The Pricing of Continuous and Discontinuous Factor Risks *

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January 15, 2022

Abstract

This study considers a continuous-time version of the Fama-French (2015) five-factor model, explicitly allowing stocks' exposures on the factors' continuous, jump, and overnight movements to be different. Our results show that stocks' continuous, jump, and overnight betas with respect to a given factor can be very different and are only weakly related. We find strong evidence for a positive pricing of continuous market exposure and a negative pricing of overnight market exposure whereas jump market exposure is not priced. This finding contradicts prior empirical evidence indicating a positive pricing of jump and overnight market exposures but zero pricing of continuous market exposure. Moreover, exposures to the size, value, profitability, and investment factors' continuous risks are mostly negatively priced while exposures to their overnight risks are positively priced, suggesting that these factors' return premia are compensation for exposure to the factors' overnight risks. Jump exposures are in general not significantly priced.

JEL-Code: G12, G14
EFM Classification Code: 310, 330
Keywords: Fama-French factors, factor betas, high-frequency, jump risk, overnight risk

*I would like to thank Manuel Ammann, Si Cheng (discussant), Roland Füss (discussant), Tobias Kalsbach (discussant), Mathis Mörke, Christopher Polk, and Paul Söderlind as well as participants of the doctoral research seminar at the University of St.Gallen, the 37th International Conference of the French Finance Association (AFFI), the 27th Annual Meeting of the German Finance Association (DGF), the 2021 Annual Meeting of the Financial Management Association (FMA), and the 2022 Annual Meeting of the American Finance Association (AFA) for helpful comments and suggestions.

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1 Introduction

The central notion in asset pricing is that investors are compensated for exposure to systematic risks by higher returns. The dominant approach to capture systematic risks are factor models such as the CAPM, the Fama-French (1993; 1996; 2015) three- and five-factor models, and the q-factor model of Hou et al. (2015). The view that the factors in these models reflect systematic risks is motivated by their empirically documented ability to capture considerable covariation in stock returns together with their considerable positive return premia. The implication of these factor models is that assets that have a higher exposure to the factors are subject to more systematic risk and should therefore earn higher expected returns. Yet, empirically, stocks with higher exposure to the factors do not earn higher average returns (see e.g. Black et al. (1972), Daniel and Titman (1997), and Jegadeesh et al. (2019)), casting doubts on the validity and the interpretation of these factor models.

In this paper, we argue that one of the reasons for the empirical failure to document the predicted relation between factor exposures and returns may be the inability of standard approaches to differentiate between exposure to continuous and discontinuous factor risks. An emerging literature shows that investors seem to treat continuous and discontinuous variation differently and independently of each other (see e.g. Cremers et al. (2015) or Bollerslev et al. (2016)). That is, investors may care only about one of the sources of variation in a factor, continuous or discontinuous, and demand compensation only for exposure to this source. However, factor models are typically formulated in discrete time, allowing only for one source of variation in the factors. The discrete-time representations of the factor models are usually estimated either with monthly or daily data. Yet, if investors care only about one of the sources of variation in a given factor, the betas estimated from such low-frequency data would not only reflect the exposure to the *priced* source of variation but also the exposure to unpriced sources of variation. If this is the case and if stocks' continuous and discontinuous exposures are sufficiently different, using discrete betas would make it difficult to confirm a positive relation between factor exposures and returns empirically.

Motivated by this argument, this paper considers continuous and discontinuous factor exposures individually and aims to evaluate whether and which of the different types of factor exposures are priced in the cross-section of stock returns. We investigate this question for the factors of the Fama-French (2015) five-factor model, which is arguably the most established factor model in the current asset pricing literature. Specifically, we account for three different sources of variation: continuous, or smooth, intraday movements, intraday jumps, and overnight movements. We refer to the intraday jumps and the overnight movements jointly as discontinuous movements but consider them separately in our empirical investigation. We find strong evidence for a positive pricing of exposure to continuous market risk as well as for a positive pricing of exposures to the other factors' (i.e. size, value, profitability, and investment) overnight risks. However, we also document substantial negative risk premia for exposure to overnight market risk and for exposures to the other factors' continuous risks while we find no significant risk premia for exposures to the factors' jump risks. On the one hand, these findings indicate which of the factors' risks are likely to be the underlying source for their positive return premia. In particular, the continuous risk seems to be the source of the market premium while overnight risks seem to be the source of the size, value, profitability, and investment premia. On the other hand, the negative risk premia documented for some of the factors' risks seem to (over-)compensate these positive risk premia. Therefore, we conclude that, overall, our results still fail to confirm an unambiguously positive relation between exposure to the factors and stock returns.

Modeling stock returns by means of factor models is ubiquitous in the asset pricing literature. The first and still most prominent factor model is the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965). The CAPM models expected returns as a positive and linear function of their exposure to the market factor. Despite the strong theoretical basis of the CAPM, Black et al. (1972) find that the relation between average returns and market betas is much weaker than predicted. Moreover, Fama and French (1992) find that stocks' market beta is unrelated to average returns after controlling for stocks' market equity and book-to-market ratios.

Following this evidence, Fama and French (1993, 1996) put forward their three-factor model which contains besides the market factor of the CAPM a size factor and a value factor. Fama and French (2015) extend their three-factor model by a profitability and an investment factor, resulting in a five-factor model. Similarly, Hou et al. (2015) propose a four-factor model that contains market, size, profitability, and investment factors. Although these factor models do better in explaining the cross-section of average stock returns as well as in capturing covariation in stock returns than the CAPM, empirical studies mostly fail to document the predicted positive relation between the factors of these multifactor models and returns (see e.g. Daniel and Titman (1997), Jegadeesh et al. (2019), and Daniel et al. (2020)). As long as this fundamental risk-return relationship cannot be confirmed, the interpretation of these factors as *risk* factors is questionable.

Furthermore, this also calls into question the standard applications of these factor models in the empirical asset pricing literature as well as for the purpose of fund performance measurement. The empirical asset pricing literature frequently examines potential anomalies in the cross-section of returns by regressing the anomalies' returns on a given factor model and evaluating the significance of their unexplained average returns (i.e. their alphas). Likewise, the performance of fund managers is measured by regressing the funds' returns on a given factor model and assessing the funds' alphas. However, as recently pointed out by Chen et al. (2020), if the goal is to obtain risk-adjusted returns, adjusting for exposure to factors that earn positive average returns does not make sense as long as higher factor exposures (i.e. betas) are *not* associated with higher average returns.

The empirical failure to confirm the positive relation between factor betas and returns is often attributed to one of three potential explanations. First, the factors are not true risk factors, that is, they do not capture risks that are of hedging concern to investors and their historically documented risk premia are just statistical artifacts or are due to market inefficiencies. Second, while they capture risks that are of hedging concern to investors, the factors are imperfect proxies for the mean-variance efficient portfolio. Third, the factors are *risk* factors and are also good proxies for the mean-variance efficient portfolio, but stocks' exposures (i.e. their betas) to these factors are estimated with error, making it difficult to confirm the predicted positive relation between factor betas and returns empirically. In this paper, we examine another potential explanation: only the exposures to some of the factors' risks - continuous, jump, and overnight - are priced, and standard approaches that rely on monthly or daily data to estimate betas fail to confirm the predicted relation because the low-frequency betas are noisy measures for the exposures to the priced sources of the factors' variation.

In our empirical analysis, we use the most comprehensive high-frequency data set employed in the empirical asset pricing literature. Specifically, we obtain high-frequency data for all common US stocks that are traded on the NYSE, AMEX, or NASDAQ in the period from January 1993 to December 2019 from NYSE's Trade and Quote (TAQ) database. Most studies in the empirical asset pricing literature that use high-frequency data restrict their sample to S&P500 stocks (e.g. Bollerslev et al. (2016) or Pelger (2020)) - probably in order to avoid the influence of microstructure issues, which are of less concern for the highly liquid S&P500 stocks. We select a broader sample of stocks as we want to ensure that our results are as general as possible rather than being restricted to the specific sample of S&P500 stocks. In order to nevertheless mitigate the influence of potential microstructure issues on our results, we employ only stocks that satisfy standard liquidity criteria and that are not subject to significant market microstructure noise as identified by the tests developed by Aït-Sahalia and Xiu (2019).

Based on our high-frequency stock dataset, we construct high-frequency versions of the five Fama-French (2015) factors. In each month, we estimate for each stock in our sample continuous, jump, and overnight betas with respect to the factors based on an estimation window of six months. Our estimation results show that that stocks' continuous, jump, and overnight betas with respect to a given factor can be very different, which is a necessary condition for a potentially different pricing of the betas. Moreover, continuous betas are in general much less cross-sectionally dispersed and much more persistent than jump and overnight betas.

We investigate the pricing of the different factor exposures by means of value-weighted univariate and bivariate portfolio sorts as well as Fama-MacBeth (1973) regressions estimated with weighted least squares. Factor models predict that there should be a positive relation between stocks' systematic risk exposure, as measured by factor betas, and their returns across the *same* period. For this reason, we use stocks' contemporaneous rather than their future returns for the examination of the factor betas' pricing. Based on both approaches, portfolio sorts as well as Fama-MacBeth (1973) regressions, we find strong evidence that the continuous market beta carries a significantly positive risk premium whereas the overnight market beta carries a significantly negative risk premium. By contrast, the jump market beta does not seem to be priced. These results are in stark contrast to the results of Bollerslev et al. (2016) who document significantly positive risk premia for jump and overnight market betas but no risk premium for continuous market betas. We trace the differences between the findings of Bollerslev et al. (2016) and our results back to three sources: we use value-weights rather than equal-weights, we use all common stocks traded on the NYSE, AMEX, and NASDAQ rather than only S&P500 stocks, and we investigate a contemporaneous rather than a predictive relation between betas and returns.

Beyond the pricing of the market betas, our results show that the continuous size, value, and investment betas are negatively priced whereas the overnight size, value, profitability, and investment betas carry uniformly and mostly significantly positive risk premia. Continuous profitability betas as well as jump betas do in general not seem to be priced. Consequently, we conclude that the empirically observed size, value, profitability, and investment premia are most likely to represent compensation for overnight exposure to these factors. Nevertheless, due to the negative risk premia for the continuous factor betas, our results fail to confirm a reliably positive relation between exposures to the factors and returns, leaving the validity of the Fama-French (2015) five-factor model still in question.

Our paper is related to several strands of literature. First, it contributes to the literature on the pricing of jump risk. The paper closest to ours is Bollerslev et al. (2016). They estimate continuous, jump, and overnight betas for the CAPM and find that stocks with higher jump and overnight market betas earn higher returns even when controlling for continuous market betas, while this does not hold vice versa. This suggests that investors command a risk premium primarily for exposure to discontinuous variations in the aggregate market, but not for exposure to continuous variations. Their findings are complementary to those of Cremers et al. (2015) who show that investors price exposures to changes in aggregate jump and volatility risks independently of each other, and that they price exposure to changes in jump risk higher than exposure to changes in volatility risk. Arouri et al. (2019) show that international equity markets carried a risk premium for exposure to continuous as well as downside jump risks in the time before the financial crisis. Similarly, Lee and Wang (2019) find a significant risk premium for exposure to downside jump risk in the international currency market. Focusing on idiosyncratic jumps, Kapadia and Zekhnini (2019) find that investors require higher expected returns for holding stocks with higher idiosyncratic jump risk, and that stocks earn their mean returns primarily on the few days on which their prices jump. Moreover, Jiang and Yao (2013) provide evidence that the size, illiquidity, and value premia in the cross-section of stock returns are mainly realized through jump returns. We contribute to this literature by examining the pricing of systematic jump and overnight risk exposures in the context of the Fama-French (2015) five-factor model. Contrary to what the majority of this literature suggests, we do not find a positive pricing of jump market risk exposure, and even a negative pricing overnight market exposure. Additionally, we show that the exposure to jumps in the four additional factors of Fama and French (2015) does also not seem to be positively priced. We rather find that continuous market risk exposure as well as exposures to the other factors' overnight movements exhibit positive risk premia.

Second, our paper is related to some recent papers that study multifactor models in a continuous-time setting. Aït-Sahalia et al. (2020) estimate the Fama-French (2018) six-factor model for a large high-frequency stock sample. They find that the additional factors beyond the market factor are useful in explaining time series variation in stocks, and provide suggestive evidence that idiosyncratic risk estimates are more reliable when the high-frequency factors are used instead of their low-frequency counterparts. Additionally, Pelger (2020) aims to capture the systematic risks that drive stock returns by means of statistical factors that are estimated from a high-frequency stock panel via principal component analysis. He identifies four systematic continuous factors and one systematic jump factor, and shows that they do somewhat better than a high-frequency version of the Fama-French-Carhart (1997) four-factor model in summarizing systematic risk. Considering also a multifactor framework, our work complements these studies by examining the pricing of systematic risk exposures in the cross-section of stocks rather than identifying systematic and idiosyncratic risks.

Third, our paper contributes to the literature that examines whether exposures to the factors of factor models are priced. Black et al. (1972) is one of the first studies to evaluate this question for the case of the CAPM, documenting that the relation between market betas and average returns is much weaker than predicted. Daniel and Titman (1997) provide evidence that the same holds for betas with respect to the factors of the Fama-French (1993; 1996) three-factor model, especially after controlling for stocks' market capitalization and book-to-market ratio. Likewise, Jegadeesh et al. (2019) find insignificant and in parts even negative relations between betas with respect to the Fama-French five-factor model and returns[1]. Our paper contributes to this literature by decomposing factor betas into continuous, jump, and overnight betas and examining the pricing of these betas separately. Despite considering factor exposures in a "higher resolution", we still fail to document a reliably positive relation between factor exposures and returns in general. Nonetheless, our results indicate at the very least that there are factor risks that are positively priced, namely continuous market risk and overnight size, value, profitability, and investment risks. To the best of our knowledge, this finding is new to the literature.

The remainder of the paper is structured as follows: Section 2 illustrates the general representation of a multifactor model in a continuous-time setting and motivates the separate pricing of continuous and discontinuous factor risks based on the concept of the stochastic discount factor. In Section 3, we introduce our data sample, detail the construction of the high-frequency versions of the five Fama-French (2015) factors, and provide summary statistics on the factors. Section 4 describes our beta estimation methodology and shows results on the estimated betas. In Section 5, we present our findings on the pricing of the decomposed factor betas. Finally, Section 6 concludes.

[1]Further related and qualitatively similar evidence is provided e.g. by Brennan et al. (1998), Daniel et al. (2020), and Chen et al. (2020).

2 Theoretical framework for the pricing of continuous and discontinuous factor risks

In this section, we discuss the theoretical motivation for the investigation of the separate pricing of continuous and discontinuous factor risks. In particular, we first introduce a general multifactor model in discrete time and review the conditions under which the factors can be viewed as *risk* factors. For this purpose, we assume the existence of an economy-wide stochastic discount factor (SDF) and express it as a function of the factors. Then, we convert the factor model into continuous time and discuss why continuous and discontinuous factor risks may be priced differently.

In discrete time, a factor model with K factors that aims to describe asset returns can in general be expressed as follows:

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

where $r_{i,t}$ is the return on asset i in period t, $r_{f,t}$ is the risk-free rate in period t, $\beta_{i,t}^{k}$ is the exposure of asset i with respect to factor k in period t, $f_{k,t}$ is the realization of factor k in period t, and $\epsilon_{i,t}$ is the residual return of asset i in period t (i.e. the part of the return that is left unexplained by the factor model). For the case of the Fama-French (2015) five-factor model, we have $K = 5$ and $k \in \{MP, SMB, HML, RMW, CMA\}$, where MP, SMB, HML, RMW, and CMA are the returns on the market, size, value, profitability, and investment factors, respectively.

So far, the factors in the general factor model in equation (1) may simply capture comovement in assets' returns without any pricing implication. In order to interpret the factor model as a factor *pricing* model, the factors have to be *risk* factors in the sense that they reflect risks that are 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. This implies that the SDF, denoted by m_t, may be approximated by a linear function of the factors[2]:

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

where b_k is the loading of the SDF on factor k and a is a constant that captures the factors' means.

As shown in Cochrane (2005), an SDF that is a linear function of the factors is equivalent to an expected return-beta model that expresses assets' expected (excess) returns as a positive

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

and linear function of their exposures to the factors:

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

where λ_k is the risk premium for exposure to factor k. The magnitude of λ_k is directly linked to the loading of the SDF on factor k, b_k, as well as to the factor k's variance. The expected return-beta representation says that investors are compensated for holding assets with exposures to the factors by higher expected returns.

In order to convert the general factor model in equation (1) into continuous time, we first define continuous-time processes for the factors. To this end, we follow the literature and model factors' continuous-time price processes as jump-diffusions. In particular, we assume that the log-price F_k of factor k over some 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 premium, $\sigma_{k,t}$ is the factor's instantaneous diffusive volatility, $dW_{k,t}$ is a Brownian motion that generates continuous movements in the price process, and ν_k is a compensated jump counting measure that generates discontinuous movements in the price process. The term $\sigma_{k,t} dW_{k,t}$ reflects the factor's continuous (diffusive) risk while the term $\int_R x \nu_k(dt, dx)$ reflects the factor's discontinuous (jump) risk.

In analogue to equation (1) and based on the expression of the factors' log-price processes in equation (4), we assume that the log-price process of stock i over some fixed time interval $[0, T]$ can be represented by:

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

where $\mu_{i,t}$ is the drift of stock i's price process and reflects the stock's instantaneous expected return, $\beta_{i,t}^{k,C}$ ($\beta_{i,t}^{k,J}$) is the exposure of stock i with respect to the continuous (discontinuous) movements in factor k, and $dZ_{i,t}$ is a jump-diffusion that reflects idiosyncratic movements in the price of stock i (since stocks' idiosyncratic risks are not the focus of this paper, we do not explicitly model their dynamics). In this framework, we explicitly allow the betas with respect to the continuous and discontinuous movements in the factors to be different.

Furthermore, the continuous-time expression for the factor process from equation (4) implies the following representation for the natural logarithm of the SDF (see e.g. Bollerslev et al. (2016)):

$$M_t = \int_0^t \alpha_s ds + \sum_{k=1}^{K} b_k \left(\int_0^t \sigma_{k,s} dW_{k,s} + \int_0^t \int_R x \nu_k(ds, dx) \right) \tag{6}$$

This representation restricts the SDF to have the same loadings on the factors' continuous and discontinuous movements. However, there exists no theoretical argument that justifies this restriction. Intuitively, different sources of variation in the factors may proxy differently for the SDF, implying that the SDF may have very different loadings on the factors' continuous and discontinuous movements. In order to allow for these potentially different loadings, we reformulate the expression in (6):

$$M_t = \int_0^t \alpha_s ds + \sum_{k=1}^{K} \int_0^t b_k^C \sigma_{k,s} dW_{k,s} + \sum_{k=1}^{K} \int_0^t \int_R b_k^J x \nu_k(ds, dx) \tag{7}$$

where b_k^C and b_k^J are the SDF's loadings on the continuous and discontinuous movements in factor k, respectively.

The representation of the SDF in (7) gives rise to the following expected return-beta model:

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

where λ_k^C (λ_k^J) is the risk premium for exposure to the continuous and discontinuous movements in factor k. This expected-return beta representation says that investors may be compensated for exposures to both sources of factors' movements - continuous and discontinuous - and that the compensations may be different. In particular, a risk premium is non-zero if and only if the SDF has a non-zero loading on the corresponding factor movements, meaning that this source of variation proxies for the SDF and is thus of hedging concern to investors.

So far, the factor and stock price processes defined in equations (4) and (5) assume that prices evolve continuously through time. However, we can only observe price movements while markets are open. Following the literature (e.g. Bollerslev et al. (2016)), we interpret the price movement from close to open as an additional source of discontinuous price movements besides intraday jumps. These overnight movements could be incorporated in the expressions for the stock, factor, and SDF processes by additional jump terms. Without explicitly doing so, we argue that stocks' betas with respect to factors' overnight movements may be different from their betas with respect to the factors' continuous movements and jumps, and that the risk premia for overnight factor exposures may also be different than the risk premia for continuous and jump factor exposures. Consequently, this implies the following expected return-beta model:

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

where $\beta_{i,t}^{k,N}$ is the exposure of stock i with respect to the overnight movements in factor k and λ_k^N is the risk premium for exposure to the overnight movements in factor k.

Before moving to our empirical analyses, we emphasize that, assuming a given factor is priced, there is little theoretical guidance on whether this pricing is due to its continuous, jump, or overnight variation. On the one hand, one may argue that jumps are large information events and that stocks' reactions to such large information events provide a better indication for their exposure to economic fundamentals (see e.g. Bollerslev et al. (2016)). On the other hand, the variation in the factors that is due to jumps is much smaller than the variation in the factors that is due to continuous movements[3]. While a considerable portion of the continuous variation may be due to noise, it is likely that most information enters prices through continuous movements. Additionally, many scheduled information releases are typically outside of trading hours (e.g. macroeconomic announcements in the US are typically at 8:30 a.m. and thus before markets open), suggesting that stocks' reaction to factors' overnight movements are also valid indicators for their exposures to economic fundamentals. Yet, overnight movements are also likely to be contaminated by microstructure issues such as illiquidity. Overall, we therefore argue that it is hard to predict ex-ante which of the factors' risks is priced, and that this may even be different for different factors.

3 Data and Factors

We begin this section by introducing the high-frequency dataset that we use for the empirical investigation of the pricing of exposures to the different factor risks. In the second subsection, we describe the construction of the high-frequency versions of the Fama-French (2015) factors. The third subsection explains the jump identification procedure and presents summary statistics on the factors' jumps.

3.1 Data Sample

For our empirical investigation, we merge data from four sources. First, we obtain monthly and daily data on stock returns, open prices, close prices, and shares outstanding from the CRSP database. We adjust holding period returns for delisting returns. Second, we retrieve data on firm fundamentals from the Compustat Annual and Quarterly databases. Third, we use the one-month T-bill rate provided by Kenneth French on his website[4] as our proxy for the risk-free rate. Finally, we obtain high-frequency data on stocks from the Monthly and Daily TAQ databases[5]. In general, our sample contains in each month all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11. Our sample period spans the period from January 1993 to December 2019 and is restricted by the availability of high-frequency data from the TAQ database.

The high-frequency data from the TAQ database requires extensive cleaning. For this purpose, we follow standard practices in the high-frequency literature[6]. First, we use only trade

[3]This is empirically verified in Table 2.

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

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

[6]Our data cleaning and manipulation procedure combines various aspects of the procedures of Barndorff-Nielsen et al. (2009), Bollerslev et al. (2016), Holden and Jacobsen (2014), and Aït-Sahalia et al. (2020).

observations with a timestamp within the regular trading hours from 9:30 a.m. to 4:00 p.m., with a price and a trade size greater than zero, a trade correction indicator of zero, and a normal sale condition[7]. Second, we delete each trade observation whose transaction price deviates by more than ten mean absolute deviations from the median transaction price of the 25 previous and the 25 subsequent trade observations.

Based on the remaining observations, we assign a price to each second in the 9:30 a.m. to 4:00 p.m. interval 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 of the trades in this second; finally, if there is no trade in the respective second, we carry forward the price from the previous second. Moreover, we follow Aït-Sahalia et al. (2020) and replace stocks' first and last prices with the daily open and close prices from CRSP, ensuring that there is a perfect correspondence between daytime CRSP and TAQ returns[8]. Consequently, we use only stock-days that have non-missing daily returns, open prices, and close prices in the CRSP database as well as at least one non-zero price in the TAQ database[9]. From these second-by-second prices, we calculate stocks' 15-, 30-, and 75-minute log-returns across the day[10]. We calculate stocks' high-frequency returns for three different sampling frequencies because we will later use a mixed-frequency approach for the estimation of stocks' betas (see Section 4.1). Finally, we calculate stocks' overnight returns as their daily gross returns from CRSP divided by their gross open-to-close returns from CRSP, minus one. By calculating overnight returns in this way rather than as close-to-open returns, we account for potential dividend payments and stock splits that occur after the close.

3.2 Factor Returns

For the construction of the high-frequency versions of the five Fama-French (2015) factors, we closely follow the portfolio formation procedure outlined by Fama and French (1993, 1996, 2015) and the high-frequency portfolio return calculation procedure of Aït-Sahalia et al. (2020). First, the market portfolio in a given month contains all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11 as well as good market equity (ME) 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

[7]We define trades with normal sale conditions as trades whose sale condition field in the TAQ database is either blank or equals @, *, E, F, @E , @F, *E, *F.

[8]In order to merge CRSP and TAQ data, we employ the linking table provided on WRDS.

[9]We exclude stock-days for which the absolute difference between the log-open price from CRSP and the log of the first price from TAQ as well as the absolute difference between the log-close price from CRSP and the log of the last price from TAQ are both larger than the log of 1.1. Intuitively, this means that we exclude stock-days for which CRSP open price and close price both deviate by more than 10% from the first and last price in TAQ, respectively. This restriction aims to catch stock-days that suffer from bad data quality or from matching errors between the databases.

[10]For the 15- and 30-minute sampling frequencies, we start at 9:30:00 a.m.; for the 75-minute sampling frequency, we start at 9:45:00 a.m.

capitalizations. The return on the market factor (MP) for a given time period is the return on the market portfolio in excess of the risk-free rate over the time period.

For the construction of the value factor, all stocks that are in the market portfolio and have non-missing ME and book-to-market ratio (BM) data[11] are at the beginning of each July independently sorted into two ME groups and into three BM groups. The breakpoints for the sorts are the median ME and the 30th and the 70th BM percentiles of all NYSE stocks, respectively. The intersections of the two ME groups and three BM groups yield six portfolios, and the stocks in each of the six portfolios are value-weighted. The return on the value factor (HML) for a given time period is the average of the returns on the two high BM portfolios minus the average of the returns on the two low BM portfolios.

The profitability factor and the investment factor are formed in the same way as the value factor, just that the second sorts are with respect to operating profitability (OP) and investment (INV), respectively, rather than with respect to BM. The return on the profitability factor (RMW) for a given time period is the average of the returns on the two high OP portfolios minus the average of the returns on the two low OP portfolios, and the return on the investment factor (CMA) for a given time period is the average of the returns on the two low INV portfolios minus the average of the returns on the two high INV portfolios. Finally, the return on the size factor (SMB) for a given time period is the average of the returns on the nine low ME portfolios resulting from the 2x3-sorts with respect to ME and any of BM, OP, and INV, minus the average of the returns on the nine high ME portfolios.

We calculate monthly, daily, overnight, and high-frequency (15-, 30-, and 75-minute) versions of these factors[12]. For each version, the value-weights of the stocks in the factor portfolios are calculated based on their market capitalizations at the beginning of the return intervals. Specifically, for the monthly version, we employ the market capitalization based on the close price of the last trading day in the previous month; for the daily and the overnight versions, we take the market capitalization based on the close price of the previous trading day; and for the high-frequency version, we calculate the market capitalization at the beginning of each interval as the market capitalization based on the close price of the previous trading day multiplied with the cumulative gross return from the close of the previous trading day until the beginning of the respective interval (including the overnight return).

Our daily market, size, value, profitability, and investment factors exhibit correlations of 1.000, 0.995, 0.982, 0.981, and 0.963 with the daily factors from Kenneth French's website. Our overnight (high-frequency factors) exhibit correlations of 0.999, 0.974, 0.936, 0.836, and 0.960 (0.995, 0.974, 0.903, 0.743, and 0.915) with the overnight (high-frequency) factors from Dacheng Xiu's website[13]. By aggregating our high-frequency factors as well as the high-frequency factors

[11] The calculation of the variables is described in Appendix A.

[12] For the calculation of the factor returns for the daily, overnight, and high-frequency versions on a given day, we use only stock-days that are available for all three versions, that is, only stocks that have non-missing daily returns, open prices, and close prices in CRSP and at least one good trade observation in TAQ for the respective day.

[13] `https://dachxiu.chicagobooth.edu/`

from Dacheng Xiu's website to the daily frequency, we find that our market, size, and value factors achieve slightly higher correlations with the daily factors from Kenneth French's website, our profitability factor achieves a considerably better correlation, and our investment factor a somewhat worse correlation. Overall, these results show that our high-frequency factors are reasonable replications of the daily Fama-French (2015) factors.

Table 1 reports summary statistics for the monthly, daily, overnight, and 30-minute versions of the five Fama-French (2015) factors for the period from January 1993 to December 2019[14]. The results for the monthly version in Panel A show that the average monthly return of the market factor is 0.69%, being the only factor that is highly significant during our sample period. The profitability factor is with its average monthly return of 0.29% the only other factor that is statistically significant at a conventional significance level. By contrast, the average monthly returns on the size, value, and investment factors of 0.14%, 0.19%, and 0.15% are insignificant. These average returns are considerably lower than the factors' average returns since July 1963, which is in line with recent studies that find that the size and value premia have become considerably weaker in the last few decades (see e.g. Hou and van Dijk (2019) and Arnott et al. (2021)). The results for the daily factors in Panel B exhibit qualitatively the same patterns.

[Insert Table 1 near here.]

Panels C and D of Table 1 depict the properties of the overnight and 30-minute versions of the factors. The most notable observation is that the market factor is the only factor that earns a significantly positive premium overnight while the overnight premia of all other factors are strongly and significantly negative. By contrast, the average 30-minute return on the market factor during trading hours is only slightly but insignificantly positive whereas the other factors earn strong and highly significant positive average 30-minute returns. This observation is consistent with the findings of Lou et al. (2019) who document 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 with close to zero or negative overnight returns. Furthermore, the results in Panels C and D show that the skewness and thus the asymmetry in the overnight and high-frequency factor returns is quite moderate and not more pronounced than for the monthly and daily versions. Yet, the kurtosis of the overnight and high-frequency factor returns is with average levels of around 22 much more pronounced than for their daily versions. This indicates that there is considerable jump activity in the factors that is averaged out and thus less visible in the daily returns.

[14] For parsimony, we 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.

3.3 Factor Jumps

After the discussion of the factor returns' general summary statistics in the last subsection, this subsection examines the jumps in the factor returns. In order to identify jumps in the factors' high-frequency returns, we rely on the TOD estimator of Bollerslev et al. (2013). This estimator classifies all returns that exceed the threshold of $\tau \cdot n^{-\omega} \cdot \hat{\sigma}_{k,d,t}$ as jumps, where n is the number of high-frequency intervals per day (i.e. in the case of the 30-minute sampling frequency, $n = 13$) and $\hat{\sigma}_{k,d,t}$ is an estimator for the local volatility of factor k in interval t on day d. Specifically, $\hat{\sigma}_{k,d,t}$ combines a jump-robust bipower estimator for the volatility of factor k on day d with an estimator for the time-of-day (TOD) volatility pattern of factor k. By estimating the volatility on a daily basis, the estimator accounts for changes in volatility. The TOD volatility pattern additionally accounts for the stylized empirical fact that volatility varies across the trading day (volatility is typically highest after the open and before the close). For the purpose of examining the descriptive statistics of the factors' jumps, we estimate the factors' TOD patterns across the entire sample period[15]. Moreover, following Bollerslev et al. (2016), we set $\tau = 3$ and $\omega = 0.49$, meaning that all high-frequency returns that are in absolute terms larger than three times the estimate for the local volatility in that interval are classified as jumps.

Table 2 presents summary statistics on the detected jumps in the factors' 30-minute versions. Panel A shows that the percentage of jump observations is for all factors in the range from 1.13% to 1.31% of all observations. Although these percentages are low in magnitude, they are about five times higher than one would expect if the factor returns were normally distributed, and is thus consistent with the factor returns' high kurtosis as documented in Table 1. The total number of jumps is for each factor quite equally divided into positive and negative jumps - if anything, positive jumps tend to be slightly more frequent than negative jumps. Additionally, comparing the 25th, 50th, and 75th percentiles of the positive jumps to the corresponding percentiles of the negative jumps suggests that the positive and negative jumps are in general similarly distributed. A notable difference in the distributions, though still moderate, can only be observed for the market factor which exhibits somewhat higher negative than positive jumps. Yet, the median absolute jump size varies considerably across the factors, ranging from around 0.4% for the market factor to slightly below 0.2% for the profitability and investment factors. Finally, the last column of Panel A of Table 1 shows that while jumps represent only somewhat more than 1% of the factors' high-frequency returns, they account for a considerable part of the total variation. The lowest jump variation as a percentage of the total variation can be observed for the market factor with 7.7% whereas the size factor exhibits the highest jump variation of 12.8%.

[Insert Table 2 near here.]

Beyond the descriptive statistics on the factors' jumps, we also examine the decomposition

[15] For the estimation of jump betas, we estimate the factors' TOD patterns only across the respective estimation window (see Section 4.2).

of the factors' daily returns into overnight and high-frequency returns as well as of the high-frequency returns into their continuous and jump parts. For this purpose, we aggregate the factors' 30-minute returns as well as their continuous and jump components on a daily basis[16]. For each of the daily, overnight, daily aggregated high-frequency, daily aggregated continuous, and daily aggregated jump returns, Panel B of Table 2 reports the average return across the sample period. 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 return premia of the other factors are exclusively earned intraday and strongly reverse overnight. Further decomposing the high-frequency returns into their continuous and jump components reveals an interesting pattern: for all factors, the continuous component is highly significant and accounts nearly completely for the intraday mean returns. By contrast, the jump component is mostly small and insignificant (for the market and size factors even slightly negative), and thus hardly contributes to the factors' return premia.

4 Continuous and Discontinuous Factor Betas

In order to investigate the pricing of the exposures to the factors' continuous, jump, and overnight risks, we need to estimate stocks' betas with respect to the different sources of factors' variation. However, individual stocks' high-frequency returns are subject to various microstructure issues that may contaminate the estimates for the stocks' continuous and jump betas. In order to mitigate the impact of these issues, we use only stocks that satisfy various criteria. The first part of this section introduces these criteria. In the second part, we describe our procedures for estimating the different betas for the eligible stocks. The third part presents summary statistics on the estimated betas, and the fourth part discusses the relations between the different betas as well as their association with prominent firm and stock characteristics. For comparison, we also estimate standard daily betas as well as simple high-frequency betas in addition to the continuous, jump, and overnight betas.

4.1 Sample Selection

Our base sample consists in each month of all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11. However, the quality of the high-frequency data for some stocks may be insufficient to obtain reliable estimates for their high-frequency, continuous, and jump betas. Bad quality in the high-frequency data can be due to various

[16]Note that all returns are log-returns and that all versions use only stock-days that are available for all versions. Therefore, the sum of a factor's continuous and jump returns on a given day is exactly the same as the sum of the factor's high-frequency returns on that day, and the sum of the factor's high-frequency returns and the factor's overnight return on that day is the same as the factor's daily return.

microstructure issues such as infrequent and asynchronous trading, bid-ask bounce, or price discreteness. In order to mitigate the effect of these microstructure issues on our results, we apply several ad-hoc exclusion criteria that are widely used in the literature on the one hand, and we employ different sampling frequencies for different stock-month pairs on the other hand. The sampling frequency for a stock-month pair thereby depends on the severity of its microstructure noise. We employ this mixed-frequency approach rather than using the same sampling frequency for each stock-month in order to make optimal use of our stock sample: we can take advantage of a high sampling frequency for the most liquid stocks while we do not need to exclude too many stocks due to their potential microstructure issues at the highest sampling frequency.

Our ad-hoc criteria exclude in each month first all stocks that have a market equity below \$10mn or a share price below \$1, and second, all stocks that have valid data on daily, overnight, and high-frequency returns for less than 50 days during the respective estimation window (we use an estimation window length of six months). For each of the stocks that satisfy these two criteria in the respective month, we select the highest sampling frequency for which both of the following criteria are satisfied (we consider sampling frequencies of 15-, 30-, and 75-minute): first, more than half of the stock's high-frequency returns during the estimation window have to be non-zero. Second, the stock's high-frequency returns during the estimation window may not exhibit significant microstructure noise. In order to test for the presence of microstructure noise, we employ the tests proposed by Aït-Sahalia and Xiu (2019). Specifically, we apply each of the three tests recommended by the authors (i.e. the jump-robust Hausman test, the Student-t test, and the autocovariance-based test) to the stock's 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 these two criteria for a given sampling frequency, we repeat the procedure for the next lower frequency. If a stock does not satisfy the criteria for any of the three considered frequencies, we exclude it from our stock sample in the respective month.

The upper graph of Figure 1 depicts the final number of stocks that remain in each month in our sample after applying the exclusion criteria to our base sample. The two ad-hoc criteria, which catch 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 base sample. By contrast, the two frequency-dependent criteria, which catch stocks with a large percentage of zero-returns and stocks with significant microstructure noise, exclude a considerable fraction of stocks during the early part of the sample period from 1993 to around 2002. This leads to a sample size of around 1,200 to 1,500 stocks during the first few years, which gradually rises from 1997 onwards. During the second part of the sample period, beginning in 2002, the two frequency-dependent criteria exclude only a small fraction of stocks, which is most likely due to the substantial increase in liquidity and trading volume in the recent two decades. Consequently, while the number of stocks in the base sample decreases from a maximum of nearly

[17] For the implementation of the tests, we use the Matlab code provided on Dacheng Xiu's website `https://dachxiu.chicagobooth.edu/`. We are very thankful to Dacheng Xiu for making this code available.

8,000 stocks in the late 1990s to below 4,000 at the end of 2019, the number of stocks in our final sample steadily increases to above 3,500 until the mid of the 2000s, and afterward remains most of the time until the end of the sample period above 3,000. In sum, we are therefore confident that our sample, especially from the beginning of the 2000s onwards, is representative for the broad US stock market. This conjecture is also supported by the lower graph of Figure 1: our final sample accounts almost always for more than 80% of the stock market's total market capitalization, and from the beginning of 2000 onwards always for more than 95%.

[Insert Figure 1 near here.]

4.2 Beta Estimation Procedure

For all stocks in our final sample, we estimate betas at the end of each month from June 1993 to December 2019 based on the stocks' and factors' returns over the previous six months. This estimation window length of six months balances two aspects: on the one hand, we would like to account for as much time-variation in the betas as possible. As we need to make the implicit assumption that the betas are constant across the estimation window, this favors a shorter estimation window. On the other hand, we would like to have a large number of observations for the estimation in order to obtain sufficiently precise estimates for the betas. While this is hardly an issue for the estimation of the continuous betas, it is an important aspect for the estimation of the jump and overnight betas. As described below, we use only factors' jump and overnight observations for the estimation of jump and overnight betas. Since jumps are relatively infrequent events[18] while overnight observations are by nature restricted to one per day, we cannot choose our estimation window too short. Based on these considerations, we compromise on a six-month estimation window. Yet, we also reexamine our central findings in Section 5.4 for other estimation window lengths and find that they remain qualitatively largely unchanged.

We estimate daily factor betas with a standard OLS regression: stocks' daily returns across the six-month estimation window are regressed on the five daily Fama-French (2015) factors and an intercept. Overnight factor betas are estimated analogously, that is, stocks' overnight returns across the six-month estimation window are regressed on the factors' overnight versions and an intercept.

For the estimation of the high-frequency factor betas, we adapt the realized market beta estimator of Andersen et al. (2006) to a multivariate estimation framework. Specifically, the realized market beta estimator is equivalent to regressing stocks' high-frequency returns on the high-frequency market factor without an intercept. Consequently, we estimate high-frequency

[18] Across our sample period from January 1993 to December 2019, the average monthly number of jumps detected by the TOD estimator described in Section 3.3 was for the 30-minute versions of all five Fama-French (2015) factors in the range between 3.0 and 3.6.

betas by regressing stocks' high-frequency log-returns across the six-month estimation window on the factors' high-frequency log-returns without an intercept.

We estimate factor betas with respect to the continuous factor movements by employing only observations for which none of the factors exhibits a jump. In particular, like the previously described multivariate estimator for the high-frequency factor betas, this estimator essentially regresses stocks' high-frequency returns on the factors' high-frequency returns without an intercept. However, the estimation excludes all observations across the six-month estimation window for which any of the factors is detected to have a jump, and additionally sets all jump returns of the stocks to zero. Our continuous beta estimator can thus be expressed as follows:

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

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 across the estimation window, $1_{\{\cdot\}}$ is an indicator function, $f_{k,s}$ ($r_{i,s}$) is the return of factor k (stock i) in interval s, and $\mu_{k,s}$ ($\mu_{i,s}$) is the jump threshold for the return of factor k (stock i) in interval s. For the determination of the jump thresholds, we apply the TOD estimator described in Section 3.3 with $\tau = 3$ and $\omega = 0.49$ to the stocks' and factors' high-frequency log-returns across the estimation window.

Finally, the estimation of stocks' jump factor betas is less straightforward. If we would consider a single factor model, we could simply use the observations for which the factor is detected to have a jump and regress stocks' returns on the factor's returns. However, in our multifactor framework, we need to account for the stocks' exposures to the other factors. For this purpose, we adopt the following procedure to estimate a stock's jump beta with respect to a given factor: first, we identify all observations for which the respective factor is detected to have a jump but no other factor is detected to have a jump. Second, we adjust the stock's high-frequency returns for these observations by subtracting the other factors' high-frequency returns multiplied by the stock's continuous betas with respect to these factors. Intuitively, this removes the part of the stock's returns that is due to the stock's continuous exposure to the other factors (since we use only observations for which the other factors do not exhibit jumps, we can safely use the estimated continuous betas for this adjustment). Third, we regress the stock's adjusted high-frequency returns on the factor's high-frequency returns, using only the previously selected observations. This jump beta estimator can be expressed as follows:

$$\begin{aligned} \beta_{i,t}^{k,J} &= (F_{k,t}^{J}{}' F_{k,t}^{J})^{-1} F_{k,t}^{J}{}' \epsilon_{i,t}^{k} \\ F_{k,t}^{J} &= F_{k,t} 1_{\{|f_{k,s}| > \mu_{k,s}\}} 1_{\{\forall l \neq k: |f_{l,s}| < \mu_{l,s}\}} \\ \epsilon_{i,t}^{k} &= \left(R_{i,t} - F_t \beta_{i,t}^{C} + F_{k,t} \beta_{i,t}^{k,C}\right) 1_{\{|f_{k,s}| > \mu_{k,s}\}} 1_{\{\forall l \neq k: |f_{l,s}| < \mu_{l,s}\}} \end{aligned} \tag{11}$$

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, and the other variables are defined as in equation (10). For the determination of the jump thresholds, we apply again the TOD estimator with $\tau = 3$ and $\omega = 0.49$.

4.3 Estimation Results

Table 3 presents summary statistics of the estimated betas. In particular, it depicts the time series averages of the betas' cross-sectional means, medians, standard deviations, skewness, kurtosis, 1st-, 10th-, 90th-, and 99th-percentiles, and rank-correlations with their six-month lagged values. The summary statistics additionally include betas' rolling 12-month volatility averaged across all stock-months as well as betas' six-month lagged time series autocorrelation averaged across stocks.

[Insert Table 3 near here.]

First, comparing the daily betas and the simple high-frequency betas, we observe that their average cross-sectional means are very similar across all factors. Yet, the average cross-sectional standard deviations of the high-frequency betas are considerably lower, meaning that they are less dispersed in the cross-section, in turn suggesting that they are more precise and suffer less from return outliers. This conjecture is further supported by other statistics: the high-frequency betas' kurtosis are substantially lower, meaning that there are fewer outliers in the cross-section of high-frequency betas; the high-frequency betas' rolling 12-month time series volatilities are roughly half the daily betas' time series volatilities while the high-frequency betas' autocorrelations are considerably higher than the daily betas' time series autocorrelations, both of which imply that the high-frequency betas are much more stable and persistent; and the high-frequency betas' cross-sectional rank-correlations are usually almost twice the daily betas' cross-sectional rank-autocorrelations, meaning that the cross-sectional ranking of stocks based on the high-frequency betas is much more stable. These results hold for all factors and illustrate the general benefits of using high-frequency data for the estimation of betas.

The properties of the continuous betas are very similar to those of the corresponding high-frequency betas. In particular, the continuous betas also have low cross-sectional standard deviations (even somewhat lower than the high-frequency betas), moderate kurtosis, low rolling 12-month time series volatilities, strong time series autocorrelations, and high six-month lagged rank-correlations. The most notable difference between continuous and high-frequency betas is that the means of the continuous betas are in general in absolute terms somewhat lower than those of the corresponding high-frequency betas.

By contrast, the properties of the jump betas are very different from those of the continuous betas. In particular, jump betas exhibit much higher cross-sectional standard deviations and kurtosis. This is in parts likely to be attributable to higher estimation errors in the jump betas due to the lower number of observations used in the estimation. In line with this conjecture, jump betas also seem to be much less persistent and stable than continuous betas: their rolling 12-month volatilities are substantially higher, their time series autocorrelations are close to zero, and their six-month lagged rank-correlations are much lower.

Finally, overnight betas display quite similar properties as jump betas. Specifically, overnight betas also exhibit high cross-sectional dispersion and low persistence. As for jump betas, part of this might be attributable to potential estimation errors given that the estimation of overnight betas relies on considerably fewer observations than the estimation of continuous betas.

Beyond the summary statistics on the raw betas, Table 3 reports also summary statistics on the absolute differences between jump and continuous betas as well as between overnight and continuous betas. The average cross-sectional medians of the absolute differences between jump and continuous betas vary strongly across the different factors but are in general quite considerable: the median absolute difference ranges between 0.30 for market betas and 0.90 for investment betas. The results on the differences between overnight and continuous betas are quantitatively quite similar: the median absolute difference ranges between 0.36 for market betas and 0.72 for investment betas. In sum, these findings indicate that continuous, jump, and overnight betas are in general far from being equal, and thus, that discrete factor models that fail to account for these differences represent an oversimplification. This finding justifies the separation of continuous, jump, and overnight betas as well as the investigation of their separate pricing.

4.4 Relation between Betas and Characteristics

Table 4 reports time series averages of monthly cross-sectional correlations between the daily, overnight, high-frequency, continuous, and jump betas. Considering that they should measure the same quantity, daily and high-frequency betas exhibit across all factors only moderate correlations in the range between 0.4 and 0.6. As expected, the simple high-frequency betas and the continuous betas exhibit quite high correlations of around 0.9. By contrast, jump betas are much less correlated to the simple high-frequency betas. Correlations between continuous and jump betas are naturally weaker, ranging between 0.24 for investment betas and 0.52 for market betas. Moreover, overnight betas exhibit even lower correlations with continuous betas, ranging from 0.15 for investment betas to 0.38 for market betas. Additionally, while both capture exposure to factors' discontinuous movements, jump, and overnight betas are with correlations below 0.25 also only moderately related. Overall, while the unanimously positive correlations indicate that there is certainly a common component in continuous, jump, and overnight betas, the results show that they are only weakly related, suggesting that they reflect in most parts very different effects. What is more, though both jumps and overnight returns are viewed as discontinuous movements, stocks' exposures to these two sources of discontinuous movements can be quite different.

[Insert Table 4 near here.]

Beyond the correlations between the different betas, Table 4 also presents the correlations of the betas with prominent stock- and firm-level characteristics. The full list of variables as well as their construction is presented in Appendix A. The most notable observation is that the continuous betas exhibit across all factors the highest correlations with the factors' sorting variables (i.e. ME for SMB, BM for HML, OP for RMW, and INV for CMA). Overnight betas exhibit the lowest correlations with the sorting variables while the correlations of jump betas are between those of continuous and overnight betas.

Furthermore, the decomposed betas correlations' with the other variables besides the sorting variables exhibit no pronounced patterns that are similar across all factors. In particular, contrary to what one might expect, there are no considerable differences in continuous, jump, and overnight betas' correlations with illiquidity, idiosyncratic risk, or higher moments of returns. This indicates that the divergence between continuous, jump, and overnight betas is not due to these effects.

In order to further illustrate the relations among the different betas and between betas and characteristics, Table 5 presents average value-weighted betas and characteristics of beta-sorted portfolios. Specifically, we sort stocks in each month into quintiles with respect to their daily, overnight, high-frequency, continuous, or jump betas. The breakpoints for the sorts are based on NYSE stocks only. Table 5 depicts the average monthly spreads in betas and characteristics between the sorts' top and bottom portfolios. By construction, the high-minus-low portfolios exhibit for all betas across all factors high spreads in the respective sorting beta. The jump and overnight beta-sorted portfolios exhibit in general considerably higher beta spreads than the continuous beta-sorted portfolios. This observation is consistent with the betas' cross-sectional dispersions documented in Table 3. Moreover, in line with the positive correlations between the different betas, the portfolios also have positive spreads in the other betas with respect to the same factor. One noteworthy result is that the spreads of the market beta-sorted portfolios are across all types of betas unanimously lower than those of the betas with respect to the other factors, reflecting the lower dispersion of market betas[19].

[Insert Table 5 near here.]

The characteristics-spreads of the beta-sorted portfolios largely confirm the observations from Table 4[20]. In particular, all high-minus-low portfolios exhibit large spreads in the sorting variable of the respective factor, whereby spreads are highest for continuous beta-sorted portfolios, lower for jump beta-sorted portfolios, and lowest for overnight beta-sorted portfolios. One notable exception are the profitability beta-sorted portfolios, which exhibit in line with their

[19]This is in line with the evidence of Fama and French (1993) who find that the differences in the pricing implications of their three-factor model are mainly due to the strong cross-sectional variation in the size and value betas. By contrast, the low variation in market betas accounts only for a minor fraction of the pricing differences.

[20]In order to facilitate the interpretability of the results, characteristics are in each month standardized to have a mean of zero and a standard deviation of one.

low correlations with OP as observed in Table 4 quite low spreads in OP. As for the correlations, the spreads of the remaining characteristics are in general not distinctly different between continuous, jump, and overnight beta-sorted portfolios.

5 Risk Premia for Continuous and Discontinuous Factor Risk Exposures

This section presents our results on the pricing of the different factor risk exposures. In the first part, we consider univariate portfolio sorts with respect to the different betas, and in the second part bivariate portfolio sorts where we control either for another beta or for the corresponding factor's underlying sorting variable. The third part reports results of Fama-MacBeth (1973) regressions, and the fourth part considers various robustness checks for the results from the Fama-MacBeth (1973) regressions. In the fifth part, we relate our results to the findings of Bollerslev et al. (2016), and in the final part, we discuss potential explanations for our central findings.

5.1 Univariate Portfolio Sorts

At the end of each month from January 1993 to June 2019, we sort all stocks into five portfolios according to their daily, high-frequency, continuous, jump, and overnight factor betas estimated across the next six months. The breakpoints of the five portfolios are the quintiles of all NYSE stocks[21]. The stocks in the portfolios are value-weighted based on their market capitalizations at the end of the sorting month. We calculate each portfolio's return across the next six months as the value-weighted average of the stocks' compounded returns, that is, we calculate the portfolios' returns across the same period across which the betas are estimated. We use contemporaneous returns because factor models predict first and foremost a contemporaneous relation between risk, as measured by betas, and expected returns. For this reason, employing contemporaneous returns is also the usual approach in the empirical asset pricing literature for the investigation of the pricing of factor betas (see e.g. Ang et al. (2006a), Cremers et al. (2015), and Jegadeesh et al. (2019)).

Panel A of Table 6 depicts the time series averages of the return spreads between the top and bottom portfolio of each sort. In order to account for the use of overlapping return periods - we evaluate the portfolios' six-month returns on a monthly basis - the return spreads' t-statistics are computed using Newey-West (1987) standard errors with six lags. Panel B reports the high-minus-low spreads in the sorting betas, and Panel C reports the high-minus-low spreads in

[21]We use only NYSE stocks for the determination of breakpoints in order to mitigate the impact of microcaps. This approach is strongly recommended by Hou et al. (2020).

the factors' underlying sorting variables. These two panels show that all portfolio sorts produce large spreads in the betas as well as in the factors' sorting variables.

[Insert Table 6 near here.]

The first notable observation from Panel A of Table 6 is that the spread portfolios sorted according to the daily betas mostly earn negative, albeit statistically insignificant, returns whereas the spread portfolios sorted according to the simple high-frequency betas earn considerably higher returns across all factors (the increase ranges from 0.1% to 0.3% per month). While the predicted positive relation between betas and returns does in general not hold for high-frequency betas either, this observation indicates that the high-frequency betas do much better than daily betas in reflecting the predicted positive relation with returns.

Turning to the pricing of the decomposed betas, Panel A documents that the return spreads between the top and bottom continuous beta-sorted portfolios are mostly somewhat lower than those of the high-frequency beta-sorted portfolios. The high-minus-low return spreads of the jump beta-sorted portfolios are in turn mostly lower than those of the continuous betas, and the return spreads of the overnight beta-sorted portfolios are the lowest. Nevertheless, the pricing pattern is the same across all the different betas: exposure to profitability risk earns positive returns, exposure to market risk earns close to zero returns, and exposures to size, value, and investment risks earn negative returns. However, almost none of the high-minus-low return spreads is statistically significant. While these findings fail to confirm the proposed positive relation between betas and returns, the positive pricing of profitability factor exposure as well as the negative pricing of size, value, and investment factor exposures are in line with the large and significant profitability premium as well as the small and insignificant size, value, and investment premia during our sample period as documented in Table 1.

The similarities in the factor exposures' pricing across the continuous, jump, and overnight betas suggest that the return spreads reflect mainly the betas' common component. In a first attempt to isolate the different betas' individual components, we additionally conduct portfolio sorts with respect to relative betas. This approach follows Ang et al. (2006a). In particular, we sort stocks into portfolios with respect to the difference between their jump and continuous betas (hf. relative jump beta) as well as with respect to the difference between their overnight and continuous betas (hf. relative overnight beta). The high-minus-low return spreads of these portfolio sorts are displayed in the last two columns of Panel A of Table 6. For all relative jump betas except the relative value jump beta, the high-minus-low return spreads are negative, but economically as well as statistically insignificant. These results suggest that investors command mostly slightly higher return premia for exposure to continuous factor risks than for exposure to jump factor risks.

Furthermore, Table 6 documents significantly negative return spreads for relative overnight market and profitability betas (-0.22% and -0.24% per month), indicating that investors command higher return premia for continuous than for overnight exposure to these factors. By contrast, the return spread of the relative overnight size beta sort is positive (0.19% per month), albeit statistically insignificant. For the relative value and investment overnight betas, the return spreads are negative but insignificant.

In sum, the results from Table 6 on the one hand reflect the usual finding that the exposures to the factors are only weakly positively or even negatively related to returns. Based on the univariate sorts, this conjecture does not seem to change when decomposing betas into their continuous, jump, and overnight components. On the other hand, the results suggest that investors command in general somewhat lower premia for exposures to the factors' jump and overnight risks than for exposures to the factors' continuous risks. This holds especially for exposures with respect to the market and profitability factors' risks.

5.2 Bivariate Portfolio Sorts

The results from the univariate portfolio sorts deliver some first indications which of the factors' risks may be priced and how the pricing of the distinct factor risks differs. Yet, although the relative beta sorts are a first step in this direction, the univariate portfolio sorts are insufficient to separate the pricing implications of continuous, jump, and overnight betas. In order to disentangle the pricing of the decomposed betas more clearly, we conduct in this subsection bivariate portfolio sorts. Specifically, we investigate the return premia associated with the different betas while controlling for one of the other betas. Additionally, in order to examine whether the pricing of betas simply reflects the predictive power of the factors' underlying characteristics, we also conduct bivariate portfolio sorts in which we control for the factors' characteristics.

Like the univariate portfolio sorts, we implement the bivariate portfolio sorts at the end of each month from January 1993 to June 2019. First, we sort all stocks into five portfolios with respect to the control variable. If the control variable is a beta, it is estimated across the next six months; if the control variable is the underlying characteristic of the respective factor, it is measured at the end of the sorting month. The breakpoints of the five portfolios are the quintiles of all NYSE stocks. Second, within each of the five control portfolios, all stocks are sorted into five portfolios according to the beta of interest. The breakpoints for the sorts within each of the five control portfolios are the quintiles of all stocks in the respective portfolio[22]. As previously, the stocks in the portfolios are value-weighted based on their market capitalizations at the end of the sorting month, and we calculate each portfolio's return across the next six months as the value-weighted average of the stocks' compounded returns. Finally, we average the same sub-portfolios from the second sorts across the five control portfolios from the first sort. Thereby, we get five beta-sorted portfolios that exhibit a large variation in the beta of interest but only a small variation in the control variable.

Panel A of Table 7 reports the time series averages of the return spreads between the top and

[22]We use breakpoints that are based on all stocks rather than NYSE stocks in the second sorts in order to avoid thinly populated portfolios.

bottom portfolios, whereby t-statistics are again computed using Newey-West (1987) standard errors with six lags. Panel B reports the high-minus-low spreads in the betas of interest, and Panel C reports the high-minus-low spreads in the control variables. These panels show that the bivariate portfolio sorts are successful in producing large spreads in the betas of interest but only small spreads in the control variables. This allows us to capture the part of the return premia associated with the betas of interest that are largely independent of the control variables.

[Insert Table 7 near here.]

The first two columns of Panel A of Table 7 provide direct evidence for the conjecture that high-frequency betas do much better than daily betas in reflecting the predicted positive relation between betas and returns. The sorts according to the high-frequency betas, controlling for the respective daily betas, yield unanimously positive and economically large high-minus-low return spreads. The opposite pattern emerges when sorting according to daily betas while controlling for the respective high-frequency betas: all high-minus-low return spreads associated with the daily betas are negative, and in parts even significant. These findings indicate that those parts of the factor exposures that the high-frequency betas reflect but are missed by the daily betas are priced in the cross-section of stocks and line up with the theoretical prediction, whereas those parts of the factor exposures measured by the daily betas but not picked up by the high-frequency betas are negatively priced. Thus, high-frequency betas seem to do a much better job than daily betas in capturing stocks' priced risk exposures.

Columns three to eight of Panel A of Table 7 depict the return premia of the continuous, jump, and overnight factor betas when controlling for one of the other betas. For the market beta, a clear picture unfolds: the return spreads associated with the continuous market beta are positive (0.28% and 0.16% per month) when controlling for either the jump or the overnight market beta. By contrast, the return spreads associated with the jump market beta are positive but small (0.03% and 0.11% per month), and the return spreads associated with the overnight market beta are negative (-0.27% and -0.16% per month) - even significantly negative when controlling for the continuous market beta. Taken together, these results indicate that the continuous market beta is positively priced, the jump market beta is lower or not at all priced, and the overnight market beta is negatively priced. This conclusion is very well in line with the results from the relative beta sorts in Table 6.

Like for the market betas, the return spreads associated with the continuous profitability beta are positive and economically but not statistically significant, whereas the return spreads associated with the jump (overnight) profitability beta are small (negative). These findings indicate that the continuous profitability beta is positively and that the overnight profitability beta is negatively priced. This is consistent with the findings from the univariate portfolio sorts in Table 6. Furthermore, for the size factor betas, Panel A of Table 7 displays negative return spreads for the jump and overnight betas, and positive return spreads for the continuous beta. However, the return spreads are economically rather moderate and statistically insignificant. Finally, the return spreads of the value and investment betas are small and do not display clear patterns, suggesting that neither of these betas is priced. Except for the negative pricing of the overnight size beta, these results are largely in line with those from the relative beta sorts in Table 6.

The last five columns of Panel A of Table 7 report the return premia associated with the different factor betas when controlling for the factors' underlying characteristics (i.e. ME for SMB betas, BM for HML betas, OP for RMW betas, and INV for CMA betas; in case of market betas, we control also for ME). First, market and profitability betas are the only betas that exhibit a positive relation to returns after controlling for their factor characteristics, while all size, value, and investment betas are priced negatively after controlling for their factor characteristics. These results are largely in line with and quantitatively similar to those from the univariate portfolio sorts in Table 6, implying that the pricing implications of the factor betas are hardly affected by controlling for the factors' characteristics.

Nevertheless, a second noteworthy observation is that the factor betas' relative ordering remains largely the same even when controlling for the factor characteristics. In particular, the continuous market and profitability betas are again priced higher than the corresponding jump and overnight betas. Moreover, high-frequency betas are again unanimously and notably higher priced than daily betas.

Overall, the results from the bivariate portfolio sorts strengthen the conjecture from the univariate portfolio sorts that continuous market and profitability exposures are priced higher than the corresponding jump and overnight exposures. Moreover, also largely in line with the previous findings, the results from the bivariate portfolio sorts suggest that the decomposed value and investment betas are hardly priced differently. The only major inconsistency between the univariate and bivariate portfolio sorts is that the bivariate sorts indicate a negative pricing of overnight size exposure whereas the relative overnight size beta sort suggested a positive pricing.

5.3 Fama-MacBeth Regressions

So far, we relied on portfolio sorts for the examination of the factor betas' pricing. However, although the bivariate portfolio sorts in the previous subsection extend the univariate portfolio sorts from Subsection 5.1 by controlling for other potential pricing factors when examining the return premia associated with the factor exposures, they still do not represent an all-encompassing pricing framework. Multifactor models imply that it is necessary to consider all potentially priced factor exposures simultaneously in order to reliably estimate their risk premia. In this subsection, we therefore estimate the factor betas' risk premia by means of cross-sectional Fama-MacBeth (1973) regressions. This approach allows us to account for all factor betas at the same time. Additionally, we can also control for further firm- and stock-level characteristics that may contain relevant pricing information.

We implement the Fama-MacBeth (1973) regressions by estimating in each month t from

January 1993 to June 2019 the following cross-sectional stock-level regression:

$$r_{i,t} - r_{f,t} = \gamma_{0,t} + \sum_{k=1}^{5} \gamma_{k,t}^{C} \cdot \hat{\beta}_{i,t}^{k,C} + \sum_{k=1}^{5} \gamma_{k,t}^{J} \cdot \hat{\beta}_{i,t}^{k,J} + \sum_{k=1}^{5} \gamma_{k,t}^{N} \cdot \hat{\beta}_{i,t}^{k,N} + \sum_{c=1}^{C} \gamma_{c,t}^{X} \cdot X_{i,t}^{c} + \epsilon_{i,t} \tag{12}$$

where $r_{i,t}$ ($r_{f,t}$) is the compounded return of stock i (risk-free rate) from month $t+1$ to $t+6$, $\hat{\beta}_{i,t}^{k,C}$ ($\hat{\beta}_{i,t}^{k,J}$, $\hat{\beta}_{i,t}^{k,N}$) is the continuous (jump, overnight) beta of stock i with respect to factor k estimated based on returns from month $t+1$ to $t+6$, $\gamma_{k,t}^{C}$ ($\gamma_{k,t}^{J}$, $\gamma_{k,t}^{N}$) is the risk premium associated with factor k's continuous (jump, overnight) beta, $X_{i,t}^{c}$ is a characteristic of stock i as measured at the end of month t, $\gamma_{c,t}^{X}$ is the risk premium associated with characteristic c, and C is the number of included characteristics. For comparison, we estimate the regression also by using only one set of betas (i.e. either only continuous betas, only jump betas, or only overnight betas) as well as by using standard daily and simple high-frequency betas.

From the estimation of the Fama-MacBeth (1973) regressions, we obtain monthly estimates for the six-month risk premia, denoted by $\hat{\gamma}_{k,t}^{C}$, $\hat{\gamma}_{k,t}^{J}$, $\hat{\gamma}_{k,t}^{N}$, and $\hat{\gamma}_{c,t}^{X}$. We calculate our final estimates for the risk premia by averaging the monthly risk premia estimates across the entire sample period of $T = 318$ months:

$$\begin{aligned} \hat{\gamma}_{k}^{z} &= \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{k,t}^{z} \qquad z \in \{Daily, HFQ, C, J, N\} \\ \hat{\gamma}_{c}^{X} &= \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{c,t}^{X} \end{aligned} \tag{13}$$

For the estimation of the Fama-MacBeth (1973) regressions, we winsorize all dependent and independent variables at the 1st and 99th percentile. Moreover, the regressions are estimated with weighted least squares (WLS) rather than ordinary least squares (OLS), whereby the weights correspond to the stocks' market capitalizations at the end of month t[23].

We control for several prominent characteristics that have been found to have predictive power for future stock returns. The first set of control variables are the characteristics underlying the Fama-French (2015) factors, namely size (ME), book-to-market ratio (BM), operating profitability (OP), and investment (INV). The second set of control variables capture several further effects that have been documented in the literature (see Jegadeesh and Titman (1993), Jegadeesh (1990), Ang et al. (2006b), Amihud (2002), Ang et al. (2006a), and Amaya et al. (2015)): momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), co-skewness (CSK), co-kurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). These characteristics are measured at the end of month t, that is, the controls are predictive (ex-ante) variables as opposed to the betas which are contemporaneous (ex-post) variables. In order to facilitate the interpretability of the results, the characteristics are in each month standardized to have a mean of zero and a standard deviation of one.

[23]Using WLS instead of OLS in Fama-MacBeth (1973) regressions is strongly recommended by Hou et al. (2020) in order to avoid overweighting small stocks.

The estimates for the average risk premia are presented in Table 8. Since the dependent returns are like in the portfolio sorts overlapping six-month returns, t-statistics are again computed using Newey-West (1987) standard errors with six lags. Contrary to the results in the original studies, Panel A shows that, no matter whether considered individually in univariate regressions or jointly in multivariate regressions, the return premia associated with the control variables are mostly insignificant and fairly weak. This is in line with the empirical finding that many anomalies have considerably weakened in recent decades, especially since their respective publications (see e.g. McLean and Pontiff (2016) and Hou et al. (2020)). Moreover, part of this result may also be due to the considered return horizon, namely six months instead of the usually employed one-month horizon.

[Insert Table 8 near here.]

Panels B and C of Table 8 display the risk premium estimates for the daily and high-frequency factor betas, respectively. As the results for the portfolio sorts, the results from the Fama-MacBeth (1973) regressions show an improvement of the high-frequency betas upon the daily betas with regard to reflecting a positive relation between betas and returns. In particular, the estimated risk premia for all factor betas except the size beta are across all specifications higher for high-frequency than for daily betas. The results further reveal that, across all specifications, market and profitability betas are consistently positively priced whereas size, value, and investment betas are consistently negatively priced. These observations are in line with the results from the portfolio sorts, but again contradict the prediction of the Fama-French (2015) model that the exposure to each factor needs to be positively priced.

Panels D, E, and F of Table 8 report the risk premium estimates for the continuous, jump, and overnight betas, respectively, when they are used separately as explanatory variables. The risk premium estimates for the continuous betas are similar to those of the high-frequency betas: the risk premia of the continuous market and profitability betas are positive (ranging between 0.36% and 0.69% respectively 0.09% and 0.19% per month, depending on the controls included in the regression model), but mostly insignificant. By contrast, the continuous size beta is insignificantly (significantly) negatively priced without (with) controls. Value and investment betas are also negatively but mostly insignificantly priced. These pricing results are consistent with the findings from the portfolio sorts.

The estimated risk premia for the jump betas documented in Panel E exhibit qualitatively largely the same pricing patterns as the estimated risk premia for the continuous betas, just with lower magnitudes. The similarity in the pricing patterns of continuous and jump betas has already been observed in the univariate portfolio sorts in Table 6. Hence, this suggests again that the risk premia primarily reflect the continuous and jump betas' common component when they are considered individually. The most relevant difference between the continuous and jump betas' estimated risk premia is that those for the jump market beta are in general close to zero while those for the continuous market beta are clearly positive. Yet, this is well in line with the results from the portfolio sorts.

The estimated overnight risk premia presented in Panel F display a somewhat different picture: the overnight market risk premium is consistently negative across all specifications. This negative pricing of overnight market exposure is consistent with the negative return spreads of the relative overnight market beta sort in Table 6 as well as the bivariate overnight market beta sorts in Table 7. Moreover, in line with the positive return premium for the relative overnight size beta, the estimated overnight size risk premia are with values of around 0.07% per month positive, albeit economically small. The overnight profitability risk premia are also consistently positive but small and insignificant. By contrast, the overnight value and investment risk premia are negative but smaller than those of the corresponding continuous betas in Panel D. Altogether, these results show that the risk premia for overnight factor risk exposure are except for overnight market exposure similar or somewhat higher than those for continuous and jump exposure. This observation is different from the findings from the portfolio sorts which suggest in general the opposite.

Finally, Panel G of Table 8 depicts the risk premium estimates when all continuous, jump, and overnight betas are jointly included, corresponding to the full regression model as depicted in equation (12). First, we document a strong and significant risk premium estimate of 0.84% per month for the continuous market beta, which even increases when controls are included. On the other hand, the overnight market risk premium is strongly and significantly negative, ranging between -0.47% and -0.55% per month. The jump market risk premium fluctuates around zero across the different specifications and is never significant. Since these results are very well in line with the results from the portfolio sorts, we conclude that there is robust evidence for a positive pricing of continuous market exposure and for a negative pricing of overnight market exposure. By contrast, jump market exposure does not seem to be priced.

Beyond the significant risk premia for continuous and overnight market exposures, Panel G further reports statistically and economically significant negative risk premia for the continuous size, value, and investment betas, especially when further controls are included (on average -0.52%, -0.44%, and -0.22% per month, respectively, across the different specifications). The estimates for the continuous profitability beta's risk premium are positive but small and insignificant. Contrary to the continuous risk premia, the estimated risk premia for overnight exposures to the size, value, profitability, and investment factors are with average values of 0.14%, 0.14%, 0.08%, and 0.11% per month, respectively, uniformly positive and mostly statistically significant. Finally, the risk premium estimates for the jump value, profitability, and investment betas are across all specifications close to zero and insignificant while the jump size risk premium estimates are all significantly negative (on average -0.13%).

Relating these results to our previous findings, we note that the mostly negative pricing of the continuous exposures as well as the zero pricing of jump exposures with respect to the factors beyond the market factor are largely in line with the results from Panels D and E as well as with the portfolio sorts in Tables 6 and 7. On the other hand, the finding that overnight exposures with respect to these factors exhibit uniformly positive risk premia, thereby exceeding the risk premia for the corresponding continuous and jump exposures, differs from the portfolio sorts' results. In particular, the relative beta sorts in Table 6 and the bivariate beta sorts in Table 7 both suggest (except for size) that the overnight betas are, if anything, lower priced than the corresponding continuous and jump betas. Yet, the positive pricing of the factors' overnight risks is well in line with the results from Panel F of Table 8: when all overnight betas are jointly considered, their risk premia are, except for the profitability overnight beta, higher than the corresponding continuous betas' risk premia in Panel D. We therefore suspect that the portfolio sorts failure to document a positive pricing of the overnight factor risk exposures is most likely due to the fact that they do not control for the other exposures. For this reason, we argue that our findings suggest that the exposures to the size, value, profitability, and investment factors' overnight movements are the most likely source of the factors' empirically documented return premia.

5.4 Robustness Checks

We conduct several robustness checks for our findings from the Fama-MacBeth (1973) regressions as discussed in the last subsection. First, we examine alternative estimation windows of three and 12 months. Second, instead of our mixed-frequency approach, we use the same frequency for all stock-months in the estimation of the betas and exclude those stock-months that do not satisfy the criteria stated in Section 4.1 for the respective frequency. Thereby, we consider 15-, 30-, and 75-minute sampling frequencies. Third, we restrict our sample to all stocks that have ever been in the S&P500 during our sample period from January 1993 to December 2019 (we identify 1,158 distinct stocks that have been included in the S&P500 somewhen during our sample period). In this robustness check, we follow the literature and assume that the S&P500 stocks do not exhibit major microstructure issues, wherefore we do not apply any of the exclusion criteria stated in Section 4.1 and use our highest sampling frequency of 15 minutes.

Fourth, we consider a different methodology for estimating jump betas: we adapt the market jump beta estimator developed by Todorov and Bollerslev (2010) and employed by Bollerslev et al. (2016) to a multivariate estimation framework. This estimator essentially regresses a stock's squared returns, multiplied by their original signs, on the squared market returns, also multiplied by their original signs, without an intercept. The intuition underlying this approach is that the continuous return components asymptotically vanish when squaring the returns, making the jump components "visible". 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. We follow this procedure and simply extend it from a univariate to a multivariate regression.

The risk premium estimates obtained from these robustness checks are presented in Panels A to G of Table 9. Although the estimated risk premia are in parts quantitatively somewhat different than those estimated with our standard procedure in Panel G of Table 8, our central findings are in general largely confirmed by the robustness checks. In particular, there is always a sizable and statistically highly significant positive (negative) risk premium for continuous (overnight) market exposure whereas jump market exposure almost never carries an economically or statistically significant risk premium. These findings hold no matter whether controls are included or not.

[Insert Table 9 near here.]

Moreover, the continuous size, value, and investment betas exhibit across all specifications negative and mostly significant risk premia while the continuous profitability beta is by tendency slightly positively but never significantly priced. The overnight size, value, profitability, and investment betas are always positively priced, although the risk premia are in general economically rather moderate, but nevertheless still mostly significant. Finally, the estimated risk premia of the jump value, profitability, and investment betas remain small and mostly insignificant whereas the significant negative pricing of the jump size beta as documented in Table 8 cannot be confirmed in all robustness checks.

There is a subtle but widely recognized problem when estimating the regression model in (12) (see e.g. Shanken (1992)): the betas used as explanatory variables are estimated quantities that measure the true betas with error, introducing an errors-in-variables bias in the risk premium estimates $\hat{\gamma}$. Measurement error in a given explanatory variable leads usually to an attenuation bias in the corresponding coefficient, meaning that the risk premium estimates of the betas would be biased towards zero. Based on this reasoning, one may expect that the true risk premia should be quantitatively higher than documented in Table 8. However, the measurement error in a given variable may in general also lead to a contamination bias of unknown direction in other variables' coefficients. In our setting, this issue is further aggravated by the fact that there are multiple variables, namely all betas, that potentially suffer from measurement error. Therefore, it is hardly possible to predict how the potential errors-in-variables bias may affect our findings.

In order to make sure that our conclusions are not due to this issue, we additionally implement the Fama-MacBeth (1973) regressions by employing the instrumental variables approach proposed by Jegadeesh et al. (2019). In particular, Jegadeesh et al. (2019) suggest to split the estimation period into two subsets and estimate the betas separately from each subset. The betas from the first subset are then used as instrumental variables for the betas from the second subset when the later are employed as explanatory variables for stocks' returns across the second subset's sample period. As pointed out by Jegadeesh et al. (2019), this approach eliminates the errors-in-variables bias because the estimation errors in the two sets of betas are uncorrelated given that they are estimated from disjoint data samples. Our concrete implementation of this approach is outlined in Appendix B.

Panel H of Table 9 depicts the risk premium estimates when the Fama-MacBeth (1973) regressions are estimated with the instrumental variables approach. In general, the estimated risk premia display the same pricing patterns as those from the standard Fama-MacBeth (1973) regressions in Table 8: the continuous (overnight) market beta is significantly positively (negatively) priced; continuous size, value, and investment betas are significantly negatively priced; and overnight size, value, profitability, and investment betas are positively and mostly significantly priced. While the estimates for the continuous betas' risk premia have similar magnitudes as those in Panel G of Table 8, the estimates for the overnight betas' risk premia are in general somewhat, in parts even considerably, larger, and become thus economically much more meaningful.

On the one hand, these results suggest that the risk premium estimates for overnight factor exposures from the standard Fama-MacBeth (1973) regressions in fact suffer from an attenuation bias towards zero that is due to estimation errors in the overnight betas. On the other hand, the results further support and even strengthen our conclusion that overnight size, value, profitability, and investment factor exposures are positively priced.

5.5 Comparison with the Findings of Bollerslev et al. (2016)

Our study is closely related to that of Bollerslev et al. (2016). However, our findings on the pricing of the different market risk exposures are at odds with the findings of Bollerslev et al. (2016). Based on univariate portfolio sorts with respect to relative jump and overnight betas (similar to our univariate portfolio sorts in Table 6), they argue that jump and overnight market betas are priced higher than continuous market betas in contemporaneous returns. Moreover, employing again univariate portfolio sorts as well as bivariate portfolio sorts and Fama-MacBeth (1973) regressions, they document that the jump and overnight market betas are significantly positively priced in one-month ahead returns and that they subsume the predictive power of the continuous market beta. These results stand in stark contrast to our conclusion that continuous market exposure is positively priced, overnight market exposure is negatively priced, and jump market exposure is not priced.

There are several important differences between the empirical approach of Bollerslev et al. (2016) and our empirical approach that could give rise to the differences in the results. First, we have naturally a longer sample period, running until December 2019 rather than December 2010. Second, we use a mixed-frequency approach and an estimation window of six months to estimate betas rather than a 75-minute sampling frequency and an estimation window of 12 months. Third, our sample includes all common US stocks traded on the NYSE, AMEX, and NASDAQ rather than only S&P500 stocks. Fourth, we use value-weights rather than equal-weights in the portfolio sorts and Fama-MacBeth (1973) regressions. Fifth, our focus lies on the contemporaneous rather than the predictive relation between betas and returns. Sixth, we use a different approach for estimating betas. Finally, we investigate the pricing of exposures to the five Fama-French (2015) factors rather than only the pricing of exposures to the CAPM market factor.

In order to trace back the source of the contradictory findings to these differences, we repeat the empirical procedure as described by Bollerslev et al. (2016) and then conduct sensitivity analyses by changing at each time only one of the aspects (unreported). First, we obtain qualitatively largely similar results as Bollerslev et al. (2016) when repeating their analyses without any changes. Second, extending the sample period to the end of 2019, estimating betas based on our mixed-frequency approach across a six-month estimation window, and implementing the Fama-French (2015) model rather than the CAPM yields qualitatively also similar results.

However, we find that the results completely reverse as soon as we use value-weights: in line with *our* results, we find a positive (zero, negative) pricing of continuous (jump, overnight) betas when value-weights are used. We also document that the reported positive relations between one-month ahead returns and jump and overnight betas hold only for the S&P500 sample but not for our extended sample. Moreover, implementing their Fama-MacBeth (1973) regressions with contemporaneous rather than one-month ahead returns leads again to a reversal of their results. Finally, the results also do not hold when we use our methodology for estimating continuous and jump betas. In sum, we therefore conclude that the differences between the findings of Bollerslev et al. (2016) and our findings are due to using value-weights, due to our extended stock sample, due to the investigation of a contemporaneous rather than a predictive relation, and due to a different beta estimation methodology.

While the approach of Bollerslev et al. (2016) is certainly not unreasonable, we believe that our approach is more appropriate. In particular, since the representative investor holds the *value*-weighted rather than the *equal*-weighted market portfolio, value-weighted results reflect the overall effects arguably better. Moreover, the focus on the contemporaneous relation between betas and returns is implied by factor pricing models, and hence, is more suited to investigate the underlying economic mechanism. Finally, contrary to the findings of Bollerslev et al. (2016), our findings hold for all common US stocks as well as for the S&P500 stocks (see Panel F of Table 9), and are also robust to the beta estimation methodology (see Panel G of Table 9).

5.6 Potential Explanations

In the last part of this section, we discuss a few potential explanations for our central findings based on the results of other empirical studies. First, there exists an interesting link between our findings and those of Lou et al. (2019). The later study shows, and we confirm in Table 2, that the market premium is largely earned overnight whereas the size, value, profitability, and investment premia are entirely earned intraday and reverse overnight. Lou et al. (2019) argue that these patterns are due to clientele effects and also provide evidence for this conjecture. Our results mirror their results: we find positive premia for exposure to continuous (i.e. intraday) market risk and overnight size, value, profitability, and investment factor risks. Based on the argument of Lou et al. (2019), our results therefore suggest that there is an investor clientele that is averse to the size, value, profitability, and investment factors' overnight risks - potentially because another clientele is trading against these factors overnight - and that investors are compensated for overnight exposure to these factors by higher intraday returns. Analogously, there may be an investor clientele that is averse to the market's intraday risk and is compensated for intraday exposure by higher overnight returns. We believe that investigating the mechanism that generates these patterns more closely would be an exciting route for future research.

Lochstoer and Tetlock (2020) document another empirical finding that may be related to our results. They decompose the variation in the factors' returns into discount rate and cash flow news, and find that the market return is mainly driven by discount rate news whereas the size, value, profitability, and investment factor returns are mainly driven by systematic cash flow news. This suggests that the market risk premium is a compensation for exposure to discount rate news while the other factors' premia are compensation for exposure to systematic cash flow news. Relating this conjecture to our results, one may suspect that the continuous market beta reflects priced discount rate news exposure while the overnight factor exposures reflect priced cash flow news exposure. Investigating whether this explanation applies may also be interesting for future research.

6 Conclusion

In this study, we consider a continuous-time representation of the Fama-French (2015) five-factor model that accounts for three sources of variation in the factors: continuous intraday movements, intraday jumps, and overnight movements. By expressing the economy-wide stochastic discount factor as a linear function of the factors and by acknowledging that the SDF may have different loadings on the factors' different sources of variation, we argue that not every type of factor risk exposure needs to be priced. In particular, only those sources of factor variation that proxy for the SDF should carry a non-zero risk price. This further implies that the risk premia for exposures to the different types of factor risks may be different.

We investigate the separate pricing of the factor risks based on the sample of all common US stocks traded on the NYSE, AMEX, and NASDAQ for the period from January 1993 to December 2019. For this purpose, we retrieve high-frequency data for this stock sample from the TAQ database, thereby creating the most comprehensive high-frequency dataset that has ever been used in the literature. Based on our high-frequency versions of the five Fama-French (2015) factors, we estimate stocks' continuous, jump, and overnight betas based on a rolling six-month estimation window. We show that stocks' continuous, jump, and overnight betas with respect to a given factor can be very different. Moreover, continuous betas are in general much less cross-sectionally dispersed and much more persistent than jump and overnight betas.

In order to examine the pricing of the different factor risks, we employ univariate and bivariate value-weighted portfolio sorts as well as Fama-MacBeth (1973) regressions estimated with weighted least squares. Since factor models predict a positive relation between risk, as measured by betas, and contemporaneous returns, we examine stocks' returns across the same period across which the stocks' factor betas are estimated. Based on both, portfolio sorts and Fama-MacBeth (1973) regressions, we find robust evidence that the continuous market beta is positively priced in the cross-section of stock returns whereas the overnight market beta is negatively priced. The jump market beta does not seem to be priced. These results are in stark contrast to the results of Bollerslev et al. (2016) who document positive risk premia for jump and overnight market betas but no risk premium for the continuous market beta. Based on repeating their empirical approach with several sensitivity analyses, we find that the differences between their and our findings are driven by our use of value-weights, our investigation of a larger stock sample, our focus on contemporaneous relations between betas and returns, and our different beta estimation methodology.

Furthermore, we document that the exposures to continuous size, value, and investment risks are negatively priced while the exposures to continuous profitability risk as well as to jump size, value, profitability, and investment risks are not priced. By contrast, the results from the Fama-MacBeth (1973) regressions indicate that exposures to the factors' overnight movements carry uniformly positive risk premia. This finding suggests that the factors' overnight risks may be the source of their empirically documented return premia.

Nevertheless, the negative risk premia for overnight market exposure and exposure to the other factors' continuous risks prevent us from unambiguously confirming the prediction of the Fama-French (2015) model that exposures to the factors carry positive risk premia. This is in line with almost every other empirical study on this topic. Our contribution to this literature is to show that this is true even when we consider the different sources of potential factor risks - continuous, jump, and overnight variation - separately. Nonetheless, our findings still indicate which of the factors' risks are the most likely for which investors command compensation in the form of higher returns.

A Variable Definitions

Market Equity (ME):
A stock's market equity is calculated as the stock's price at the end of month t times the stock's shares outstanding at the end of month t. In particular, a stock's ME for the end of June of year y is calculated as the stock's price at the end of June of year y times the stock's shares outstanding at the end of June of year y. In order to reduce the skewness in ME, we transform it by the natural logarithm. If ME is non-positive, the ME data is considered to be missing.

Book-to-Market Equity Ratio (BM):
A stock's book-to-market equity ratio for the end of month t is calculated as the firm's book equity from the last fiscal year ending at least six months and less than 18 months ago, divided by the firm's ME at the end of the month of the last fiscal year ending[24]. Following Davis et al. (2000), book equity is the book value of stockholders' equity 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 the book value of total assets and the book value of total liabilities (in that order). In order to reduce the skewness in BM, we transform it by the natural logarithm. If either ME or book equity is non-positive, the BM data is considered to be missing.[25]

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

Investment (INV):
A stock's investment for the end of month t is calculated as the firm's total assets from the last fiscal year ending at least six months and less than 18 months ago divided by the firm's total assets one year prior, minus 1. In order to reduce the skewness in INV, we transform it by the natural logarithm. If total assets are non-positive, the INV data is considered to be missing.

[24] In the calculation of the BM ratio for the formation of the factor portfolios for the value factor, we slightly deviate from this method. In order to exactly follow Fama and French (2015), we divide the book equity by the firm's ME from the end of December of the year of the last fiscal year ending.

[25] For the calculation of BM, we supplement the Compustat data with the hand-collected book equity data from Kenneth French's website.

Momentum (MOM):

A stock's momentum for the end of month t is the stock's return from the end of month $t-12$ to the end of month $t-1$. If a stock does not have good price data for the end of month $t-12$ or good return data for month $t-1$, its MOM data is considered to be missing.

Short-Term Reversal (STR):

A stock's short-term reversal for the end of month t is the stock's return from the end of month $t-1$ to the end of month t. If a stock does not have good price data for the end of month $t-1$ or good return data for month t, its STR data is considered to be missing.

Idiosyncratic Volatility (IVOL):

A stock's idiosyncratic volatility for the end of month t is the standard deviation of the stock's residual returns from regressing the stock's 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[26]. If a stock has less than 100 daily return observations, its IVOL data is considered to be missing.

Illiquidity (ILLIQ):

Following Amihud (2002), a stock's illiquidity for the end of month t is the average ratio of the stock's daily absolute return to the stock's 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 daily trading volume in shares times its daily closing price. We adjust the daily trading volume of NASDAQ stocks following Gao and Ritter (2010): before February 1, 2001, we divide trading volume by 2; from February 1, 2001, to December 31, 2001, we divide trading volume by 1.8; and from January 1, 2002, to December 31, 2003, we divide trading volume by 1.6. In order to reduce the skewness in ILLIQ, we transform it by the natural logarithm. If a stock has less than 100 daily observations, its ILLIQ data is considered to be missing.

Co-skewness (CSK):

Following Ang et al. (2006a), a stock's coskewness for the end of month t is estimated from its daily returns during month t by

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

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.

[26] Daily factor returns and risk-free rates are retrieved from Kenneth French's website.

Co-kurtosis (CKT):

Following Ang et al. (2006a), a stock's cokurtosis 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 CSK.

Realized Variance (RV):

Following Amaya et al. (2015), we estimate the realized variance of stock i on day d from the stock's 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. A stock's realized variance for the end of month t is the stock's average daily realized variance in month t.

Realized Skewness (RSK):

Following Amaya et al. (2015), we estimate the realized skewness of stock i on day d from the stock's 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 RV. A stock's realized skewness for the end of month t is the stock's average daily realized skewness in month t.

Realized Kurtosis (RKT):

Following Amaya et al. (2015), we estimate the realized kurtosis of stock i on day d from the stock's 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 RV. A stock's realized kurtosis for the end of month t is the stock's average daily realized kurtosis in month t.

Volatility of Return on Equity (vROE):

A stock's return on equity (ROE) volatility for the end of month t is the standard deviation of its ROE from the fiscal quarters that ended within the previous three years and were already publicly announced. Following Hou et al. (2015), a stock's ROE is income before extraordinary items divided by 1-quarter-lagged book equity. Book equity is calculated as the quarterly version of the annual book equity used in the calculation of BM. If fourth-quarter book equity data is missing, we use the annual book equity data from the corresponding fiscal year ending. If book equity is non-positive, the ROE data is considered to be missing. If there are less than six fiscal quarter endings with non-missing ROE data, the vROE data is considered to be missing.

Dividend-to-Book Equity Ratio (DB):
A stock's dividend-to-book equity ratio for the end of month t is its common dividend (from Compustat) divided by its book equity, both from the last fiscal year ending at least six months and less than 18 months ago. Book equity is calculated in the same way as for BM. If book equity is non-positive, the DB data is considered to be missing.

Sales Growth (SG):
A stock's sales growth for the end of month t is calculated as the firm's sales from the last fiscal year ending at least six months and less than 18 months ago divided by the firm's sales one year prior, minus 1. In order to reduce the skewness in SG, we transform it by the natural logarithm. If sales are non-positive, the SG data is considered to be missing.

Book Leverage (BL):
A stock's book leverage for the end of month t is calculated as the firm's total assets divided by the firm's book equity, both from the last fiscal year ending at least six months and less than 18 months ago. Book equity is calculated in the same way as for BM. In order to reduce the skewness in BL, we transform it by the natural logarithm. If book equity or total assets are non-positive, the BL data is considered to be missing.

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.

B Fama-MacBeth (1973) Regressions with Instrumental Variables Approach

Our implementation of the instrumental variables approach proposed by Jegadeesh et al. (2019) is as follows: we first split every six-month estimation window into two subsets on a daily basis, that is, the first, third, fifth, ... day of the estimation window is assigned to the first subset, and the second, fourth, sixth, ... day of the estimation window is assigned to the second subset. Within each of these two subsets, we estimate all types (daily, high-frequency, continuous, jump, and overnight) of factor betas as described in Section 4.2. Then, we regress each factor beta from the first subset on all factor betas of the same type estimated from the second subset. Formally, we run in each month t the following cross-sectional regression for each beta:

$$\beta_{i,t}^{k,z,1} = \delta_{0,t}^{z,2} + \sum_{k=1}^{5} \delta_{k,t}^{z,2} \cdot \beta_{i,t}^{k,z,2} + \nu_{i,t} \qquad z \in \{Daily, HFQ, C, J, N\} \tag{14}$$

where $\beta_{i,t}^{k,z,1}$ ($\beta_{i,t}^{k,z,2}$) is the type z beta of stock i with respect to factor k as estimated from the first (second) subset of the period from month $t+1$ to $t+6$.

We use the fitted values for the betas (i.e. $\hat{\beta}_{i,t}^{k,z,1}$) as the explanatory variables in the monthly cross-sectional regression in (12) instead of the betas estimated across the entire estimation window. Moreover, we 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 $r_{i,t}$ and $r_{f,t}$ in (12) by $2r_{i,t}^1$ and $2r_{f,t}^1$. That is, we use only the stocks' compounded excess returns across the days in the first subset; the multiplication by two is done to get again six-month returns.

By implementing the Fama-MacBeth (1973) regressions with this instrumental variables approach, we obtain monthly estimates for the six-month risk premia, denoted by $\hat{\gamma}_{k,t}^{C,1}$, $\hat{\gamma}_{k,t}^{J,1}$, $\hat{\gamma}_{k,t}^{N,1}$, and $\hat{\gamma}_{c,t}^{X,1}$. Additionally, we repeat the procedure by changing the roles of the estimated betas from the first and second subset, that is, the $\beta_{i,t}^{k,z,1}$ are now the instrumental variables for the $\beta_{i,t}^{k,z,2}$. Thereby, we obtain a second set of monthly estimates for the six-month risk premia, denoted by $\hat{\gamma}_{k,t}^{C,2}$, $\hat{\gamma}_{k,t}^{J,2}$, $\hat{\gamma}_{k,t}^{N,2}$, and $\hat{\gamma}_{c,t}^{X,2}$. We calculate our final estimates for the risk premia by averaging the two sets of risk premium estimates, and then averaging across the entire sample period of $T = 318$ months:

$$\begin{aligned} \hat{\gamma}_k^z &= \frac{1}{T} \sum_{t=1}^{T} \frac{\hat{\gamma}_{k,t}^{z,1} + \hat{\gamma}_{k,t}^{z,2}}{2} \qquad z \in \{Daily, HFQ, C, J, N\} \\ \hat{\gamma}_c^X &= \frac{1}{T} \sum_{t=1}^{T} \frac{\hat{\gamma}_{c,t}^{X,1} + \hat{\gamma}_{c,t}^{X,2}}{2} \end{aligned} \tag{15}$$

Like in our standard implementation of the Fama-MacBeth (1973) regressions, we winsorize all dependent and independent variables at the 1st and 99th percentile when estimating the monthly cross-sectional regression in (12). Moreover, we estimate the regressions in (12) and in (14) with weighted least squares (WLS) rather than ordinary least squares (OLS), whereby the weights correspond to the stocks' market capitalizations at the end of month t.

Furthermore, Jegadeesh et al. (2019) note that there is the possibility that the cross-product of the dependent betas and independent betas in the estimation of (14) might be close to singular, which would lead to unreasonably large risk premium estimates. We address this issue by considering monthly risk premium estimates that deviate by five or more mean absolute deviations from their median to be missing.

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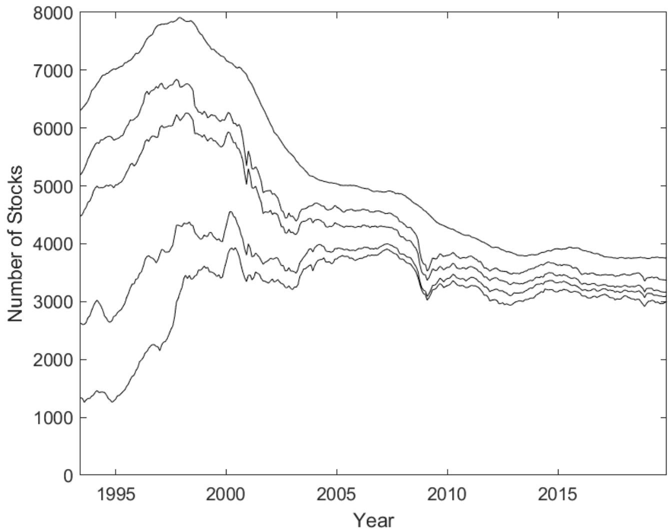

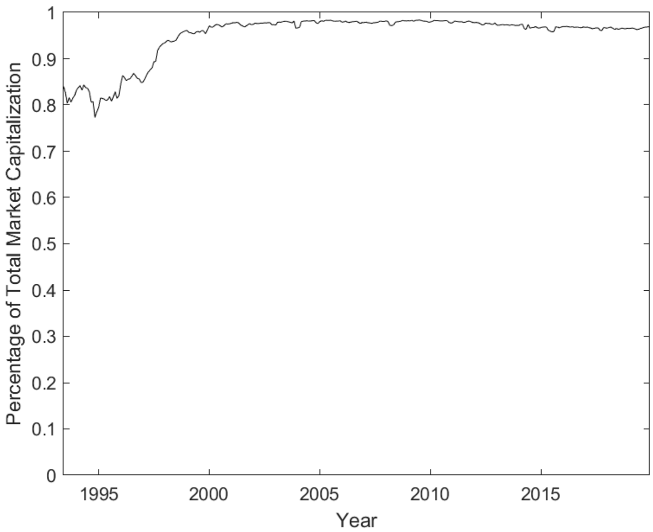

Figure 1
Stock Sample after Screening

The upper graph of this figure displays for each month in the period 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 base sample consisting of all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11. The second line from the top reflects the number of stocks in the sample after excluding stocks with a market capitalization below \$10mn and a share price below \$1. The third line from the top reflects the number of stocks in the sample after further excluding stocks that have data for less than 50 days on daily, overnight, and high-frequency returns available during the beta estimation window across the prior six months. The second line from the bottom reflects the number of stocks in the sample after further excluding stocks for which more than half of the high-frequency returns during the estimation window are zero. The bottommost line reflects the number of stocks in the sample after further excluding stocks for which the null hypothesis of no market microstructure noise over the respective estimation window is rejected at the 1% significance level based on each of the three recommended tests of Aït-Sahalia and Xiu (2019). The lower graph shows the aggregate market capitalization of the stocks in the final sample as a percentage of the total market capitalization of the base sample consisting of all stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11.

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 stocks traded on the NYSE, AMEX, or NASDAQ (for the monthly version of the market factor, we deduct the one-month T-bill rate from the return on the market portfolio). For the formation of the size, value, profitability, and investment factors, stocks are at the beginning of each July sorted into two market equity (ME) groups, three book-to-market (BM) groups, three operating profitability (OP) groups, and three investment (INV) groups. The breakpoints for the ME sorts are the median ME of all NYSE stocks and the breakpoints for the BM, OP, and INV sorts are the 30th and 70th BM, OP, and INV percentiles of all NYSE stocks, respectively. The intersections of the two ME groups with the three BM groups, with the three OP groups, and with 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 for which observations for all three versions are available.

Panel A: Monthly Factors

	Mean	t-Stat	Std	Skew	Kurt	Min	P1	P10	Median	P90	P99	Max
MP	0.6851	2.92	4.22	−0.75	4.35	−17.18	−10.43	−4.82	1.2512	5.58	9.11	11.34
SMB	0.1371	0.82	3.01	0.48	8.92	−15.51	−5.86	−3.21	0.0158	3.46	7.08	18.74
HML	0.1933	1.15	3.03	0.30	5.34	−11.78	−8.06	−3.04	0.0186	3.53	8.19	12.55
RMW	0.2863	1.86	2.77	−0.37	13.14	−18.79	−8.02	−2.08	0.2429	3.02	9.25	13.87
CMA	0.1525	1.55	1.77	0.52	4.24	−5.59	−3.67	−1.82	0.0427	2.29	5.40	7.29

Panel B: Daily Factors

	Mean	t-Stat	Std	Skew	Kurt	Min	P1	P10	Median	P90	P99	Max
MP	0.0378	2.78	1.12	−0.32	11.06	−9.38	−3.12	−1.20	0.0774	1.19	3.14	10.76
SMB	0.0043	0.61	0.58	−0.17	6.36	−4.31	−1.47	−0.68	0.0153	0.67	1.50	4.35
HML	0.0090	1.15	0.64	0.36	13.66	−5.06	−1.79	−0.59	−0.0039	0.62	1.95	5.33
RMW	0.0141	2.35	0.49	0.17	10.85	−3.34	−1.39	−0.47	0.0061	0.51	1.46	4.68
CMA	0.0059	1.27	0.39	−0.55	13.08	−5.40	−1.05	−0.39	0.0004	0.43	1.04	2.52

Panel C: Overnight Factors

	Mean	t-Stat	Std	Skew	Kurt	Min	P1	P10	Median	P90	P99	Max
MP	0.0314	4.40	0.59	−0.80	17.14	−7.52	−1.82	−0.53	0.0512	0.58	1.58	5.68
SMB	−0.0078	−2.90	0.22	−0.32	11.70	−2.08	−0.67	−0.23	−0.0041	0.21	0.61	1.98
HML	−0.0206	−6.24	0.27	2.12	45.92	−2.44	−0.78	−0.25	−0.0225	0.19	0.82	5.71
RMW	−0.0261	−10.46	0.21	−0.45	17.43	−2.55	−0.66	−0.21	−0.0178	0.15	0.52	1.94
CMA	−0.0163	−7.60	0.18	−0.01	16.89	−2.19	−0.50	−0.19	−0.0152	0.16	0.47	1.97

Panel D: High-Frequency Factors

	Mean	t-Stat	Std	Skew	Kurt	Min	P1	P10	Median	P90	P99	Max
MP	0.0005	0.62	0.24	0.32	24.92	−3.21	−0.68	−0.24	0.0056	0.23	0.64	6.27
SMB	0.0008	1.66	0.15	−0.12	12.28	−2.23	−0.42	−0.15	0.0023	0.15	0.41	1.93
HML	0.0023	5.01	0.13	−0.13	28.48	−3.06	−0.38	−0.12	0.0008	0.12	0.40	2.82
RMW	0.0032	9.61	0.10	0.22	27.27	−2.24	−0.27	−0.09	0.0010	0.10	0.30	2.18
CMA	0.0017	6.30	0.08	−0.12	14.69	−1.75	−0.23	−0.08	0.0001	0.08	0.24	1.04

Table 2
Factor Jumps

Panel A of this table displays summary statistics on the jumps in the 30-minute versions of the five Fama-French (2015) factors for the sample 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. The column Total depicts the number of jumps as a percentage of all return observations, and the column Positive (Negative) shows the number of positive (negative) jumps as a percentage of all jumps. JumpDays is the percentage of days in the sample period 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). The column JV depicts the factors' variation that is due to jumps as a percentage of the factors' total variation. Panel B displays the additive decomposition of daily factor returns into overnight and high-frequency factor returns, and the additive decomposition of the high-frequency factor 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.

Panel A: Jump Summary Statistics

	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

Panel B: Return Decomposition

	Daily	ON	HFQ	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 3
Distribution of Betas

This table reports summary statistics for the estimated betas with respect to the market factor (Panel A), the size factor (Panel B), the value factor (Panel C), the profitability factor (Panel D), and the investment factor (Panel E). Betas are estimated at the end of each month from June 1993 to December 2019 based on return data across the previous six months. Each panel displays statistics on the estimated daily, overnight (ON), high-frequency (HFQ), continuous (Cont), and jump betas as well as on the absolute differences between the jump and the continuous betas (A(JmC)) and between the overnight and the continuous betas (A(ONmC)). The cross-sectional summary statistics of the betas (mean, median, standard deviation, skewness, kurtosis, 1st-, 10th-, 90th-, and 99th-percentile, and the 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) of the betas is calculated for each stock-month in our sample and then averaged across stock-months. The six-month lagged time series autocorrelation (AC(TS)) is calculated for each individual stock over the entire sample period and then averaged across stocks.

Panel A: MP Betas

	Mean	Std	Skew	Kurt	P1	P10	Med	P90	P99	Vola	AC(TS)	AC(CS)
Daily	0.98	0.64	−0.28	24.02	−0.65	0.27	0.96	1.71	2.65	0.29	0.07	0.35
HFQ	0.93	0.51	0.15	7.81	−0.27	0.30	0.93	1.55	2.25	0.16	0.27	0.66
Cont	0.84	0.51	0.14	7.10	−0.33	0.22	0.84	1.46	2.14	0.16	0.27	0.66
Jump	0.91	0.88	−0.11	17.94	−1.52	0.01	0.91	1.83	3.29	0.39	0.06	0.32
ON	0.94	0.85	−0.49	51.56	−1.15	0.13	0.89	1.85	3.30	0.38	0.04	0.33
A(JmC)	0.48	0.60	4.36	49.65	0.01	0.05	0.30	1.09	2.82	0.26	0.04	0.19
A(ONmC)	0.54	0.63	5.01	89.41	0.01	0.06	0.36	1.20	2.87	0.29	0.05	0.19

Panel B: SMB Betas

	Mean	Std	Skew	Kurt	P1	P10	Med	P90	P99	Vola	AC(TS)	AC(CS)
Daily	0.70	0.97	0.61	28.65	−1.46	−0.32	0.62	1.86	3.39	0.43	0.05	0.42
HFQ	0.67	0.64	0.38	5.55	−0.65	−0.09	0.64	1.48	2.32	0.19	0.27	0.73
Cont	0.59	0.61	0.39	6.73	−0.69	−0.11	0.55	1.35	2.18	0.18	0.26	0.71
Jump	0.63	1.13	0.16	19.11	−2.32	−0.45	0.56	1.88	3.85	0.49	0.03	0.36
ON	0.60	1.39	0.55	58.24	−2.72	−0.64	0.50	2.02	4.53	0.64	−0.01	0.27
A(JmC)	0.64	0.80	4.14	45.46	0.01	0.07	0.40	1.48	3.80	0.34	0.03	0.22
A(ONmC)	0.83	1.06	5.46	93.93	0.01	0.09	0.53	1.84	4.69	0.47	0.00	0.18

Panel C: HML Betas

	Mean	Std	Skew	Kurt	P1	P10	Med	P90	P99	Vola	AC(TS)	AC(CS)
Daily	0.06	1.22	−0.01	36.13	−3.30	−1.27	0.09	1.34	3.09	0.57	0.03	0.31
HFQ	0.06	0.76	0.00	8.29	−2.06	−0.81	0.08	0.87	2.09	0.29	0.15	0.49
Cont	0.05	0.72	0.00	8.82	−1.99	−0.75	0.07	0.79	2.01	0.27	0.15	0.47
Jump	0.01	1.72	−0.30	17.79	−5.05	−1.74	0.06	1.67	4.67	0.85	0.00	0.19
ON	0.05	1.68	−1.87	126.13	−4.54	−1.47	0.09	1.50	4.29	0.79	−0.04	0.12
A(JmC)	1.02	1.27	4.11	39.68	0.01	0.11	0.63	2.32	6.00	0.58	0.04	0.19
A(ONmC)	1.01	1.34	7.39	183.96	0.01	0.11	0.65	2.27	5.73	0.58	0.01	0.18

Panel D: RMW Betas

	Mean	Std	Skew	Kurt	P1	P10	Med	P90	P99	Vola	AC(TS)	AC(CS)
Daily	−0.21	1.41	−0.95	19.03	−4.45	−1.83	−0.07	1.18	2.97	0.67	−0.01	0.25
HFQ	−0.18	0.85	−0.70	10.20	−2.81	−1.22	−0.07	0.64	1.71	0.31	0.14	0.48
Cont	−0.16	0.80	−0.59	13.76	−2.66	−1.10	−0.05	0.60	1.68	0.29	0.14	0.46
Jump	−0.22	2.00	−0.47	19.70	−6.24	−2.31	−0.09	1.63	4.91	0.98	−0.02	0.15
ON	−0.14	1.71	−1.28	74.17	−5.27	−1.78	−0.04	1.36	4.13	0.81	−0.05	0.10
A(JmC)	1.21	1.50	4.18	41.67	0.01	0.13	0.76	2.76	7.08	0.67	0.03	0.20
A(ONmC)	1.08	1.37	5.64	109.40	0.01	0.12	0.69	2.45	6.09	0.60	0.01	0.19

Panel E: CMA Betas

	Mean	Std	Skew	Kurt	P1	P10	Med	P90	P99	Vola	AC(TS)	AC(CS)
Daily	0.00	1.61	0.74	29.62	−4.27	−1.73	0.02	1.63	4.33	0.82	0.00	0.20
HFQ	0.01	0.87	−0.11	9.66	−2.49	−0.94	0.04	0.89	2.39	0.36	0.12	0.35
Cont	0.00	0.82	−0.11	10.32	−2.42	−0.88	0.03	0.82	2.28	0.34	0.11	0.34
Jump	−0.01	2.33	0.11	30.97	−6.64	−2.27	0.02	2.21	6.61	1.21	−0.02	0.09
ON	0.00	1.78	1.08	118.55	−4.75	−1.63	0.02	1.55	4.77	0.85	−0.05	0.09
A(JmC)	1.43	1.77	4.31	54.09	0.02	0.15	0.90	3.25	8.36	0.83	0.03	0.20
A(ONmC)	1.12	1.46	6.55	157.43	0.01	0.12	0.72	2.54	6.34	0.64	0.01	0.19

Table 4
Correlations

This table displays time series averages of monthly cross-sectional correlations between daily, overnight, high-frequency, continuous, and jump betas, separately for betas with respect to the market factor (Panel A), the size factor (Panel B), the value factor (Panel C), the profitability factor (Panel D), and the investment factor (Panel E). Betas are estimated at the end of each month from June 1993 to December 2019 based on return data across the previous six months. The table further displays time series averages of monthly cross-sectional correlations of the betas with several stock and firm characteristics. The characteristics are market equity (ME), book-to-market equity ratio (BM), operating profitability (OP), investment (INV), dividend-to-book equity ratio (DB), 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), coskewness (CSK), and cokurtosis (CKT). The construction of these variables is described in Appendix A. In order to align them with the betas' estimation windows, RV, RSK, RKT, CSK, and CKT are rolling six-month averages of their monthly values.

Panel A: MP Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.00	0.45	0.56	0.52	0.34	0.15	−0.07	0.00	0.04	−0.03	0.03	0.01	0.01	0.00	−0.18	0.04	0.02	−0.05	−0.04	−0.30	−0.02	0.46
ON		1.00	0.38	0.38	0.24	0.10	−0.08	−0.01	0.04	−0.03	0.04	−0.02	0.01	−0.03	−0.14	0.03	0.08	0.01	−0.02	−0.25	0.00	0.25
HFQ			1.00	0.92	0.58	0.28	−0.12	0.00	0.06	−0.04	0.04	−0.03	0.01	0.02	−0.35	0.06	0.02	−0.10	−0.02	−0.48	−0.01	0.45
Cont				1.00	0.52	0.31	−0.13	0.00	0.07	−0.03	0.05	−0.03	0.01	0.04	−0.38	0.06	0.00	−0.10	−0.03	−0.50	−0.01	0.45
Jump					1.00	0.19	−0.07	0.00	0.04	−0.02	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: SMB Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.00	0.34	0.56	0.51	0.32	−0.26	0.02	−0.02	0.02	−0.06	0.02	−0.07	0.01	−0.17	0.21	0.00	0.18	0.09	−0.02	−0.03	−0.04	−0.02
ON		1.00	0.32	0.31	0.18	−0.17	0.00	−0.03	0.02	−0.05	0.02	−0.06	0.01	−0.13	0.15	0.01	0.13	0.08	0.00	−0.02	−0.01	0.00
HFQ			1.00	0.91	0.57	−0.32	0.02	−0.03	0.03	−0.08	0.03	−0.09	0.02	−0.23	0.24	0.01	0.20	0.07	−0.01	−0.11	−0.01	0.07
Cont				1.00	0.45	−0.28	0.01	−0.03	0.03	−0.07	0.04	−0.09	0.02	−0.21	0.20	0.01	0.18	0.06	−0.02	−0.15	−0.01	0.09
Jump					1.00	−0.18	0.01	−0.02	0.02	−0.04	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: HML Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.00	0.35	0.54	0.49	0.26	0.01	0.23	0.03	−0.05	0.02	−0.04	0.20	−0.02	0.08	−0.01	−0.06	−0.13	−0.06	0.00	0.04	−0.02	0.05
ON		1.00	0.22	0.21	0.11	0.02	0.12	0.01	−0.03	0.01	−0.03	0.10	−0.01	0.04	−0.01	−0.03	−0.09	−0.05	0.00	0.01	0.00	0.04
HFQ			1.00	0.87	0.47	0.03	0.31	0.03	−0.08	0.03	−0.08	0.24	−0.03	0.13	−0.02	−0.07	−0.19	−0.11	0.01	0.05	−0.01	0.09
Cont				1.00	0.35	0.03	0.29	0.03	−0.07	0.02	−0.07	0.23	−0.03	0.12	−0.02	−0.07	−0.17	−0.09	0.00	0.03	−0.01	0.09
Jump					1.00	0.01	0.16	0.02	−0.04	0.01	−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: RMW Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.00	0.33	0.50	0.45	0.22	0.09	0.08	0.06	−0.04	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
ON		1.00	0.21	0.19	0.09	0.03	0.05	0.02	−0.02	0.03	−0.02	0.06	0.00	0.07	−0.02	−0.03	−0.13	−0.07	0.00	0.03	0.00	0.01
HFQ			1.00	0.86	0.45	0.13	0.12	0.08	−0.06	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
Cont				1.00	0.30	0.11	0.11	0.07	−0.06	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
Jump					1.00	0.06	0.05	0.04	−0.02	0.03	−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: CMA Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.00	0.31	0.41	0.36	0.17	−0.02	0.03	−0.01	−0.11	0.03	−0.07	0.01	0.01	0.06	0.04	0.01	0.02	0.03	0.00	0.03	−0.02	−0.06
ON		1.00	0.16	0.15	0.06	0.00	0.01	−0.01	−0.07	0.02	−0.05	0.02	0.00	0.04	0.01	0.01	−0.01	0.00	0.00	0.01	0.00	−0.02
HFQ			1.00	0.83	0.39	−0.04	0.06	−0.01	−0.16	0.04	−0.11	0.03	0.01	0.09	0.06	0.00	0.00	0.02	0.01	0.05	0.00	−0.07
Cont				1.00	0.24	−0.03	0.05	0.00	−0.15	0.03	−0.10	0.03	0.01	0.09	0.05	0.00	−0.01	0.01	0.00	0.04	0.01	−0.06
Jump					1.00	−0.01	0.03	−0.01	−0.07	0.02	−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 5
Characteristics of Beta-sorted Portfolios

This table displays results on betas and characteristics of beta-sorted portfolios. At the end of each month from June 1993 to December 2019, all NYSE, AMEX, and NASDAQ stocks with share code 10 or 11 are sorted into quintiles with respect to their daily, overnight, high-frequency, continuous, or jump betas. Breakpoints are based only on NYSE stocks. Betas are estimated at the end of each month based on return data across the previous six months. The table depicts the time series averages of the spreads in betas and characteristics between the top and bottom quintile portfolios. The stocks in the portfolios are value-weighted based on their market capitalizations at the end of the sorting month. Panel A (B, C, D, E) shows the results for portfolios sorted with respect to market (size, value, profitability, investment) betas. The characteristics are market equity (ME), book-to-market equity ratio (BM), operating profitability (OP), investment (INV), dividend-to-book equity ratio (DB), 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), coskewness (CSK), and cokurtosis (CKT). The construction of these variables is described in Appendix A. In order to align them with the betas' estimation windows, RV, RSK, RKT, CSK, and CKT are rolling six-month averages of their monthly values. All characteristics are in each month standardized to have a mean of zero and a standard deviation of one.

Panel A: Sort with respect to MP Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	1.17	0.82	0.64	0.61	0.62	−0.15	0.19	−0.02	0.04	−0.25	0.06	0.40	0.01	−0.55	0.11	0.06	0.23	0.09	−0.04	−0.09	−0.04	1.19
ON	0.59	1.45	0.48	0.47	0.46	0.25	−0.03	−0.01	0.05	−0.07	0.06	0.31	0.01	−0.26	−0.21	0.03	0.15	0.07	−0.04	−0.18	−0.02	0.79
HFQ	0.79	0.82	0.96	0.91	0.90	0.05	0.09	−0.02	0.12	−0.22	0.10	0.36	0.02	−0.42	−0.13	0.08	0.31	0.11	−0.03	−0.26	−0.03	0.99
Cont	0.76	0.81	0.92	0.94	0.85	0.22	0.07	−0.02	0.10	−0.17	0.08	0.36	0.01	−0.23	−0.28	0.05	0.25	0.09	−0.03	−0.34	−0.01	1.07
Jump	0.58	0.58	0.68	0.64	1.33	0.03	0.14	−0.02	0.05	−0.17	0.03	0.33	0.00	−0.21	−0.09	0.01	0.18	0.07	−0.02	−0.19	0.03	0.81

Panel B: Sort with respect to SMB Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	2.05	1.19	1.20	1.08	1.13	−2.08	0.32	−0.08	0.14	−0.39	0.16	−0.35	0.04	−1.49	1.55	0.13	0.85	0.34	0.01	0.34	−0.18	−0.70
ON	0.90	2.27	0.73	0.67	0.68	−1.34	0.10	−0.06	0.11	−0.28	0.12	−0.29	0.02	−1.10	0.98	0.12	0.56	0.22	0.00	0.22	−0.09	−0.43
HFQ	1.49	1.24	1.58	1.42	1.53	−2.37	0.42	−0.10	0.12	−0.43	0.14	−0.32	0.05	−1.60	1.82	0.14	0.85	0.37	0.04	0.38	−0.08	−0.53
Cont	1.44	1.21	1.53	1.46	1.39	−2.33	0.42	−0.11	0.12	−0.43	0.14	−0.31	0.05	−1.57	1.78	0.14	0.81	0.35	0.04	0.34	−0.09	−0.51
Jump	1.19	0.99	1.27	1.09	2.01	−2.11	0.35	−0.09	0.11	−0.36	0.12	−0.24	0.04	−1.47	1.60	0.11	0.73	0.33	0.03	0.34	−0.07	−0.52

Panel C: Sort with respect to HML Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	2.37	1.67	1.42	1.31	1.41	−0.39	1.17	−0.06	−0.07	−0.21	−0.06	1.01	−0.02	−0.25	0.30	−0.16	−0.01	0.03	0.00	0.07	−0.08	0.21
ON	1.30	2.77	0.97	0.92	0.95	−0.33	0.85	−0.05	−0.07	−0.14	−0.06	0.70	−0.02	−0.20	0.25	−0.11	0.01	0.03	0.01	0.04	−0.02	0.14
HFQ	1.75	1.47	1.66	1.50	1.65	−0.52	1.36	−0.08	−0.08	−0.25	−0.06	1.00	−0.02	−0.29	0.40	−0.13	−0.02	0.03	0.01	0.10	−0.12	0.17
Cont	1.70	1.46	1.60	1.53	1.51	−0.50	1.33	−0.07	−0.09	−0.23	−0.07	0.99	−0.02	−0.26	0.38	−0.14	−0.03	0.03	0.01	0.09	−0.12	0.17
Jump	1.37	1.23	1.33	1.17	2.66	−0.38	1.01	−0.05	−0.05	−0.18	−0.04	0.81	−0.01	−0.17	0.29	−0.12	0.00	0.04	0.00	0.07	−0.08	0.14

Panel D: Sort with respect to RMW Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	2.53	1.53	1.33	1.21	1.38	0.24	−0.22	0.12	−0.17	0.49	−0.12	0.09	0.00	0.89	−0.17	−0.05	−0.25	−0.07	0.03	−0.05	−0.01	−0.16
ON	1.25	2.81	0.91	0.84	0.91	0.31	−0.18	0.08	−0.12	0.36	−0.09	0.11	0.00	0.77	−0.19	−0.06	−0.22	−0.06	0.01	−0.04	−0.07	−0.02
HFQ	1.67	1.31	1.69	1.51	1.79	0.39	−0.26	0.17	−0.22	0.52	−0.14	0.07	0.00	1.22	−0.30	−0.08	−0.32	−0.11	0.03	−0.08	−0.08	−0.10
Cont	1.62	1.27	1.62	1.55	1.53	0.38	−0.27	0.17	−0.21	0.51	−0.14	0.08	0.00	1.22	−0.29	−0.07	−0.32	−0.10	0.02	−0.08	−0.09	−0.09
Jump	1.25	1.01	1.28	1.07	3.00	0.26	−0.17	0.11	−0.16	0.35	−0.11	0.03	0.00	0.88	−0.19	−0.06	−0.23	−0.07	0.01	−0.06	−0.07	−0.12

Panel E: Sort with respect to CMA Betas

	Daily	ON	HFQ	Cont	Jump	ME	BM	OP	INV	DB	SG	BL	vROE	Age	ILLIQ	MOM	IVOL	RV	RSK	RKT	CSK	CKT
Daily	3.10	1.86	1.62	1.48	1.63	0.05	0.04	0.05	−0.52	0.44	−0.33	−0.02	0.00	1.03	−0.01	−0.10	−0.18	−0.07	0.04	−0.01	0.01	−0.42
ON	1.70	3.00	1.21	1.12	1.22	−0.02	0.07	0.04	−0.45	0.28	−0.27	0.09	0.00	0.82	0.02	−0.08	−0.15	−0.05	0.04	−0.01	0.04	−0.23
HFQ	2.04	1.61	1.92	1.73	1.99	0.02	0.09	0.06	−0.66	0.48	−0.41	0.09	0.00	1.17	0.00	−0.08	−0.20	−0.07	0.07	−0.02	0.06	−0.40
Cont	2.00	1.60	1.87	1.79	1.78	0.01	0.11	0.06	−0.64	0.47	−0.40	0.10	0.00	1.16	0.01	−0.09	−0.20	−0.07	0.07	−0.01	0.05	−0.39
Jump	1.59	1.30	1.52	1.30	3.51	−0.06	0.10	0.04	−0.49	0.35	−0.29	0.11	0.00	0.74	0.06	−0.08	−0.12	−0.05	0.05	0.01	0.01	−0.30

Table 6
Univariate Portfolio Sorts

This table displays average returns, betas, and characteristics of univariate portfolios. At the end of each month from January 1993 to June 2019, all NYSE, AMEX, and NASDAQ stocks with share code 10 or 11 are sorted into quintiles with respect to their daily, high-frequency, continuous, jump, and overnight factor betas estimated across the next six months as well as with respect to their differences between jump and continuous betas (JmC) and their differences between overnight and continuous betas (ONmC). Breakpoints are based only on NYSE stocks. The stocks in the portfolios are value-weighted based on their market capitalizations at the end of the sorting month. The portfolios' returns are calculated as the value-weighted averages of the stocks' compounded returns across the next six months. Panels A, B, and C depict the time series averages of the return spreads (in percent), the spreads in the sorting betas, and the spreads in the factor characteristics, respectively, between the top and bottom portfolios. For portfolios sorted according to MP, SMB, HML, RMW, and CMA betas, the factor characteristics are ME, ME, BM, OP, and INV, respectively. Factor characteristics are in each month standardized to have a mean of zero and a standard deviation of one. t-statistics are reported in parentheses. The return spreads' t-statistics in Panel A are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags, while beta and characteristic spreads' t-statistics in Panels B and C are computed using 12 lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High-minus-low Return Spreads

	Daily	HFQ	Cont	Jump	ON	JmC	ONmC
MP	−0.03	0.08	−0.03	0.00	−0.10	−0.14	−0.22*
	(−0.13)	(0.25)	(−0.10)	(0.00)	(−0.48)	(−1.03)	(−1.65)
SMB	−0.35	−0.09	−0.05	−0.19	−0.21	−0.07	0.19
	(−1.27)	(−0.34)	(−0.18)	(−0.92)	(−1.40)	(−0.58)	(1.35)
HML	−0.37	−0.07	−0.12	−0.24	−0.33*	0.11	−0.13
	(−1.59)	(−0.26)	(−0.45)	(−1.17)	(−1.92)	(0.99)	(−1.16)
RMW	0.18	0.32	0.31	0.16	0.03	−0.10	−0.24**
	(0.70)	(1.25)	(1.26)	(0.74)	(0.14)	(−0.91)	(−2.04)
CMA	−0.28	−0.01	−0.02	−0.11	−0.17	−0.04	−0.01
	(−1.14)	(−0.03)	(−0.08)	(−0.52)	(−0.88)	(−0.47)	(−0.08)

Panel B: High-minus-low Beta Spreads

	Daily	HFQ	Cont	Jump	ON	JmC	ONmC
MP	1.16***	0.95***	0.93***	1.32***	1.46***	1.00***	1.29***
	(26.82)	(33.72)	(37.26)	(18.17)	(15.59)	(12.75)	(12.70)
SMB	2.05***	1.58***	1.46***	2.00***	2.29***	1.28***	1.97***
	(65.55)	(76.49)	(76.73)	(46.35)	(47.36)	(18.62)	(39.40)
HML	2.37***	1.66***	1.53***	2.65***	2.80***	2.10***	2.51***
	(41.28)	(40.61)	(38.10)	(28.21)	(39.95)	(15.50)	(28.94)
RMW	2.52***	1.68***	1.55***	2.98***	2.83***	2.57***	2.69***
	(38.87)	(27.85)	(29.23)	(28.50)	(58.25)	(19.63)	(39.45)
CMA	3.09***	1.92***	1.79***	3.50***	3.01***	3.01***	2.76***
	(50.67)	(29.19)	(29.62)	(32.05)	(62.07)	(24.91)	(39.59)

Panel C: High-minus-low Characteristic Spreads

	Daily	HFQ	Cont	Jump	ON	JmC	ONmC
MP	−0.16***	0.02	0.20**	0.01	0.28***	−0.16***	0.28***
	(−2.69)	(0.25)	(2.01)	(0.13)	(3.46)	(−3.99)	(4.62)
SMB	−2.09***	−2.39***	−2.35***	−2.12***	−1.32***	−0.14***	0.32***
	(−40.62)	(−70.78)	(−61.69)	(−38.20)	(−16.76)	(−2.87)	(6.36)
HML	1.15***	1.33***	1.31***	0.98***	0.83***	0.03	0.04
	(32.24)	(31.94)	(33.50)	(22.37)	(18.03)	(1.20)	(1.12)
RMW	0.14***	0.16***	0.16***	0.11***	0.09***	0.02***	−0.01
	(7.80)	(6.89)	(6.71)	(8.19)	(7.01)	(2.80)	(−1.23)
CMA	−0.56***	−0.69***	−0.68***	−0.49***	−0.48***	−0.06***	−0.07***
	(−24.34)	(−26.03)	(−26.80)	(−23.23)	(−21.29)	(−4.12)	(−3.21)

Table 7
Bivariate Portfolio Sorts

This table displays average returns, betas, and controls of bivariate portfolios. At the end of each month from January 1993 to June 2019, all NYSE, AMEX, and NASDAQ stocks with share code 10 or 11 are first sorted into quintiles with respect to a control variable (either a beta estimated across the next six months or a factor characteristic as measured at the end of the sorting month). Breakpoints are based only on NYSE stocks. Second, within each of the five control portfolios, all stocks are sorted into five quintiles according to the beta of interest (also estimated across the next six months). The stocks in the portfolios are value-weighted based on their market capitalizations at the end of the sorting month. The portfolios' returns are calculated as the value-weighted averages of the stocks' compounded returns across the next six months. Returns, betas, and controls are averaged across the control portfolios. The column names depict first the control variable and then the beta of interest, separated by an "x". D, HFQ, C, J, and ON denote the daily, high-frequency, continuous, jump, and overnight betas, respectively. FV denotes the respective factor characteristic. If the beta of interest is an MP (SMB, HML, RMW, CMA) beta, the factor characteristic is ME (ME, BM, OP, INV). Panels A, B, and C depict the time series averages of the return spreads (in percent), the spreads in the betas of interest, and the spreads in the control variables, respectively, between the top and bottom portfolios. Factor characteristics are in each month standardized to have a mean of zero and a standard deviation of one. t-statistics are reported in parentheses. The return spreads' t-statistics in Panel A are computed using Newey-West (1987) heteroskedasticity-robust standard errors with six lags, while beta and control spreads' t-statistics in Panels B and C are computed using 12 lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High-minus-low Return Spreads

	DxHFQ	HFQxD	JxC	ONxC	CxJ	ONxJ	CxON	JxON	FVxD	FVxHFQ	FVxC	FVxJ	FVxON
MP	0.34	−0.08	0.28	0.16	0.03	0.11	−0.27**	−0.16	0.14	0.50	0.45	0.16	0.00
	(1.25)	(−0.59)	(1.13)	(0.61)	(0.35)	(0.80)	(−2.11)	(−1.12)	(0.56)	(1.31)	(1.22)	(0.76)	(0.01)
SMB	0.27	−0.30*	0.15	0.05	−0.13	−0.14	−0.13	−0.16	−0.50**	−0.25	−0.25	−0.24*	−0.16
	(1.15)	(−1.70)	(0.56)	(0.16)	(−1.32)	(−0.67)	(−1.09)	(−1.12)	(−2.50)	(−0.91)	(−0.94)	(−1.85)	(−1.23)
HML	0.39	−0.36**	0.02	−0.05	0.02	−0.11	0.00	−0.13	−0.38	−0.15	−0.17	−0.20	−0.16
	(1.49)	(−2.47)	(0.07)	(−0.16)	(0.19)	(−0.51)	(−0.04)	(−0.88)	(−1.56)	(−0.49)	(−0.56)	(−0.89)	(−1.02)
RMW	0.32	−0.12	0.30	0.36	−0.04	0.15	−0.21	−0.06	0.05	0.33	0.29	0.07	−0.10
	(1.52)	(−0.63)	(1.09)	(1.24)	(−0.34)	(0.70)	(−1.54)	(−0.30)	(0.18)	(1.07)	(0.97)	(0.30)	(−0.53)
CMA	0.17	−0.25	0.03	−0.10	−0.02	−0.06	0.01	0.01	−0.37	−0.20	−0.25	−0.19	−0.21
	(0.87)	(−1.64)	(0.12)	(−0.39)	(−0.19)	(−0.32)	(0.14)	(0.04)	(−1.43)	(−0.72)	(−0.89)	(−0.91)	(−1.11)

Panel B: High-minus-low Beta Spreads

	DxHFQ	HFQxD	JxC	ONxC	CxJ	ONxJ	CxON	JxON	FVxD	FVxHFQ	FVxC	FVxJ	FVxON
MP	0.88***	1.05***	0.84***	0.96***	1.30***	1.52***	1.53***	1.62***	1.35***	1.10***	1.07***	1.67***	1.78***
	(24.23)	(20.86)	(23.34)	(26.25)	(13.54)	(15.54)	(11.87)	(12.53)	(23.61)	(25.17)	(25.17)	(14.93)	(13.14)
SMB	1.25***	1.62***	1.19***	1.39***	1.76***	2.13***	2.55***	2.65***	1.82***	1.10***	1.05***	1.92***	2.54***
	(27.93)	(30.57)	(28.49)	(41.97)	(22.09)	(29.26)	(34.03)	(36.59)	(28.56)	(26.19)	(25.44)	(20.17)	(31.41)
HML	1.34***	2.00***	1.37***	1.48***	2.74***	3.02***	2.93***	3.07***	2.46***	1.65***	1.53***	3.04***	3.14***
	(39.82)	(24.33)	(40.65)	(47.77)	(17.45)	(21.59)	(28.67)	(28.80)	(34.15)	(57.66)	(59.71)	(22.61)	(31.43)
RMW	1.49***	2.29***	1.51***	1.59***	3.16***	3.48***	3.01***	3.19***	2.66***	1.68***	1.55***	3.37***	3.18***
	(47.18)	(27.13)	(64.25)	(66.38)	(21.90)	(27.66)	(44.80)	(56.06)	(34.10)	(38.67)	(44.88)	(26.06)	(58.31)
CMA	1.61***	2.78***	1.63***	1.69***	3.78***	3.97***	3.16***	3.29***	3.17***	1.87***	1.74***	3.90***	3.22***
	(48.71)	(43.55)	(51.41)	(43.58)	(31.47)	(35.34)	(45.28)	(48.86)	(51.88)	(32.94)	(35.33)	(32.98)	(48.95)

Panel C: High-minus-low Control Spreads

	DxHFQ	HFQxD	JxC	ONxC	CxJ	ONxJ	CxON	JxON	FVxD	FVxHFQ	FVxC	FVxJ	FVxON
MP	0.15***	0.13***	0.16***	0.10***	0.14***	0.08***	0.08***	0.06***	0.05**	0.11***	0.13***	0.07***	0.10***
	(21.75)	(17.68)	(29.63)	(12.29)	(28.57)	(9.83)	(11.87)	(11.22)	(2.07)	(4.07)	(5.30)	(3.47)	(5.44)
SMB	0.17***	0.15***	0.13***	0.08***	0.13***	0.06***	0.07***	0.07***	−0.23***	−0.31***	−0.31***	−0.19***	−0.06***
	(17.80)	(20.80)	(16.09)	(6.07)	(24.48)	(5.83)	(17.65)	(10.95)	(−21.55)	(−26.67)	(−23.72)	(−14.69)	(−4.14)
HML	0.33***	0.32***	0.22***	0.24***	0.29***	0.19***	0.18***	0.10***	0.07***	0.09***	0.09***	0.05***	0.03***
	(17.95)	(12.41)	(11.96)	(9.81)	(10.76)	(7.73)	(11.28)	(6.65)	(7.15)	(8.60)	(8.81)	(5.56)	(4.82)
RMW	0.31***	0.32***	0.19***	0.20***	0.24***	0.14***	0.18***	0.08***	0.06*	0.07**	0.06**	0.02*	0.00
	(16.10)	(14.89)	(10.05)	(10.02)	(10.83)	(6.45)	(8.84)	(5.30)	(1.91)	(2.00)	(2.11)	(1.76)	(0.07)
CMA	0.29***	0.32***	0.16***	0.20***	0.26***	0.17***	0.20***	0.10***	0.00	0.00	0.00	0.00	0.00
	(12.91)	(12.79)	(9.72)	(12.17)	(10.54)	(8.80)	(10.85)	(5.19)	(−1.46)	(−1.30)	(−0.92)	(−0.04)	(0.23)

Table 8
Fama-MacBeth Regressions

This table reports risk premium estimates from monthly cross-sectional Fama-MacBeth (1973) regressions across the period from January 1993 to June 2019. The independent variables are the daily, high-frequency (HFQ), continuous (Cont), jump, and overnight (ON) betas with respect to the five Fama-French (2015) factors (MP, SMB, HML, RMW, and CMA). Betas are estimated at the end of each month based on return data across the next six months. The dependent returns are stocks' compounded returns across the next six months in excess of the compounded risk-free rate. The control variables are market equity (ME), book-to-market equity ratio (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), coskewness (CSK), cokurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The variables are measured at the end of the regression month and are in each month standardized to have a mean of zero and a standard deviation of one. Their construction is described in Appendix A. All dependent and independent variables are in each month winsorized at the 1st and 99th percentile. The regressions are estimated with weighted least squares, whereby the weights correspond to the stocks' market capitalizations at the end of the regression month. In each panel, row UV displays the risk premium estimates from univariate regressions, row (1) displays the risk premium estimates when only betas are used as independent variables, row (2) displays the risk premia estimates when betas as well as the factors' characteristics (ME, BM, OP, and INV) are used as independent variables, and row (3) displays the risk premium estimates when betas as well as all controls are used as independent variables (Panel G omits the controls' risk premium estimates for space reasons). $\bar{R}^2$ is the time series average of the monthly regressions' adjusted R^2. 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

	Const	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		−0.07	0.03	4.36	−0.15*	0.26	0.07	0.01	0.12	−0.01	0.02	0.01	0.20	
		(−0.74)	(0.30)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(1.53)	
(1)	0.71***													0.098
	(3.28)													
(2)	0.96***	−0.09	−0.02	8.18	−0.10*									0.152
	(3.16)	(−1.09)	(−0.25)	(1.54)	(−1.67)									
(3)	0.95***	−0.28**	−0.03	5.39*	−0.10**	0.23**	0.03	−0.03	−0.27	0.04	−0.02	−0.05	0.19*	0.217
	(2.95)	(−2.12)	(−0.35)	(1.74)	(−2.26)	(1.96)	(0.54)	(−0.13)	(−1.46)	(1.54)	(−0.36)	(−1.24)	(1.89)	

Panel B: Daily Betas

	Const	MP Daily	SMB Daily	HML Daily	RMW Daily	CMA Daily	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		−0.12	−0.07	−0.14	0.06	−0.09	−0.07	0.03	4.36	−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)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(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***	6.34	−0.10**									0.304
	(5.07)	(1.44)	(−2.47)	(−2.45)	(0.80)	(−1.74)	(−4.31)	(2.99)	(1.46)	(−2.34)									
(3)	1.49***	0.18	−0.31**	−0.37***	0.12	−0.12	−0.26**	0.17***	5.82	−0.11***	−0.06	−0.22***	0.22	−0.07	0.04**	0.02	0.03	0.25**	0.332
	(6.11)	(0.75)	(−2.48)	(−2.77)	(0.86)	(−1.31)	(−2.12)	(3.51)	(1.47)	(−2.60)	(−0.64)	(−4.78)	(1.51)	(−0.40)	(1.97)	(0.61)	(0.70)	(2.06)	

Panel C: High-Frequency Betas

	Const	MP HFQ	SMB HFQ	HML HFQ	RMW HFQ	CMA HFQ	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		0.16	0.09	−0.05	0.15	−0.04	−0.07	0.03	4.36	−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)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(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)	1.19***	0.73**	−0.76***	−0.21	0.20	−0.10	−0.54***	0.07	4.18	−0.11**									0.303
	(5.00)	(2.36)	(−4.80)	(−1.15)	(1.24)	(−1.00)	(−5.06)	(1.50)	(1.15)	(−2.31)									
(3)	1.62***	0.61*	−0.76***	−0.30	0.16	−0.10	−0.30**	0.09**	4.35	−0.11**	−0.12	−0.21***	0.12	0.26	0.04*	0.02	0.03	0.16	0.332
	(5.64)	(1.80)	(−4.75)	(−1.56)	(0.91)	(−0.91)	(−2.26)	(2.08)	(1.17)	(−2.54)	(−1.29)	(−4.45)	(0.77)	(1.60)	(1.73)	(0.51)	(0.67)	(1.18)	

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Panel D: Continuous Betas

	Const	MP Cont	SMB Cont	HML Cont	RMW Cont	CMA Cont	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		0.09	0.10	−0.08	0.16	−0.07	−0.07	0.03	4.36	−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)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(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*	4.88	−0.12**									0.298
	(5.43)	(2.18)	(−4.50)	(−1.30)	(1.18)	(−1.25)	(−4.84)	(1.93)	(1.29)	(−2.50)									
(3)	1.60***	0.56	−0.75***	−0.35*	0.15	−0.12	−0.29**	0.12**	5.05	−0.12***	−0.11	−0.20***	0.11	0.26	0.04	0.02	0.04	0.11	0.327
	(5.88)	(1.63)	(−4.35)	(−1.68)	(0.86)	(−1.11)	(−2.17)	(2.52)	(1.30)	(−2.74)	(−1.13)	(−4.31)	(0.70)	(1.52)	(1.62)	(0.65)	(0.85)	(0.81)	

Panel E: Jump Betas

	Const	MP Jump	SMB Jump	HML Jump	RMW Jump	CMA Jump	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		−0.01	0.01	−0.08	0.04	−0.03	−0.07	0.03	4.36	−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)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(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	6.43	−0.13**									0.254
	(5.30)	(0.58)	(−3.24)	(−1.07)	(0.39)	(−1.57)	(−2.34)	(0.58)	(1.47)	(−2.51)									
(3)	1.42***	−0.01	−0.23***	−0.11	0.02	−0.07*	−0.21	0.06	4.91	−0.14***	0.06	−0.11*	0.20	−0.08	0.05*	0.02	−0.02	0.25**	0.294
	(5.29)	(−0.03)	(−3.76)	(−1.59)	(0.40)	(−1.67)	(−1.62)	(1.02)	(1.53)	(−2.85)	(0.59)	(−1.94)	(0.87)	(−0.45)	(1.81)	(0.46)	(−0.31)	(2.24)	

Panel F: Overnight Betas

	Const	MP ON	SMB ON	HML ON	RMW ON	CMA ON	ME	BM	OP	INV	MOM	STR	IVOL	ILLIQ	CSK	CKT	RSK	RKT	$\bar{R}^2$
UV		−0.22	0.01	−0.06	0.01	−0.04	−0.07	0.03	4.36	−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)	(1.05)	(−1.85)	(1.59)	(1.17)	(0.05)	(1.12)	(−0.19)	(0.33)	(0.20)	(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	7.17	−0.13***									0.264
	(4.10)	(−0.14)	(0.73)	(−1.02)	(0.13)	(−1.18)	(−0.98)	(0.49)	(1.43)	(−2.69)									
(3)	1.40***	−0.28	0.09	−0.11	0.06	−0.04	−0.12	0.05	5.77	−0.13***	0.15	−0.08	0.22	−0.20	0.06**	0.06*	0.00	0.28**	0.297
	(4.88)	(−1.29)	(1.22)	(−1.14)	(0.76)	(−0.61)	(−0.94)	(0.97)	(1.58)	(−3.02)	(1.44)	(−1.42)	(1.16)	(−1.15)	(2.39)	(1.91)	(−0.03)	(2.40)	

Panel G: Continuous, Jump, and Overnight Betas

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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)	(0.56)	(−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
	(6.16)	(3.76)	(0.23)	(−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
	(6.59)	(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 9
Fama-MacBeth Regressions: Robustness Checks

This table reports risk premium estimates from monthly cross-sectional Fama-MacBeth (1973) regressions across the period from January 1993 to June 2019. The independent variables are the continuous (Cont), jump, and overnight (ON) betas with respect to the five Fama-French (2015) factors (MP, SMB, HML, RMW, and CMA). Betas are estimated at the end of each month. The dependent returns are stocks' compounded returns across the estimation window in excess of the compounded risk-free rate. The control variables are market equity (ME), book-to-market equity ratio (BM), operating profitability (OP), investment (INV), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), coskewness (CSK), cokurtosis (CKT), realized skewness (RSK), and realized kurtosis (RKT). The variables are measured at the end of the regression month and are in each month standardized to have a mean of zero and a standard deviation of one. Their construction is described in Appendix A. All dependent and independent variables are in each month winsorized at the 1st and 99th percentile. The regressions are estimated with weighted least squares, whereby the weights correspond to the stocks' market capitalizations at the end of the regression month. In each panel, row UV displays the risk premium estimates from univariate regressions, row (1) displays the risk premium estimates when only betas are used as independent variables, row (2) displays the risk premium estimates when betas as well as the factors' characteristics (ME, BM, OP, and INV) are used as independent variables, and row (3) displays the risk premium estimates when betas as well as all controls are used as independent variables (the controls' risk premium estimates are omitted for space reasons). $\bar{R}^2$ is the time series average of the monthly regressions' adjusted R^2. The robustness checks modify the standard estimation procedure as described in Section 4.2 in the following ways: in Panels A and B, the estimation window lengths are three and 12 months, respectively. 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 our sample and the sampling frequency is 15 minutes. In Panel G, an alternative methodology for the estimation of jump betas is used. 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

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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***	0.78***	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
	(6.87)	(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)	1.90***	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
	(7.19)	(2.42)	(0.51)	(−3.65)	(−4.57)	(−2.74)	(2.26)	(−1.75)	(0.84)	(1.61)	(1.35)	(0.09)	(1.57)	(−1.39)	(0.00)	(1.92)	

Panel B: 12-month Estimation Window

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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
	(5.82)	(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

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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
	(6.17)	(3.81)	(−0.30)	(−3.51)	(−3.88)	(−2.49)	(2.54)	(−3.11)	(0.96)	(1.87)	(1.22)	(0.00)	(2.04)	(−2.85)	(−0.12)	(1.74)	
(3)	2.24***	1.21***	−0.04	−0.65***	−0.92***	−0.17**	0.18***	−0.65***	0.03	0.14*	0.18	0.01	0.12**	−0.33***	0.01	0.11	0.373
	(7.84)	(3.64)	(−0.60)	(−4.13)	(−4.45)	(−2.44)	(2.76)	(−3.32)	(0.72)	(1.73)	(1.11)	(0.21)	(2.39)	(−2.76)	(0.29)	(1.64)	

Panel D: 30-minute Sampling Frequency

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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
	(6.08)	(3.46)	(1.89)	(−3.58)	(−5.66)	(−0.72)	(2.46)	(−1.99)	(−1.86)	(1.80)	(1.43)	(−1.17)	(1.44)	(−2.01)	(−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
	(7.45)	(3.23)	(1.79)	(−4.01)	(−5.89)	(−0.76)	(2.43)	(−2.37)	(−1.87)	(1.49)	(1.26)	(−1.25)	(1.75)	(−1.97)	(−2.27)	(1.51)	

Panel E: 75-minute Sampling Frequency

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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
	(5.22)	(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
	(6.12)	(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

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
UV		0.19	0.05	−0.18	0.52*	0.26*	0.11	−0.12	−0.10	−0.08	0.12	0.05	0.03	−0.13	−0.04	−0.07	
		(0.46)	(0.19)	(−0.94)	(1.83)	(1.67)	(1.53)	(−0.53)	(−1.01)	(−1.17)	(0.59)	(0.52)	(0.43)	(−0.87)	(−0.55)	(−1.00)	
(1)	0.65***	0.77**	0.08	−0.53***	0.24	−0.07	0.21***	−0.26	0.03	0.10	−0.14	0.00	0.10*	−0.27***	−0.01	0.12	0.322
	(3.83)	(2.40)	(0.90)	(−3.32)	(1.07)	(−0.87)	(3.09)	(−1.44)	(0.66)	(1.24)	(−0.96)	(−0.12)	(1.87)	(−2.59)	(−0.32)	(1.61)	
(2)	0.71***	0.98***	0.05	−0.42**	−0.49*	−0.15*	0.16**	−0.42**	0.04	0.07	0.05	0.01	0.11**	−0.30***	−0.01	0.09	0.345
	(4.26)	(3.05)	(0.55)	(−2.55)	(−1.89)	(−1.82)	(2.47)	(−2.19)	(0.79)	(0.87)	(0.36)	(0.25)	(2.03)	(−2.73)	(−0.41)	(1.29)	
(3)	1.04***	0.82***	0.01	−0.48***	−0.50**	−0.13*	0.17**	−0.45**	0.04	0.07	0.02	0.01	0.12**	−0.25**	−0.01	0.08	0.378
	(5.13)	(2.58)	(0.12)	(−2.90)	(−1.98)	(−1.72)	(2.57)	(−2.43)	(0.86)	(0.90)	(0.17)	(0.26)	(2.39)	(−2.27)	(−0.26)	(1.28)	

Panel G: Alternative Estimation Methodology

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
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)	(−2.41)	(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
	(6.04)	(4.98)	(−1.26)	(−3.46)	(−4.95)	(−0.05)	(1.98)	(−3.24)	(1.94)	(1.88)	(0.23)	(1.58)	(1.52)	(−3.30)	(1.80)	(1.56)	
(3)	1.81***	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
	(6.71)	(4.74)	(−1.94)	(−3.98)	(−4.63)	(−0.53)	(2.16)	(−3.38)	(1.74)	(1.69)	(−0.20)	(1.89)	(1.92)	(−3.05)	(1.57)	(1.58)	

Panel H: Instrumental Variables Approach

	Const	MP Cont	MP Jump	MP ON	SMB Cont	SMB Jump	SMB ON	HML Cont	HML Jump	HML ON	RMW Cont	RMW Jump	RMW ON	CMA Cont	CMA Jump	CMA ON	$\bar{R}^2$
UV		−0.25	−0.18	−0.28	−0.03	−0.08	−0.02	−0.19	−0.14	−0.13	0.30	0.21	0.18	−0.04	−0.10	0.08	
		(−0.64)	(−0.45)	(−0.85)	(−0.13)	(−0.31)	(−0.09)	(−0.95)	(−0.77)	(−0.65)	(1.45)	(1.20)	(0.94)	(−0.24)	(−0.69)	(0.44)	
(1)	0.78**	0.60**	−0.04	−0.65***	−0.15	−0.08	0.58***	−0.26*	0.07	0.37***	−0.02	0.01	0.22*	−0.19**	−0.11	0.14	0.244
	(2.19)	(2.54)	(−0.19)	(−3.09)	(−1.02)	(−0.59)	(3.05)	(−1.74)	(0.64)	(2.59)	(−0.16)	(0.09)	(1.81)	(−2.19)	(−1.54)	(1.09)	
(2)	1.46***	0.80***	−0.26	−0.54**	−0.74***	−0.20	0.47**	−0.50***	−0.04	0.27**	0.05	0.04	0.20*	−0.27***	−0.16**	0.13	0.268
	(3.71)	(3.49)	(−1.18)	(−2.49)	(−4.77)	(−1.28)	(2.07)	(−3.31)	(−0.32)	(1.98)	(0.38)	(0.32)	(1.76)	(−2.96)	(−2.05)	(1.00)	
(3)	2.09***	0.68***	−0.18	−0.73***	−0.77***	−0.21	0.41*	−0.56***	−0.03	0.24*	0.00	0.02	0.21*	−0.27***	−0.18**	0.14	0.291
	(4.96)	(2.76)	(−0.76)	(−3.41)	(−4.79)	(−1.39)	(1.80)	(−3.75)	(−0.28)	(1.73)	(−0.03)	(0.16)	(1.90)	(−2.94)	(−2.19)	(1.12)	