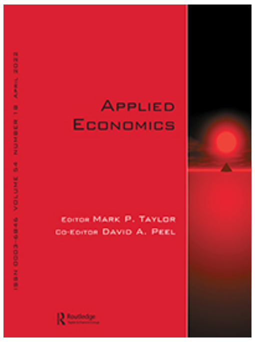

Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

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To cite this article: Jiali Fang, Wei Hao & Udomsak Wongchoti (2022) Time-series momentum in individual stocks: is it there and where to look?, Applied Economics, 54:18, 2048-2066, DOI: 10.1080/00036846.2021.1983151

To link to this article: https://doi.org/10.1080/00036846.2021.1983151

Published online: 01 Dec 2021.

APPLIED ECONOMICS
2022, VOL. 54, NO. 18, 2048–2066
https://doi.org/10.1080/00036846.2021.1983151

Time-series momentum in individual stocks: is it there and where to look?

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ABSTRACT
Time series momentum (TSMOM), which is found in various asset classes, offers investors several practical advantages over traditional cross-sectional momentum. However, recent studies raise questions about its general existence and urge researchers to extensively search for optimal combinations in time horizon, asset characteristics, and market conditions in which TSMOM may be profitable. With a comprehensive study covering 2.25 million monthly returns on over 20,000 US individual stocks from 1986 to 2017, we find that TSMOM profits are more prominent among stocks and during market states characterized by inferior information dissemination.

KEYWORDS
Time series momentum; economic policy uncertainty; sentiment; market states

JEL CLASSIFICATION
Codes: G12; G14

I. Introduction

Moskowitz, Ooi, and Pedersen (2012) document a trend-based trading strategy that buys (sells) the underlying asset if the asset's ***own*** past excess returns are positive (negative). As there is no need to compare the performance of a certain asset against others to define winners or losers, Moskowitz, Ooi, and Pedersen (2012) name such a trading strategy 'time series momentum (TSMOM)' and find it highly profitable for each of the 58 liquid instruments they consider, including equity indices, currency, commodity and bond futures. Following their study, researchers have provided out-of-sample tests on different versions of TSMOM on various asset classes (using samples from different international markets and time periods). Examples of studies that provide supportive evidence include Hurst, Ooi, and Pedersen (2017), Ham et al. (2019), Gao et al. (2018), Jin et al. (2020) and Pitkäjärvi, Suominen, and Vaittinen (2020), among others.[1] However, the validity of TSMOM is still debatable, as several studies conclude with the opposite findings. For example, Kim, Tse, and Wald (2016) show that the profitability of TSMOM largely disappears if the returns of each asset class are not scaled by their volatilities, as per Moskowitz, Ooi, and Pedersen (2012). Such scaling has an impact on assigning weights in a multi-asset class portfolio and is used in assessing the profitability of TSMOM. In the context of common stocks, Goyal and Jegadeesh (2018) further document that such scaling magnifies the weight of the long and short positions in the past winner/loser stocks, as well as the net long positions and the magnitude of the profits. In other words, TSMOM could manifest the profitability of the conventional momentum effect (as introduced by Jegadeesh and Titman (1993)) when scaling is used. This is in line with He and Li's (2015) theoretical model, which predicts that TSMOM is profitable only when momentum traders dominate the market and a short-term time horizon is considered.

In a recent study, Huang et al. (2020) comprehensively re-examine Moskowitz et al.'s TSMOM profitability in a 'time series regression' framework. They report that TSMOM profit is rather weak at best, especially when applied to a large cross-section of assets. Not ruling out the

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[1]Hurst, Ooi, and Pedersen (2017) apply a TSMOM strategy to global markets using a longer sample period and confirm that this strategy has been effective over the past 137 years. Their sample includes 29 commodities, 11 equity indices, 15 bond markets and 12 currency pairs. Ham et al. (2019) document significant TSMOM profits in ten commodity futures from 2006 to 2018 in the Chinese market. Gao et al. (2018) analyse US and ten international ETFs from 1993 to 2013 and provide strong evidence of intraday TSMOM that the first half-hour return of the trading day significantly predicts the last half-hour return. Jin et al. (2020) document a similar intraday TSMOM across four Chinese Commodity future contracts (copper, steel, soybean, and soybean meal) from 2002 to 2013. Pitkäjärvi, Suominen, and Vaittinen (2020) document a cross-asset time series momentum. Using data from 20 countries from 1980 to 2016, they show that past bond market returns are positive predictors of future equity market returns and past equity market returns are negative predictors of future bond market returns.

possibility of TSMOM profits altogether, however, they urge researchers to perform a more thorough review of the possible optimal combinations of time horizon, market conditions, and individual characteristics to determine the viability of TSMOM as a trading strategy. In this paper, we aim to provide such an empirical investigation on US common stocks.

We investigate the profitability of the TSMOM among all available US individual stocks during the period from July 1986 to December 2017. Our investigation provides an advantageous empirical setting in examining the TSMOM profitability debate. First, as noted by Moskowitz, Ooi, and Pedersen (2012), time series momentum is true to the spirit of prominent behavioural models introduced by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (2005), and Hong and Stein (1999), as it is *'single-asset'* based. Furthermore, these behavioural models have the most direct applicability to common stocks. Together with the suggestion by Huang et al. (2020) that one should explore the large sample of 'single' assets to provide a comprehensive look at TSMOM, it is surprising that there is little evidence on TSMOM profitability on the most common asset class – individual stocks.[2] We intend to fill this gap. Second, the existence of TSMOM profitability could represent an appealing investment alternative to retail investors or investors who are more exposed to informational disadvantages and transaction cost burdens. For example, compared to the closely related cross-sectional momentum (XSMOM) strategy (e.g. Jegadeesh and Titman 1993), TSMOM only requires data for the underlying asset's own past returns but none for those of its peers. Therefore, it can be directly applicable to trading individual stocks at lower information costs. Moreover, it is often costly to long (short) a large number of stocks as required to properly implement XSMOM (or TSMOM in the 'portfolio' version of existing studies[3]). As such, investigating TSMOM profitability on individual stocks has important implications for retail investors, as it is relatively more practical. Third, we reinvestigate TSMOM profits while taking into account technical critiques raised by recent studies that question its existence. For example, by focusing on only common stocks, we do not need to scale our returns to reflect the varied volatility across asset classes (as originally done by Moskowitz, Ooi, and Pedersen (2012) and criticized by Kim, Tse, and Wald (2016), among others). We also apply Huang et al.'s (2020) time series regression framework on TSMOM profits in US common stocks to check for robustness.

Applying TSMOM to 2.52 million stock-month observations on over 20,000 individual stocks and using various combinations of time horizons in terms of lookback and holding periods (required to form a TSMOM strategy), during the 1986–2017 period, we find that TSMOM profits on US common stocks are weak in the full sample. This is consistent with recent studies that question the viability of TSMOM as a trading strategy. In terms of raw returns, 58% of US stocks generate positive TSMOM returns on average. However, once adjusted for risk, this percentage decreases to 45%. This finding remains consistent across various asset pricing factor models. Corresponding to Huang et al.'s (2020) question, we find that combining longer lookback periods (12 months) with shorter holding periods (1 month) generates the highest TSMOM profits on common stocks on average. These results are based on all 25 TSMOM strategies we construct using different combinations of time horizons.

As implied by Huang et al. (2020), TSMOM may not be observable in all assets. We provide a closer look into which common stocks (based on characteristics) and when (based on market-wide conditions) TSMOM may be profitable. On a broader level, TSMOM relates closely to the classic strand of literature that examines the autocorrelation

[2]While previous studies investigate TSMOM profits on portfolios formed from individual stocks based on their past returns (see, e.g. Goyal and Jegadeesh (2018), Lim, Wang, and Yao (2018), Cheema, Nartea, and Man (2018) and Cheema and Nartea (2018), and Cheema, Nartea, and Szulczyk (2018)), their strategy is different from ours as they take a long (short) position in all stocks with positive (negative) past excess returns in a certain month (e.g. effectively a portfolio-based approach). In contrast, we study each individual stock as a separate and independent investment opportunity. Related to our study, Qin, Pan, and Bai (2020) investigate the TSMOM profitability in a sample of 289 Chinese individual stocks.

[3]As an example, Goyal and Jegadeesh (2018) analyse the effectiveness of TSMOM on portfolios formed from US individual stocks, and they document TSMOM portfolios may require investors to take bigger long position than short position as more stocks earned positive returns during a sample period. They conclude that the seemingly superior performance of TSMOM over XSMOM is driven by TSMOM's net long position.

among stock returns. Thus, trading strategies that make use of past stock returns would be exploitable (e.g. TSMOM, XSMOM and technical analysis (TA) strategies). Much of the existing evidence (Lim, Wang, and Yao 2018; Neely et al. 2014) suggests that price autocorrelation tends to be higher when information uncertainty is high, as fundamental information during these periods is relatively inaccurate or hard to obtain (i.e. less useful to investors). Stock prices become less revealing (on true fundamentals) and thus autocorrelated when information is gradually incorporated into prices only later on (Brown and Jennings 1989; Zhu and Zhou 2009; Han, Yang, and Zhou 2013; Zhang 2006). As a result, we postulate that market-wide information uncertainty is higher during periods of high Economic Policy Uncertainty (EPU), low sentiment, economic contraction, and high market volatility.[4] At individual stock level, information uncertainty may be higher for stocks with low synchronicity, low turnover, low beta, low skewness and low volatility (i.e. lower investor attention). Evidence linking these market-wide and stock-level proxies for information uncertainty to TSMOM is scarce in the literature.[5]

Our evidence largely confirms the positive association between information uncertainty and TSMOM returns, as postulated. However, on a practical level, the actual risk-adjusted returns are only positive when a specific set of conditions in which both high stock-level and market-wide information uncertainty are simultaneously satisfied. Specifically, TSMOM returns are positive only among stocks with low synchronicity, low turnover, low beta ***or*** low skewness. This happens only during periods of high EPU, low sentiment, economic contraction ***or*** high market volatility. The monthly TSMOM returns in these conditions range from 0.05% to 2.13%. However, for a stricter test on TSMOM profitability (as stressed by both Moskowitz, Ooi, and Pedersen (2012) and Huang et al. (2020)), one needs to perform several tests using the magnitude and sign of an individual asset's own past returns to predict its future returns (i.e. time series regression framework). We find that only when a stricter set of conditions at the stock level are met do the results pass such tests. In line with our estimated risk-adjusted returns, the robustness of TSMOM profits prevails in high EPU, low sentiment, economic contraction ***or*** high market volatility periods, and for stocks with low synchronicity, low turnover, low beta ***and*** low skewness.

Overall, our empirical findings add new and timely evidence to the ongoing puzzling debate regarding TSMOM profitability between Moskowitz, Ooi, and Pedersen (2012) and Huang et al.'s (2020) opposing views. As Lo and MacKinlay (1990) and Huang et al. (2020) point out, the best remedy for uncertainty is to employ a new and large sample. By applying fundamental yet powerful tests (while taking into account practical issues), we highlight the importance of thoroughly revisiting trading opportunities already documented in the literature.

II. Data and methodology

Calculating TSMOM profits

To calculate TSMOM profits, we obtain the monthly US individual stock return data from CRSP and the corresponding risk-free rate (rf_t), market risk premium $(rm_t - rf_t)$, SMB (SMB_t), HML (HML_t) and MOM (MOM_t) factors from Kenneth French's website. We include all possible observations from 1986[6] to 2017. Our final sample includes more than 2.52 million monthly stock returns from 20,492 individual stocks in total.

Following Moskowitz, Ooi, and Pedersen (2012), for each individual stock i and month t, we examine whether the excess return (i.e. $r_t^i - rf_t$) over the past k months is positive or negative. We then long (short) the stock in month $t + 1$ if the past excess return is positive (negative) and hold the position for h months. For months with no trading signal, we invest in risk-free assets. To avoid market microstructure issues, we skip one month between the lookback and holding periods, similar

[4]Market volatility serves as a direct measure of market uncertainty. We thank our anonymous reviewer for this point.
[5]Lim, Wang, and Yao (2018) provide longitudinal evidence that TSMOM profits are more pronounced in periods with positive market sentiment. We extend their study by also looking at the effect of Economic Policy Uncertainty (EPU), business cycles and market volatility on TSMOM profits for US common stocks.
[6]Economic Policy Uncertainty (EPU) data is available from 1986 onwards.

to Jegadeesh and Titman (1993). Therefore, we denote each trading strategy as (k, h), where k and h refer to the lookback and holding periods, respectively. In line with Moskowitz, Ooi, and Pedersen (2012), our choices for k and h include 1, 3, 6, 9 and 12 months.[7] In total, this results in 25 TSMOM strategies.

For each strategy, we first calculate monthly raw returns (RAW_t^i) per the methodology described above. Then, excess returns are calculated as the difference between raw and risk-free returns ($EXCESS_t^i$). Additionally, we calculate three sets of risk-adjusted returns based on CAPM ($CAPM_t^i$), Fama-French three-factor (1993) ($FF3_t^i$), and Carhart four-factor (1997) ($CAHART4_t^i$)models captured by the intercept terms of Equations (1), (2) and (3), respectively:

$$RAW_t^i - rf_t = CAPM_t^i + \beta_t^i(rm_t - rf_t) +_t^i \quad (1)$$

$$RAW_t^i - rf_t = FF3_t^i + \beta 1_t^i(rm_t - rf_t) + \beta 2_t^i SMB_t + \beta 3_t^i HML_t +_t^i \quad (2)$$

$$RAW_t^i - rf_t = CAHART4_t^i + \beta 4_t^i(rm_t - rf_t) + \beta 5_t^i SMB_t + \beta 6_t^i HML_t + \beta 7_t^i MOM_t +_t^i \quad (3)$$

Forming portfolios based on market states and stock-level characteristics

First, we conjecture that TSMOM profitability is conditional on market states. According to Moskowitz, Ooi, and Pedersen (2012), TSMOM is more profitable when markets experience greater uncertainty. In a related study, Cujean and Hasler (2017) posit that disagreement among investors is the theoretical mechanism behind stock return predictability as investors learn and adjust to information at different speeds and reassess fundamental uncertainty differently in various market states. Their theoretical model predicts that TSMOM is more profitable in the presence of disagreement with a return profile that is concentrated in bad times. In a subsequent study, Lim, Wang, and Yao (2018) document higher TSMOM profitability during down markets.

Motivated by the above studies, we distinguish between various market states using four sets of criteria. First, we separate our sample into high, medium and low periods based on the tercile values of the Economic Policy Uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016), the sentiment index of Baker and Wurgler (2006), and the monthly stock market volatility (calculated as the standard deviation of daily market returns obtained from Kenneth French's data library). Specifically, for each month, if the previous month's EPU (sentiment or market volatility) value is in the 67th percentile or above, the month is denoted as a high EPU (high sentiment or high market uncertainty) month. On the other hand, if the previous month's value is lower than the 33rd percentile value, then the month is denoted as a low EPU (low sentiment or low market uncertainty) month. We also separate our sample into expansion and contraction periods based on the commonly used NBER business cycle definition from 1986 to 2017.

Second, at the individual stock level, positive autocorrelation in stock returns (Lewellen 2002) and gradual information diffusion (Chen and Lu 2017) indicate stronger stock price continuation, allowing for more exploitable stock price predictability. To investigate whether TSMOM profitability is conditional on stock-level characteristics (in addition to market-wide conditions), we further employ five stock-level proxies to capture information diffusion and price autocorrelation, namely synchronicity (*Sync*), turnover (*Turn*), skewness (*Skew*), beta (*Beta*) and volatility (*Vol*).

To facilitate comparisons, a lower value of these proxies indicates slower information diffusion or a higher level of autocorrelation (and thus a more profitable TSMOM trading strategy). Specifically, lower synchronicity implies

[7]Moskowitz, Ooi, and Pedersen (2012) also employ 24-, 36- and 48-months lookback/holding periods, we do not study these strategies for several reasons. First, the authors find the TSMOM profits are strongest for shorter lookback and holding periods, such profitability disappears or even reverses over longer horizons. Due to this reason, many studies on TSMOM focus on lookback/holding periods up to 12 months including Huang et al. (2020), for more examples, see Kim, Tse, and Wald (2016) and Marshall, Nguyen, and Visaltanachoti (2017). Second, studying longer periods on an individual stock basis means a significant proportion of the stocks could be excluded from our sample. For example, forming a (48, 48) strategy requires approximately 8 years of stock return data. While the median life of an average stock in CRSP is 7.5 years according to Bessembinder (2018).

a weaker information environment and less firm-specific information being incorporated into stock prices (see, e.g. Dasgupta, Gan, and Gao 2010; Devos et al. 2015; Hao, Prevost, and Wongchoti 2018 and others). Similarly, based on the premise that information (both positive and negative) increases stock beta (Patton and Verardo 2012), stocks with lower beta are also associated with slower information diffusion. Regarding trading activities (investor attention), Campbell, Grossman, and Wang (1993) also identify a negative relation between trading volume and autocorrelation in stock returns. Lin, Wu, and Chiang (2014) find that financial analysts are less motivated to process information on less actively traded stocks. This results in slower information diffusion. Finally, researchers document that stocks with lower volatility (LeBaron 1992; Booth and Loutmos, 1998) and skewness (Chen, Hong, and Stein 2001) exhibit stronger price (positive) autocorrelation. Thus, TSMOM trading strategy should be more exploitable among these stocks.

We collect monthly data to construct the above proxies from CRSP. Specifically, we calculate monthly synchronicity based on the market industry model.[8] Monthly return skewness and return volatility are calculated using daily returns. Stock beta is estimated based on the Carhart four-factor model. For each month, we group stocks into three characteristic terciles (using 33rd and 67th percentile cut-offs) based on their synchronicity, turnover, return skewness, stock beta and volatility values.

In addition to single-sorting based on market states or the abovementioned stock characteristics, we perform double-sorting analysis combining both market-level and stock-level conditions. This results in 3 × 3 groups for each stock-level characteristic under EPU, sentiment, and market volatility states (and 3 × 2 groups under market expansion/contraction states). For all sorting (single and double), our tercile groups are rebalanced monthly.

III. TSMOM profits for individual stocks

Overall profitability: pooled analysis

Following Section 2.1, we apply the 25 TSMOM trading strategies to each individual stock in our sample. Then, for each trading strategy, we pool all monthly TSMOM returns for the full sample and take the average to calculate its overall profitability.

We report the results in Table 1. Panels A to E present the results for raw returns (RAW_t^i), excess returns($EXCESS_t^i$), CAPM risk-adjusted returns ($CAPM_t^i$), Fama-French three-factor adjusted returns ($FF3_t^i$), and Carhart four-factor adjusted returns ($CAHART4_t^i$), respectively. In each panel, we report the lookback periods in the columns and the holding periods in the rows. The last column reports the average returns of the TSMOM strategies that have the same holding but different lookback periods. The last row of each panel reports the average returns of the TSMOM strategies that have the same lookback but different holding periods. We look at the average values by row/column to identify the most effective lookback and holding periods. Therefore, the interaction of the last column and the last row of each panel represents the overall average TSMOM profit across all 25 strategies.

The results in Panel A indicate great variation in the average RAW_t^i across different strategies. Across different lookback periods (e.g. columns), the TSMOM strategies that utilize only the past one-month's return (second column) produce a low average return of only 0.01%. By extending the lookback periods to 9 and 12 months, the average monthly TSMOM returns increase to 0.14% (fifth column) and 0.09% (sixth column), respectively. The choice of holding period also matters. TSMOM strategies with shorter holding periods generally perform best (e.g. by comparing the results in different rows). For example, the average returns generated by TSMOM strategies that hold the position for one and three months are 0.13% (first row of Panel A) and 0.10% (second row). This is in contrast to the lower average return

[8]The market industry model is widely used in the literature for estimating stock return synchronicity (see, e.g. Durnev, Morck, and Yeung (2004), Chen, Goldstein, and Jiang (2007), Stowe and Xing (2011), Hao et al. (2020), among others). We follow the literature in constructing our market industry model. Monthly stock return synchronicity is then calculated based on daily market and industry returns.

Table 1. Average monthly TSMOM returns in US individual stocks – pooled analysis.

Lookback period	1 L	3 L	6 L	9 L	12 L	Average
Holding period						
Panel A: Raw returns (RAW)						
1 H	0.01%	0.06%	0.13%	0.21%	0.22%	0.13%
3 H	0.02%	0.01%	0.10%	0.20%	0.18%	0.10%
6 H	0.01%	0.03%	0.14%	0.18%	0.09%	0.09%
9 H	0.00%	0.08%	0.15%	0.11%	0.01%	0.07%
12 H	0.02%	0.05%	0.06%	0.00%	−0.04%	0.02%
Average	0.01%	0.05%	0.12%	0.14%	0.09%	0.08%
Panel B: Excess returns (EXCESS)						
1 H	−0.29%	−0.23%	−0.17%	−0.09%	−0.08%	−0.17%
3 H	−0.28%	−0.29%	−0.20%	−0.10%	−0.12%	−0.20%
6 H	−0.29%	−0.27%	−0.16%	−0.12%	−0.21%	−0.21%
9 H	−0.30%	−0.22%	−0.15%	−0.18%	−0.28%	−0.23%
12 H	−0.28%	−0.25%	−0.23%	−0.30%	−0.34%	−0.28%
Average	−0.29%	−0.25%	−0.18%	−0.16%	−0.21%	−0.22%
Panel C: CAPM returns (CAPM)						
1 H	−0.22%	−0.14%	−0.09%	−0.02%	−0.02%	−0.10%
3 H	−0.26%	−0.27%	−0.18%	−0.09%	−0.10%	−0.18%
6 H	−0.28%	−0.26%	−0.15%	−0.10%	−0.19%	−0.20%
9 H	−0.29%	−0.22%	−0.14%	−0.17%	−0.29%	−0.22%
12 H	−0.28%	−0.25%	−0.23%	−0.30%	−0.35%	−0.28%
Average	−0.27%	−0.23%	−0.16%	−0.14%	−0.19%	−0.20%
Panel D: Fama French 3-factor risk-adjusted returns (FF3)						
1 H	−0.23%	−0.19%	−0.13%	−0.04%	−0.02%	−0.12%
3 H	−0.26%	−0.28%	−0.19%	−0.09%	−0.10%	−0.19%
6 H	−0.28%	−0.26%	−0.14%	−0.09%	−0.18%	−0.19%
9 H	−0.29%	−0.23%	−0.15%	−0.16%	−0.28%	−0.22%
12 H	−0.27%	−0.25%	−0.22%	−0.30%	−0.34%	−0.28%
Average	−0.27%	−0.24%	−0.17%	−0.13%	−0.18%	−0.20%
Panel E: Carhart 4-factor risk-adjusted returns (CARHART4)						
1 H	−0.42%	−0.44%	−0.42%	−0.38%	−0.35%	−0.40%
3 H	−0.26%	−0.30%	−0.24%	−0.15%	−0.16%	−0.22%
6 H	−0.30%	−0.29%	−0.17%	−0.11%	−0.20%	−0.21%
9 H	−0.28%	−0.23%	−0.14%	−0.15%	−0.27%	−0.21%
12 H	−0.27%	−0.23%	−0.20%	−0.28%	−0.33%	−0.26%
Average	−0.31%	−0.30%	−0.23%	−0.21%	−0.26%	−0.26%

In this table, we apply 25 TSMOM trading strategies, formed based on 1-, 3-, 6-, 9-, and 12-month holding periods and 1-, 3-, 6-, 9-, and 12-month lookback periods, to each individual US stock in our sample. The pooled average monthly TSMOM return is calculated for each trading strategy. Panels A to E present the results for raw returns, excess returns, CAPM risk-adjusted returns, Fama-French three-factor adjusted returns, and Carhart four-factor adjusted returns, respectively. The last column in each panel reports the average returns of the TSMOM strategies with the same holding but different lookback periods. The last row of each panel reports the average returns of the TSMOM strategies with the same lookback but different holding periods.

of only 0.02% (fifth row) generated by the strategies with twelve-month holding periods. Overall, the average monthly RAW_t^i is 0.08% across all TSMOM strategies. Most strategies generate at least some positive average monthly returns (with one exception being the (L12, H12) strategy), but the average returns are rather small for many of them. In general, longer lookback periods combined with shorter holding periods generate the best performance. The best-performing strategy (L12, H1) generates an average monthly return of 0.22%. This indicates that the prediction tends to be more accurate when past returns over a longer time span are used to predict short-term future returns. In other words, such predictability, if any, tends to be short-lived.

Next, we present the $EXCESS_t^i$ returns in Panel B. Strikingly, after deducting risk-free returns, none of the 25 TSMOM strategies generates a positive mean $EXCESS_t^i$, with the average value across all 25 strategies being −0.22%. We also document similar findings by calculating different risk-adjusted returns. The overall average $CAPM_t^i$ is −0.20%, as shown in Panel C. The average $FF3_t^i$ and $CAHART4_t^i$ are −0.20% and −0.26%, respectively, as shown in Panels D and E. So far, our findings do not lend much support to the profitability of TSMOM on an 'average' basis, especially after taking into account compensation for common risk factors.

Overall profitability: individual stock analysis

In Section 3.1, a stock with more monthly observations available (i.e. longer life) is allocated more weight in calculating average returns. This may not reflect the true profitability of applying TSMOM strategies to each stock. To account for this possible issue, we first calculate the average TSMOM return over the entire life of each individual stock and then determine the average return across all stocks. This approach weights all individual stocks equally in calculating the final average returns. Table 2 present the results. In general, the average TSMOM returns are consistently higher compared to the pooled analysis. This indicates that the TSMOM is possibly more efficient for a subset of stocks. In Panel A, we find that the average RAW_t^i across all strategies is 0.27% per month (i.e. 3.24% per annum), compared to 0.08% (that is, 0.96% per annum) in Table 1. Nevertheless, although the losses in Table 2 are all lower than those in Table 1, a negative overall average $EXCESS_t^i, CAPM_t^i, FF3_t^i$ and $CAHART4_t^i$ persist across the board.

Table 2. Average monthly TSMOM returns in US individual stocks – individual stock analysis.

Lookback period	1 L	3 L	6 L	9 L	12 L	Average
Holding period						
Panel A: Raw returns (RAW)						
1 H	0.25%	0.32%	0.44%	0.47%	0.49%	0.39%
3 H	0.22%	0.20%	0.33%	0.42%	0.41%	0.32%
6 H	0.13%	0.16%	0.30%	0.35%	0.31%	0.25%
9 H	0.09%	0.21%	0.31%	0.31%	0.24%	0.23%
12 H	0.10%	0.20%	0.23%	0.19%	0.17%	0.18%
Average	0.16%	0.22%	0.32%	0.35%	0.32%	0.27%
Panel B: Excess returns (EXCESS)						
1 H	−0.08%	−0.01%	0.11%	0.14%	0.16%	0.06%
3 H	−0.10%	−0.13%	0.00%	0.09%	0.08%	−0.01%
6 H	−0.20%	−0.17%	−0.03%	0.02%	−0.02%	−0.08%
9 H	−0.24%	−0.12%	−0.02%	−0.02%	−0.09%	−0.10%
12 H	−0.23%	−0.13%	−0.10%	−0.14%	−0.16%	−0.15%
Average	−0.17%	−0.11%	−0.01%	0.02%	−0.01%	−0.06%
Panel C: CAPM returns (CAPM)						
1 H	−0.02%	0.07%	0.19%	0.22%	0.22%	0.14%
3 H	−0.09%	−0.12%	0.01%	0.10%	0.09%	0.00%
6 H	−0.20%	−0.18%	−0.03%	0.03%	−0.02%	−0.08%
9 H	−0.23%	−0.13%	−0.02%	−0.02%	−0.10%	−0.10%
12 H	−0.23%	−0.13%	−0.10%	−0.15%	−0.17%	−0.16%
Average	−0.15%	−0.10%	0.01%	0.04%	0.00%	−0.04%
Panel D: Fama French 3-factor risk-adjusted returns (FF3)						
1 H	−0.06%	−0.02%	0.10%	0.16%	0.18%	0.07%
3 H	−0.08%	−0.13%	−0.01%	0.09%	0.08%	−0.01%
6 H	−0.20%	−0.19%	−0.03%	0.03%	−0.02%	−0.08%
9 H	−0.23%	−0.14%	−0.02%	0.00%	−0.10%	−0.10%
12 H	−0.24%	−0.13%	−0.09%	−0.14%	−0.16%	−0.15%
Average	−0.16%	−0.12%	−0.01%	0.03%	0.00%	−0.05%
Panel E: Carhart 4-factor risk-adjusted returns (CARHART4)						
1 H	−0.25%	−0.25%	−0.16%	−0.15%	−0.11%	−0.18%
3 H	−0.09%	−0.14%	−0.06%	0.04%	0.04%	−0.04%
6 H	−0.20%	−0.21%	−0.05%	0.01%	−0.04%	−0.10%
9 H	−0.22%	−0.15%	−0.02%	0.00%	−0.10%	−0.10%
12 H	−0.25%	−0.13%	−0.08%	−0.14%	−0.16%	−0.15%
Average	−0.20%	−0.18%	−0.07%	−0.05%	−0.07%	−0.11%

This table presents the average monthly TSMOM returns calculated with equal weight for each individual stock. We apply 25 TSMOM trading strategies, formed based on 1-, 3-, 6-, 9-, and 12-month holding periods and 1-, 3-, 6-, 9-, and 12-month lookback periods, to each individual US stock in our sample. We first calculate the average return of each individual stock over its entire life and then calculate the average return across all stocks. Panels A to E present the results for raw returns, excess returns, CAPM risk-adjusted returns, Fama-French three-factor adjusted returns, and Carhart four-factor adjusted returns, respectively. The last column in each panel reports the average returns of the TSMOM strategies with the same holding but different lookback periods. The last row of each panel reports the average returns of the TSMOM strategies with the same lookback but different holding periods.

Furthermore, in terms of the best-performing strategies, we find that trading strategies with 1-month holding periods generally generate positive average returns (as seen in the first row of each panel).

Percentage of stocks with positive TSMOM returns

Our analyses in Tables 1 and 2 do not seem to support the *average* profitability of TSMOM strategies on individual stocks. However, as implied by Huang et al. (2020), it is still possible that TSMOM strategies are effective for a subset of stocks (given we cover a large sample of 20,492 stocks). This conjecture is also widely documented in the XSMOM literature.[9] To investigate this possibility, we begin by calculating the percentage of stocks that have positive average TSMOM returns.

Table 3 reports such percentages for each TSMOM strategy. Indeed, TSMOM profits still prevail for a considerable number of individual stocks. In terms of RAW_t^i, the majority of stocks (57.91%) generate positive TSMOM returns, as shown in Panel A. Based on excess returns (Panel B), TSMOM strategies' average monthly returns are positive for 45.64% of stocks. In addition, the same percentages are more or less similar after risk adjustments. The most conservative figure is 44.68% for $CAHART4_t^i$. Taken together, our results in Section 3 offer several interesting insights regarding the TSMOM. First, it is not profitable for all stocks but possibly prevails among a subset of stocks. Second, TSMOM performs best when one applies longer lookback but shorter holding periods.

Time trend of overall TSMOM profitability

It is intuitive to ask whether there is a time trend in TSMOM profitability. For example, does it become weaker in time as the stock market becomes generally more efficient in later years?[10] We therefore provide a visual glance on the overtime TSMOM profit throughout our sample period. Figure 1 shows the average monthly profit ($CAHART4_t^i$) of five different TSMOM strategies that employ different lookback periods, but all use the 1-month holding period. We do not observe a clear decline in TSMOM profit over time. This indicates that the overall weak profitability of the TSMOM strategy reported in Section 3 is unlikely to be driven by the

[9]For instance, Lee and Swaminathan (2000) suggest that trading volume can predict the magnitude and persistence of future XSMOM returns; winner stocks with high past trading volume experience faster XSMOM reversal than loser stocks with low past trading volume. Zhang (2006) documents stronger XSMOM returns among stocks with higher idiosyncratic volatility. Given the above, it is possible that TSMOM remains a more effective strategy for stocks with certain characteristics.

[10]We thank our anonymous reviewer for this comment.

Table 3. Percentage of stocks with positive average TSMOM returns.

Lookback period	1 L	3 L	6 L	9 L	12 L	Average
Holding period						
Panel A: Raw returns (RAW)						
1 H	52.64%	55.16%	57.16%	60.18%	61.89%	57.41%
3 H	53.81%	54.24%	57.04%	60.70%	61.50%	57.46%
6 H	53.42%	54.72%	58.87%	61.32%	61.12%	57.89%
9 H	53.07%	56.54%	60.05%	61.39%	61.53%	58.52%
12 H	55.24%	57.07%	58.88%	59.72%	60.52%	58.29%
Average	53.64%	55.55%	58.40%	60.66%	61.31%	57.91%
Panel B: Excess returns (EXCESS)						
1 H	44.15%	46.18%	47.66%	49.23%	49.47%	47.34%
3 H	45.19%	45.12%	46.70%	49.49%	48.34%	46.97%
6 H	43.95%	44.51%	47.39%	48.64%	46.19%	46.14%
9 H	41.96%	44.64%	47.07%	46.78%	44.60%	45.01%
12 H	41.93%	43.44%	44.22%	42.81%	41.38%	42.75%
Average	43.44%	44.78%	46.61%	47.39%	46.00%	45.64%
Panel C: CAPM returns (CAPM)						
1 H	45.35%	47.72%	49.16%	50.50%	50.50%	48.65%
3 H	45.43%	45.39%	46.96%	49.47%	49.03%	47.26%
6 H	44.07%	44.67%	47.70%	48.83%	46.26%	46.31%
9 H	42.25%	44.82%	47.22%	47.01%	44.63%	45.19%
12 H	42.03%	43.48%	44.57%	43.03%	41.56%	42.93%
Average	43.82%	45.22%	47.12%	47.77%	46.40%	46.07%
Panel D: Fama French 3-factor risk-adjusted returns (FF3)						
1 H	45.40%	47.04%	48.38%	50.05%	50.28%	48.23%
3 H	45.47%	44.87%	46.81%	49.23%	49.12%	47.10%
6 H	43.99%	44.30%	47.34%	48.84%	46.63%	46.22%
9 H	42.09%	44.49%	47.56%	47.05%	44.81%	45.20%
12 H	41.80%	43.76%	44.92%	43.28%	41.59%	43.07%
Average	43.75%	44.89%	47.00%	47.69%	46.49%	45.96%
Panel E: Carhart 4-factor risk-adjusted returns (CARHART4)						
1 H	42.13%	42.98%	42.92%	43.22%	43.69%	42.99%
3 H	45.38%	44.56%	45.81%	47.81%	47.55%	46.22%
6 H	44.11%	43.60%	46.95%	48.47%	45.97%	45.82%
9 H	42.57%	44.36%	47.37%	47.10%	44.68%	45.22%
12 H	41.83%	44.08%	44.92%	43.41%	41.58%	43.16%
Average	43.20%	43.92%	45.59%	46.00%	44.69%	44.68%

This table presents the percentage of stocks with positive average TSMOM returns. We apply 25 TSMOM trading strategies, formed based on 1-, 3-, 6-, 9-, and 12-month holding periods and 1-, 3-, 6-, 9-, and 12-month lookback periods, to each individual US stock in our sample. Panels A to E present the percentage results for raw returns, excess returns, CAPM risk-adjusted returns, Fama-French three-factor adjusted returns, and Carhart four-factor adjusted returns, respectively. The last column in each panel reports the average percentage of the TSMOM strategies with the same holding but different lookback periods. The last row of each panel reports the average percentage of the TSMOM strategies with the same lookback but different holding periods.

increased market efficiency observed in more recent years. However, we loosely observe that TSMOM profits experience peaks and troughs when market conditions change. For example, the TSMOM strategy generally performed well during economic downturns (e.g. July 1990–March 1991, April 2001–November 2001, January 2008–June 2009, defined by the NBER business cycle). In particular, the monthly risk-adjusted TSMOM return reached 5% during the 2008 financial crisis period.

IV. Where do TSMOM profits prevail? Market-wide conditions and stock characteristics

Pursuing the empirical questions Huang et al. (2020) leave for future research, we examine the market-wide conditions and stock characteristics where TSMOM profits may prevail. We tackle this important question by first employing single-sorting based on market conditions and stock characteristics separately and then in combination as a double-sorting process. For brevity, we base our analysis in this section on TSMOM strategies that have different lookback periods but the same 1-month holding period, as they tend to perform best based on our findings in Section 3. Moreover, our previous analyses show that it is necessary to consider risk-adjusted returns to reflect the true profitability of TSMOM strategies. To be conservative, we use $CAHART4_t^i$ to also exclude any impact of cross-sectional momentum (XSMOM).[11]

Single sorting based on market states or stock characteristics

First, we examine the performance of TSMOM in four different sets of market states: (1) periods with low, medium and high EPU; (2) low, medium and high sentiment periods; (3) economic expansion and contraction periods; and (4) low, medium and high market volatility periods. The results are presented in Table 4. We find that TSMOM strategies generate minor positive average returns (0.05%) only during market contraction periods. However, despite the negative average returns, we observe a clear pattern in which Carhart risk-adjusted

[11]Results of using other methods to calculate returns are generally consistent. TSMOM profitability and the identified monotonic trends across market- and stock-level characteristics become weaker (or sometimes even reversed) with longer holding periods (i.e. 3, 6, 9, 12 months). These results are available upon request.

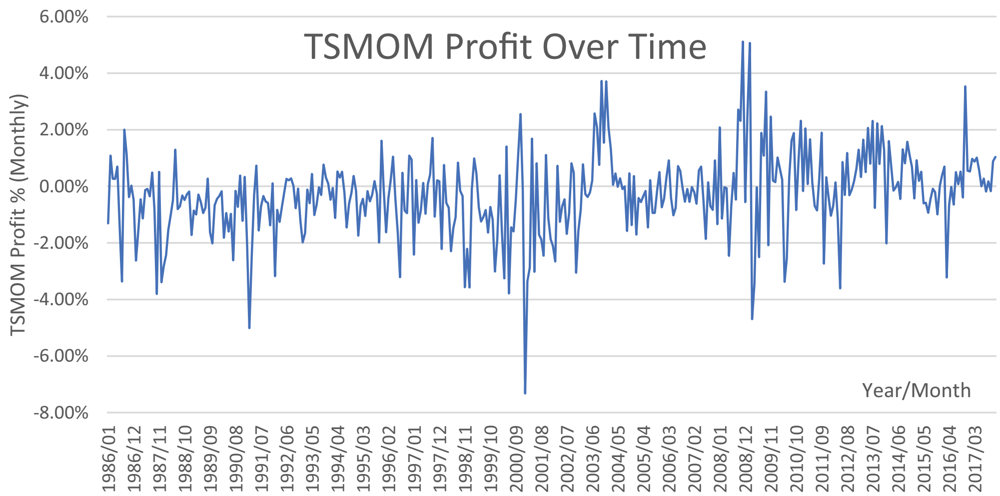

Figure 1. Average monthly TSMOM returns over time. The figure below shows the average monthly profit of five different TSMOM strategies that employ different lookback periods, but all use the 1-month holding period from 1986 to 2017. TSMOM profit is calculated based on the Carhart four-factor (1997) ($CAHART4_t^i$) model.

Table 4. TSMOM returns sorted by market states.

TSMOM strategy		(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12,H1)	Average
Market state							
EPU	low	−0.49%	−0.59%	−0.43%	−0.37%	−0.43%	−0.46%
	medium	−0.58%	−0.52%	−0.38%	−0.45%	−0.40%	−0.47%
	high	−0.22%	−0.24%	−0.46%	−0.37%	−0.30%	−0.32%
	high-low	0.27%	0.35%	−0.03%	0.00%	0.13%	0.15%
Sentiment	low	−0.13%	0.09%	−0.13%	−0.22%	−0.27%	−0.13%
	medium	−0.28%	−0.64%	−0.48%	−0.43%	−0.34%	−0.44%
	high	−0.84%	−0.76%	−0.60%	−0.50%	−0.52%	−0.64%
	low-high	0.71%	0.84%	0.47%	0.28%	0.24%	0.51%
Business cycle	contraction	0.09%	0.24%	0.19%	−0.08%	−0.17%	0.05%
	expansion	−0.29%	−0.27%	−0.23%	−0.31%	−0.37%	−0.29%
	contr-expan	0.37%	0.51%	0.42%	0.23%	0.20%	0.34%
Market Volatility	low	−0.55%	−0.55%	−0.46%	−0.54%	−0.47%	−0.52%
	medium	−0.44%	−0.49%	−0.48%	−0.41%	−0.35%	−0.44%
	high	−0.64%	−0.60%	−0.52%	−0.53%	−0.59%	−0.58%
	high-low	−0.09%	−0.04%	−0.05%	0.01%	−0.11%	−0.06%

This table reports average TSMOM returns (Carhart four-factor adjusted returns) across three tercile levels of EPU, investor sentiment, and market volatility, as well as market contraction and expansion periods. Each month, if the previous month's EPU (sentiment, market volatility) value is higher than the 67th percentile EPU (sentiment, market volatility) value, the month is denoted as a high EPU (high sentiment, high market volatility) month; if the previous month's EPU (sentiment, market volatility) value is lower than the 33rd percentile EPU (sentiment, market volatility) value, then the month is denoted as a low EPU (low sentiment, low market volatility) month. Market expansion and contraction periods are defined based on the NBER business cycle definition. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. The last column reports the average return of the TSMOM strategies with the 1-month holding but different lookback periods. All average TSMOM returns and low-minus-high (or contraction-minus-expansion) differences are significantly different from 0 at 1% based on t-test.

TSMOM returns are higher during high EPU, low sentiment[12] and market contraction periods. The trends are also largely monotonic (low versus medium versus high). The differences in TSMOM returns of high EPU versus low EPU, low sentiment versus high sentiment, and contraction versus expansion periods are largely positive and statistically significant at the 1%

[12]Whether and how TSMOM profitability varies with investor sentiment remain inconclusive questions in the existing literature. On one hand, Moskowitz, Ooi, and Pedersen (2012) document that the Baker and Wurgler sentiment index is irrelevant to TSMOM profitability. On the other hand, Lim, Wang, and Yao (2018) find that high investor sentiment (measured by a refined Baker and Wurgler sentiment index) is associated with higher subsequent TSMOM profit when using raw return and FF5 alpha to estimate TSMOM profit. Our analysis provides new evidence that uncertainty and disagreement among investors are escalated during negative sentiment periods, resulting in a slower information diffusion process and greater TSMOM.

Table 5. TSMOM returns sorted by stock characteristics.

TSMOM strategy		(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12, H1)	Average
Stock characteristic							
Sync	low	−0.23%	−0.18%	−0.12%	−0.10%	−0.10%	−0.15%
	medium	−0.38%	−0.43%	−0.41%	−0.37%	−0.35%	−0.39%
	high	−0.74%	−0.82%	−0.77%	−0.74%	−0.73%	−0.76%
	low-high	0.51%	0.64%	0.64%	0.64%	0.63%	0.61%
Turn	low	−0.25%	−0.25%	−0.17%	−0.07%	0.03%	−0.14%
	medium	−0.54%	−0.55%	−0.46%	−0.44%	−0.37%	−0.47%
	high	−0.53%	−0.59%	−0.63%	−0.66%	−0.81%	−0.64%
	low-high	0.28%	0.34%	0.46%	0.59%	0.84%	0.50%
Skew	low	−0.05%	−0.02%	0.10%	0.17%	0.20%	0.08%
	medium	−0.34%	−0.32%	−0.24%	−0.15%	−0.10%	−0.23%
	high	−0.90%	−1.01%	−1.06%	−1.12%	−1.17%	−1.05%
	low-high	0.85%	0.98%	1.16%	1.29%	1.37%	1.13%
Beta	low	−0.32%	−0.27%	−0.26%	−0.25%	−0.22%	−0.26%
	medium	−0.29%	−0.29%	−0.21%	−0.17%	−0.12%	−0.22%
	high	−0.67%	−0.77%	−0.73%	−0.70%	−0.73%	−0.72%
	low-high	0.35%	0.50%	0.47%	0.45%	0.51%	0.46%
Vol	low	−0.39%	−0.40%	−0.27%	−0.27%	−0.18%	−0.30%
	medium	−0.34%	−0.33%	−0.23%	−0.14%	−0.09%	−0.23%
	high	−0.57%	−0.64%	−0.69%	−0.71%	−0.78%	−0.68%
	low-high	0.18%	0.24%	0.42%	0.44%	0.60%	0.38%

This table reports average TSMOM returns (Carhart four-factor adjusted returns) across three tercile levels of five stock characteristics, namely, synchronicity (Sync), turnover (Turn), skewness (Skew), beta (Beta) and volatility (Vol). Each month, we group sample stocks into 3 characteristic terciles using 33rd and 67th percentile cut-offs based on their synchronicity, turnover, return skewness, stock beta and volatility values. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. The last column reports the average return of the TSMOM strategies with the 1-month holding but different lookback periods. All average TSMOM returns and low-minus-high differences are significantly different from 0 at 1% based on t-test.

level. Regarding market volatility states, TSMOM returns in different states show no clear pattern. Nevertheless, TSMOM risk-adjusted returns appear to be less negative during medium market volatility states.[13]

Next, in each month, we sort individual stocks cross-sectionally into different portfolios characterized by five proxies relating to gradual information diffusion and positive price autocorrelation – *Sync, Turn, Skew, Beta* and *Vol*. We then examine the TSMOM profits of each tercile portfolio. We conjecture that TSMOM strategies should generate higher profits on stocks with low *Sync, Turn, Skew, Beta* or *Vol*, as they tend to incorporate information slowly and exhibit positive price autocorrelation, particularly in the short run. The results in Table 5 confirm our conjecture. We observe that risk-adjusted returns are higher (e.g. less negative) for stocks that score low in *Sync, Turn, Skew, Beta, and Vol*. Low-minus-high differences in TSMOM risk-adjusted returns are positive and significant at the 1% level across all stock-level characteristics and trading strategy formations.

Double-sorting based on both market states and stock characteristics

While showing that the results are largely consistent with our conjecture that TSMOM returns should be higher when either stock-level or market-wide information uncertainty is higher, the average risk-adjusted returns of the single-sorted portfolios in the previous sections are still largely negative. Thus, we narrow down the search for TSMOM profits by performing double-sorting analysis combining both market states and stock characteristics. Tables 6–9 present the results of TSMOM risk-adjusted returns sorted by market states, together with five stock-level characteristics. For thorough investigation, the average TSMOM return ($CAHART4_t^i$) is calculated for each stock-level characteristic tercile within each market state and for five different trading strategy formations. To better illustrate the overall trend, we present low-minus-high results in the last row for each market state tercile. We expect to find significantly positive low-minus-high differences if TSMOM profits are higher among stocks with greater information uncertainty. Additionally, the low-minus-high differences should be greatest during high EPU, low sentiment, market contraction, and high market volatility periods. In the last column of each characteristic results section, we present average TSMOM returns for five trading strategies formed on the 1-month holding period and 1-, 3-, 6-, 9-, and 12-month lookback periods.

In Table 6, except for *Vol*, we find that the average TSMOM returns decrease monotonically with the increase in *Sync, Turn, Skew, Beta* in each EPU tercile state. This trend is further corroborated by the low-minus-high results, in which the low-minus-high differences in TSMOM returns are

[13]Our results are in line with Stivers and Sun (2010) and Daniel and Moskowitz (2016), who find low momentum profits (momentum crashes) when market volatility is high.

Table 6. TSMOM returns sorted by EPU states and stock characteristics.

Market state	Stock char	TSMOM strategy	(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12,H1)	Average
EPU_low	Sync	low	−0.36%***	−0.40%***	−0.21%***	−0.18%***	−0.18%***	−0.26%**
		medium	−0.39%***	−0.52%***	−0.36%***	−0.28%***	−0.35%***	−0.38%***
		high	−0.74%***	−0.86%***	−0.73%***	−0.67%***	−0.79%***	−0.76%***
		low-high	**0.39%*** **	**0.46%*** **	**0.52%*** **	**0.49%*** **	**0.61%*** **	**0.49%*** **
EPU_medium	Sync	low	−0.31%***	−0.20%***	−0.09%**	−0.14%***	−0.14%***	−0.18%**
		medium	−0.57%***	−0.52%***	−0.37%***	−0.45%***	−0.39%***	−0.46%***
		high	−0.90%***	−0.88%***	−0.72%***	−0.79%***	−0.71%***	−0.80%***
		low-high	**0.59%*** **	**0.68%*** **	**0.63%*** **	**0.65%*** **	**0.57%*** **	**0.62%*** **
EPU_high	Sync	**low**	**0.04%**	**0.14%*** **	**−0.04%**	**0.05%**	**0.05%**	**0.05%**
		medium	−0.18%***	−0.21%***	−0.51%***	−0.41%***	−0.32%***	−0.32%**
		high	−0.57%***	−0.71%***	−0.88%***	−0.80%***	−0.67%***	−0.73%***
		low-high	**0.61%*** **	**0.85%*** **	**0.84%*** **	**0.85%*** **	**0.72%*** **	**0.77%*** **
EPU_low	Turn	low	−0.40%***	−0.46%***	−0.33%***	−0.22%***	−0.13%***	−0.31%**
		medium	−0.61%***	−0.70%***	−0.50%***	−0.45%***	−0.42%***	−0.54%***
		high	−0.46%***	−0.60%***	−0.45%***	−0.43%***	−0.72%***	−0.53%***
		low-high	**0.05%**	**0.15%*** **	**0.11%** **	**0.22%*** **	**0.59%*** **	**0.22%**
EPU_medium	Turn	low	−0.37%***	−0.31%***	−0.11%***	−0.10%***	0.01%	−0.18%
		medium	−0.70%***	−0.61%***	−0.38%***	−0.47%***	−0.37%***	−0.51%***
		high	−0.67%***	−0.64%***	−0.65%***	−0.77%***	−0.84%***	−0.71%***
		low-high	**0.30%*** **	**0.33%*** **	**0.53%*** **	**0.67%*** **	**0.85%*** **	**0.54%** **
EPU_high	Turn	**low**	**0.07%*** **	**0.09%*** **	**0.00%**	**0.15%*** **	**0.26%*** **	**0.11%** **
		medium	−0.26%***	−0.28%***	−0.48%***	−0.38%***	−0.28%***	−0.33%***
		high	−0.48%***	−0.52%***	−0.91%***	−0.89%***	−0.90%***	−0.74%***
		low-high	**0.56%*** **	**0.61%*** **	**0.90%*** **	**1.04%*** **	**1.17%*** **	**0.86%*** **
EPU_low	Skew	low	−0.24%***	−0.35%***	−0.20%***	−0.07%**	−0.17%***	−0.20%**
		medium	−0.39%***	−0.46%***	−0.27%***	−0.16%***	−0.18%***	−0.29%**
		high	−0.82%***	−0.94%***	−0.79%***	−0.85%***	−0.92%***	−0.86%***
		low-high	**0.58%*** **	**0.59%*** **	**0.59%*** **	**0.78%*** **	**0.75%*** **	**0.66%*** **
EPU_medium	Skew	low	−0.14%***	0.00%	0.26%***	0.16%***	0.26%***	0.11%
		medium	−0.47%***	−0.39%***	−0.25%***	−0.26%***	−0.14%***	−0.30%**
		high	−1.09%***	−1.11%***	−1.08%***	−1.17%***	−1.24%***	−1.14%***
		low-high	**0.95%*** **	**1.11%*** **	**1.34%*** **	**1.33%*** **	**1.50%*** **	**1.25%*** **
EPU_high	Skew	**low**	**0.34%*** **	**0.43%*** **	**0.38%*** **	**0.53%*** **	**0.66%*** **	**0.47%*** **
		medium	−0.10%***	−0.04%	−0.20%***	−0.03%	0.06%*	−0.06%
		high	−0.81%***	−0.99%***	−1.41%***	−1.45%***	−1.45%***	−1.22%***
		low-high	**1.14%*** **	**1.42%*** **	**1.80%*** **	**1.97%*** **	**2.10%*** **	**1.69%*** **
EPU_low	Beta	low	−0.46%***	−0.44%***	−0.30%***	−0.30%***	−0.25%***	−0.35%***
		medium	−0.55%***	−0.63%***	−0.49%***	−0.52%***	−0.51%***	−0.54%***
		high	−0.46%***	−0.65%***	−0.46%***	−0.28%***	−0.48%***	−0.46%***
		low-high	**−0.01%**	**0.22%*** **	**0.16%*** **	**−0.03%**	**0.23%*** **	**0.11%**
EPU_medium	Beta	low	−0.44%***	−0.33%***	−0.21%***	−0.28%***	−0.30%***	−0.31%***
		medium	−0.51%***	−0.48%***	−0.37%***	−0.43%***	−0.37%***	−0.43%***
		high	−0.73%***	−0.67%***	−0.49%***	−0.57%***	−0.50%***	−0.59%***
		low-high	**0.29%*** **	**0.34%*** **	**0.28%*** **	**0.28%*** **	**0.20%*** **	**0.28%*** **
EPU_high	Beta	**low**	**0.07%**	**0.31%*** **	**0.09%**	**0.11%** **	**0.15%*** **	**0.14%**
		medium	−0.20%***	−0.19%***	−0.34%***	−0.28%***	−0.22%***	−0.25%***
		high	−0.40%***	−0.58%***	−0.85%***	−0.70%***	−0.61%***	−0.63%***
		low-high	**0.46%*** **	**0.88%*** **	**0.94%*** **	**0.81%*** **	**0.76%*** **	**0.77%*** **
EPU_low	Vol	low	−0.48%***	−0.49%***	−0.36%***	−0.38%***	−0.33%***	−0.41%***
		medium	−0.44%***	−0.48%***	−0.26%***	−0.21%***	−0.23%***	−0.33%***
		high	−0.55%***	−0.76%***	−0.63%***	−0.52%***	−0.69%***	−0.63%***
		low-high	**0.06%**	**0.28%*** **	**0.27%*** **	**0.15%** **	**0.36%*** **	**0.22%* **
EPU_medium	Vol	low	−0.43%***	−0.44%***	−0.20%***	−0.27%***	−0.19%***	−0.31%**
		medium	−0.40%***	−0.31%***	−0.18%***	−0.18%***	−0.11%***	−0.23%**
		high	−0.85%***	−0.78%***	−0.69%***	−0.81%***	−0.81%***	−0.79%***
		low-high	**0.42%*** **	**0.35%*** **	**0.49%*** **	**0.54%*** **	**0.63%*** **	**0.48%*** **
EPU_high	Vol	low	−0.18%***	−0.24%***	−0.21%***	−0.10%***	0.06%***	−0.14%
		medium	−0.14%***	−0.13%***	−0.25%***	0.00%	0.12%***	−0.08%
		high	−0.32%***	−0.34%***	−0.78%***	−0.85%***	−0.88%***	−0.63%**
		low-high	**0.13%* **	**0.10%**	**0.57%*** **	**0.75%*** **	**0.94%*** **	**0.50%**
EPU_high	low Sync & low Turn & low Beta & low Skew		**0.87%*** **	**1.42%*** **	**1.56%*** **	**1.81%*** **	**1.96%*** **	**1.52%*** **

This table reports the double-sorting results combining the EPU terciles and the terciles of each stock-level characteristic. The average TSMOM return (Carhart four-factor adjusted returns) is calculated for each stock-level characteristic tercile within each EPU tercile. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. Low-minus-high results are provided in the last row for each EPU tercile. Average TSMOM returns across five trading strategies are reported in the last column. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels.

generally significantly positive for all stock characteristics. It thus confirms the positive relationship between stock-level information uncertainty and TSMOM returns. More importantly, the TSMOM strategy demonstrates positive returns when *Sync, Turn, Skew,* ***or*** *Beta* are low **during the periods** when EPU is high. Strikingly, the opposite is true for the rest of the tercile results, as the average TSMOM risk-adjusted returns are almost all negative. The highest monthly risk-adjusted return of 0.66% (equivalent to 7.92% per annum) is reported in the low *Skew* and high EPU group using the TSMOM strategy constructed based on a 12-month lookback and 1-month holding period (L12,H1).

We perform similar double sorting analyses for sentiment states in Table 7, business cycles in Table 8, and market volatility states in Table 9. The results are generally consistent with Table 6, with relatively weaker but still consistent patterns identified over different market volatility states. Viewed collectively, the double sorting results confirm that TSMOM profits are positively associated with stock- and market-level proxies for information uncertainty. Specifically, when both stock- and market-level conditions of high information uncertainty are satisfied, positive TSMOM risk-adjusted returns prevail. In other words, when one requires a stock to satisfy all the stock-level measures of high information uncertainty simultaneously (i.e. have low synchronicity, low turnover, low beta and low skewness), she or he could find the average monthly TSMOM profits on these stocks. TSMOM profits on these stocks could be significantly positive and sizable during high information-uncertain market states – 1.52% during high EPU periods, 1.39% during low sentiment periods, 3.92% during market contraction times, and 2.04% during high market volatility periods. Overall, the double-sorting results show that TSMOM strategies could still be effective, but largely only when both stock- and market-level conditions of high information uncertainty are simultaneously met. This is the condition where TSMOM profits on US individual stocks may prevail, on average.

V. Robustness of TSMOM profitability in time-series regression (Huang et al. 2020) and other constraints

So far, we document evidence that TSMOM strategies could still be effective if applied to stocks with certain characteristics AND during certain market states. For the final robustness check, we employ two tests employed in both Moskowitz, Ooi, and Pedersen (2012) and Huang et al. (2020) to verify the TSMOM profitability reported in Section 4. In the first test, we run the following regression for each stock:

$$r^i_{t+1} = \alpha + \beta r^i_{t-k,t} + \varepsilon^i_{t+1} \tag{4}$$

where r^i_{t+1} is the return of stock i in month $t+1$ and $r^i_{t-k,t}$ is its past k-month (the lookback period) return. According to Huang et al. (2020), if the TSMOM strategy is of merit, the magnitude of past returns of the stock itself should predict the magnitude of its future returns. We test this by examining the regression slope β and the model's R^2. Moreover, we run this regression with industry fixed effects since Huang et al. (2020) conclude that at least a part of Moskowitz et al.'s (2012) results are driven by different mean returns across asset classes. Thus, controlling for fixed effects is necessary. It is also worth noting that while our results are all based on common stocks (i.e. the same asset class), we follow the rationale to control for any industry fixed effects for conservatism.[14]

The second test examines whether the sign of the past returns forecasts the direction of the future returns of a stock itself. The model is presented below:

$$r^i_{t+1} = \alpha + \beta sign(r^i_{t-k,t}) + \varepsilon^i_{t+1} \tag{5}$$

where *sign* is the sign function of stock *i*'s past returns and equals 1 when $r^i_{t-k,t}$ is non-negative and 0 otherwise. We also follow Moskowitz, Ooi, and Pedersen (2012) and Huang et al. (2020) in clustering the standard errors by month.

Note that the above two tests are based on the excess returns of the individual stocks (which are used to form trading signals of TSMOM strategies) but not the returns of specific TSMOM strategies. The idea is to test whether the past returns of

[14]Our results are stronger without industry fixed effects.

Table 7. TSMOM returns sorted by sentiment states and stock characteristics.

Market state	Stock char	TSMOM strategy	(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12,H1)	Average
Sent_low	Sync	**low**	**0.16%*** **	**0.43%*** **	**0.23%*** **	**0.12%*** **	**0.03%**	**0.19%**
		medium	−0.11%***	0.09%**	−0.19%***	−0.25%***	−0.31%***	−0.15%
		high	−0.47%***	−0.26%***	−0.49%***	−0.59%***	−0.59%***	−0.48%***
		low-high	**0.63%*** **	**0.69%*** **	**0.72%*** **	**0.71%*** **	**0.62%*** **	**0.67%*** **
Sent _medium	Sync	low	−0.07%*	−0.35%***	−0.11%***	−0.09%**	−0.05%***	−0.13%
		medium	−0.22%***	−0.55%***	−0.42%***	−0.39%***	−0.29%***	−0.37%***
		high	−0.61%***	−0.99%***	−0.88%***	−0.82%***	−0.75%***	−0.81%***
		low-high	**0.53%*** **	**0.64%*** **	**0.77%*** **	**0.73%*** **	**0.70%*** **	**0.68%*** **
Sent _high	Sync	low	−0.70%***	−0.53%***	−0.43%***	−0.30%***	−0.26%***	−0.44%**
		medium	−0.77%***	−0.74%***	−0.58%***	−0.45%***	−0.44%***	−0.60%***
		high	−1.06%***	−1.09%***	−0.87%***	−0.79%***	−0.83%***	−0.93%***
		low-high	**0.36%*** **	**0.56%*** **	**0.44%*** **	**0.49%*** **	**0.57%*** **	**0.48%*** **
Sent _low	Turn	**low**	**0.03%**	**0.12%*** **	**0.06%***	**0.14%*** **	**0.25%*** **	**0.12%**
		medium	−0.27%***	−0.06%*	−0.22%***	−0.28%***	−0.29%***	−0.22%**
		high	−0.13%**	0.26%***	−0.25%***	−0.53%***	−0.80%***	−0.29%
		low-high	**0.15%** **	**−0.14%** **	**0.31%*** **	**0.68%*** **	**1.05%*** **	**0.41%**
Sent _medium	Turn	low	−0.11%***	−0.25%***	−0.13%***	−0.11%***	0.03%	−0.11%
		medium	−0.34%***	−0.64%***	−0.48%***	−0.43%***	−0.30%***	−0.44%***
		high	−0.40%***	−0.94%***	−0.74%***	−0.70%***	−0.77%***	−0.71%***
		low-high	**0.29%*** **	**0.70%*** **	**0.62%*** **	**0.59%*** **	**0.81%*** **	**0.60%*** **
Sent _high	Turn	low	−0.62%***	−0.57%***	−0.40%***	−0.22%***	−0.16%***	−0.39%*
		medium	−0.94%***	−0.87%***	−0.62%***	−0.56%***	−0.49%***	−0.70%***
		high	−0.95%***	−0.91%***	−0.82%***	−0.72%***	−0.85%***	−0.85%***
		low-high	**0.33%*** **	**0.34%*** **	**0.42%*** **	**0.50%*** **	**0.69%*** **	**0.46%*** **
Sent _low	Skew	**low**	**0.17%*** **	**0.31%*** **	**0.37%*** **	**0.50%*** **	**0.73%*** **	**0.42%** **
		medium	−0.04%	0.18%***	0.01%	0.02%	0.05%	0.05%
		high	−0.45%***	−0.15%***	−0.69%***	−1.06%***	−1.43%***	−0.76%*
		low-high	**0.62%*** **	**0.46%*** **	**1.06%*** **	**1.56%*** **	**2.16%*** **	**1.17%** **
Sent _medium	Skew	**low**	**0.10%*** **	**−0.01%**	**0.16%*** **	**0.10%*** **	**0.03%**	**0.07%**
		medium	−0.23%***	−0.46%***	−0.30%***	−0.23%***	−0.09%***	−0.26%*
		high	−0.68%***	−1.29%***	−1.13%***	−1.04%***	−0.92%***	−1.01%***
		low-high	**0.78%*** **	**1.28%*** **	**1.29%*** **	**1.14%*** **	**0.95%*** **	**1.09%*** **
Sent _high	Skew	low	−0.34%***	−0.30%***	−0.15%***	−0.03%	−0.06%*	−0.18%
		medium	−0.67%***	−0.58%***	−0.38%***	−0.21%***	−0.23%***	−0.42%**
		high	−1.49%***	−1.45%***	−1.29%***	−1.25%***	−1.20%***	−1.33%***
		low-high	**1.15%*** **	**1.15%*** **	**1.14%*** **	**1.22%*** **	**1.14%*** **	**1.16%*** **
Sent _low	Beta	**low**	**0.13%** **	**0.31%*** **	**0.12%** **	**−0.01%**	**−0.10%***	**0.09%**
		medium	−0.21%***	0.06%*	−0.09%**	−0.25%***	−0.27%***	−0.15%
		high	−0.20%***	0.02%	−0.32%***	−0.33%***	−0.38%***	−0.24%
		low-high	**0.32%*** **	**0.29%*** **	**0.45%*** **	**0.32%*** **	**0.28%*** **	**0.33%*** **
Sent _medium	Beta	low	−0.28%***	−0.35%***	−0.17%***	−0.21%***	−0.13%***	−0.23%**
		medium	−0.33%***	−0.64%***	−0.50%***	−0.50%***	−0.44%***	−0.48%***
		high	−0.26%***	−0.75%***	−0.59%***	−0.47%***	−0.41%***	−0.50%***
		low-high	**−0.02%**	**0.40%*** **	**0.43%*** **	**0.26%*** **	**0.28%*** **	**0.27%**
Sent _high	Beta	low	−0.68%***	−0.46%***	−0.40%***	−0.30%***	−0.23%***	−0.41%**
		medium	−0.73%***	−0.70%***	−0.58%***	−0.50%***	−0.42%***	−0.59%***
		high	−1.06%***	−1.07%***	−0.80%***	−0.65%***	−0.76%***	−0.87%***
		low-high	**0.38%*** **	**0.61%*** **	**0.41%*** **	**0.35%*** **	**0.53%*** **	**0.45%*** **
Sent _low	Vol	low	−0.30%***	−0.06%***	−0.09%***	−0.07%***	0.03%	−0.10%
		medium	−0.12%***	0.09%***	−0.08%***	−0.01%	0.04%*	−0.02%
		high	−0.04%	0.20%***	−0.22%***	−0.50%***	−0.73%***	−0.26%
		low-high	**−0.26%*** **	**−0.26%*** **	**0.13%**	**0.42%*** **	**0.76%*** **	**0.16%**
Sent _medium	Vol	low	−0.38%***	−0.58%***	−0.44%***	−0.46%***	−0.34%***	−0.44%***
		medium	−0.19%***	−0.40%***	−0.23%***	−0.17%***	−0.12%***	−0.22%**
		high	−0.33%***	−0.83%***	−0.67%***	−0.63%***	−0.57%***	−0.61%***
		low-high	**−0.05%**	**0.26%*** **	**0.23%*** **	**0.17%*** **	**0.24%*** **	**0.17%**
Sent _high	Vol	low	−0.45%***	−0.49%***	−0.26%***	−0.25%***	−0.20%***	−0.33%**
		medium	−0.67%***	−0.59%***	−0.36%***	−0.22%***	−0.19%***	−0.41%*
		high	−1.30%***	−1.20%***	−1.14%***	−0.98%***	−1.05%***	−1.13%***
		low-high	**0.85%*** **	**0.71%*** **	**0.88%*** **	**0.73%*** **	**0.85%*** **	**0.80%*** **
Sent _low	low Sync & low Turn & low Beta & low Skew		**1.67%*** **	**1.13%*** **	**1.40%*** **	**1.76%*** **	**1.97%*** **	**1.39%*** **

This table reports the double-sorting results combining the sentiment terciles and the terciles of each stock-level characteristic. The average TSMOM return (Carhart four-factor adjusted returns) is calculated for each stock-level characteristic tercile within each sentiment tercile. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. Low-minus-high results are provided in the last row for each sentiment tercile. Average TSMOM returns across five trading strategies are reported in the last column. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels.

Table 8. TSMOM returns sorted by business cycle states and stock characteristics.

Market state	Stock char	TSMOM strategy	(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12,H1)	Average
Contraction	Sync	**low**	**0.34%*** **	**0.47%*** **	**−0.14%**	**0.42%*** **	**0.35%*** **	**0.29%**
		medium	−0.32%***	−0.39%***	−1.02%***	−0.33%***	−0.35%***	−0.48%
		high	−0.99%***	−1.16%***	−1.71%***	−0.93%***	−1.18%***	−1.19%***
		low-high	**1.33%*** **	**1.63%*** **	**1.57%*** **	**1.36%*** **	**1.53%*** **	**1.48%*** **
Expansion	Sync	low	−0.28%***	−0.24%***	−0.12%***	−0.15%***	−0.14%***	−0.19%***
		medium	−0.39%***	−0.43%***	−0.35%***	−0.38%***	−0.35%***	−0.38%***
		high	−0.72%***	−0.80%***	−0.69%***	−0.73%***	−0.70%***	−0.73%***
		low-high	**0.44%*** **	**0.56%*** **	**0.57%*** **	**0.58%*** **	**0.56%*** **	**0.54%*** **
Contraction	Turn	**low**	**0.42%*** **	**0.57%*** **	**0.36%*** **	**0.80%*** **	**0.83%*** **	**0.60%*** **
		medium	−0.50%***	−0.48%***	−0.97%***	−0.32%***	−0.42%***	−0.54%**
		high	−0.81%***	−1.08%***	−2.19%***	−1.25%***	−1.52%***	−1.37%***
		low-high	**1.23%*** **	**1.64%*** **	**2.55%*** **	**2.06%*** **	**2.36%*** **	**1.97%*** **
Expansion	Turn	low	−0.31%***	−0.33%***	−0.22%***	−0.15%***	−0.04%**	−0.21%*
		medium	−0.54%***	−0.56%***	−0.41%***	−0.44%***	−0.36%***	−0.46%***
		high	−0.51%***	−0.55%***	−0.51%***	−0.61%***	−0.75%***	−0.59%***
		low-high	**0.19%*** **	**0.23%*** **	**0.29%*** **	**0.46%*** **	**0.71%*** **	**0.38%* **
Contraction	Skew	**low**	**1.30%*** **	**1.73%*** **	**2.00%*** **	**2.84%*** **	**2.75%*** **	**2.13%*** **
		medium	−0.11%	0.14%*	−0.48%***	0.19%**	0.06%	−0.04%
		high	−1.88%***	−2.59%***	−3.95%***	−3.41%***	−3.53%***	−3.07%***
		low-high	**3.18%*** **	**4.32%*** **	**5.95%*** **	**6.25%*** **	**6.28%*** **	**5.20%*** **
Expansion	Skew	low	−0.16%***	−0.17%***	−0.06%***	−0.06%***	−0.02%	−0.09%
		medium	−0.36%***	−0.36%***	−0.22%***	−0.18%***	−0.11%***	−0.25%**
		high	−0.82%***	−0.87%***	−0.82%***	−0.93%***	−0.97%***	−0.88%***
		low-high	**0.66%*** **	**0.70%*** **	**0.76%*** **	**0.87%*** **	**0.95%*** **	**0.79%*** **
Contraction	Beta	**low**	**0.29%** **	**0.77%*** **	**0.10%**	**0.54%*** **	**0.47%*** **	**0.43%* **
		medium	0.01%	0.19%**	−0.28%***	0.29%***	0.29%***	0.10%
		high	−0.98%***	−1.57%***	−2.23%***	−1.30%***	−1.53%***	−1.52%***
		low-high	**1.27%*** **	**2.34%*** **	**2.34%*** **	**1.84%*** **	**2.00%*** **	**1.96%*** **
Expansion	Beta	low	−0.37%***	−0.36%***	−0.29%***	−0.31%***	−0.28%***	−0.32%***
		medium	−0.31%***	−0.33%***	−0.20%***	−0.21%***	−0.16%***	−0.24%***
		high	−0.64%***	−0.70%***	−0.60%***	−0.65%***	−0.67%***	−0.65%***
		low-high	**0.27%*** **	**0.34%*** **	**0.31%*** **	**0.34%*** **	**0.39%*** **	**0.33%*** **
Contraction	Vol	low	−0.23%***	−0.03%	−0.25%***	0.22%***	0.21%***	−0.01%
		medium	−0.10%	−0.01%	−0.51%***	0.22%***	0.13%**	−0.06%
		high	−0.51%***	−0.78%***	−1.71%***	−0.96%***	−1.15%***	−1.02%**
		low-high	**0.28%**	**0.75%*** **	**1.46%*** **	**1.18%*** **	**1.36%*** **	**1.01%** **
Expansion	Vol	low	−0.40%***	−0.44%***	−0.28%***	−0.31%***	−0.22%***	−0.33%***
		medium	−0.36%***	−0.35%***	−0.21%***	−0.17%***	−0.11%***	−0.24%**
		high	−0.58%***	−0.63%***	−0.61%***	−0.69%***	−0.75%***	−0.65%***
		low-high	**0.18%*** **	**0.20%*** **	**0.33%*** **	**0.37%*** **	**0.54%*** **	**0.32%** **
Contraction	low Sync & low Turn & low Beta & low Skew		**2.04%*** **	**3.53%*** **	**4.03%*** **	**4.91%*** **	**5.09%*** **	**3.92%*** **

This table reports the double-sorting results combining the two business cycle states (i.e. market contraction and expansion) and the terciles of each stock-level characteristic. The average TSMOM return (Carhart four-factor adjusted returns) is calculated for each stock-level characteristic tercile within each market contraction/expansion state. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. Low-minus-high results are provided in the last row for each contraction/expansion state. Average TSMOM returns across five trading strategies are reported in the last column. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels.

a stock itself contain information for future returns on a broader basis, which underpins the profitability of TSMOM strategies. Moreover, we do not scale the left-hand side returns by volatility, as our instruments are all common stocks (i.e. the same asset class).

We display the results for the two models above side-by-side in Table 10. Test (1) presents the results for Equation (4). Test (2) contains the results for Equation (5). For both regressions, we report the estimates of the regression slopes and their p values. We also report the model's R^2 for regression (1). The results are displayed for different lookback periods (all holding periods are 1 month) and in periods with high economic policy uncertainty (Panel A), low sentiment (Panel B), contraction (Panel C) and high volatility (Panel D) periods separately.

In Panel A, under periods with high economic policy uncertainty and for stocks that simultaneously satisfy the conditions of having low synchronicity, low turnover, low beta and low skewness, we find that their past returns at different horizons (Test (1)) and the signs (Test (2)) show predictive ability for future returns. In other words, the reported TSMOM risk-adjusted returns are somewhat robust in the 'time series' framework. With only one exception for the shortest lookback

Table 9. TSMOM returns sorted by market volatility states and stock characteristics.

Market volatility	Stock char	TSMOM strategy	(L1,H1)	(L3,H1)	(L6,H1)	(L9,H1)	(L12,H1)	Average
MktVol_low	Sync	low	−0.16%***	−0.18%***	−0.18%***	−0.09%***	−0.05%	−0.13%**
		medium	−0.25%***	−0.26%***	−0.30%***	−0.25%***	−0.22%***	−0.26%***
		high	−0.44%***	−0.57%***	−0.57%***	−0.50%***	−0.49%***	−0.52%***
		low-high	**0.28%*** **	**0.39%*** **	**0.39%*** **	**0.41%*** **	**0.45%*** **	**0.38%*** **
MktVol _med	Sync	low	−0.25%***	−0.25%***	−0.17%***	−0.12%***	−0.06%*	−0.17%**
		medium	−0.36%***	−0.51%***	−0.47%***	−0.37%***	−0.30%***	−0.40%***
		high	−0.69%***	−0.83%***	−0.79%***	−0.78%***	−0.71%***	−0.76%***
		low-high	**0.45%*** **	**0.58%*** **	**0.62%*** **	**0.66%*** **	**0.65%*** **	**0.59%*** **
MktVol _high	Sync	low	−0.28%***	−0.12%**	−0.02%	−0.09%**	−0.19%***	−0.14%
		medium	−0.54%***	−0.50%***	−0.44%***	−0.49%***	−0.53%***	−0.50%***
		high	−1.09%***	−1.07%***	−0.93%***	−0.93%***	−0.99%***	−1.00%***
		low-high	**0.82%*** **	**0.95%*** **	**0.92%*** **	**0.84%*** **	**0.80%*** **	**0.87%*** **
MktVol_low	Turn	low	−0.26%***	−0.30%***	−0.29%***	−0.20%***	−0.08%***	−0.23%**
		medium	−0.37%***	−0.41%***	−0.38%***	−0.31%***	−0.25%***	−0.34%***
		high	−0.21%***	−0.28%***	−0.37%***	−0.31%***	−0.40%***	−0.31%***
		low-high	−0.05%	**−0.02%**	**0.08%**	**0.11%** **	**0.32%*** **	**0.09%**
MktVol _med	Turn	low	−0.37%***	−0.43%***	−0.33%***	−0.18%***	−0.03%	−0.27%*
		medium	−0.50%***	−0.61%***	−0.47%***	−0.44%***	−0.30%***	−0.46%***
		high	−0.40%***	−0.52%***	−0.59%***	−0.61%***	−0.71%***	−0.57%***
		low-high	**0.04%**	**0.09%***	**0.26%*** **	**0.43%*** **	**0.68%*** **	**0.30%**
MktVol _high	Turn	**low**	−0.13%***	−0.02%	**0.11%*** **	**0.16%*** **	**0.20%*** **	**0.06%**
		medium	−0.73%***	−0.64%***	−0.51%***	−0.55%***	−0.55%***	−0.60%***
		high	−0.99%***	−0.97%***	−0.94%***	−1.07%***	−1.31%***	−1.06%***
		low-high	**0.86%*** **	**0.95%*** **	**1.05%*** **	**1.23%*** **	**1.52%*** **	**1.12%*** **
MktVol_low	Skew	low	−0.15%***	−0.22%***	−0.30%***	−0.39%***	−0.30%***	−0.27%***
		medium	−0.16%***	−0.15%***	−0.16%***	−0.06%**	0.00%	−0.11%
		high	−0.51%***	−0.60%***	−0.56%***	−0.37%***	−0.43%***	−0.50%***
		low-high	**0.37%*** **	**0.38%*** **	**0.26%*** **	**−0.02%**	**0.13%*** **	**0.22%**
MktVol _med	Skew	low	−0.50%***	−0.54%***	−0.45%***	−0.36%***	−0.31%***	−0.44%***
		medium	−0.32%***	−0.44%***	−0.37%***	−0.24%***	−0.13%***	−0.30%**
		high	−0.46%***	−0.58%***	−0.57%***	−0.62%***	−0.59%***	−0.56%***
		low-high	−0.05%	**0.03%**	**0.11%** **	**0.26%*** **	**0.28%*** **	**0.13%**
MktVol _high	Skew	**low**	**0.55%*** **	**0.73%*** **	**1.10%*** **	**1.28%*** **	**1.23%*** **	**0.97%*** **
		medium	−0.52%***	−0.35%***	−0.18%***	−0.14%***	−0.16%***	−0.27%*
		high	−1.73%***	−1.85%***	−2.05%***	−2.36%***	−2.48%***	−2.09%***
		low-high	**2.28%*** **	**2.58%*** **	**3.15%*** **	**3.63%*** **	**3.71%*** **	**3.07%*** **
MktVol_low	Beta	low	−0.23%***	−0.19%***	−0.35%***	−0.25%***	−0.19%***	−0.24%***
		medium	−0.26%***	−0.30%***	−0.24%***	−0.17%***	−0.13%***	−0.22%***
		high	−0.34%***	−0.46%***	−0.44%***	−0.39%***	−0.39%***	−0.40%***
		low-high	**0.12%** **	**0.26%*** **	**0.09%***	**0.14%*** **	**0.21%*** **	**0.16%** **
MktVol _med	Beta	low	−0.32%***	−0.36%***	−0.28%***	−0.24%***	−0.19%***	−0.28%***
		medium	−0.30%***	−0.35%***	−0.28%***	−0.26%***	−0.14%***	−0.27%***
		high	−0.61%***	−0.79%***	−0.76%***	−0.67%***	−0.65%***	−0.70%***
		low-high	**0.29%*** **	**0.44%*** **	**0.48%*** **	**0.42%*** **	**0.47%*** **	**0.42%*** **
MktVol _high	Beta	low	−0.41%***	−0.26%***	−0.15%***	−0.25%***	−0.30%***	−0.27%***
		medium	−0.30%***	−0.22%***	−0.10%***	−0.08%**	−0.10%***	−0.16%*
		high	−1.05%***	−1.05%***	−0.97%***	−1.03%***	−1.15%***	−1.05%***
		low-high	**0.63%*** **	**0.79%*** **	**0.82%*** **	**0.79%*** **	**0.85%*** **	**0.78%*** **
MktVol_low	Vol	low	−0.40%***	−0.39%***	−0.30%***	−0.31%***	−0.27%***	−0.33%***
		medium	−0.26%***	−0.27%***	−0.25%***	−0.12%***	−0.08%***	−0.20%**
		high	−0.23%***	−0.35%***	−0.47%***	−0.40%***	−0.40%***	−0.37%***
		low-high	−0.17%***	−0.04%	**0.17%*** **	**0.08%**	**0.13%** **	**0.04%**
MktVol _med	Vol	low	−0.40%***	−0.53%***	−0.44%***	−0.45%***	−0.32%***	−0.43%***
		medium	−0.34%***	−0.41%***	−0.31%***	−0.24%***	−0.14%***	−0.29%***
		high	−0.52%***	−0.62%***	−0.63%***	−0.56%***	−0.57%***	−0.58%***
		low-high	**0.12%** **	**0.10%**	**0.19%*** **	**0.11%*** **	**0.25%*** **	**0.15%** **
MktVol _high	Vol	low	−0.36%***	−0.28%***	−0.06%***	−0.03%***	**0.05%** **	−0.14%
		medium	−0.43%***	−0.29%***	−0.14%***	−0.06%***	−0.07%**	−0.20%
		high	−0.95%***	−0.94%***	−0.97%***	−1.16%***	−1.37%***	−1.08%***
		low-high	**0.59%*** **	**0.66%*** **	**0.92%*** **	**1.13%*** **	**1.43%*** **	**0.94%*** **
MktVol _high	low Sync & low Turn & low Beta & low Skew		**1.19%*** **	**1.75%*** **	**2.18%*** **	**2.38%*** **	**2.71%*** **	**2.04%*** **

This table reports the double-sorting results combining the market volatility terciles and the terciles of each stock-level characteristic. The average TSMOM return (Carhart four-factor adjusted returns) is calculated for each stock-level characteristic tercile within each market volatility tercile. Average TSMOM returns are calculated for five TSMOM trading strategies formed based on the 1-month holding and 1-, 3-, 6-, 9-, and 12-month lookback periods. Low-minus-high results are provided in the last row for each market volatility tercile. Average TSMOM returns across five trading strategies are reported in the last column. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels.

Table 10. Further tests for low synchronicity & low turnover & low beta & low skewness stocks.

	Test 1: Magnitude			Test 2: Sign	
	beta	p value	r-square	beta	p value
Panel A: EPU_high (N of Stocks = 5,082; N of Obs = 15,188)					
L1	−0.0033	0.6734	0.3418	0.0131	0.1163
L3	0.0150	0.0016	0.3403	0.0146	0.0006
L6	0.0127	<.0001	0.3407	0.0079	0.0516
L9	0.0165	<.0001	0.3430	0.0139	0.0104
L12	0.0143	<.0001	0.3430	0.0174	0.0010
Panel B: Sentiment_low (N of Stocks = 5,049; N of Obs = 15,576)					
L1	0.0036	0.6434	0.3427	0.0046	0.0054
L3	0.0191	<.0001	0.3427	0.0103	<.0001
L6	0.0206	<.0001	0.3470	0.0100	<.0001
L9	0.0188	<.0001	0.3456	0.0083	<.0001
L12	0.0170	<.0001	0.3456	0.0122	<.0001
Panel C: Contraction (N of Stocks = 2,724; N of Obs = 5,597)					
L1	0.0038	0.798	0.4581	0.0160	0.2578
L3	0.0196	0.0506	0.4607	0.0114	0.1144
L6	−0.0135	0.1754	0.4573	−0.0038	0.6292
L9	−0.0047	0.6431	0.4615	0.0187	0.0373
L12	0.0068	0.5031	0.4637	0.0080	0.4429
L1	−0.0387	<.0001	0.3564	−0.0002	0.9578
L3	−0.0097	0.0432	0.3540	0.0110	0.0006
L6	0.0046	0.1102	0.3564	0.0105	0.0025
L9	0.0047	0.1094	0.3556	0.0090	0.0103
L12	0.0036	0.1828	0.3585	0.0164	<.0001

In this table, we verify the TSMOM profitability identified on the simultaneous stock portfolio in Tables 6–9. The simultaneous stock portfolio contains stocks that simultaneously meet the conditions of low Sync & low Turn & low Beta & low Skew. Model details for Test 1 and Test 2 are outlined in Section 5. In test 1, we examine whether a stock's past returns predict its future returns by regressing the returns of each individual stock in month t + 1 on its returns from the previous K-month (the lookback period). We report the regression slope coefficient beta, p value and model R^2 for TSMOM trading strategies formed on the 1-month holding period and 1-, 3-, 6-, 9-, and 12-month lookback periods. Industry fixed effects are controlled. In test 2, we examine whether the sign of a stock's past returns predicts the direction of its future returns by regressing the returns of each individual stock in month t + 1 on the sign function of its returns from the previous K-month (the lookback period). Standard errors are clustered by month. For both tests, the results for high EPU, low sentiment, market contraction, and high market volatility periods are presented in Panels A–D respectively.

period (1 month), the regression slopes are all statistically significant. Additionally, the model's R^2 is reasonably high in all cases (approximately 0.34). Nevertheless, it is worth noting that the number of observations that satisfy such conditions is only 15,188, covering 5,082 stocks. Given the size of our full sample, this still indicates a rather cautious applicability of TSMOM strategies.

Panel B results are very similar. For stocks with the same characteristics as in Panel A but during low sentiment periods, we find that their past returns at different horizons generally show predictive ability for their future returns (except for the 1-month lookback period). However, the number of stocks that satisfy such conditions is only 5,049 (15,576 observations).

Regarding Panels C and D, during economic contraction and high market volatility periods and for the same stocks as above, we find that the Test 1 results are generally weak. The magnitude of the future returns can only be correctly anticipated by the magnitude of past 3-month returns only. Additionally, the Test 2 results in Panel C show that only the sign of the past 9-month returns can predict the sign of the future returns significantly. However, this reduced significance could be a result of the small sample size (5,597 observations covering 2,724 stocks). In Panel D, significant results of Test 2 are documented for all lookback periods except for the shortest period of 1-month.

Note that the reported results in this section are based on the stocks selected using multiple stock-level parameters (i.e. these stocks simultaneously have low *Sync*, low *Turn*, low *Beta* and low *Skew*) and during a single market state, which are shown to generate the highest TSMOM returns in Tables 6–9.[15]

VI. Conclusion

As the original authors of TSMOM remarked, time series momentum is true to the spirit of behavioural models, which are intended for individual risky assets. While Moskowitz, Ooi, and Pedersen (2012) examine only eight equity indices in Australia, Germany, Spain, France, Italy, Japan, the Netherlands, the UK, and the US (S&P 500), they imply that TSMOM profits should be largely applicable to individual stocks as well. In the wake of more recent studies that raise questions about the general existence of TSMOM (especially critiques by Huang et al. (2020)), we comprehensively examine the TSMOM profitability of US common stocks from 1986 to 2017 covering more than 2.25 million stock-month observations. This is largely motivated by Huang et al.'s (2020) recommendation to examine the issue through a large sample that allows for the search for optimal time-horizon

[15]In unreported results, we carry out the same analyses by performing the sample selection based on single market-wide and single stock-level parameter sorting. As expected, we generally find weak supportive evidence for the predictive ability of past returns on the future months.

combinations, market-wide conditions, and stock characteristics to determine whether TSMOM strategies may prevail at all.

Surprisingly, in contrast to Moskowitz et al.'s (2012) claim regarding the existence of TSMOM profits among common stocks, we find that these opportunities are generally weak in our full sample analysis. We further identify whether TSMOM strategies could have merits if we only apply them under certain market conditions and for a certain subset of stocks. Being supportive of this idea, we find some strict combinations of these conditions that do lead to profitability. When there is lower confidence among investors (e.g. in higher Economic Policy Uncertainty periods, low sentiment periods, market contractions, and high market volatility) and for stocks that are associated with lower information transparency and investor attention (e.g. lower synchronicity, lower trading volume, among other factors), TSMOM profitability is more pronounced. However, while these returns are sizable (up to 5.09% per month), one must be cautious in exploiting them due to the reduced occasions of when and where TSMOM strategies can actually be applied (numbers of stocks and observations are significantly reduced). With further concerns regarding transaction costs and limits to arbitrage, whether TSMOM profits are truly exploitable is still a question that investors must approach with care.

As a concluding remark, our comprehensive and longitudinal investigations in this study reconcile two opposing views regarding TSMOM profitability through the lens of individual common stocks, which is limited in the literature. Our study thus relates to the strand of literature that urges researchers to avoid prematurely ruling out published predictors of stock returns due to reasons such as data snooping (Zakamulin and Giner 2020; Jegadeesh and Titman 2002), publication bias (Chen and Zimmermann, 2020), and changes in the market environment or investor behaviour (Borroso and Santa-Clara, 2015; Daniel and Moskowitz 2016), among others. In the context of time series momentum of US individual stocks, we show that profits may not be generally available. However, they do exist and might justify TSMOM as a worthwhile trading strategy if one is meticulous enough in searching for when and where to look.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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