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The Impact of Post-trade Transparency on Investors: Evidence from an Emerging Market

Cheng-Huei Chiao, Chiou-Fa Lin, and Bin Qiu

Abstract

This study examines the effects of a post-trade transparency event on the payoff to informed and uninformed traders of large and small size firms. The evidence indicates that the event leads to a significant decrease in the payoff only to informed traders of large firms, while there is little change in the payoff to other investors. The implications are two-fold, that the event is beneficial to market fairness for large firms although it has the drawback of discouraging informed traders from producing/sharing information; and secondly, the event has no universal and equivalent impact for different groups of investors.

Keywords: post-trade transparency, information asymmetry, realized spread, payoff

I. Introduction

In stock market trading, transparency refers to what and how much information market participants have access to during the trading process[1]. Transparency may be categorized as one of two types, pre- or post-trade transparency. Changes in transparency may influence the amount and depth of information available to market participants, which in turn affects their trading behavior and the payoff among traders. In this study, we examine the impact of the Taiwan Stock Exchange's (TSEC's) post-trade transparency event[2], on information asymmetry and the realized spreads, which are the payoffs for informed and uninformed traders, respectively.

Our study is related to the body of research that examines how post-trade transparency affects market participants' welfare and market quality. There are positive and negative viewpoints on these issues. On the positive side, it is argued that post-transparency will improve market quality , price information, price efficiency, market liquidity and market fairness is improved while volatility is reduced; see Adamati and Pfleiderer (1991), De Frutos and Manzano (2005), Baruch (2005), Bessembinder and Maxwell (2008), and Baruch and Glosten (2013). On the other hand, from the negative viewpoint, it is suggested that post-trade transparency provides little additional information, decreases liquidity and price efficiency, and is not necessary to improve welfare among traders; see Madhavan (1996), Glosten (1994),

Cheng-Huei Chiao (cchiao@missouriwestern.edu), corresponding author, Missouri Western State University; Chiou-Fa Lin (cflin@gs.nfu.edu.tw), National Formosa University, Taiwan; and Bin Qiu (bqiu@missouriwestern.edu), Missouri Western State University

[1] See O'Hara (1995).

[2] Before 2 January 2003, the reference information available to all traders on the TSEC included only the transaction price, transaction volume, the best one bid/ask and the corresponding orders. Beginning at this date, the TSEC changed its disclosure policy after each trade to include information about four more best bids/asks and their corresponding orders. That is, from that date on, the TSEC requires disclosure of the transaction price, transaction volume, and the best five bids/asks and concurrent orders to all traders after each trade. This is called the post-trade transparency event.

Seppi (1997), Madhavan et al. (2005), Asriyan et al. (2017), Banerjee et al. (2018), and Goldstein and Yang (2019). There have been several empirical studies on post-trade transparency focusing on liquidity, volatility, information fairness, price discovery, and profit distribution including those by Madhavan et al. (2005), Eom et al. (2007), Hendershott et al. (2011), Riordan and Storkenmaier (2012), Lewis and Schwert (2018). Although much effort has been made, the empirical results have been mixed and inconsistent.

A review of the existing literature shows a lack of direct empirical evidence on how increased post-trade transparency impacts the payoff distribution between informed and uninformed traders of stock for different sized firm. We seek to fill this gap by examining changes in the components of effective spread, realized spread and information asymmetry, before and after the TSEC event described above. To the best of our knowledge, this study is the first to use the realized spread and information asymmetry to measure the payoff among traders. There are two general questions to be answered. First, whether post-trade transparency is beneficial to market fairness. Second, whether post-trade transparency is helpful or harmful to different types of traders. These two questions have rarely been touched upon in the literature, but we will try to make up for the shortage of research.

Although this dramatic change in transparency happened several years ago, it is still valuable to study the TSEC's experience of increased post-trade transparency because, first of all, a shift in post-trade transparency requirements for a stock market is very rare, the TSEC's experience affords a reference for other stock exchanges around the world. Secondly, since all stocks listed on the TSEC were affected by the changes in 2003, this condition allows us to study the effects on the same stocks in the same market. In addition, the difference in payoff to informed and uninformed traders for both large and small size firms has not been discussed in the past. The findings of this study indicate that, with the exception of a significant decrease in the payoff to informed traders of large firms, there is no obvious change in the payoff to other types of traders.

The rest of this paper is organized as follows: Section 2 is literature review and hypothesis development; Section 3 gives a description of the Taiwan Stock Exchange (TSEC) and the data sources; the methodology is discussed in Section 4; the empirical results and their economic meanings are provided in Section 5, and in the final section some conclusions are offered.

II. Literature review and hypothesis development

Past studies have paid a lot of attention to the post-trade transparency argument, but the findings have been mixed and inconclusive. On the positive side of the argument, Adamati and Pfleiderer (1991) and De Frutos and Manzano (2005) theoretically demonstrated that sunshine trading or trade disclosure would increase the information contained in prices, elevating price efficiency, while reducing volatility. Baruch (2005) argued that an open limit-order book would increase market quality by reducing the bid-ask spread and increase information efficiency of price because it strengthens the competitive pressure among liquidity traders and promotes even more aggressive trading among informed traders. Bessembinder and Maxwell (2008) found that it is not easy for informed traders to exploit liquidity traders in a transparent bond market. Baruch and Glosten (2013) pointed out that updating the limit-order book represents the offer of liquidity and allows for information to be revealed in the prices. Aİt-Sahalia and Saglam (2013) found that reduced latency produces higher profit for traders and makes liquidity provision higher.

On the negative side of the argument for post-transparency, Glosten (1994) and Seppi (1997) found that additional disclosure of other bids and asks beyond the best bid and ask conveyed little information. Madhavan (1996) argued that the impact of transparency was different for different types of stocks. If a stock's liquidity is not as much as it needs, the transparency measure will harm the price equilibrium, increasing the volatility and the execution cost, thereby diminishing price efficiency. Madhavan et al. (2005) constructed a theoretical model and predicted that limit-order book disclosure would decrease the liquidity as measured by the depth and price impact. Furthermore, others have investigated how transparency negatively affects efficiency. Asriyan et al. (2017) found that when assets are correlated, higher transparency does not necessarily lead to higher welfare and efficiency. Banerjee et al. (2018) argued that higher transparency would actually prevent liquidity traders from learning about the fundamentals of a stock because of lower informativeness. Goldstein and Yang (2019) discussed the possible adverse impact of public transparency on price efficiency. In short, the results of empirical studies of transparency impact have been mixed and inconclusive. Madhavan et al. (2005) developed a model and used Toronto Stock Exchange data to test it. They found larger spreads and higher volatility after transparency was increased. Eom et al. (2007) investigated the impact of transparency on the Korean market. Their findings indicated that market quality would improve with exposure to increased numbers of bid and ask prices, but the benefit would diminish as the numbers reached beyond a critical point. Hendershott et al. (2011) and Riordan and Storkenmaier (2012) investigated the impacts of algorithmic trading and reduced latency and obtained results showing that these measures are beneficial to market liquidity, information fairness and price discovery. Lewis and Schwert (2018) found that the introduction of trade data dissemination in the bond market caused dealers to earn lower profits, which is consistent with but not completely driven by reductions in bid-ask spreads. However, they also provided evidence that prices are less informative when trades are publically disseminated, in line with the dealers' improved ability to respond to market variation reducing the motives for informed investors to trade in the market.

Most of the existing literature has focused on price information, price efficiency, price discovery, execution cost, market liquidity and volatility. The drawback is that it has not been definitively shown how increased post-trade transparency impacts the payoff distribution among different types of traders of stocks for different size firms. Hence, we arrive at the following four hypotheses which will be tested using intraday transaction data from the TSEC:

H1a: The post-trade transparency event has no impact on the payoff to informed traders of large firms.

H1b: The post-trade transparency event has no impact on the payoff to informed traders of small firms.

H2a: The post-trade transparency event has no impact on the payoff to uninformed traders of large firms.

H2b: The post-trade transparency event has no impact on the payoff to uninformed traders of small firms.

III. TSEC Description and Data

The TSEC is a purely order-driven market with no designated market makers, specialists, or dealers[3]. It started disclosing additional information from only the best bid/ask price with orders to the best five bids/asks with orders, after each trade, beginning on January 2, 2003. Based on their 2001 year-end capitalization, we sorted the firms listed on the TSEC into two groups with the top tier composed of the larger capitalization stocks, and the bottom tier comprised of smaller capitalization stocks. The simple random sampling approach used in

[3] For additional information please referred to our related paper by Lin et al. (2016).

statistics was applied to both the top and bottom tiers, to obtain the 100 large firms and 100 small firms comprising our sample. The capitalizations values are 2,087–54,649 million of NTD for large firm stocks and 189–1,017million of NTD for small firm stocks. Our sample firms are distributed across various industries, representative of the TSEC stock market. The estimation period is defined as one year before the event; the year after the event is called event period. The sample period is from January 2, 2002 to December 31, 2004. All the intraday data used were retrieved from the Taiwan Economic Journal (TEJ) database.

IV. Methodology

There has been a lack of direct empirical evidence on how increased post-trade transparency impacts the payoff distribution between informed and uninformed traders for different size firm stocks. One common and simple measure of payoff distribution is the realized spread and information asymmetry, which are the component of effective spread. The effective spread is deduced from quoted spread which is defined as follows:

$$Quoted\ spread_{i,t} = ((Ask_{i,t} - Bid_{i,t})/Mid_{i,t})/2) \quad (1)$$

where $Mid_{i,t}$ is the midpoint of the ask and bid price for stock i at time t. The difference between the ask and bid price measures the round-trip trading cost, but since a single trade is expected, the quoted spread is divided by 2. However, trades usually occur between the ask and bid price, not at the quoted prices, so the quoted spread probably biases the trading cost. To overcome this problem, the effective spread is substituted for the quoted spread which can be computed as follows:

$$Effective\ spread_{i,t} = q_{i,t}(p_{i,t} - Mid_{i,t}) / Mid_{i,t} \quad (2)$$

where $p_{i,t}$ is the transaction price for stock i at time t. The term $q_{i,t}$ is an indicator whose value is +1(-1) if $p_{i,t}$ is greater (less) than $Mid_{i,t}$.

As in Huang and Stoll (1996), the effective spread is further decomposed into two components, the realized spread (RS) and information asymmetry (IA), which are defined as follows:

$$RS_{i,t} = q_{i,t}(p_{i,t} - mid_{i,t+5m})/mid_{i,t} \quad (3)$$

$$IA_{i,t} = q_{i,t}\ (mid_{i,t+5m} - mid_{i,t})/mid_{i,t} \quad (4)$$

here $mid_{i,t+5m}$ is the middle point price 5-min after a trade[4]. Huang and Stoll (1996) argued that the realized spread refers to the price reversal since a dealer realizes his earnings only when the price reverses[5]. Bessembinder and Venkataraman (2010) and Bacidores and Sofianos (2002) further expanded and explained the argument that the liquidity supplier's revenue net losses to better informed traders can be measured by the reversal from the trade price ($p_{i,t}$) to the post trade value ($mid_{i,t+5m}$). The realized spread captures the range of reversal. They thought of information asymmetry as the amount lost to informed traders, as measured by equation (4). In short, in a trade, the realized spread is the payoff for liquidity or uninformed traders while information asymmetry is the payoff for informed traders.

[4] Following Riordan and Storenmaier (2002).

[5] See Huang and Stoll (1996) p326.

We first test the difference in the realized spread and information asymmetry before and after the 2003 event. Since the difference could be caused by other factors, rather than being due to the event. Robustness testing is carried out employing the methodology of Madhavan et al. (2005):

$$\overline{m_{i,t}} = \beta_0 + \beta_1 \overline{A_{i,t}} + \delta D_{i,t} + \varepsilon_{it} \tag{5}$$

where $\overline{m_{i,t}}$ is the mean value of the realized spread or information asymmetry for stock i pre- and post-event, respectively; $\overline{A_{i,t}}$ is the control variables, including the mean value of volatility, turnover rate, inverse of average price, and log market capitalization for stock i before and after the event[6]; $D_{i,t}$ is a dummy variable, with a value of 1 after the event; otherwise 0. The $\varepsilon_{i,t}$ is assumed to obey classical assumptions. Running model (5) by ordinary least squares (OLS) regression, we observe the coefficient of the dummy variable indicating whether the transparency event truly impacts the realized spread and information asymmetry.

V. Empirical Findings

By using TSEC transaction data and applying the methodology described in this study, we can test the hypotheses and arrive at empirical results which are discussed below.

The patterns of information asymmetry and realized spread around the event for large- and small firms are depicted in Figures 1 and -2, respectively. From Figure 1, we can see that there is a gradual decrease in information asymmetry for large firms after the event but this does not occur for small firms. For the realized spread (Figure 2), there is no obvious change for either large- or small firms. Next, we further test for any difference in information asymmetry and realized spread for large- and small firms before and after the post-trade transparency event. The results are shown in Table 1 and -2 and are similar to the patterns shown in Figures 1 and -2. The results indicate that after the event, there is a significant decrease only in the payoff to informed traders of large firms; there is no remarkable change in the payoff to informed traders of small firms or uninformed traders of either large- or small firms. Thus, based on these empirical results, H1a is rejected while H1b, H2a, and H2b cannot be rejected.

Institutional or informed traders in the TSEC prefer trading in large firm stocks,[7] so post-trade transparency makes the competition more intense, lessening information asymmetry between informed and uninformed traders (from 7.853 to 7.081), thereby decreasing the level of payoff to informed traders (i.e., information asymmetry; -0.772). The reason for this is similar to the arguments of Bessembinder and Maxwell (2008) and Schultz and Song (2019) who suggested that transparency makes it more difficult for informed traders to extract rents from uninformed traders, while opacity protects inefficient high-cost dealers. Moreover, the decreased payoff to informed traders discourages them from gathering/sharing information. We suggest that there is a lack of competition for small firms because the number of informed traders interested in these firms is not enough, leading to an insignificant change in the information asymmetry (from 7.863 to 8.037) and the payoff to informed traders (+0.174). In terms of payoff to uninformed traders (i.e., realized spread), the event has clearly brought little benefit to them. In the TSEC, almost all individuals, usually thought to be liquidity or uninformed traders with limited ability, refer to the increase in information of post-trade

[6] The control variables are referred to Hendershott et al. (2011).

[7] See https://www.twse.com.tw/zh/page/trading/fund/MI_QFIIS.html

transparency. Hence, the event has not helped to increase the payoff for individual investors. This explanation is different from that advanced by De Frutos and Manzano (2005), who argued that trade disclosure effects are short-lived and that the impact on the traders' welfare is ambiguous. All in all, there are two implications which can be derived from our findings. First, the event is beneficial to fairness in the stock market for large firms, but it has the drawback of preventing informed traders from producing and/or sharing information. Second, the impact of the reforms is neither universal nor equivalent for different groups of investors, because they are affected in different ways.

Figure 1 Information asymmetry

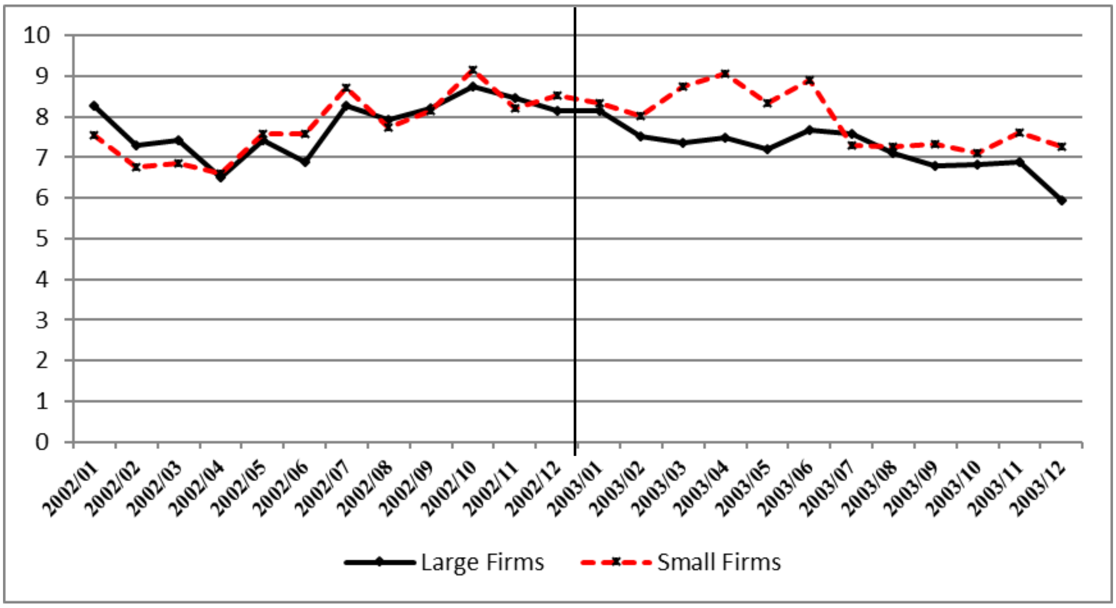

Figure 2 Realized spreads

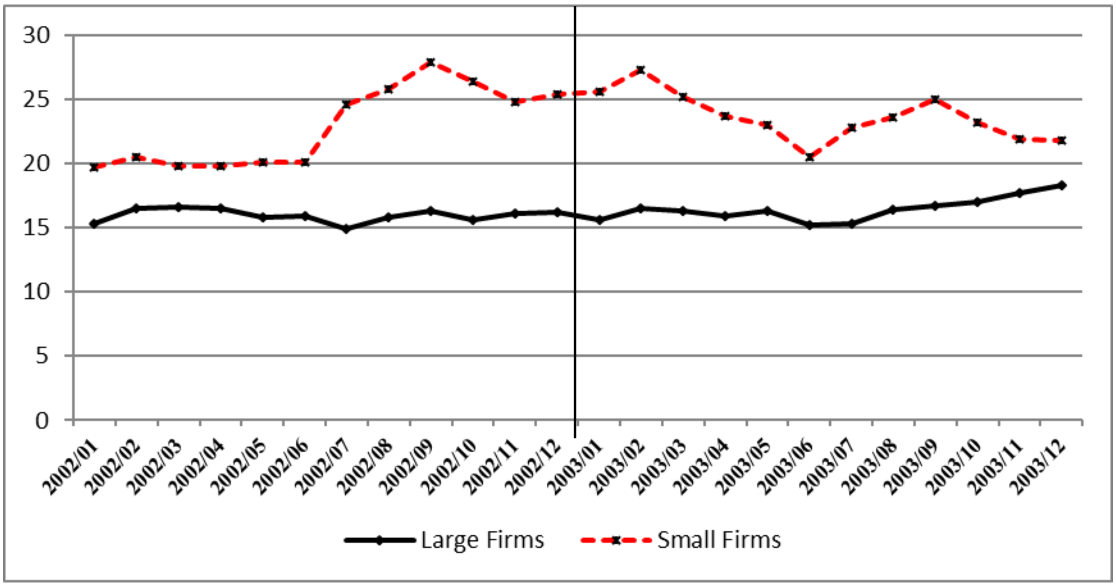

Table 1 Information asymmetry and realized spread before and after the event

The Wilcoxon sign rank test is used to test the differences between before and after the event. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Periods	Before event (1)	After event (2)	Diff. (3)
Panel A: Large firms			
Information asymmetry	7.853	7.081	-0.772*** (<0.000)
Realized spreads	16.200	16.677	0.477 (0.1832)
Panel B: Small firms			
Information asymmetry	7.863	8.037	0.174 (0.3980)
Realized spreads	23.921	24.807	0.886 (0.2365)

Table 2 Robustness testing

The model is formulated as follows: $\overline{M_{\iota,t}}= \beta_0+\beta_1\overline{A_{\iota,t}}\ +\delta D_{i,t}+\varepsilon_{i,t}$.
The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Dummy variables	T-values
Panel A: **Large firms**		
Information Asymmetry	-0.328*	-1.70
Realized spreads	0.231	0.28
Panel B: **Small firms**		
Information Asymmetry	0.274	1.46
Realized spreads	0.037	0.05

VI. Conclusion

Post-trade transparency is an important issue because it matters for market quality. Although there has been much research, both theoretical and empirical, on this topic, the results showing its impact on market quality have been inconclusive. The controversy continues to the present. However, we have been presented with a rare opportunity to study this topic using real data.

Beginning 2 January 2003, the TSEC increased its open limit-order book after each trade. Hence, we are able to investigate the payoff distribution among traders in the time surrounding this event.

The outcome shows that, after the event, there was only a significant decrease in the payoff to informed traders of large firms, but there was not an obvious change in the payoff to informed traders of small firms or uninformed traders of either large- or small firms. Our explanation for the payoff to informed traders of large firms is similar to that offered by Bessembinder and Maxwell (2008) and Schultz and Song (2019). The explanation for why the event was of little influence to informed traders of small firms or uninformed traders of both large- and small firms is different from the argument advanced by De Frutos and Manzano (2005). There are two implications which can be derived from our findings. First, the event is beneficial to market fairness for large firms in the stock market, but it has the drawback of preventing informed traders from producing and/or sharing information. Second, the impact of the reforms is neither universal nor equivalent for different groups of investors. They are affected in different ways.

To best of our knowledge, this study is the first to use realized spread and information asymmetry to measure the payoff for different types of investors. This study also supplies direct empirical evidence on how post-trade transparency impacts the payoff distribution between informed and uninformed traders for different size stocks.

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Does Market Timing Beat Dollar Cost Averaging?

Yan He and Junbo Wang

Abstract

This paper explores several methods for investing monthly cash contributions in an equity index, such as the S&P 500 or the Nikkei 225. The dollar cost averaging (DCA), three variations of market timing (MT1, MT2, and MT3), and 12-month perfect foresight (PF) are examined, and they are built on the same assumptions, such as monthly cash inflows, no borrowing of cash, and no selling of equity. The PF outcomes, unachievable by human beings, serve as optimal boundaries. Our results show that in both the U.S. and Japanese markets, the PF dominates the DCA, while the MTs tend to deliver similar results as the DCA. Thus, the DCA seems to be a compelling investment method.

JEL classification: G10
Keywords: Dollar cost averaging; Market timing; Perfect foresight

I. Introduction

Dollar cost averaging (DCA) is a popular investment method in real-world practice. However, in the research literature, the DCA seems less effective than the lump sum (LS), asset allocation (AA), and various market timing methods. Specifically, we categorize the research literature into three veins as follows.

First, the DCA seems inferior to the LS and AA methods. Constantinides (1979) points out that in a rational expectations framework, the LS is an optimal strategy in which 100% of total wealth is invested in risky assets at the beginning. The DCA is suboptimal, in which the total wealth is divided into a series of small investments in risky assets over time. Rozeff (1994) argues that if the market has a positive expected risk premium, the LS policy is superior to the DCA policy. Leggio and Lien (2003) find that the DCA consistently remains an inferior strategy to the LS, using risk-adjusted performance measures. Bierman and Hass (2004) illustrate that if the cash fund is currently available, the optimum decision is to invest the entire sum, and dividing the initial sum into segments for future investment is not recommended. Panyagometh and Zhu (2016) demonstrate that the DCA is analogous to the AA strategy in which about 50% to 65% of total wealth is invested in risky assets once at the beginning and the rest in riskless assets. They find that the AA strategy has a better risk-return tradeoff than the DCA.

Second, the DCA seems inferior to various market timing methods, which contain rebalancing, value averaging, augmented DCA, enhanced DCA, modified DCA, etc. Brennan, Li, and Torous (2005) document that the DCA is dominated by the rebalancing strategy in which 50% of wealth is invested in the market portfolio, and 50% in cash, and the portfolio is rebalanced monthly to maintain the proportions. Chen and Estes (2007) show that the value-averaging strategy generates

Yan He (yanhe@ius.edu), corresponding author, Indiana University Southeast, and Junbo Wang (jwang2@cityu.edu.hk), City University of Hong Kong

a higher terminal value for the 401 (k) retirement portfolio than the DCA. Chen and Estes (2010) compare the performances of three strategies in the 401 (k) plan framework: the DCA, value averaging, and proportional rebalancing, and report that value averaging generates a higher terminal value than the other two strategies. Lai, Tseng, and Huang (2016) point out that value averaging, often combined with portfolio rebalancing, is superior to the DCA. Richardson and Bagamery (2011) augment the DCA by investing more in the month following a down market and less in the month following an up market. Dunham and Friesen (2012) introduce the enhanced DCA, which invests a fixed additional amount after a down month and reduces the investment by a fixed amount after an up month. Lin and Xu (2016) present the modified DCA that outperforms the DCA across all of the international stock markets investigated. Kapalczynski and Lien (2021) propose the augmented DCA that is more aggressive if the economy is expanding and more conservative if the economy is contracting.

Third, the DCA may become a preferred method under certain situations of markets and investors. Statman (1995) points out that the DCA is consistent with the elements of behavioral finance: prospect theory, aversion to regret, cognitive errors, and self-control. Atra and Mann (2001) find that the DCA seems superior to the LS when invoked from February to September, yet inferior when started from October to January. Dichtl and Drobetz (2011) argue that the DCA is attractive for prospect theory investors, and the loss aversion and probability weighting are important in explaining the popularity of the DCA. Grable and Chatterjee (2015) reveal that when working with clients with less financial risk tolerance, the DCA provides a way to outperform if a bear market, rather than a bull market, emerges. Cho and Kuvvet (2015) advise that the DCA can be used to lower investment risk. Luskin (2017) reports that the DCA is superior to the LS in certain periods of flat or downward-trending market performance. Smith and Artigue (2018) demonstrate that the DCA can diversify investment risk across time.

In this paper, we explore several methods for investing a series of monthly cash contributions in an equity index over a long horizon. It is assumed that investors do not possess lump-sum cash at the beginning, cannot borrow cash, and cannot sell equity within the investment horizon. The equity index can be either the S&P 500 or the Nikkei 225. Monthly data are used, ranging from December 1989 to December 2019. We choose the equity indexes of the U.S. and Japan because their returns are very different.[1] Our investment methods include the DCA, three variations of market timing (MT1, MT2, and MT3), and 12-month perfect foresight (PF). These methods are built on the same set of assumptions. The outcomes of the methods are mainly measured by the net return in the entire period. The PF outcomes, unachievable by human beings, serve as optimal boundaries.

Our study yields the following findings. In both the U.S. and Japanese markets, the PF indeed dominates the DCA, while the MTs tend to deliver similar results as the DCA. Additionally, the statistical tests of 5-year, 10-year, and 20-year rolling periods produce no evidence of any consistent and significant advantage of the MTs against the DCA. Thus, the DCA seems to be an effective investment method.

[1] See Table 1 for the % change in price from Dec 1989 to Dec 2019, the mean of monthly returns, and the median of monthly returns. As shown, the returns of the U.S. are much higher than those of Japan.

II. Data and Methods

II.1. Data sample and investment assumptions

Our data sample contains monthly prices of the S&P 500 and Nikkei 225 indexes. The time period stretches from December 1989 to December 2019. In addition, the month-by-month rolling periods are also examined, including the 5-year, 10-year, and 20-year rolling periods.

We set up the assumptions below for investing a series of monthly cash contributions in an equity index.

- The time horizon for cash contributions and equity investments is 30 years (360 months), covering from January 1990 to December 2019.
- An amount of 10,000 cash contribution occurs monthly in the same currency of the equity index. Each contribution can be invested in the equity index immediately, saved as cash, or partially invested and partially saved.
- Investors can only use the cash contributions currently received and previously saved to buy the equity index. They cannot borrow cash to invest.
- Investors can only buy and hold the equity index. They cannot sell the equity index within 30 years.
- Cash savings earn 0% interest rate.

II.2. Investment methods

Based on the assumptions above, we apply and compare several investment methods, including the DCA, MT1, MT2, MT3, and PF. Please note two issues here. First, our study does not employ the LS (or AA) method, which would require 100% (or 50%) of total cash contributions in 30 years invested one time in January 1990. It is impossible to hold such a large amount of cash at the beginning due to the assumptions of monthly cash contributions and no borrowing. Second, our study does not conduct rebalancing or value averaging due to the assumptions of no borrowing and no selling. Next, we discuss the DCA, MTs, and PF one by one.

First, the DCA method is to invest 10,000 in an equity index monthly, where the cash contribution and the equity index are in the same currency. Thus, each cash contribution is invested entirely and immediately, leading to zero cash savings. In the real world, the DCA is a widely applied method, and it can be set up automatically for investments in mutual funds and certain types of pension funds.

Second, the three market timing methods (MT1, MT2, and MT3) deviate from the DCA by investing less (more) than the monthly cash contribution if the equity index has risen (declined). These MT methods are subject to the constraint of available cash. They are to invest a varying amount of cash in an equity index monthly, but they calculate the invested amount differently. The MT1 calculation is:

$$\text{minimum } [10{,}000+s,\ (1-r_m)*10{,}000],$$

where s is the cumulative cash savings from the previous months, and r_m is the monthly return of the equity index. The first term, 10,000+s, denotes the cash constraint. The second term, $(1-r_m)*10{,}000$, represents the potential amount that could be invested without any cash constraint. The minimum of the two terms is the actually invested amount. In specific, if the equity index has risen and the monthly return is positive, the invested amount will be less than 10,000. If the equity index has stayed the same and the monthly return is zero, the invested amount will be equal to

10,000. If the equity index has declined and the monthly return is negative, the invested amount, which is constrained by the amount of cash currently received and previously saved, will be equal to or more than 10,000.

The MT2 and MT3 distinguish the first month from the following months in a year. For the amount invested in the first month of a year, the MT2 computation is the same as that of the MT1, whereas the MT3 computation is:

$$\text{minimum }[10{,}000+s,\ (1-r_a)*10{,}000],$$

where r_a is the annual return of the equity index. For the amount invested in each following month of the year, the MT2 and MT3 definitions are the same:

$$\text{minimum }[10{,}000+s,\ (1-r_m)*\text{the previous invested amount}].$$

Overall, the MT strategy may or may not defeat the DCA. If equity prices stay flat and fluctuate, the MTs might lead the DCA because the MTs tend to buy at lower prices than the DCA. However, if equity prices go up persistently, the MTs might fall behind the DCA because the MTs tend to buy fewer shares than the DCA. In real-world practice, the MTs seem to involve complicated executions, which may not be conducted automatically for long-term investments. Therefore, unless the MTs beat the DCA consistently and significantly, the DCA will remain an effective method.

Third, the PF method is to correctly foresee the following 12 monthly prices of an equity index so that a decision can be made about whether to invest immediately or in the future. Namely, this method guarantees that every investment, under the cash constraint, occurs at the lowest price of the current and next 12 months. Let s_0 be the cumulative cash savings from the previous months that can be invested in the current month, and s_1 be the cumulative cash savings from the previous and current months that can be invested in the next month. If the current equity price is lower than or equal to the lowest price of the next 12 months, the invested amount of the current month will be $10{,}000+s_0$, and s_1 will be zero. Otherwise, the invested amount of the current month will be zero, and s_1 will be $10{,}000+s_0$. Since humans cannot correctly predict equity prices in the coming months, the PF method is not meant for real-world practice. In this paper, we use it to specify the optimal boundaries of investment outcomes. That is, the DCA and MT results are expected to be worse than or the same as the PF results.

Finally, using the first 24 months as examples, we show the results of periodical invested amounts, calculated respectively according to the MT1, MT2, MT3, and PF methods. See Appendix A for these month-by-month examples from January 1990 to December 1991.

II.3. Investment outcome measures

The total cash contributions in 30 years are 3.6 million, all or parts of which are invested in an equity index of the same currency at various times. At the end of 30 years, investors will hold a portfolio of the equity index and cash, where the cash amount may be zero or positive. The portfolio's ending value may or may not exceed 3.6 million, depending on both the equity index performance and the investment method. After 30 years, investors may liquidize the portfolio and purchase an annuity to receive regular income.

Given the above arrangement, the most important outcome measure is the Net Return in the entire period, defined as:

$$(\text{Ending Value} - \text{Total Cash Contributions}) / \text{Total Cash Contributions},$$

where the Ending Value is calculated as the sum of the ending equity value and ending cash. The ending equity value equals the multiplication of the ending equity index price and the total shares purchased in the entire period. The ending cash equals the difference between the total cash contributions and the total invested amounts in the entire period. A positive (negative) Net Return implies that the equity investment creates (destroys) value. A significantly higher Net Return suggests a better method when different investment methods are employed under the same assumptions and the same equity index performance.

Furthermore, two additional measures, the Average Monthly Return and the Modified Sharpe Ratio, are explored and used as references. The Average Monthly Return refers to the mean of monthly portfolio returns. The Modified Sharpe Ratio denotes the risk-adjusted average monthly return, calculated as:

Average Monthly Return / SD,

where SD is the standard deviation of monthly portfolio returns. Here the average monthly portfolio return is compared with the 0% cash return rather than the risk-free rate of Treasury bills. For different investment methods, a significantly higher average monthly return or risk-adjusted average monthly return may indicate a better method, if this method generates a significantly higher net return in the entire period. Thereby, a better method must deliver a significantly higher Net Return, while it may or may not provide a significantly higher Average Monthly Return or Modified Sharpe Ratio.

III. Empirical Results

III.1. The entire period

Figures 1 and 2 display monthly prices over the entire period. In Figure 1, the monthly prices of the S&P 500 Index show a broadly upward trend. In Figure 2, the monthly prices of the Nikkei 225 Index present a chiefly volatile picture.

Figure 1. Monthly Prices of the S&P 500 Index

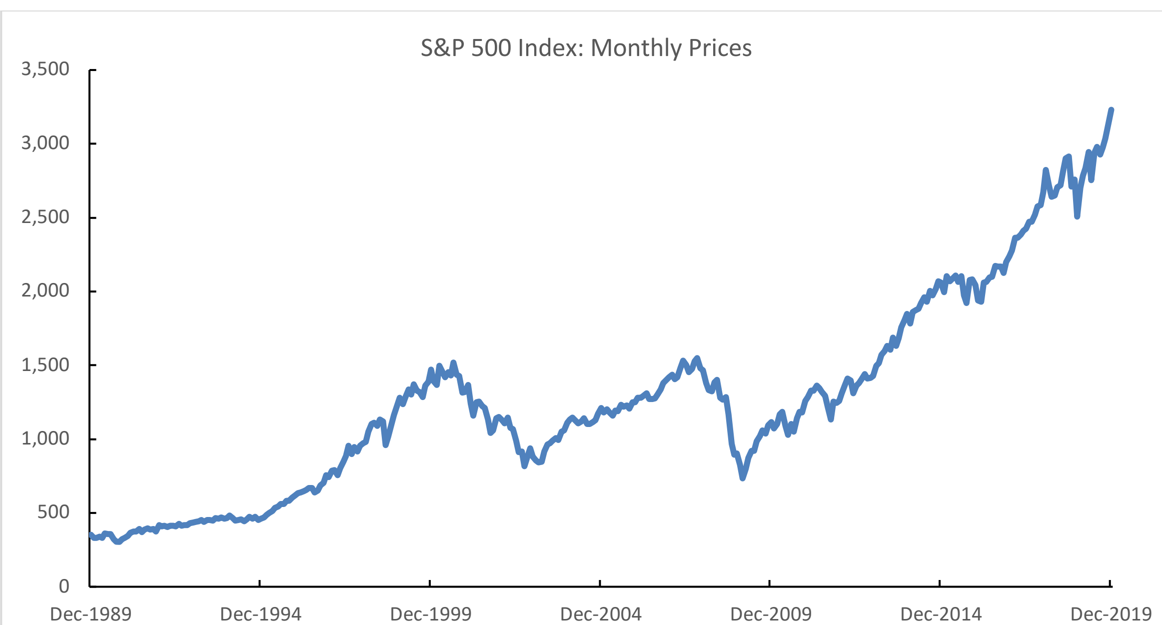

Figure 2. Monthly Prices of the Nikkei 225 Index

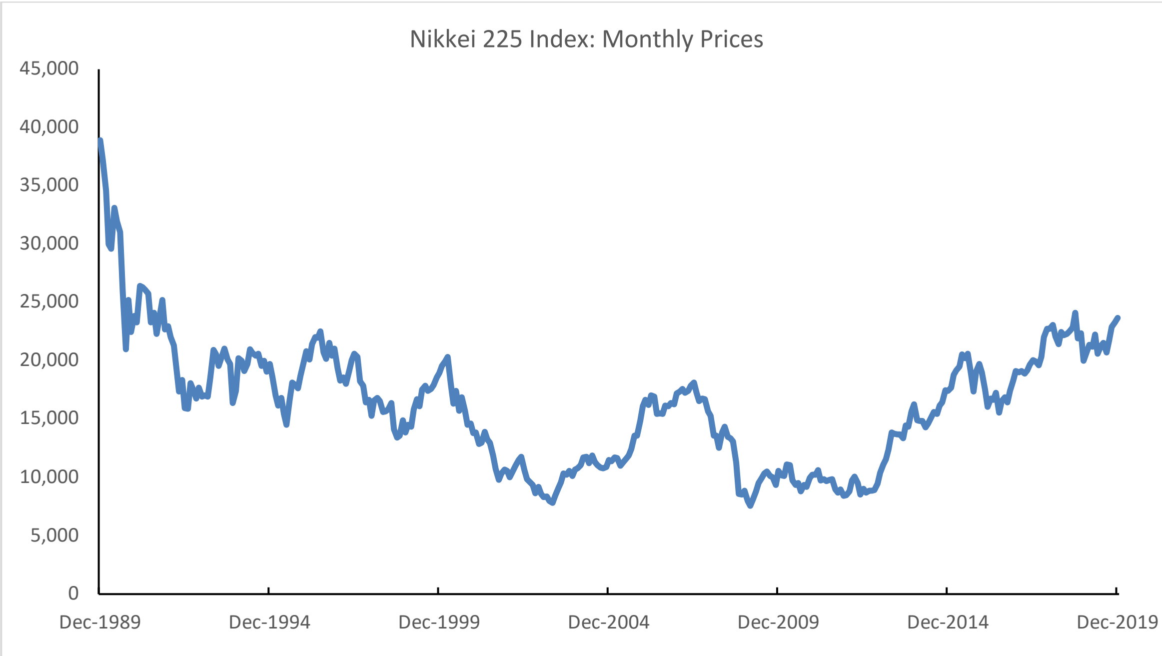

Table 1 presents summary statistics of the S&P 500 and Nikkei 225 indexes in the entire period of December 1989 to December 2019. Our first observation of Table 1 is that the average index price reported here is higher than the average cost per share reported in Table 2. For example, the average price of the S&P 500 Index is \$1,267.93, while the average cost per share for purchasing the index is respectively \$913.35 (DCA), \$913.44 (MT1), \$911.96 (MT2), \$902.46 (MT3), and \$812.40 (PF). Likewise, the average price of the Nikkei 225 Index is ¥16,213.88, while the average cost per share for purchasing the index is respectively ¥14,522.56 (DCA), ¥14,504.14 (MT1), ¥14,348.27 (MT2), ¥14,238.00 (MT3), and ¥11,474.90 (PF). Therefore, the average purchase cost per share tends to be cheaper than the average index price, which is the advantage of the DCA, MT, and PF methods.

Table 1. Summary Statistics of the S&P 500 and Nikkei 225 Indexes

The table presents summary statistics of the S&P 500 and Nikkei 225 indexes. Monthly data are used, ranging from December 1989 to December 2019.

	S&P 500	**Nikkei 225**
Beginning index price (December 1989)	\$353.40	¥38,915.87
Ending index price (December 2019)	\$3,230.78	¥23,656.62
Average index price	\$1,267.93	¥16,213.88
% change in price from Dec 1989 to Dec 2019	814.20%	-39.21%
Mean of monthly returns	0.7014%	0.0469%
S.D. of monthly returns	4.0984%	6.0418%
Median of monthly returns	1.1078%	0.3691%
Maximum of monthly returns	11.1588%	20.0662%
Minimum of monthly returns	-16.9425%	-23.8269%

Our second observation of Table 1 is that over the entire period, the % change in price is 814.20% for the S&P 500 Index and -39.21% for the Nikkei 225 Index. In addition, the mean of monthly returns is 0.7014% for the S&P 500 Index and 0.0469% for the Nikkei 225 Index; and the median of monthly returns is 1.1078% for the S&P 500 Index and 0.3691% for the Nikkei 225 Index. Hence, the returns of the U.S. are much higher than those of Japan.

Our third observation of Table 1 is that the S&P 500 Index has a lower standard deviation of monthly returns (4.0984%) than the Nikkei 225 Index (6.0418%). On the one hand, the higher return and lower risk of the S&P 500 Index are in accordance with the features of a long bull market. On the other hand, the lower return and higher risk of the Nikkei 225 Index are in line with the characteristics of a long bear market.

Table 2 presents the investment outcomes of the entire period based on the DCA, MT1, MT2, MT3, and PF methods. Our first view of Table 2 is that the Total Shares Purchased, the Average Cost per Share, and the Ending Cash are necessary elements of investment activities, but they are not the measures of ultimate outcomes. As we observe, the DCA has more Total Shares Purchased than the MTs, but much fewer Total Shares Purchased than the PF. Additionally, the DCA may have a higher or lower Average Cost per Share than the MTs, but it has a much higher Average Cost per Share than the PF. Finally, the DCA has zero Ending Cash, while the others have positive amounts of Ending Cash. These observations do not allow us to determine which method is consistently better than the others.

Our second view of Table 2 is that given the same total cash contributions and monthly patterns, the Ending Value and the Net Return are the key outcome measures.[2] As the results show, the DCA may have a higher or lower Ending Value and Net Return than the MTs, but it has a much lower Ending Value and Net Return than the PF. For instance, regarding the investment in the S&P 500 Index, the Net Return is separately 253.73% (DCA), 251.82% (MT1), 243.50% (MT2), 226.81% (MT3), and 288.59% (PF). Concerning the investment in the Nikkei 225 Index, the Net Return is separately 62.90% (DCA), 62.86% (MT1), 63.64% (MT2), 61.79% (MT3), and 102.62% (PF). In summary, the PF generates much higher net returns than the DCA, while the MTs may deliver either higher or lower net returns than the DCA. Therefore, the PF certainly dominates the DCA, but the MTs do not beat the DCA consistently.

Our third view of Table 2 is that the two reference measures, the Average Monthly Return and the Modified Sharpe Ratio, support the implication from our second view. Specifically, the DCA may have a higher or lower Average Monthly Return and Modified Sharpe Ratio than the MTs, but it has a much lower Average Monthly Return and Modified Sharpe Ratio than the PF. In other words, the PF generates much higher average returns and risk-adjusted average returns than the DCA, while the MTs may deliver either higher or lower results than the DCA. Hence, there lacks evidence for the perspective of the MTs beating the DCA consistently, even though the PF tops the DCA. To further examine both the consistency and the significance, we conduct some statistical tests in the next, based on the data of month-by-month rolling periods.

[2] For example, in Panel A of Table 2, the Ending Value for the DCA investment in the S&P 500 Index is $12.734 million, calculated as $3,230.78 * 3,941.53 shares + $0 = $12,734,216, where $3,230.78 is the ending index price, 3,941.53 is the total shares purchased, and $0 is the ending cash. In addition, the Net Return is calculated as ($12.734216 million - $3.6 million) / $3.6 million = 253.73%.

Table 2. Investment Outcomes: Entire Period

The table presents the investment outcomes of the entire period, based on the dollar cost averaging (DCA), market timing (MT1, MT2, and MT3), and 12-month perfect foresight (PF) methods. Monthly data are examined, covering from January 1990 to December 2019. The total cash contributions in the entire period are 3.6 million, in the same currency of their matching equity index.

Panel A. Investment in the S&P 500 Index

	DCA	MT1	MT2	MT3	PF
Total Shares Purchased	3,941.53	3,912.02	3,780.31	3,506.89	4,295.89
Average Cost per Share	$913.35	$913.44	$911.96	$902.46	$812.40
Ending Cash	$0	$26,624	$152,512	$435,164	$110,000
Ending Value	$12.734 million	$12.665 million	$12.366 million	$11.765 million	$13.989 million
Net Return	253.73%	251.82%	243.50%	226.81%	288.59%
Average Monthly Return	0.7225%	0.7191%	0.7030%	0.6735%	0.7753%
Modified Sharpe Ratio	0.1769	0.1769	0.1771	0.1780	0.1991

Panel B. Investment in the Nikkei 225 Index

	DCA	MT1	MT2	MT3	PF
Total Shares Purchased	247.89	247.24	246.13	236.19	303.27
Average Cost per Share	¥14,522.56	¥14,504.14	¥14,348.27	¥14,238.00	¥11,474.90
Ending Cash	¥0	¥13,991	¥68,390	¥237,106	¥120,000
Ending Value	¥5.864 million	¥5.823 million	¥5.891 million	¥5.825 million	¥7.294 million
Net Return	62.90%	62.86%	63.64%	61.79%	102.62%
Average Monthly Return	0.0594%	0.0612%	0.0672%	0.0627%	0.3981%
Modified Sharpe Ratio	0.0098	0.0102	0.0114	0.0107	0.0764

III.2. Various rolling periods

Table 3 compares the investment outcomes of the DCA, MT1, MT2, MT3, and PF methods, based on the monthly data of 5-year rolling periods. The total cash contributions every 5 years are 0.6 million, in the same currency of their matching equity index. First, we examine the Net Return in Table 3. For the investment in the S&P 500 Index, the mean of rolling 5-year net returns is respectively 24.76% (DCA), 24.55% (MT1), 23.52% (MT2), 21.89% (MT3), and 42.54% (PF). In particular, the difference between the PF and the DCA is positive and significant, with a t-value of 6.88. In contrast, the differences between the MTs and the DCA are insignificant in the U.S. market.

For the investment in the Nikkei 225 Index, the mean of rolling 5-year net returns is respectively 6.23%

Table 3. Investment Outcomes: 5-Year Rolling Periods

The table compares the investment outcomes of several methods (DCA, MT1, MT2, MT3, and PF). Monthly data of 5-year rolling periods are tested. The total cash contributions in every 5 years are 0.6 million, in the same currency of their matching equity index. The star (*) represents statistical significance at the 5% level.

Panel A. Net Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	24.76%			6.23%		
MT1	24.55%	-0.21%	-0.08	6.17%	-0.06%	-0.02
MT2	23.52%	-1.24%	-0.51	6.42%	0.20%	0.08
MT3	21.89%	-2.87%	-1.23	6.34%	0.12%	0.05
PF	42.54%	17.77%	6.88*	32.85%	26.62%	8.55*

Panel B. Average Monthly Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.6854%			0.1426%		
MT1	0.6817%	-0.0037%	-0.07	0.1432%	0.0006%	0.01
MT2	0.6650%	-0.0204%	-0.37	0.1474%	0.0047%	0.07
MT3	0.6338%	-0.0516%	-0.95	0.1442%	0.0015%	0.02
PF	0.7280%	0.0426%	0.77	0.3490%	0.2064%	3.26*

Panel C. Modified Sharpe Ratio

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.1985			0.0377		
MT1	0.1985	0.0000	0.00	0.0378	0.0001	0.01
MT2	0.1986	0.0001	0.01	0.0383	0.0006	0.05
MT3	0.1985	0.0000	0.00	0.0393	0.0016	0.13
PF	0.2140	0.0155	0.97	0.0738	0.0361	2.94*

(DCA), 6.17% (MT1), 6.42% (MT2), 6.34% (MT3), and 32.85% (PF). Specifically, the difference between the PF and the DCA is positive and significant, with a t-value of 8.55, while the differences between the MTs and the DCA are insignificant in the Japanese market. Therefore, when the PF absolutely outperforms the DCA, the MTs and the DCA create similar net returns. No doubt, the MTs hold neither a consistent nor a significant advantage against the DCA.

Second, we examine the reference measures in Table 3. Regarding the Average Monthly Return and the Modified Sharpe Ratio, the differences between the PF and the DCA are positive but insignificant in the U.S. market, and positive and significant in the Japanese market. However, the differences between the MTs and the DCA are insignificant, endorsing the proposition from our first examination of Table 3.

Table 4 compares the investment outcomes of various methods based on the monthly data of 10-year rolling periods. The total cash contributions every 10 years are 1.2 million, in the same

Table 4. Investment Outcomes: 10-Year Rolling Periods

The table compares the investment outcomes of several methods (DCA, MT1, MT2, MT3, and PF). Monthly data of 10-year rolling periods are tested. The total cash contributions in every 10 years are 1.2 million, in the same currency of their matching equity index. The star (*) represents statistical significance at the 5% level.

Panel A. Net Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	41.34%			9.45%		
MT1	41.11%	-0.23%	-0.07	9.49%	0.04%	0.01
MT2	40.14%	-1.20%	-0.35	10.31%	0.86%	0.26
MT3	37.96%	-3.38%	-1.04	10.78%	1.33%	0.40
PF	65.60%	24.26%	6.72*	37.50%	28.05%	7.62*

Panel B. Average Monthly Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.5822%			0.0609%		
MT1	0.5791%	-0.0032%	-0.09	0.0614%	0.0005%	0.01
MT2	0.5648%	-0.0174%	-0.53	0.0668%	0.0059%	0.17
MT3	0.5376%	-0.0446%	-1.39	0.0659%	0.0050%	0.15
PF	0.6287%	0.0465%	1.40	0.2566%	0.1957%	6.32*

Panel C. Modified Sharpe Ratio

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.1390			0.0125		
MT1	0.1389	0.0000	0.00	0.0126	0.0001	0.02
MT2	0.1389	-0.0001	-0.01	0.0132	0.0008	0.13
MT3	0.1393	0.0004	0.04	0.0144	0.0020	0.32
PF	0.1545	0.0155	1.80	0.0481	0.0357	6.36*

currency of their matching equity index. First, the results of the Net Return show the same patterns as those in Table 3. Regarding the investment in the S&P 500 Index, the mean of rolling 10-year net returns is separately 41.34% (DCA), 41.11% (MT1), 40.14% (MT2), 37.96% (MT3), and 65.60% (PF). Moreover, the difference between the PF and the DCA is positive and significant, with a t-value of 6.72, while the differences between the MTs and the DCA are insignificant in the U.S. market. Concerning the investment in the Nikkei 225 Index, the mean of rolling 10-year net returns is separately 9.45% (DCA), 9.49% (MT1), 10.31% (MT2), 10.78% (MT3), and 37.50% (PF).

Furthermore, the difference between the PF and the DCA is positive and significant, with a t-value of 7.62. In contrast, the differences between the MTs and the DCA are insignificant in the Japanese market. Second, the results of the Average Monthly Return and the Modified Sharpe Ratio demonstrate the same patterns as those in Table 3. In total, the findings of Table 4 are compatible with those of Table 3.

Table 5. Investment Outcomes: 20-Year Rolling Periods

The table compares the investment outcomes of several methods (DCA, MT1, MT2, MT3, and PF). Monthly data of 20-year rolling periods are tested. The total cash contributions in every 20 years are 2.4 million, in the same currency of their matching equity index. The star (*) represents statistical significance at the 5% level.

Panel A. Net Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	77.30%			22.30%		
MT1	76.94%	-0.36%	-0.18	22.31%	0.01%	0.00
MT2	75.63%	-1.67%	-0.83	23.44%	1.15%	0.31
MT3	71.52%	-5.78%	-2.87*	23.10%	0.80%	0.22
PF	106.85%	29.55%	12.55*	55.16%	32.86%	7.76*

Panel B. Average Monthly Return

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.5793%			0.0594%		
MT1	0.5761%	-0.0031%	-0.41	0.0599%	0.0005%	0.03
MT2	0.5619%	-0.0173%	-2.32*	0.0653%	0.0059%	0.34
MT3	0.5350%	-0.0443%	-6.13*	0.0645%	0.0051%	0.30
PF	0.6259%	0.0466%	5.99*	0.2551%	0.1957%	13.39*

Panel C. Modified Sharpe Ratio

	S&P 500			Nikkei 225		
	Mean	MT-DCA PF- DCA	t-value on Difference	Mean	MT-DCA PF- DCA	t-value on Difference
DCA	0.1333			0.0115		
MT1	0.1333	-0.0001	-0.04	0.0116	0.0001	0.03
MT2	0.1331	-0.0002	-0.15	0.0128	0.0012	0.41
MT3	0.1339	0.0006	0.36	0.0129	0.0014	0.47
PF	0.1490	0.0156	9.12*	0.0487	0.0371	14.20*

Table 5 compares the investment outcomes of various methods based on the monthly data of 20-year rolling periods. The total cash contributions every 20 years are 2.4 million, in the same currency as their matching equity index. First, the outcomes of the Net Return reveal similar features as those in Table 3. About the investment in the S&P 500 Index, the mean of rolling 20-year net returns is respectively 77.30% (DCA), 76.94% (MT1), 75.63% (MT2), 71.52% (MT3), and 106.85% (PF). Besides, the difference between the PF and the DCA is positive and significant, with a t-value of 12.55, while the differences between the MTs and the DCA are either insignificant, or significant but negative in the U.S. market. As for the investment in the Nikkei 225 Index, the mean of rolling 20-year net returns is respectively 22.30% (DCA), 22.31% (MT1), 23.44% (MT2), 23.10% (MT3), and 55.16% (PF). In addition, the difference between the PF and the DCA is positive and significant, with a t-value of 7.76, while the differences between the MTs and the DCA are insignificant in the Japanese market. Second, the outcomes of the Average Monthly Return and the Modified Sharpe Ratio convey similar attributes as those in Table 3. Specifically, the differences between the PF and the DCA are positive and significant. However, the differences between the MTs and the DCA are insignificant or significant but negative. All told, the findings of Table 5 are congruent with those of Table 3.

IV. Conclusions

Our study investigates a few equity investment methods: the dollar cost averaging, three variations of market timing, and 12-month perfect foresight. The investment target is, respectively, the S&P 500 and Nikkei 225 indexes. The investment period is from January 1990 to December 2019. The investment methods are constructed according to the same assumptions: a series of monthly cash contributions, no equity selling allowed, no cash borrowing allowed, 0% interest rate for cash savings, etc. The dollar cost averaging method is to invest every monthly cash contribution immediately in an equity index. The three market timing methods are to invest more (less) than the monthly cash contribution, under the cash constraint, if the equity price has declined (risen). The 12-month perfect foresight method is to invest, under the cash constraint, at the lowest equity price of the current and next 12 months. To compare the outcomes of these methods, we define the net return in the entire period as the most important measure, which reflects the net gain of the ending value relative to the total cash contributions.

Our study brings forth two critical findings. First, the 12-month perfect foresight method produces consistently and significantly higher net returns than the dollar cost averaging in both the U.S. and Japanese markets. Nevertheless, the perfect foresight method is unattainable by human beings and unintended for any real-world application. It is used in this paper to identify the optimal boundaries.

Second, the market timing and the dollar cost averaging methods provide similar net returns in both the U.S. and Japanese markets. As shown by the respective 5-year, 10-year, and 20-year rolling period tests, most of the differences between the two methods (MT−DCA) are insignificant, with a few cases being significant but negative. As for the real-world application, automatic investments are usually available for the dollar cost averaging, but perhaps not for the market timing. In a consistent, significant, and practical manner, the market timing does not beat the dollar cost averaging at all. Therefore, to invest a series of monthly cash contributions in an equity index over a long time, we may prefer the dollar cost averaging to the market timing method.

Of course, when we implement an investment plan of dollar cost averaging, our decision may be affected by financial variables such as the net return and many other issues. For example, it tends to be easy to carry on a plan of dollar cost averaging in a secular bull market but difficult to stick with it in a secular bear market due to the economic recession, the pessimistic mood, and the herding behavior. Besides, equity selling, portfolio rebalancing, and cash borrowing are permitted in real-world operations, and they may be applied with the dollar cost averaging together. All these cyclical, psychological, and operational issues will complicate our investment practice, but they are beyond the scope of this paper.

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Appendix A. Examples of Invested Amounts

The appendix shows examples of invested amounts from January 1990 to December 1991, according to the MT1, MT2, MT3, and PF methods.

Panel A. Investment in the S&P 500 Index

	Price ($)	Invested Amount ($)			
	S&P 500	MT1	MT2	MT3	PF
January 1990	329.08	10,000.00	10,000.00	10,000.00	0
February 1990	331.89	9,914.61	9,914.61	9,914.61	0
March 1990	339.94	9,757.45	9,674.13	9,674.13	0
April 1990	330.80	10,268.87	9,934.24	9,934.24	0
May 1990	361.23	9,080.11	9,020.40	9,020.40	0
June 1990	358.02	10,088.86	9,100.56	9,100.56	0
July 1990	356.15	10,052.23	9,148.09	9,148.09	0
August 1990	322.56	10,837.87	10,010.88	10,010.88	0
September 1990	306.05	10,000.00	10,523.28	10,523.28	0
October 1990	304.00	10,000.00	10,593.77	10,593.77	100,000
November 1990	322.22	9,400.66	9,958.84	9,958.84	10,000
December 1990	330.22	9,751.72	9,711.59	9,711.59	10,000
January 1991	343.93	9,584.82	9,584.82	9,548.74	10,000
February 1991	367.07	9,327.19	8,939.94	8,906.29	10,000
March 1991	375.22	9,777.97	8,741.45	8,708.55	0
April 1991	375.34	9,996.80	8,738.66	8,705.76	0
May 1991	389.83	9,613.95	8,401.30	8,369.68	0
June 1991	371.16	10,478.93	8,803.66	8,770.52	40,000
July 1991	387.81	9,551.41	8,408.74	8,377.08	0
August 1991	395.43	9,803.51	8,243.51	8,212.48	0
September 1991	387.86	10,191.44	8,401.33	8,369.70	0
October 1991	392.45	9,881.66	8,301.90	8,270.65	0
November 1991	375.22	10,439.04	8,666.39	8,633.76	50,000
December 1991	417.09	8,884.12	7,699.32	7,670.34	0

(Continued)

Appendix A continued.

Panel B. Investment in the Nikkei 225 Index

	Price (¥)	Invested Amount (¥)			
	Nikkei 225	MT1	MT2	MT3	PF
January 1990	37,188.95	10,000.00	10,000.00	10,000.00	0
February 1990	34,591.99	10,000.00	10,000.00	10,000.00	0
March 1990	29,980.45	10,000.00	10,000.00	10,000.00	0
April 1990	29,584.80	10,000.00	10,000.00	10,000.00	0
May 1990	33,130.80	8,801.41	8,801.41	8,801.41	0
June 1990	31,940.24	10,359.35	9,117.69	9,117.69	0
July 1990	31,035.66	10,283.21	9,375.91	9,375.91	0
August 1990	25,978.37	10,556.03	10,903.73	10,903.73	0
September 1990	20,983.50	10,000.00	11,801.25	11,801.25	90,000
October 1990	25,194.10	7,993.38	9,433.19	9,433.19	0
November 1990	22,454.63	11,087.35	10,458.90	10,458.90	0
December 1990	23,848.71	9,379.16	9,809.57	9,809.57	0
January 1991	23,293.14	10,232.96	10,232.96	10,298.35	0
February 1991	26,409.22	8,662.23	8,864.02	8,920.67	0
March 1991	26,292.04	10,044.37	8,903.36	8,960.25	0
April 1991	26,111.25	10,068.76	8,964.58	9,021.86	0
May 1991	25,789.62	10,123.18	9,075.00	9,132.99	0
June 1991	23,290.96	10,968.86	9,954.24	10,017.85	0
July 1991	24,120.75	9,643.73	9,599.60	9,660.95	0
August 1991	22,335.87	10,739.98	10,309.95	10,375.83	0
September 1991	23,916.44	9,292.36	9,580.38	9,641.60	0
October 1991	25,222.28	9,454.00	9,057.29	9,115.17	0
November 1991	22,687.35	11,005.04	9,967.58	10,031.28	0
December 1991	22,983.77	9,869.35	9,837.35	9,900.21	0

ESG Risk in Times of Crisis: Evidence from the COVID-19 Pandemic

Samuel Kyle Jones

Abstract

This study compares the volatility of the S&P 500 ESG index and its conventional counterpart during the COVID-19 pandemic. The conditional volatility of each index is generated from an EGARCH model, with these series then used in a vector autoregression. Impulse response functions computed from the VAR show an increase in the conditional volatility of both the ESG and conventional index in response to various pandemic related shocks. However, the impact on the ESG index is significantly less than that of the conventional index, providing further evidence backing the claim that socially responsible investments are less risky than other investments during times of economic crisis.

Keywords: Conditional Volatility, COVID, ESG, Vector Autoregression
JEL Classifications: C32, G01

I. Introduction

In 2020 the CFA Institute released a study detailing the expected future of sustainable investment management.[1] Within the study are the results of a survey of investment firms regarding their motivations for incorporating ESG information into their investment process and decision making. High among the reasons put forward was client demand, the perception that sustainable investments produce superior returns, and the ability to help manage investment risks. These investment firms may be into something. While the empirical evidence regarding the performance benefits of ESG is mixed, there has been strong investor demand, and there has been both theoretical and empirical support that an ESG focus helps to mitigate investment risk.

Heinkel et al. (2001) develop a theoretical model in which the market is segmented, with traditional investors basing their investment decisions solely on expected financial performance, while socially conscious investors gain utility from both the financial and social performance of a firm. This potentially creates a larger client base for socially responsible investments, leading to excess demand for shares that drives up stock and bond prices of such companies. While this reduces expected returns for investors, it has the favorable effect of lowering the firm’s cost of capital and reducing its systematic risk. The risk management hypothesis developed by Godfrey (2005), and later tested by Godfrey et al. (2009) proposes that firms can create moral capital, which improves the relationships between the firm and its stakeholders and provides insurance-like protection against various reputational risks.

Samuel Kyle Jones (sjones@sfasu.edu), Stephen F. Austin State University

[1] Fender, R., Stammers, R., Urwin, R., and Preece, R. (2020). Future of sustainability in investment management: from ideas to reality. CFA Institute.

Early studies of socially responsible investing (SRI) in the mutual fund universe found there to be no statistical difference between the performance of ESG versus conventional funds (Hamilton et al., 1993; Statman, 2000). More recent studies have looked further into the performance of ESG versus conventional funds during recent financial crisis periods, including the 2008-2009 financial crisis and the 2020-2021 COVID-19 pandemic. The results of these studies have been mixed as to the crisis attributes of ESG oriented funds. Nofsinger and Varma (2014) find ESG funds outperform during two crisis periods that occurred from 2000-2011, while conventional funds outperform during non-crisis periods. This result is supported by Ferriani and Natoli (2021) who find that fund flows during the COVID-19 pandemic are positively correlated with ESG rating. Also looking at fund flows during the pandemic, but with opposite findings, Dottling and Kim (2022) find that funds with high sustainability ratings experience larger declines in net fund flows and have a greater likelihood of experiencing net outflows relative to conventional funds.

In a departure from the prior studies, Morales et al. (2019) test SRI indices and their conventional benchmarks or counterparts and find that the SRI indices tend to underperform during times of political uncertainty and economic crises. Unlike tests of mutual funds, indices are used to remove the bias imparted from active fund management. Capelle-Blancard et al. (2021) also test SRI and conventional indices during the COVID-19 pandemic but find that the SRI indices perform similar to the conventional indices, neither outperforming, nor exhibiting less downside risk than their conventional counterparts.

While these previous studies have looked into fund performance and fund flows, no study appears to have looked specifically at fund volatility. If the models of Heinkel et al. (2001) and Godfrey (2005) are correct, then several implications arise regarding the likely risk-related attributes of socially responsible investments during crisis periods. First, if a segment of socially conscious investors makes investment decisions predicated on more than just financial metrics, such investors should be stickier in their investment holdings when financial performance varies. Consequently, such investors should be less prone to exit their investments when financial performance is poor. Further, since insurance helps guard against tail risks, the implication is that the ESG efforts of firms should reduce their exposure to various idiosyncratic risks such as litigation, or more broad-based episodes of risk that arise during from economic crises. As such, investments seen as having higher ESG ratings should be less risky than either investments with lower ESG ratings, or even conventional investments that make no such distinction. Because this benefit should be most prevalent during periods of economic crisis, the COVID-19 pandemic provides a mechanism by which to test this prediction.

This study investigates the impact of pandemic related shocks on the volatility of conventional and socially responsible investments. Specifically, the conditional volatility of the S&P 500 ESG index and the more conventional S&P 500 index is estimated using an autoregressive conditional heteroskedasticity model. The two conditional volatility series are then subject to COVID-related shocks using a vector autoregression, from which generalized impulse response functions are generated.

The rest of this paper is organized as follows. Section two details the variables used to represent US ESG and conventional investments, as well as those variables related to the pandemic that may have an impact on financial markets. It also presents the EGARCH modeling of the conditional volatility of the indices, as well as the vector autoregression and impulse response function analysis. Section three provides a discussion of the results of the vector autoregressions and impulse response function analysis. Finally, section four presents concluding remarks, summarizing the findings of this study.

II. Data and Methodology

Financial time series are often characterized by periods of persistently high or low volatility, leading to heteroscedasticity in the variance of the errors. This conditional volatility tends to have the additional characteristic of asymmetry, where volatility rises more in response to bad news than it falls in response to good news. GARCH models were first proposed by Engel (1982) to model conditional volatility but fail to account for asymmetry. The EGARCH model of Nelson (1991) allows for asymmetric conditional volatility and is used here to generate the conditional volatility series for each of the S&P indices. Generalized impulse response functions are computed from a vector autoregression (VAR), where the conditional volatility of the S&P 500 and S&P 500 ESG indices are subject to direct and indirect shocks arising from the pandemic. These shocks include the direct impact of COVID-19 infections and vaccinations, and the indirect impact where these shocks affect the market through their impact on the VIX and pandemic related news.

Financial data for this study is obtained from FactSet. Daily closing prices for the S&P 500 large-cap index, the S&P 500 ESG index, and the VIX volatility index are collected for the sample period December 31, 2019, to February 28, 2022. The length of this sample is chosen to allow for the initial financial market impact of the pandemic, subsequent mutations of the virus, and the arrival of vaccines.

Data related to the pandemic comes from two sources. First, U.S. state level daily data on COVID-19 infections comes from the Centers for Disease Control and Prevention. This data is aggregated across all states to produce a daily time series at the national level, denoted as CASE. The second source of pandemic-related data includes a time series of daily vaccinations which come from Johns Hopkins, denoted as VACC.

A series reflecting market sentiment arising from pandemic related news is constructed by measuring internet searches related to the pandemic. Searches on Google Trends for the term's pandemic, coronavirus, and COVID across the sample period are used to construct the index GTRENDS. This index is scaled from 1 to 100, where 1 is a period with the minimum number of queries, and 100 is a period with the maximum number of search queries. Google Trends has been shown to be related to behavioral aspects of the market and to have power in forecasting volatility (Preis et. al., 2013; Hamid and Heiden, 2015), and has been used as an investor sentiment indicator in other empirical work on the financial effects of the pandemic (Milani, 2021).

The final variables to be used in the VAR are the conditional volatility series for each of the S&P indices. Specifically, the conditional volatility of each of the two S&P indexes is estimated using an EGARCH(1,1) model. Using Box-Jenkins techniques, an ARMA(1,1) is found to be the best fitting mean equation for each index, where the price indices have been first transformed into log returns. ARCH LM tests are then conducted and confirm the presence of ARCH effects. For the S&P500 and the S&P500ESG indices, the null hypothesis of no heteroskedasticity is rejected at the 5% level. Consequently, following Nelson (1991), the following EGARCH(1,1) model is estimated via the method of maximum likelihood:

$$(1) \qquad r_t = b_0 + b_1 r_{t-1} + b_2 \varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d.}(0, \sigma_t^2)$$

(2) $$\log(\sigma_t^2) = b_3 + b_4 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + b_5 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b_6 \log(\sigma_{t-1}^2)$$

where r_t is the index log return, and σ_t^2 is the conditional variance of ε_t. The parameter estimates for the EGARCH models are reported in Table 1. The coefficient for asymmetry of volatility, often referred to as leverage effects, b_5, is negative and significant at the 5% level, indicating that negative shocks have a greater impact on volatility than positive shocks. All other coefficients are significant at the 1% level

Table 1. EGARCH Parameter Estimates.

(1) $$r_t = b_0 + b_1 r_{t-1} + b_2 \varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d.}(0, \sigma_t^2)$$

(2) $$\log(\sigma_t^2) = b_3 + b_4 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + b_5 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b_6 \log(\sigma_{t-1}^2)$$

	SP500ESG	SP500
b_0	0.001584**	0.001414**
b_1	0.594106**	0.610676**
b_2	-0.692510**	-0.696273**
b_3	-0.773451**	-0.866311**
b_4	0.398507**	0.447496**
b_5	-0.080183*	-0.100687*
b_6	0.947788**	0.942143**
Log likelihood	1399.820	1408.148

Notes: ** indicates significance at the 1% level, and * indicates significance at the 5% level.

The empirical impact of the pandemic on the two conditional volatility series is estimated using a vector autoregression model (VAR) and computing the corresponding generalized impulse response functions from the VAR (Koop et. al., 1996; Pesaran and Shin, 1998). Because the VAR model used in this study assumes that each variable is stationary, unit root tests are conducted on each variable. Augmented Dickey-Fuller tests confirm that the VIX and the two conditional volatility series estimated from the EGARCH(1,1) model are stationary, rejecting the hypothesis of a unit root at the 5% level. Unit roots tests of CASE, VACC, and GTRENDS fail to reject the hypothesis of a unit root at the 5% level. To obtain stationarity, each of these series is transformed by taking the first difference of the logarithm of the series. Descriptive statistics for all variables used in the VARs and impulse response functions are presented in Table 2.

Table 2. Descriptive Statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
SP500ESG	0.00027	0.00010	0.00638	0.00002	0.00060	5.7905	44.2349
SP500	0.00027	0.00009	0.00714	0.00002	0.00064	6.1103	49.4654
CASE	0.02665	0.00870	0.72920	0.00035	0.06751	6.1058	50.1720
VACC	0.04229	0.00623	1.13708	0.00152	0.12855	6.2818	46.7448
GTRENDS	0.00816	0.00181	0.11672	0.00069	0.01852	3.3226	13.7837
VIX	0.00390	-0.01200	0.61640	-0.23370	0.09349	2.0990	11.7667

Notes: Descriptive statistics are reported for all variables used in the vector autoregressions. The first difference log transformation is used for CASE, VACC, and GTRENDS. SP500ESG and SP500 are the conditional volatility series estimated from the EGARCH(1,1) model. All data is daily. Observations for VACC span December 14, 2020 to February, 28, 2022, while all other variables start in December 31, 2019.

The Akaike information criteria is used to determine the optimal order of the VARs. Based on this measure, each VAR is estimated with eight lags.[2] The estimated VARs are then used to compute the related impulse response functions. Generalized impulse response functions are computed rather than the more common Cholesky decomposition to trace out the effects of shocks from CASE, VACC, GTRENDS, and VIX.[3]

III. Empirical Results

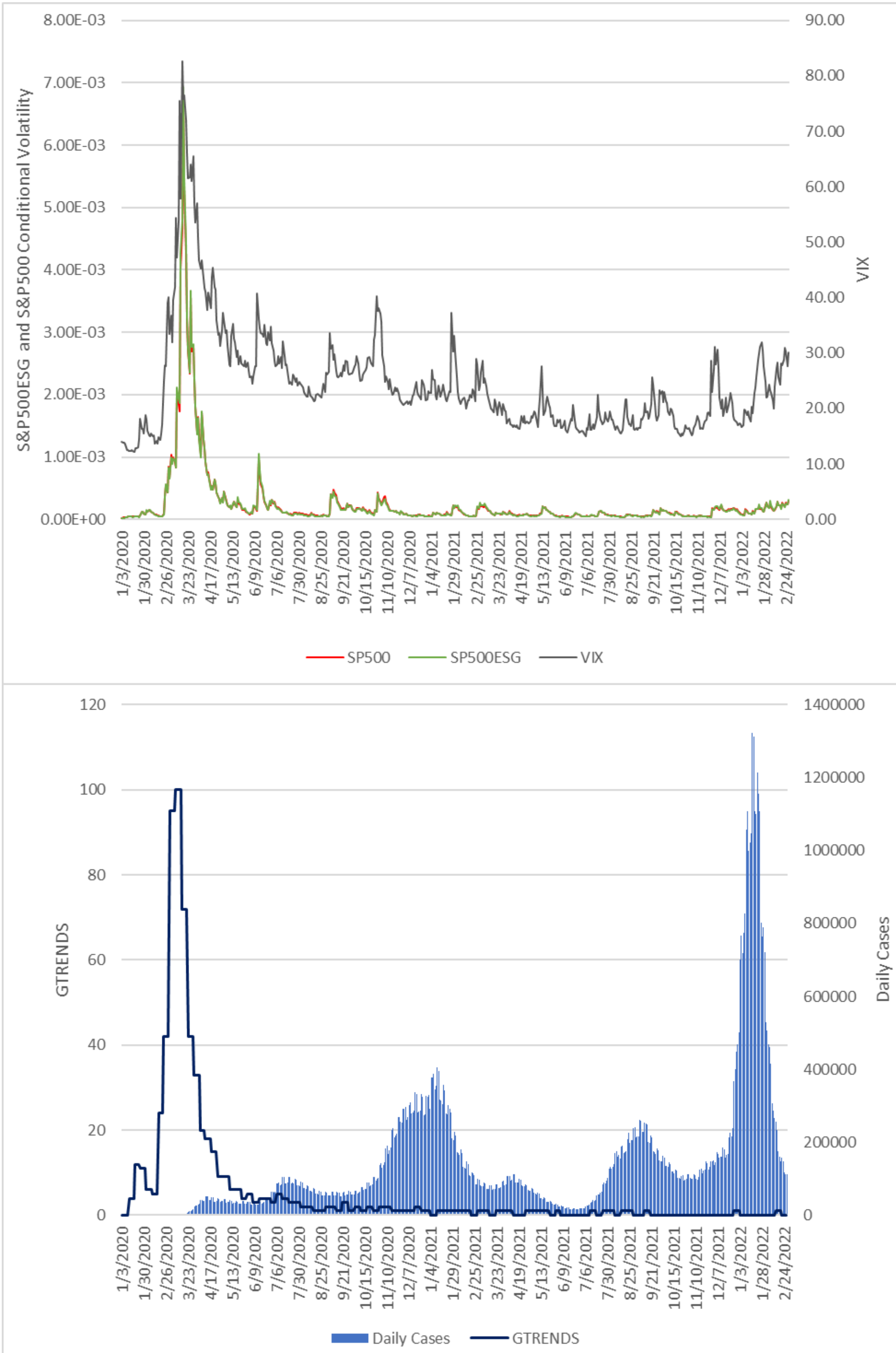
Before analyzing the results of the VARs and associated impulse response function analysis, it is worth discussing several features that present themselves in the time series charts shown in Figure 1. Both S&P conditional volatility series reached their pandemic maximum on March 17, 2020, and the VIX on March 16. In the first week of that same month, Google Trends searches seeking pandemic related information hit their peak. However, while COVID-19 infections surged, they didn't hit their peak until January 18, 2022. Yet, even with the omicron variant of the virus producing the largest numbers of daily infections recorded in the US, the impact on the market indexes, and pandemic information seeking as measured by Google Trends, was minimal. As the chart shows, the behavioral impact of the virus as proxied by Google Trends seems to be visually much more closely aligned with the increase in the market's conditional volatility. Finally, there appears to be no relationship between vaccinations and the conditional volatility of either index.

The impact of shocks on the conditional volatility of the S&P500ESG index and the S&P500 conventional index are shown in Figure 2. The graphs show the response to a one standard deviation increase each in COVID-19 infections (CASE), vaccinations (VACC), Google

[2] Impulse response standard errors are valid only if the VAR is stable. This requires all roots to have a modulus less than one, a result confirmed for each estimated VAR.

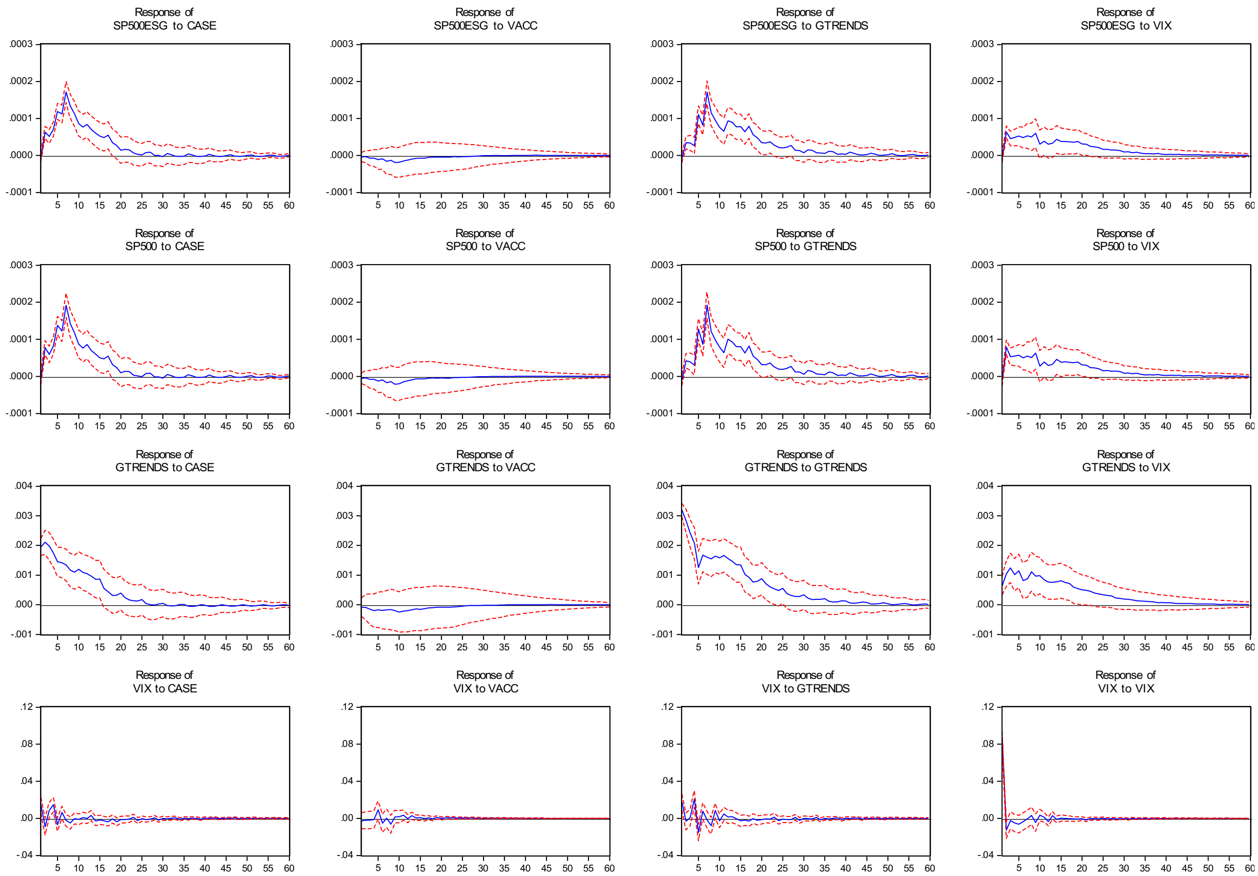
[3] The traditional orthogonalized impulse response employs a Cholesky decomposition from the covariance matrix, whereas the generalized version does not impose this restriction. Unlike the Cholesky decomposition, the generalized impulse responses do not depend on the ordering of the variables in the VAR.

Figure 1.



Notes: S&P500ESG and S&P500 Conditional Volatility, VIX, COVID Infections, Vaccinations, and Google Trends Searches during sample period December 31, 2019 to February 28, 2022.

Figure 2. Impulse Response Functions for Shocks applied to Conditional Volatility Series



Notes: Impulse Response Functions from a six variable VAR with the variables SP500ESG, SP500, CASE, VACC, GTRENDS, and VIX. Each graph shows the effects of a one standard deviation shock. 95% confidence interval represented by the dashed lines.

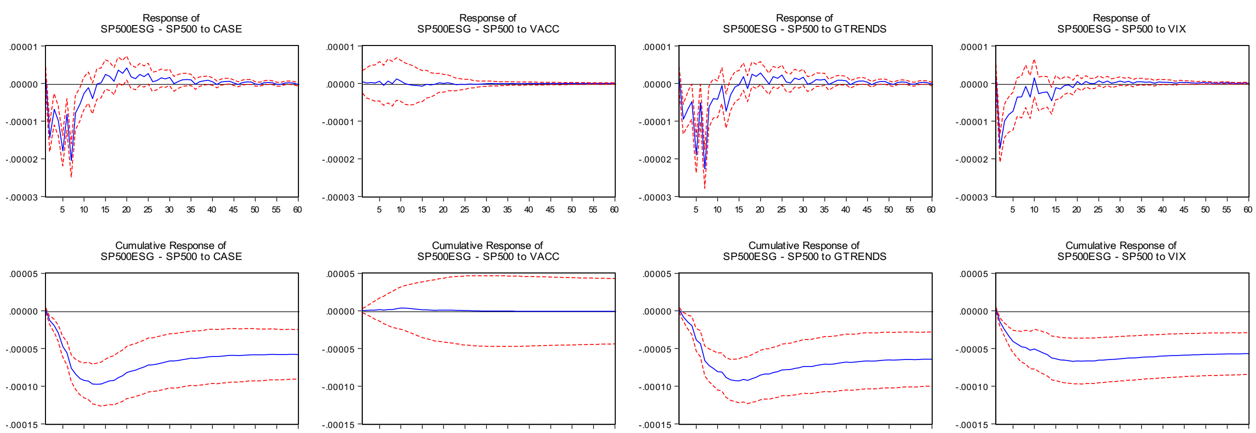
Trends pandemic searches (GTRENDS), and the VIX volatility index, with the dashed lines representing a 95 percent confidence interval around each shock. The conditional volatility of the S&P 500 ESG and S&P 500 indices increases by a statistically significant amount in direct response to shocks from CASE, GTRENDS, and VIX. The impact of these shocks is also quite persistent, with significant impact continuing for up to 18 days for CASE, to as many as 23 days in response to GTRENDS.

Figure 2 also points to several indirect channels through which COVID-19 infections affects the conditional volatility of the indices. Specifically, an increase in infections leads to increases in GTRENDS and the VIX, which, in turn, have a direct impact on the conditional volatility of the indices.

Lastly, vaccinations are shown to have no impact on either conditional volatility series. Intuition would suggest that market conditional volatility would decrease due to the vaccine, as might investor anxiety towards the pandemic as proxied by GTRENDS, and overall market volatility as measured by the VIX. However, none of this happens. The vaccine didn't become available until mid-December of 2020. This suggests that by the time the vaccine appeared, the impact of COVID on the market had passed. Thus, while COVID had a dramatic impact on market volatility, this impact appears to have been largely relegated to the early months of the pandemic. By the end of 2020, other factors outside the realm of this study were largely affecting markets.

From the time series charts in Figure 1 and the impulse responses in Figure 2, it appears that both the S&P 500 ESG and the S&P 500 had highly similar conditional volatility, even at their peak in mid-March at the start of the pandemic. To test if the conditional volatility of the ESG index responds to shocks by a magnitude statistically different than that of the conventional index, the difference between these two conditional volatility series is subject to the same shocks as before. From the results of the shocks applied to the individual conditional volatility series as shown in Figure 2, the two volatility series display near identical responses to the shocks. However, applying the same shocks to the difference in the conditional volatility series provides a different result. As shown in Figure 3, the difference in the conditional volatility series decreases in response to shocks from CASE, GTRENDS, and VIX, while it is unaffected by shocks from VACC. Because this variable is constructed as SP500ESG less SP500, a decrease indicates that the conditional volatility of the ESG index responds less than the conditional volatility of the conventional index. Thus, while both conditional volatility series increase in response to pandemic-related shocks, the ESG index is less affected. This is perhaps the most important result from the perspective of ESG advocates, as it supports the claim that socially responsible or high ESG investments are less volatile than conventional or low ESG investments during times of market crisis.

Figure 3. Impulse Response Functions and Cumulative Impulse Response Functions for Shocks applied to Difference in Conditional Volatility Series



Notes: Impulse Response Functions and Cumulative Impulse Response Functions from a five variable VAR with the variables SP500, CASE, VACC, GTRENDS, VIX, and the difference of the two conditional volatility series constructed as SP500ESG less SP500. Each graph shows the effects of a one standard deviation shock. 95% confidence interval represented by the dashed lines.

IV. Concluding Remarks

This study looks at the impact of the COVID-19 pandemic on the conditional volatility of the S&P 500 ESG index and its conventional counterpart, the S&P 500. The VAR and impulse response function analysis shows that the conditional volatility of each of the indices increases in direct response to an increase in infections. Indirectly, increases in infections produce to heightened market volatility as measured by the VIX, and increased interest or concern about the virus as measured by Google Trends searches related to the pandemic. In turn, increases in the VIX and Google Trends searches corresponds to increased conditional volatility in the indices. On the other hand, while COVID-19 infections have a significant and negative impact on the volatility of these indices, vaccinations have no impact.

A central question of this study was whether the conditional volatility of the ESG index behaves differently than that of the conventional index. While the empirical evidence from prior studies is mixed, advocates of ESG have long contended that sustainable investments tend to have lower risk, especially during periods of extreme market volatility. The results of this study support this claim. While the conditional volatility of both the S&P 500 ESG index and the S&P 500 increased in response to the pandemic, the sustainable index increased to a lesser extent than did its conventional counterpart, indicating favorable tail risk properties of the S&P 500 ESG index.

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The Post-IPO Performance of Private Equity Backed Firms During the Great Recession

Jack Trifts and Gary E Porter

Abstract

We examine the performance of PE-backed firms following their IPOs during the expansionary period of the early 2000s and their performance during the "great recession." We employ a control group using multi-digit NAICS codes, which allows us to match firms much more closely than prior studies. The results during the market expansion of the early decade parallel those of the existing literature, showing PE-backed firms perform as well or better than non-PE-backed firms. However, while those studies conclude that IPOs are generally a positive addition to the market and its investors, we show their performance is significantly worse than their non-PE-backed peers during the great recession, suggesting the success of these firms is particularly dependent on the state of the economy.

I. Introduction

Private Equity (PE) groups play a significant role in bringing firms public. In some cases, growing firms accept or even seek PE investment and management guidance as the final step in their move from privately held to public companies. In these cases, the PE groups often have extensive experience in the industry and with taking companies through the preparations for, and execution of, their initial public offering (IPO). In other cases, PE involvement occurs as part of a management buyout of an existing public company, or a division of a public company. In these cases, the resulting independent company operates a portfolio company with the PE groups guidance for a period from one to several years before reemerging as an independent entity on the public market through an IPO.

In all cases, the PE group plays a significant role in the governance of the firm before and immediately after its IPO. Almost invariably, the PE group will appoint one or more board members. It is also common for PE groups to enter consulting relationships with their portfolio companies and receive compensation for this role. It is also common for the PE backed private firm to raise significant debt, some of which may be paid to the PE groups in a special dividend. As a result, these firms may come to the public market with significant leverage.

Our study examines the post-IPO financial performance of PE-backed firms compared to similar firms without PE backing. Unlike other studies, we focus on the group of IPOs occurring in the five years leading up to the "great recession," which began in January 2.008 and ending in mid-2009. While prior studies have examined the post-IPO performance of PE backed firms, none have examined their performance in such challenging economic conditions.

Jack Trifts (jacktrifts@yahoo.com), Professor Emeritus, Bryant University and Gary E. Porter (g.porter@northeastern.edu), corresponding author, Northeastern University.

This paper is organized as follows. In the next section, we discuss the existing literature and contrast the prior authors work with ours. We next discuss our data and methodology and follow that with a discussion of our findings. We end with a summary and discussion of the implications of our work and suggestions for further research.

II. The Literature

In their seminal work, Holthausen and Larcker (1996) studied the financial performance in the four years following reverse LBOs occurring from 1976 to 1988. They found evidence that the post-IPO performance of these companies was better than that of similar firms that had not been subject to reverse IPOs. They attribute this enhanced performance to organizational incentives, namely higher degrees of managerial ownership and increased monitoring by active investors (the PE firms). While this paper is widely cited, the generality of these findings is limited by the timing of their data. While their study included IPOs from 1976 through 1988, 65 of their 90 IPOs occurred between 1983 and 1986 with only two occurring later than 1986. As a result, their effectively four-year study was focused overwhelmingly in the period from 1987 to 1990, well after the recessionary period in 1980 to 1982 and before the recession from July 1990 to March 1991. In contrast, our sample firms came to market in the period prior to the great recession and experienced a very different economic environment than most of Holthausen and Larcker's sample.

Cao and Lerner (2009) also studied the performance of reverse LBOs using a dataset of 526 transactions from 1981 to 2003. They followed the post-IPO firms for five years and found evidence that these firms performed as well or better than other IPOs during the period. While their study was more comprehensive than Holthausen and Larcker's initial work, their period of study did not include the great recession. Of the 526 transactions, only 16 were from 2003 and 25 were from 2002. The end of the five-year window of study for the 2003 observations would have included the recessionary period in 2008. The study window for IPOs occurring near the end of 2002 would have included the very beginning of the recession starting January 2008. However, observations from these two years combined represent only 7.8 percent of the total sample and would be unlikely to significantly influence the results. Interestingly, Cao and Lerner did document some decline in performance near the end of their five-year windows. Perhaps inclusion of these firms having IPOs that were affected by the recession influenced this result.

The choice of time period for studies such as this one is very important and can be reasonably expected to affect, if not drive the results. As Prassl (2015) notes in his review of two scholarly books on the topic, by Appelbaum and Batt (2014) and Gospel, Pendelton and Vitols (2013), "given the high degrees of debt, or leverage, and frequent refinancing models involved, even relatively small changes in the business environment can quickly lead to bankruptcies."

An element that is potentially very important to the outcome of the study of post-IPO performance is the selection of the control group against which to measure differences in performance. Holthausen and Larcker (1996) compare the performance of their sample of reverse LBOs to an industry group of firms sharing the same two-digit SIC (Standard Industrial Classification) code. While using a broad definition of industry such as theirs will result in a large number of comparable firms, the similarity of the sample firms to their control firms is questionable. For example, the two-digit SIC code 58 is for "Eating and Drinking Places." This category includes both the NASDAQ listed Ruth's Hospitality Group, operators of Ruth's Chris Steakhouse, and the NYSE listed McDonalds Corporation. Admittedly, both are clearly eating and drinking establishments but by most measures are quite different companies. Furthermore, one might reasonably expect these companies to be affected quite differently by recessions and other changes in the business environment.

Cao and Lerner (2009) improve the benchmarking process by using industry portfolios of companies with similar size and book-to-market ratios. The addition of size and market-to-book comparisons is likely to improve the comparability of the benchmark firms. However, the problems with the selection of the industry persists as they use benchmark industry portfolios assembled each year by Kenneth French.[1] While this process is much more detailed, it still can result in quite different firms being used as benchmarks. For example, the authors' use of French's second-most detailed portfolio group results in the market being divided into 48 distinct industries. Extending the example used above with restaurants, presumably both McDonalds and Ruth's Chris are still considered part of the "meals" industry.

Another element of methodology that varied across existing studies is the length of the period over which the performance of the sample firms is studied. Holthausen and Larcker (1996) studied the performance of their sample over the subsequent four years. Cao and Lerner (2009) study IPO post-performance over 5 years. Levis (2011), who examined the performance of PE-backed IPOs, studied his sample's post-performance for three years. The evaluation of performance over a short window of three to five years may bias the results towards finding superior or at least non-inferior performance. This may occur because of a sort of "emergence bias."[2]

III. Data and Methodology

Using Factset, we identified 224 IPOs potentially backed by PE groups occurring between January 1, 2002 and June 30, 2007 on the NASDAQ, NYSE and NYSE MKT LLC (former AMEX). In addition, we used the dataset provided by Dalseth and Larsen (2018) in their working paper. Their dataset of US, PE-backed IPOs included 116 IPOs from 2002 through mid-2007. While there was a substantial overlap between the two sources, they were not identical. The Factset generated list included many more transactions than Dalseth and Larsen and their dataset contained some not identified by Factset. In total, there were 103 IPOs that appeared on both lists.

While these differences might initially seem worrisome, they result from two causes. First, the list provided by Dalseth and Larsen had already been culled of observations that were not PE-backed transactions. Of the 52 transactions we eliminated because we did not believe that they were actually PE backed, only six were included in Dalseth and Larsen's final sample.

Determining that a particular IPO is or is not backed by a PE group is more difficult than it might appear. PE groups typically do not publicly announce new investments, nor do many firms that receive investments. While most PE groups today maintain websites that disclose their portfolio companies, most do not show historical investments, particularly in companies in which they no longer have any stake. Further, it is common practice for PE groups to structure the investments in their portfolio so that there is no shared liability between group companies. The investment vehicles they use have different names which may or may not include the name of the

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

[2] As Appelbaum and Batt (2014) detail, many of the firms in which PE groups invest never make it to completed IPOs. Portfolio companies that do not perform well enough to bring to an IPO are sold to other PE groups specializing in their industry or to larger companies seeking expansion through acquisition. Also, some portfolio firms fail. As a result, the firms that successfully come to market through IPOs do not represent a cross section of PE-backed firms but rather the most successful of the group. This being so, it is reasonable to expect that these firms might be expected to perform well, at least initially.

backing PE group. Additionally, growing firms receive investment from many sources other than PE groups, including venture capital groups and individuals.

To ensure the accuracy of our sample, the security registration statement (S-1) for each IPO was retrieved from the Securities and Exchange Commission's EDGAR site. To verify the participation of a PE group, we searched the document for reference to a PE group. The participation of PE groups shows up in several ways in S-1 statements. For example, S-1 statements include brief bios of the company board of directors and these bios often reference directors with management position in PE groups. Each S-1 also includes sections on "Principal Stockholders" and "Certain Relationships and Related Party Transactions." Using these, we were able to verify PE participation for the sample firms.

In some cases, investment groups were identified without specifically identifying them as PE groups. To distinguish PE investments from other investments, we used two techniques. First, Appelbaum and Batt (2014, p. 118) provide a list of the 26 largest PE groups and many of our sample firms include investments from these firms. Second, for firms that are not listed among the largest, we researched the companies via an internet search. We include only those companies that are clearly involved in PE investment.

Our final sample includes 147 IPOs. A list of these transactions is shown in the Appendix. The accompanying table shows the distribution of IPOs by year. The data show some clustering towards the end of the sample period, probably reflecting the buoyant economy in the final years of the expansion before the financial collapse.

Table 1: Private Equity-Backed IPOs occurring on the NASDAQ, NYSE and NYSE MKT LLC	
2002	10
2003	13
2004	30
2005	45
2006	49
Total	147

We believe that one of the contributions of our study is in the improvement in the selection of the control sample. After identifying the sample of IPOs with PE backing, we built a control sample against which to compare their performance in the subsequent period. Prior studies have used two approaches, comparing the sample firms to a portfolio of all firms with the same two-digit SIC and against broad market indices. There are two potential problems with the use of two-digit SICs. First, as noted earlier, two-digit codes capture a wide range of firms and associated business models within each industry.

The second problem is less obvious but very important. We noticed a "clustering" phenomenon in our sample, where some industries have large numbers of PE-backed IPOs over a relatively short period. For example, our sample contains 17 firms in the "Business Services" industry (SIC 73), 13 firms in the "Chemicals and Allied Products" industry (SIC 28), 11 firms in the "Insurance Carriers" industry (SIC 63), and 7 firms in each of the "Communications" and "Instruments and Related Products" industries (SIC 48 and 38). As a result of this clustering within industries, comparing the performance of a particular PE-backed IPO firm against a portfolio of all firms with the same two-digit SICs results in a control group that may contain one or more firms also backed by PE groups. This makes the study of portfolios of IPOs problematic.

To make better comparisons, we sought a matched set of control firms based on six-digit NAICS (North American Industrial Classification System) codes, eliminating any firms that were themselves backed by PE groups. From a list of all publicly traded firms with data during the test period, we selected the company with the same six-digit NAICS code and nearest in size by Market Capitalization. We then examined the company's 10-K in the year of the sample firm's IPO for evidence of PE backing, followed by an internet search for such evidence. In the final sample of 147 firms, 119 have control firms with matching six-digit NAICS codes and no evidence of PE-backing. In those cases where there was no matching six-digit code, we attempted to match using the first five digits of the NAICS code. If that did not result in a match, we continued to drop the ending digits of the sample firm's NAICS code until a match was reached. As shown in the accompanying table, we were able to find a six-digit match for 119 (81 percent) companies in the sample. In only one case did we have to rely on only the first two digits, and this pair was a suitable match.

Table 2: NAICS Distribution

Number of NAICS Code Digits Matched	Number of Sample Firms
6 of 6	119
5 of 6	4
4 of 6	10
3 of 6	13
2 of 6	1
Total	147

This study follows the sample firms from the date of their IPO to June 2010 (three years after the sample selection period) or until they are delisted, acquired, or otherwise cease to operate as the entity that emerged from the IPO. This lengthy period of study, ranging from three to over eight years, is important since it will allow the capture of events that may take substantial time to unfold but still be related to the firm's prior status as an LBO target. For example, Campbell, Hilscher and Szilagyi (2010) develop and test a model to predict financial distress. Their model shows predictive power three years in advance of what Campbell et al term a failure event, defined as a bankruptcy filing, delisting for distress-related reasons, or the receipt of a D credit rating. Since it is highly unlikely that a PE group could successfully bring a firm showing signs of financial distress to market, a study window of three or four years is likely to miss many firms that will develop financial distress but not show significant underperformance, or experience failure events, until significantly later.

To compare performance, we examined a range of financial and market-related data. The accompanying table shows the list of metrics. The post-IPO performance of the sample firms is compared to the control firms in each of the years following the IPO. This list of metrics was chosen to examine four broad categories of performance. Comparisons of ROA and Net Profit Margin show differences in the profitability. Comparisons of the number of employees, research and development expenditures, advertising expense and Capital Expenditures (CapEx) show whether the sample firms appear to be capital constrained due to the high leverage resulting from their LBOs. Comparing working capital will show whether there are differences in liquidity. Finally, the debt related metrics allow direct comparisons of the use of leverage.

Table 3: Accounting Metrics Used to Measure Performance
ROA
Net Profit Margin
Number of Employees/Sales
R&D Expenditures/Sales
Advertising Expense/Sales
CapEx/Sales
Working Capital/TA
Long Term Debt/Total Assets
Long-Term Debt/Market Cap

In addition to accounting-based metrics, the sample firms are compared to their control sample peers using market-based metrics. Borrowing from Levis (2011), buy and hold adjusted returns (BHAR) are computed for each sample firm/control sample pair as follows:

$$BHAR = \prod_{t=1}^{T}\left(1 + r_{i,t}\right) - \prod_{t=1}^{T}\left(1 + r_{Ci,t}\right)$$

where $r_{i,t}$ is the return to sample company i during period t and r_{Ci} is the return to the control company for sample firm i over the same period.

IV. Results

Table 4 shows the Buy and Hold Adjusted Returns (BHAR) for our sample of PE-backed firms compared to their non-PE-backed control firms during the 36 months following their IPO in the pre-recessionary period defined as March 2002 through December 2007.[3] We truncated our analysis at 36 months because at this point, the number of sample firms drops below 30 and tests of statistical significance become less meaningful.

As shown in Table 4, the performance of PE-backed firms did not significantly exceed that of their control firms in their first year of existence. The period from 9 to 17 months following the IPOs did show significant out-performance at either the 10 or 5 percent levels. However, the counts of the number of positive and negative observations shows similar proportions throughout the time period. For example, the average BHAR in the 13 months following the IPO was 14.28 percent, significant at the 5 percent level. However, that result included BHARs for 119 pairs of companies and the mix of positive and negative observations was 62 positive and 57 negatives, far from

[3] The National Bureau of Economic Research (NBER) reports that the business cycle peaked in the fourth quarter of December 2007 and bottomed in June 2009.

Table 4: Buy and Hold Adjusted Returns (BHAR) during the Non-Recessionary Period 2002 through 2007 for Sample of Post-IPO PE-Backed Firms Compared to Non-PE-back Control Companies by Month Relative to IPO Date

Month relative to IPO	Average BHAR	N	t-Statistic	Significance Level (One-Tail Test)	Number Positive	Number Negative	Binomial Probability[1]
1	0.50%	147	0.42	0.339	76	71	0.690
2	-0.22%	147	-0.12	0.452	67	80	0.161
3	0.13%	147	0.05	0.480	66	81	0.124
4	0.97%	147	0.36	0.359	69	78	0.255
5	0.29%	147	0.10	0.461	70	77	0.310
6	2.76%	147	0.80	0.213	71	76	0.371
7	2.36%	143	0.62	0.269	69	74	0.369
8	5.00%	139	1.13	0.131	69	70	0.500
9	9.19%	133	1.66	0.050	69	64	0.698
10	10.44%	130	1.65	0.051	66	64	0.604
11	12.70%	130	2.00	0.024	67	63	0.669
12	15.07%	128	1.91	0.029	67	61	0.732
13	14.28%	119	2.12	0.018	62	57	0.709
14	14.88%	118	1.89	0.031	57	61	0.391
15	16.76%	115	1.73	0.043	55	60	0.355
16	16.52%	110	1.94	0.027	55	55	0.538
17	15.70%	102	1.54	0.064	51	51	0.539
18	9.93%	99	1.23	0.112	46	53	0.273
19	1.88%	95	0.27	0.393	42	53	0.152
20	5.73%	93	0.73	0.234	40	53	0.107
21	3.09%	93	0.40	0.344	41	52	0.150
22	0.58%	89	0.08	0.469	41	48	0.263
23	-0.36%	83	-0.05	0.481	36	47	0.136
24	4.28%	79	0.49	0.311	36	43	0.250
25	4.27%	72	0.49	0.313	32	40	0.205
26	3.14%	66	0.36	0.361	31	35	0.356
27	1.09%	64	0.12	0.451	25	39	0.052
28	3.06%	64	0.32	0.373	25	39	0.052
29	5.13%	61	0.54	0.297	28	33	0.304
30	-5.03%	57	-0.55	0.292	22	35	0.056
31	-0.70%	52	-0.07	0.473	20	32	0.063
32	-6.33%	45	-0.55	0.292	17	28	0.068
33	-2.67%	42	-0.21	0.418	17	25	0.140
34	0.10%	42	0.01	0.497	17	25	0.140
35	6.36%	41	0.39	0.349	16	25	0.106
36	-1.72%	35	-0.09	0.465	13	22	0.088

[1]The binomial probability is the probability of at least the observed number of positive occurring randomly in a sample of N observations, assuming equal likelihood of positive and negative observations

Table 5: Buy and Hold Adjusted Returns (BHAR) during the Non-Recessionary Period 2002 through 2007 for Sample of Post-IPO PE-Backed Firms Compared to Non-PE-back Control Companies, by Calendar Month

Month	Cumulative Average BHAR	N	t-statistic	Monthly Average Difference	Number Positive	Number Negative	Binomial Probability[1]
Mar-02	21.409%	1		21.409%	1	0	
Apr-02	44.740%	2	10.01	19.217%	2	0	1.0000
May-02	53.803%	3	7.71	6.261%	2	1	0.8750
Jun-02	47.068%	5	4.70	-4.379%	2	3	0.5000
Jul-02	30.003%	5	2.27	-11.604%	2	3	0.5000
Aug-02	38.595%	7	4.65	6.609%	5	2	0.9375
Sep-02	49.439%	7	5.68	7.824%	4	3	0.7734
Oct-02	42.934%	7	4.88	-4.353%	3	4	0.5000
Nov-02	46.678%	9	5.47	2.619%	5	4	0.7461
Dec-02	43.691%	10	5.61	-2.036%	4	6	0.3770
Jan-03	54.776%	11	9.64	7.714%	8	3	0.9673
Feb-03	36.970%	11	7.49	-11.504%	3	8	0.1133
Mar-03	46.146%	12	16.34	6.699%	8	4	0.9270
Apr-03	50.436%	12	11.05	2.935%	7	5	0.8062
May-03	52.743%	12	9.15	1.534%	9	3	0.9807
Jun-03	59.156%	12	11.31	4.199%	7	5	0.8062
Jul-03	76.320%	12	20.27	10.784%	9	3	0.9807
Aug-03	80.485%	13	17.84	2.362%	6	7	0.5000
Sep-03	69.055%	15	7.39	-6.333%	7	8	0.5000
Oct-03	64.359%	17	16.98	-2.778%	8	9	0.5000
Nov-03	62.206%	18	26.20	-1.310%	7	11	0.2403
Dec-03	65.407%	21	24.80	1.974%	14	7	0.9608
Jan-04	58.592%	23	15.92	-4.120%	10	13	0.3388
Feb-04	61.027%	23	22.43	1.536%	12	11	0.6612
Mar-04	57.463%	27	27.00	-2.213%	10	17	0.1239
Apr-04	59.862%	29	32.29	1.523%	15	14	0.6445
May-04	53.087%	31	13.47	-4.238%	13	18	0.2366
Jun-04	47.991%	31	21.47	-3.329%	14	17	0.3601
Jul-04	52.416%	33	24.65	2.991%	20	13	0.9186
Aug-04	52.450%	42	21.04	0.022%	20	22	0.4388
Sep-04	53.274%	43	23.95	0.540%	24	19	0.8198
Oct-04	48.406%	44	14.57	-3.176%	23	21	0.6742
Nov-04	51.411%	46	19.68	2.025%	25	21	0.7693
Dec-04	52.080%	49	20.73	0.442%	26	23	0.7159
Jan-05	50.211%	53	37.63	-1.229%	28	25	0.7084
Feb-05	49.364%	59	30.95	-0.564%	32	27	0.7825
Mar-05	52.259%	63	33.21	1.938%	38	25	0.9615

Month	Cumulative Average BHAR	N	t-statistic	Monthly Average Difference	Number Positive	Number Negative	Binomial Probability[1]
Apr-05	54.054%	63	27.44	1.179%	39	24	0.9785
May-05	53.594%	66	23.16	-0.299%	32	34	0.4511
Jun-05	61.498%	69	40.70	5.146%	44	25	0.9923
Jul-05	67.468%	77	32.61	3.697%	51	26	0.9986
Aug-05	67.998%	81	43.31	0.316%	41	40	0.5878
Sep-05	67.414%	87	40.50	-0.348%	43	44	0.5000
Oct-05	69.512%	89	46.33	1.253%	48	41	0.8017
Nov-05	65.167%	90	33.67	-2.563%	39	51	0.1231
Dec-05	70.272%	95	46.97	3.091%	56	39	0.9679
Jan-06	70.344%	97	47.40	0.042%	45	52	0.2713
Feb-06	67.771%	99	42.18	-1.510%	55	44	0.8862
Mar-06	71.911%	106	42.83	2.467%	57	49	0.8089
Apr-06	75.305%	109	77.33	1.975%	60	49	0.8749
May-06	72.765%	112	58.81	-1.449%	45	67	0.0234
Jun-06	74.459%	112	48.41	0.980%	63	49	0.9220
Jul-06	76.759%	119	54.04	1.318%	58	61	0.4273
Aug-06	71.949%	122	44.74	-2.721%	55	67	0.1597
Sep-06	72.293%	124	74.84	0.200%	63	61	0.6061
Oct-06	71.684%	128	47.05	-0.353%	72	56	0.9337
Nov-06	71.297%	134	56.87	-0.226%	69	65	0.6670
Dec-06	72.840%	139	69.88	0.901%	78	61	0.9367
Jan-07	70.717%	147	58.08	-1.228%	72	74	0.4670
Feb-07	72.529%	147	77.34	1.061%	77	69	0.7718
Mar-07	74.179%	147	67.71	0.957%	81	65	0.9204
Apr-07	74.119%	147	76.84	-0.034%	73	73	0.5330
May-07	73.936%	147	62.30	-0.105%	70	77	0.3104
Jun-07	77.549%	147	81.11	2.077%	90	57	0.9976
Jul-07	75.703%	147	69.69	-1.040%	69	78	0.2548
Aug-07	69.105%	147	59.41	-3.755%	58	89	0.0065
Sep-07	69.014%	147	60.84	-0.053%	73	74	0.5000
Oct-07	66.875%	147	41.04	-1.276%	69	78	0.2548
Nov-07	66.923%	146	49.51	0.039%	73	73	0.5330
Dec-07	67.692%	146	51.67	0.461%	76	70	0.7187

[1]The binomial probability is the probability of at least the observed number of positive occurring randomly in a sample of N observations, assuming equal likelihood of positive and negative observations.

significant using a binomial test. Depending on one's preference for statistic, one might interpret the overall table as either weakly supportive of the argument that PE-backed IPOs out-perform their peers or that the performance of these firms is at least as good as, but not statistically better than their peers. This result is different than the findings of Holthausen and Larcker (1996) who found that the PE-backed firms performance exceeded their broader control group. Our results are more consistent with Cao, J. and J Lerner, (2009) who found that their sample performed "as well or better." Perhaps the difference in results occurs because of differences in the sample period or the methodology. Our sample of PE-backed firms was matched to control firms with very similar characteristics and perhaps because of this close matching, the returns of the PE-backed group, while strong over most of the period, were not significantly better than the control firms.

While the results shown in Table 4, by month relative to each firm's IPO date, are useful in gauging the overall returns of post-IPO firms in aggregate, these returns could not be replicated by an investor because the returns are calculated in event time (i.e., relative to each firm's IPO date, not calendar time). It is, of course, impossible for an investor to simultaneously invest in an IPO occurring in, for example, March of 2002 and May of 2005. To measure the returns that could have been earned by an investor, with a caveat to be discussed later, we calculated the BHARs in calendar time. Table 5 shows the BHARs by calendar month from the date of the earliest IPO in our sample, March 2002, through the last month of the pre-recessionary period, December 2007.

At first glance, this table would appear to suggest that PE-backed firms in the pre-recessionary period outperform their non-PE backed peers by substantial amounts. The BHARs from the first month are large, positive and statistically significant. This result is consistent with the findings of Holthausen and Larcker (1996) who found that the PE-backed firms performance exceeded their broader control group. Before ending the story here, however, one must consider two additional pieces of information. First, as shown in Table 5, binomial tests of the individual differences support the opposite conclusion. In only two months, May 2006 and August of 2007, did the number of positive differences exceed the proportion that could be expected to randomly occur by an amount statistically significant at a level under 5 percent. Second, the large magnitudes occur largely because of a few very large positive returns early in the sample period. In the first two months of the period, two firms had large positive returns and the BHAR at the end of the second month, April 2002, was an impressive 44.7 percent. The BHARs peaked in June of 2007, six months prior to the official start of the recession, then dropping from 77.5 percent to 67.69 percent.

The combined results of the t-tests and binomial tests support the following conclusions: First, our findings are generally consistent with prior research, all of which used samples taken from periods of a mostly expanding economy. However, while the aggregate returns to PE-backed IPOs do seem to be at least as strong, and maybe somewhat better, than that of their non-PE backed peers during good economic conditions, many individual PE-backed IPOs underperformed their peers.[4] Second, while the performance of our sample of PE-backed firms performed as well or better than their non-PE-backed control firms in the expansionary period of the first half of the 2000s, the differences were quite different during the great recession. Table 6 shows the returns to the sample firms, compared to their control firms, for the 30-month period beginning in January 2008, the official start of the recession. During the recession, the PE-backed firms performed significantly worse than their non-PE-backed peers.

[4] A critically important caveat should be considered before an investor considers an investment strategy of buying PE-backed IPOs. The results show that the overall returns, while positive, result from a combination of very good and very bad investments with returns to the good deals more than offsetting the losses from the bad ones. If this result is true and generalizable to future periods (which we will see is very dependent on being able to accurately predict future market conditions), it is critical that an investor participate in *every* PE-backed IPO. The likelihood that any investor, let alone an individual investor, could participate in every IPO is remote. Since one might logically expect that inside investors would have better insights into which deals have significant long-run potential, market conditions could result in most investors missing the best deals and getting an oversize portion of the ones that will subsequently under-perform.

By the end of July 2008, the PE-backed firms had under-performed their peers by a statistically significant -7.43 percent (p=0.031). By the end of one year, at the end of December 2008, the under-performance had worsened to -14.86 percent (p=0.041). Over the 30-month period, the cumulative BHAR, or difference between the return on the PE-backed IPOs and that of their control firms, was -22.93 percent (p=0.043) worse than their non-PE-backed peers.[5] We also examined the number of positive and negative BHARs by month during the period. Except for the first month of the recessionary period, January 2008, the number of positive observations was well below their expected value and statistically significant using a binomial test. The results provide the first evidence that PE-backed firms significantly under-perform their non-PE-backed peers during downturns in the economy.

To explain why the differential performance turned so negative once the economy moved toward recession, we examined the financial characteristics of the firms using the accounting metrics discussed earlier. Table 7 shows the differences in the accounting metrics between the sample and control firms in the pre-recession and recession period. Consistent with the differences in market performance during the pre-recessionary period, the PE-backed firms exhibit significantly higher levels of Return-on-Assets and Profit Margin during the earlier period. Once the economy turned downward, the differences in ROA and Profit Margin declined and are not statistically different in the recessionary period.

The other most notable (and predictable) result highlighted in Table 6 is the difference in leverage between the PE-backed sample and the non-PE-backed control companies. As Appelbaum (2014) notes, it is typical for PE groups to add substantial leverage to the firms they control and to use this leverage to extract significant cash dividends from the company. In our sample, the average difference in long-term debt-to-total assets ratio was nearly 11 percent higher pre-recession and 14.1 percent higher during the recession for the PE-backed firms compared to their controls. Differences in long-term debt-to-market capitalization ratios also increased during the recessionary period, from a 9.3 percent (t=2.10) to 62.4 percent (t=5.07).[6] While firms with high leverage may do well in strong economic conditions, high leverage makes it more difficult for companies to perform well in (and in many cases even survive) economic downturns. Since the so-called "great recession" was so pronounced, the results we show in this study may be uncharacteristically dramatic.

Table 7 also shows that the PE-backed firms came to market with fewer employees and less working capital than equivalent non-PE-backed firms. This is also expected as PE firms are well-known for streamlining their firms to make them as profitable as possible and this attractive

[5] When considering the six month period before the official start of the recession, during which the PE-backed firms began to show weakness, a 36-month BHAR was -35.78 percent, (p=0001).

[6] When including the 6 six-month period leading up to the official start of the recession, the pre-recession difference in Market Debt Ratios was 4.2 percent, and not significantly different than zero.

Table 6: Buy and Hold Adjusted Returns (BHAR) during the Recessionary Period January 2008 through June 2010 for Sample of Post-IPO PE-Backed Firms Compared to Non-PE-back Control Companies

Month	Average BHAR	N	t-statistic	Significance Level (One-Tail Test)	Number Positive	Number Negative	Binomial Probability[1]
Jan-08	-2.025%	146	-1.431	0.0773	71	75	0.4020
Feb-08	-2.494%	146	-1.325	0.0936	64	82	0.0796
Mar-08	-4.027%	145	-1.604	0.0555	60	85	0.0229
Apr-08	-3.993%	144	-1.415	0.0796	58	86	0.0121
May-08	-2.080%	143	-0.605	0.2731	63	80	0.0904
Jun-08	-2.876%	142	-0.738	0.2309	58	84	0.0178
Jul-08	-7.432%	141	-1.877	0.0313	52	89	0.0012
Aug-08	-5.206%	140	-1.132	0.1299	57	83	0.0171
Sep-08	-8.541%	140	-1.693	0.0464	42	98	0.0000
Oct-08	-8.290%	138	-1.328	0.0932	41	97	0.0000
Nov-08	-12.336%	132	-1.676	0.0481	36	96	0.0000
Dec-08	-14.856%	130	-1.749	0.0413	34	96	0.0000
Jan-09	-12.133%	129	-1.229	0.1106	34	95	0.0000
Feb-09	-12.340%	129	-1.045	0.1490	32	97	0.0000
Mar-09	-18.559%	127	-1.824	0.0352	36	91	0.0000
Apr-09	-29.019%	126	-2.888	0.0023	29	97	0.0000
May-09	-32.121%	125	-3.982	0.0001	25	100	0.0000
Jun-09	-21.242%	125	-2.366	0.0098	32	93	0.0000
Jul-09	-18.315%	123	-1.670	0.0488	31	92	0.0000
Aug-09	-25.441%	122	-3.121	0.0011	33	89	0.0000
Sep-09	-24.202%	120	-2.455	0.0078	28	92	0.0000
Oct-09	-22.870%	117	-2.031	0.0223	29	88	0.0000
Nov-09	-24.102%	117	-2.318	0.0111	33	84	0.0000
Dec-09	-27.056%	115	-2.655	0.0045	27	88	0.0000
Jan-10	-27.507%	114	-2.585	0.0055	29	85	0.0000
Feb-10	-27.472%	114	-2.595	0.0054	27	87	0.0000
Mar-10	-24.704%	114	-2.045	0.0216	26	88	0.0000
Apr-10	-24.574%	112	-2.321	0.0111	27	85	0.0000
May-10	-23.716%	108	-2.084	0.0197	25	83	0.0000
Jun-10	-22.293%	108	-1.729	0.0433	27	81	0.0000

[1]The binomial probability is the probability of at least the observed number of positive occurring randomly in a sample of N observations, assuming equal likelihood of positive and negative observations.

Table 7: Differences in Financial Variable between PE-backed Sample Firms and non-PE-backed Control Firms Before and During the Recession			
Financial Variable	**Definition**	**Mean Difference (Sample – Control) Before Recession**	**Mean Difference (Sample – Control) During Recession**
Return on Assets	Net Income / Total Assets	0.0195 t = (1.98)***	-0.0100 t = (-0.59)
Profit Margin	Net Income / Revenue	0.2091 t = (2.73)***	0.1541 t = (1.04)
Employees	Number of Employees / Revenue	-0.0017 t = (-4.74)***	-0.0011 t = (-4.84)***
Research and Development	Research & Development Expense / Revenue	-0.0003 t = (-0.77)	-0.0002 t = (-1.44)*
Working Capital	Working Capital[1] / Total Assets	-0.0489 t = (-4.06)***	-0.0097 t = (-0.69)
Advertising Expense	Advertising Expense / Revenue	-0.0025 t = (-0.59)	-0.0091 t = (-0.54)
Capital Expenditures	Capital Expenditures / Revenue	-0.2723 t = (-1.32)*	-0.1314 t = (-0.49)
Book Debt Ratio	Long Term Debt[2] / Total Assets	0.1092 t = (7.52)***	0.1408 t = (7.72)***
Market Debt Ratio	Long-Term Debt / Market Capitalization[3]	0.0927 t = (2.10)**	0.6237 t = (5.07)***

1. Working Capital = Current Assets less Current Liabilities not including Current Portion of Long-term Debt
2. Long-Term Debt includes Capital Leases and the Current Portion of Long-Term Debt and Capital Leases
3. Market Capitalization = Long Term Debt + Market Value of Equity

IPO candidates. In our sample, the number of employees, standardized by sales, was statistically significantly less in the recessionary period. Working capital-to-total assets was less in the pre-recessionary period but not during the recession indicating either that the PE-backed firms were able to shore up their working capital or that both groups of firms had low working capital during the recession. We found no statistically significant differences in expenditures for research and development, advertising, or capital expenditures between the two groups.

V. Summary and Extensions

In this study, we examine the performance of PE-backed firms following their IPOs during the expansionary period of the early 2000s and these same firm's performance later in the decade during the "great recession." Unlike studies that compare performance to groups of somewhat similar firms with the same two-digit SIC codes, we have created a matched control group based on the more detailed multi-digit NAICS codes.

The results during the market expansion of the early decade generally parallel those of the existing literature which finds that PE-backed IPOs perform at least as well and perhaps better than their non-PE-backed peers. While prior studies conclude that IPOs are a positive addition to the market and its investors, we go further and compare performance during the great recession. Here we find very different results, with PE-backed firms performing poorly compared to their non-PE-backed peers.

During recessionary periods, our sample of PE-backed firms compare dramatically worse than their peers. The reason for this poor performance can be seen on the balance sheets of the new IPO firms, which, on average, carry more debt than their non-PE-backed peers. The leveraging process is fundamental to the role of private equity groups. In the typical deal, the PE firm takes control of a fledgling firm or purchases an established public or private firm.

In return for their management guidance and the promise of large financial gains to the founders and management of the acquired firms, the PE groups often extract significant cash from the business by raising debt to fund large dividend payouts, and management fees. After some time under the new management structure, the PE firm uses their expertise to bring the firm to the public market through an IPO. This IPO provides significant gains to the firm's existing investors but leaves the new firm heavily levered. While these newly public firms may do well if the economy stays strong, their high leverage makes them extremely vulnerable during economic downturns.

There are many opportunities for further study of PE-backed firms. Our results show that the success of PE-backed firms, post IPO, is particularly dependent on the state of the economy. During the great recession of the late 2000s, these firms performed much worse than very similar firms not backed by PE groups. How will these firms perform during less severe recessions?

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Appendix: Data Date and Company Name

20051231	A R C Document Solutions (Then American Reprographics Co.)
20051231	Accuride Corp.
20061231	AerCap Holdings NV
20030131	Aeropostale (now ARO LIQUIDATION INC)
20061231	Aircastle Ltd.
20061231	Allegiant Travel Co.
20061231	Allied World Assurance Co. Holdings Ltd.
20061231	Alphatec Holdings, Inc.
20061231	Altra Industrial Motion (Then Altra Holdings)
20051231	Amerisafe, Inc.
20031231	AMIS Holdings, Inc.
20021231	Asbury Automotive Group, Inc.
20041231	Asset Acceptance Capital Corp
20041231	Auxilium Pharmaceuticals, Inc.
20031231	AXIS Capital Holdings Ltd.
20061231	Bare Escentuals, Inc.
20040930	Beacon Roofing Supply Inc
20021231	Big 5 Sporting Goods Corp.
20041231	Blackbaud Inc
20051231	Brookdale Senior Living, Inc.
20061231	Buckeye GP Holdings LP
20041231	Bucyrus International Inc
20031231	Buffalo Wild Wings, Inc.
20051231	Builders FirstSource, Inc.
20041231	C B R E Group (Then CB Richard Ellis Group, Inc.)
20031231	CapitalSource, Inc.
20061231	Carrols Restaurant Group (Carrols Holding Corp.)
20031231	Carter's, Inc.
20051231	CBeyond Communications, Inc.
20051231	Celanese Corp.
20011231	Chart Industries, Inc.
20041231	Cherokee International Corp.
20031231	Citadel Broadcasting Corp.
20060131	Citi Trends, Inc.
20061231	Clayton Holdings, Inc.
20041231	Commercial Vehicle Group, Inc.
20070331	CommVault Systems, Inc.
20061231	Complete Production Services, Inc.
20051231	Consolidated Communications Holdings, Inc.
20041231	Copano Energy LLC
20021130	Corel Corp.
20050630	D F C Global (Then Dollar Financial Corp.)

20061231	Dayton Superior Corp.
20051231	DealerTrack Holdings, Inc.
20041231	Design Within Reach, Inc.
20041231	Domino's Pizza, Inc.
20051231	Dover Saddlery, Inc.
20051231	Dresser-Rand Group, Inc.
20011231	E X C O Resources, Inc.
20051231	Eagle Bulk Shipping, Inc.
20061231	Eagle Rock Energy Partners LP
20060930	Eagle Test Systems, Inc.
20061231	Eastern Insurance Holdings, Inc.
20061231	eHealth, Inc.
20051231	Emergency Medical Services Corp.
20031231	Endurance Specialty Holdings Ltd.
20050331	EnerSys, Inc.
20041231	Entorian Technologies, Inc. (Then Staktek Holdings)
20051231	ev3, Inc.
20051231	Everi Holdings (Then Global Cash Access Holdings)
20061231	First Mercury Financial Corp.
20041231	Foundation Coal Holdings, Inc. (now Alpha Natural Resources)
20051231	Freightcare of America (Then FCA Acquisition Corp)
20051231	G F I Group, Inc.
20061231	GateHouse Media, Inc.
20061231	GeoMet, Inc.
20061231	Globalstar, Inc.
20061231	Golfsmith International Holdings, Inc.
20041231	Greenfield Online Inc
20061231	H & E Equipment Services, Inc.
20061231	HealthSpring, Inc.
20011231	Herbalife Ltd. (filed S-1 as WH Holdings. Now Herbalife Nutrition)
20051231	Hercules Offshore, Inc.
20051231	Hittite Microwave Corp.
20051231	Horizon Lines, Inc.
20061231	Houston Wire & Cable Co.
20051231	Huntsman Corp.
20061231	I C F International, Inc.
20061231	Innophos Holdings, Inc.
20041231	Intersections, Inc.
20041231	Iowa Telecommunications Services, Inc.
20021231	JetBlue Airways Corp
20051231	Kenexa Corp
20030131	Kirkland's, Inc.
20061231	Koppers Holdings, Inc.
20031231	L E C G Corp
20061231	LeMaitre Vascular, Inc.
20051231	Lincoln Educational Services Corp.
20050930	M W I Veterinary Supply, Inc.
20051231	Maidenform Brands, Inc.

20041231	Market Leader (Then HouseValues, Inc.)
20041231	McCormick & Schmick's Seafood Restaurants, Inc.
20060331	Micrus Corp.
20021231	Montpelier Res Holdings Ltd.
20011231	Morton's Restaurant Group, Inc.
20041231	Nalco Holding Co.
20031231	National Financial Partners Corp.
20041231	NeuroMetrix, Inc.
20051231	NeuStar, Inc.
20061231	NewStar Financial, Inc. (Now First Eagle Private Credit, LLC)
20061231	NightHawk Radiology Holdings, Inc.
20061231	NTELOS Holdings Corp.
20061231	Obagi Medical Products, Inc.
20051231	optionsXpress Holdings, Inc.
20061231	P G T Innovations (then P G T, Inc.)
20061231	Physicians Formula Holdings, Inc.
20041231	PlanetOut, Inc.
20050331	Prestige Consumer Healthcare (Then Prestige Brands Holdings)
20041231	ProCentury Corp.
20031231	Quality Distribution, Inc.
20051231	Quintana Maritime Ltd.
20060331	R B C Bearings, Inc.
20050131	R T W Retailwinds (then New York & Co.)
20021231	Red Robin Gourmet Burgers, Inc.
20051231	Reddy Ice Holdings, Inc.
20021231	Regal Entertainment Group
20061231	Regency Energy Partners LP
20051231	Rockwood Holdings, Inc.
20051231	Ruths Hospitality (then Ruth's Chris Steak House, Inc.)
20021231	S I International - now Serco Services
20051231	SeaBright Insurance Holdings, Inc. (Now SeaBright Holdings, Inc.)
20030630	Seagate Technology LLC
20061130	Sealy Corp.
20051231	Silicon Graphics International Corp. (was Rackable Systems)
20060831	SMART Modular Technologies (WWH), Inc.
20061231	Spirit AeroSystems Holdings, Inc.
20061231	Susser Holdings Corp.
20041231	Symmetry Medical, Inc.
20051231	SYNIVERSE Holdings, Inc.
20041231	T N S, Inc.
20041231	T R W Automotive Holdings Corp. (ZF TRW Automotive Holdings)
20051231	Taleo Corp.
20031231	Temper Sealy (was Tempur-Pedic International)
20061231	Town Sports International Holdings, Inc.
20060930	TransDigm Group, Inc.
20061231	U S BioEnergy Corp.
20041231	Ultra Clean Holdings, Inc.
20051231	Union Drilling, Inc.

20040930	Universal Technical Institute, Inc.
20061231	VeraSun Energy Corp.
20051031	Verifone Systwems (then VeriFone Holdings)
20051231	W & T Offshore, Inc.
20061231	Warner Chilcott Ltd.
20041231	WellCare Health Plans, Inc.
20051231	Xerium Technologies, Inc.
20060131	Zumiez, Inc.
20021231	ZymoGenetics, Inc.

The Impact of Chinese Capital Outflows on Bitcoin vs. Yuan Relationships: A Multi-Period Analysis

Michael Williams, Mucahit Kochan, and David Green

Abstract

We examine the relationships among Bitcoin (BTC), the Chinese Yuan (CNY), and Chinese capital outflows between 2014-2021. We find that BTC returns strongly comove with CNY returns after 2018Q1, while no significant BTC/CNY relationship exists before 2018Q1. Further, the strength of the BTC/CNY relationship increases throughout 2018 to the present date. Yet, this relationship strength cannot be explained by periods of ascending BTC prices, changes in crypto mining location, nor changes in the use of BTC "mining pools". Instead, we find that the strength of the BTC/CNY relationship is strongly and directly related to Chinese capital outflows. We find no similar relationship with a "bogey" currency, the Euro, implying that the capital outflows -to-BTC/CNY relationship is unique to China and its capital outflow environment. In total, our novel results suggest that BTC is used as part of a process to move economically significant amounts of capital from mainland China.

Keywords: Bitcoin, BTC, cryptocurrency, Chinese Yuan, CNY, capital outflows

I. Introduction

Decentralized cryptocurrencies allow individuals to conduct business and transfer digital coins without binding government interference. As such, one of the most recognized cryptocurrencies, Bitcoin (BTC), has a significant potential to be used as a channel of global capital outflows and to bypass capital controls. As seen in the 2019 Global Digital Asset AML Research Report, published by blockchain security firm Peckshield, capital flight from China via BTC and other cryptocurrencies amounted to around $11.4 billion in 2019, alone (Redman, 2020). These facts raise the important question as to whether BTC and countries' "home currencies" are related to those countries' capital outflows. Our paper provides compelling evidence that this is, indeed, the case: periods of enhanced capital outflows are associated with stronger contemporaneous movements between BTC and the Chinese Yuan (CNY).

Although BTC *networks* are generally decentralized and anyone willing to devote computer power can mine BTC, BTC *mining* is predominantly centralized in China. According to the Cambridge Bitcoin Electricity Consumption Index and Stoll et al. (2019), China accounted for more than 75.5 percent of global BTC mining in late-2019. Further, while any set of mining participants may pool their mining efforts in order to enhance their expected mining profits, the majority of BTC mining pools are managed by individuals or organizations located in China. Mining pool concentration has been of such a concern to Chinese authorities that Vice Premier Liu He recently warned financial officials of a “clamp down on Bitcoin mining and trading activity” to ensure financial stability.

Michael Williams (michaelwilliams15@govst.edu), Governors State University; Mucahit Kochan (mkochan2@govst.edu), Governors State University; and David Green (dgreen@govst.edu), corresponding author, Governors State University

Capital outflows and capital control evasion is an especially strong concern for Chinese monetary policy makers, whose multi-decade battle with these issues is well known. These concerns have lead to decades of strong regulatory- and market- based interventions. In particular, China uses various restrictions to limit the depletion of Chinese foreign currency reserves while keeping the value of the Chinese Renminbi, also known as the Yuan, low. For example, regulators at the People's Bank of China (PBOC) and the State Administration of Foreign Exchange (SAFE) have put tight restrictions on Chinese citizens from participating in international markets; Chinese citizens are not allowed to move more than $50,000 per year out of the country. Further, the PBOC has routinely intervened in the exchange markets to hold CNY exchange rates low, with several U.S. Policymakers calling these interventions "currency manipulation" (Staiger and Sykes, 2010).

Speaking directly of PBOC/SAFE intervention in cryptocurrencies, the PBOC banned financial institutions from handling BTC transactions in 2013 and even shut down local cryptocurrency exchanges in 2017 (Library of Congress, 2018). This intervention has slowly but consistently continued to the present date where, in June, 2021, several bitcoin mining companies halted their operations including BTC.TOP which accounts more than 18 percent of China's hash rate (Campbell, 2021). As a result of these interventions, many BTC investors have moved to neighboring countries and a non-trivial number of BTC mining pools have sprouted up in the European Union. These effects are significant enough to create cross-country premiums in BTC. For example, Choi et al. (2020) report that BTC held in Korea demanded a 4.73% premium over BTC held in the U.S., something known as the "Kimchi Premium".

Yet, despite the capital controls, the regulatory burdens, and the movement of some BTC investors offshore, BTC mining and mining pools are nevertheless uniquely concentrated in China; a concentration that has been and is remarkably consistent over time. Just as there is a "Kimchi Premium" due to BTC investor location, it is not unreasonable to hypothesize that there is also a BTC pricing effect induced by the considerable concentration of BTC production in China. Further, it is also not unreasonable to hypothesize that a BTC vs. CNY relationship should covary with changes in Chinese capital outflows; outflows that may have, in part, been facilitated by BTC's transaction-obscuring power.

We examine these hypotheses in this paper wherein BTC, CNY, and Chinese capital outflows are compared and linked. Specifically, we find that BTC and CNY exhibit significant comovement behavior at daily intervals. This cross-rate comovement, however, only appears in the latter half of our sample; a time marked by increasing Chinese capital outflows. We further test BTC/CNY comovement against Chinese capital outflows using a rolling-regression approach. Both by visual inspection as well as through rigorous econometric modeling, we find that the strength of BTC/CNY comovement increases with stronger Chinese capital outflows. Note that we do not find a similar set of relationships when using a "bogey" currency (i.e. the European Union Euro) or capital outflow data (i.e. from the European Union).

Thus, our results describe and provide evidence towards Chinese capital outflows impacting the strength of cross-price movements between BTC and CNY. These results have implications for BTC and CNY market participants, central bank regulators, and everyday cryptocurrency users. We continue in Section 2 with a review of the existing literature, explain our methodological approach in Section 3, present our results in Section 4, and then provide concluding remarks in Section 5.

II. Literature Review

Since Bitcoin's (BTC) 2009 introduction as the world's first cryptocurrency, the aggregate market value of all cryptocurrencies exceeded $2 trillion in April, 2021 (Kharpal, 2021). Due to cryptocurrencies' popularity, there is a growing interest in research related to cryptocurrencies, especially BTC. Many papers in the extant literature cover such topics as market efficiency from both the transactions-processing and informational perspectives (e.g. see Kim, 2017; Tiwari et al., 2018; Urquhart, 2016; Wei, 2018); pricing dynamics during extreme market fluctuations, an aspect that's almost synonymous with BTC (e.g. see Corbet et al., 2018; Fry and Cheah, 2016; Fry, 2018); volatility dynamics, clustering, and causes (e.g. see Katsiampa, 2019; Urquhart, 2017; Aalborg et al., 2019); news announcement effects (e.g. see Corbet et al., 2020; Vidal-Tomása and Ibañez, 2018; Feng et al., 2018); diversification, hedging, and risk reduction for use in both traditional-asset portfolios as well as within cryptocurrency portfolios (e.g. see Bouri et el, 2017a; Baur et al., 2018; Urquhart and Zhang, 2019); regulation and the impact of regulatory regimes (e.g. see Ju et al., 2016; Viglione et al., 2015; Luther and Salter, 2017); and more (e.g. see Corbet et al., 2019 for a comprehensive overview of cryptocurrency literature).

Limited portions of the prior literature argue against the existence of interactions between cryptocurrencies and home currencies. For example, Yermack (2015) finds no correlation between BTC and fiat currency rates during economic announcements between July, 2010 and March, 2014. Similarly, Bouri et al. (2017b) analyze BTC's ability to act as a "safe haven" for the United States Dollar (USD), among other assets. While their results do suggest that BTC can act as a limited diversifier, BTC would not be considered as a "safe haven" for USD fluctuations.

Yet, the majority of existing literature finds that BTC prices co-move and, at times bi-causally impact, home currency exchange rates. For example, but using relatively low frequency data, Carrick (2016) compares the correlation of BTC and emerging market currency returns from January, 2011 to December, 2015. Carrick finds statistically significant correlations among BTC and the various exchange rates. Of particular note is that the BTC vs. Chinese Yuan (CNY) correlation is positive while the non-BTC/CNY correlations are negative. Pieters (2016) uses daily data to show that BTC price changes can be used to estimate countries' exchange rate changes and that sub-daily data frequencies may not capture BTC vs. home currency interactions.

In addition to existing at daily intervals, BTC vs. home currency effects also detectable at higher frequencies. For instance, Urquhart and Zhang (2019) use hourly BTC and exchange-rate data to analyze BTC's properties as a hedge or safe-haven. Here, the authors find that BTC can act as a safe haven for four exchange rates and a diversifier for three others. Sensoy (2019) tests the weak form efficiency of BTC vs. a variety of home currencies. Sensoy finds that different exchange rates have different cross-rate dynamics but that market efficiency has increased over time for Euro- and USD- based BTC prices. Further, as inefficiency increases with data frequency, Sensoy provides evidence that there is a time delay to efficiency. Finally, Sensoy shows that differences in different countries' exchange rates, alone, do not govern BTC vs. exchange rate dynamics. For example, liquidity increases cross-price efficiency whereas volatility decreases this efficiency.

To be sure, the extent of BTC vs. home currency interactions are not economically trivial. For example, Kim (2017) finds the potential for cross-rate arbitrage profits across 16 different exchange rates. Further, these profits primarily derive from BTC's surprisingly-smaller average bid-ask spreads, relative to the home currencies. Not only does Kim show that BTC vs. home currency relationships exist and the fact that these relationships are economically significant, but also that traders can efficiently use BTC as a means of currency conversion.

With respect to the general issue of capital controls, flows, and flight, more-traditional studies examine capital outflows via bond issuances, foreign direct investment, and trade of goods (e.g. see Bruno and Shin, 2015; Feyen et al., 2015; Avdjiev et al., 2014; Wang and Wang, 2015; Aizenman, 2004; Lin and Ye 2018 while still others specifically focus on Chinese capital outflows (e.g. see Gunter, 2004; Ljungwall and Wang, 2008; Cheung and Qian, 2010).

While the literature on general capital flows is vast, the prior literature regarding the interaction among BTC, home currencies, and capital flows is more limited and indirect. For example, Cheng and Dai (2020) show the potential for using BTC to facilitate CNY/USD carry trade using BTC and where this relationship strengthens during heightened PBOC restrictions on BTC. No such relationship was found for currencies with relatively unrestricted capital flows. In net, the authors' results suggest that BTC transactions can be used to bypass regulations and capital controls. Pieters (2016) finds similar results wherein BTC may be a means for bypassing capital controls. Makarov and Schoar (2020) more directly link BTC usage with capital outflows in that cross-rate arbitrage opportunities arise from either the slow-moving of capital (Duffie, 2010) or binding capital controls.

Looking at the literature showing a more-direct link between BTC usage and capital outflows, Ju et al. (2016) examine capital outflows via BTC transactions from the CNY to the USD. The authors find evidence of capital flight shortly before the PBOC's December 5, 2013 announcement prohibiting BTC transactions for financial institutions and intermediaries. Ju et al.'s results are reinforced by Yu and Zhang (2018) who document that economic uncertainties induce heightened cryptocurrency demand. Yu and Zhang assist Ju et al. in that we would expect an intuitive relationship between economic uncertainty and the desire to shield wealth from this uncertainty (read: capital outflows).

Another relevant study is Griffin and Shams (2020) who investigate whether Tether influenced BTC during BTC's rapid price appreciation during its 2017 boom. This study is relevant in that Tether is a stablecoin whose value is pegged to the USD and is frequently used as a transaction facilitator among various means of exchange. In other words, Tether's relationship with BTC is an exchange rate equivalent of BTC's relationship with a home currency. Here, the authors find that Tether transaction flows explain BTC prices, indicating that cryptocurrencies may act as decentralized and partially-anonymizing financial intermediary in the capital outflow process.

Where the current paper fits into and expands the existing literature is that our empirical methodology allows for a *direct* examination of the BTC, home currency, and capital outflow relationship. Our modeling approach relies on little hand waiving or indirect inference and is, instead, a direct statistical test on this triad of relationships. Also, our paper bridges the gap between a.) Ju et al. (2016) who show a linkage between BTC *transactions* and capital outflows and b.) Griffen and Shams (2020) who show a relationship between BTC *prices* and capital outflows; we examine how capital outflows drive BTC vs. home currency price dynamics, thus examining both mechanisms simultaneously.

III. Methodology

This study employs two methodological approaches to understand Bitcoin (BTC) vs. "home currency" interactions and, especially, how these interactions may be shaped by capital outflows. While each approach is, ultimately, focused on the Chinese Yuan (CNY) vs. BTC relationship, we employ a "bogey" home currency, the Euro (European Union; EUR) to help clarify the relationship among CNY, BTC, and Chinese capital outflows.

The first methodological approach focuses on uncovering the presence and extent of BTC vs. home currency relationships. Here, daily BTC prices are collected from CoinMarketCap and merged with daily, directly-quoted currency data for the CNY and EUR from Yahoo! Finance. This process leads to a merged dataset spanning September, 2014 to March, 2021. Note that March, 2021 was designated as the sample end date as, past this time, a myriad of potentially confounding central bank and regulatory interventions were enacted. Returns for the various BTC and currency rates are calculated as follows:

$$r_X = \frac{(P_t - P_{t-1})}{P_{t-1}}$$

and was chosen over alternative return definitions (e.g. "log normal returns") to preserve the full extent of tail behavior in all series.

From there, the following two regression models are estimated using Ordinary Least Squares (OLS) with Newey-West (1987) heteroskedasticity- and autocorrelation- corrected standard errors:

$$r_{BTC,t} = \alpha_0 + \sum_{j=1}^{5} \beta_j \, r_{BTC,t-j} + \sum_{j=1}^{5} \gamma_j \, r_{CNY,t-j} + \lambda_{CNY} \, r_{CNY,t} + \varepsilon_t \qquad \text{(Eq. 1A)}$$

$$r_{BTC,t} = \alpha_0 + \sum_{j=1}^{5} \beta_j \, r_{BTC,t-j} + \sum_{j=1}^{5} \gamma_j \, r_{EUR,t-j} + \lambda_{EUR} \, r_{EUR,t} + \varepsilon_t \qquad \text{(Eq. 1B)}$$

Here, BTC returns are modeled as a function of lagged own-returns to account for own-autocorrelation effects, lagged home currency returns to account for cross-autocorrelation effects (e.g. inefficient spillovers between BTC and a given currency), as well as a contemporaneous home currency return variable that reflects the direction and strength of BTC vs. home currency comovement.

As seen in Figure 1, BTC has experienced tremendous price appreciation over its life and, especially, during 2020-2021. To ensure that our results are robust to potential breakdates, and to extend the richness of our results, each estimation is performed under four separate time regimes: a Full sample extending from September, 2014 to March, 2021; an Early sample spanning September, 2014 to April, 2018; a Late sample extending from May, 2018 to March, 2021; and a separate, Bubble sample spanning March, 2020 to March, 2021. The breakdate for the Early and Late samples is chosen using a Chow Breakpoint Test (Chow, 1960) while the beginning of the Bubble sample was based on the lowest BTC price in 2020 (i.e. March 12th, 2020).

Three Wald Coefficient Restriction tests are employed against Equations 1A/B, for each BTC/currency pair, and for all four samples:

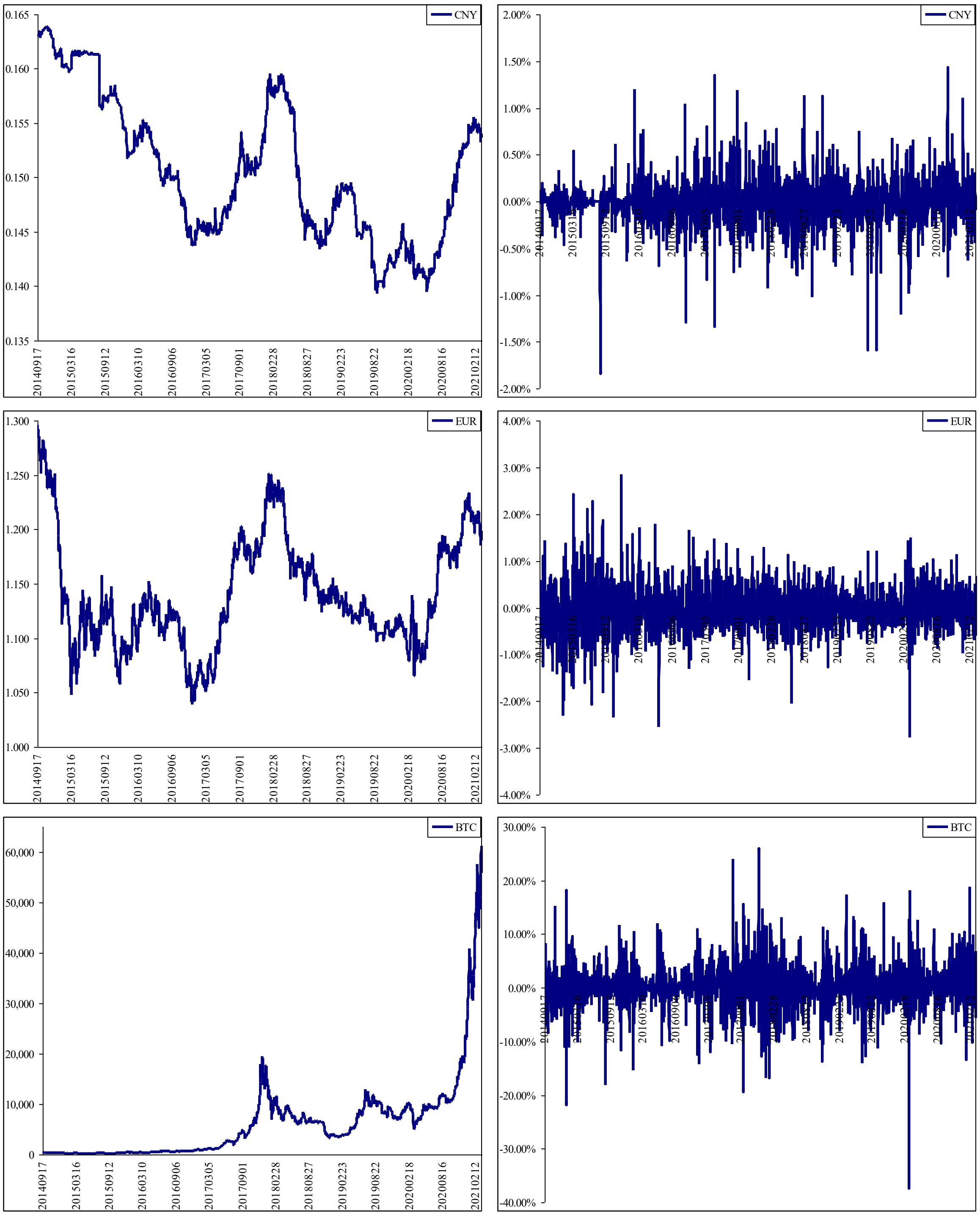
$$\gamma_1 = .. = \gamma_5 = 0 \qquad \text{(W1)}$$

$$\gamma_1 + .. + \gamma_5 = 0 \qquad \text{(W2)}$$

$$\lambda_{Currency} = 0 \qquad \text{(W3)}$$

Figure 1 Price Data

The following figures report the levels (left) and returns (right) of Chinese Yuan (CNY), European Union Euro (EUR), and Bitcoin (BTC) exchange rates, all relative to the United States Dollar (USD), and across the September, 2014 to March, 2021 time periods.



W1 tests if the collection of (cross-autoregressive) currency-to-BTC impacts are jointly significant. W2 tests a slightly more stringent form of W1 wherein currency-to-BTC impacts may be cumulatively (and jointly) significant. W3 tests whether the currency-vs.-BTC relationship exists on a contemporaneous basis, hence measuring currency vs. BTC comovement after own- and cross- autoregressive effects have been accounted for. Note that, through our use of the Newey West correction in each of our estimations, results from the above restriction tests should be free from auto-regressive and heteroskedastic interference. Also note that we've selected five own- and cross- autoregressive terms for use in Equation 1 A/B to explicitly model up to one, full week's worth of trading activity.

As is seen in the Literature Review and elsewhere, we believe that there is a strong case for BTC being used, in part, for capital outflows in countries with binding capital controls. It follows, then, that any use of BTC for capital outflows should have a contemporaneous impact on BTC vs. home currency relationships. That is: capital outflow demand via BTC should induce capital outflow participants to exchange their home currency with BTC, thus leading to discernable BTC vs. home currency effects. Further, this BTC vs. home currency relationship should be positively-related to capital outflows such that increases (decreases) in capital outflows should be associated with stronger BTC vs. home currency relationships.

To test the above hypothesis, we model the strength of BTC vs. home currency relationships (i.e. the estimated parameter from Equation 1 A/B; $\lambda_{Currency,t}$; CNY and EUR) as a function of capital outflows ($Value_{Country}$; China and EU; FXEmpire.com), linear (T) and quadratic (T^2) trend variables to account for autonomous changes in the BTC vs. home currency relationship over time, and a binary Outlier variable equal to one when capital outflows for a given country is greater than one standard deviation away from the historical mean:

$$\hat{\lambda}_{Currency,t} = \alpha_0 + \psi_{Country}\, Value_{Country,t} + \theta_1 T_t + \theta_2 T_t^2 + \theta_3\, Outlier_t + \omega_t \qquad \text{(Eq. 2)}$$

We operationalize the above approach by, first, parsing the Full (daily) dataset into quarterly segments. Then, we estimate Equation 1A (1B) for CNY (EUR) and for each quarterly time period, separately. With each quarterly estimate, we capture a quarterly measure of BTC vs. home currency strength, $\lambda_{Currency,t}$, and compare it against each country's quarterly-reported level of capital outflows. Here, we use the inverse of each country's capital account as a proxy, broad measure of capital outflows; see Schneider (2003) for different definitions of capital outflows used in the literature. Note that we use the level value for each country's capital outflows as, both visually and via regression estimates, flight is mean reverting and is not unitary persistent (i.e. a unit root process).

If capital outflows are, indeed, related to a given currency's contemporaneous relationship with BTC, we should see that the following hypothesis test (W3) is rejected at a sample-appropriate level of significance:

$$\hat{\lambda}_{Currency,t} = 0$$

IV. Results

We begin our analysis with Figure 1 which plots the Chinese Yuan (CNY), European Union Euro (EUR), and Bitcoin (BTC) level and returns series. Here, we note that all series exhibit various trend regimes and, most prominently, with BTC experiencing a massive appreciation in value, starting in early-2020. Also, while CNY and EUR returns are constrained within modest bounds, BTC has experienced significant price shocks over time; some these extending ± 30%. Thus, throughout our analysis, we pay particular attention to ensuring robustness against data-, structural break-, and model instability- issues. Also, while this study does not explicitly model own- or cross- volatility dynamics, we do employ the Newey-West (1987) heteroskedasticity- and autocorrelation- correction to each estimation.

Table 1 reports the estimation results for Equations 1A and 1B across the four sample periods. In total, these results are consistent with strong (weak), time-varying BTC vs. CNY (BTC vs. EUR) relationships. Specifically, across the Early sample and using a 5% significance level, we fail to reject both the causal- (i.e. W1 and W2) and coincident- (W3) restriction tests; this applies to both CNY and EUR. While these findings do not completely rule out BTC vs. home currency relationships at the intraday frequency during the Early period (e.g. see Chan at el., 2011), our results do suggest that BTC is not impacted by home countries' exchange rate movements at the daily -to- weekly time scales from September, 2014 to April, 2018.

Table 1 Returns Comovement

The following tables report regression results for the Bitcoin (BTC) vs. Chinese Yuan (CNY) relationship (Table 1A; Eq. 1A) and the Bitcoin (BTC) vs. European Union Euro (EUR) relationship (Table 1B; Eq. 1B) across four samples: Full (September, 2014 to March, 2021), Early (September, 2014 to April, 2018), Late (May, 2018 to March, 2021), and Bubble (March, 2020 to March, 2021). Note that "Wald Zero p-Value" and "Wald Sum p-Value" refer to the p-Values calculated from Wald coefficient equality- (W1) and summed- (W2) restriction tests, respectively, on each model's causality parameters. Further, "Comovement p-Value" and "Comovement Coef." represent each model's coincident parameter restriction test (W3) p-Value and estimated coefficient, respectively. Please see the Methodology section regarding Equation 1 for more details on the econometric modeling.

Table 1A BTC vs. CNY

	Full	Early	Late	Bubble
Wald Zero p-Value	0.678	0.825	0.702	0.035
Wald Sum p-Value	0.644	0.345	0.687	0.665
Comovement p-Value	0.026	0.352	0.020	0.008
Comovement Coef.	-0.882	-0.546	-1.223	-2.924

Table 1B BTC vs. EUR

	Full	Early	Late	Bubble
Wald Zero p-Value	0.886	0.988	0.517	0.152
Wald Sum p-Value	0.430	0.884	0.068	0.013
Comovement p-Value	0.622	0.805	0.536	0.361
Comovement Coef.	-0.089	-0.054	-0.220	0.530

Yet, during the Late sample period, we find that BTC vs. home currency relationships do emerge and especially so as the sample nears the present date. Specifically, we find that BTC co-moves contemporaneously with CNY in both the Late (p-Value: 0.020) and Bubble samples (p-

Value: 0.008). Further, the magnitude of the BTC/CNY relationship increases by more than 2.39 times in the Bubble sample, relative to the Late sample. These narrowly-focused results indicate that the BTC relationship with CNY is time-varying and increased substantially during BTC's recent price bubble. Note that, in addition to the strong contemporaneous relationship, we find limited evidence of causality in the BTC/CNY relationship during the Bubble sample. While this finding may indicate that the BTC/CNY relationship is prone to extended inefficiencies during extraordinary market conditions, nevertheless, the contemporaneous relationship remains.

Contrasting with the above BTC/CNY results, we find that the BTC vs. EUR relationship is never significant at the contemporaneous level and across any of the four sample periods. Further, while we find limited evidence of EUR-to-BTC causality in the Bubble sample (p-Value of Wald Sum test: 0.013), the lack of contemporaneous BTC/EUR relationships may suggest that Bubble sample BTC/EUR causality is transitory; perhaps related more to market-induced inefficiencies than a consistent, economic phenomena.

For robustness purposes and in unreported results (available upon request), we extend Equations 1A and 1B by adding five return lags of a multi-cryptocurrency index variable (i.e. the CMC Crypto 200 Index; CoinMarketCap) to account for systematic crypto currency effects. We find that the BTC/CNY results described above still hold despite the addition of this systematic variable. However, when employing these same index returns to Equation 1A, we do not find evidence of BTC/EUR relationships, causal or coincident, and for any sub-period. This provides further evidence that the limited and weak EUR-to-BTC causality noted above is not likely a bona fide and consistent economic phenomena. BTC/EUR causality is, instead, likely a result of temporary market inefficiencies or the influencing effects of systematic crypto market conditions.

As noted in the Methodology section, we are using a split sample design to not only gain a richer understanding of BTC vs. home currency effects, but also as BTC has experienced significant volatility and price trends over its life. A related concern of this volatility is the possibility that the above results are biased by additional, unaddressed model instability. To test for this, we perform recursive -residual and -coefficient analyses on each Full sample (i.e. Equation 1A and 1B) estimation. We find that, with the exception of a few minor disturbances, the results in Table-1 A/B are robust to potential model-, data-, and relationship- instability; results available upon request. Additionally, as some in the prior literature opt for Quantile Regression approaches (as opposed to OLS; e.g. see Bouri et al., 2017 and Balcilar et al., 2017) in order to account for volatile BTC price swings and tail behavior, we have similarly employed Quantile approaches for robustness purposes. We find that our results in Table-1 A/B are qualitatively unchanged when extending from an "averaging" OLS approach to a more tail-oriented, Quantile approach; results available upon request.

Thus, from Figure-1 and Table-1 A/B, a picture of BTC vs. CNY relationships emerges wherein BTC and CNY interact, mostly on a contemporaneous basis, and especially so during the recent rise in BTC prices. Yet, the question remains as to "what influences BTC vs. CNY comovement at daily intervals?" and, relatedly, "why do we not see this same effect for BTC vs. EUR?".

A potential explanation, as seen in much of the prior literature, is hedging. That is: in addition to the hedging plain vanilla portfolio risk, traders may wish to also hedge home currency movements with BTC, and vice versa (e.g. see Urquhart and Zhang, 2019). Yet, while intuitively appealing, this potential explanation is not supported by our findings of a.) strong BTC/CNY relationships in the face of b.) weak BTC/EUR relationships. If hedging currency risk was a suitable explanation for our results, we should see similarly strong BTC vs. home currency effects in both the CNY and EUR. The currency hedging hypothesis is further refuted by our findings (above) that the (expected-value oriented) OLS regression results are qualitatively similar to the (tail-value oriented) Quantile regression results. If currency hedging was a suitable hypothesis, we should see that the OLS-based BTC/CNY and BTC/EUR relationships were also captured, and equally so, in the Quantile-based results; they were not.

Beyond the currency hedging hypothesis, other explanations may also intuitively seem to hold. For example, it may be possible that the solid (weak) BTC/CNY (BTC/EUR) relationship is a result of coin-mining location and, in particular, China's dominance of the BTC mining space. Here, we know from prior literature (e.g. see Romiti et al., 2019) and from empirical data obtained from “btc.com”, that China’s mining market power has not fallen below 50 percent. In fact, China is and has been for some time the dominant location for BTC mining. Yet, China's relatively consistent mining market power cannot explain our findings that BTC/CNY relationships increased over the latter half of the sample; particularly so during the massive price appreciation that began in mid-2020. We see a similar argument against crypto "mining pools" being behind BTC/CNY relationships as a.) China's abundant use of BTC mining pools hasn't significantly changed over time whereas b.) the BTC/CNY relationship has changed over time. Further, attempts at linking the changing BTC vs. home currency relationship with periods of BTC price appreciation also fail. If BTC price appreciation was to blame for BTC vs. home currency effects, both BTC/CNY and BTC/EUR relationships should behave similarly (but do not).

Thus, it seems a bit of a paradox that BTC/CNY relationships exist and seem to be related to phenomena occurring predominantly after 2018, despite the lack of change in mining dominance and other possible explanations. One explanation receiving only sparse attention in the prior literature rests in the evading of capital controls and capital outflows. As summarized in Ocampo (2017): the People's Bank of China (PBOC) has enacted several capital control regimes over the past decade, sometimes proactively and sometimes reactively. This contrasts with the European Central Bank's relatively lax capital control policies (e.g. see Honohan, 2020). Could it be that Chinese capital outflow demand mixed with the resulting failure of binding capital controls, is related-to and possibly an explanation-for BTC/CNY relationships?

To test for this possibility, we begin by plotting quarterly-aggregated capital outflows for both China and the EU in Figure 2. Additionally, we co-plot the quarterly-estimated "BTC vs. home currency strength" coefficient ($\lambda_{Currency,t}$; see Methodology for more estimation details). Here, we see that Chinese capital outflows have experienced wild swings throughout time, starting quite strong in 2014 to 2015 when the PBOC was attempting a series of liberalizations, dually oriented at preventing so-called "hot money flows" (e.g. see Ding et. al, 2014). From about 2015 to 2018, Chinese capital outflows began to fluctuate, decline, and then escalate significantly in early-2020. This contrasts with EU capital outflows which, while volatile, do not surpass Chinese capital flight in magnitude and does not experience a clear, early-2020 acceleration.

What's more is that, when we plot the quarterly-estimated "relationship strength" coefficient against capital outflows in Figure 2, an interesting pattern emerges. Specifically, Chinese capital outflows vary in remarkably similar ways to BTC/CNY strength but does not vary contemporaneously with EU capital outflows. Also, visually speaking, EU (Chinese) capital outflows are loosely (not) related to the BTC/EUR relationship strength coefficient. This differential behavior is in line with our estimation results in Table 1. Further, these findings provide initial evidence that Chinese BTC participants, whether they be miners, traders, or others, evade quasi-binding PBOC capital controls through the use of BTC.

To test this capital outflow hypothesis more formally, we estimate Equation 2 for the 2x2 combination of capital outflows (Chinese and EU) and relationship strength (BTC/CNY and

Figure 2 Capital Outflow & Relationship Strength

The following figures plot quarterly Chinese (Figure 2A) and European Union (Figure 2B) capital outflows (solid black lines) from 2014Q4 to 2020Q4 and where positive (negative) values represent capital outflows (inflows) from (to) a given country. Also, quarterly-estimated comovement parameters (see Methodology section; light grey dotted line) for the Bitcoin/Yuan (left) and Bitcoin/Euro (right) relationships are plotted. All individual-level figure scales have been matched for illustrative purposes.

Figure 2A Chinese Capital Outflows

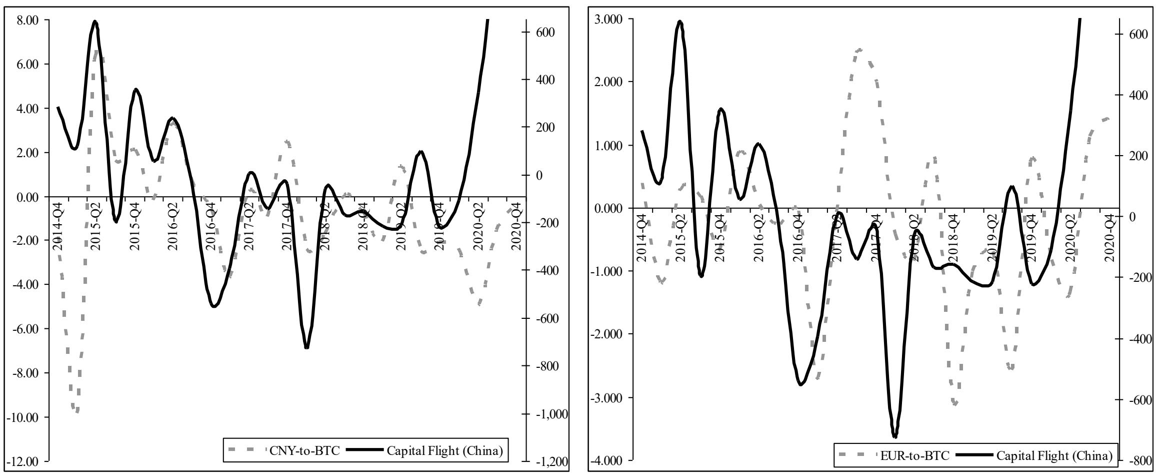
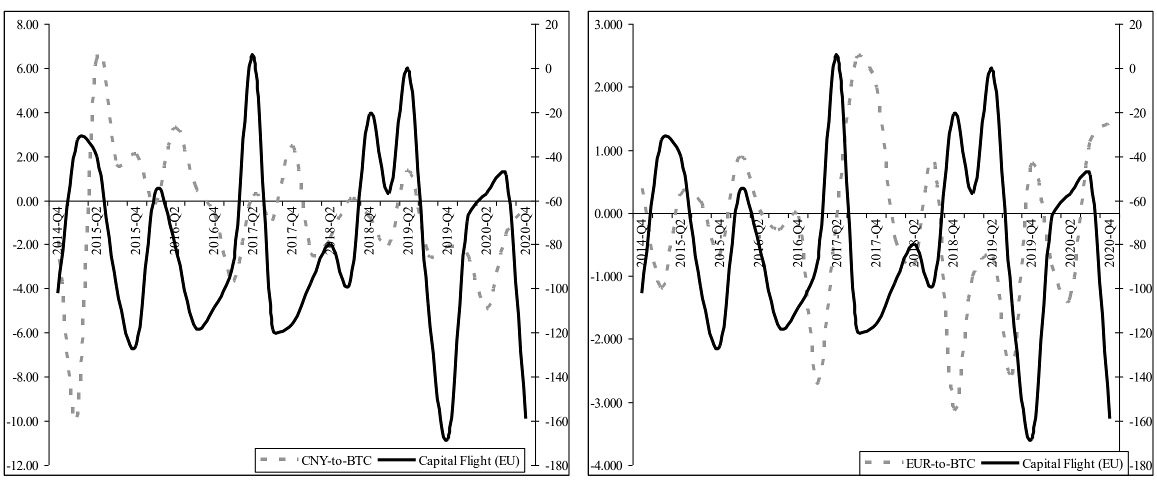


Figure 2B European Union Capital Outflows



BTC/EUR). As reported in Table 2A and using a 10% significance level due to sample considerations, both the BTC/CNY and BTC/EUR relationships are significantly- and positively-related to contemporaneous changes in Chinese capital outflows. Further, the relationship between Chinese capital outflows and the BTC/CNY relationship is remarkably stronger than the BTC/EUR relationship; the impact parameter (*Value*) for the BTC/CNY relationship is more than

3.51 times that of the BTC/EUR relationship; the BTC/EUR-focused estimation also has an effectively-zero adjusted R^2.

Table 2 Capital Outflows & Relationship Regressions

The following tables report the regression estimation results for Chinese capital outflows (Table 2A) and European Union capital outflows (Table 2B) against a quarterly-estimated coincident parameter for the Chinese Yuan (CNY) vs. Bitcoin (BTC) relationship (left panels) and EU Euro (EUR) vs. Bitcoin (BTC) relationship (right panels). Within each table, Alpha refers to each model's intercept, Value represents the capital outflow impact variable, T1 (T2) represents a linear (quadratic) trend variable, and Outlier is a binary variable equal to one when a given region's capital outflows are greater or less than one standard deviation from the mean. Please see the Methodology section regarding Equation 1 (for time-varying coincident parameter modeling) and Equation 2 (for the estimation results reported in the tables below).

Table 2A Chinese Capital Outflows

	CNY vs. BTC		EUR vs. BTC	
	Coef	p-Value	Coef	p-Value
Alpha	-5.025	0.111	-0.774	0.315
Value	0.005	0.008	0.001	0.066
T1	1.118	0.045	0.154	0.474
T2	-0.048	0.024	-0.007	0.410
Outlier	0.520	0.675	0.062	0.914
Adj R2	0.209		≈ 0.000	

Table 2B European Union Capital Outflows

	CNY vs. BTC		EUR vs. BTC	
	Coef	p-Value	Coef	p-Value
Alpha	-1.458	0.613	-0.502	0.456
Value	-0.006	0.592	-0.011	0.038
T1	0.226	0.546	-0.094	0.523
T2	-0.012	0.323	0.003	0.613
Outlier	-0.330	0.859	-0.278	0.637
Adj R2	≈ 0.000		≈ 0.000	

Note that, in separate, unreported results (available upon request), we re-estimate Equation 2 where the *difference* in comovement coefficients (i.e. $\lambda_{China,t}$ - $\lambda_{EU,t}$) serves as the dependent variable. Based on this analysis, the comovement differential variable is positive and statistically significant at the 10% level (p-Value of 0.051) meaning that the qualitative difference seen in Table 2A (i.e. 3.51 times) is significant, both statistically and economically. Also, for robustness purposes, we applied different forms of the BTC vs. home currency coefficient as Equation 2's dependent variable (i.e. using the estimated t-Stats, as opposed to raw, estimated coefficients) and found that our results are quantitatively unchanged. Thus, the above findings that the BTC/CNY relationship is positively related to Chinese capital outflows (and more so than the BTC/EUR relationship) are robust to statistical noise and dependent variable specifications.

Contrasting with the Chinese capital outflow results found in Table 2A, the results in Table 2B examine how BTC/CNY and BTC/EUR co-vary with EU capital outflows. Here, we find that the BTC/CNY relationship is not at all related to EU capital outflows and has an effectively-zero adjusted R^2. The results of the BTC/EUR relationship with EU capital outflows are just as underwhelming as the estimated adjusted R^2 is, also, effectively zero. Additionally, the estimated coefficient for *Value* is negative (-0.011). These results either imply a nonsensical economic outcome or that EU capital outflows are achieved in ways unrelated to BTC and cryptocurrencies. Thus, while there is some evidence that the BTC/EUR relationship is related to EU capital outflows, the results are weak statistically, weak economically, and collectively suggest that BTC/EUR is more related to EU capital inflows than outflows.

In net, our results indicate that BTC and CNY have formed a statistically- and economically-significant contemporaneous relationship over time and especially after early-2020. The BTC/CNY relationship is remarkably similar of and statistically related to the patterns and strength of Chinese capital outflows. Conversely, BTC and EUR share inconsistent relationships with one another and have little to do with either Chinese or EU capital outflows. Thus, we provide evidence that Chinese market participants are (or are attempting) evading quasi-binding PBOC capital controls through the use of BTC. This evasive behavior causes an efficient, contemporaneous relationship between BTC and CNY to form and to strengthen as more evasion occurs. We do not find similar behavior for the EU, suggesting that EU market participants do not consistently evade, nor would they really need to evade, EU capital controls through the use of BTC.

V. Conclusion

The prior literature generally shows that Bitcoin (BTC) interacts with home currency exchange rates and, according to a smaller sampling of this literature, these interactions are potentially the byproduct of capital outflows. We build on and expand the extant literature by directly testing whether capital outflows significantly impact BTC's relationship with home currencies. Unlike prior studies our novel empirical approach allows us to directly measure capital outflow impacts on BTC/rate dynamics and to do so in a way that respects the time-varying nature of adaptive markets.

Using daily data spanning 2014 to 2021, we find that BTC is statistically correlated to the Chinese Yuan (CNY) and, to a much lower degree, the European Union Euro (EUR). Specifically, CNY and BTC positively comove, even after accounting for own- and cross- autoregressive effects. This comovement is time varying and is particularly strong after 2018Q1. Thus, CNY and BTC are correlated and this relationship has increased over time.

Unfortunately, factors such as BTC mining location, mining pool location, price bubbles, price crashes, and more fail to adequately explain the heightened BTC/CNY relationship over time. Yet, what can explain the heightened BTC/CNY relationship is capital outflows. Specifically, we find through both visual inspection and rigorous econometric analysis that Chinese capital outflows are positively and directly linked to the strength of the BTC/CNY relationship. That is, higher levels of Chinese capital outflows are concurrently associated with stronger correlations (read: strength) between BTC/CNY. We find much more limited evidence that Chinese capital outflows impact the BTC/EUR (European Union Euro; EUR) relationship, possibly due to the co-ownership of Chinese and European BTC mining pools. We find no evidence, however, that European Union capital outflows are associated with either BTC/CNY or BTC/EUR relationships. Our results have implications for individual traders, speculative investors, money managers, as well as financial regulatory bodies: capital outflows, exchange rate usage, and exchange rate impacts are co-determinative and must be simultaneously addressed to ensure optimal policy outcomes.

Thus, we find that BTC/home currency relationships can be driven by capital outflows, but not always. Looking towards future research: China's unique capital outflow situation, especially after 2018, may simply be an outlier. Alternatively, it may also be the case that China's extreme capital outflows have inadvertently-revealed behavior that is systematically replicated during other countries' periods of strong capital outflows. In addition to questions of the uniqueness or ubiquity of capital outflow induced BTC/rate effects, there is also the confounding impact of the US/China trade war which, coincidentally, began in early-2018. Did the trade war exacerbate the need for alternative currencies while, unrelatedly, increasing capital outflows? Or, was the US/China trade war a coincident but unrelated factor in the increased demand for Chinese capital outflows and BTC transactions? These questions, along with the impact of Central Bank interventions on BTC/rates, merit examination in future research.

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