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# Stock Price Synchronicity and Technical Trading Effectiveness

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## Abstract

This study investigates how stock price synchronicity, as a measure of how stock prices reflect market-wide information relative to firm-specific information, explains the profitability of moving-average (MA) technical trading. The stocks of firms with less synchronicity have more information uncertainty (IU) (i.e., they reflect less firm-specific information), which amplifies investors' underreaction bias and the price momentum effect, and are therefore more profitable. Testing a sample of stocks listed on the Taiwan and the Taipei stock exchanges over July 1997-June 2021, we provide evidence consistent with the synchronicity-related IU hypothesis. For a low-synchronicity stock price quintile portfolio, the abnormal returns of an MA strategy relative to a buy-and-hold strategy as estimated by the Fama-French 5-factor model are high at 18.05% per annum and even higher for a high-synchronicity stock price quintile portfolio (9.22% per annum). The MA strategy for low-synchronicity stock price portfolio remains more effective even when considering equally and value-weighted portfolios, testing various sub-periods, considering alternative MA lag lengths and controlling for market variables such as liquidity, sentiment, economic policy uncertainty, and economic cycle.

## Keywords

Stock Price Synchronicity, Technical Trading, Information Uncertainty, Moving Average Strategy

## 1. Introduction

While studies show mixed results regarding the success of technical trading rules, recent papers have presented evidence that a moving-average (MA) strategy using technical analysis is superior to a buy-and-hold strategy on portfolios with a high level of information uncertainty (IU) (Zhu & Zhou, 2009; Han, Yang, & Zhou, 2013; Chen, Su, & Lin, 2016; Smith et al., 2016)[1]. The existence of significant profits using MA trading appears to contradict the market efficiency theory (Brock, Lakonishok, & LeBaron, 1992; Olson, 2004). When facing an uncertain informational environment—as characterized by the young stocks of small firms, low trading volume, high idiosyncratic volatility, or little analyst coverage—investors underreact to gradual information diffusion (Jiang, Lee, & Zhang, 2005; Zhang, 2006). When information spread slowly, it leads to greater short-term price continuation (i.e., uninterrupted up or down trends in stock prices) (Hong & Stein, 1999; Hong, Lim, & Stein, 2000). Han, Yang, and Zhou (2013) stated that "the idea of the MA is that an investor should hold an asset when the asset price is on an uninterrupted up trend" (p. 1437). Therefore, as an investment timing signal, an MA strategy detects price trends and is expected to generate abnormal returns for such stocks (Zhu & Zhou, 2009; Han, Yang, & Zhou, 2013). We call this the "information uncertainty hypothesis" (IUH).

This study investigates the effectiveness of technical trading rules, primarily an MA scheme, at the portfolio level grouped by the degree of stock price synchronicity (hereafter, synchronicity) on the basis of the IUH. Our paper is motivated by the literature examining how a firm's informational environment (i.e., financial disclosure policy or analyst following) is associated with firm-specific or market-wide factors, which suggests that lower synchronicity, as an indicator of more firm-specific information being integrated into the stock price, reflects more idiosyncratic noise (Roll, 1988; Durnev et al., 2003) or a less transparent informational environment (Chan & Hameed, 2006; Dasgupta, Gan, & Gao, 2010).

This raises an issue about the role of synchronicity in the cross-sectional profitability of MA technical analysis. When stocks reflect more idiosyncratic noise (i.e., less synchronicity), other signals are likely imprecise and cause investors to rely more heavily on technical signals. Assuming that technical signals are profitable, one implication of this on the basis of the IUH is that since stocks with less synchronicity cause higher IU and greater price continuation, the performance of MA technical analysis for those stocks, *ceteris paribus*, might be superior.

To conduct this analysis, we follow Chan, Hameed, and Kang (2013) and regress weekly stock returns on three types of market returns—contemporaneous, leading, and lagged returns—to extract the firm-specific component of returns based on standard market model regressions. Following previous literature, we measure synchronicity as the R-squared value of stocks from the market model regression, which reflects the proportion of variation in stock returns explained

[1]As defined by Jiang, Lee, and Zhang (2005), information uncertainty can be described as "the degree to which a firm's value can be reasonably estimated by even the most knowledgeable investors at reasonable costs" (p. 185). Zhang (2006) stated, "by information uncertainty, I mean ambiguity with respect to the implications of new information for a firm's value" (p. 105).

by market returns. The lower a firm's synchronicity (i.e., a lower R-squared value), the more firm-specific information is incorporated into a stock price (French & Roll, 1986; Roll, 1988) and the more idiosyncratic noise or less transparent information we should expect.

Testing a sample of stocks listed on the Taiwan Stock Exchange (TWSE) and the Taipei Exchange (TPEx) over 1997-2021, our findings support the hypothesis that when portfolios are sorted by synchronicity, an MA strategy can generate superior performance than a buy-and-hold strategy, especially for low-synchronicity portfolios. First, the IU degree is significantly higher for stocks of a lower-synchronicity quintile portfolio, which are characterized by smaller firm size, a lower share price, higher return volatility, less share turnover, and higher illiquidity. Second, the 20-day MA strategy generates a significant return of 14.42% per annum relative to the buy-and-hold strategy for the low-synchronicity quintile portfolio, while it is insignificant at 4.80% per annum for the high-synchronicity quintile portfolio and yields an annual Sharpe ratio of 1.01 for the low-synchronicity quintile portfolio, which is 0.58 higher than that for the high-synchronicity quintile portfolio. Third, risk-adjusted returns, estimated by the Fama and French (2015) 5-factor model, are even greater for the 20-day MA strategy on a low-synchronicity quintile portfolio than on a high-synchronicity quintile portfolio. The risk-adjusted returns of the MA strategy remain greater for the low-synchronicity portfolio, after considering the equal-/value-weighted grouped synchronicity portfolio, sub-sample period selection, MA lag length, Carhart (1997) momentum factor, Amihud (2002) illiquidity, market sentiment, market-wide economic policy uncertainty (EPU), and economic cycle.

This study makes two contributions to the literature. First, we investigate how the cross-sectional profitability of technical analysis is explained by synchronicity. Although existing studies are inconclusive as to whether technical trading rules yields superior returns (e.g., Park and Irwin (2007)), studies have documented the superior cross-sectional profitability of an MA timing strategy relative to a buy-and-hold strategy, focusing on portfolios sorted by volatility and firm size (Han et al., 2013), firm life cycle (Chen et al., 2021), and stock option issuance (Chen, Su, & Lin, 2016). Our study extends this strand of literature and discovers that a larger firm-specific component in returns exacerbates the degree of IU and therefore helps improve an MA strategy's effectiveness.

Second, most studies on synchronicity have concentrated on the U.S. stock market (Xing & Anderson, 2011; Chue, Gul, & Mian, 2019; Abedifar, Bouslah, & Zheng, 2021). This study analyzes the emerging market of Taiwan, which has implications for trading strategy. Given that emerging markets' institutional characteristics, informational environment, and degree of stock return co-movements differ from those of developed markets (e.g., Morck, Yeung and Yu (2000); Chan and Hameed (2006)), our study complements the literature by demonstrating that an MA strategy's profitability depends on how much stock prices reflect firm-specific information. In a typical emerging market like Taiwan, this is influenced by the fact that the dissemination of firm-specific information to public investors is usually inadequate.

The main innovation of this paper lies in a novel application of formalized technical analysis to synchronicity-ranked stocks, which help market participants apply the framework to plan their development schemes for stock portfolio management. Specifically, from a practical perspective, market participants can implement stock selection ideas by including lower synchronicity-ranked stocks into their traders' portfolio and then adopt the MA technical analysis for buy and sell signals on these stocks, which may have given significantly higher returns when compared to the benchmark. Overall, the findings of this study are practical implications highlighted and conclusions are presented for potentially effective stock portfolio management.

The remainder of this study proceeds as follows. Section 2 develops the research hypotheses. Section 3 describes our data sources and methodology. Section 4 presents empirical evidence on the link between synchronicity and a technical trading strategy. Section 5 concludes.

## 2. Literature Review and Hypothesis Development

Stock prices and information flows have a symbiotic and inseparable relationship in financial markets. An informative stock price is expected to reflect a firm's fundamental value and have less synchronicity with market-wide information (Roll, 1988; Morck, Yeung, & Yu, 2000). These pioneering papers motivated several follow-up studies that verified the relationship between synchronicity (i.e., IU) and capital allocation efficiency (Wurgler, 2000), analyst coverage (Piotroski & Roulstone, 2004; Chan & Hameed, 2006), future earnings (Durnev et al., 2003), transparency (Jin & Myers, 2006; Dasgupta et al., 2010), earnings management (Hutton, Marcus, & Tehranian, 2009), audit quality (Gul et al., 2010), liquidity (Chan et al., 2013), corporate governance (Boubaker, Mansali, & Rjiba, 2014), institutional investors' shareholding (Li, 2017), investor sentiment (Chue et al., 2019), media coverage (Dang et al., 2020), economic policy uncertainty (Shen et al., 2021), financial derivative usage (Su, Zhang, & Liu, 2022), messages in online stock forums (Huang et al., 2022), and stock market liberalization (Li et al., 2022).

Although the linear relationship between the amount of public firm-specific information available and synchronicity has been debated (e.g., Xing and Anderson (2011)), the literature has documented that less synchronicity—as an indicator of firm-specific information being integrated into stock prices to a higher degree—reflects more idiosyncratic noise (Roll, 1988; Durnev et al., 2003) or a less transparent informational environment (Chan & Hameed, 2006; Dasgupta et al., 2010). Morck et al. (2000) found that a firm with higher opacity could discourage trading by increasing the cost of arbitrage in an informed environment and prevent the incorporation of firm-specific information into stock prices. Chan et al. (2013) argued that synchronicity affects stock liquidity. They discovered a negative effect of stock return co-movement and systematic volatility on liquidity.

To the extent that less synchronicity is characterized by more idiosyncratic noise or a more opaque informational environment, synchronicity might be related to the profitability of MA technical analysis based on the IUH. The literature suggests that when facing an uncertain informational environment, investors tend to exhibit an underreaction bias to gradual information diffusion (Jiang, Lee, & Zhang, 2005; Zhang, 2006), which furthers slows down information flows and prompts more short-term price continuation (i.e., uninterrupted up or down trends in stock prices) (Hong & Stein, 1999; Hong, Lim, & Stein, 2000).

Investors are more willing to rely on technical analysis when faced with possibly inaccurate firm fundamentals. IU could enhance the effectiveness of technical indicators. Lin, Yang, Chou, and Ko (2022) verified the effectiveness of an MA strategy and the predictability of a momentum strategy and attempted to determine whether both could be attributed to IU. Their results suggest that technical analysis increases the profitability of a momentum strategy and that profits could be increased by investors via technical analysis in more uncertain environments.

Given that an MA strategy is based on technical analysis that is designed to chase an uninterrupted up or down trend in stock prices, the strategy's profitability is hypothesized to be higher (lower) for stocks with a less (more) synchronicity. We thus test the following hypothesis:

**Hypothesis.** The profitability of MA technical analysis is higher for stocks with less synchronicity, *ceteris paribus*.

# 3. Data and Methodology

## 3.1. Sample Construction

Our sample consists of stocks listed on the TWSE and the TPEx during 1997-2021. All data were generated from the Taiwan Economic Journal (TEJ) database unless otherwise stated.

Our variable of interest, synchronicity, is comprised of weekly stock return data following Chan and Hameed (2006). We regress weekly stock returns on three types of market returns—contemporaneous, leading, and lagged returns—to extract the firm-specific component in returns based on a standard market model regression as follows:

$$R_{i,w} = \alpha + \sum_{k=-1}^{+1} \beta_{i,k} R_{mkt,w-k} + u_{i,k} \tag{1}$$

where $R_{i,w}$ is stock *i*'s weekly returns in week *w*, and $R_{mkt,w-k}$ is the Taiwan TAIEX value-weighted weekly market returns in week *w*. We measure synchronicity as the R-squared value of stocks from the market model regression in Equation (1). Because the R-squared value is bounded by zero and one, we take the log transformation of the R-squared value as $\ln\left(\frac{R_i^2}{1-R_i^2}\right)$. We denote $\ln\left(\frac{R_i^2}{1-R_i^2}\right)$ as *Synch* hereafter.

We measure the degree of uncertainty of firm-specific information by considering five proxies for IU—year-end market value (*MV*), year-end closing price per share (*Price*), as well as the standard deviation of monthly stock returns (*STD*), the sum of the monthly share turnover ratio (*Turnover*), and Amihud (2002) average daily illiquidity (*Illiq*) over a specific year.

To estimate the risk-adjusted returns of an MA strategy, we used data on Fama and French's (2015) well-known five risk factors (i.e., *MKT*, *SMB*, *HML*, *RMW*, and *CMA*). For robustness, we include other market-wide factors such as the Carhart (1997) momentum factor (*MOM*), market illiquidity (*Milliq*), market sentiment (*VIX*), EPU, and a recession dummy (*Recession*). Data on EPU were collected from the Federal Reserve Bank of St. Louis (FRED).

### 3.2. Summary Statistics: Synchronicity and IU

**Table 1** presents the descriptive statistics for IU characteristics across *Synch*-based quintiles. In June of each year *y* during 1996-2020, firms are classified into

**Table 1.** Summary statistics sorted by *Synch*-based quintiles. This table reports the descriptive statistics for each *Synch*-based quintile. The sample contains stocks listed on the Taiwan Stock Exchange (TWSE) and the Taipei Exchange (TPEx) during 1997-2021. In June of each year *y* during 1996-2020, firms are classified into low, Q2, Q3, Q4, and high-*Synch* quintile portfolios based on their *Synch* in year *y* − 1 and the average of *Synch* and the information asymmetry-related variable for each *Synch* quintile is computed. *Synch* is stock price synchronicity, $\ln\left(\frac{R_i^2}{1-R_i^2}\right)$, where $R_i^2$ is stock *i*'s R-squared value, estimated based on the standard market model: $R_{i,w} = \alpha + \sum_{k=-1}^{+1} \beta_{i,k} R_{mkt,w-k} + u_{i,k}$, where $R_{i,w}$ is stock *i*'s weekly returns in week *w* and $R_{mkt,w-k}$ is Taiwan TAIEX value-weighted weekly market returns in week *w*. *MV* is the year-end market value. *Price* is the year-end closing price per share. *STD* is the standard deviation of monthly stock returns in a specific year. *Turnover* is sum of the monthly share turnover ratio over a specific year. *Illiq* is the Amihud (2002) average daily illiquidity over a specific year. The values of each statistic are first computed cross-sectionally year by year, and report the time-series averages of those values. The *t*-test is used to examine the difference between two means of low- and high-*Synch* quintiles. *** represents significance at the 1% level. All data were collected from the TEJ database.

| Quintiles | *Synch* | *MV* (NT$ in Million) | *Price* | *STD* (%) | *Turnover* (%) | *Illiq* |
|---|---|---|---|---|---|---|
| Low | −2.83 | 5852.23 | 33.69 | 14.13 | 138.21 | 27.21 |
| Q2 | −1.69 | 8275.09 | 35.74 | 12.96 | 182.23 | 8.54 |
| Q3 | −1.15 | 10372.43 | 37.34 | 12.52 | 210.83 | 2.10 |
| Q4 | −0.70 | 16297.24 | 37.77 | 11.99 | 223.18 | 1.20 |
| High | 0.01 | 43162.10 | 38.91 | 11.53 | 218.13 | 0.60 |
| Low-High | −2.84 | −37309.87 | −5.23 | 2.60 | −79.92 | 26.61 |
| | | (−6.72)*** | (−3.59)*** | (4.48)*** | (−8.22)*** | (6.12)*** |

low, Q2, Q3, Q4, and high-*Synch* quintile portfolios based on their *Synch* in year $y-1$. The average of the *Synch* and information asymmetry-related variables (i.e., *MV*, *Price*, *STD*, *Turnover*, and *Illiq*) for each *Synch* quintile is then computed. Each descriptive statistic is computed cross-sectionally with each passing year. The time-series average of those values is reported in **Table 1**.

Firms in the low-*Synch* quintiles sequentially present a smaller *MV*, a lower *Price*, a higher *STD*, a lower *Turnover*, and a higher *Illiq* than firms in the high-*Synch* quintiles. A difference test indicates that the average *STD* difference between the low- and high-*Synch* quintiles is positively significant at 2.60 ($t$ = 4.48), and the average *Illiq* difference between the low- and high-*Synch* quintiles is significantly negative at 26.61 ($t$ = 6.21). These findings, presented in **Table 1**, propose that stocks with a low-*Synch* are characterized by a high level of IU, which strengthens our motivation to investigate how MA profitability is explained by *Synch*-linked IU.

### 3.3. Using a Moving-Average Timing Strategy on a Synchronicity-Based Portfolio

To investigate the profitability of an MA strategy on portfolios sorted by degree of *Synch*, we establish a price index for each *Synch* quintile portfolio following Han, Yang, and Zhou (2013) and Chen et al. (2021). First, we integrate daily returns of individual stocks from the TWST from the TEJ's equity database into our dataset, which contains approximately 4.1 million firm-day trading records. In June of each year, *y*, of the 1996-2020 period, firms are classified into low, Q2, Q3, Q4, and high-*Synch* quintile portfolios based on their *Synch* in year $y-1$, and their post-formation, cross-sectional, value-weighted daily returns in the subsequent year (rebalanced annually) are linked across years during the period between July 2, 1997 and June 30, 2021. We set NT$1 as the portfolio price on the first trading day—July 2, 1997—and adopt a future value formula to calculate the portfolio price on every subsequent day and take the corresponding buy-and-hold portfolio's daily return for the same day. This is how the low, Q2, Q3, Q4, and high-*Synch* quintile portfolios' price indices from July 2, 1997 to June 30, 2021 are formed.

Given a daily price index for the *Synch* portfolio, we denote $P_{S,d}$ as the baseline portfolio, *S*, on day $d$ to form the MA strategy. The *N*-day MA price on day $d$ for *Synch* quintile portfolio $S$ ( $A_{N,S,d}$ ) is defined in Equation (2) as follows:

$$A_{N,S,d} = \left(P_{S,d-(N-1)} + P_{S,d-(N-2)} + \cdots + P_{S,d-1} + P_{S,d}\right) \Big/ N \tag{2}$$

We follow Han, Yang, and Zhou (2013) and set the MA trading rules as follows: 1) the buy signal—if the *Synch* portfolio price on day $d-1$ is greater than the MA price on day $d-1$ to previous $N$ days ($N$-day), $N$ is the period used in MA rules, (e.g., $P_{S,d-1} > A_{N,S,d-1}$), and we take a long position in the *Synch* portfolio on day $d$; and 2) the sell signal—if the *Synch* portfolio price on day $d-1$ is less than the MA price on day $d-1$ to previous $N$ days, $N$ is the period used in MA rules, (e.g., $P_{S,d-1} < A_{N,S,d-1}$), then investors clear that long position in the *Synch* portfolio and invest in risk-free, one-year certificates of deposit.

### 3.4. Measuring the MA's Returns on the Synchronicity-Based Portfolios

Guided by Han, Yang, and Zhou (2013), we measure daily returns from the MA strategy on each *Synch* quintile portfolio on day $d$ to previous $N$ days ( $R_{N,S,d}$ ) as follows:

$$R_{N,S,d} = \begin{cases} R_{S,d}, \text{ if } P_{S,d-1} > A_{N,S,d-1} \\ Rf_d, \text{ otherwise} \end{cases} \tag{3}$$

where $R_{S,d}$ is the daily return of a *Synch* quintile portfolio (i.e., Low, Q2, Q3, Q4, and High) on day *d*, and $Rf_d$ is the daily return of a risk-free asset on day *d*, which uses the one-year certificate of deposit fixed rates reported by the Bank of Taiwan.

We measure the MA's abnormal returns relative to the buy-and-hold strategies' returns on each *Synch* quintile portfolio ( $MAP_{N,S,d}$ ) as follows:

$$MAP_{N,S,d} = R_{N,S,d} - R_{S,d} \tag{4}$$

where $R_{N,S,d}$ is daily returns from the MA strategy on each *Synch* quintile portfolio on day $d$ to the previous N days. $R_{S,d}$, the *Synch* quintile portfolio's daily returns (i.e., Low, Q2, Q3, Q4, and High) on day *d*. We focus the analysis on the 20-day MA strategy ( $MA_{20}$ ) and examine the robustness of the 10-, 50-, 100-, and 200-day MA strategies in Section 4.3.

## 4. MA Strategy's Returns on the Synchronicity-Based Portfolios

### 4.1. MA Strategy's Trading Information and Preliminary Results

Summaries of the 20-day MA's performance on the *Synch* quintile portfolio—including the total number of trades (Trading #), the average, minimum, and maximum holding days for each trade of the 20-day MA (MA's Average HP, MA's Min HP, and MA's Max HP), the average buy-and-hold returns on low, Q2, Q3, Q4, and high-*Synch* quintile portfolios (BHR), the average transaction cost-adjusted returns of the 20-day MA (MA20), the average returns of the 20-day MA buy-and-sell strategy relative to the buy-and-hold strategy (MAP), and the MAP's Sharpe ratio—are reported in **Table 2**. We report that the BHR, MA20, and MAP are annualized and in percentage.

These results illustrate that there were 268 20-day MA's trades on the low-*Synch* portfolio from July 2, 1997 to June 30, 2021, which is less than on the high-*Synch* portfolio (309). The fewer 20-day MA's trades on the low-*Synch* portfolio prompts its longer holding period, with an average of 12.7 days in a complete round of buy-and-sell signals from the trading rule.

As shown in Column 6, the BHR is an increasing function of low, Q2, Q3, Q4, and high-*Synch* quintile portfolios, ranging from 2.83% per annum for the low-*Synch* quintile to 8.81% per annum for the high-*Synch* quintile. The bottom

**Table 2.** MA20's trading information and return performance for *Synch* quintile portfolios. This table reports the MA20 strategy's trading information and the return performance for low, Q2, Q3, Q4, and high-*Synch* quintile portfolios, and their differences between low- and high-*Synch* quintile portfolios. The sample contains stocks listed on the Taiwan Stock Exchange (TWSE) and the Taipei Exchange (TPEx) during the period 1997-2021. In June of each year $y$ during 1996-2020, firms are classified into low, Q2, Q3, Q4, and high-*Synch* quintile portfolios based on their *Synch* in year $y - 1$ and their post-formation cross-sectional value-weighted daily returns in the subsequent year (rebalanced annually) are linked across years from July 2, 1997 to June 30, 2021. The portfolio price index is assigned a price equal to NT$1 on the first day—July 2, 1997—and the portfolio prices for each subsequent day are calculated by adopting the future value formula while using the corresponding buy-and-hold portfolio's daily return for that day. Therefore, the low, Q2, Q3, Q4, and high-*Synch* quintile portfolios' price indices from July 2, 1997 to June 30, 2021, are formed, as well as their 20-day MA price index is formed adopting Equation (2). Trading # is the total number of trades via the 20-day MA buy-and-sell rule during July 2, 1997-June 30, 2021. MA's Average HP, MA's Min HP, and MA's Max HP (days) is the average, minimum, and maximum holding days for each trade via the 20-day MA buy-and-sell rule. BHR is the average of the buy-and-hold returns on low, Q2, Q3, Q4, and high-*Synch* quintile portfolios. MA20 is the average of transaction cost-adjusted returns via the 20-day MA buy-and-sell rule on low, Q2, Q3, Q4, and high-*Synch* quintile portfolios. MAP is the average of returns of via the 20-day MA buy-and-sell strategy relative to the buy-and-hold strategy. MAP's Sharpe Ratio is the Sharpe ratio for low, Q2, Q3, Q4, and high-*Synch* quintile portfolios. BHR, MA20, and MAP are annualized and in percentage. The $t$-tests are used to test whether the means for the entire sample are equal to zero and examine the difference between two means of low- and high-*Synch* quintiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All data were collected from the TEJ database.

| Quintiles | Trading# | MA's Average HP (days) | MA's Min HP (days) | MA's Max HP (days) | BHR (%) | MA20 (%) | MAP (%) | MAP's Sharpe Ratio |
|---|---|---|---|---|---|---|---|---|
| Low | 268 | 12.7 | 1 | 113 | 2.83 | 17.25 | 14.42 | 1.01 |
| | | | | | (0.77) | (7.63)*** | (4.95)*** | |
| Q2 | 273 | 12.9 | 1 | 82 | 8.40 | 18.62 | 10.22 | 0.62 |
| | | | | | (1.92)* | (6.75)*** | (3.03)*** | |
| Q3 | 278 | 12.7 | 1 | 82 | 8.10 | 18.76 | 10.66 | 0.62 |
| | | | | | (1.79)* | (6.56)*** | (3.05)*** | |
| Q4 | 293 | 11.8 | 1 | 92 | 9.29 | 16.52 | 7.24 | 0.43 |
| | | | | | (2.09)** | (5.89)*** | (2.10)** | |
| High | 309 | 10.7 | 1 | 67 | 8.81 | 13.61 | 4.80 | 0.58 |
| | | | | | (1.82)* | (4.45)*** | (1.28) | |
| Low-High | −41 | 2 | 0 | 46 | −5.98 | 3.64 | 9.62 | 0.43 |
| | | | | | (−1.80)* | (1.90)* | (3.47)*** | |

row in this column provides the difference between the low- and high-*Synch* quintiles. Contrary to the BHR, as reported in Column 7, the 20-day MA strategy's portfolios return (MA20) for the low-*Synch* quintile is higher (17.25%) than that for the high-*Synch* quintile (13.61%). Their difference is significantly postive at 3.64% ($t = 1.90$).

Column 8 reports the results for the MAPs, which decrease monotonically from 14.42% to 4.80% per annum across the quintiles and show significant evidence of each *Synch* quintile portfolio (except for the highest-*Synch* quintile), including the difference between the low- and high-*Synch* quintiles (9.62% per annum with a *t*-statistic of 3.47). In the final column, we describe the Sharpe ratio of the 20-day MA strategy's portfolios, which is similar to Column 8 (except for the fourth-*Synch* quintile), ranging from 1.01 to 0.58, indicating superior performance of the 20-day MA strategy's portfolios. The summary statistics indicate that the profitability of MA technical analysis is higher (lower) for stocks with lower (higher) synchronicity, *ceteris paribus*, consistent with the synchronicity-related IUH.

Whether abnormal returns can be explained by well-known risk-based models is ambiguous. This inspires our investigation of the MAP in the context of factor models.

## 4.2. MA Strategy's Risk-Adjusted Alphas

To examine whether the MAP portfolios' returns across *Synch* can be explained by the risk-based factor model, we follow Han, Yang, and Zhou (2013) and estimate the risk-adjusted returns of the MAP *Synch* portfolios based on the Fama and French (2015) 5-factor model as follows:

$$\begin{aligned} MAP_{j,d} = {} & \alpha_j + \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d + \beta_j^{rmw} RMW_d \\ & + \beta_j^{cma} CMA_d + u_{j,d} \end{aligned} \tag{5}$$

where $MAP_{j,d}$ is the low, Q2, Q3, Q4, and high-*Synch* portfolio *j*'s 20-day MA strategy daily returns relative to its corresponding underlying portfolio on day *t* from July 2, 1997 to June 30, 2021. $MKT_t$, $SMB_t$, $HML_t$, $RMW_t$, and $CMA_t$ are Fama and French's (2015) five factors on day *t*, generated based on the French's data library.

**Table 3** reports the results for Fama and French's (2015) regressions of the MAPs formed with a 20-day MA strategy. The alpha is even greater than in the unadjusted ones, ranging from 18.05% to 9.22%. The alpha decreases monotonically from the low-*Synch* quintile to the high-*Synch* quintiles, except that the median-*Synch* quintile generates an alpha that is 15.19% greater than the second-*Synch* quintile. The bottom row reports the difference between the low- and high-*Synch* quintiles' alphas, which is extremely significant at 8.83% per annum with a t-statistic of 3.43.

As shown in Columns 3 to 6 of **Table 3**, the beta on *MKT* and *SMB* is negatively significant across the *Synch* quintiles. The magnitude of the beta on the *SMB* is less than those of *MKT*. The beta on *HML* has an increasing trend across the *Synch* quintiles, and that of the high-*Synch* quintiles is positive and significant, implying that value stocks feature more synchronicity than growth stocks.

**Table 3.** MAP's risk-adjusted alphas for *Synch* quintile portfolios. This table reports the MAP's risk-adjusted alphas for low, Q2, Q3, Q4, and high-*Synch* quintile portfolios, and the difference in alphas between low- and high-*Synch* quintile portfolios, based on the Fama-French 5-factor model:
$MAP_{j,t} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{smb} SMB_t + \beta_j^{hml} HML_t + \beta_j^{rmw} RMW_t + \beta_j^{cma} CMA_t + u_{j,t}$ where $MAP_{j,t}$ is the low, Q2, Q3, Q4, and high-*Synch* portfolio *j*'s 20-day MA strategy return performances relative to its corresponding underlying portfolio on day *t* from July 2, 1997 to June 30, 2021. $MKT_t$, $SMB_t$, $HML_t$, $RMW_t$, and $CMA_t$ are Fama and French's (2015) five factors on day *t*. The numbers in parentheses are *t*-values. N is the number of time-series observations. *** and ** represent significance at the 1% and 5% levels, respectively. All data were collected from the TEJ database.

| Quintiles | *Alpha* (%) | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | N | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| Low | **18.05** | −1.29 | −0.89 | −2.12 | −1.00 | −3.26 | 6012 | 49.8% |
| | **(8.73)***** | (−70.98)*** | (−23.64)*** | (−0.60) | (−0.23) | (−0.76) | | |
| Q2 | **14.41** | −1.51 | −0.86 | 0.52 | −1.48 | −12.28 | 6012 | 50.8% |
| | **(6.07)***** | (−72.14)*** | (−19.87)*** | (0.13) | (−0.30) | (−2.49)** | | |
| Q3 | **15.19** | −1.63 | −0.93 | 0.03 | 0.03 | −7.85 | 6012 | 55.4% |
| | **(6.48)***** | (−79.00)*** | (−21.83)*** | (0.01) | (0.01) | (−1.61) | | |
| Q4 | **11.30** | −1.57 | −0.69 | 2.81 | 14.74 | −2.68 | 6012 | 55.8% |
| | **(4.92)***** | (−77.68)*** | (−16.54)*** | (0.72) | (3.05)*** | (−0.56) | | |
| High | **9.22** | −1.69 | −0.40 | 11.31 | 11.44 | −6.11 | 6012 | 57.9% |
| | **(3.79)***** | (−78.93)*** | (−9.00)*** | (2.73)*** | (2.24)** | (−1.21) | | |
| Low-High | **8.83** | 0.40 | −0.49 | −13.43 | −12.44 | 2.85 | 6012 | 14.0% |
| | **(3.43)***** | (17.57)*** | (−10.47)*** | (−3.06)*** | (−2.30)** | (0.53) | | |

The last row shows that all betas on the 5-factor model are statistically significant, except for the *CMA* factor.

The overall findings in **Table 3** support the IUH, even after well-known risk factors are considered.

## 4.3. Robustness Checks

In this subsection, we investigate the robustness of the MAP's risk-adjusted alphas, estimated using the Fama-French 5-factor model in several dimensions. First, we consider cross-sectional, equal-weighted *Synch* quintile portfolios and analyze two sub-periods: July 2, 1997-June 30, 2008 and July 1, 2008-June 30, 2021. We finally consider alternative lag lengths for the MA indicator.

Thus far, the daily returns of the *Synch* quintile portfolios have been value-weighted, so we now check if these stocks perform differently than those in the equally weighted portfolios. We use the post-formation cross-sectional equally weighted *Synch* quintile portfolios' daily returns to further check robustness. Panel A of **Table 4** reports the Fama and French (2015) alphas for the MAPs

**Table 4.** Robustness analyses. This table reports a variety of the robustness analysis results of MAP's risk-adjusted alphas, estimated based on the Fama-French 5-factor model in **Table 3**, for low, Q2, Q3, Q4, and high-*Synch* quintile portfolios. Panel A reports the results for cross-sectionally equal-weighted *Synch* quintile portfolios. Panel B reports the results for two sub-periods: July 2, 1997-June 30, 2008 and July 1, 2008-June 30, 2021. Panel C reports the results for alternative lag lengths for the MA indicator (i.e., MA10, MA50, MA100, and MA200). For brevity, only the MAP's risk-adjusted alphas of each low, Q2, Q3, Q4, and high-*Synch* quintile portfolio are reported. The numbers in parentheses are *t*-values. N is the number of time-series observations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All data were collected from the TEJ database. (a) *Synch*-based Equally Weighted Quintile Portfolios; (b) Sub-Periods; (c) Alternative Lags of MA.

(a)

| Quintiles | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|
| Low | **20.97**<br>**(11.48)***** | Yes | 6012 | 57.0% |
| Q2 | **19.90**<br>**(9.78)***** | Yes | 6012 | 58.5% |
| Q3 | **20.36**<br>**(9.33)***** | Yes | 6012 | 59.8% |
| Q4 | **18.61**<br>**(8.37)***** | Yes | 6012 | 60.3% |
| High | **15.76**<br>**(7.65)***** | Yes | 6012 | 60.3% |
| Low-High | **5.21**<br>**(1.99)**** | Yes | 6012 | 16.5% |

(b)

| | **1997.07.02-2008.06.30** | | | | **2008.07.01-2021.06.30** | | | |
|---|---|---|---|---|---|---|---|---|
| Quintiles | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ |
| Low | **22.89**<br>**(6.64)***** | Yes | 2806 | 50.4% | **13.99**<br>**(5.74)***** | Yes | 3206 | 49.4% |
| Q2 | **15.52**<br>**(3.90)***** | Yes | 2806 | 49.5% | **14.08**<br>**(5.17)***** | Yes | 3206 | 54.7% |
| Q3 | **16.92**<br>**(4.37)***** | Yes | 2806 | 56.7% | **13.80**<br>**(4.94)***** | Yes | 3206 | 53.7% |
| Q4 | **9.90**<br>**(2.53)**** | Yes | 2806 | 55.4% | **12.91**<br>**(4.92)***** | Yes | 3206 | 56.5% |

**Continued**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| High | **10.02**<br>**(2.43)***** | Yes | 2806 | 58.9% | **8.83**<br>**(3.14)***** | Yes | 3206 | 56.2% |
| Low-High | **12.86**<br>**(2.90)***** | Yes | 2806 | 14.9% | **5.17**<br>**(1.79)*** | Yes | 3206 | 13.1% |

(c)

| | **MA10** | | | | **MA50** | | | |
|---|---|---|---|---|---|---|---|---|
| Quintiles | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ |
| Low | **17.98**<br>**(8.56)***** | Yes | 6012 | 47.4% | **15.76**<br>**(7.62)***** | Yes | 6012 | 48.3% |
| Q2 | **18.05**<br>**(7.57)***** | Yes | 6012 | 50.9% | **11.82**<br>**(5.00)***** | Yes | 6012 | 51.4% |
| Q3 | **16.69**<br>**(7.10)***** | Yes | 6012 | 56.0% | **12.72**<br>**(5.39)***** | Yes | 6012 | 56.0% |
| Q4 | **13.34**<br>**(5.73)***** | Yes | 6012 | 55.0% | **8.71**<br>**(3.82)***** | Yes | 6012 | 56.4% |
| High | **12.41**<br>**(4.99)***** | Yes | 6012 | 56.4% | **6.92**<br>**(2.85)***** | Yes | 6012 | 58.0% |
| Low-High | **5.57**<br>**(2.12)**** | Yes | 6012 | 15.1% | **8.84**<br>**(3.54)***** | Yes | 6012 | 16.1% |
| | **MA100** | | | | **MA200** | | | |
| Quintiles | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ | ***Alpha* (%)** | Control for Five Factors | N | $R^2$ |
| Low | **11.23**<br>**(5.39)***** | Yes | 6012 | 44.2% | **8.28**<br>**(3.91)***** | Yes | 6012 | 41.6% |
| Q2 | **8.08**<br>**(3.32)***** | Yes | 6012 | 47.9% | **5.54**<br>**(2.25)**** | Yes | 6012 | 45.2% |
| Q3 | **8.48**<br>**(3.51)***** | Yes | 6012 | 52.8% | **6.72**<br>**(2.73)***** | Yes | 6012 | 49.6% |
| Q4 | **5.08**<br>**(2.18)**** | Yes | 6012 | 53.7% | **3.58**<br>**(1.50)** | Yes | 6012 | 50.9% |
| High | **5.29**<br>**(2.13)**** | Yes | 6012 | 56.5% | **3.32**<br>**(1.31)** | Yes | 6012 | 54.1% |
| Low-High | **5.94**<br>**(2.32)**** | Yes | 6012 | 18.4% | **4.95**<br>**(1.85)*** | Yes | 6012 | 17.2% |

based on the equally weighted *Synch* quintile portfolios based on TWSE-listed stocks. The results are similar to those using the *Synch* quintile portfolios, the alphas, ranging from 20.97% to 15.79%, is greater than ones compared to the valued-weighted *Synch* quintile portfolios. The bottom row presents the differences between the low- and the high-*Synch* quintiles, which is both economically and statistically significant.

Next, to check if the previous results are period-specific, we perform an analysis of the two sub-periods (i.e., July 2, 1997-June 30, 2008 and July 1, 2008-June 30, 2021). The results are similar to those in Panel B of **Table 4**. All alphas are positive and statistically significant in the different sub-periods, which proves that the superior performance of the MA strategy's abnormal returns for the low-*Synch* quintile is not period-specific.

We consider the average returns of the MAP by adopting a 10-, 50-, 100-, and 200-day MA strategy (i.e., $MA_{10}$, $MA_{50}$, $MA_{100}$, and $MA_{200}$). Panel C of **Table 4** reports the alphas for the MAPs of various lag lengths by controlling for the Fama and French (2015) 5-factor model. The results are the same, but two interesting features emerge. First, most alphas are the same as those in *Synch* quintile portfolio in the $MA_{50}$, $MA_{100}$, and $MA_{200}$. When the MA strategy is based on 50-day lag lengths, risk-adjusted abnormal returns decease from 15.76% to 6.92% per annum (except for the median-*Synch* quintile). The alpha of the second-*Synch* quintile (18.05%) is greater than for the low-*Synch* quintile (17.98%) when the MA strategy is based on 10-day lag lengths. Second, the alphas of both the fourth-*Synch* quintile (3.58%) and the high-*Synch* quintile (3.32%) are positive but insignificant. Our main results are therefore not sensitive to the MA strategy lag length.

## 4.4. Controlling for Other Market States

### 4.4.1. Controlling for the Momentum Factor

It is worth noting that the feature of trend chasing in MA is highly similar to the momentum, and the momentusm profits are increased by greater IU that has been identified to drive price continuations (e.g., Jiang, Lee, and Zhang (2005); Zhang (2006); Chen and Zhao (2012)). We examine if the MAP's abnormal returns across the *Synch* quintile portfolios are subsumed by the momentum effect through the momentum factor is embedded to the Fama and French (2015) 5-factor model. The model is as follows:

$$\begin{aligned} MAP_{j,d} = \alpha_j^{FF5+MOM} &+ \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d \\ &+ \beta_j^{rmw} RMW_d + \beta_j^{cma} CMA_d + \beta_j^{mom} MOM_d + u_{j,d} \end{aligned} \tag{6}$$

where $MOM_d$ is the Carhart (1997) momentum factor and the other variables are consistent with those in Equation (5). Panel A in **Table 5** presents the results that the betas on low-*Synch* quintile, fourth-*Synch* quintile, and high-*Synch* quintile are positive and significant at 8.48, 6.90, and 8.46, respectively. All $\alpha_j^{FF5+MOM}$ in the low, Q2, Q3, Q4, and high-*Synch* quintile portfolios is still positive and statistically significant at 17.86%, 14.35%, 15.19%, 11.14%, and

Table 5. Controlling for a variety of market states. This table reports the MAP's risk-adjusted alphas for low, Q2, Q3, Q4, and high-*Synch* quintile portfolios, and the difference in alphas between low- and high-quintile portfolios, based on the Fama-French 5-factor model in Table 3 augmented with other market state factors. Panels A, B, C, D, and E report the results by running the Fama-French 5-factor model augmented with the momentum factor (*MOM*), the market illiquidity factor (Δ*Milliq*), the market sentiment (Δ*VIX*), the economic policy uncertainty (Δ*EPU*), and the recession dummy (*Recession*), respectively. For brevity, only the MAP's risk-adjusted alphas and the coefficients on other market state factors for low, Q2, Q3, Q4, and high-*Synch* quintile portfolio are reported. The numbers in parentheses are *t*-values. N is the number of time-series observations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period for market sentiment (Δ*VIX*) runs from December 1, 2006 and the Δ*EPU* runs from January 2, 2007. Data on the economic policy uncertainty were collected from the Federal Reserve Bank of St. Louis (FRED). Other data were collected from the TEJ database. (a): Control for the Momentum Factor (*MOM*); (b): Control for the Illiquidity Factor (Δ*Milliq*); (c): Control for the Market Sentiment (Δ*VIX*); (d): Control for the Economic Policy Uncertainty (Δ*EPU*); (e): Control for the Recession Dummy (*Recession*).

(a)

| Quintiles | ***Alpha*** **(%)** | *MOM* | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|---|
| Low | **17.86** | 8.48 | Yes | 6012 | 49.9% |
| | **(8.64)*** ** | (3.49)*** | | | |
| Q2 | **14.35** | 2.42 | Yes | 6012 | 50.8% |
| | **(6.04)*** ** | (0.87) | | | |
| Q3 | **15.19** | −0.43 | Yes | 6012 | 55.4% |
| | **(6.48)*** ** | (−0.16) | | | |
| Q4 | **11.14** | 6.90 | Yes | 6012 | 55.8% |
| | **(4.85)*** ** | (2.55)** | | | |
| High | **9.03** | 8.46 | Yes | 6012 | 57.9% |
| | **(3.71)*** ** | (2.95)*** | | | |
| Low-High | **8.83** | 0.02 | Yes | 6012 | 14.0% |
| | **(3.42)*** ** | (0.01) | | | |

(b)

| Quintiles | ***Alpha*** **(%)** | Δ*Milliq* | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|---|
| Low | **18.04** | −3.50 | Yes | 6012 | 49.8% |
| | **(8.72)*** ** | (−0.90) | | | |
| Q2 | **14.40** | −5.74 | Yes | 6012 | 50.7% |
| | **(6.07)*** ** | (−1.29) | | | |
| Q3 | **15.17** | −2.36 | Yes | 6012 | 55.3% |
| | **(6.48)*** ** | (−0.54) | | | |

**Continued**

| | | | | | |
|---|---|---|---|---|---|
| Q4 | **11.29** | −1.75 | Yes | 6012 | 55.9% |
| | **(4.91)***** | (−0.40) | | | |
| High | **9.24** | −3.29 | Yes | 6012 | 57.7% |
| | **(3.79)***** | (−0.72) | | | |
| Low-High | **8.80** | −0.21 | Yes | 6012 | 13.9% |
| | **(3.41)***** | (−0.04) | | | |

(c)

| Quintiles | ***Alpha*** **(%)** | Δ *VIX* | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|---|
| Low | **13.11** | −0.53 | Yes | 3593 | 48.6% |
| | **(5.60)***** | (−1.23) | | | |
| Q2 | **13.74** | −1.12 | Yes | 3593 | 53.6% |
| | **(5.23)***** | (−2.31)** | | | |
| Q3 | **13.45** | −0.52 | Yes | 3593 | 54.1% |
| | **(5.03)***** | (−1.05) | | | |
| Q4 | **12.24** | −0.41 | Yes | 3593 | 56.1% |
| | **(4.81)***** | (−0.87) | | | |
| High | **8.36** | −1.08 | Yes | 3593 | 56.9% |
| | **(3.10)***** | (−2.18)** | | | |
| Low-High | **4.75** | 0.55 | Yes | 3593 | 13.7% |
| | **(1.71)*** | (1.07) | | | |

(d)

| Quintiles | ***Alpha*** **(%)** | Δ*EPU* | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|---|
| Low | **9.04** | −21.61 | Yes | 2532 | 42.1% |
| | **(3.69)***** | (−0.76) | | | |
| Q2 | **10.51** | −2.94 | Yes | 2532 | 49.3% |
| | **(3.67)***** | (−0.09) | | | |
| Q3 | **12.46** | −68.97 | Yes | 2532 | 50.3% |
| | **(4.12)***** | (−1.96)* | | | |
| Q4 | **10.30** | −0.88 | Yes | 2532 | 51.8% |
| | **(3.56)***** | (−0.03) | | | |
| High | **5.30** | 14.56 | Yes | 2532 | 53.9% |
| | **(1.83)*** | (0.43) | | | |
| Low-High | **3.75** | −36.17 | Yes | 2532 | 14.6% |
| | **(1.69)*** | (−0.98) | | | |

(e)

| Quintiles | *Alpha* (%) | *Recession* | Control for Five Factors | N | $R^2$ |
|---|---|---|---|---|---|
| Low | **19.01** | −3.49 | Yes | 6012 | 49.8% |
| | **(7.83)***** | (−0.75) | | | |
| Q2 | **16.35** | −7.06 | Yes | 6012 | 50.8% |
| | **(5.87)***** | (−1.33) | | | |
| Q3 | **17.91** | −9.90 | Yes | 6012 | 55.5% |
| | **(6.51)***** | (−1.89)* | | | |
| Q4 | **14.17** | −10.44 | Yes | 6012 | 55.8% |
| | **(5.25)***** | (−2.03)** | | | |
| High | **11.88** | −9.68 | Yes | 6012 | 57.9% |
| | **(4.16)***** | (−1.77)* | | | |
| Low-High | **7.13** | 6.19 | Yes | 6012 | 14.0% |
| | **(2.36)**** | (1.87)* | | | |

9.03%, respectively. The difference in $\alpha_j^{FF5+MOM}$ between low- and high-*Synch* quintile portfolios is statistically significant at 8.83% per annum ($t$ = 3.42). Therefore, the momentum factor does not drive the risk-adjusted alpha of the information-uncertainty-related MA strategy across *Synch* portfolios.

#### 4.4.2. Controlling for Market Liquidity

Motivated by the fact that market liquidity is related to IU, Chan, Hameed, and Kang (2013) concluded that illiquidity measures have a negative association with synchronicity. Therefore, liquidity is added to the Fama and French (2015) 5-factor model to verify if it affected the main results. The model is as follows:

$$\begin{aligned} MAP_{j,d} = {} & \alpha_j^{FF5+\Delta Milliq} + \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d \\ & + \beta_j^{rmw} RMW_d + \beta_j^{cma} CMA_d + \beta_j^{\Delta milliq} \Delta Milliq_d + u_{j,d} \end{aligned} \tag{7}$$

where $\Delta Milliq_d$ is market illiquidity, measured as innovation in market liquidity on day $d$ (i.e., $Milliq_d - Milliq_{d-1}$). $Milliq_d$ is Amihud's (2002) market illiquidity on day $d$, measured by an equally weighted average of Amihud's (2002) firm-level daily return-to-volume ratio in the cross-section on a given day. The other variables are consistent with Equation (5). The results are reported in Panel B of **Table 5**. The $\alpha_j^{FF5+\Delta Milliq}$ in the low, Q2, Q3, Q4, and high-*Synch* quintile portfolios is significantly positive, and the difference in $\alpha_j^{FF5+\Delta Milliq}$ between the low- and high-*Synch* quintile portfolios is statistically significant at 8.80% per annum. The beta on all *Synch* quintile portfolios is negative and insignificant, which confirms our preliminary results.

#### 4.4.3. Controlling for Market Sentiment

Mbanga, Darrat, Park (2019) investigated the relationship between investor sentiment and stock performance controlling for market sentiment and found that investor attention is associated with stock return predictability. As a robustness check, $\alpha_j^{FF5+\Delta VIX}$ is inspected for each *Synch* quintile portfolio by embedding the relevant risk factor into Equation (8):

$$MAP_{j,d} = \alpha_j^{FF5+\Delta VIX} + \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d + \beta_j^{rmw} RMW_d + \beta_j^{cma} CMA_d + \beta_j^{\Delta vix} \Delta VIX_d + u_{j,d} \quad (8)$$

where $\Delta VIX_t$ is innovation in market sentiment, measured as the daily change in the TAIEX Options Volatility Index (denoted as *VIX*) (e.g., Chen, Liu, and Zhao (2020)). The other variables are consistent with Equation (5). $\alpha_j^{FF5+\Delta VIX}$ is positive and statistically significant for all *Synch* quintile portfolios at 13.11%, 13.74%, 13.45%, 12.24%, and 8.36%, respectively (see Panel C of **Table 5**). The risk-adjusted alpha, $\alpha_j^{FF5+\Delta VIX}$, the difference between low- and high-*Synch* quintile portfolios, is positive and significant at 4.75% per annum (t = 1.71). The robustness tests prove that the main results are not sensitive to market sentiment risk factors.

#### 4.4.4. Controlling for Economic Policy Uncertainty

Shen, Liu, Xiong, Hou, and Tang (2021) suggested that EPU negatively affects synchronicity. To mitigate any problems due to EPU, we reinvestigate the baseline regression while controlling for EPU effects. The model is as follows:

$$MAP_{j,d} = \alpha_j^{FF5+\Delta EPU} + \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d + \beta_j^{rmw} RMW_d + \beta_j^{cma} CMA_d + \beta_j^{\Delta epu} \Delta EPU_d + u_{j,d} \quad (9)$$

where $\Delta EPU_d$ is innovation in EPU on day *d*. We download the quarterly *EPU* from the FRED[2] and assign quarterly changes in *EPU* to our daily sample period. The other variables are consistent with Equation (5). As shown in Panel D of **Table 5**, the risk-adjusted alpha, $\alpha_j^{FF5+\Delta EPU}$, is significantly positive, and the value of $\alpha_j^{FF5+\Delta EPU}$ in the difference between the low- and high-*Synch* quintile portfolios is 3.75% per annum and is significantly positive ($t = 1.69$). All coefficients of the change in *EPU* remain negative and insignificant on *Synch* quintile portfolios (except for the third *Synch* quintile).

#### 4.4.5. Controlling for Economic Cycle

Petkova and Zhang (2005) deduced that stock returns are associated with the degree of expected risk in various periods, especially during a recession. We add a recession dummy variable following Han, Yang, and Zhou (2013) to the Fama and French (2015) 5-factor model to test the business cycle effect, and the alpha ($\alpha_j^{FF5+Recession}$) is estimated for each *Synch* quintile portfolio. The model is as follows:

$$MAP_{j,d} = \alpha_j^{FF5+Recession} + \beta_j^{mkt} MKT_d + \beta_j^{smb} SMB_d + \beta_j^{hml} HML_d + \beta_j^{rmw} RMW_d + \beta_j^{cma} CMA_d + \beta_j^{recession} Recession_d + u_{j,d} \quad (10)$$

where $Recession_d$ is the recession dummy variable on day *d*. We identify the

[2]See the website: https://fred.stlouisfed.org/series/WUITWN.

recessionary months during the sample period according to the business cycle monitoring indicator of the Taiwanese National Development Council. The other variables are consistent with Equation (5). As shown in Panel E of Table 5, the risk-adjusted alpha, $\alpha_j^{FF5+Recession}$, is consistent with previous results; it is positive and significant at 19.01%, 16.35%, 17.91%, 14.17%, and 11.88%. The difference in $\alpha_j^{FF5+Recession}$ between the low and high quintiles is 7.13% per annum, which is significant ($t$ = 2.36). The coefficients of the recession measure remain negatively and monotonically increasing across the *Synch* quintiles (except for the high-*Synch* quintile) and are statistically significant (except for the low- and second-*Synch* quintiles). As a result, the abnormal returns in lower-synchronicity portfolios are more associated with IU than the abnormal returns in higher-synchronicity portfolios during a recession.

## 5. Conclusion

We proposed a potentially influencing financial determinant, synchronicity, to examine if it explains the profitability of MA technical trading when applied to portfolios sorted by synchronicity. Existing research has demonstrated an association between asset prices and IU, referencing the fact that public information in the market is aggravated by underreaction due to greater IU, which creates more price continuation.

We estimate the synchronicity measure, $R^2$, to sort the quintile portfolios and examine TWSE-/TPEx-listed stocks from July 2, 1997 to June 30, 2021. The findings confirm the IUH—the performance of the MA strategy's portfolios is significantly superior to those of the buy-and-hold strategy. In addition, the profitability of the MA strategy's portfolios is monotonically decreasing, and its annually abnormal performance on the lowest synchronicity quintile (18.05%) outperforms the highest synchronicity quintile (9.22%) by 8.83% based on a 20-day MA strategy, after adjusting for the Fama and French (2015) 5-factor model. To test the robustness, we control for other risk factors (e.g., equally weighted synchronicity portfolios; alternative sub-sample periods; alternative lag lengths on MA strategies, and diverse market states) and find that the MA profitability's monotonically decreasing pattern across synchronicity portfolios is consistent and significant.

Our study contributes to the literature in that the results provide an in-depth understanding of how IU related to synchronicity influences the profitability of an MA strategy. This study focuses on TWSE-/TPEx-listed stocks, which provides practical information regarding the typical characteristics of an emerging stock market. The Taiwanese stock exchange is characterized by the fact that the dissemination of firm-specific information to public investors is inadequate, which causes market participants to rely heavily on technical analysis. Given the extensive literature on technical analysis and anomalies in the financial field, future studies should consider exploring additional questions in this direction, such as applying new technical indicators to synchronicity-sorted Taiwan-listed stocks, as well as discussing the potential relation between the profitability of technical analysis and price synchronicity for other assets in Taiwan.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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