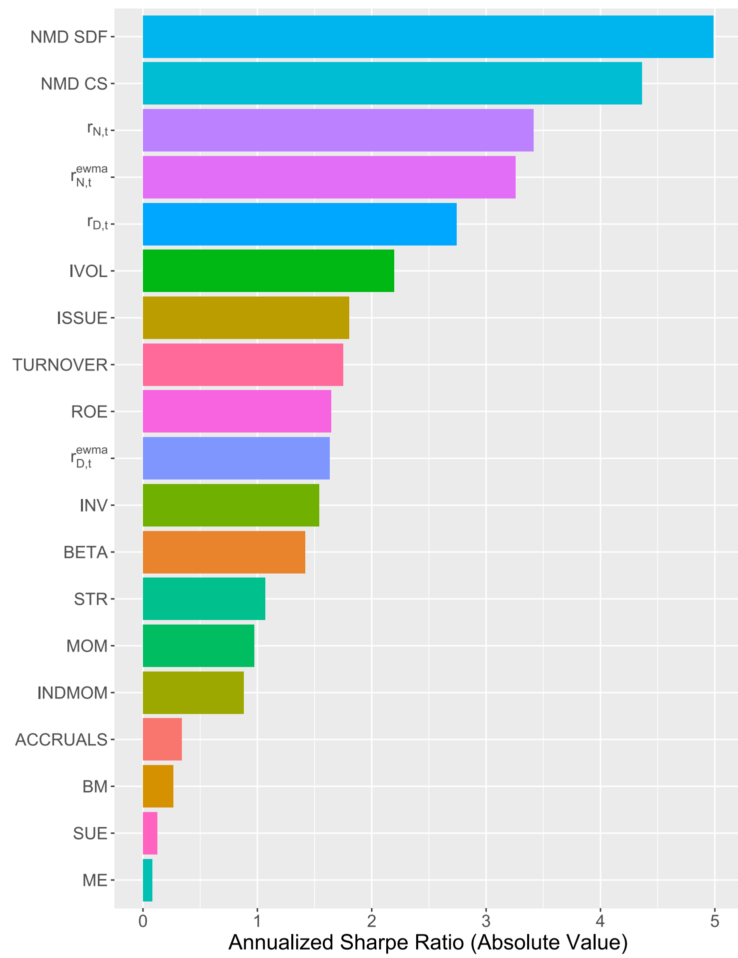
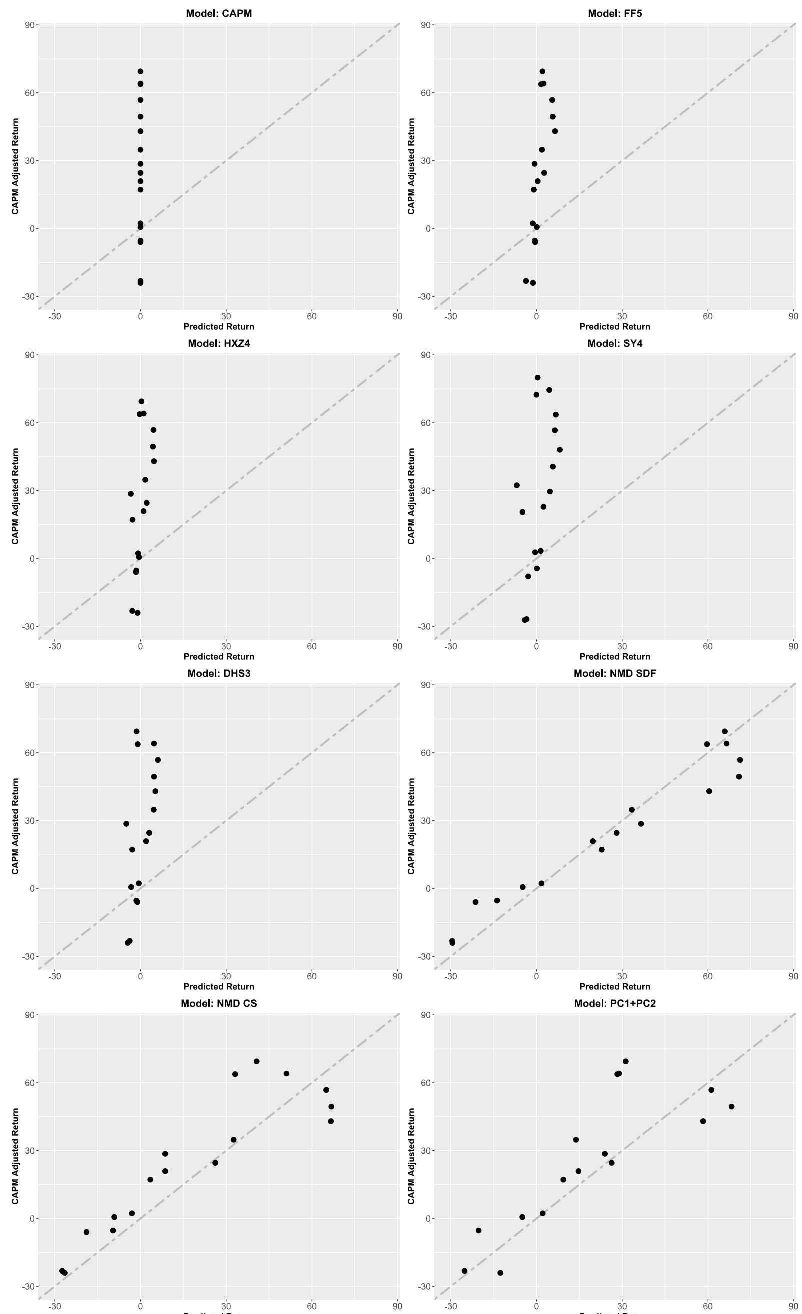


Figure 2: Cross-sectional Pricing Performance

This figure plots the average (market-adjusted) NMD return against the predicted NMD returns from five benchmark factor models (CAPM, FF5, HXZ4, SY4, and DHS3), our proposed one-factor models based on NMD SDF or NMD CS, and a two-factor model based on the first two PCs. In Panel A, the test assets include the 17 LPS portfolios. In Panel B, the test assets include the 17 LPS portfolios and 80 long-short portfolios sorted on additional anomaly signals from Green, Hand, and Zhang (2017). The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

Panel A - 17 LPS Portfolios



Panel B - Expanded Test Assets

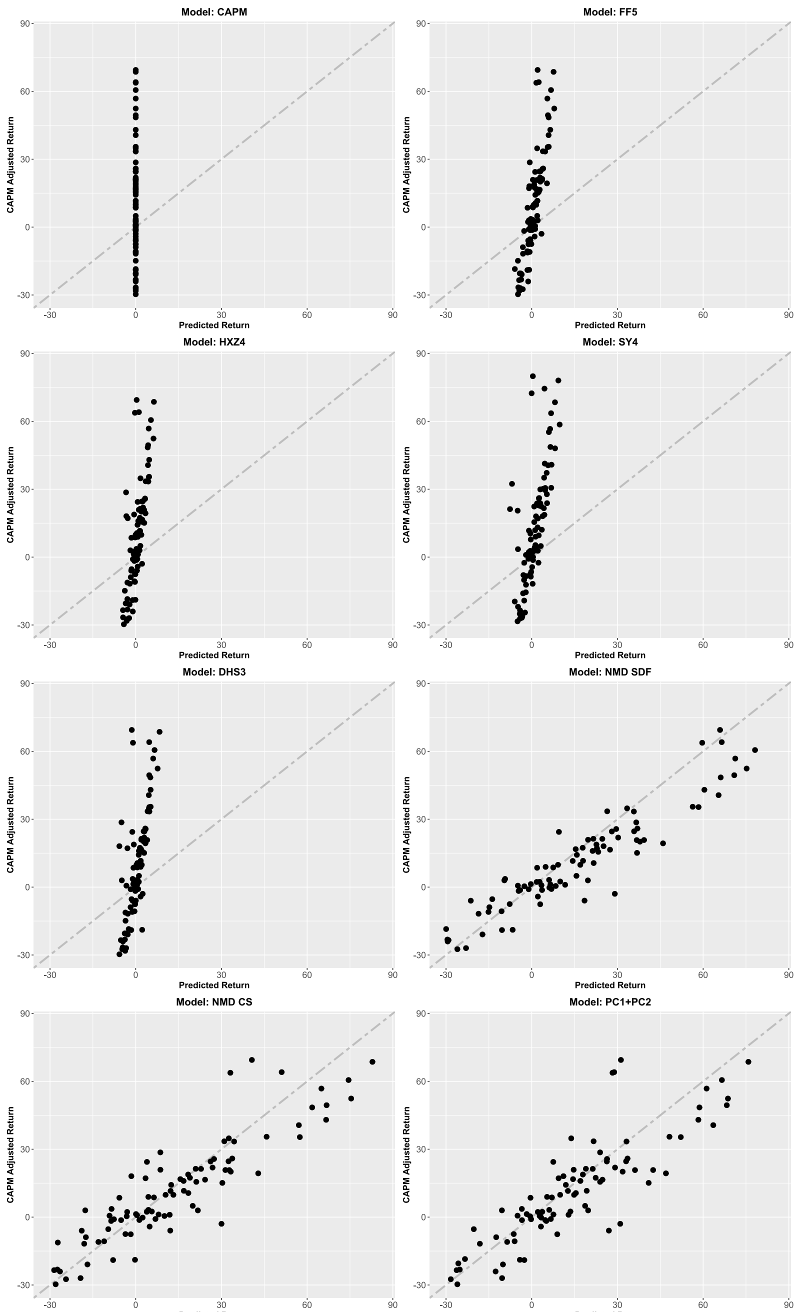


Figure 3: Distribution of t-statistics

This figure compares the t-distribution under the null hypothesis of zero alphas to the histogram of the t-statistics for the alphas of the NMD returns relative to various factor models. We include the benchmark factor models (CAPM, FF5, HXZ4, SY4, and DHS3), our proposed one-factor models based on NMD SDF or NMD CS, and a two-factor model based on the first two PCs. The test assets include the 17 LPS portfolios and 80 long-short portfolios sorted on additional anomaly signals from Green, Hand, and Zhang (2017). We compute t-statistics computed based on Newey and West (1987) standard errors with 21 lags in the parentheses. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

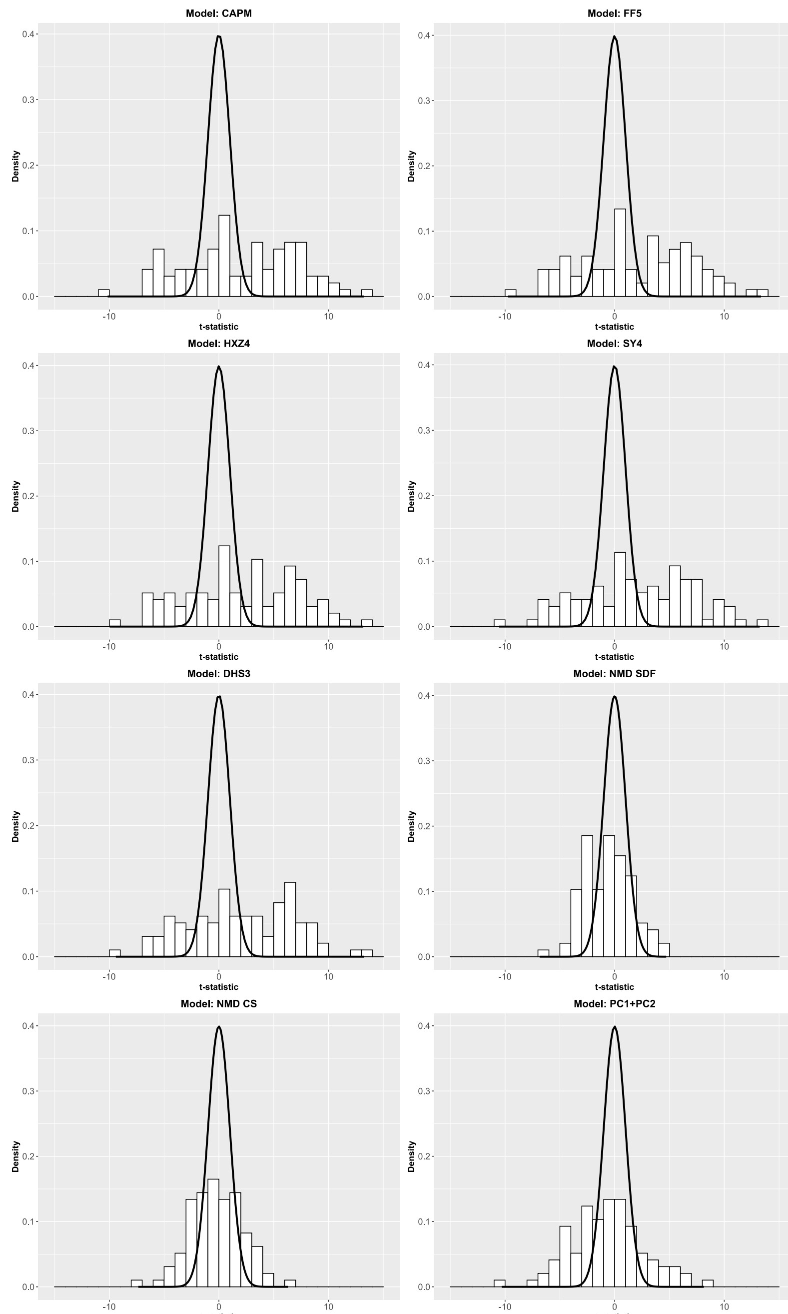


Figure 4: Long-term Predictability of NMD CS

This figure plots the time-series average of the overnight (RN), intraday (RD), night-minus-day (NMD), and close-to-close (RET) returns of the long-short portfolio sorted on CS (the composite predictive signal for NMD returns) 1 to 60 months after the portfolio formation. We report 95% confidence intervals based on Newey and West (1987) standard errors with 21 lags. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

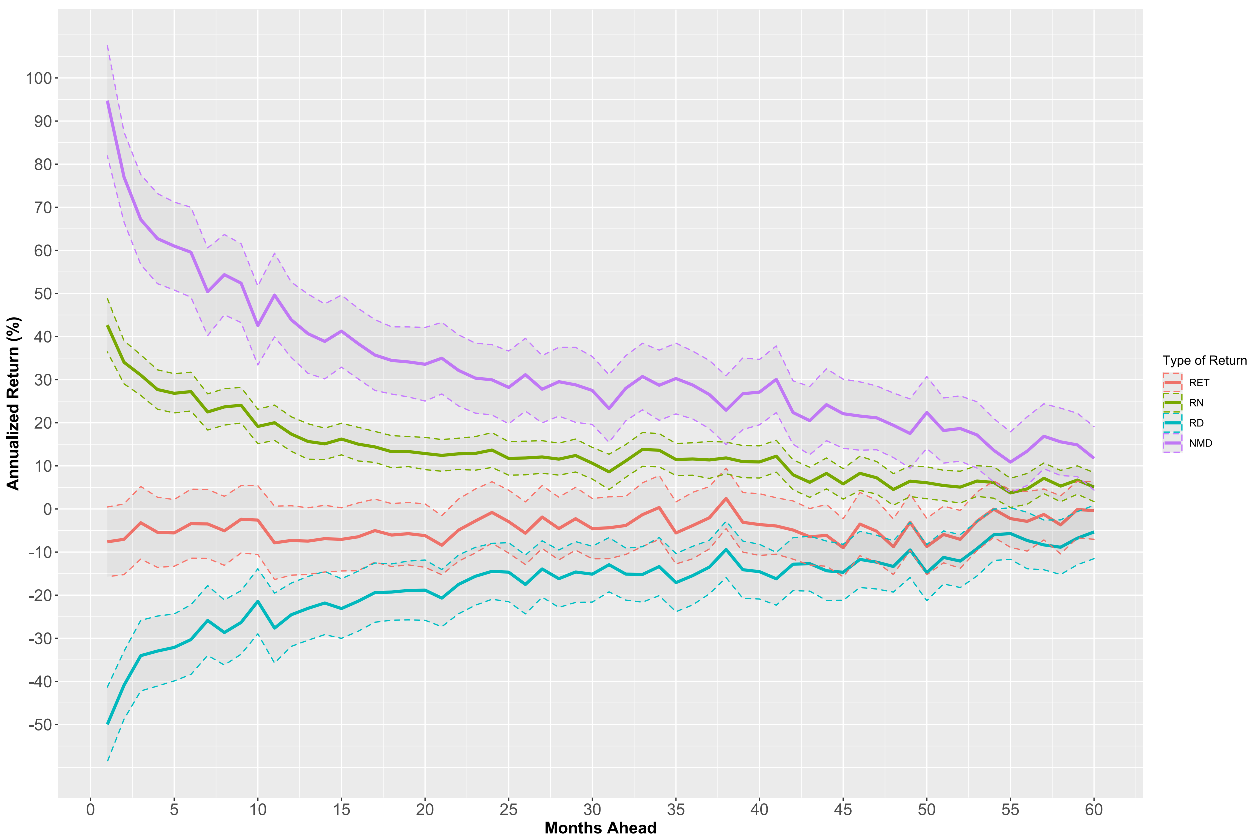
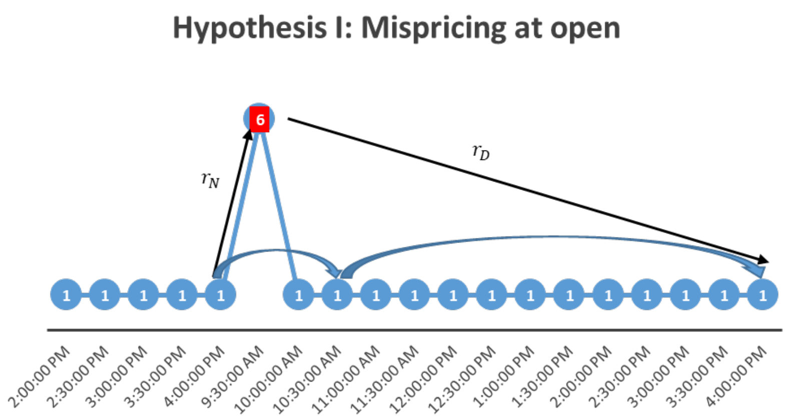


Figure 5: Timing of the Mispricing Underlying NMD Return Predictabilities

Panel A (Panel B) visualizes the hypothesis that the NMD return predictabilities are driven by sentiment-driven demand that repeatedly occurs each day at the market open (at the market close), while the opposing clientele demand offsets such demands during the rest of the day. We assume the price is equal to the fundamental value at the market close (open) in Panel A (B) to simplify the exposition, but such an assumption is not necessary for what we want to show. In Panel A, the fundamental value of the stock is \$1. The price at 9:30 am is overpriced at \$6, and the overpricing is fully corrected by 10:00 am. Using the 9:30 am price as P^{open} to compute returns results in a positive r_N and a negative r_D. In contrast, using the 10:00 am price as P^{open} to compute returns results in a zero r_N and r_D and thus no NMD predictability. In Panel B, the fundamental value of the stock is \$6. The price at 4:00 pm is underpriced at \$1, and the underpricing is fully corrected by the market open of the next day. Using the 4:00 pm price as P^{close} to compute returns results in a positive r_N and negative r_D. In contrast, using the 3:30 pm price as P^{close} to compute returns results in a zero r_N and r_D and thus no NMD predictability.

Panel A



Panel B

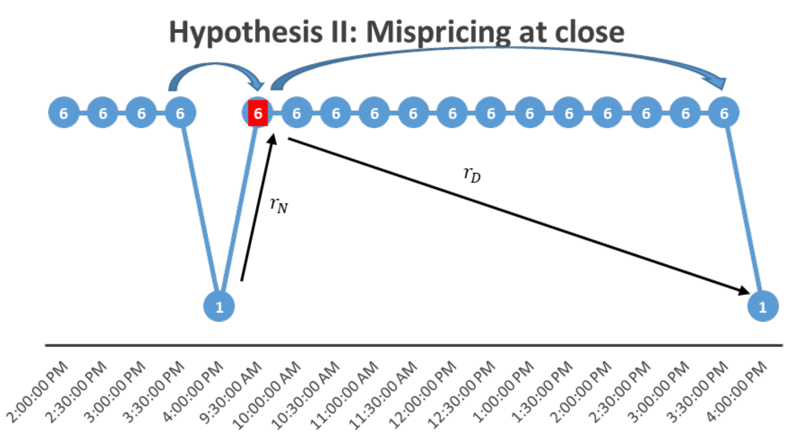
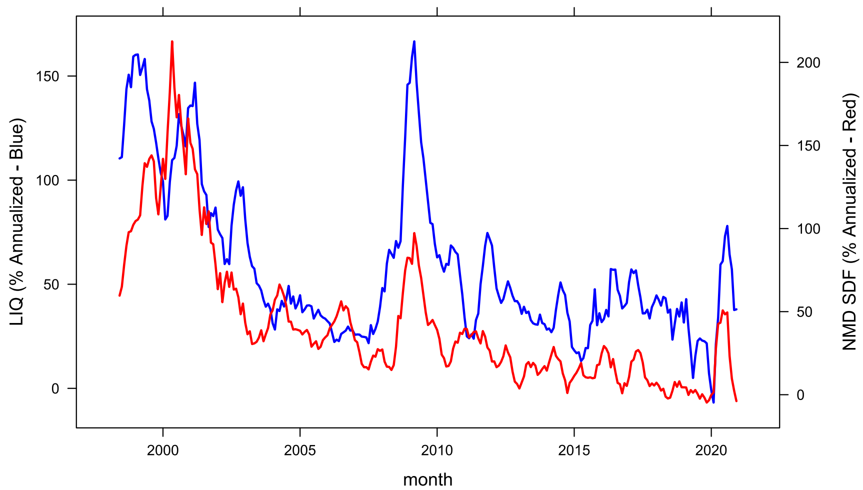


Figure 6: Relation with Liquidity Provision Factor

This figure plots the six-month moving average of the liquidity provision factor (LIQ) proposed by Nagel (2012) against those of NMD SDF and NMD CS. The left axis refers to the scale of LIQ and the right axis refers to the scale of the NMD pricing factor. The sample period is from January 1998 to December 2020.



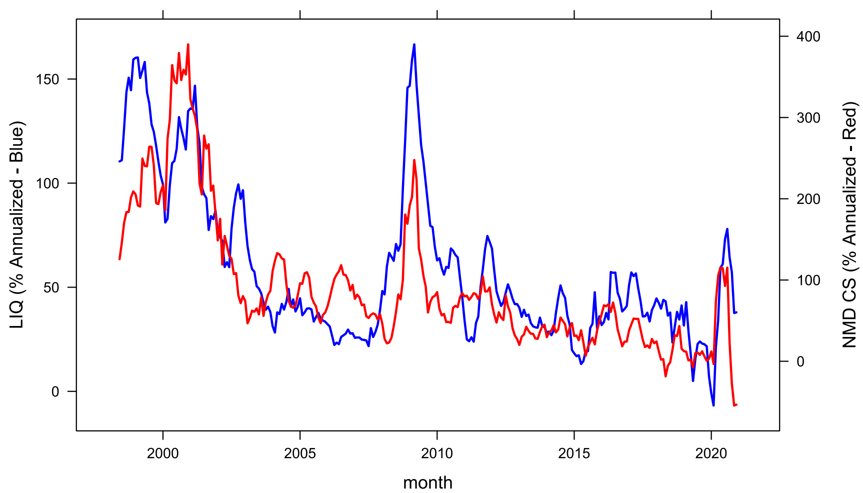


Table 1: The NMD Test Assets

This table presents the time-series average of the overnight, intraday, and NMD returns of the 17 LPS portfolios defined in Section 1.3, as well as the NMD alphas relative to standard factor models. The standard factor models include the CAPM, the five-factor model of Fama and French (2016) (FF5), the four-factor model of Hou, Xue, and Zhang (2015) (HXZ4), the four-factor model of Stambaugh and Yuan (2017) (SY4), or the three-factor model of Daniel, Hirshleifer, and Sun (2020) (DHS3). All portfolio returns are annualized to be in percentage points per annum. We report t-statistics computed based on Newey and West (1987) standard errors with 21 lags in the parentheses. The returns are measured between February 1st, 1996 and December 31st, 2020, except for SY4 factors, which are available up to the end of 2016.

Signal	R_N	R_D	R_{NMD}	α^{CAPM}	α^{FF5}	α^{HXZ4}	α^{SY4}	α^{DHS3}
$r_{D,t}$	34.15	-31.72	65.87	66.94	64.42	65.87	72.44	62.10
	(11.37)	(-7.21)	(10.58)	(10.79)	(10.79)	(10.81)	(10.98)	(10.15)
$r_{N,t}$	33.87	-35.69	69.57	70.40	68.32	70.09	80.36	71.74
	(11.40)	(-9.28)	(11.94)	(11.98)	(12.25)	(11.98)	(11.74)	(12.14)
$r_{D,t}^{\text{ewma}}$	16.09	-20.11	36.20	36.93	34.99	35.30	36.64	32.21
	(6.48)	(-5.04)	(7.19)	(7.38)	(7.16)	(7.19)	(6.71)	(6.72)
$r_{N,t}^{\text{ewma}}$	31.62	-32.75	64.37	65.21	63.57	65.51	73.64	66.11
	(12.77)	(-9.38)	(13.34)	(13.42)	(13.63)	(13.39)	(13.28)	(13.46)
BETA	25.55	-23.44	49.00	53.10	46.39	48.52	48.46	47.46
	(8.70)	(-4.26)	(7.92)	(9.04)	(8.22)	(8.42)	(7.40)	(8.16)
IVOL	27.97	-32.04	60.01	62.38	56.79	57.91	61.54	56.04
	(9.50)	(-5.76)	(8.98)	(9.63)	(9.76)	(9.76)	(8.74)	(9.09)
BM	-2.62	2.48	-5.10	-5.27	-4.81	-3.68	-4.41	-4.20
	(-1.45)	(0.73)	(-1.32)	(-1.36)	(-1.44)	(-1.01)	(-1.05)	(-1.10)
ISSUE	9.32	-16.41	25.73	26.76	24.04	24.63	26.75	23.64
	(6.32)	(-6.19)	(8.07)	(8.37)	(8.12)	(8.09)	(7.69)	(7.85)
ACCRUALS	-4.65	0.68	-5.33	-5.59	-5.01	-4.14	-4.77	-4.12
	(-3.10)	(0.25)	(-1.64)	(-1.71)	(-1.62)	(-1.26)	(-1.34)	(-1.28)
INV	8.52	-12.55	21.07	21.50	21.08	20.44	20.88	19.52
	(5.34)	(-5.08)	(6.68)	(6.85)	(6.96)	(6.61)	(6.18)	(6.28)
ROE	-10.44	13.43	-23.87	-25.24	-21.51	-22.39	-25.10	-21.36
	(-6.40)	(4.34)	(-6.38)	(-6.92)	(-6.83)	(-6.85)	(-6.62)	(-6.53)
ME	-0.55	-1.73	1.18	-0.09	-0.19	0.41	1.26	3.20
	(-0.49)	(-0.60)	(0.37)	(-0.03)	(-0.09)	(0.18)	(0.51)	(1.06)
SUE	3.63	2.04	1.59	1.70	3.02	2.52	2.76	2.31
	(2.70)	(0.91)	(0.55)	(0.59)	(1.10)	(0.89)	(0.85)	(0.81)
MOM	19.42	-7.61	27.03	27.50	28.22	30.87	38.34	32.53
	(7.05)	(-1.43)	(4.48)	(4.51)	(4.91)	(5.09)	(5.78)	(5.57)
STR	-12.10	13.90	-26.00	-26.34	-25.05	-25.35	-25.04	-21.77
	(-4.34)	(3.14)	(-4.53)	(-4.57)	(-4.50)	(-4.50)	(-3.99)	(-3.79)
TURNOVER	28.58	-24.86	53.43	55.90	50.09	51.64	55.70	50.91
	(9.65)	(-5.06)	(9.43)	(10.17)	(9.61)	(9.87)	(9.32)	(9.42)
INDMOM	9.59	-6.88	16.47	16.47	17.43	19.25	24.86	19.40
	(5.49)	(-1.84)	(3.92)	(3.91)	(4.26)	(4.48)	(5.26)	(4.48)

Table 2: Summary Statistics for Various Factors

This table presents the mean, standard deviation, Sharpe ratio, skewness, kurtosis, and the first-order autoregressive (AR1) coefficient for NMD SDF, NMD CS, the first three PCs of the 17 LPS portfolios, the liquidity provision factor of Nagel (2012) (LIQ), and the short-term reversal factor provided by Ken French (FF Rev). All returns are in percentage points per annum. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

	Mean	SD	SR	Skewness	Kurtosis	AR1
NMD SDF	44.89	9.01	4.99	0.20	31.54	0.07
NMD CS	94.73	21.72	4.36	-0.17	20.36	0.05
PC1	34.16	12.47	2.74	-0.42	29.80	0.02
PC2	21.33	11.13	1.92	-0.46	30.50	-0.02
PC3	10.01	10.03	1.00	-0.08	14.48	-0.08
LIQ	59.26	10.17	5.83	-0.92	59.78	0.01
FF REV	14.02	15.18	0.92	1.58	25.12	0.16

Table 3: The Pricing Performance of the Factor Models

This table presents the pricing performance of several factor models for explaining NMD returns. Columns (1) and (2) report the cross-sectional means of the absolute alpha and the absolute $t-$statistic, respectively. Column (3) reports the cross-sectional R^2 calculated using Eq. (12). We include five standard factor models: CAPM, FF5, HXZ4, SY4, and DHS3. Our proposed one-factor models are based on NMD SDF or NMD CS. We also include a two-factor model based on the first two PCs. In Panel A, the test assets consist of the 17 LPS portfolios. In Panel B, the test assets include the 17 LPS portfolios and 80 long-short portfolios sorted on additional anomaly characteristics from Green, Hand, and Zhang (2017). We report t-statistics computed based on Newey and West (1987) standard errors with 21 lags. All returns are in percentage points per annum. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

Panel A - 17 LPS Portfolios

Model	$\lvert\alpha\rvert$	$\lvert t\rvert$	$R^{2,\text{XS}}$
CAPM	31.42	6.29	0.00
FF5	29.54	6.31	0.11
HXZ4	30.30	6.29	0.06
SY4	33.82	6.38	0.10
DHS3	29.82	6.07	0.09
NMD SDF	7.34	1.26	0.94
NMD CS	12.38	2.06	0.84
PC1+PC2	14.57	3.36	0.76

Panel B - Expanded Test Assets

Model	$\lvert\alpha\rvert$	$\lvert t\rvert$	$R^{2,\text{XS}}$
CAPM	19.43	4.49	0.00
FF5	17.28	4.44	0.19
HXZ4	17.86	4.43	0.14
SY4	20.17	4.44	0.18
DHS3	17.66	4.25	0.17
NMD SDF	9.20	1.86	0.79
NMD CS	9.36	1.91	0.78
PC1+PC2	10.05	2.68	0.72

Table 4: The Factor Structure of the NMD Return Space

This table reports on the percentage of the total variance explained by the first 10 PCs extracted from the NMD returns of the 17 LPS portfolios. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020.

Type		PC1	PC2	PC3	PC4	PC5	PC6 to PC10
R_N	Perc Variance	0.25	0.21	0.13	0.07	0.06	0.17
	Cumulative Perc	0.25	0.46	0.59	0.66	0.72	0.89
R_D	Perc Variance	0.27	0.23	0.13	0.06	0.06	0.15
	Cumulative Perc	0.27	0.50	0.63	0.70	0.75	0.90
NMD	Perc Variance	0.26	0.22	0.13	0.07	0.06	0.16
	Cumulative Perc	0.26	0.48	0.61	0.68	0.73	0.90

Table 5: The NMD Pricing Factor and the Dominant Common Risks of the NMD Return Space

This table reports on time-series regressions of the NMD pricing factor on the first three PCs of the NMD returns of the 17 LPS portfolios. The dependent variable is either NMD SDF or NMD CS. We report t-statistics computed based on Newey and West (1987) standard errors with 21 lags in the parentheses. All returns are in percentage points per annum. The portfolio returns are measured between February 1st, 1996 and December 31st, 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	NMD SDF_t			NMD CS_t		
	(1)	(2)	(3)	(4)	(5)	(6)
$PC1_t$	0.49***	0.47***	0.47***	1.33***	1.30***	1.29***
	(11.22)	(15.56)	(15.73)	(21.47)	(24.33)	(24.78)
$PC2_t$		0.34***	0.34***		0.47***	0.47***
		(7.94)	(9.42)		(5.65)	(5.94)
$PC3_t$			0.18***			0.12*
			(5.96)			(1.84)
Constant	28.02***	21.59***	19.89***	49.28***	40.43***	39.32***
	(13.06)	(10.81)	(10.67)	(12.52)	(10.94)	(10.50)
N	6,273	6,273	6,273	6,273	6,273	6,273
Adjusted R^2	0.47	0.65	0.69	0.58	0.64	0.64

Table 6: The NMD Pricing Factor and Sentiment-driven Demand

Columns "9:30 am" to "11:00 am" of Panel A reports the average returns of NMD SDF and NMD CS when using the first midquote after 9:30 am, 10:00 am, 10:30 am, and 11:00 am to replace the CRSP open price as P^{open} to compute the NMD returns, respectively. Columns "2:30 pm" to "4:00 pm" of Panel A reports the average returns of NMD SDF and NMD CS when using the last midquote before 2:30 pm, 3:00 pm, 3:30 pm, and 4:00 pm as P^{close} to compute the NMD returns. Panel B presents the time-series average of the order imbalances associated with NMD SDF and NMD CS. Each column presents the ending point of a half-hour trading interval during market trading hours, with the first (last) column ending at 10:00 am (4:00 pm). OI is the total order imbalances identified by the Lee and Ready (1991) algorithm and ROI is the retail order imbalances identified by the Boehmer, Jones, Zhang, and Zhang (2020) algorithm. We report t-statistics computed based on Newey and West (1987) standard errors with 21 lags in the parentheses. The portfolio returns are in percentage per annum and are measured between February 1st, 1996 and December 31st, 2020. The order imbalances are in annualized percentages of the market capitalization and are measured between November 1st, 2007 and December 31st, 2020.

Panel A - Alternative Specifications of P_d^{open} and P_d^{close}

NMD SDF	9:30 am	10:00 am	10:30 am	11:00 am	02:30 pm	03:00 pm	3:30 pm	4:00 pm
r_D	-24.99	-9.18	-6.12	-4.71	-24.15	-24.85	-26.34	-25.68
	(-11.48)	(-6.36)	(-4.91)	(-4.27)	(-12.46)	(-12.00)	(-11.76)	(-11.49)
r_N	23.68	7.45	4.25	2.82	21.82	22.83	23.84	23.10
	(15.47)	(6.42)	(3.46)	(1.97)	(13.19)	(13.39)	(13.61)	(13.99)
NMD	48.67	16.62	10.37	7.54	45.97	47.68	50.18	48.78
	(14.91)	(9.19)	(6.48)	(4.36)	(15.11)	(14.71)	(14.27)	(14.30)

NMD CS	9:30 am	10:00 am	10:30 am	11:00 am	02:30 pm	03:00 pm	3:30 pm	4:00 pm
r_D	-52.51	-18.05	-10.43	-8.89	-51.18	-52.32	-55.40	-53.59
	(-9.74)	(-4.57)	(-3.19)	(-3.12)	(-10.62)	(-10.38)	(-10.45)	(-10.01)
r_N	54.08	18.45	10.50	8.94	54.93	56.28	58.26	56.35
	(14.96)	(5.94)	(3.13)	(2.32)	(14.35)	(14.55)	(15.21)	(15.44)
NMD	106.60	36.50	20.93	17.83	106.11	108.60	113.66	109.94
	(14.08)	(7.57)	(5.12)	(4.11)	(15.56)	(15.20)	(15.20)	(14.95)

Panel B - Intraday Order Imbalances

NMD SDF	10:00 am	10:30 am	11:00 am	11:30 am	12:00 pm	12:30 pm	1:00 pm	1:30 pm	2:00 pm	2:30 pm	3:00 pm	3:30 pm	4:00 pm
OI	1.41	1.03	0.76	0.61	0.60	0.47	0.37	0.41	0.34	0.25	0.64	0.28	0.89
	(3.97)	(5.71)	(2.98)	(3.53)	(4.19)	(4.93)	(3.74)	(4.24)	(3.34)	(2.93)	(4.34)	(2.19)	(4.98)
ROI	1.12	0.62	0.48	0.40	0.36	0.31	0.29	0.25	0.22	0.24	0.24	0.14	-0.07
	(7.12)	(6.42)	(6.09)	(6.51)	(6.96)	(5.36)	(5.78)	(6.09)	(5.72)	(4.80)	(5.70)	(3.20)	(-1.13)
OI-ROI	0.29	0.41	0.28	0.21	0.24	0.16	0.09	0.16	0.12	0.01	0.41	0.14	0.96
	(1.08)	(3.00)	(1.36)	(1.52)	(1.98)	(2.19)	(0.90)	(1.70)	(1.37)	(0.20)	(3.40)	(1.17)	(6.71)

NMD CS	10:00 am	10:30 am	11:00 am	11:30 am	12:00 pm	12:30 pm	1:00 pm	1:30 pm	2:00 pm	2:30 pm	3:00 pm	3:30 pm	4:00 pm
OI	2.99	1.64	1.59	1.42	0.77	0.84	0.63	0.45	0.16	0.18	0.86	-0.32	1.14
	(3.24)	(3.07)	(2.44)	(2.97)	(1.89)	(2.29)	(2.16)	(1.11)	(0.44)	(0.73)	(1.65)	(-0.78)	(1.76)
ROI	3.01	1.63	1.19	0.97	0.87	0.72	0.69	0.52	0.46	0.49	0.47	0.20	-0.36
	(8.68)	(8.87)	(8.65)	(7.90)	(9.37)	(6.25)	(7.31)	(5.73)	(5.33)	(4.72)	(5.27)	(1.94)	(-1.70)
OI-ROI	-0.02	0.01	0.39	0.45	-0.11	0.11	-0.06	-0.07	-0.31	-0.31	0.38	-0.52	1.50
	(-0.02)	(0.01)	(0.70)	(1.08)	(-0.30)	(0.36)	(-0.22)	(-0.20)	(-0.95)	(-1.48)	(0.79)	(-1.27)	(2.54)

Table 7: The NMD Pricing Factor and the Required Returns from Liquidity Provision

This table presents time-series regressions of the monthly average returns of the NMD pricing factor on that of the liquidity provision factor (LIQ) proposed by Nagel (2012) or the short-term reversal factor provided by Ken French (FF REV). We report t-statistics computed based on Newey and West (1987) standard errors with 12 lags in the parentheses under the coefficients. All returns are in percentage points per annum. The sample period is from January 1998 to December 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	NMD SDF_t	NMD CS_t	NMD SDF_t	NMD CS_t
	(1)	(2)	(3)	(4)
LIQ_t	0.65^{***}	1.30^{***}		
	(5.49)	(5.72)		
FF REV_t			0.06	-0.06
			(1.01)	(-0.42)
Constant	5.06	14.66	42.82^{***}	92.03^{***}
	(1.09)	(1.45)	(4.84)	(5.26)
N	276	276	276	276
Adjusted R^2	0.36	0.28	-0.0003	-0.003

Table 8: Sentiment-driven Demand vs. Required Returns from Liquidity Provision

This table presents monthly time-series regressions of the NMD pricing factor on sentiment-driven demand proxied by the OI (ROI) in the first 30-minute trading interval and the required returns from liquidity provision proxied by Nagel (2012)'s liquidity provision factor (LIQ). To facilitate the interpretation of the coefficients, the independent variables are scaled by their standard deviations. In Panel A, we use LIQ as our proxy for the required returns from liquidity provision. In Panel B, we scale LIQ by its forecasted volatility to proxy for the required returns from liquidity provision per unit of risk. We compute forecasts of LIQ's 1-day ahead volatility from a GARCH(1,1) model. We report t-statistics computed based on Newey and West (1987) standard errors with 12 lags in the parentheses under the coefficients. OI and LIQ are available from January 1998 to December 2020, and ROI is available from November 2007 to December 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A - Sentiment-driven Demand and Required Returns from Liquidity Provision

	NMD SDF$_t$		NMD CS$_t$		NMD SDF$_t$		NMD CS$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OI SDF$_t$	13.25***	12.84***						
	(3.47)	(3.21)						
OI CS$_t$			25.44***	24.35***				
			(2.90)	(2.62)				
ROI SDF$_t$					6.79**	4.92**		
					(2.49)	(1.99)		
ROI CS$_t$							11.64*	12.12**
							(1.73)	(2.06)
LIQ$_t$		16.30***		35.00***		16.27***		41.98***
		(5.69)		(4.46)		(3.76)		(4.18)
Pre-Decim$_t$	73.05***	46.89***	136.06***	80.33*				
	(4.94)	(2.86)	(3.59)	(1.92)				
Constant	24.42***	8.10**	54.06***	19.13*	12.44**	−1.73	32.10**	−11.63
	(5.22)	(2.17)	(5.60)	(1.92)	(2.26)	(−0.49)	(2.17)	(−0.97)
N	276	276	276	276	158	158	158	158
Adjusted R^2	0.48	0.55	0.34	0.39	0.04	0.27	0.01	0.21

Panel B - Sentiment-driven Demand and Required Returns from Liquidity Provision Per Unit of Risk

	NMD SDF_t		NMD CS_t	
	(1)	(2)	(3)	(4)
OI SDF_t	12.75^{***}			
	(3.04)			
OI CS_t		24.11^{**}		
		(2.57)		
ROI SDF_t			4.75^{*}	
			(1.80)	
ROI CS_t				10.92^{*}
				(1.67)
LIQ SR_t	12.50^{***}	26.66^{***}	12.80^{**}	31.38^{***}
	(3.78)	(3.37)	(2.45)	(2.97)
Pre-$Decim_t$	53.25^{***}	94.39^{**}		
	(3.13)	(2.30)		
Constant	9.01^{**}	21.34^{**}	-0.43	-5.13
	(2.36)	(2.15)	(-0.09)	(-0.38)
N	276	276	158	158
Adjusted R^2	0.52	0.37	0.17	0.12