The Pricing of Continuous and Discontinuous Factor Risks*

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Abstract

This study considers the Fama-French five-factor model in continuous time, allowing stocks' exposures to the factors' continuous, jump, and overnight movements to differ. Empirically, stocks' continuous, jump, and overnight betas on a given factor can be very different and are only weakly positively related. Contrary to existing evidence, I find continuous market exposure to be positively priced and overnight market exposure to be negatively priced. Moreover, overnight exposures to the size, value, profitability, and investment factors are positively priced, while continuous exposures to these factors are mostly negatively priced. Jump exposures are not consistently priced. I show that these pricing patterns likely arise to compensate investors for being exposed to a tug of war between institutional investors trading intraday and retail investors trading overnight. Finally, I document that the factors' overnight risk prices have predictive power for their future returns.

Keywords: Fama-French factors, jump risk, overnight risk, intraday returns, overnight returns, investor clienteles

JEL Classification: G12, G14

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1 Introduction

The central notion in asset pricing is that investors are compensated for exposures to systematic risks by higher expected returns. Factor models are the dominant approach to capturing systematic risks. The Fama-French (2015) five-factor model is, in this regard, currently the most established model, containing market, size, value, profitability, and investment factors. The view that factors like those of Fama and French (2015) reflect systematic risks is motivated by their ability to capture covariation in returns coupled with their positive historical return premia. A major implication of factor models is that stocks with higher exposures to the factors are subject to more systematic risks and should therefore earn higher expected returns. However, empirically, stocks with higher factor exposures do not earn higher average returns (see, e.g., Black et al., 1972; Daniel and Titman, 1997; Jegadeesh et al., 2019; Daniel et al., 2020). This finding casts doubt on the validity of factor models and the view that their factors capture systematic risks. This applies in particular also to the Fama-French (2015) five-factor model.

The failure to empirically confirm the predicted positive relation between factor exposures and returns is usually attributed to one of three potential reasons. First, the factors are not true risk factors, meaning they do not capture systematic risks of hedging concern for investors. This explanation implies that the factors' historical return premia are due to market inefficiencies or just statistical artifacts. Second, while they capture systematic risks of hedging concern for investors, the factors are imperfect proxies for the mean-variance efficient portfolio and thus capture systematic risks imperfectly. Third, the factors are true risk factors and good proxies for the mean-variance efficient portfolio, but stocks' exposures to the factors are estimated with error, leading to biases in the estimates for the factors' risk prices.

In this paper, I suggest and evaluate another potential explanation for the failure to document a positive risk-return relation for the Fama-French (2015) five-factor model: exposures to only some sources of factor variation are priced. I account for three different sources of factor variation: continuous intraday movements, intraday jumps, and overnight movements.[1] Differentiating between these sources of factor variation is motivated by recent findings from the literature suggesting that investors treat continuous and discontinuous risks differently and independently of each other (see, e.g., Cremers et al., 2015; Bollerslev et al., 2016). Thus, investors may care only about some sources of variation in the factors—continuous intraday movements, intraday jumps, or overnight movements—and demand compensation only for exposures to these sources. In this case, standard approaches investigating the relation between factor exposures and returns may fail to document a positive risk-return relation because they estimate stocks' exposures to the factors (i.e., factor betas) from monthly or daily data. These low-frequency betas do not differentiate between the different sources of factor variation, implying they would reflect not only exposures to the priced but also the unpriced sources of variation. If stocks' exposures to the different sources of factor variation are sufficiently differ-

[1] I refer to the intraday jumps and overnight movements jointly as discontinuous movements but consider them separately in my empirical investigation.

ent, the low-frequency betas would therefore be noisy measures for the exposures to the priced factor risks, making it difficult to empirically confirm a positive relation between the estimated factor exposures and returns.

Shedding light on why factor models, especially the Fama-French (2015) five-factor model, fail to generate a positive risk-return relation is important for at least three reasons. First, the Fama-French (2015) model is currently the most widely used factor model in academia and practice for determining risk-adjusted returns, capital costs, and investment performance. However, the missing risk-return relation calls into question its validity. In particular, as pointed out by Chen et al. (2023), accounting for exposures to factors that earn positive average returns does not make sense if higher factor exposures are not associated with higher average returns. Second, the existing literature has yet to come to a final conclusion regarding whether the factors' return premia are due to risk, mispricing, or data mining. New evidence on the risk-return relation for exposures to the factors can facilitate the understanding of the factors' drivers. Third, the factors are frequently targeted by quantitative investment strategies. Examining the pricing of different types of factor variation may yield valuable insights for investment managers to optimize their factor investing strategies.

I investigate the pricing of exposures to the different factor risks based on a comprehensive high-frequency stock data sample. Specifically, I obtain high-frequency data for all common US stocks traded on the NYSE, AMEX, and NASDAQ from 1993 to 2019 from the Trade and Quote (TAQ) database. Most studies in the empirical asset pricing literature using high-frequency data restrict their sample to S&P500 stocks (e.g., Bollerslev et al., 2016; Pelger, 2020). I employ a broader sample of stocks to ensure that my results are broadly applicable. Nevertheless, to mitigate the influence of potential microstructure issues on my results, I retain only stocks that satisfy standard liquidity criteria and are not subject to significant market microstructure noise.

Based on this high-frequency stock data set, I construct high-frequency versions of the five Fama-French (2015) factors and estimate stocks' continuous, jump, and overnight betas on the factors using rolling six-month estimation windows.[2] The results show that the different betas' properties (e.g., dispersion and persistence) differ considerably. Critically, they also reveal that stocks' continuous, jump, and overnight betas on a given factor can be very different and are only weakly positively related. This is a necessary condition for the different types of factor exposures to be priced differently.

I estimate risk prices for the different types of factor exposures based on the Fama-MacBeth (1973) two-stage approach. I find that continuous market exposure carries a significantly positive risk price, whereas overnight market exposure carries a significantly negative risk price. Jump market exposure is not robustly priced. These results contradict Bollerslev et al.'s (2016) finding that jump and overnight market exposures are positively priced while continuous market exposure is not priced. I show that differences in the empirical setting are the reason for the

[2] Using high-frequency data to estimate betas has further advantages besides allowing to distinguish between exposures to continuous and discontinuous variation in the factors. Specifically, the increased number of observations available for estimating betas is beneficial for the estimates' accuracy and allows for shorter estimation windows to account for more time variation in the betas.

differential results. In particular, my sample includes all common US stocks rather than only S&P500 stocks, I use value-weights rather than equal-weights to estimate the Fama-MacBeth (1973) regressions, and I investigate a contemporaneous rather than a predictive relation between factor exposures and returns. Given that I use a broader cross-section of stocks, appropriately account for small and micro caps, and my contemporaneous setting is more in line with theory, I believe my results to be a better indication of the true relations than Bollerslev et al.'s (2016) results.

The results for the pricing of the non-market factors' risks are strikingly uniform. Specifically, continuous exposures to the size, value, and investment factors are negatively priced, whereas overnight exposures to the size, value, profitability, and investment factors are positively priced. The exception to this pattern is that continuous exposure to the profitability factor is not negatively priced. Like jump exposure to the market factor, jump exposures to the non-market factors are not robustly priced. These results also hold when controlling for an extensive set of characteristics that have been shown to be related to returns as well as in various robustness checks. Thus, my results reveal positive risk-return trade-offs for one of each factor's different types of risk—continuous intraday risk in the case of the market factor and overnight risk in the case of the non-market factors. However, given the negative risk prices for overnight market exposure and continuous intraday exposures to most non-market factors, these results fail to establish a reliably positive relation between factor exposures and returns. Thus, the validity of the Fama-French (2015) five-factor model is still in question.

Nevertheless, the remarkably consistent disparities between the risk prices for exposures to the factors' continuous intraday and overnight risks point to an underlying economic mechanism. Notably, there are similar disparities between the factors' intraday and overnight returns. Specifically, in line with Lou et al. (2019), I document that the market premium is earned overnight with flat intraday returns, while the size, value, profitability, and investment premia are earned intraday with negative overnight returns. These patterns are almost the perfect mirror image of the factors' continuous intraday and overnight risk prices. Lou et al. (2019) argue that the factors' intraday versus overnight patterns are due to the trading behaviors of different investor clienteles. They provide evidence suggesting that intraday trading is dominated by institutional investors while overnight trading is driven by retail investors.

I examine whether this clientele effect also drives my results. For this purpose, I investigate the realization of the risk prices in intraday and overnight returns. The results reveal that the risk prices for overnight factor exposures are realized in intraday returns, while the risk prices for continuous intraday returns are realized in overnight returns. These findings indicate that the disparities between the factors' continuous intraday and overnight risk prices are in fact driven by a tug of war between intraday and overnight investors. In particular, they suggest that the intraday clientele is more averse to market risk, leading to subdued market returns intraday, while the overnight clientele is more averse to size, value, profitability, and investment factor risks, leading to negative returns on these factors overnight. The positive risk price for continuous intraday market exposure compensates investors for holding the market intraday despite its flat intraday return, and the positive risk prices for overnight exposures to the non-market factors compensate investors for holding these factors overnight despite their negative overnight returns. Thus, the patterns in the factors' risk prices are a direct consequence of the patterns in the factors' returns.

Given that institutional investors have been found to trade on factors whereas retail investors have been found to trade against factors (see, e.g., Calluzzo et al., 2019; McLean et al., 2022), the above reasoning is also consistent with the view that the intraday clientele primarily consists of institutional investors while the overnight clientele consists of retail investors. To evaluate how institutional and retail investors drive my results, I split my sample based on stocks' institutional ownership and separately estimate the factors' risk prices in both subsamples. The results reveal that the disparities between the factors' continuous intraday and overnight risk prices are primarily observable for stocks with high institutional ownership. Since the tug of war between institutional and retail investors should be more pronounced for these stocks, this finding corroborates that the differential pricing of continuous intraday and overnight factor exposures is likely due to institutional and retail investors' different preferences and trading behaviors.

Finally, I investigate whether the decomposed risk prices have predictive power for the factors' future returns. To this end, I implement time-series regressions. I find that the factors' overnight risk prices positively predict their returns. The predictive power emanates from the overnight risk prices' positive predictive power for the factors' intraday returns. By contrast, the continuous intraday risk prices positively predict the factors' overnight returns. Yet, they have no significant predictive power for the factors' total returns. These results align with the conjecture that the non-market factors' return premia are compensation for overnight respectively retail investors' aversion to the factors. Moreover, they indicate that the decomposed risk prices contain valuable information for investors who try to time the factors.

This study relates to several strands of literature. First, it contributes to the literature that examines whether factor exposures are positively related to returns. Black et al. (1972) and Frazzini and Pedersen (2014) evaluate this question for the CAPM, documenting that the relation between market betas and average returns is much weaker than predicted. Savor and Wilson (2014), Antoniou et al. (2016), Hong and Sraer (2016), Jylhä (2018), and Hendershott et al. (2020) show that the relation between market betas and returns is stronger under certain conditions, such as on days with scheduled macroeconomic announcements, when sentiment is pessimistic, when disagreement among investors is low, when borrowing constraints are loose, or when markets are closed. Daniel and Titman (1997) find that the weak unconditional relation between betas and returns holds not only for the market factor but also for the size and value factors of the Fama-French (1993; 1996) three-factor model. Similarly, Jegadeesh et al. (2019), Daniel et al. (2020), and Chen et al. (2023) find insignificant and in parts even negative relations between betas and returns for the factors of the Fama-French (2015) five-factor model. I extend this literature by decomposing betas on the Fama-French (2015) factors into continuous, jump, and overnight betas and examining their separate pricing. Like virtually every other study in this stream of literature, I fail to document a reliably positive relation between factor exposures and returns. Nevertheless, my results reveal a positive risk-return relation for some of the factors' risks, namely continuous market risk and overnight size, value, profitability, and investment risks. Thereby, the results on the pricing of the non-market factors' overnight risks yield valuable insights and are—to the best of my knowledge—new to the literature.

Second, I contribute to the literature on the pricing of jump and overnight risks.[3] Todorov and Bollerslev (2010) and Alexeev et al. (2017) document that stocks' continuous and jump market betas can be very different. Bollerslev et al. (2016) estimate continuous, jump, and overnight market betas and find that stocks with higher jump and overnight market betas earn higher returns while the continuous market beta is not significantly related to returns. These results suggest that investors command a risk premium for exposures to discontinuous market risks. Relatedly, Cremers et al. (2015) show that investors price exposures to aggregate jump and volatility risks independently and that they price exposure to changes in jump risk higher than exposure to changes in volatility risk. In contrast, Van Oordt and Zhou (2016) find no premium for tail market betas. Riedel and Wagner (2015) document that market tail risk, particularly downside tail risk, is substantially higher overnight than intraday. Moreover, Perras and Wagner (2020) provide evidence that investors command a premium for holding the market portfolio overnight, attributing it to the lack of liquidity. Evidence on the pricing of jump, crash, tail, and overnight exposures to non-market factors is thin. As one of the few studies in this regard, Chabi-Yo et al. (2022) find that exposure to the multivariate crash risk of seven factors, including the five Fama-French (2015) factors, command a premium in the cross-section of stock returns. Aleti (2022) and Aït-Sahalia et al. (2023) examine the pricing of continuous and jump betas on the Fama-French (2015) factors but neglect overnight betas. I contribute to this literature by examining the pricing of jump and overnight exposures not only to the market factor but also to the non-market factors of Fama and French (2015). Contrary to existing evidence in the literature—in particular Bollerslev et al. (2016)—I do not find exposure to jump market risk to be positively priced and document even a negative pricing of exposure to overnight market risk. I rather find continuous market risk exposure to be positively priced. Additionally, my results indicate that overnight exposures to the non-market factors of Fama and French (2015) are priced, whereas jump exposures are not.

Third, this study provides further evidence for the recently emerging literature on intraday versus overnight patterns in factor returns. Kelly and Clark (2011) document that overnight returns on the aggregate stock market are higher than intraday returns. In contrast to market returns, Lou et al. (2019) find that the returns on popular anomalies—including the size, value, profitability, and investment anomalies underlying the Fama-French (2015) factors—are earned

[3]Note that the existing literature does not always clearly distinguish between discontinuous intraday jumps and discontinuous overnight returns. Thus, it is unclear whether the documented risk premia for jump risks are compensation for intraday jump risk or overnight risk.

entirely intraday with mostly negative returns overnight. They argue that the opposing signs of the anomalies' intraday and overnight returns are due to a tug of war between intraday and overnight investor clienteles with differential preferences for the anomalies. The degree of the anomalies' tug of war has predictive power for their future returns. Bogousslavsky (2021), Lu and Qin (2021), and Lu et al. (2023) provide evidence suggesting that the disparity between the anomalies' intraday and overnight returns is in particular due to institutional investors' intraday trading against retail investors' overnight order flow.[4] Concerning the pricing of betas in intraday and overnight returns, Hendershott et al. (2020) find that the market beta is positively priced in overnight returns but negatively in intraday returns. My study extends this literature by providing evidence on the pricing of intraday and overnight factor exposures in total returns as well as in intraday and overnight returns separately. Consistent with the literature, my results reveal strong intraday versus overnight patterns that are arguably due to the diverging trading behaviors of institutional and retail investors and that are different for the market versus non-market factors. Moreover, my results suggest that the patterns in the factors' return premia have pricing implications in the sense that investors demand compensation for being exposed to the adverse side of these patterns.

Finally, my paper also relates to recent studies considering continuous-time versions of multifactor models. Aït-Sahalia et al. (2020) estimate the Fama-French (2018) six-factor model for a large high-frequency stock sample, documenting that the non-market factors are useful in explaining time-series variation in stock returns. Pelger (2020) aims to capture the systematic risks that drive stock returns through statistical factors estimated from a high-frequency stock sample via principal component analysis. He identifies four systematic continuous factors and one systematic jump factor. Similar to the characteristics-based factors of Fama and French (2015), the statistical factors earn positive intraday returns that reverse overnight, corroborating the pervasiveness of the intraday versus overnight pattern in factor returns. Both studies, Aït-Sahalia et al. (2020) and Pelger (2020), highlight the benefits of using high-frequency data to estimate factor models but also emphasize the necessity to differentiate between continuous and jump movements. While also adopting a continuous-time multifactor framework, my work differs from these studies by examining the pricing of systematic risk exposures rather than identifying systematic and idiosyncratic risks.

2 Theoretical Motivation

A discrete-time factor model with K factors that aims to describe assets' excess returns can be expressed as follows:

$$r_{i,t} - r_{f,t} = \sum_{k=1}^{K} \beta_{i,t}^{k} f_{k,t} + \epsilon_{i,t} \tag{1}$$

[4] Aboody et al. (2018), Akbas et al. (2022), and Berkman et al. (2012) also propose investor clientele effects as an explanation for patterns in intraday versus overnight returns.

where $r_{i,t}$ is asset i's return, $r_{f,t}$ is the risk-free rate, $\beta_{i,t}^{k}$ is the asset's exposure to factor k, $f_{k,t}$ is factor k's realization, and $\epsilon_{i,t}$ is the asset's idiosyncratic return (i.e., the part of the return left unexplained by the factor model). For the Fama-French (2015) five-factor model, $K = 5$ and $k \in \{MP, SMB, HML, RMW, CMA\}$, where MP, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors, respectively.

So far, the factors in equation (1) may simply capture covariation in assets' returns without any pricing implication. To be pricing-relevant *risk* factors, they need to reflect risks of hedging concern to investors. Put differently, assuming the absence of arbitrage and thus the existence of an economy-wide stochastic discount factor (SDF), the factors need to be proxies for the SDF. In this case, the SDF may be approximated by a linear function of the factors:[5]

$$m_t = a_t + \sum_{k=1}^{K} b_{k,t}(f_{k,t} - E(f_{k,t})) \tag{2}$$

where $b_{k,t}$ is the SDF's loading on factor k and a_t is a constant capturing the factors' means.

Cochrane (2005) shows that an SDF that is linear in the factors is equivalent to an expected return-beta model that expresses assets' expected excess returns as a linear function of their exposures to the factors:

$$E(r_{i,t}) - r_{f,t} = \sum_{k=1}^{K} \beta_{i,t}^{k} \lambda_{k,t} \tag{3}$$

where $\lambda_{k,t}$ is the risk price for exposure to factor k. This representation states that investors are compensated for exposures to the factors by higher expected returns. The risk price for exposure to a given factor is directly linked to the SDF's loading on this factor.

To convert the factor model in equation (1) to a continuous-time framework, I follow the literature and model factors' continuous-time price processes as jump-diffusions. In particular, I assume that factor k's log price across the fixed time interval $[0, T]$ is generated by:

$$dF_{k,t} = \mu_{k,t}dt + \sigma_{k,t}dW_{k,t} + \int_R x\nu_k(dt, dx) \tag{4}$$

where $\mu_{k,t}$ is the drift of the process and reflects the factor's instantaneous risk price, $\sigma_{k,t}$ is the factor's instantaneous diffusive volatility, $dW_{k,t}$ is a Brownian motion that generates continuous movements in the price, and ν_k is a compensated jump counting measure that generates discontinuous movements in the price. The term $\sigma_{k,t}dW_{k,t}$ reflects the factor's continuous risk, and the term $\int_R x\nu_k(dt, dx)$ reflects the factor's discontinuous risk.

In analog to equation (1) and using the expression for the factors' log price processes in equation (4), I assume that the log price process of stock i across the fixed time interval $[0, T]$

[5]As pointed out by Cochrane (2005), the assumption of a linear relation between the SDF and the factors is not very restrictive.

can be represented as follows:

$$dP_{i,t} = \mu_{i,t}dt + \sum_{k=1}^{K} \beta_{i,t}^{k,C} \sigma_{k,t} dW_{k,t} + \sum_{k=1}^{K} \int_R \beta_{i,t}^{k,D} x \nu_k(dt, dx) + dZ_{i,t} \tag{5}$$

where $\mu_{i,t}$ is the drift of the process and reflects the stock's instantaneous expected return, $\beta_{i,t}^{k,C}$ and $\beta_{i,t}^{k,D}$ are the stock's exposures to factor k's continuous and discontinuous movements, respectively, and $dZ_{i,t}$ is a jump-diffusion that captures the idiosyncratic continuous and discontinuous movements in the stock's price. Importantly, the expression in (5) allows the stock's betas on the continuous and discontinuous factor movements to differ.

The continuous-time expression for the factor process in equation (4) suggests the following approximate representation of the SDF:[6]

$$m_t \approx a_t + \sum_{k=1}^{K} b_{k,t} \left(\int_{t-1}^{t} \sigma_{k,s} dW_{k,s} + \int_{t-1}^{t} \int_R x \nu_k(ds, dx) \right) \tag{6}$$

However, this representation restricts the SDF to have the same loadings on the factors' continuous and discontinuous movements. No theoretical argument exists that justifies this restriction. Different sources of variation in the factors may proxy differently for the SDF, implying that the SDF may have different loadings on the factors' continuous and discontinuous movements.[7] To allow for different loadings on factors' continuous and discontinuous movements, I adjust the representation of the SDF in (6):

$$m_t \approx a_t + \sum_{k=1}^{K} \int_{t-1}^{t} b_{k,t}^{C} \sigma_{k,s} dW_{k,s} + \sum_{k=1}^{K} \int_{t-1}^{t} \int_R b_{k,t}^{D} x \nu_k(ds, dx) \tag{7}$$

where $b_{k,t}^{C}$ and $b_{k,t}^{D}$ are the SDF's loadings on factor k's continuous and discontinuous movements, respectively.

The representation of the SDF in (7) implies that exposures to the factors' continuous and discontinuous risks are compensated separately. The corresponding expected return-beta model is as follows:

$$E(r_{i,t}) - r_{f,t} = \sum_{k=1}^{K} \beta_{i,t}^{k,C} \lambda_{k,t}^{C} + \sum_{k=1}^{K} \beta_{i,t}^{k,D} \lambda_{k,t}^{D} \tag{8}$$

where $\lambda_{k,t}^{C}$ and $\lambda_{k,t}^{D}$ are the risk prices for exposures to factor k's continuous and discontinuous movements, respectively. This expected-return beta representation states that investors may be compensated for exposures to both sources of factor movements—continuous and discontinuous—and that the compensations may differ. In particular, a risk price is non-zero if and only if the SDF has a non-zero loading on the corresponding type of factor movement, meaning that this source of variation proxies for the SDF and is thus of hedging concern to

[6]This representation assumes that a factor's demeaned discrete return $(f_{k,t} - E(f_{k,t}))$ can be approximated by the factor's log return (i.e., its log price change) in excess of the drift of the factor's log price process. This approximation is done for ease of exposition of the concept.

[7]This argument follows, for example, Bollerslev et al. (2016) and Pelger (2020).

investors.

So far, the derivations in this section assume that prices evolve continuously through time. However, price movements are only observable while markets are open. The literature suggests that the price change from the closing of the trading session to the opening of the next trading session can be interpreted as a discontinuous price movement (see, e.g., Bollerslev et al., 2016). Thus, there are two different types of discontinuous price movements: intraday jumps occurring during the trading session and overnight price changes occurring from close to open. To account for the different nature of these two types of discontinuous price movements and their potentially different pricing, the expected return-beta model in (8) may be adjusted as follows:

$$E(r_{i,t}) - r_{f,t} = \sum_{k=1}^{K} \beta_{i,t}^{k,C} \lambda_{k,t}^{C} + \sum_{k=1}^{K} \beta_{i,t}^{k,J} \lambda_{k,t}^{J} + \sum_{k=1}^{K} \beta_{i,t}^{k,N} \lambda_{k,t}^{N} \tag{9}$$

where $\beta_{i,t}^{k,J}$ and $\beta_{i,t}^{k,N}$ are stock i's exposures to factor k's intraday jumps and overnight movements, and $\lambda_{k,t}^{J}$ and $\lambda_{k,t}^{N}$ are the corresponding risk prices for these risk exposures.

The risk prices in equation (9) are the quantities of interest this study aims to examine. Importantly, assuming a given factor is priced, there is little theoretical indication of whether exposure to the factor's continuous, jump, or overnight risk is compensated. Nevertheless, there are some intuitive arguments suggesting that the risks may be priced differently. On the one hand, the information content of the different types of movements is likely to be different. In particular, intraday jumps are likely to emanate from major information events. By contrast, continuous movements may be due to the gradual revelation of private information but may also reflect noise. Additionally, many scheduled information releases are typically outside trading hours (e.g., macroeconomic announcements in the US are typically at 8:30 a.m. and thus before market opening, and companies' earnings announcements are typically in the evening after market closing) and are thus reflected in overnight movements. On the other hand, the different types of movements may reflect the different trading behaviors and preferences of heterogeneous investor clienteles. Specifically, intraday trading is most likely dominated by professional traders and investors, such as market makers and asset managers, implying that intraday movements primarily reflect their trading patterns. By contrast, orders submitted between market closing and opening are most likely from retail investors, meaning that overnight movements are driven by their preferences. These considerations call for investigating the separate pricing of the factors' different types of risks.

3 Data and Factors

3.1 Data Sample

For the empirical examination of the pricing of the factors' different risks, I merge data from four sources. First, I obtain monthly and daily data on stock returns, open prices, close prices, and shares outstanding from the CRSP database. I adjust holding period returns for delisting returns. Second, I retrieve data on firm fundamentals from the Compustat Annual and Quarterly databases. Third, I use the one-month T-bill rate from Kenneth French's website as risk-free rate.[8] Finally, I obtain high-frequency stock trading data from the Monthly and Daily TAQ databases.[9] My sample covers all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11. It spans the period from January 1993 to December 2019, being restricted by the availability of high-frequency data from TAQ.

The high-frequency data from TAQ requires extensive cleaning. For this purpose, I follow standard practices in the high-frequency literature (see, e.g., Barndorff-Nielsen et al., 2009; Holden and Jacobsen, 2014; Bollerslev et al., 2016; Aït-Sahalia et al., 2020). First, I use only trade observations with timestamps in the regular trading hours from 9:30:00 a.m. to 4:00:00 p.m., prices and trade sizes greater than zero, trade correction indicators of zero, and normal sale conditions.[10] Second, I delete trade observations whose transaction prices deviate by more than ten mean absolute deviations from the median transaction price of the 25 previous and subsequent trade observations.

Based on the remaining trade observations, I assign stock prices to each second in the interval from 9:30:00 a.m. to 4:00:00 p.m. as follows: if there is one trade in the respective second, the price is the transaction price of this trade; if there are multiple trades in the respective second, the price is the volume-weighted average transaction price; if there is no trade in the respective second, I carry forward the price from the previous second. Moreover, I follow Aït-Sahalia et al. (2020) and replace stocks' prices at 9:30:00 a.m. and 4:00:00 p.m. with the daily open and close prices from CRSP, ensuring that intraday CRSP and TAQ returns are equal. Therefore, I keep only stock-days with non-missing daily returns, open prices, and close prices in CRSP and at least one valid trade observation in TAQ.[11] Based on the stocks' second-by-second prices, I calculate their 15-, 30-, and 75-minute log returns across the day.[12] I calculate stocks' high-frequency returns for three different sampling frequencies because I use a mixed-frequency approach for the estimation of stocks' betas (see Section 4.1). Finally, I calculate stocks' overnight returns as their daily gross returns divided by their gross open-to-close returns, minus one. By calculating overnight returns in this way rather than as close-to-open returns, I account for potential dividend payments and stock splits occurring after market closing.

[8] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[9] Data from the Daily TAQ database is only available from September 10, 2003. For the period from January 1, 1993, to September 9, 2003, I use data from the Monthly TAQ database.

[10] Trades with normal sale conditions are trades whose sale condition field in TAQ is either blank or equals @, *, E, F, @E , @F, *E, *F.

[11] I exclude stock-days for which the absolute difference between the log of the open price from CRSP and the log of the first price from TAQ as well as the absolute difference between the log of the close price from CRSP and the log of the last price from TAQ are both larger than the log of 1.1. This filter excludes stock-days for which CRSP open and close prices deviate by more than roughly 10% from the first and last prices in TAQ and aims to catch stock-days that suffer from bad data quality or matching errors between the databases.

[12] The 15- and 30-minute sampling frequencies start at 9:30:00 a.m.; the 75-minute sampling frequency starts at 9:45:00 a.m.

3.2 Factor Returns

For the construction of the high-frequency versions of the Fama-French (2015) factors, I closely follow their portfolio formation procedure. First, the market portfolio contains each month all stocks that are listed on the NYSE, AMEX, or NASDAQ, have a CRSP share code of 10 or 11, and have good market equity data at the beginning of the month. The market portfolio is newly formed at the beginning of each month, and the stocks in the market portfolio are value-weighted based on their market capitalizations. The return on the market factor (MP) is the return on the market portfolio in excess of the risk-free rate.

For the construction of the value factor, stocks are at the end of each June independently sorted into two size groups and three book-to-market groups (see Appendix A for the construction of the variables). The sorting breakpoints are the median market equity and the 30th and 70th book-to-market percentiles of all NYSE stocks. The intersections of the two size and three book-to-market groups yield six portfolios. The stocks in the portfolios are value-weighted. The return on the value factor (HML) is the average of the returns on the two high book-to-market portfolios minus the average of the returns on the two low book-to-market portfolios.

The profitability and investment factors are formed in the same way as the value factor, just that the second sort is with respect to operating profitability and investment, respectively. The return on the profitability factor (RMW) is the average of the returns on the two high profitability portfolios minus the average of the returns on the two low profitability portfolios. The return on the investment factor (CMA) is the average of the returns on the two low investment portfolios minus the average of the returns on the two high investment portfolios. Finally, the return on the size factor (SMB) is the average of the returns on the nine small portfolios resulting from the three sorts minus the average of the returns on the nine big portfolios.

I calculate monthly, daily, overnight, and high-frequency (15-, 30-, and 75-minute) versions of the factors.[13] For each version, the stocks' value-weights in the factor portfolios are calculated based on their market capitalizations at the beginning of the return intervals. Specifically, for the monthly version, I use the market capitalization based on the close price of the previous month's last trading day; for the daily and overnight versions, I use the market capitalization based on the previous day's close price; and for the high-frequency versions, I follow Aït-Sahalia et al. (2020) and use the market capitalization based on the previous day's close price multiplied with the cumulative gross return from the previous day's close until the beginning of the respective interval (including the overnight return).

Table 1 reports summary statistics for the factors' monthly, daily, overnight, and 30-minute versions for the period from January 1993 to December 2019.[14] The results for the factors' monthly versions in Panel A show that all factors earn positive mean returns. However, only the market factor's mean return is highly significant. The profitability factor's mean return is

[13] For the calculation of the factors' daily, overnight, and high-frequency versions, I use only stock-days with non-missing daily returns, open prices, and close prices in CRSP and at least one valid trade observation in TAQ. This ensures that each version uses the same stock-days.

[14] For parsimony, I focus on the 30-minute version in the discussion of the high-frequency factors' properties. The properties of the 15- and 75-minute versions are qualitatively the same.

marginally significant, while the size, value, and investment factors' mean returns are insignificant. The attenuation of the factors' mean returns compared to those reported by Fama and French (2015) for the period from 1963 to 2013 is in line with recent studies' findings that the factor returns weakened in the last few decades (see, e.g., McLean and Pontiff, 2016; Hou and van Dijk, 2019; Arnott et al., 2021). The results for the factors' daily versions in Panel B are qualitatively similar.

Panels C and D present the results for the factors' overnight and 30-minute versions. Most notably, only the market factor earns a positive overnight premium. By contrast, the other factors' overnight mean returns are strongly and significantly negative. The picture reverses for the factors' high-frequency versions: the market factor's mean return is close to zero, whereas the other factors earn strong and significantly positive mean returns during trading hours. These results are consistent with Lou et al.'s (2019) observations that the market premium is realized primarily overnight, whereas the return premia of the size, value, profitability, and investment anomalies are realized during the day. Panels C and D further reveal that the kurtosis of the factors' overnight and high-frequency returns are much more pronounced than the kurtosis of the factors' monthly and daily returns, indicating that the factors exhibit substantial high-frequency tail risk that is averaged out and thus less visible in their monthly and daily returns.

3.3 Factor Jumps

To identify the factors' intraday jumps, I rely on the time-of-day (TOD) estimator of Bollerslev et al. (2013). This estimator classifies returns exceeding the threshold of $\tau \cdot n^{-\omega} \cdot \hat{\sigma}_{k,d,t}$ as jumps, where n is the number of return intervals per day (e.g., $n = 13$ for the 30-minute frequency) and $\hat{\sigma}_{k,d,t}$ is a local volatility estimate for factor k in interval t on day d. Specifically, $\hat{\sigma}_{k,d,t}$ combines a jump-robust bipower estimate for factor k's volatility on day d with an estimate for the factor's time-of-day volatility pattern (see Bollerslev et al. (2013) for more details). Thereby, the estimator accounts for time and intraday variation in volatility (volatility is typically highest after the open and before the close). Following Bollerslev et al. (2016), I set $\tau = 3$ and $\omega = 0.49$. Thus, roughly speaking, all high-frequency returns that are in absolute terms larger than three times the factor's local volatility estimate are classified as jumps.

Table 2 presents summary statistics on the jumps in the factors' 30-minute returns.[15] The percentage of jump observations ranges between 1.13% and 1.31% of all observations across the factors. Although these percentages seem low, they are about five times higher than expected if the factors' 30-minute returns were normally distributed. This result is consistent with the high kurtosis of the factors' high-frequency returns documented in Panel D of Table 1. The jumps are quite equally divided into positive and negative jumps. Additionally, comparing the positive and negative jumps' quartiles suggests that they are, in general, similarly distributed. These results suggest that the upside potential and the downside risk emanating from jumps

[15] For the factors' jump statistics, their TOD patterns are estimated based on data across the entire sample period. For the estimation of stocks' jump betas in Section 4.2, the factors' TOD patterns are estimated only based on data across the respective estimation window.

are balanced. Finally, despite being rare events, jumps contribute between 7.7% and 12.8% to the total variance of the factors' high-frequency returns.

3.4 Decomposition of Factor Premia

Table 3 reports the decomposition of the factors' daily mean returns into their overnight and high-frequency components and the decomposition of the high-frequency components into their continuous and jump components. For this purpose, I aggregate the factors' 30-minute returns as well as their continuous and jump components on a daily basis.[16] The decomposition of the factors' daily returns into overnight and high-frequency intraday returns displays the same pattern already observed in Table 1: the market premium is primarily earned overnight while the non-market factors' return premia are exclusively earned intraday and strongly reverse overnight. Decomposing the high-frequency intraday returns into their continuous and jump components reveals that the non-market factors' continuous returns are highly significant and account almost completely for their intraday return premia. By contrast, the factors' jump returns are small and hardly contribute to their return premia.

4 Continuous and Discontinuous Factor Betas

4.1 Sample Selection

Investigating the pricing of exposures to the factors' continuous, jump, and overnight risks requires estimating stocks' betas on the different types of factor movements. However, individual stocks' high-frequency returns are subject to various microstructure issues, such as infrequent and asynchronous trading, bid-ask bounce, and price discreteness. These issues may contaminate the beta estimates and introduce an errors-in-variables bias in the risk price estimates. To mitigate the impact of these microstructure issues, I retain only stocks in my sample that satisfy several criteria and select stocks' sampling frequencies depending on the severity of their microstructure issues (microstructure issues decrease with the sampling frequency).

In detail, I apply in each estimation window (I estimate betas based on a rolling six-month estimation window; see Section 4.2 for further details) two ad-hoc exclusion criteria widely used in the high-frequency literature. First, I exclude stocks with market equity below \$10mn or share prices below \$1 at the beginning of the estimation window. Second, I exclude stocks with valid data on daily, overnight, and high-frequency returns for less than 50 days during the estimation window.

Next, I determine in each estimation window for each remaining stock the appropriate sampling frequency. In particular, I select the highest frequency from the 15-, 30-, and 75-minute frequencies for which both of the following criteria are satisfied. First, less than half

[16] Note that all returns are log returns and that all versions use the same stock-days. Thus, the sum of a factor's continuous and jump returns on a given day equals the sum of the factor's high-frequency returns. The sum of a factor's high-frequency and overnight returns does not exactly correspond to the factor's daily return due to the intraday changes of the stocks' weights in the factor portfolios (see Section 3.2).

of the stock's high-frequency return observations are zero. Second, the stock does not suffer from significant microstructure noise according to the tests proposed by Aït-Sahalia and Xiu (2019). Specifically, I apply the three tests recommended by Aït-Sahalia and Xiu (2019)—the jump-robust Hausman test, the Student-t test, and the autocovariance-based test—to the stock's high-frequency returns and require that at least one of the tests cannot reject the null hypothesis of no microstructure noise at the 1% significance level.[17] If a stock fails to satisfy the two criteria for any of the three frequencies, it is excluded from the sample. Using this mixed-frequency approach balances two aspects. On the one hand, I can take advantage of a high sampling frequency for the least contaminated stocks. On the other hand, I can retain a comprehensive stock sample by using a lower sampling frequency for stocks with more severe microstructure issues without the need to exclude them.

Panel A of Figure 1 depicts the number of stocks in the final sample after applying the exclusion criteria. The two ad-hoc criteria, catching very small stocks, penny stocks, and stocks with insufficient data during the estimation window, exclude in general only a moderate fraction of stocks from the full sample. By contrast, the two frequency-dependent criteria, catching stocks with a large percentage of zero returns and significant microstructure noise, exclude a considerable fraction of stocks during the early part of the sample period. The resulting sample size is around 1,200 to 1,500 stocks during the first few years, gradually increasing afterward. In the later part of the sample period, the two frequency-dependent criteria exclude only a small fraction of stocks, reflecting the substantial increase in liquidity and trading volume in recent decades. Thus, while the number of stocks in the full sample decreases from a maximum of nearly 8,000 in the late 1990s to below 4,000 at the end of 2019, the number of stocks in the final sample increases to above 3,500 in the 2000s and fluctuates around 3,000 afterward.

Furthermore, Panel B shows that the final sample accounts almost always for more than 80% of the full sample's total market capitalization and, from the beginning of the 2000s onwards, always for more than 95%. These observations indicate that my final sample is representative of the broad US stock market, especially from the beginning of the 2000s onwards.

4.2 Estimation of Betas

I estimate daily, simple high-frequency, continuous, jump, and overnight betas on the factors for all stocks in my final sample at the end of each month from June 1993 to December 2019 based on data over the previous six months. The estimation window length of six months balances two aspects.[18] On the one hand, it is short enough to account for time variation in the betas, alleviating the impact of the assumption that betas are constant across the estimation window when estimating the risk prices. On the other hand, it is long enough to have a large number of observations to ensure sufficiently precise beta estimates. Setting the estimation window

[17] For the implementation of the tests, I use the Matlab code provided by Dacheng Xiu on his website: `https://dachxiu.chicagobooth.edu/`. I am grateful to Dacheng Xiu for making this code available.

[18] In the Internet Appendix, I show that my key results are robust to using estimation window lengths of three and 12 months.

long enough is particularly relevant for estimating jump and overnight betas because jumps are infrequent and overnight observations are naturally restricted to one per day.

I estimate daily betas with a standard OLS regression; that is, stocks' daily excess returns across the six-month estimation window are regressed multivariately on the Fama-French (2015) factors' daily returns and an intercept. Overnight betas are estimated analogously by regressing stocks' overnight excess returns multivariately on the factors' overnight returns and an intercept.

To estimate simple high-frequency betas, I adapt the realized market beta estimator of Andersen et al. (2006) to a multifactor framework. Andersen et al.'s (2006) estimator is equivalent to regressing stocks' high-frequency returns on the market factor's high-frequency returns without an intercept. Thus, I estimate high-frequency betas by multivariately regressing stocks' high-frequency returns on the factors' high-frequency returns without an intercept.

I estimate continuous betas analogously to the simple high-frequency betas but use only observations for which none of the five factors exhibits a jump. Thus, continuous betas are estimated by regressing stocks' high-frequency returns multivariately on the factors' high-frequency returns without an intercept, excluding all observations across the six-month estimation window for which any of the factors is detected to jump. Additionally, stocks' jump returns are set to zero. Hence, the continuous beta estimator can be expressed as follows:

$$\begin{aligned} \beta_{i,t}^{C} &= (F_t^{C\prime} F_t^{C})^{-1} F_t^{C\prime} R_{i,t}^{C} \\ F_t^{C} &= F_t \circ 1_{\{\forall k: |f_{k,s}| < \mu_{k,s}\}} \\ R_{i,t}^{C} &= R_{i,t} \circ 1_{\{\forall k: |f_{k,s}| < \mu_{k,s}\}} \circ 1_{\{|r_{i,s}| < \mu_{i,s}\}} \end{aligned} \tag{10}$$

where F_t is a matrix containing the factors' high-frequency returns across the estimation window from the beginning of month $t-5$ to the end of month t, $R_{i,t}$ is a vector containing stock i's high-frequency returns, $1_{\{.\}}$ is a vector whose elements equal one if the condition is fulfilled and zero otherwise, $f_{k,s}$ ($r_{i,s}$) is factor k's (stock i's) return in interval s, and $\mu_{k,s}$ ($\mu_{i,s}$) is factor k's (stock i's) jump threshold in interval s. The jump thresholds are determined by applying the TOD estimator from Section 3.3 with $\tau = 3$ and $\omega = 0.49$ to the factors' and stocks' high-frequency returns across the estimation window.

Finally, I adopt the following procedure to estimate stocks' jump betas on a given factor. First, I identify all observations in the estimation window for which the respective factor exhibits a jump, but no other factor exhibits a jump. Thereby, I ensure that the stocks are not driven by jumps in the other factors. Second, I adjust the stocks' high-frequency returns by subtracting the other factors' high-frequency returns multiplied by the stocks' continuous betas on these factors. This step removes the parts of the stocks' returns driven by the other factors' continuous movements. Third, I regress the stocks' adjusted high-frequency returns univariately on the factor's high-frequency returns, using only the observations for which the factor exhibits a jump but no other factor. This jump beta estimator can be expressed as follows:

$$\beta_{i,t}^{k,J} = (F_{k,t}^{J}{}' F_{k,t}^{J})^{-1} F_{k,t}^{J}{}' \epsilon_{i,t}^{k}$$

$$F_{k,t}^{J} = F_{k,t} \circ 1_{\{|f_{k,s}| \geq \mu_{k,s}\}} \circ 1_{\{\forall l \neq k : |f_{l,s}| < \mu_{l,s}\}} \tag{11}$$

$$\epsilon_{i,t}^{k} = \left(R_{i,t} - F_t \beta_{i,t}^{C} + F_{k,t} \beta_{i,t}^{k,C}\right) \circ 1_{\{|f_{k,s}| \geq \mu_{k,s}\}} \circ 1_{\{\forall l \neq k : |f_{l,s}| < \mu_{l,s}\}}$$

where $F_{k,t}$ is a vector containing factor k's high-frequency returns across the estimation window from the beginning of month $t-5$ to the end of month t. The other variables are defined as in equation (10). The jump thresholds are again determined by applying the TOD estimator with $\tau = 3$ and $\omega = 0.49$.

4.3 Distributions of Betas

Table 4 presents descriptive statistics for the estimated betas. The cross-sectional statistics are calculated each month and then averaged across time. The table further reports betas' rolling 12-month volatilities averaged across stock-months, their six-month time-series autocorrelations averaged across stocks, and their cross-sectional rank-correlations with their six-month lagged values averaged across time.

The daily and simple high-frequency betas' means are similar across all factors, but the latters' cross-sectional standard deviations and kurtosis are considerably lower. Thus, the high-frequency betas are less dispersed, suggesting they are less affected by return outliers and more precisely estimated. This conjecture is further corroborated by their lower time-series volatilities, higher time-series autocorrelations, and higher cross-sectional autocorrelations, indicating that they are more stable and persistent than the daily betas. These results illustrate the benefits of using high-frequency data to estimate betas.

The properties of the continuous betas are similar to those of the high-frequency betas. In particular, they also exhibit low cross-sectional standard deviations, moderate kurtosis, low time-series volatilities, and strong time-series and cross-sectional autocorrelations. The properties of the jump and overnight betas are very different from those of the continuous betas. They exhibit higher cross-sectional standard deviations and kurtosis, higher time-series volatilities, and lower autocorrelations. Thus, both types of discontinuous betas are more dispersed, less stable, and less persistent than continuous betas.[19]

Table 4 also reports statistics on the absolute differences between jump and continuous betas and between overnight and continuous betas. The median absolute differences between jump and continuous betas vary across the different factors but are in general considerable, ranging between 0.30 for market betas and 0.90 for investment betas. The median absolute differences between overnight and continuous betas are quantitatively similar, ranging between 0.37 for market betas and 0.73 for investment betas. Furthermore, Figure 2 presents estimates for the

[19] These results may in part reflect the less accurate estimation of the jump and overnight betas due to the lower number of observations used in their estimation.

empirical densities of the differences between jump and continuous betas and between overnight and continuous betas, showing that they are quite widespread. Altogether, these observations show that jump and overnight betas often deviate considerably from continuous betas.

Table 5 reports time-series averages of monthly cross-sectional correlations between the different types of betas. Jump and overnight betas are only weakly correlated to continuous betas, with correlations between 0.14 and 0.52. Additionally, the jump and overnight betas also exhibit low correlations below 0.25. These correlations show that stocks' exposures to factors' continuous, jump, and overnight movements are in general only weakly positively related, suggesting that they capture different effects. This holds in particular also for stocks' exposures to the two sources of discontinuous risks. Together with the previous observation that continuous, jump, and overnight betas can be very different, these results indicate that factor models that fail to account for the different types of factor exposures represent an oversimplification and highlight the need to differentiate between them. The dissimilarities of the continuous, jump, and overnight betas also corroborate that it is reasonable to investigate their separate pricing.

4.4 Relation between Betas and Characteristics

Table 5 also presents the betas' correlations with prominent characteristics. The full list of characteristics and their construction is described in Appendix A. The most notable observation is that, across all factors, the continuous betas exhibit the highest correlations with the factors' sorting variables (i.e., market equity for the size factor, book-to-market for the value factor, etc.). Nevertheless, the correlations are still rather muted, ranging in absolute terms between 0.07 and 0.29. The correlations of jump and overnight betas with the respective sorting variables are similar but notably lower than those of the continuous betas.

Furthermore, the betas correlations' with the other characteristics besides the sorting variables exhibit no pronounced patterns that are uniform across the factors. In particular, there are hardly any differences in continuous, jump, and overnight betas' correlations with illiquidity, idiosyncratic risk, or higher return moments. This finding indicates that the divergence between continuous, jump, and overnight betas is not driven by effects related to these characteristics.

5 Risk Prices for Continuous, Jump, and Overnight Exposures

5.1 Fama-MacBeth (1973) Regressions

The findings in the previous section establish that continuous, jump, and overnight betas can be very different and are only weakly positively related. This is the prerequisite that investigating their separate pricing makes sense. To this end, I estimate the risk prices for the different types of factor exposures based on cross-sectional Fama-MacBeth (1973) regressions. As advocated in the recent literature (see, e.g., Ang et al., 2020; Jegadeesh et al., 2019), I use individual stocks rather than portfolios as test assets. That is, I run at the end of each month t from June 1993 to December 2019 the following cross-sectional regression:

$$r_{i,t} - r_{f,t} = \gamma_t^{ZB} + \sum_{k=1}^{5} \gamma_t^{k,C} \cdot \hat{\beta}_{i,t}^{k,C} + \sum_{k=1}^{5} \gamma_t^{k,J} \cdot \hat{\beta}_{i,t}^{k,J} + \sum_{k=1}^{5} \gamma_t^{k,N} \cdot \hat{\beta}_{i,t}^{k,N} + \sum_{z=1}^{Z} \gamma_t^{z} \cdot X_{i,t}^{z} + \epsilon_{i,t} \quad (12)$$

where $r_{i,t}$ is stock i's compounded return from month $t-5$ to t, $r_{f,t}$ is the compounded one-month T-bill rate from month $t-5$ to t, $\hat{\beta}_{i,t}^{k,C}$, $\hat{\beta}_{i,t}^{k,J}$, and $\hat{\beta}_{i,t}^{k,N}$ are the stock's continuous, jump, and overnight betas on factor k estimated from month $t-5$ to t, $X_{i,t}^{z}$ is a characteristic of the stock measured at the end of month $t-6$, and Z is the number of characteristics. I winsorize all variables at the 1% and 99% levels and use weighted least squares with stocks' market capitalizations at the end of month $t-6$ as weights.[20] The estimated coefficients $\gamma_t^{k,C}$, $\gamma_t^{k,J}$, and $\gamma_t^{k,N}$ are the risk price estimates for exposures to factor k's continuous, jump, and overnight movements in the period from month $t-5$ to t.[21] The final risk price estimates are calculated as time-series averages of the monthly risk price estimates. For comparison, I estimate the regression in (12) also in a univariate setting (i.e., by using only one of the betas at a time) and based on daily and simple high-frequency betas.

I control for several prominent characteristics that have been found to predict individual stock returns. The first set of characteristics consists of the sorting variables underlying the Fama-French (2015) factors: size, book-to-market, operating profitability, and investment. The second set of characteristics captures several further effects documented in the literature (see, e.g., Jegadeesh, 1990; Jegadeesh and Titman, 1993; Amihud, 2002; Ang et al., 2006a,b; Amaya et al., 2015): momentum, short-term reversal, idiosyncratic volatility, illiquidity, co-skewness, co-kurtosis, realized skewness, and realized kurtosis. The characteristics are standardized each month to have means of zero and standard deviations of one.

Table 6 presents the final risk price estimates. Since the dependent returns are overlapping six-month returns, t-statistics are computed using Newey-West (1987) standard errors with six lags. Panel A displays the risk price estimates when using daily betas. None of them is significantly positive, no matter whether estimated univariately or multivariately and no matter the control variables. Daily size, value, and investment betas are in part even significantly negatively priced. Consistent with the findings in the literature, daily betas thus fail to generate a positive relation between factor exposures and returns.

Panel B shows that simple high-frequency betas improve somewhat upon daily betas, generating almost unanimously higher risk price estimates. Nevertheless, the size, value, and investment factors' risk prices remain negative, and the market and profitability factors' risk prices remain mostly insignificant. Thus, high-frequency betas also fail to generate unambiguously positive relations between factor exposures and returns.

Panel C depicts the risk price estimates for the continuous, jump, and overnight exposures to

[20] Using weighted rather than ordinary least squares in Fama-MacBeth (1973) regressions to avoid overweighting small and micro caps is strongly recommended, for example, by Hou et al. (2020).

[21] Estimating factor risk prices in a contemporaneous setting follows the literature (see, e.g., Ang et al., 2006b; Ang and Kristensen, 2012; Kim and Skoulakis, 2018; Jegadeesh et al., 2019; Raponi et al., 2019).

the factors. The results reveal strong and significant risk prices for continuous market exposure, no matter whether controls are included or not. By contrast, the risk prices for overnight market exposure are strongly and significantly negative, while the risk prices for jump market exposure are close to zero. Thus, continuous market risk is positively priced, overnight market risk is negatively priced, and jump market risk is not priced. These findings suggest that investors are averse to and therefore demand compensation for exposure to continuous intraday market risk.

The results for the pricing of the non-market factors' risks display quite uniform patterns. In particular, except for the profitability factor, the exposures to the factors' continuous movements are mostly significantly negatively priced, irrespective of the controls. By contrast, the risk prices for overnight exposures to the non-market factors are uniformly positive and significant or only marginally insignificant. Finally, risk prices for jump exposures to the factors are, except for the size factor, close to zero and insignificant. These findings indicate that investors demand compensation for overnight exposures to the non-market factors.

Table 7 compares the continuous, jump, and overnight risk prices. Panel A tests the differences between the risk prices for significance, and Panel B reports the correlations between the risk prices. The results are based on the monthly risk prices estimated in a multivariate setting without controls (i.e., specification (1) in Panel C of Table 6). Panel A shows that the patterns in the factors' continuous and overnight risk prices are mostly significant. In particular, the positive risk price for continuous intraday market exposure is significantly higher than the negative risk price for overnight market exposure, and the negative risk prices for continuous intraday value and investment factor exposures are significantly lower than the positive risk prices for overnight value and investment factor exposures.

Panel B reveals that the continuous risk prices exhibit the highest correlations with the daily risk prices. Overnight risk prices are considerably less correlated with the daily risk prices. These observations explain why the non-market factors' daily risk prices in Panel A of Table 6 are zero or negative: they reflect primarily the factors' zero or negative continuous risk prices but hardly their positive overnight risk prices. By contrast, the market factor's daily risk price is positive because it reflects the positive price for continuous market risk.

Panel B further shows that the continuous, jump, and overnight risk prices are in general weakly and by tendency negatively correlated. Especially the continuous intraday risk prices and the overnight risk prices comove negatively: the lower—and thus the more negative—the market's overnight and the non-market factors' continuous intraday risk prices, the higher—and thus the more positive—the market's continuous intraday and the non-market factors' overnight risk prices, respectively. Hence, the factors' continuous intraday and overnight risks are not only oppositely priced, but there also seems to be a tug of war between the continuous intraday and overnight risk prices.

Overall, contrary to the vast majority of the literature, the results in this subsection reveal positive risk-return relations for some of the factors' risks—the market's continuous intraday risk and the non-market factors' overnight risks. However, exposures to other risks of the factors are negatively priced—the market factor's overnight risk and the non-market factors' continuous intraday risks. For the size, value, and investment factors, the negative prices for exposures to their continuous intraday risks seem to overcompensate the positive risk prices for exposures to their overnight risks, given that the formers' magnitudes are higher than the latters' magnitudes. Consequently, similar to the evidence in the related literature, my findings fail to establish an unambiguously positive risk-return relation for exposures to the factors and therefore cast further doubts on the validity and usefulness of the Fama-French (2015) model.

Nevertheless, the results reveal a striking link to the factors' intraday versus overnight return patterns documented in Table 3. In particular, the market factor's intraday return is close to zero and the non-market factors' overnight returns are significantly negative, but the market factor's continuous intraday risk and the non-market factors' overnight risks are positively priced. Conversely, the market factor's overnight return and the non-market factors' intraday returns are significantly positive, but the market factor's overnight risk and the non-market factors' continuous intraday risks are negatively priced. Thus, the pricing of the factors' risks displays almost the perfect mirror image of the realization of the factors' returns. This apparent regularity suggests that there is an underlying economic mechanism at play.

5.2 Robustness Checks

I conduct various robustness checks for the findings from the Fama-MacBeth (1973) regressions in Table 6. First, I estimate the Fama-MacBeth (1973) regressions by using only one type of beta (i.e., either only continuous, only jump, or only overnight betas). Second, I employ alternative estimation window lengths of three and 12 months. Third, instead of the mixed-frequency approach outlined in Section 4.1, I use the same frequency for all stocks to estimate the betas and exclude those stocks that do not satisfy the criteria for the respective frequency. Thereby, I consider 15-, 30-, and 75-minute sampling frequencies. Fourth, I restrict my sample to all stocks that were in the S&P500 at some point during my sample period from January 1993 to December 2019.[22] In this robustness check, I follow the literature and assume that S&P500 stocks do not suffer major microstructure issues. Therefore, I do not apply the exclusion criteria outlined in Section 4.1 and use the highest sampling frequency of 15 minutes. Fifth, I employ a different methodology for estimating jump betas: I adapt the market jump beta estimator suggested by Todorov and Bollerslev (2010) and used by Bollerslev et al. (2016) to a multivariate framework. This estimator essentially regresses stocks' squared returns, multiplied by their original signs, on the market factor's squared returns, also multiplied by their original signs, without an intercept. The final estimate for the jump beta is obtained by taking the square root of the regression coefficient's absolute value and multiplying it by its original sign. I extend this procedure to a multivariate regression. Finally, I account for a potential errors-in-variables bias in the risk price estimates by implementing the instrumental variables approach proposed by Jegadeesh et al. (2019) to estimate the Fama-MacBeth (1973) regressions. This approach splits each estimation

[22] I identify 1,158 distinct stocks that were in the S&P500 during my sample period.

window into two subsets and estimates the betas separately from both subsets. The betas from the first subset are then used as instrumental variables for the betas from the second subset, and vice versa.[23]

The Internet Appendix reports the risk price estimates from these robustness checks. Although the risk price estimates from the robustness checks differ quantitatively somewhat from those in Panel C of Table 6, the qualitative patterns are intact. In particular, the risk prices for continuous (overnight) market exposure are consistently positive (negative), mostly sizable, and highly significant. The risk prices for jump market exposure are usually close to zero and insignificant. Moreover, continuous size, value, and investment factor exposures are consistently and mostly significantly negatively priced. The risk price for continuous profitability exposure is by tendency slightly positive but never significant. Overnight size, value, profitability, and investment exposures are almost always positively and usually significantly priced. Finally, the risk prices for jump exposures to the non-market factors remain small and mostly insignificant.

5.3 Comparison to Bollerslev et al. (2016)

My study is closely related to Bollerslev et al. (2016) who investigate the pricing of continuous, jump, and overnight market exposures. They document that jump and overnight market exposures are significantly positively priced, whereas continuous market exposure is not priced. These conclusions contrast with my findings that continuous market exposure is positively priced, overnight market exposure is negatively priced, and jump market exposure is not priced.

My setting differs from Bollerslev et al.'s (2016) setting in several aspects. First, my sample period is longer, running until December 2019 rather than December 2010. Second, I use a mixed-frequency approach and a six-month estimation window to estimate betas rather than a uniform 75-minute sampling frequency and a 12-month estimation window. Third, my sample includes all common US stocks traded on the NYSE, AMEX, and NASDAQ rather than only S&P500 stocks. Fourth, I use weighted rather than ordinary least squares to estimate the risk prices with Fama-MacBeth (1973) regressions. Fifth, I estimate the risk prices from contemporaneous six-month rather than one-month ahead returns. Sixth, I use a different approach for estimating continuous, jump, and overnight betas. Finally, I investigate the pricing of exposures to the five Fama-French (2015) factors rather than only the market.

To trace the reasons for the differential results, I repeat Bollerslev et al.'s (2016) approach and then conduct sensitivity analyses by changing one aspect at a time (the results are unreported). I obtain qualitatively similar results as Bollerslev et al. (2016) when implementing their approach without any changes. Moreover, extending the sample period to 2019, using the mixed-frequency approach with a six-month estimation window, or accounting for exposures to the size, value, profitability, and investment factors also yields positive risk prices for jump and overnight market exposures but an insignificant risk price for continuous market exposure.

[23] The Internet Appendix provides a detailed description of the instrumental variables approach.

However, the results completely change when using weighted least squares. In line with my results, I find a positive pricing of continuous market exposure, no pricing of jump market exposure, and a negative pricing of overnight market exposure. Bollerslev et al.'s (2016) results also reverse when investigating the pricing of the different types of market exposures in contemporaneous rather than future returns. Moreover, the positive pricing of jump and overnight market exposures is only observable for S&P500 stocks but not for my extended sample including all common US stocks. Finally, Bollerslev et al.'s (2016) results also do not hold when using my beta estimation methodology described in Section 4.2.

I believe my approach to be more appropriate and my findings to be more robust. In particular, using weighted least squares with stocks' market capitalization as weights rather than ordinary least squares with equal weights is more sensible because the representative investor holds the value-weighted rather than equal-weighted market portfolio. Moreover, estimating risk prices from contemporaneous returns aligns more with the theory underlying factor models suggesting that stocks' expected returns are high in the same period in which their factor exposures are high. Finally, the observations that my findings hold even when varying the stock sample and the beta estimation methodology—while those of Bollerslev et al. (2016) do not—speak to their heightened robustness.[24]

6 Investor Clienteles

6.1 Realization of Risk Prices in Intraday and Overnight Returns

The results in the previous section establish that continuous intraday market exposure and overnight exposures to the non-market factors are positively priced, whereas overnight market exposure and continuous intraday exposures to the non-market factors are negatively priced. As discussed, these pricing patterns are almost the perfect mirror image of the factor returns' realization documented by Lou et al. (2019) and in Table 3. Lou et al. (2019) argue that the intraday versus overnight patterns in the factor returns are due to a tug of war between intraday and overnight investor clienteles. It seems plausible that such an investor clientele effect also drives the pricing patterns of the factors' continuous intraday and overnight risks.

To shed light on the link between the factor risks' pricing and the factor returns' realization and on the mechanism driving these patterns, I examine the realization of the factors' risk prices in intraday and overnight returns. For this purpose, I again implement Fama-MacBeth (1973) regressions like in equation (12) but use compounded intraday and overnight excess returns as dependent variables rather than the total compounded excess return. Table 8 presents the results. Panel A depicts the pricing of the factor exposures in intraday returns, and Panel B depicts the pricing of the factor exposures in overnight returns. The results reveal that the risk prices for overnight factor exposures tend to be realized in intraday returns, while the risk prices for continuous intraday exposures tend to be realized in overnight returns. Specifically, the

[24]As outlined in Section 5.2 and shown in the Internet Appendix, my findings are robust to restricting my sample to S&P500 stocks and to using Bollerslev et al.'s (2016) estimation methodology.

negative risk price for overnight market exposure and the positive risk prices for overnight size, profitability, and investment exposures are realized in intraday returns. The intraday returns for these overnight factor exposures are uniformly and mostly highly significant. Notably, their overnight returns are opposite in sign and usually also significant. The only exception to this rule is the positively priced overnight exposure to the value factor, exhibiting not only positive intraday returns but also positive overnight returns, both of which are statistically insignificant.

Analogously, the mostly negatively priced continuous intraday exposures to the value, profitability, and investment factors exhibit strongly and significantly negative overnight returns. In contrast, their intraday returns are positive. Although the pattern is weaker, the positive risk price for continuous intraday market exposure also tends to be realized overnight, exhibiting generally higher overnight than intraday returns. The exception is the negative risk price for continuous exposure to the size factor, which is realized in intraday rather than overnight returns.

These results again relate to the realization of the factors' returns. The risk prices for the positively priced factor risks are realized at the same time as the factors' returns. Specifically, the positive risk price for continuous intraday market exposure tends to be realized overnight—like the market premium. The positive risk prices for overnight exposures to the non-market factors tend to be realized intraday—like these factors' return premia. Consequently, these results are also consistent with a tug of war between intraday and overnight investor clienteles. Importantly, while arguably closely related, the realizations of the factors' return premia and of the factors' risk prices are distinct phenomena: the results on the realization of the factors' risk prices in Table 8 hold no matter whether I control for the factors' sorting variables. Thus, they are complementary patterns rather than two sides of the same coin.

The documented patterns in the factors' return premia and risk prices suggest the following mechanism. The overnight clientele is more averse to and requires higher expected returns for holding the non-market factors than the intraday clientele.[25] At the market closing, the factors' prices align with the required returns of the intraday clientele. Since the overnight clientele demands higher expected returns for holding the factors than the intraday clientele, the factors are overvalued in the overnight clientele's view and therefore face selling pressure from the overnight clientele. At the market opening, the factors' prices align with the overnight clientele's required returns. Since the intraday clientele is content with lower expected returns on the factors than the overnight clientele, the factors are undervalued in the intraday clientele's view and therefore face buying pressure from the intraday clientele. In line with the realization of the factors' return premia, the selling pressure from the overnight clientele and the buying pressure from the intraday clientele imply negative overnight returns and positive intraday returns for the factors.

Amid the pattern of positive intraday returns and negative overnight returns, a representative investor wants to avoid taking on exposures to the factors during the night but wants

[25] The reasoning for the market factor is analogous.

to take on exposures during the day. Thus, the investor demands positive compensations for overnight exposures to the factors but accepts negative compensations for intraday exposures. In line with the positive pricing of overnight exposures and the negative pricing of continuous intraday exposures to the factors, this reasoning implies that stocks with high overnight exposures to the factors have higher expected returns and stocks with high continuous intraday exposures to the factors have lower expected returns.

Overnight investors beat down stocks the more their prices increased during the day alongside the factors' positive intraday returns. Similarly, intraday investors bid up stocks the more their prices decreased during the night alongside the factors' negative overnight returns.[26] In line with the realization of the factors' risk prices in intraday and overnight returns, this conjecture means that stocks with high continuous intraday exposures to the factors earn highly negative returns overnight, while stocks with high overnight exposures to the factors earn highly positive returns during the day.

Importantly, my results do not suggest that the factors' empirical return premia are compensation for specific types of factor risks. Specifically, they do not imply that the market premium is compensation for the positively priced continuous intraday market exposure and that the non-market factors' return premia are compensation for the positively priced overnight exposures to these factors. My results rather suggest that the pricing of exposures to the factors' continuous intraday and overnight risks are a consequence of the intraday versus overnight patterns in the factors' returns. Put differently, investors demand compensation for being exposed to these patterns.

6.2 Risk Prices and Institutional Ownership

The vast majority of the literature argues, and often provides supporting empirical evidence, that the overnight clientele consists of retail investors, whereas the intraday clientele consists of institutional investors such as asset managers and intermediaries (e.g., Akbas et al., 2022; Berkman et al., 2012; Bogousslavsky, 2021; Lu et al., 2023; Lou et al., 2019; Lu and Qin, 2021). My line of reasoning on the trading patterns of the overnight and intraday clienteles is consistent with extant evidence from the literature on the trading behaviors of retail and institutional investors. In particular, McLean et al. (2022) document that retail investors tend to trade against popular factors like the Fama-French (2015) factors while Calluzzo et al. (2019) find that sophisticated institutional investors, such as hedge funds, trade on factors. Moreover, Li et al. (2023) provide evidence that retail investors' preferences are one of the main drivers of variation in factor returns. This finding is in line with the implication that factors' return premia are compensation for the overnight clientele's, and thus retail investors', aversion to the

[26]This mechanism is consistent with the intraday-overnight reversal pattern in individual stocks' returns documented, for example, by Akbas et al. (2022), Berkman et al. (2012), and Lou et al. (2019).

factors.[27]

If my results on the pricing of exposures to the factors' continuous intraday and overnight risks are also driven by a tug of war between retail and institutional investors, they should be especially pronounced for stocks whose intraday trading is dominated by institutional investors and whose overnight trading is dominated by retail investors. I identify such stocks based on their institutional ownership. For stocks with high institutional ownership, intraday trading should be dominated by institutional investors, while overnight trading should still be dominated by retail investors, given that institutional investors hardly trade overnight. In contrast, for stocks with low institutional ownership, even intraday trading may be less dominated by institutional investors than retail investors.

Table 9 presents risk price estimates when the Fama-MacBeth (1973) regression in equation (12) is estimated separately for stocks with high (Panel A) and low (Panel B) institutional ownership. I construct the subsamples by splitting my sample based on stocks' median institutional ownership at the beginning of each six-month estimation window.[28] The results show that the documented patterns are much stronger in stocks with high institutional ownership. In particular, continuous market and overnight size, value, profitability, and investment exposures are positively and mostly significantly priced, whereas overnight market and continuous size, value, and investment exposures are negatively and mostly significantly priced in high institutional ownership stocks. By contrast, the pricing of overnight exposures largely disappears in low institutional ownership stocks. Additionally, the risk prices for continuous exposures to the factors attenuate towards zero and are frequently insignificant. Given that the tug of war between institutional investors' intraday trading and retail investors' overnight trading should be particularly strong for stocks with high institutional ownership, these findings corroborate that the differential pricing of continuous intraday and overnight exposures is due to different trading behaviors and preferences of institutional and retail investors.

7 Predictive Power of Risk Prices

The risk price estimates capture information about investors' aversion to exposures to the factors. Therefore, they should be informative about the factors' future returns. To examine this conjecture, I implement time-series regressions that aim to predict the factors' returns across the next six months based on the estimated risk prices. Specifically, I estimate for each factor the following regression:

$$f_{k,t+6} = \delta_k^0 + \delta_k^C \gamma_t^{k,C} + \delta_k^J \gamma_t^{k,J} + \delta_k^N \gamma_t^{k,N} + \nu_{k,t+6} \quad (13)$$

[27]Note that neither the evidence from the literature nor my results and my reasoning imply or require that investors' trading behavior is rational. In fact, Kozak et al. (2018) argue that a positive association between returns and factor exposures does not need to imply rational pricing and that it can also arise from irrational behavior. Thus, my conjectures encompass rational risk-based as well as behavioral explanations for investors' preferences—especially for overnight investors' apparent aversion to the non-market factors.

[28]I calculate stocks' institutional ownership as the percentage of shares owned by institutions based on the institutional (13f) holdings data from Thomson Reuters.

where $f_{k,t+6}$ is factor k's average return from month $t+1$ to $t+6$, and $\gamma_t^{k,C}$, $\gamma_t^{k,J}$, and $\gamma_t^{k,N}$ are the risk prices for continuous, jump, and overnight exposures to factor k estimated across the estimation window from month $t-5$ to t. For comparison, I also estimate the regressions using the risk prices estimated from daily betas as predictive variables.

Panel A of Table 10 presents the regression results. Since the dependent variables are overlapping six-month returns, t-statistics are computed using Newey-West (1987) standard errors with six lags. First, the results show that the risk prices estimated from daily betas have no predictive power: their coefficients are insignificant, and the regressions' adjusted R^2s are close to zero. In contrast, the continuous, jump, and overnight risk prices together generate adjusted R^2s between 5% and 13%, implying that they exhibit notable predictive power for factors' future returns. Their predictive power emanates primarily from the overnight risk prices. In particular, the overnight risk prices exhibit uniformly positive and mostly significant coefficients, whereas the continuous and jump risk prices have almost always small and insignificant coefficients. Amid the discussion in Section 6.1, high overnight risk prices mean that investors demand high compensation for being exposed to the risk that overnight investors beat down the factors. This compensation is arguably high when overnight investors are particularly averse to the factors and therefore demand higher expected returns for holding the factors. Thus, the positive predictive power of overnight risk prices for factors' future returns is consistent with the previously proposed mechanism.

To further evaluate the source of the overnight risk prices' predictive power for future returns, Panels B and C present the results when the factors' average six-month ahead intraday and overnight returns rather than their total returns are predicted. In line with the tug of war between intraday and overnight investors, the results reveal that the positive predictive power of the non-market factor's overnight risk prices arises because they positively predict the factors' intraday returns. In contrast, there is no clear pattern in their predictive power for the factors' overnight returns. The results for the market factor differ from those for the non-market factors. Specifically, the market factor's overnight risk price positively predicts its future return because it positively predicts the overnight rather than intraday return.

The risk prices for continuous intraday exposures to the factors significantly positively predict the factors' overnight returns. This predictive power does not translate into predictive power for the factors' total returns because they negatively, albeit mostly only marginally significantly or insignificantly, predict the factors' intraday returns. This result holds for market and non-market factors equally.

Overall, this section's results on the predictive power of the non-market factors' risk prices align well with the previously proposed mechanism. In contrast, the results on the predictive power of the market factor's risk prices do not align very well with the proposed mechanism. However, this is consistent with the less clear-cut intraday versus overnight patterns for the market factor already observed in Tables 3 and 8. Importantly, the results show for both the market and non-market factors that the decomposed risk prices—especially the overnight risk prices—are useful for investors to time the factors. In particular, investors should scale up their investments in the factors if the factors' overnight risk prices have been positive and scale down their investments if the factors' overnight risk prices have been negative.

8 Conclusion

This study investigates the pricing of exposures to the five Fama-French (2015) factors by decomposing their variation into continuous intraday movements, intraday jumps, and overnight movements. Based on the concept of an economy-wide stochastic discount factor, I argue that the different types of factor risks may be priced differently. In particular, only those sources of factor variation that proxy for the SDF should carry non-zero risk prices.

I investigate the pricing of the different types of factor risks for the sample of all common US stocks in the period from January 1993 to December 2019. For this purpose, I retrieve high-frequency stock data from the TAQ database. Based on high-frequency versions of the five Fama-French (2015) factors, I estimate stocks' six-month rolling continuous, jump, and overnight betas on the factors. The estimation results reveal that the different types of betas exhibit very different properties. In particular, continuous betas are in general less dispersed and more persistent than jump and overnight betas. Moreover, stocks' continuous, jump, and overnight betas on a given factor are only weakly positively related.

To evaluate the pricing of exposures to the different types of factor risks, I implement Fama-MacBeth (1973) regressions. The results show that continuous market exposure is positively priced in the cross-section of stock returns, whereas overnight market exposure is negatively priced. Intraday jump market exposure is not priced. These results contrast with the findings of Bollerslev et al. (2016) that jump and overnight market exposures are positively priced while continuous market exposure is not priced. I find that my differing results are due to more sensible methodological choices and a broader stock sample used to estimate the risk prices. Furthermore, I document that overnight exposures to the size, value, profitability, and investment factors are uniformly positively priced, while continuous exposures to these factors (apart from the profitability factor) carry negative risk prices. As for the market factor, jump exposures to the non-market factors are not robustly priced. All of these findings hold across various robustness checks.

Like the vast majority of the related literature, my results fail to establish an unambiguous risk-return relation for exposures to the Fama-French (2015) factors. However, the results are all but a perfect mirror image of the findings of Lou et al. (2019). They find that the market premium accrues primarily overnight and that the non-market factors' return premia accrue intraday, while the intraday market return and the non-market factors' overnight returns are flat or negative. Lou et al. (2019) propose and provide evidence that an investor clientele effect causes the intraday versus overnight patterns in the factors' returns. In particular, the patterns point to a tug of war between intraday and overnight investors, whereby intraday investors are more averse to market exposure and overnight investors are more averse to exposure to the non-market factors.

This investor clientele effect is also likely to drive my findings. Specifically, I find that the negative risk price for overnight market exposure and the positive risk prices for overnight exposures to the non-market factors tend to be realized in intraday returns. Conversely, the positive risk price for continuous intraday market exposure and the negative risk prices for continuous intraday exposures to the non-market factors tend to be realized overnight. Based on these results, I conclude that the pricing of continuous intraday and overnight exposures to the factors arises because investors demand compensation for being exposed to the intraday versus overnight patterns in the factors' returns. Furthermore, I show that the patterns in the factors' continuous intraday and overnight risk prices are considerably more pronounced for stocks with high institutional ownership. This observation suggests that a tug of war between institutional investors trading intraday and retail investors trading overnight is responsible for the patterns in the factors' return premia and risk prices.

Finally, I show that the decomposed risk prices contain predictive information for the factors' future returns. In particular, the factors' overnight risk prices positively predict their future returns. This result is in line with the notion that the factors' positive mean returns represent compensation for retail investors' aversion to the factors and that the factors' overnight risk prices reflect retail investors' degree of aversion to the factors. Thus, the factors' decomposed risk prices yield not only insights into the pricing implications of the factor returns' intraday versus overnight patterns but are also valuable for investors who want to time these factors.

A Variable Definitions

Market Equity (ME): A stock's market equity for the end of month t is calculated as its price times its shares outstanding at the end of month t. To reduce the skewness in ME, I take its natural logarithm. ME is considered missing if it is non-positive.

Book-to-Market (BM): A stock's book-to-market for the end of month t is calculated as book equity from the firm's last fiscal year ending at least six months and less than 18 months ago, divided by market equity at the end of the month of the fiscal year ending.[29] Following Davis et al. (2000), book equity (BE) is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock (depending on availability, the redemption, liquidation, or par value of preferred stock is used, in that order); if the book value of stockholders' equity is not directly available, it is measured as the book value of common equity plus the par value of preferred stock or as the difference between total assets and total liabilities (in that order).[30] To reduce the skewness in BM, I take its natural logarithm. BM is considered missing if market equity or book equity is non-positive.

Operating Profitability (OP): A stock's operating profitability for the end of month t is calculated as revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, divided by book equity, all from the firm's last fiscal year ending at least six months and less than 18 months ago. OP is considered missing if revenues are missing, if each of cost of goods sold, interest expense, and selling, general, and administrative expenses are missing, or if book equity is non-positive.

Investment (INV): A stock's investment for the end of month t is calculated as total assets from the firm's last fiscal year ending at least six months and less than 18 months ago, divided by total assets one year prior, minus 1. To reduce the skewness in INV, I take its natural logarithm. INV is considered missing if total assets are non-positive.

Momentum (MOM): A stock's momentum for the end of month t is its return from the end of month $t-12$ to the end of month $t-1$. MOM is considered missing if the stock does not have good price data for the end of month $t-12$ or good return data for month $t-1$.

Short-Term Reversal (STR): A stock's short-term reversal for the end of month t is its return from the end of month $t-1$ to the end of month t. STR is considered missing if the stock does not have good price data for the end of month $t-1$ or good return data for month t.

Idiosyncratic Volatility (IVOL): A stock's idiosyncratic volatility for the end of month t is calculated as the standard deviation of the residual returns from regressing its daily excess returns from the end of month $t-12$ to the end of month t on the market, size, value, profitability, investment, and momentum factors.[31] IVOL is considered missing if the stock has less than 100 daily return observations during the 12-month estimation window.

[29] For the formation of the value factor, I calculate BM slightly differently. To exactly follow Fama and French (2015), I divide book equity by market equity from the end of December of the year of the fiscal year ending.

[30] I supplement the Compustat data with the hand-collected book equity data from Kenneth French's website.

[31] The daily factor returns and risk-free rate are retrieved from Kenneth French's website.

Illiquidity (ILLIQ): Following Amihud (2002), a stock's illiquidity for the end of month t is calculated as the average ratio of its daily absolute return to its daily dollar trading volume from the end of month $t-12$ to the end of month t. A stock's daily dollar trading volume is its trading volume in shares times its closing price on that day. I adjust the daily trading volume of NASDAQ stocks following Gao and Ritter (2010): before February 1, 2001, I divide trading volume by 2; from February 1, 2001, to December 31, 2001, I divide trading volume by 1.8; and from January 1, 2002, to December 31, 2003, I divide trading volume by 1.6. To reduce the skewness in ILLIQ, I take its natural logarithm. ILLIQ is considered missing if the stock has less than 100 daily observations during the 12-month estimation window.

Co-Skewness (CSK): Following Ang et al. (2006a), a stock's co-skewness for the end of month t is estimated from its daily returns during month t by

$$CSK_{i,t} = \frac{\frac{1}{N}\sum_d (r_{i,d} - \bar{r}_i)(r_{m,d} - \bar{r}_m)^2}{\sqrt{\frac{1}{N}\sum_d (r_{i,d} - \bar{r}_i)^2}(\frac{1}{N}\sum_d (r_{m,d} - \bar{r}_m)^2)}$$

where $r_{i,d}$ is the stock's return on day d, $\bar{r}_i$ is the stock's average daily return in month t, $r_{m,d}$ is the market return on day d, $\bar{r}_m$ is the market's average daily return in month t, and N is the number of trading days in month t.

Co-Kurtosis (CKT): Following Ang et al. (2006a), a stock's co-kurtosis for the end of month t is estimated from its daily returns during month t by

$$CKT_{i,t} = \frac{\frac{1}{N}\sum_d (r_{i,d} - \bar{r}_i)(r_{m,d} - \bar{r}_m)^3}{\sqrt{\frac{1}{N}\sum_d (r_{i,d} - \bar{r}_i)^2}(\frac{1}{N}\sum_d (r_{m,d} - \bar{r}_m)^2)^{3/2}}$$

where the variables are the same as in the estimation of the stock's co-skewness.

Realized Variance (RV): Following Amaya et al. (2015), a stock's realized variance on day d is estimated from its five-minute returns between 9:45 a.m. and 4:00 p.m. by

$$RV_{i,d} = \sum_{l=1}^{L} r_{i,l}^2$$

where $r_{i,l}$ is the stock's return in interval l and L is the number of intraday intervals. The stock's realized variance for the end of month t is its average daily realized variance in month t.

Realized Skewness (RSK): Following Amaya et al. (2015), a stock's realized skewness on day d is estimated from its five-minute returns between 9:45 a.m. and 4:00 p.m. by

$$RSK_{i,d} = \frac{\sqrt{L}\sum_{l=1}^{L} r_{i,l}^3}{(\sum_{l=1}^{L} r_{i,l}^2)^{3/2}}$$

where the variables are the same as in the estimation of the stock's realized variance. The stock's realized skewness for the end of month t is its average daily realized skewness in month t.

Realized Kurtosis (RKT): Following Amaya et al. (2015), a stock's realized kurtosis on day d is estimated from its five-minute returns between 9:45 a.m. and 4:00 p.m. by

$$RSK_{i,d} = \frac{L \sum_{l=1}^{L} r_{i,l}^4}{(\sum_{l=1}^{L} r_{i,l}^2)^2}$$

where the variables are the same as in the estimation of the stock's realized variance. The stock's realized kurtosis for the end of month t is its average daily realized kurtosis in month t.

Volatility of Return on Equity (vROE): The volatility of a stock's return on equity (ROE) for the end of month t is calculated as the standard deviation of its ROE from the fiscal quarters that ended within the previous three years and have already been publicly announced. Following Hou et al. (2015), a stock's ROE is calculated as income before extraordinary items divided by one-quarter lagged book equity. Book equity is calculated as the quarterly version of the annual book equity used to calculate book-to-market. If fourth-quarter book equity is missing, I use annual book equity from the corresponding fiscal year ending. ROE is considered missing if book equity is non-positive. vROE is considered missing if there are less than six fiscal quarter endings with non-missing ROE during the three-year estimation window.

Sales Growth (SG): A stock's sales growth for the end of month t is calculated as sales from the firm's last fiscal year ending at least six months and less than 18 months ago, divided by sales one year prior, minus 1. To reduce the skewness in SG, I take its natural logarithm. SG is considered missing if sales are non-positive.

Book Leverage (BL): A stock's book leverage for the end of month t is calculated as total assets divided by book equity, both from the firm's last fiscal year ending at least six months and less than 18 months ago. To reduce the skewness in BL, I take its natural logarithm. BL is considered missing if book equity or total assets are non-positive.

Age: A stock's age for the end of month t is the number of months since its first appearance in the CRSP Monthly Stock database.

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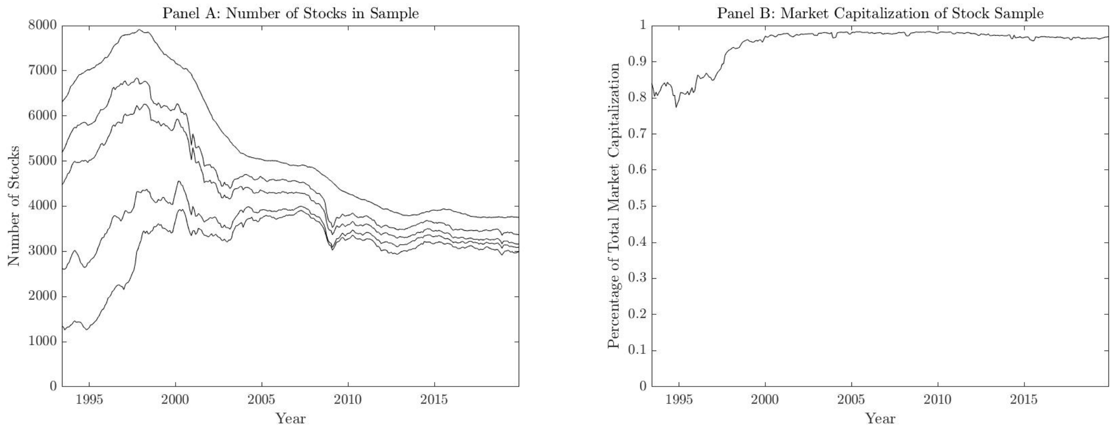

Figure 1
Sample Size

Panel A of this figure displays for each month from June 1993 to December 2019 the number of stocks that remain in the sample after applying several exclusion criteria. The topmost line reflects the number of stocks in the full sample consisting of all common US stocks listed on the NYSE, AMEX, and NASDAQ. The next lines, from the top, reflect the number of stocks in the sample after excluding stocks (1) with market capitalizations below \$10mn and share prices below \$1, (2) that have data available for less than 50 days on daily, overnight, and high-frequency returns during the beta estimation window across the prior six months, (3) for which more than half of the high-frequency returns during the estimation window are zero, and (4) for which the null hypothesis of no market microstructure noise during the estimation window is rejected at the 1% significance level based on all three recommended tests of Aït-Sahalia and Xiu (2019). Panel B displays the total market capitalization of the stocks in the final sample as a percentage of the total market capitalization of the full sample.

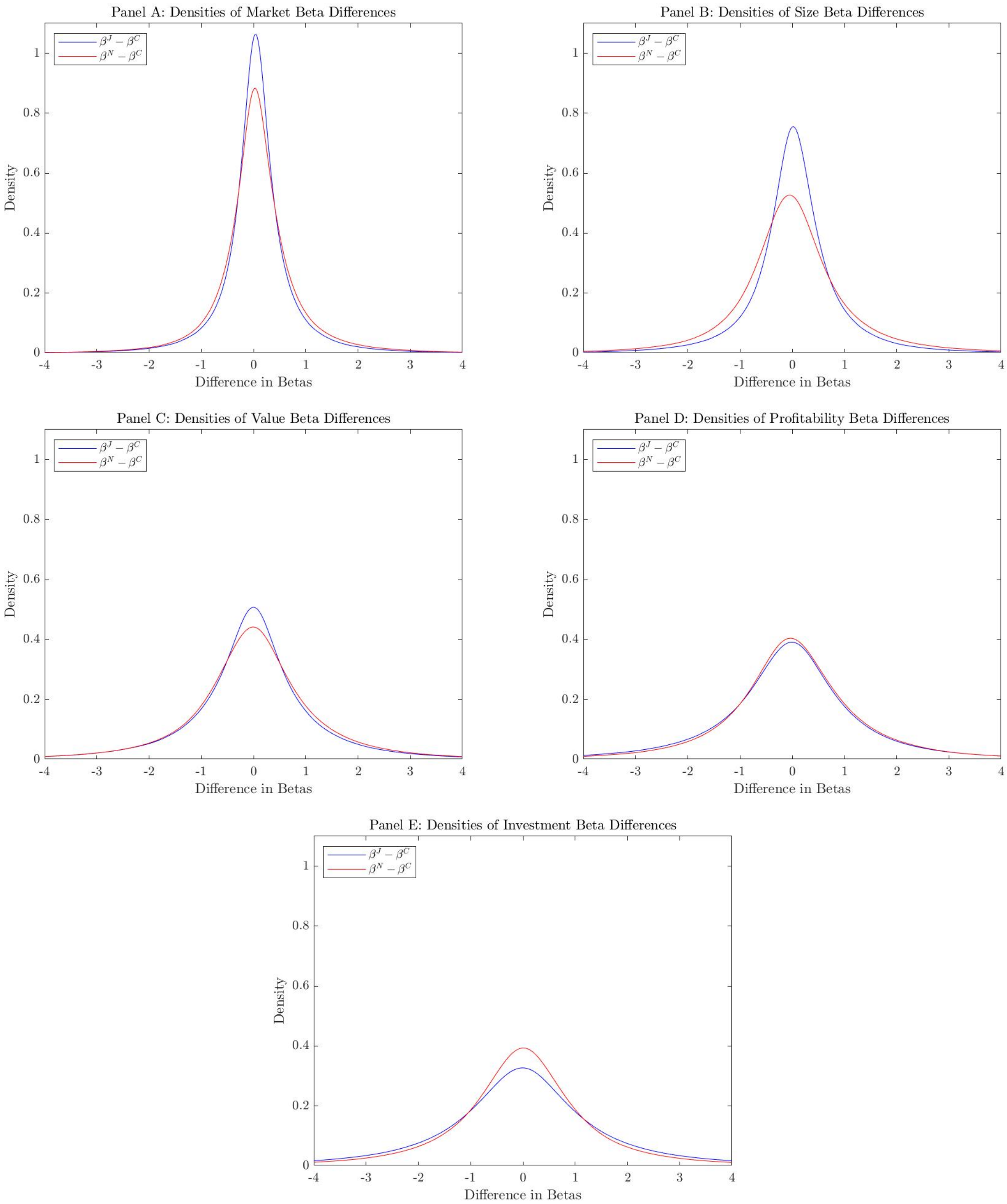

Figure 2
Empirical Densities of Beta Differences

This figure displays empirical densities for the differences between jump (J) and continuous (C) betas (in blue) and between overnight (N) and continuous betas (in red) with respect to the market (Panel A), size (Panel B), value (Panel C), profitability (Panel D), and investment (Panel E) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. Each month, probability density estimates for the distributions of the differences are obtained based on a normal kernel function. The monthly probability density estimates are then averaged across the sample period.

Table 1
Factor Returns

This table displays summary statistics for the returns (in percent) on the monthly, daily, overnight, and 30-minute versions of the five Fama-French (2015) factors for the period from January 1993 to December 2019. The return on the market factor (MP) is the value-weighted return on the market portfolio consisting in each month of all common US stocks traded on the NYSE, AMEX, and NASDAQ. For the formation of the size, value, profitability, and investment factors, stocks are at the end of each June independently sorted into two size (ME) groups, three book-to-market (BM) groups, three operating profitability (OP) groups, and three investment (INV) groups. The sorting breakpoints are the median ME and the 30th and 70th BM, OP, and INV percentiles of all NYSE stocks. The intersections of the two ME groups with the three BM groups, the three OP groups, and the three INV groups yield 18 portfolios. The return on the size factor (SMB) is the average of the value-weighted returns on the nine low ME portfolios minus the average of the value-weighted returns on the nine high ME portfolios. The return on the value factor (HML) is the average of the value-weighted returns on the two high BM portfolios minus the average of the value-weighted returns on the two low BM portfolios. The return on the profitability factor (RMW) is the average of the value-weighted returns on the two high OP portfolios minus the average of the value-weighted returns on the two low OP portfolios. The return on the investment factor (CMA) is the average of the value-weighted returns on the two low INV portfolios minus the average of the value-weighted returns on the two high INV portfolios. The daily, overnight, and 30-minute versions use only stock-days available for all three versions.

Panel A: Monthly Factors

	Mean	t-Stat	Std	Skew	Kurt	P1	P10	Median	P90	P99
MP	0.6851	2.92	4.22	−0.75	4.35	−10.43	−4.82	1.2512	5.58	9.11
SMB	0.1371	0.82	3.01	0.48	8.92	−5.86	−3.21	0.0158	3.46	7.08
HML	0.1933	1.15	3.03	0.30	5.34	−8.06	−3.04	0.0186	3.53	8.19
RMW	0.2863	1.86	2.77	−0.37	13.14	−8.02	−2.08	0.2429	3.02	9.25
CMA	0.1525	1.55	1.77	0.52	4.24	−3.67	−1.82	0.0427	2.29	5.40

Panel B: Daily Factors

	Mean	t-Stat	Std	Skew	Kurt	P1	P10	Median	P90	P99
MP	0.0378	2.78	1.12	−0.32	11.06	−3.12	−1.20	0.0774	1.19	3.14
SMB	0.0043	0.61	0.58	−0.17	6.36	−1.47	−0.68	0.0153	0.67	1.50
HML	0.0090	1.15	0.64	0.36	13.66	−1.79	−0.59	−0.0039	0.62	1.95
RMW	0.0141	2.35	0.49	0.17	10.85	−1.39	−0.47	0.0061	0.51	1.46
CMA	0.0059	1.27	0.39	−0.55	13.08	−1.05	−0.39	0.0004	0.43	1.04

Panel C: Overnight Factors

	Mean	t-Stat	Std	Skew	Kurt	P1	P10	Median	P90	P99
MP	0.0314	4.40	0.59	−0.80	17.14	−1.82	−0.53	0.0512	0.58	1.58
SMB	−0.0078	−2.90	0.22	−0.32	11.70	−0.67	−0.23	−0.0041	0.21	0.61
HML	−0.0206	−6.24	0.27	2.12	45.92	−0.78	−0.25	−0.0225	0.19	0.82
RMW	−0.0261	−10.46	0.21	−0.45	17.43	−0.66	−0.21	−0.0178	0.15	0.52
CMA	−0.0163	−7.60	0.18	−0.01	16.89	−0.50	−0.19	−0.0152	0.16	0.47

Panel D: 30-minute Factors

	Mean	t-Stat	Std	Skew	Kurt	P1	P10	Median	P90	P99
MP	0.0005	0.62	0.24	0.32	24.92	−0.68	−0.24	0.0056	0.23	0.64
SMB	0.0008	1.66	0.15	−0.12	12.28	−0.42	−0.15	0.0023	0.15	0.41
HML	0.0023	5.01	0.13	−0.13	28.48	−0.38	−0.12	0.0008	0.12	0.40
RMW	0.0032	9.61	0.10	0.22	27.27	−0.27	−0.09	0.0010	0.10	0.30
CMA	0.0017	6.30	0.08	−0.12	14.69	−0.23	−0.08	0.0001	0.08	0.24

Table 2
Factor Jumps

This table displays summary statistics on the jumps in the 30-minute returns of the five Fama-French (2015) factors for the period from January 1993 to December 2019. The jump identification is based on the TOD estimator of Bollerslev et al. (2013), and the threshold is set to $3 \cdot 13^{-0.49} \cdot \hat{\sigma}_{k,d,t}$, where $\hat{\sigma}_{k,d,t}$ is an estimator for the local volatility of factor k in interval t on day d. "Total" depicts the number of jumps as a percentage of all return observations. "Positive" ("Negative") shows the number of positive (negative) jumps as a percentage of the number of jumps. "JumpDays" is the percentage of days on which at least one jump is detected. P25+, P50+, and P75+ (P25-, P50-, and P75-) are the 25th, 50th, and 75th percentiles of the positive (negative) jump returns (in percent). "JV" depicts the factors' variance due to jumps as a percentage of the factors' total variance.

	Total	Positive	Negative	JumpDays	P25+	P50+	P75+	P25-	P50-	P75-	JV
MP	1.19	48.95	51.05	14.37	0.25	0.37	0.54	−0.59	−0.42	−0.29	7.7
SMB	1.31	50.52	49.48	15.77	0.23	0.34	0.48	−0.49	−0.34	−0.24	12.2
HML	1.22	54.07	45.93	14.66	0.16	0.26	0.39	−0.43	−0.26	−0.16	12.8
RMW	1.15	49.56	50.44	13.66	0.12	0.19	0.30	−0.28	−0.18	−0.12	9.4
CMA	1.13	52.05	47.95	13.50	0.12	0.18	0.26	−0.24	−0.16	−0.11	9.7

Table 3
Decomposition of Factor Returns

This table displays the decomposition of the factors' daily returns into overnight and high-frequency returns and the decomposition of the high-frequency returns into continuous and jump returns. Daily and overnight returns are as in Table 1. High-frequency returns as well as their continuous and jump components are aggregated on a daily basis. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Daily	Overnight	High-Frequency	Continuous	Jump
MP	0.0378***	0.0314***	0.0064	0.0095	−0.0031
	(2.78)	(4.40)	(0.56)	(0.87)	(−1.06)
SMB	0.0043	−0.0078***	0.0108	0.0109*	−0.0001
	(0.61)	(−2.90)	(1.59)	(1.70)	(−0.05)
HML	0.0090	−0.0206***	0.0295***	0.0269***	0.0025
	(1.15)	(−6.24)	(4.24)	(4.16)	(1.20)
RMW	0.0141**	−0.0261***	0.0417***	0.0413***	0.0004
	(2.35)	(−10.46)	(7.87)	(8.11)	(0.31)
CMA	0.0059	−0.0163***	0.0225***	0.0203***	0.0021*
	(1.27)	(−7.60)	(5.47)	(5.25)	(1.93)

Table 4
Distributions of Betas

This table displays summary statistics for the estimated betas on the market (Panel A), size (Panel B), value (Panel C), profitability (Panel D), and investment (Panel E) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. Each panel displays statistics on the estimated daily (D), high-frequency (Q), continuous (C), jump (J), and overnight (N) betas as well as on the absolute differences between the jump and continuous betas and between the overnight and continuous betas. The cross-sectional summary statistics—mean, median, standard deviation, skewness, kurtosis, 1st-, 10th-, 90th-, and 99th-percentile, and six-month lagged cross-sectional rank-correlation (AC(CS))—are calculated in each month and then averaged across the sample period. The rolling 12-month volatility (Vola) is calculated for each stock-month and then averaged across stock-months. The six-month time-series autocorrelation (AC(TS)) is calculated for each individual stock over the entire sample period and then averaged across stocks.

Panel A: Market Betas

	Mean	Std	Skew	Kurt	P1	P10	Median	P90	P99	Vola	AC(TS)	AC(CS)
β^D	0.98	0.64	−0.28	24.02	−0.65	0.27	0.96	1.71	2.65	0.29	0.07	0.35
β^Q	0.93	0.51	0.15	7.81	−0.27	0.30	0.93	1.55	2.25	0.16	0.27	0.66
β^C	0.84	0.51	0.14	7.10	−0.33	0.22	0.84	1.46	2.14	0.16	0.27	0.66
β^J	0.91	0.88	−0.11	17.94	−1.52	0.01	0.91	1.83	3.29	0.39	0.06	0.32
β^N	0.93	0.91	−0.61	57.44	−1.36	0.09	0.88	1.87	3.41	0.39	0.03	0.32
$\lvert\beta^J - \beta^C\rvert$	0.48	0.60	4.36	49.65	0.01	0.05	0.30	1.09	2.82	0.26	0.04	0.19
$\lvert\beta^N - \beta^C\rvert$	0.56	0.69	5.12	91.99	0.01	0.06	0.37	1.26	3.06	0.29	0.06	0.20

Panel B: Size Betas

	Mean	Std	Skew	Kurt	P1	P10	Median	P90	P99	Vola	AC(TS)	AC(CS)
β^D	0.70	0.97	0.61	28.65	−1.46	−0.32	0.62	1.86	3.39	0.43	0.05	0.42
β^Q	0.67	0.64	0.38	5.55	−0.65	−0.09	0.64	1.48	2.32	0.19	0.27	0.73
β^C	0.59	0.61	0.39	6.73	−0.69	−0.11	0.55	1.35	2.18	0.18	0.26	0.71
β^J	0.63	1.13	0.16	19.11	−2.32	−0.45	0.56	1.88	3.85	0.49	0.03	0.36
β^N	0.60	1.49	0.62	59.50	−3.03	−0.68	0.51	2.06	4.72	0.64	−0.01	0.27
$\lvert\beta^J - \beta^C\rvert$	0.64	0.80	4.14	45.46	0.01	0.07	0.40	1.48	3.80	0.34	0.03	0.22
$\lvert\beta^N - \beta^C\rvert$	0.87	1.15	5.42	90.03	0.01	0.09	0.55	1.94	5.01	0.47	0.01	0.19

Panel C: Value Betas

	Mean	Std	Skew	Kurt	P1	P10	Median	P90	P99	Vola	AC(TS)	AC(CS)
β^D	0.06	1.22	−0.01	36.13	−3.30	−1.27	0.09	1.34	3.09	0.57	0.03	0.31
β^Q	0.06	0.76	0.00	8.29	−2.06	−0.81	0.08	0.87	2.09	0.29	0.15	0.49
β^C	0.05	0.72	0.00	8.82	−1.99	−0.75	0.07	0.79	2.01	0.27	0.15	0.47
β^J	0.01	1.72	−0.30	17.79	−5.05	−1.74	0.06	1.67	4.67	0.85	0.00	0.19
β^N	0.04	1.79	−1.48	125.60	−4.90	−1.56	0.09	1.57	4.63	0.80	−0.04	0.12
$\lvert\beta^J - \beta^C\rvert$	1.02	1.27	4.11	39.68	0.01	0.11	0.63	2.32	6.00	0.58	0.04	0.19
$\lvert\beta^N - \beta^C\rvert$	1.07	1.44	7.35	179.49	0.01	0.12	0.67	2.40	6.19	0.59	0.02	0.19

Panel D: Profitability Betas

	Mean	Std	Skew	Kurt	P1	P10	Median	P90	P99	Vola	AC(TS)	AC(CS)
β^D	−0.21	1.41	−0.95	19.03	−4.45	−1.83	−0.07	1.18	2.97	0.67	−0.01	0.25
β^Q	−0.18	0.85	−0.70	10.20	−2.81	−1.22	−0.07	0.64	1.71	0.31	0.14	0.48
β^C	−0.16	0.80	−0.59	13.76	−2.66	−1.10	−0.05	0.60	1.68	0.29	0.14	0.46
β^J	−0.22	2.00	−0.47	19.70	−6.24	−2.31	−0.09	1.63	4.91	0.98	−0.02	0.15
β^N	−0.14	1.88	−1.44	74.96	−5.52	−1.84	−0.04	1.41	4.45	0.82	−0.05	0.09
$\lvert\beta^J - \beta^C\rvert$	1.21	1.50	4.18	41.67	0.01	0.13	0.76	2.76	7.08	0.67	0.03	0.20
$\lvert\beta^N - \beta^C\rvert$	1.13	1.52	5.62	105.69	0.01	0.12	0.71	2.55	6.52	0.61	0.01	0.20

Panel E: Investment Betas

	Mean	Std	Skew	Kurt	P1	P10	Median	P90	P99	Vola	AC(TS)	AC(CS)
β^D	0.00	1.61	0.74	29.62	−4.27	−1.73	0.02	1.63	4.33	0.82	0.00	0.20
β^Q	0.01	0.87	−0.11	9.66	−2.49	−0.94	0.04	0.89	2.39	0.36	0.12	0.35
β^C	0.00	0.82	−0.11	10.32	−2.42	−0.88	0.03	0.82	2.28	0.34	0.11	0.34
β^J	−0.01	2.33	0.11	30.97	−6.64	−2.27	0.02	2.21	6.61	1.21	−0.02	0.09
β^N	0.00	1.93	0.72	117.11	−5.03	−1.68	0.02	1.59	5.04	0.86	−0.05	0.08
$\lvert\beta^J - \beta^C\rvert$	1.43	1.77	4.31	54.09	0.02	0.15	0.90	3.25	8.36	0.83	0.03	0.20
$\lvert\beta^N - \beta^C\rvert$	1.16	1.60	6.49	150.65	0.01	0.12	0.73	2.60	6.69	0.64	0.01	0.19

Table 5

Correlations of Betas

This table displays time-series averages of monthly cross-sectional correlations between daily (D), overnight (N), high-frequency (Q), continuous (C), and jump (J) betas, separately for betas on the market (Panel A), size (Panel B), value (Panel C), profitability (Panel D), and investment (Panel E) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The table also displays time-series averages of monthly cross-sectional correlations of the betas with characteristics. The characteristics are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), sales growth (SG), book leverage (BL), volatility of return on equity (vROE), age, illiquidity (ILLIQ), momentum (MOM), idiosyncratic volatility (IVOL), realized variance (RV), realized skewness (RSK), realized kurtosis (RKT), co-skewness (CSK), and co-kurtosis (CKT). The construction of these characteristics is described in Appendix A. To align them with the betas' six-month estimation window, RV, RSK, RKT, CSK, and CKT are rolling six-month averages of their monthly values.

Panel A: Market Betas

	β^D	β^N	β^Q	β^C	β^J	ME	BM	OP	INV	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
β^D	1.00	0.42	0.56	0.52	0.34	0.15	−0.07	0.00	0.04	0.03	0.01	0.01	0.00	−0.18	0.04	0.02	−0.05	−0.04	−0.30	−0.02	0.46
β^N		1.00	0.37	0.36	0.23	0.11	−0.07	−0.01	0.04	0.03	−0.02	0.01	−0.02	−0.14	0.02	0.05	−0.01	−0.01	−0.24	0.00	0.25
β^Q			1.00	0.92	0.58	0.28	−0.12	0.00	0.06	0.04	−0.03	0.01	0.02	−0.35	0.06	0.02	−0.10	−0.02	−0.48	−0.01	0.45
β^C				1.00	0.52	0.31	−0.13	0.00	0.07	0.05	−0.03	0.01	0.04	−0.38	0.06	0.00	−0.10	−0.03	−0.50	−0.01	0.45
β^J					1.00	0.19	−0.07	0.00	0.04	0.02	−0.02	0.00	0.03	−0.23	0.02	−0.01	−0.07	−0.02	−0.31	0.00	0.29

Panel B: Size Betas

	β^D	β^N	β^Q	β^C	β^J	ME	BM	OP	INV	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
β^D	1.00	0.31	0.56	0.51	0.32	−0.26	0.02	−0.02	0.02	0.02	−0.07	0.01	−0.17	0.21	0.00	0.18	0.09	−0.02	−0.03	−0.04	−0.02
β^N		1.00	0.31	0.29	0.18	−0.17	0.00	−0.02	0.02	0.01	−0.05	0.01	−0.12	0.15	0.00	0.12	0.08	0.00	−0.01	0.00	0.00
β^Q			1.00	0.91	0.57	−0.32	0.02	−0.03	0.03	0.03	−0.09	0.02	−0.23	0.24	0.01	0.20	0.07	−0.01	−0.11	−0.01	0.07
β^C				1.00	0.45	−0.28	0.01	−0.03	0.03	0.04	−0.09	0.02	−0.21	0.20	0.01	0.18	0.06	−0.02	−0.15	−0.01	0.09
β^J					1.00	−0.18	0.01	−0.02	0.02	0.02	−0.05	0.01	−0.13	0.14	0.00	0.10	0.04	−0.02	−0.06	0.01	0.04

Panel C: Value Betas

	β^D	β^N	β^Q	β^C	β^J	ME	BM	OP	INV	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
β^D	1.00	0.32	0.54	0.49	0.26	0.01	0.23	0.03	−0.05	−0.04	0.20	−0.02	0.08	−0.01	−0.06	−0.13	−0.06	0.00	0.04	−0.02	0.05
β^N		1.00	0.21	0.20	0.10	0.02	0.12	0.01	−0.03	−0.03	0.09	−0.01	0.04	−0.01	−0.03	−0.09	−0.05	0.00	0.01	0.00	0.04
β^Q			1.00	0.87	0.47	0.03	0.31	0.03	−0.08	−0.08	0.24	−0.03	0.13	−0.02	−0.07	−0.19	−0.11	0.01	0.05	−0.01	0.09
β^C				1.00	0.35	0.03	0.29	0.03	−0.07	−0.07	0.23	−0.03	0.12	−0.02	−0.07	−0.17	−0.09	0.00	0.03	−0.01	0.09
β^J					1.00	0.01	0.16	0.02	−0.04	−0.04	0.12	−0.02	0.06	0.00	−0.03	−0.09	−0.04	0.01	0.02	−0.01	0.04

Panel D: Profitability Betas

	β^D	β^N	β^Q	β^C	β^J	ME	BM	OP	INV	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
β^D	1.00	0.30	0.50	0.45	0.22	0.09	0.08	0.06	−0.04	−0.04	0.10	−0.02	0.13	−0.07	−0.01	−0.23	−0.15	0.00	0.02	0.01	0.05
β^N		1.00	0.20	0.18	0.08	0.03	0.04	0.03	−0.02	−0.02	0.05	−0.01	0.06	−0.03	−0.03	−0.13	−0.07	0.00	0.02	0.00	0.01
β^Q			1.00	0.86	0.45	0.13	0.12	0.08	−0.06	−0.06	0.13	−0.03	0.19	−0.10	−0.02	−0.29	−0.19	0.00	0.04	0.00	0.05
β^C				1.00	0.30	0.11	0.11	0.07	−0.06	−0.06	0.12	−0.03	0.18	−0.08	−0.02	−0.26	−0.16	0.00	0.04	−0.01	0.04
β^J					1.00	0.06	0.05	0.04	−0.02	−0.02	0.05	−0.02	0.09	−0.05	−0.01	−0.13	−0.08	−0.01	0.01	0.00	0.02

Panel E: Investment Betas

	β^D	β^N	β^Q	β^C	β^J	ME	BM	OP	INV	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
β^D	1.00	0.27	0.41	0.36	0.17	−0.02	0.03	−0.01	−0.11	−0.07	0.01	0.01	0.06	0.04	0.01	0.02	0.03	0.00	0.03	−0.02	−0.06
β^N		1.00	0.15	0.14	0.06	0.00	0.01	−0.01	−0.07	−0.04	0.02	0.01	0.05	0.01	0.01	−0.01	−0.01	0.00	0.01	0.00	−0.02
β^Q			1.00	0.83	0.39	−0.04	0.06	−0.01	−0.16	−0.11	0.03	0.01	0.09	0.06	0.00	0.00	0.02	0.01	0.05	0.00	−0.07
β^C				1.00	0.24	−0.03	0.05	−0.01	−0.15	−0.10	0.03	0.01	0.09	0.05	0.00	−0.01	0.01	0.00	0.04	0.01	−0.06
β^J					1.00	−0.01	0.03	−0.01	−0.07	−0.05	0.02	0.00	0.04	0.02	0.00	−0.01	0.01	0.00	0.02	0.00	−0.03

Table 6
Factor Risk Prices

This table displays average monthly risk price estimates (in percent) from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1993 to December 2019. The dependent variable is the compounded return across the prior six months in excess of the compounded one-month T-bill rate. The independent variables are a constant and the daily (D), high-frequency (HFQ), continuous (C), jump (J), and overnight (N) betas on the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The control variables are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The characteristics are lagged by six months and are in each month standardized to have means of zero and standard deviations of one. Their construction is described in Appendix A. All variables are in each month winsorized at the 1% and 99% levels. The regressions are estimated with weighted least squares with stocks' six-month lagged market capitalizations as weights. In each panel, "UV" displays the risk price estimates from univariate regressions, "(1)" displays the risk price estimates when only betas are used as independent variables, "(2)" displays the risk price estimates when betas and the factors' sorting variables (ME, BM, OP, and INV) are used as independent variables, and "(3)" displays the risk price estimates when betas and all control variables are used as independent variables (Panel C omits the coefficient estimates on the control variables for space reasons). R^2 is the average adjusted R-squared. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Daily Betas

	γ^{ZB}	$\gamma^{MP,D}$	$\gamma^{SMB,D}$	$\gamma^{HML,D}$	$\gamma^{RMW,D}$	$\gamma^{CMA,D}$	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		−0.12	−0.07	−0.14	0.06	−0.09	−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(−0.54)	(−0.53)	(−1.31)	(0.47)	(−1.10)	(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.57***	0.26	−0.13	−0.23*	0.07	−0.09													0.280
	(3.88)	(1.10)	(−1.01)	(−1.67)	(0.53)	(−1.03)													
(2)	1.06***	0.35	−0.31**	−0.33**	0.11	−0.15*	−0.29***	0.15***	6.19	−0.10**									0.304
	(5.08)	(1.44)	(−2.47)	(−2.45)	(0.80)	(−1.74)	(−4.31)	(3.00)	(1.43)	(−2.34)									
(3)	1.49***	0.18	−0.31**	−0.37***	0.12	−0.12	−0.26**	0.17***	5.68	−0.11***	−0.06	−0.21***	0.21	−0.07	0.04**	0.02	0.03	0.25**	0.332
	(6.13)	(0.75)	(−2.48)	(−2.77)	(0.86)	(−1.31)	(−2.13)	(3.51)	(1.44)	(−2.59)	(−0.64)	(−4.77)	(1.51)	(−0.41)	(1.97)	(0.61)	(0.70)	(2.07)	

Panel B: High-Frequency Betas

	γ^{ZB}	$\gamma^{MP,Q}$	$\gamma^{SMB,Q}$	$\gamma^{HML,Q}$	$\gamma^{RMW,Q}$	$\gamma^{CMA,Q}$	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		0.16	0.09	−0.05	0.15	−0.04	−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(0.42)	(0.55)	(−0.24)	(0.81)	(−0.29)	(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.40**	0.43	−0.06	−0.06	0.10	−0.04													0.280
	(2.11)	(1.45)	(−0.45)	(−0.35)	(0.65)	(−0.37)													
(2)	1.20***	0.73**	−0.76***	−0.21	0.20	−0.10	−0.54***	0.07	4.12	−0.11**									0.303
	(5.00)	(2.36)	(−4.80)	(−1.15)	(1.24)	(−1.00)	(−5.06)	(1.50)	(1.14)	(−2.31)									
(3)	1.61***	0.61*	−0.76***	−0.30	0.16	−0.10	−0.30**	0.09**	4.27	−0.11**	−0.12	−0.21***	0.11	0.26	0.04*	0.02	0.03	0.17	0.332
	(5.65)	(1.80)	(−4.75)	(−1.56)	(0.91)	(−0.91)	(−2.27)	(2.08)	(1.15)	(−2.54)	(−1.29)	(−4.45)	(0.76)	(1.58)	(1.73)	(0.51)	(0.67)	(1.19)	

Panel C: Continuous, Jump, and Overnight Betas

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.09	−0.01	−0.22	0.10	0.01	0.01	−0.08	−0.08	−0.06	0.16	0.04	0.01	−0.07	−0.03	−0.04	
		(0.24)	(−0.07)	(−1.21)	(0.56)	(0.05)	(0.15)	(−0.37)	(−0.84)	(−0.94)	(0.84)	(0.45)	(0.19)	(−0.46)	(−0.43)	(−0.67)	
(1)	0.56***	0.84***	0.04	−0.54***	−0.09	−0.09*	0.16***	−0.30*	0.05	0.15*	0.03	−0.02	0.07	−0.19*	−0.02	0.12*	0.317
	(3.58)	(2.84)	(0.57)	(−3.61)	(−0.59)	(−1.71)	(2.78)	(−1.77)	(1.25)	(1.90)	(0.24)	(−0.71)	(1.37)	(−1.86)	(−0.92)	(1.86)	
(2)	1.28***	1.12***	0.02	−0.47***	−0.72***	−0.15***	0.12**	−0.47***	0.05	0.14*	0.11	−0.01	0.08	−0.24**	−0.03	0.10	0.342
	(6.17)	(3.76)	(0.24)	(−3.14)	(−4.27)	(−2.65)	(2.13)	(−2.68)	(1.17)	(1.77)	(0.83)	(−0.20)	(1.64)	(−2.30)	(−1.52)	(1.58)	
(3)	1.72***	1.09***	−0.01	−0.55***	−0.74***	−0.15***	0.13**	−0.55***	0.04	0.12	0.07	0.00	0.10**	−0.24**	−0.03	0.10	0.367
	(6.61)	(3.53)	(−0.15)	(−3.67)	(−4.22)	(−2.73)	(2.24)	(−3.05)	(1.08)	(1.60)	(0.48)	(−0.10)	(2.03)	(−2.23)	(−1.30)	(1.61)	

Table 7
Comparison of Factor Risk Prices

This table displays results on the relation between the risk price estimates for daily (γ^D), continuous (γ^C), jump (γ^J), and overnight (γ^N) exposures to the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. The continuous, jump, and overnight risk prices are estimated from the Fama-MacBeth (1973) regressions in equation (12). They are estimated at the end of each month from June 1993 to December 2019 and use only the continuous, jump, and overnight betas as explanatory variables but no further control variables. The risk price estimates for daily exposures are obtained from analogous Fama-MacBeth (1973) regressions that use daily betas. Panel A displays differences between the average monthly risk price estimates. Panel B displays correlations between the monthly risk price estimates. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Differences between Risk Price Estimates

	MP			SMB			HML			RMW			CMA		
	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N
γ^D	−0.55***	0.20	0.76***	−0.03	−0.01	−0.28**	0.06	−0.29**	−0.36***	0.05	0.12	0.02	0.11	−0.04	−0.17**
	(−2.85)	(0.87)	(3.60)	(−0.37)	(−0.06)	(−2.12)	(0.76)	(−2.14)	(−2.80)	(0.70)	(1.01)	(0.18)	(1.33)	(−0.59)	(−2.05)
γ^C		0.75***	1.31***		0.02	−0.25		−0.34**	−0.42**		0.07	−0.03		−0.15*	−0.28**
		(2.59)	(3.95)		(0.15)	(−1.41)		(−2.25)	(−2.41)		(0.60)	(−0.22)		(−1.69)	(−2.13)
γ^J			0.56***			−0.27***			−0.08			−0.10			−0.13*
			(3.61)			(−3.13)			(−0.76)			(−1.51)			(−1.92)

Panel B: Correlations between Risk Price Estimates

	MP			SMB			HML			RMW			CMA		
	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N	γ^C	γ^J	γ^N
γ^D	0.67	0.16	0.49	0.77	0.14	0.09	0.83	0.09	0.35	0.82	0.31	0.38	0.58	0.30	0.36
γ^C		−0.26	−0.14		−0.20	−0.32		−0.04	−0.05		0.08	0.03		0.02	−0.37
γ^J			0.15			−0.11			−0.18			−0.13			−0.03

Table 8

Factor Risk Prices in Intraday and Overnight Returns

This table displays average monthly risk price estimates (in percent) from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1993 to December 2019. The dependent variables are the compounded intraday (Panel A) and overnight (Panel B) returns across the prior six months in excess of the compounded one-month T-bill rate (proportionally allocated to intraday and overnight periods). The independent variables are a constant and the continuous (C), jump (J), and overnight (N) betas on the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The control variables are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The characteristics are lagged by six months and are in each month standardized to have means of zero and standard deviations of one. Their construction is described in Appendix A. All variables are in each month winsorized at the 1% and 99% levels. The regressions are estimated with weighted least squares with stocks' six-month lagged market capitalizations as weights. In each panel, "UV" displays the risk price estimates from univariate regressions, "(1)" displays the risk price estimates when only betas are used as independent variables, "(2)" displays the risk price estimates when betas and the factors' sorting variables (ME, BM, OP, and INV) are used as independent variables, and "(3)" displays the risk price estimates when betas and all control variables are used as independent variables. The coefficient estimates on the control variables are omitted for space reasons. R^2 is the average adjusted R-squared. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Risk Prices in Intraday Returns

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		−1.13***	−0.50***	−0.62***	0.15	−0.01	0.09	0.36*	0.03	0.07	0.80***	0.29***	0.29***	0.49***	0.20***	0.20***	
		(−4.59)	(−2.98)	(−4.30)	(0.86)	(−0.07)	(1.38)	(1.72)	(0.37)	(1.04)	(5.32)	(3.61)	(5.18)	(4.28)	(3.74)	(3.64)	
(1)	1.30***	−0.07	0.15**	−1.01***	−0.01	−0.15**	0.26***	0.21	−0.03	0.12	0.37***	0.03	0.24***	0.12	0.00	0.16**	0.304
	(9.99)	(−0.28)	(2.05)	(−5.52)	(−0.09)	(−2.28)	(3.85)	(1.53)	(−0.51)	(1.03)	(2.89)	(0.70)	(4.14)	(1.21)	(0.13)	(2.32)	
(2)	2.13***	0.21	0.13*	−0.95***	−0.67***	−0.21***	0.22***	0.19	−0.03	0.09	0.41***	0.03	0.24***	0.11	0.00	0.13*	0.336
	(11.59)	(0.88)	(1.66)	(−4.93)	(−4.31)	(−3.36)	(3.20)	(1.42)	(−0.62)	(0.75)	(3.09)	(0.66)	(4.10)	(1.08)	(−0.20)	(1.94)	
(3)	2.73***	0.40*	0.08	−1.00***	−0.78***	−0.23***	0.22***	0.02	−0.02	0.08	0.39***	0.03	0.25***	0.06	0.00	0.12*	0.362
	(8.63)	(1.68)	(1.22)	(−5.02)	(−4.85)	(−3.62)	(2.99)	(0.15)	(−0.46)	(0.63)	(3.11)	(0.78)	(4.49)	(0.65)	(0.10)	(1.83)	

Panel B: Risk Prices in Overnight Returns

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		1.51***	0.68***	0.51***	0.39**	0.25***	−0.04	−0.56**	−0.10	−0.12	−1.18***	−0.48***	−0.51***	−0.70***	−0.29***	−0.31***	
		(5.66)	(5.96)	(5.73)	(2.14)	(2.67)	(−0.28)	(−2.00)	(−0.85)	(−1.08)	(−3.97)	(−3.61)	(−4.04)	(−4.79)	(−4.46)	(−5.64)	
(1)	−0.54***	0.24	−0.06	1.26***	0.49**	0.16***	−0.21	−0.69***	0.07	0.12	−0.58***	−0.08**	−0.46***	−0.18	−0.03	−0.17***	0.322
	(−5.27)	(0.64)	(−0.69)	(3.56)	(2.32)	(2.73)	(−1.41)	(−4.44)	(1.48)	(0.49)	(−2.94)	(−2.42)	(−3.80)	(−1.49)	(−1.46)	(−2.76)	
(2)	−0.29**	0.43	−0.01	1.11***	0.07	0.13**	−0.24	−0.82***	0.08	0.19	−0.41**	−0.06	−0.36***	−0.25**	−0.03*	−0.12**	0.299
	(−2.51)	(1.12)	(−0.11)	(3.36)	(0.42)	(2.23)	(−1.54)	(−4.60)	(1.59)	(0.87)	(−2.23)	(−1.64)	(−3.38)	(−2.14)	(−1.77)	(−2.31)	
(3)	0.19	0.13	−0.02	1.00***	0.10	0.14***	−0.21	−0.72***	0.06	0.19	−0.33*	−0.06	−0.34***	−0.21**	−0.03*	−0.10*	0.327
	(1.48)	(0.28)	(−0.23)	(3.19)	(0.49)	(2.63)	(−1.48)	(−4.07)	(1.38)	(0.90)	(−1.84)	(−1.56)	(−3.31)	(−2.00)	(−1.77)	(−1.96)	

Table 9
Factor Risk Prices and Institutional Ownership

This table displays average monthly risk price estimates (in percent) from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1993 to December 2019. The regressions in Panel A (B) use each month only stocks with above (below) median institutional ownership. The dependent variable is the compounded return across the prior six months in excess of the compounded one-month T-bill rate. The independent variables are a constant and the continuous (C), jump (J), and overnight (N) betas on the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The control variables are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The characteristics are lagged by six months and are in each month standardized to have means of zero and standard deviations of one. Their construction is described in Appendix A. All variables are in each month winsorized at the 1% and 99% levels. The regressions are estimated with weighted least squares with stocks' six-month lagged market capitalizations as weights. In each panel, "UV" displays the risk price estimates from univariate regressions, "(1)" displays the risk price estimates when only betas are used as independent variables, "(2)" displays the risk price estimates when betas and the factors' sorting variables (ME, BM, OP, and INV) are used as independent variables, and "(3)" displays the risk price estimates when betas and all control variables are used as independent variables. The coefficient estimates on the control variables are omitted for space reasons. R^2 is the average adjusted R-squared. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Risk Prices in Stocks with High Institutional Ownership

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.04	−0.03	−0.26	0.14	0.04	0.01	−0.07	−0.08	−0.07	0.21	0.05	0.04	−0.07	−0.03	−0.02	
		(0.11)	(−0.13)	(−1.44)	(0.71)	(0.37)	(0.09)	(−0.33)	(−0.89)	(−1.08)	(1.09)	(0.55)	(0.49)	(−0.46)	(−0.37)	(−0.28)	
(1)	0.61***	0.80**	0.03	−0.50***	−0.09	−0.08	0.16***	−0.28	0.06	0.11	0.04	−0.02	0.08	−0.19*	−0.02	0.13**	0.307
	(3.52)	(2.53)	(0.36)	(−3.29)	(−0.60)	(−1.28)	(2.67)	(−1.56)	(1.25)	(1.41)	(0.28)	(−0.53)	(1.55)	(−1.93)	(−0.96)	(1.99)	
(2)	1.03***	1.08***	0.01	−0.43***	−0.75***	−0.14**	0.12*	−0.45**	0.06	0.09	0.18	−0.01	0.10*	−0.25**	−0.03	0.10*	0.330
	(5.44)	(3.39)	(0.17)	(−2.83)	(−4.41)	(−2.04)	(1.96)	(−2.44)	(1.22)	(1.17)	(1.38)	(−0.30)	(1.88)	(−2.39)	(−1.23)	(1.65)	
(3)	1.37***	0.97***	−0.03	−0.48***	−0.75***	−0.13**	0.11*	−0.49***	0.05	0.09	0.15	−0.01	0.10**	−0.22**	−0.03	0.10*	0.359
	(6.35)	(3.10)	(−0.53)	(−3.15)	(−4.22)	(−2.02)	(1.90)	(−2.80)	(1.04)	(1.23)	(1.14)	(−0.16)	(2.05)	(−2.12)	(−1.05)	(1.66)	

Panel B: Risk Prices in Stocks with Low Institutional Ownership

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.25	0.10	−0.05	0.09	−0.03	0.06	−0.06	−0.04	−0.05	−0.09	−0.03	−0.09	−0.12	−0.02	−0.09	
		(0.76)	(0.57)	(−0.27)	(0.44)	(−0.28)	(0.68)	(−0.23)	(−0.37)	(−0.62)	(−0.37)	(−0.29)	(−0.81)	(−0.57)	(−0.38)	(−1.14)	
(1)	0.48***	0.47**	0.12	−0.24	0.03	−0.08	0.14*	−0.17	0.04	0.06	0.00	−0.02	−0.07	0.02	0.01	0.04	0.411
	(3.78)	(2.39)	(1.57)	(−1.46)	(0.17)	(−1.52)	(1.80)	(−0.98)	(0.85)	(0.81)	(−0.02)	(−0.71)	(−1.06)	(0.18)	(0.60)	(0.59)	
(2)	1.73***	0.62***	0.07	−0.04	−0.39*	−0.15***	0.03	−0.29*	0.04	0.04	−0.05	−0.03	−0.08	0.08	−0.01	0.01	0.493
	(6.37)	(3.16)	(0.83)	(−0.23)	(−1.82)	(−2.75)	(0.46)	(−1.79)	(0.70)	(0.54)	(−0.27)	(−0.81)	(−1.06)	(0.62)	(−0.57)	(0.14)	
(3)	1.97***	0.93***	0.08	−0.02	−0.40*	−0.16***	−0.02	−0.46***	0.04	−0.07	−0.12	−0.03	−0.07	−0.01	−0.02	−0.02	0.529
	(5.74)	(4.84)	(0.99)	(−0.09)	(−1.81)	(−3.26)	(−0.21)	(−2.70)	(0.79)	(−0.73)	(−0.64)	(−0.69)	(−0.91)	(−0.10)	(−0.91)	(−0.33)	

Table 10
Prediction of Factor Returns with Factor Risk Prices

This table displays results from time-series regressions that predict the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors' average six-month ahead returns from June 1993 to June 2019. The independent variables are risk price estimates for daily (γ^D), continuous (γ^C), jump (γ^J), and overnight (γ^N) exposures to the respective factor. The continuous, jump, and overnight risk prices are estimated from the Fama-MacBeth (1973) regressions in equation (12). They are estimated at the end of each month from June 1993 to June 2019 and use only the continuous, jump, and overnight betas as explanatory variables but no further control variables. The risk price estimates for daily exposures are obtained from analogous Fama-MacBeth (1973) regressions that use daily betas. In Panel A (B, C), the dependent variable is the average total (intraday, overnight) factor return across the next six months. R^2 is the adjusted R-squared. T is the number of observations. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total Factor Returns

	MP	MP	SMB	SMB	HML	HML	RMW	RMW	CMA	CMA
Constant	0.007***	0.009***	0.001	0.000	0.001	0.000	0.003**	0.002*	0.001	0.001
	(2.88)	(4.69)	(1.00)	(0.22)	(0.84)	(0.22)	(2.03)	(1.83)	(1.42)	(0.80)
γ^D	0.064		0.009		0.021		0.136		0.033	
	(0.61)		(0.08)		(0.14)		(0.87)		(0.29)	
γ^C		−0.073		0.032		−0.016		−0.041		−0.092
		(−1.06)		(0.33)		(−0.13)		(−0.31)		(−0.96)
γ^J		−0.316		−0.291*		0.292		0.027		−0.230
		(−1.31)		(−1.82)		(0.82)		(0.06)		(−0.92)
γ^N		0.306*		0.398**		0.633		1.014***		0.341*
		(1.93)		(2.00)		(1.48)		(3.64)		(1.83)
R^2	0.001	0.056	−0.003	0.052	−0.003	0.081	0.011	0.129	−0.002	0.084
T	313	313	313	313	313	313	313	313	313	313

Panel B: Intraday Factor Returns

	MP	MP	SMB	SMB	HML	HML	RMW	RMW	CMA	CMA
Constant	0.002	0.004***	0.005***	0.004***	0.006***	0.004**	0.007***	0.007***	0.005***	0.004***
	(1.47)	(3.00)	(3.38)	(2.80)	(2.70)	(2.42)	(4.74)	(5.23)	(4.09)	(3.77)
γ^D	−0.160**		−0.121		−0.097		−0.216		−0.063	
	(−2.31)		(−1.10)		(−0.57)		(−1.03)		(−0.38)	
γ^C		−0.213***		−0.057		−0.132		−0.301*		−0.226*
		(−4.29)		(−0.57)		(−1.02)		(−1.93)		(−1.90)
γ^J		−0.350***		−0.446***		0.096		−0.421		−0.580*
		(−2.67)		(−2.71)		(0.25)		(−0.91)		(−1.77)
γ^N		0.073		0.389*		0.884**		0.795**		0.459***
		(0.76)		(1.84)		(2.21)		(2.25)		(3.09)
R^2	0.047	0.109	0.007	0.072	0.002	0.162	0.036	0.184	−0.001	0.170
T	313	313	313	313	313	313	313	313	313	313

Panel C: Overnight Factor Returns

	MP	MP	SMB	SMB	HML	HML	RMW	RMW	CMA	CMA
Constant	0.006***	0.006***	0.000	−0.001	−0.005***	−0.004***	−0.007***	−0.007***	−0.003***	−0.003***
	(4.67)	(4.95)	(−0.31)	(−0.67)	(−3.36)	(−2.86)	(−5.41)	(−5.10)	(−3.76)	(−3.64)
γ^D	0.231***		0.101*		0.097		0.324**		0.140	
	(3.69)		(1.85)		(0.83)		(2.50)		(1.62)	
γ^C		0.161***		0.081*		0.124*		0.257***		0.165*
		(2.75)		(1.79)		(1.79)		(2.89)		(1.91)
γ^J		0.026		0.074		0.276		0.453		0.436**
		(0.19)		(0.82)		(1.27)		(1.49)		(2.03)
γ^N		0.201**		0.165*		−0.443***		0.058		−0.082
		(2.19)		(1.77)		(−3.12)		(0.24)		(−0.65)
R^2	0.157	0.127	0.024	0.021	0.009	0.132	0.135	0.113	0.026	0.096
T	313	313	313	313	313	313	313	313	313	313

The Pricing of Continuous and Discontinuous Factor Risks: Internet Appendix

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Abstract

This Internet Appendix contains supplementary analyses and results for "The Pricing of Continuous and Discontinuous Factor Risks."

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B Instrumental Variables Approach

There is a widely recognized problem when estimating the regression model in (12) (see, e.g., Shanken, 1992): the betas used as explanatory variables are estimated quantities measuring the true betas with error, introducing an errors-in-variables bias in the risk price estimates. To ensure that this issue does not affect my conclusions, I employ the instrumental variables approach proposed by Jegadeesh et al. (2019) addressing this bias. I implement the approach as follows. First, I split every six-month estimation window into two subsets on a daily basis; that is, the estimation window's first, third, fifth, ... day is assigned to the first subset, and the second, fourth, sixth, ... day is assigned to the second subset. Within each of the two subsets, I estimate betas as described in Section 4.2. Then, I regress the betas estimated from the first subset on all betas of the same type estimated from the second subset. Formally, I run at the end of each month t from June 1993 to December 2019 the following cross-sectional regressions:

$$\hat{\beta}_{i,t}^{k,z,1} = \delta_t^{0,z,2} + \sum_{k=1}^{5} \delta_t^{k,z,2} \cdot \hat{\beta}_{i,t}^{k,z,2} + \nu_{i,t} \qquad z \in \{C, J, N\} \tag{IA1}$$

where $\hat{\beta}_{i,t}^{k,z,1}$ ($\hat{\beta}_{i,t}^{k,z,2}$) is stock i's z beta on factor k estimated from the first (second) subset of the estimation window from month $t-5$ to t. I use the fitted values from these regressions as explanatory variables in the monthly cross-sectional regression in (12) instead of the betas estimated across the entire estimation window. Moreover, I use stocks' compounded excess returns in the first subset as the dependent variable. That is, I calculate the stocks' and the risk-free rate's compounded returns across the days in the first subset, denoted by $r_{i,t}^1$ and $r_{f,t}^1$, and replace $r_{i,t} - r_{f,t}$ in (12) by $2 \cdot (r_{i,t}^1 - r_{f,t}^1)$ (the multiplication by 2 is done to get again six-month returns). I again winsorize all variables at the 1% and 99% levels and use weighted least squares with stocks' market capitalizations at the end of month $t-6$ as weights.

From this procedure, I obtain monthly estimates for the six-month risk prices, denoted by $\hat{\gamma}_t^{k,C,1}$, $\hat{\gamma}_t^{k,J,1}$, and $\hat{\gamma}_t^{k,N,1}$. I repeat the procedure by changing the roles of the estimated betas from the first and second subsets; that is, the $\hat{\beta}_{i,t}^{k,z,1}$ are now the instrumental variables for the $\hat{\beta}_{i,t}^{k,z,2}$. Thereby, I obtain a second set of monthly risk price estimates, denoted by $\hat{\gamma}_t^{k,C,2}$, $\hat{\gamma}_t^{k,J,2}$, and $\hat{\gamma}_t^{k,N,2}$. I calculate the final risk price estimates by averaging the two sets of risk price estimates and then averaging across the entire sample period of $T = 319$ months:

$$\hat{\gamma}^{k,z} = \frac{1}{T} \sum_{t=1}^{T} \frac{\hat{\gamma}_t^{k,z,1} + \hat{\gamma}_t^{k,z,2}}{2} \qquad z \in \{C, J, N\} \tag{IA2}$$

Jegadeesh et al. (2019) note the possibility that the cross-product of the dependent and independent betas in the estimation of (IA1) might be close to singular, leading to unreasonably large risk price estimates. I address this issue by considering monthly risk price estimates that deviate by five or more mean absolute deviations from their median to be missing.

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Table IA1

Factor Risk Prices: Controls, Continuous Betas, Jump Betas, and Overnight Betas

This table displays average monthly risk price estimates (in percent) from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1993 to December 2019. The dependent variable is the compounded return across the prior six months in excess of the compounded one-month T-bill rate. The independent variables are a constant and the continuous (C), jump (J), and overnight (N) betas on the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The control variables are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The characteristics are lagged by six months and are in each month standardized to have means of zero and standard deviations of one. Their construction is described in Appendix A. All variables are in each month winsorized at the 1% and 99% levels. The regressions are estimated with weighted least squares with stocks' six-month lagged market capitalizations as weights. In each panel, "UV" displays the risk price estimates from univariate regressions, "(1)" displays the risk price estimates when only betas are used as independent variables, "(2)" displays the risk price estimates when betas and the factors' sorting variables (ME, BM, OP, and INV) are used as independent variables, and "(3)" displays the risk price estimates when betas and all control variables are used as independent variables. R^2 is the average adjusted R-squared. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Only Controls

	γ^{ZB}	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.71***													0.098
	(3.28)													
(2)	0.97***	−0.09	−0.02	7.96	−0.10*									0.152
	(3.17)	(−1.09)	(−0.25)	(1.50)	(−1.67)									
(3)	0.95***	−0.28**	−0.03	5.16*	−0.10**	0.23**	0.03	−0.03	−0.27	0.04	−0.02	−0.05	0.19*	0.217
	(2.98)	(−2.13)	(−0.35)	(1.67)	(−2.26)	(1.96)	(0.54)	(−0.12)	(−1.47)	(1.54)	(−0.36)	(−1.23)	(1.90)	

Panel B: Continuous Betas

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{SMB,C}$	$\gamma^{HML,C}$	$\gamma^{RMW,C}$	$\gamma^{CMA,C}$	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		0.09	0.10	−0.08	0.16	−0.07	−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(0.24)	(0.56)	(−0.37)	(0.84)	(−0.46)	(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.50***	0.36	−0.04	−0.09	0.09	−0.06													0.274
	(2.80)	(1.22)	(−0.28)	(−0.48)	(0.53)	(−0.61)													
(2)	1.24***	0.69**	−0.75***	−0.25	0.19	−0.13	−0.52***	0.10*	4.79	−0.12**									0.298
	(5.44)	(2.18)	(−4.50)	(−1.30)	(1.18)	(−1.25)	(−4.84)	(1.93)	(1.27)	(−2.50)									
(3)	1.60***	0.56	−0.75***	−0.35*	0.15	−0.12	−0.30**	0.12**	4.93	−0.12***	−0.11	−0.20***	0.11	0.25	0.04	0.02	0.04	0.11	0.327
	(5.89)	(1.63)	(−4.35)	(−1.68)	(0.86)	(−1.11)	(−2.18)	(2.53)	(1.27)	(−2.73)	(−1.13)	(−4.31)	(0.69)	(1.51)	(1.62)	(0.65)	(0.86)	(0.82)	

- Continued on next page -

Panel C: Jump Betas

	γ^{ZB}	$\gamma^{MP,J}$	$\gamma^{SMB,J}$	$\gamma^{HML,J}$	$\gamma^{RMW,J}$	$\gamma^{CMA,J}$	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		−0.01	0.01	−0.08	0.04	−0.03	−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(−0.07)	(0.05)	(−0.84)	(0.45)	(−0.43)	(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.72***	0.05	−0.03	−0.06	0.02	−0.04													0.219
	(5.34)	(0.28)	(−0.38)	(−0.81)	(0.30)	(−0.80)													
(2)	1.08***	0.10	−0.21***	−0.08	0.03	−0.08	−0.21**	0.04	6.29	−0.13**									0.254
	(5.32)	(0.58)	(−3.24)	(−1.07)	(0.39)	(−1.57)	(−2.34)	(0.58)	(1.44)	(−2.51)									
(3)	1.42***	0.00	−0.23***	−0.11	0.02	−0.07*	−0.21	0.06	4.75	−0.14***	0.06	−0.11*	0.20	−0.08	0.05*	0.02	−0.02	0.25**	0.294
	(5.32)	(−0.03)	(−3.75)	(−1.59)	(0.40)	(−1.67)	(−1.63)	(1.02)	(1.48)	(−2.84)	(0.59)	(−1.93)	(0.87)	(−0.46)	(1.81)	(0.46)	(−0.31)	(2.25)	

Panel D: Overnight Betas

	γ^{ZB}	$\gamma^{MP,N}$	$\gamma^{SMB,N}$	$\gamma^{HML,N}$	$\gamma^{RMW,N}$	$\gamma^{CMA,N}$	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	R^2
UV		−0.22	0.01	−0.06	0.01	−0.04	−0.07	0.03	4.34	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(−1.21)	(0.15)	(−0.94)	(0.19)	(−0.67)	(−0.74)	(0.30)	(1.04)	(−1.85)	(1.59)	(1.13)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.21)	(1.53)	
(1)	0.89***	−0.09	0.07	−0.07	0.03	−0.03													0.229
	(6.09)	(−0.38)	(1.03)	(−0.64)	(0.35)	(−0.40)													
(2)	1.01***	−0.03	0.05	−0.11	0.01	−0.09	−0.09	0.03	7.03	−0.13***									0.264
	(4.11)	(−0.14)	(0.73)	(−1.02)	(0.13)	(−1.18)	(−0.98)	(0.49)	(1.41)	(−2.68)									
(3)	1.40***	−0.28	0.09	−0.11	0.06	−0.04	−0.12	0.05	5.62	−0.13***	0.15	−0.08	0.22	−0.20	0.06**	0.06*	0.00	0.28**	0.297
	(4.90)	(−1.29)	(1.22)	(−1.14)	(0.76)	(−0.61)	(−0.95)	(0.97)	(1.54)	(−3.01)	(1.44)	(−1.42)	(1.17)	(−1.16)	(2.39)	(1.92)	(−0.03)	(2.41)	

Table IA2
Factor Risk Prices: Robustness Checks

This table displays average monthly risk price estimates (in percent) from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1993 to December 2019. The dependent variable is the compounded return across the prior six months in excess of the compounded one-month T-bill rate. The independent variables are a constant and the continuous (C), jump (J), and overnight (N) betas on the market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Betas are estimated at the end of each month from June 1993 to December 2019 using data from the prior six months. The control variables are market equity (ME), book-to-market (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The characteristics are lagged by six months and are in each month standardized to have means of zero and standard deviations of one. Their construction is described in Appendix A. All variables are in each month winsorized at the 1% and 99% levels. The regressions are estimated with weighted least squares with stocks' six-month lagged market capitalizations as weights. In each panel, "UV" displays the risk price estimates from univariate regressions, "(1)" displays the risk price estimates when only betas are used as independent variables, "(2)" displays the risk price estimates when betas and the factors' sorting variables (ME, BM, OP, and INV) are used as independent variables, and "(3)" displays the risk price estimates when betas and all control variables are used as independent variables. The coefficient estimates on the control variables are omitted for space reasons. R^2 is the average adjusted R-squared. The robustness checks modify the standard estimation procedure as follows: in Panel A (B), the beta estimation window length is three (12) months, the dependent variable is the compounded excess return across the prior three (12) months, the regressions are estimated from March (December) 1993 onwards, and the control variables and the market capitalization are lagged by three (12) months. In Panels C, D, and E, the sampling frequencies are 15, 30, and 75 minutes, respectively. In Panel F, only stocks that were at some point from January 1993 to December 2019 in the S&P500 are in my sample, and the sampling frequency is 15 minutes. In Panel G, jump betas are estimated by adapting the market jump beta estimator of Todorov and Bollerslev (2010) to a multivariate framework. In Panel H, the Fama-MacBeth (1973) regressions are implemented with the instrumental variables approach of Jegadeesh et al. (2019) as described in Appendix B. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with lags equal to the respective estimation window length. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Three-month Estimation Window

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		−0.04	−0.09	−0.23*	0.21	0.04	0.04	0.01	−0.04	−0.04	0.21	0.04	0.01	−0.03	0.00	0.00	
		(−0.12)	(−0.57)	(−1.72)	(1.24)	(0.57)	(0.92)	(0.06)	(−0.50)	(−0.73)	(1.24)	(0.57)	(0.11)	(−0.21)	(0.08)	(−0.07)	
(1)	0.70***	0.52**	0.05	−0.40***	−0.03	−0.06	0.12***	−0.13	0.02	0.10*	0.11	−0.02	0.04	−0.10	0.01	0.08**	0.302
	(5.11)	(2.24)	(1.11)	(−3.38)	(−0.20)	(−1.57)	(2.81)	(−0.86)	(0.71)	(1.75)	(0.86)	(−0.72)	(0.97)	(−1.19)	(0.29)	(1.99)	
(2)	1.41***	0.77***	0.04	−0.38***	−0.60***	−0.11***	0.09**	−0.25	0.02	0.10*	0.16	0.00	0.06	−0.16*	0.00	0.08*	0.324
	(6.86)	(3.15)	(0.74)	(−3.08)	(−4.50)	(−2.70)	(2.09)	(−1.63)	(0.72)	(1.78)	(1.34)	(−0.04)	(1.22)	(−1.86)	(−0.06)	(1.81)	
(3)	1.89***	0.60**	0.02	−0.45***	−0.63***	−0.11***	0.10**	−0.27*	0.03	0.09	0.17	0.00	0.07	−0.11	0.00	0.08*	0.349
	(7.20)	(2.42)	(0.51)	(−3.65)	(−4.57)	(−2.74)	(2.25)	(−1.75)	(0.84)	(1.61)	(1.35)	(0.09)	(1.57)	(−1.39)	(0.00)	(1.92)	

Panel B: 12-month Estimation Window

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.24	0.06	−0.06	0.02	−0.02	0.00	−0.18	−0.12	−0.10	0.09	0.03	0.00	−0.14	−0.10	−0.08	
		(0.57)	(0.22)	(−0.28)	(0.09)	(−0.17)	(0.00)	(−0.66)	(−0.98)	(−1.05)	(0.39)	(0.24)	(−0.02)	(−0.78)	(−1.03)	(−0.99)	
(1)	0.40*	1.20***	−0.05	−0.56***	−0.19	−0.08	0.19**	−0.46**	0.07	0.19*	−0.03	−0.02	0.05	−0.26*	−0.06**	0.16	0.353
	(1.95)	(2.87)	(−0.55)	(−3.12)	(−1.12)	(−1.25)	(2.28)	(−2.13)	(1.48)	(1.87)	(−0.15)	(−0.43)	(1.09)	(−1.68)	(−2.21)	(1.55)	
(2)	1.27***	1.49***	−0.06	−0.46***	−0.95***	−0.14**	0.12*	−0.70***	0.06	0.16	0.08	0.01	0.08*	−0.31**	−0.08***	0.14	0.384
	(5.44)	(3.59)	(−0.65)	(−2.70)	(−5.32)	(−2.19)	(1.68)	(−2.89)	(1.20)	(1.63)	(0.43)	(0.11)	(1.69)	(−2.03)	(−2.73)	(1.35)	
(3)	1.53***	1.65***	−0.10	−0.49***	−0.97***	−0.14**	0.12*	−0.86***	0.05	0.14	−0.01	0.01	0.09**	−0.37**	−0.07***	0.13	0.409
	(5.83)	(3.60)	(−1.21)	(−2.88)	(−5.11)	(−2.31)	(1.70)	(−3.18)	(1.11)	(1.42)	(−0.03)	(0.10)	(2.19)	(−2.20)	(−2.59)	(1.30)	

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Panel C: 15-minute Sampling Frequency

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.20	0.01	−0.20	0.13	0.02	0.05	−0.20	−0.09	−0.09	0.12	0.05	0.01	−0.16	−0.04	−0.08	
		(0.49)	(0.04)	(−1.09)	(0.60)	(0.15)	(0.78)	(−0.76)	(−0.89)	(−1.19)	(0.57)	(0.55)	(0.09)	(−0.95)	(−0.57)	(−1.12)	
(1)	0.59***	1.05***	0.00	−0.65***	−0.11	−0.11	0.22***	−0.37**	0.06	0.17**	−0.01	−0.02	0.08	−0.28**	−0.01	0.14**	0.321
	(3.41)	(3.16)	(0.00)	(−4.29)	(−0.64)	(−1.63)	(3.43)	(−2.05)	(1.27)	(2.07)	(−0.08)	(−0.47)	(1.54)	(−2.46)	(−0.16)	(2.02)	
(2)	1.51***	1.23***	−0.02	−0.55***	−0.81***	−0.18**	0.16**	−0.60***	0.05	0.15*	0.18	0.00	0.11**	−0.34***	0.00	0.12*	0.345
	(6.18)	(3.82)	(−0.30)	(−3.51)	(−3.88)	(−2.49)	(2.54)	(−3.10)	(0.96)	(1.87)	(1.21)	(0.00)	(2.04)	(−2.85)	(−0.12)	(1.74)	
(3)	2.24***	1.21***	−0.04	−0.65***	−0.91***	−0.17**	0.18***	−0.65***	0.03	0.14*	0.18	0.01	0.12**	−0.33***	0.01	0.11	0.373
	(7.86)	(3.64)	(−0.61)	(−4.13)	(−4.45)	(−2.43)	(2.76)	(−3.32)	(0.71)	(1.72)	(1.11)	(0.21)	(2.38)	(−2.76)	(0.29)	(1.63)	

Panel D: 30-minute Sampling Frequency

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.23	0.08	−0.21	0.13	0.08	0.03	−0.08	−0.13	−0.06	0.20	−0.02	0.01	−0.12	−0.06	−0.06	
		(0.63)	(0.44)	(−1.15)	(0.69)	(0.75)	(0.55)	(−0.38)	(−1.47)	(−0.94)	(0.99)	(−0.19)	(0.14)	(−0.83)	(−0.98)	(−0.91)	
(1)	0.47***	0.94***	0.11*	−0.60***	−0.25	0.01	0.19***	−0.23	−0.04	0.16**	0.10	−0.06	0.05	−0.19*	−0.04*	0.13*	0.325
	(2.59)	(2.92)	(1.71)	(−4.13)	(−1.61)	(0.16)	(3.14)	(−1.38)	(−1.03)	(2.04)	(0.66)	(−1.49)	(1.02)	(−1.75)	(−1.91)	(1.94)	
(2)	1.29***	1.13***	0.13*	−0.54***	−0.92***	−0.04	0.14**	−0.35**	−0.07*	0.14*	0.21	−0.04	0.08	−0.23**	−0.06**	0.10	0.348
	(6.09)	(3.47)	(1.87)	(−3.59)	(−5.67)	(−0.71)	(2.45)	(−1.99)	(−1.86)	(1.79)	(1.43)	(−1.17)	(1.43)	(−2.00)	(−2.50)	(1.54)	
(3)	1.91***	1.10***	0.12*	−0.59***	−0.97***	−0.04	0.14**	−0.42**	−0.08*	0.12	0.19	−0.04	0.09*	−0.22**	−0.06**	0.10	0.375
	(7.47)	(3.23)	(1.77)	(−4.02)	(−5.89)	(−0.75)	(2.43)	(−2.37)	(−1.87)	(1.48)	(1.26)	(−1.25)	(1.75)	(−1.96)	(−2.27)	(1.51)	

Panel E: 75-minute Sampling Frequency

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.21	0.01	−0.22	0.10	0.07	0.01	−0.09	−0.05	−0.06	0.15	0.05	0.01	−0.10	−0.04	−0.04	
		(0.66)	(0.07)	(−1.21)	(0.58)	(0.82)	(0.15)	(−0.54)	(−0.70)	(−0.95)	(0.86)	(0.50)	(0.19)	(−0.88)	(−0.76)	(−0.67)	
(1)	0.52***	0.94***	−0.01	−0.53***	−0.14	0.00	0.14**	−0.33**	0.03	0.15*	0.09	−0.05*	0.03	−0.19**	−0.02	0.11**	0.329
	(3.22)	(3.58)	(−0.13)	(−4.13)	(−0.93)	(0.09)	(2.58)	(−2.13)	(0.85)	(1.94)	(0.61)	(−1.66)	(0.59)	(−2.13)	(−0.87)	(2.06)	
(2)	1.06***	1.03***	0.01	−0.46***	−0.53***	−0.04	0.10*	−0.47***	0.03	0.13*	0.14	−0.03	0.03	−0.24***	−0.03	0.09	0.351
	(5.23)	(3.68)	(0.14)	(−3.39)	(−3.41)	(−0.90)	(1.77)	(−2.91)	(0.82)	(1.68)	(0.98)	(−0.87)	(0.66)	(−2.70)	(−1.04)	(1.57)	
(3)	1.46***	0.96***	0.00	−0.50***	−0.51***	−0.05	0.11**	−0.53***	0.02	0.12	0.12	−0.03	0.04	−0.22**	−0.03	0.08	0.375
	(6.14)	(3.43)	(−0.01)	(−3.69)	(−3.25)	(−1.05)	(1.98)	(−3.19)	(0.47)	(1.53)	(0.78)	(−0.99)	(0.80)	(−2.47)	(−1.04)	(1.58)	

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Panel F: S&P500 Stocks

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.16	0.03	−0.18	0.53*	0.27*	0.12	−0.12	−0.10	−0.08	0.11	0.05	0.03	−0.13	−0.04	−0.07	
		(0.40)	(0.11)	(−0.95)	(1.88)	(1.71)	(1.61)	(−0.53)	(−1.00)	(−1.13)	(0.59)	(0.52)	(0.45)	(−0.83)	(−0.51)	(−0.97)	
(1)	0.70***	0.72**	0.07	−0.52***	0.26	−0.07	0.20***	−0.26	0.03	0.11	−0.14	−0.01	0.10*	−0.27**	−0.01	0.11	0.321
	(4.19)	(2.24)	(0.82)	(−3.23)	(1.16)	(−0.86)	(3.13)	(−1.47)	(0.70)	(1.30)	(−0.98)	(−0.14)	(1.85)	(−2.56)	(−0.29)	(1.61)	
(2)	0.77***	0.91***	0.04	−0.40**	−0.46*	−0.15*	0.16**	−0.43**	0.04	0.07	0.05	0.01	0.11**	−0.30***	−0.01	0.09	0.343
	(4.72)	(2.88)	(0.46)	(−2.46)	(−1.81)	(−1.79)	(2.49)	(−2.23)	(0.85)	(0.92)	(0.35)	(0.21)	(1.99)	(−2.73)	(−0.36)	(1.30)	
(3)	1.11***	0.74**	0.00	−0.46***	−0.48*	−0.13*	0.16**	−0.44**	0.04	0.08	0.02	0.01	0.12**	−0.25**	−0.01	0.08	0.376
	(5.63)	(2.33)	(0.05)	(−2.82)	(−1.89)	(−1.69)	(2.57)	(−2.41)	(0.91)	(0.95)	(0.18)	(0.21)	(2.35)	(−2.22)	(−0.23)	(1.27)	

Panel G: Alternative Jump Beta Estimation Methodology

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		0.16	−0.02	−0.22	0.10	0.06	0.01	−0.11	−0.05	−0.06	0.21	0.05	0.01	−0.06	0.01	−0.04	
		(0.38)	(−0.08)	(−1.21)	(0.50)	(1.06)	(0.15)	(−0.41)	(−0.75)	(−0.94)	(1.00)	(1.03)	(0.19)	(−0.35)	(0.26)	(−0.67)	
(1)	0.60***	1.10***	−0.07	−0.60***	−0.17	0.01	0.16***	−0.40**	0.06**	0.16*	−0.05	0.03	0.07	−0.32***	0.03**	0.12*	0.318
	(3.57)	(3.96)	(−0.62)	(−4.04)	(−1.10)	(0.42)	(2.75)	(−2.40)	(2.12)	(1.93)	(−0.38)	(1.49)	(1.33)	(−3.06)	(2.17)	(1.86)	
(2)	1.33***	1.41***	−0.14	−0.52***	−0.81***	0.00	0.11**	−0.54***	0.05*	0.15*	0.03	0.03	0.08	−0.36***	0.03*	0.10	0.342
	(6.05)	(4.98)	(−1.26)	(−3.46)	(−4.95)	(−0.05)	(1.98)	(−3.24)	(1.93)	(1.87)	(0.23)	(1.58)	(1.52)	(−3.30)	(1.80)	(1.56)	
(3)	1.80***	1.43***	−0.20*	−0.60***	−0.81***	−0.02	0.13**	−0.59***	0.04*	0.14*	−0.03	0.04*	0.10*	−0.33***	0.02	0.10	0.366
	(6.73)	(4.74)	(−1.94)	(−3.98)	(−4.63)	(−0.53)	(2.16)	(−3.38)	(1.74)	(1.69)	(−0.20)	(1.89)	(1.92)	(−3.04)	(1.56)	(1.58)	

Panel H: Instrumental Variables Approach

	γ^{ZB}	$\gamma^{MP,C}$	$\gamma^{MP,J}$	$\gamma^{MP,N}$	$\gamma^{SMB,C}$	$\gamma^{SMB,J}$	$\gamma^{SMB,N}$	$\gamma^{HML,C}$	$\gamma^{HML,J}$	$\gamma^{HML,N}$	$\gamma^{RMW,C}$	$\gamma^{RMW,J}$	$\gamma^{RMW,N}$	$\gamma^{CMA,C}$	$\gamma^{CMA,J}$	$\gamma^{CMA,N}$	R^2
UV		−0.26	−0.19	−0.37	−0.02	−0.05	0.00	−0.19	−0.15	−0.14	0.29	0.20	0.20	−0.05	−0.11	0.08	
		(−0.66)	(−0.48)	(−1.09)	(−0.08)	(−0.21)	(−0.02)	(−0.95)	(−0.82)	(−0.73)	(1.45)	(1.12)	(1.05)	(−0.34)	(−0.72)	(0.44)	
(1)	0.75**	0.55**	−0.07	−0.41*	−0.15	−0.16	0.39*	−0.28*	0.11	0.31**	−0.02	0.03	0.25*	−0.18**	−0.12*	0.17	0.244
	(2.02)	(2.30)	(−0.35)	(−1.83)	(−1.05)	(−1.20)	(1.65)	(−1.83)	(0.99)	(2.34)	(−0.16)	(0.25)	(1.80)	(−2.11)	(−1.66)	(1.24)	
(2)	1.41***	0.82***	0.02	−0.41*	−0.75***	−0.25	0.23	−0.53***	−0.03	0.24*	0.04	0.07	0.25*	−0.26***	−0.13*	0.15	0.268
	(3.68)	(3.26)	(0.09)	(−1.89)	(−4.86)	(−1.63)	(0.89)	(−3.41)	(−0.23)	(1.68)	(0.34)	(0.64)	(1.89)	(−2.88)	(−1.69)	(1.20)	
(3)	1.99***	0.67**	−0.12	−0.54**	−0.78***	−0.25*	0.24	−0.58***	0.06	0.26*	0.00	0.11	0.27**	−0.25***	−0.11	0.12	0.291
	(4.73)	(2.55)	(−0.51)	(−2.57)	(−4.89)	(−1.68)	(0.97)	(−3.79)	(0.51)	(1.75)	(−0.04)	(0.97)	(2.12)	(−2.82)	(−1.28)	(0.93)	