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Two Essays in Economics and Finance

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Two Essays in Economics and Finance

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By

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Abstract

This dissertation contains two essays. The first essay investigates the measure of FX liquidity and determinants of the change in FX liquidity. Using 20 cross currency exchange rates over spanning period of 1999 to 2016, funding constraints and global risks are responsible for the main drivers of changing in FX liquidity. The magnitudes of both G7 and emerging volatility index are offsetting each other in all the regression models indicating that FX investors take diversification trading strategies to diversify their portfolios. The financial crisis provides an evidence that the more financial constraint issues contribute to the change in FX market illiquidity more than non-financial crisis period. Extending to liquidity predictability, I find, however, that the lag of market FX liquidity is responsible for the change in FX liquidity than any other explanatory variables

My second essay investigates the momentum returns of U.S. equities by presenting comprehensive approaches. Traditionally, momentum portfolios are constructed by ranking based on excess returns. Using this sorting technique, I confirm that there is a presence of momentum returns in U.S. equities for all of the 48 industries. The results also indicate that the portfolios that are sorted by idiosyncratic volatility as well as by diversification strategy cannot achieve the highest returns as for sorting based on excess returns. Further, I examine the momentum portfolio predictability using the inverse conditional volatility proposed by Moreira and Muir (2017), and show that the momentum returns are affected by the size of liquidity and the risk factors rather than by the economic variables.

Keywords: Currency; Emerging Market; Idiosyncratic Risk; Momentum; Diversification; Liquidity

Chapter 1

"Changes in FX liquidity: Roles of Funding Constraints and Global Risks"

1. Introduction

Why do investors pay attention to liquidity? The answer is that liquidity can influence the expected returns as well as the investment decisions[1]. It is not surprising that there is substantial amount of studies on the change in liquidity especially in stock market[2]. These studies, however, focus mainly on the stock markets, mainly in the U.S. By far, the size of trading activity of US stock market is relatively smaller than that of foreign exchange (FX) market[3]. Then, there is a need to investigate the impact of liquidity in FX market. The presence of FX liquidity is very important since the characteristics of FX market are distinctively different from both those of bond and equity markets, in which FX investors incorporate with information flow in the market better than in equity or bond markets (Phylaktis and Chen, 2010, Pasquariello, 2014). Then, FX investors are more aware of the public as well as private information before they initiate to such trading activities.

In this paper, I investigate the factors that drive the change in liquidity of foreign exchange (FX). I divide the factors that may influence the change in FX liquidity into two categories, namely funding constraints and global risks. In the literature, there is an ongoing debate the factors that change in FX liquidity (Mancini et al., 2013, Karnauhk et al., 2015, Banti et al., 2012, Banti and Phylaktis, 2015). In general, they conclude that the funding constraints, especially VIX spread contribute to the change in FX liquidity. This conclusion, however, ignores the fact that, as in equity market, the global risks can play in the role of FX liquidity change. Only paper that investigates the presence of global risk is Banti and Phylaktis (2015)

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[1] See. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) for the effect of changing in stock liquidity to the expected returns.
[2] i.e. Coughenour and Saad (2004), Korolyi, Lee, and van Dijk (2012), Brockman and Chung (2002).
[3] Bank for International Settlements (BIS) 2016 report that the average daily trading volume of FX market is $5.1 trillion.

which introduces JP Morgan volatility index as the measure of the global risk. The paper, however, does not address the differences between G7 countries and emerging countries which may potentially result upward bias[4].

This paper, I attempt to explain the gap in the literature whether other funding constraints can explain the change in FX liquidity as well as introducing the global risk index for both G7 and emerging countries to measure the magnitude of the change in liquidity. Mancini et al. (2013) state that the change in VIX is the only variable that can explain the change in liquidity, but Karnaukh et al. (2015) show that the change in TED can also explain the change in liquidity. The recent work by Banti and Phylaktis (2015) shows that only TED is the variable that can explain the change in FX liquidity. This conflict in literature motivates my interest to investigate and resolve the issue.

Furthermore, I test further to see whether the change in liquidity can be predictable. Using the set of the past information, I estimate the impact of the change in liquidity based on the past information. Then, I test for the excess return predictability based on the factors both funding constraints and global risks that are being determined in the first step adding with the predicted liquidity as well as using the average volatility and average correlation (Cedenese et al., 2014) to control for the predictability.

This paper, I introduce

(i) Using a new global risk (JP Morgan Volatility index) for both G7 and emerging to determine the change in FX liquidity.

(ii) Presenting that the magnitude of G7 and emerging indexes are offsetting with each other as the zero-sum game which one currency appreciates and one currency depreciates. Investors try to take opposite position when they are trading in the FX market.

(iii) FX investors tend to diversify their risks by investing in both G7 and emerging currencies as the evidence of the magnitudes for both indexes almost cancelling out each other.

[4] JP Morgan launched FX volatility index for both G7 and emerging market economies.

(iv) Using average correlation and average variance to determine the change in FX excess return, I find that liquidity can contribute to the change in excess return; however, the magnitude is very small compared to the past information of the currency itself. Investors interpret the risk from the past information and determine what will happen in the future as the average variance contributes to the most predictability of the change in currency excess return.

Foreign exchange (FX) market is considered the largest market in the world with the average trading of $5.1 trillion per day in April 2016 (BIS, 2016)[5]. The currencies are highly traded in developed currencies as they are accounted for 70% of daily trading. The presence of the FX market becomes one of the most discussing topics among academia and researchers. However, the big question of FX market is that, unlike the studies of bond and equity markets, what is the appropriate measurement of the FX liquidity and what would be the factors that drive the change in liquidity.

Galati, Heath, and McGuire (2007) observe the trader behavior in currency and other markets, and they find that the FX traders are taking at highly leveraged positions than participants of the other markets. Their findings provide a significant important in FX literature that FX investors are, in fact, looking to leverage and diversify their risks than investors in equity or bond markets. To observe the behaviors of FX investors, Phylaktis and Chen (2010) investigate the information asymmetry in FX market with top trading banks. Their result suggests the FX market provides private information that banks incorporate and transform the information into adjusted price based on the private information. Their finding is supporting the presence of efficient market hypothesis that private information plays in a role of price adjustment. Then, FX investors somehow are well-informed and adjust their trading behaviors according to new information in the market. Pasquariello (2014) studies the effects of FX market and reports the finding that the presence of FX market is to provide an efficiency and arbitrage parity conditions in the other markets. In sum, the

[5] Bank for International Settlements Annual Report 2016.

characteristics of FX market are different from the other markets such as bond and equity. Then, if the hypothesis of market efficiency in FX market is true, the FX liquidity should be somehow different from liquidity that are observed in the other markets.

In this paper, the market wide liquidity measure is constructed based on the bid-ask spread series of 20 cross currency exchange rates. The choice of these currencies is based on the trading activities reported by Bank for International Settlements (BIS) and data availability[6]. The series is constructed by using USD against foreign currency, i.e. USD as a numerator and foreign currency as denominator, to be consistent with many documented literature (Banti et al., 2012, Menkhoff et al., 2012, Brunnermeier et al., 2009). The sample period starts January 1999 and ends December 2016. The sample period is used to capture the recent financial crisis in 2008 as well as the introduction of EURO currency[7].

Then, I analyze possible factors that could be used to capture the change in FX liquidity as they are proposed in literature; repos, VIX, TED, JP Morgan VXY Volatility index, market return, and capital flows since these variables are widely used to proxy the change in illiquidity for equity, bond, and foreign exchange markets. Based on the regression models, the findings show that the change in TED, repos for both US and UK, volatility index for both G7 and emerging countries, and market returns are significant variables which they support the funding constraints hypothesis of the change in FX liquidity.

Then, I test with 5-factor model of Fama-French. Using only market return as independent variable may omit some possible explanatory and importance of individual variables to explain the change in liquidity. The result, using individual risk loadings, suggests that profitability and investment factors can contribute to the change in FX liquidity. However, out result reports that the investment factor is the only statistically significant variable. The result can infer that investment factor can partially explain the need for liquidity for investors to fund their investment strategies as to compensate the higher risk from their investments.

[6] To be included in the sample, currencies must have at least 5 years data availability and reported by Bloomberg Terminal at 16 GMT.

[7] Many literatures report the presence of EURO to affect the change in liquidity. See. Beber et al. (2008), Hua et al. (2002), De Santis (2014).

I analyze further to see whether financial crisis contributes to the funding constraint more than non-financial crisis period. The result indicates that the change in VIX now contributes to the change in FX liquidity while the change in TED does not. This result is surprising since the initial result only indicates the change in TED to be significant while VIX is not. The plausible explanation is that the change in VIX can capture the presence of global risk better than TED during the financial crisis period. Investors perceive the risk associated with the change in liquidity in the market. When the volatility is high, investors tend to slowdown the investment and result in less liquid in the foreign exchange market.

Once determining that global risks and funding constraints can play roles of the change in liquidity, the next question is whether the change in liquidity can be used to predict the change in currency excess returns. The study of currency predictability has been documented as Cedenese et al. (2014) test for the currency predictability using the average volatility and average correlation as proxies for the change in the excess returns. They find that the average volatility, defined as the average variance of portfolio currency, is the factor that drives the change in currency excess returns. Poti and Siddique (2013) provide an empirical evidence using carry trade approach on two groups of investors, namely diversified investors and undiversified investors. They find that undiversified investors require higher liquidity then diversified investors due to the capital constraints. These finding shows that the change in liquidity can be used to predict the change in currency returns.

Motivated by these findings, I estimate the change in liquidity based on the past information to determine the change in liquidity, I use the DCC model to estimate the impact of the change in liquidity based on the previous information. The result shows that the impact of the lagged variables are good indicators for the change in liquidity and they support the presence of return reversals as indicated by Banti et al. (2012). The funding constraints and global risks can be used to predict the change in liquidity in FX market.

Following the Cedenese et al. (2014) approach, I use average correlation and average variance as control variables with other explanatory variables, namely the change in TED, the predictive liquidity, and the change in volatility indexes. I find that most of the independent variables are able to use for currency prediction; however, the change in indexes cannot. The average variance provides the strongest magnitude more than other variables. The change in currency excess returns depends highly on their own risks rather other factors indicating that currencies themselves provide substantial information to predict the future returns than other factors included the change in liquidity.

The contributions of this paper are: (i) I confirm the presence of the funding constraints and global risks as the possible explanation of the change in market FX liquidity, especially repo rates, volatility indexes, and the change in TED spread, (ii) during the financial crisis period, the global risks play an important role than funding constraints to explain the change in FX liquidity as the change in volatility indexes for both G7 and emerging countries can capture the change in liquidity much more than non-crisis period, (iii) I test for the liquidity predictability and find that the FX liquidity is dependable on the past information from the market-wide risks; however, the funding constraints seem to appear having less effect to determine the change in liquidity, and (iv) the currency excess return predictability depends on the average variance more than other variables, including the predicted liquidity variable.

This paper is organized as follows: Section 2 summarizes the related literatures. Section 3 explains the data and methodology used in this paper. The choice of currencies as well as the sample period is explained. Then, I introduce the data description of each determined variables for both global risks and funding constraints in Section 4. The empirical analysis is presented in Section 5. Then, I provide discussion based on predictability in Section 6. The paper provides conclusion and remarks in Section 7.

2. Literature Review

Amihud (2002) presents measures of the illiquidity of cross-section and time-series of liquidity premium. His finding of the presence of liquidity premium provides a substantially significant contribution to the literature and to the following literatures (Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005, Baker and Stein, 2004, Bekaert and Harvey, 2007)[8] to observe the liquidity measure and the presence of liquidity premium in the stock and bond returns.

There is no general agreement on the methods used to determine the presence of liquidity premium, especially in FX market. The most common methodology used to observe the change in liquidity in financial assets is bid-ask spread. Most of literatures (see. Stoll, 1989, Bessembinder, 1994, Hsieh and Kleidon, 1996) report the similar finding that bid-ask can be used to measure the liquidity since the methodology provide the pressure of buyers and sellers initiating in such transaction. The spread of bid-initiated and ask-initiated transaction creates the need for liquidity. However, such methodology is widely used in financial assets (asset pricing). Then, the next question is "can bid-ask spread measure the change in FX liquidity?"

Mancini et al. (2013) observe the liquidity in foreign exchange markets of major trading currencies. They analyze the impact of FX liquidity risk using carry trade approach, trading technique to borrow lower interest rate currencies and invest in high interest rate currencies, and their finding suggests that there is an existence of liquidity premium in FX market. Consistent with Amihud's illiquidity measure, they conclude that the change in bid and ask spread is the appropriate proxy to observe the change liquidity and the liquidity risk in FX market. Karnaukh et al. (2015) also provide evidence of liquidity in FX market by observing the bid and ask spread. They provide the determinants of changing in FX liquidity by using demand-side hypothesis and supply-side hypothesis. Their finding indicates that FX liquidity declines when facing funding constraints. Furthermore, they find strong co-movements between liquidities in distressed markets when funding is constrained, volatility of the market is high, and FX speculators incur losses.

The extensive study on the impact of FX liquidity is reported by Banti et al. (2012). They observe 20 cross currency exchange rates using a modification of Pastor and Stambaugh's liquidity approach and sorting portfolios based on level of currency sensitivities. Using the spread between bid-quotes and ask-quotes,

[8] These papers observe the presence of liquidity in equity and bond markets. They provide a general conclusion that there is a presence of liquidity premium for investors to take a position in the market.

they find that the equity liquidity measure from Pastor and Stambaugh (2003) provides an evidence of return reversals in currencies and they find that the estimate liquidity risk premium in FX market is approximately 4.7 percent per annum. Their finding supports the point of view that investors require higher premium when they invest in the higher risk or more sensitive currencies, and they require the higher excess returns to compensate their risks.

Banti and Phylaktis (2015) investigate the determinants of the time variation of the common component of FX liquidity using cross currency exchange rates for both developed and emerging currencies. They argue that funding liquidity constraints and capital flows are associated with the FX market liquidity. The funding constraints using in their paper are the repos (both US and UK), and stock returns while the capital flows are the flows both inflow and outflow of bond and equity from U.S. database. They also provide the empirical evidence that using global FX volatility (JP Morgan VXY Volatility index) be the appropriate proxy for measuring global FX volatility. Their finding shows that the funding constraints severely affect to the change in FX liquidity meanwhile the volatility index depicts the significant result confirming that investors require higher returns when they are facing liquidity issues.

In sum, bid-ask spread is the most widely used to measure liquidity in both financial assets and FX market and most of the literature supports such methodology is appropriate to capture the change in liquidity in foreign exchange market. Furthermore, many literatures document the findings that liquidity measure in FX markets is mainly driven by the funding constraints. However, it is not well-documented whether what specific factors drive the change in FX liquidity. Then, there is a need of the study of the factors that drive the change in FX liquidity. From this reason, it motivates my interest towards the measure of FX liquidity and determinants to the change of FX liquidity.

3. Data Description

In this paper, I collet 20 daily cross currency exchange rates spanning from December 1999 to December 2016. The primary data sources are from Bloomberg Terminal and Thompson and Reuters with the closing time of 16 GMT since it is highly traded period in FX markets and correlated with the bid-ask measure as discussed by Karnaukh et al. (2015). The total trading transactions are provided by Bank of International Settlement (BIS). The exchange rates are defined as USD against foreign currency as it is widely used to measure the changes in US dollar value. Of the 20 currencies on the sample, 10 are of developed currencies, and 10 are of emerging currencies, namely Australian Dollar (AUD), Brazilian Real (BRL), Canadian Dollar (CAD), Swiss Franc (CHF), Czech Koruna (CZK), Danish Krone (DKK), Euro (EUR), British Pound (GBP), Hungarian Forint (HUF), Japanese Yen (JPY), South Korean Won (KRW), Mexican Peso (MXN), Norwegian Krone (NOK), New Zealand Dollar (NZD), Polish Zloty (PLN), Swedish Krona (SEK), Singapore Dollar (SGD), Turkish Lira (TRY), Chilean Peso (CLP). The choice of currencies is based on the trading activities provided by BIS database, in which these currencies are accounted for more than 70% of daily trading activities[9].

3.1 FX Liquidity Measures

The most widely accepted of measuring FX liquidity is to use bid and ask spread (Mancini et al., 2013; Banti and Phylaktis, 2015; Karnaukh et al., 2015). The price impact of seller and buyer initiated creates the need for liquidity. Then, the bid-ask spread measures the transaction costs of buyer and seller initiated in such transactions. The higher the spread means that the higher the transaction costs, and lower the liquidity level. Therefore, the bid-ask spread represents in fact the measure of illiquidity. Note that the illiquidity measure can be changed to liquidity by multiplying a negative sign.[10]

I define the bid and ask spread as the proxy for illiquidity measure as:

$$BA_{i,t} = (ask_{i,t} - bid_{i,t})/mid_{i,t}, \tag{1}$$

[9] BIS 2016 provides the annual report and ranks the currencies based on the trading volumes. The trading volumes are calculated daily for both buying and selling activities. Each currency must present at least 5 years of data availability with bid and ask quotes.

[10] For example, refer to Karnukh et al. (2015).

where $ask_{i,t}$, $bid_{i,t}, and\ mid_{i,t}$ are the monthly series of the ask, bid, and mid prices of the quotes of the USD against currency i.[11]

Table 1: Summary statistic of bid-ask spread of 20 cross currency exchange rates from December 1999 to December 2016. The bid-ask spread is calculated from equation (1): $BA_{i,t} = (ask_{i,t} - bid_{i,t})/mid_{i,t}$. $ask_{i,t}$, $bid_{i,t}, and\ mid_{i,t}$ are the monthly series of the ask, bid, and mid prices of the quotes of the USD against currency i. the series is taken log difference to preserve the stationary assumption in time series.

No.	Currency	Obs	Mean	Std. Dev
1	USDAUD	216	0.000549	0.000678
2	USDBRL	216	0.000890	0.000904
3	USDCAD	216	0.000427	0.000471
4	USDCHF	216	0.000636	0.000859
5	USDCZK	216	0.002084	0.001651
6	USDDKK	216	0.000361	0.000357
7	USDEUR	216	0.000239	0.000356
8	USDGBP	216	0.000264	0.000341
9	USDHUF	216	0.003417	0.002800
10	USDJPY	216	0.000369	0.000409
11	USDKRW	216	0.000842	0.001717
12	USDMXN	216	0.001260	0.001430
13	USDNOK	216	0.001362	0.001552
14	USDNZD	216	0.000863	0.000944
15	USDPLN	216	0.002543	0.003414
16	USDSEK	216	0.001012	0.000867
17	USDSGD	216	0.000884	0.001151
18	USDTRY	216	0.003623	0.007291
19	USDZAR	216	0.003588	0.003348
20	USDCLP	216	0.001205	0.005431

Table 1 presents the mean and standard deviation of bid and ask spread. The bid-ask spreads in developed currencies, as expected, are lower in both means and standard deviations than emerging currencies. Consistent with Carrieri et el. (2013), the developed market is more integrated than developing market. Then, the spread of the developed currencies is to be less volatile then emerging currencies. Note that Turkish Lira[12] has the highest spread and highest standard deviation since Turkey experienced the currency

[11] Bid and ask spread measure can be estimated using $BA_{i,t} = (ask_{i,t} - bid_{i,t})/2$ as suggested in literatures (See. Pastor and Stambuagh, 2003, Bekaert and Harvey, 2007).
[12] The inclusion of Turkish Lira is to compare the change in highly exposure currency among other currencies.

crisis in early 2000s and my sample covers during the period. The result is consistent that the higher spread, the currency is more volatile.

Table 2: summary statistics of regression of individual currency illiquidity on market illiquidity from December 1999 to December 2016. The coefficient of the regression is reported with betas. T-test is also reported by using an adjustment of Newey-West (1987) and reported on the t-test column.

No.	Currency	beta	t-test
1	USDAUD	0.069385	10.24
2	USDBRL	0.015862	3.25
3	USDCAD	0.053835	9.58
4	USDCHF	0.073358	10.3
5	USDCZK	0.030046	4.87
6	USDDKK	0.063252	9.32
7	USDEUR	0.045564	6.01
8	USDGBP	0.041855	6.13
9	USDHUF	0.045111	7.62
10	USDJPY	0.052286	7.92
11	USDKRW	0.034407	3.4
12	USDMXN	0.072173	8.74
13	USDNOK	0.051687	10.23
14	USDNZD	0.048947	7.56
15	USDPLN	0.046705	7.14
16	USDSEK	0.048771	8.83
17	USDSGD	0.061522	9.23
18	USDTRY	0.047258	7.34
19	USDZAR	0.057443	8.69
20	USDCLP	0.057652	6.78

Following Chordia et al. (2000a) and Pastor and Stambaugh (2003), I calculate the market-wide illiquidity as $\frac{1}{20}(\sum_{i=1}^{20} BA_{i,t})$, where *BA* is the bid-ask spread. The market-wide illiquidity is the equally weighted average of individual spread series for all 20 exchange rates. To see whether the market-wide illiquidity can explain the change in individual currency illiquidity, I regress the change in individual currency illiquidity measure against the change in market-wide illiquidity and the results are presented in Table 2. Consistent with literature, I find that market illiquidity can explain the change in individual currency illiquidity, as reported by T-test. Developed currency illiquidity tends to be explained more by the change in market wide illiquidity than emerging currency illiquidity.

3.2 Determinants of FX Illiquidity

The change in FX liquidity (or illiquidity), as documented by many literatures, is affected by the funding constraints and global risks (Karnaukh et al., 2015, Banti et al., 2012, Banti and Phylaktis, 2015). This section I provide the determinants used in literature to determine the FX liquidity.

3.2.1 The Repo

Repo or repurchase agreement is the short-term borrowing for financing purpose. Investors enter the repo market to finance purchase of securities (Adrian and Shin, 2010, Gorton and Metrick, 2012). The most common collateral of repo is US and UK markets which provide relatively low credit risk and high liquidity. Repo is a part of funding constraint in the FX market since repos can change the liquidity in financial markets. Banti and Phylaktis (2015) estimate using outstanding repos for both US and UK, and find that repos provide the funding constraints in FX liquidity. However, they use the amount of outstanding in their estimation. In this paper, I estimate the repos using the repo closing price since the price impact of repos may significantly affect the change in liquidity as there was the huge drop in repo price for both US and UK after the financial crisis in 2008. The repo data are collected from Bloomberg using the end of the day data. I construct using the last price of the month to determine the monthly repo price.

Table 3: summary statistic of US and UK repo from December 1999 to December 2016. The period is included during the recent financial crisis period in 2008. The table represents the first difference order to preserve the stationary assumption.

Variable	Mean	Std. Dev.	Min	Max
US Repo	-0.01084	0.264002	-1.42712	1.203973
UK Repo	-0.01586	0.090292	-0.65387	0.313503

Table 3 presents the summary statistics of both US and UK repos. As expected, US repo are more volatile than UK repo. The higher standard deviation of the US repo is due to the cumulative of the volatility period during the financial crisis. This is evident that US and UK repo be used as the funding constraint in the FX liquidity, especially during the financial crisis period.

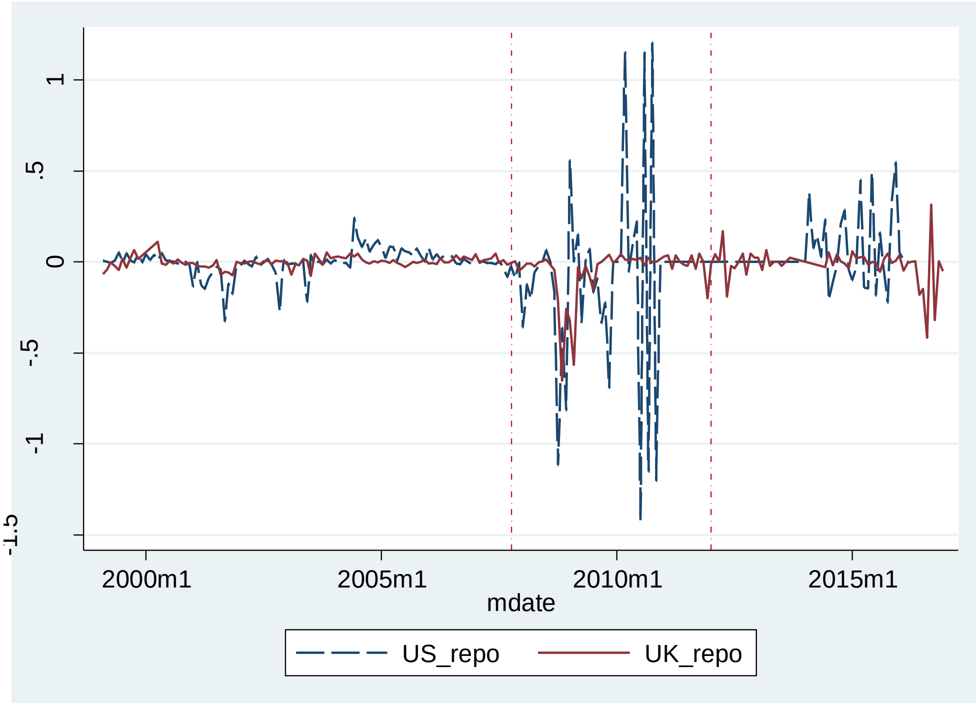

Figure 1: US and UK Repos. The graph shows the difference in end of the month price of US and UK repos. US repo represents by the dash line and UK repo is solid line. The vertical lines represent the financial crisis period from 2008 to 2012.

Figure 1 presents the change in repos for both US and UK repos. The stationary is satisfied by taking the difference at the end of the month price. As shown on the figure, during the financial crisis period, the repurchase agreements were very volatile. US repo reached up to +1.2 and lowest at almost -1.5 while UK repos moved between +0.1 and -0.6 which this reflects that UK repos were less volatile than US repo market during the financial crisis. The change in repo markets are perceived as the funding constraint issues in the financial market and they experienced the huge drop after the financial crisis for both US and UK markets.

3.2.2 VIX and TED

Recent documented literature suggests that VIX and TED spread can explain the change in FX liquidity (Karnaukh et al., 2015). VIX, as the definition from Chicago Board of Options Exchange (CBOE), indicates the implied volatility of S&P500 index options. This measures the fear or expectation of volatility in the option market. TED, on the other hands, implies the interest rates differences on interbank loan and T-bills.

Both VIX and TED are used as the indicators of the funding constraints[13] that investors are facing during the volatile period. My initial hypothesis is that VIX and TED spread should have the same direction for FX illiquidity since these measures are used to determine the market-based implied volatility. The data are collected through FRED website[14].

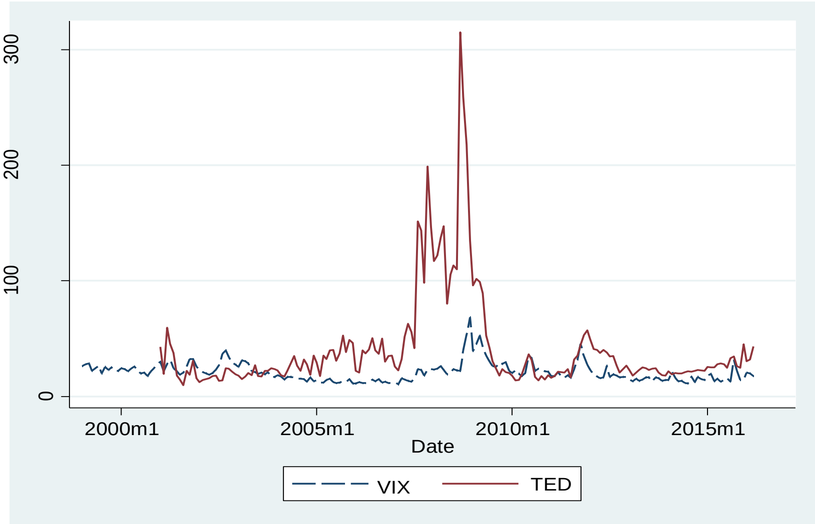

Figure 2: VIX and TED. VIX is represented by dash-line while TED is solid line. The graph shows VIX and TED from December 1999 to December 2016.

The figure 2 represents VIX and TED indexes. During the financial crisis, the explosive of the VIX and TED reached to the highest. Investors perceived the risks of the financial market that market were illiquid. Karnaukh et al. (2015) explain that the liquidity declines with funding constraints. Also, when VIX and TED increase, FX liquidity becomes more illiquid. Brunnermeier, Nagel, and Pedersen (2008) also suggests the TED spread as the measurement of market illiquidity.

3.2.3 Volatility Index

I include the volatility index in my analysis. The volatility index is used to control the level of uncertainty of FX market (Menkhoff et al., 2012) as an increase in volatility can affect the riskiness of the currency

[13] See. Menkhoff et al. (2012)
[14] The Federal Reserve Bank of St. Louis.

exchange rates. The primary volatility index is JP Morgan VXY volatility index[15]. Banti and Phylakits (2015) include this volatility index in their model and suggest that the index can be used to indicate the level of riskiness of holding inventory in currency exchange.

The data are collected from Bloomberg the spanning period from December 1999 to December 2016 to be consistent with cross-currency exchange rate data. I construct the data using end of the month volatility index for both G7 and emerging index. The reason to include both emerging (JPMVXYEM) and G7 (JPMVXYG7) in the sample is that the volatility pressure from one market should affect the volatility of the other market. For example, once US Dollar weakens, the other currencies will be appreciated as the change in US Dollar is now volatile. Moreover, FX investors tend to diversify their risk by investing in both developed and emerging currencies. Then, for the diversification purpose, the change in volatility of one market will either advantage or disadvantage to the other market. I hypothesize that since both indexes can capture the level of riskiness in currency market, then I should see the similar movement of the indexes, and co-movement with the market illiquidity.

Figure 3 and 4 show the volatility index for emerging and G7 countries, respectively. For both indexes, the market was very volatile during the financial crisis period. Consistent with what I expected, the market perceived the riskiness of currency market investment. The indexes reached to almost 25 points under emerging countries and 20 points for G7 countries. The higher volatility should incorporate with higher illiquidity of FX.

[15] The JP Morgan VXY volatility indexes are based on the aggregate volatility of individual currencies and calculated with value-weighted approach.

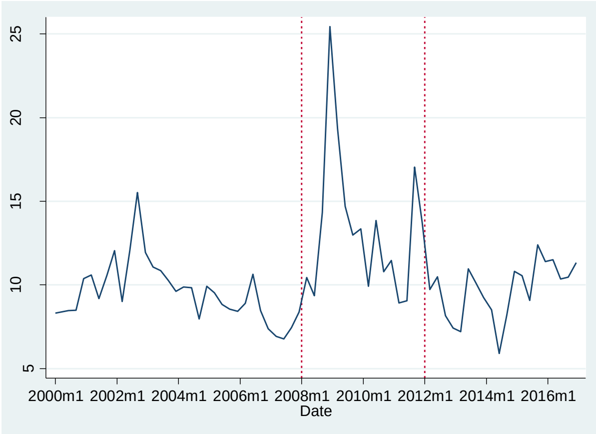

Figure 3

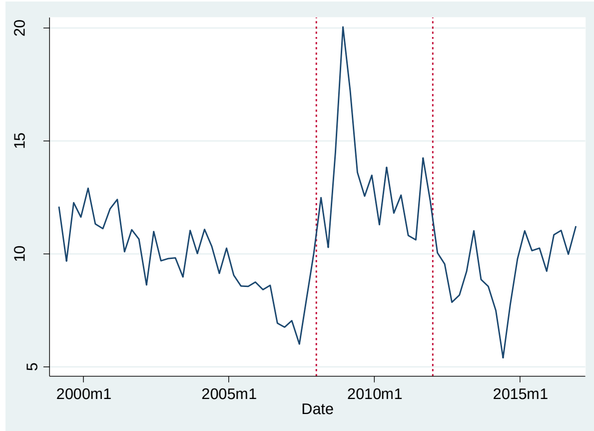

Figure 4

Figure 3 and 4: Volatility indexes, Emerging and G7 countries, respectively.
The dash lines represent the period of financial crisis from 2008 to 2012.

3.2.4 Market Returns

I also hypothesize that the market return should provide a good indicator for amount available capital in market. The financial constraint can be binding when the performance of financial institution declines. Acharya and Viswanathan (2011) suggest that the less funding or tighter funding constraint can severely affect the ability to generate the money for lending in the capital market. Then, I expect to see the market returns to be positively correlated with the FX market illiquidity since investors would demand higher returns during the less liquid period. The data are obtained from Kenneth R. French Website[16]. I estimate using the five-factor model since the model includes investment risk loading factor which indicates the funding availability.

3.2.5 Capital flows

I investigate the capital flows as part of the change in liquidity in FX market. Banti and Phylakits (2015) measure the capital flows as the aggregated flow of international capital between the US and foreign countries, and suggest that larger capital flows can improve the market liquidity since sophisticated investors are more active in the FX market and these investors are more likely to reduce the spreads due to the lower inventory risks and trade increases. The data are obtained from the U.S. Department of Treasury.

[16] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

I estimate the capital flows using the net flows end of the month reported by the U.S. Department of Treasury. The initial hypothesis of capital flows is that the presence of capital flows should not have any effect to the change in FX liquidity since the capital flows are used mainly to measure the change in liquidity in equity market. Since the size of FX market is much larger than equity market, the change in capital flows should not be pronounced.

The capital flows estimation is based on the net flow of the capital between the US and other countries. I take the first difference the capital flows to preserve the stationary assumption of the time series. The capital flows may affect the change in FX market liquidity; however, the flows are aggregated. Then, using the aggregated capital flows of the US equity and bonds may overestimate my result or insignificant.

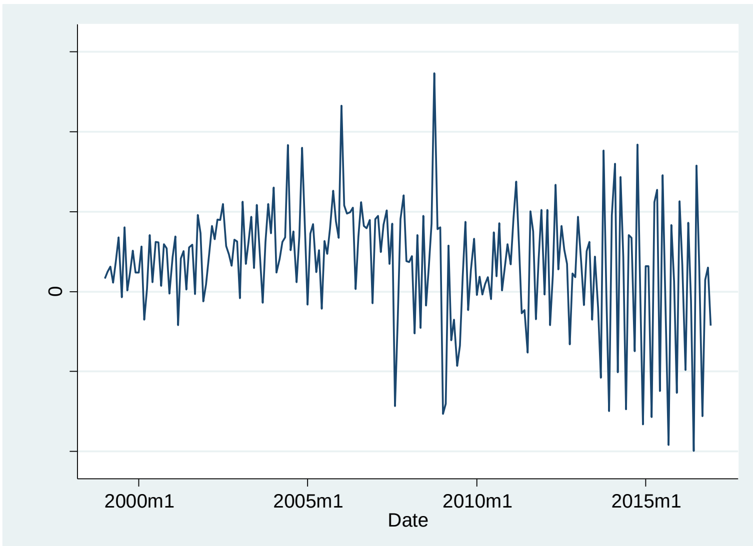

Figure 5: the change in net capital flows. The change in net capital flows is estimated by the net change in capital flows at the end of the month reported by the U.S. Department of Treasury.

3.3 Correlation among variables

To track the possibility of multi-collinearity, I run the correlation test among the independent variables to see whether any potential multi-collinearity, especially in US and UK repos. The result, as shown in table 4, shows that there is a weak negative relation between US and UK repos. Banti and Phylakits (2015) track the change in the amount of outstanding of US and UK repos, and report the correlation of 0.26. Then, using the change in the repo price does not change the fact that US and UK repo are not showing any collinearity issue. Other variables seem to have reasonable correlation among others. Note that JPMVXYG7 and JPMVXYEM are highly negatively correlated. This result is expected since these two volatility indexes are used to diversify portfolio and help rebalancing the possible shocks in either developed or developing market.

Table 4: Correlation among proposed variables from December 1999 to December 2016.

	MKT_Illiq	JPMVXYG7	JPMVXYEM	UK Repo	US Repo	VIX	TED	BA	Flows
MKT_Illiq	1.00								
JPMVXYG7	-0.04	1.00							
JPMVXYEM	-0.05	-0.89	1.00						
UK Repo	-0.19	0.04	0.09	1.00					
US Repo	-0.04	0.03	0.03	-0.09	1.00				
VIX	0.15	-0.10	-0.08	0.06	-0.24	1.00			
TED	0.21	-0.15	-0.14	-0.02	-0.05	0.25	1.00		
BA	0.50	-0.02	-0.02	-0.09	-0.02	0.07	0.10	1.00	
Flows	0.13	-0.20	-0.23	-0.05	-0.15	0.12	-0.10	0.06	1.00

4. Methodology

I conduct the regression test to observe whether variables can explain the change in FX market illiquidity. The regression is determined by the following model:

$$\Delta Illiq_{i,t} = ai + \beta'^{(\Delta X_t)} + \gamma' \Delta Vol_t + \delta' \Delta Illiq_{t-1} + \varepsilon_t + Fixed\ effect \quad (2)$$

where $\Delta Illiq_t$is the change in FX market illiquidity, $\Delta X_t$is the determinants that are described in the previous section. The variables are listed as following:

- ΔVIX_t – the change in VIX spread
- ΔTED_t – the change in TED spread
- $\Delta US\ Repo_t$ – the change in US repo
- $\Delta UK\ Repo_t$ – the change in UK repo
- $\Delta Mkt\ Ret_t$ – the change in market excess return

- $\Delta Flows_t$ – the change in net capital flows

Vol_t is JP Morgan Volatility index (JPM) for both G7 (JPM $G7_t$) and emerging countries (ΔJPM EM_t). The change in volatility index is used as the control variable for market uncertainty. The lag of FX market illiquidity ($\Delta illiq_{t-1}$) is also being used as a control variable.

I test further to see whether when using other variables from 5-factor would have an impact on the market returns of international asset portfolios[17]. I estimate using the regression below:

$$\Delta Illiq_t = a + \beta'^{(\Delta X_t)} + \Psi'(FF_t) + \gamma'\Delta Vol_t + \delta'\Delta Illiq_{t-1} + \varepsilon_t + fixed\ effect, \tag{3}$$

where FF_t is the 5-factor of Fama-French. I also use ΔVol_t and $\Delta Illiq_{t-1}$ as proxies for the change in FX market illiquidity.

Brunnermeier and Pedersen (2009) suggest that the liquidity dry-ups are worse during the financial crisis period. Banti and Phylaktis (2015) estimate the recent financial crisis, the collapse of Lehman Brother during September 2008 to July 2009, and their result indicates that during the financial crisis the effects of funding constraints and aggregated flows are stronger. To test for the change in liquidity during the financial crisis period, I assign the dummy variable equal to 1 indicating financial crisis period, and zero otherwise. I assign the dummy variable from March 2007 to June 2009 to be consistent with the change in volatility index for both G7 and emerging market economics. The impact of market failure can be observed from the VIX and TED spread as the volatility accumulation started to increase since beginning of 2007 and smoothed out after June 2009. The regression is estimated as following:

$$\Delta Illiq_t = a + \beta'\left(\Delta X_t * Dummy_t^{crisis}\right) + \Phi'\Delta X_t * Dummy_t^{nocrisis} + \gamma'\Delta Vol_t + \delta'\Delta Illiq_{t-1} + \varepsilon_t + Fixed\ effect \tag{4}$$

[17] Fama and French (2016) test 5-factor model with international asset portfolios and find that these factors can depict the market returns of international asset portfolios.

where $\Delta Illiq_t$ is the change in FX market illiquidity, ΔX_t is the determinants that are described in the previous section. Vol_t is JP Morgan Volatility index (JPM) for both G7 (JPM $G7_t$) and emerging countries (ΔJPM EM_t). The lag of FX market illiquidity ($\Delta illiq_{t-1}$) is also being used as control variable.

5. Empirical Results

5.1 Regression Analysis

Table 5 reports my preliminary result based on equation (2). Under model (1), I use all the proposed variables to track the change in market illiquidity. The result suggests that most of the variables are statistically significant except for ΔVIX_t and $\Delta Flows_t$. The insignificance of ΔVIX_t can partially be explained that VIX spread cannot capture the change in FX liquidity as it does for equity market due to the differences of characteristics between equity and FX market. Unlike VIX, TED can be used to explain the change in FX market illiquidity (Karnaukh et al., 2015, Brunnermeier, Nagel, and Pedersen, 2008). Inconsistent with Banti and Phylaktis (2015), I find that the change in aggregated capital flows of US equity and bonds ($\Delta Flows_t$) are not significant. The plausible explanation is that the capital flows of equity and bond are way less than the flows of the currencies ($3.2 Trillion approximately according to Forex annual report in 2016[18]). Then, the change in capital flows does not reflect to the change in FX market illiquidity. The change in repos is statistically significant for both US and UK repo in contrast to Banti and Phylaktis (2015). Their measurement is to use US and UK repo outstanding, not the repo price and their results suggest that the proxies for repos are not statistically significant. The change in repo price can be interpreted that tightening the funding constraints result in an increase in transaction costs. Then, the market becomes more illiquid as the repo prices are getting higher.

[18] Annual Report is available at www.Forex.com

Table 5: empirical result from regression equation (2): $\Delta Illiq_t = a + \beta(\Delta X_t) + \gamma\Delta Vol_t + \delta\Delta Illiq_{t-1} + \varepsilon_t$ where ΔX_t variables are: ΔVIX_t is the change in VIX spread, ΔTED_t is the change in TED spread, ΔUS $Repo_t$ is the change in US repo, ΔUK $Repo_t$ is the change in UK repo, ΔMkt Ret_t is the change in market excess return, and $\Delta Flows_t$ is the change in net capital flows. Vol_t is JP Morgan Volatility index (JPM) for both G7 (JPM $G7_t$) and emerging countries (ΔJPM EM_t), and $\Delta illiq_{t-1}$ is the lag of FX market illiquidity. The sample period is from December 1999 to December 2016. The t-test are adjusted via Newey-West (1987) and reported in parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)	(3)
ΔVIX_t	0.0685		
	(1.35)		
ΔTED_t	0.3846	0.3890	0.4122
	(12.58) **	(13.44) **	(13.56) **
ΔUS $Repo_t$	-0.0835	-0.0738	0.1332
	(-3.97) **	(-3.64) **	(6.46) **
ΔUK $Repo_t$	-0.0105	-0.0104	
	(-9.35) **	(-9.32) **	
ΔMkt Ret_t	0.0154	0.0162	0.0150
	(8.75) **	(9.76) **	(9.01) **
$\Delta Flows_t$	0.0001		
	(1.12)		
ΔJPM $G7_t$	0.0279	0.0279	0.0036
	(3.57) **	(3.56) **	(0.94)
ΔJPM EM_t	-0.0268	-0.0273	
	(-4.35) **	(-4.46) **	
$\Delta illiq_{t-1}$	-0.6151	-0.6175	-0.6532
	(-48.41) **	(-49.59) **	(-52.65) **
Constant	0.0093	0.0156	0.0452
	(0.23)	(0.39)	(1.12)

As demonstrated from the data and methodology section, I use the JPMorgan Volatility Indexes for both G7 and Emerging as the global risk variables to test for the change in market illiquidity. The result, interestingly, suggests that volatility index for G7 is positively correlated with the change in market illiquidity while volatility index for emerging shows negative relation with market illiquidity, both are statistically significant. Also, the magnitudes of these volatility indexes are almost cancelling out each other (0.0279 for G7 and -0,0269 for emerging). This result indicates that, although the indexes are moving along at the same direction as suggested in figure 3 and 4, the currency trade is a zero-sum game meaning that one currency benefits from the expense of the other. For example, USD appreciates while other currencies to be depreciated. Then, the similar magnitudes with opposite signs of G7 and EM indexes can be explained by the presence of currency gain from one country to currency loss from the other.

Next, I consider the model (2) to run regression only significant variables from model (1). Consistent with the result from model (1), I find that the significant variables from model (1) are also significant in model (2). Furthermore, the G7 and emerging volatility indexes have the similar magnitudes but different signs as I find in model (1). The result confirms that both indexes can capture the change in market illiquidity but they provide different signs indicating the gains from currencies at the expense of the others.

To confirm whether the presences of the severe funding constraints and global risks from developed currencies influence the change of market illiquidity, I test using only G7 volatility index and US repo. According to the volume of currency trading, G7 currencies account for more than 70% of daily trading[19], then using only these variables should be, at least partially, able to explain the change in market illiquidity. Running the regression under model (3), I find, however, that the G7 volatility index becomes insignificant, which is different from model (1) and (2). Then, to take into an account for measuring FX market illiquidity, using both indexes provide a clear picture than using only one index. Note that I also test for emerging volatility index (not reported), and the index becomes insignificant as I find it under in model (3)[20]. Since there is no theory support the differences in the presence of the volatility index, my finding provides an important discussion whether the result is driven by either G7 countries or emerging countries. Only plausible explanation is that investors in FX market are well-informed to the change in price and be more sensitive to the risks involved in currency trading than investors of other markets (Galati, Heath, and McGuire, 2007). Then, they always take trading positions in both developed and emerging currencies reflecting the coefficients of these indexes to be offsetting each other.

[19] BIS annual report and Forex annual report.

[20] Testing for emerging volatility index provides similar magnitude and different sign compared to G7 volatility index.

The lag of the change in market illiquidity is negatively statistically significant as suggested by documented literature (Pastor and Stambaugh, 2003, Menkhoff et al., 2012, Banti et al, 2012, Mancini et al., 2015) that the lag of market illiquidity is a measure for return reversal. The market return also affects the change in FX market illiquidity. The influence of return of equity market depicts certain movement of the equity market along with currency market. These variables are statistically significant for all three models.

In sum, the change in market illiquidity can be explained the change in funding constraints. FX liquidity perceive the change in funding as the sign of liquidity movement. The result also suggests that the volatility indexes, or global risks, can contribute the change in FX market illiquidity.

5.2 Regression Test with Fama-French Model

The result from the previous section suggests that the market return from the equity can influence the change in FX market illiquidity. Then, I analyze further using equation (3) to see the effect of 5-factor to the change in liquidity.

The result is reported on the table 6. I estimate using each of 5-factor for each model: model (1) – HML, model (2) – SMB, model (3) – RMW, model (4) – CMA, and model (5) – all factors. Using one variable at a time does not show any statistically significance except for model (3) and (4). Using the comprehensive model (model (5)), only CMA is positively statistically significant while other variables in 5-factor are not significant. The result suggests that, CMA, conservative investment minus aggressive investment, investors tend to be more risk averse in FX market than being aggressive. This can also be interpreted that sophisticated investors take positions in the FX market to provide more liquidity position in their investment strategies. Moskowitz, Ooi, and Pedersen (2012) provide empirical evidence that the hedgers and speculators take short and long position and generate the substantial amount of the liquidity needs for the FX market. Hedgers tend to provide more stabilization to the FX market better than speculators do for FX market.

Other variables are statistically significant as it shows in the previous regression result. Also, the coefficients of volatility index of G7 and emerging countries are, again, almost entirely offsetting each other. For example, under model (5), 0.0299 in G7 countries and -0.0269 in emerging countries. This result suggest that these variables can contribute to the change in FX market illiquidity. However, when observing individual factor of 5-factor model, only investment factor can contribute to the change in FX market illiquidity. This finding contributes that market return, as in previous section, can provide an insight of the change in FX liquidity; however, not all the variables of returns contribute to this change. Only investment factor suggests the contribution of the change in FX market illiquidity.

5.3 Financial Crisis

Table 7 provides the result of the impact of financial crisis. Model (1) and (3) report during non-financial crisis period while model (2) and (4) report during the financial crisis period. Model (3) and (4) use only significant variables from model (1) and (2) to check the robustness of the primary results. Consistent with previous result, the capital flows do not take an account of explaining the change in FX market illiquidity. Then, the result confirms that the capital flows have relatively no impact on the funding constraint in FX market. This regression, however, provides an interesting result. For both financial crisis and non-financial crisis period, the change in VIX now has an explanatory power and it is stronger during the financial crisis period, contradicting to the main regression result in table 3 indicating that the change in VIX is not statistically significant. The change in VIX is stronger during the financial crisis period indicates that the VIX spread can capture the volatility of the FX market providing an insight information that during the financial crisis period the equity market plays in an important role and provides spillover effects to other markets. The FX market is also affected by the spread of spillover effects as it happens to bonds and commodity markets. Furthermore, the change in VIX can incorporate with the information regarding the future change in the currency market[21].

[21] See. Mancini et al. (2013), Menkhoff et al. (2012b), Karnaukh et al. (2015).

Table 6: empirical result from regression equation (2): $\Delta Illiq_t = a + \beta(\Delta X_t) + \Psi(FF_t) + \gamma\Delta Vol_t + \delta\Delta Illiq_{t-1} + \varepsilon_t$ where FF_t is the 5-factor as Fama-French 5-factor model: HML, SMB, RMW, and CMA. ΔX_t variables are: ΔVIX_t is the change in VIX spread, ΔTED_t is the change in TED spread, $\Delta US\ Repo_t$ is the change in US repo, and $\Delta UK\ Repo_t$ is the change in UK repo. Vol_t is JP Morgan Volatility index (JPM) for both G7 ($JPM\ G7_t$) and emerging countries ($\Delta JPM\ EM_t$), and $\Delta illiq_{t-1}$ is the lag of FX market illiquidity. The sample period is from December 1999 to December 2016. The t-test are adjusted via Newey-West (1987) and reported in parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)	(3)	(4)	(5)
HML_t	0.0135				-0.0229
	(0.42)				(-0.50)
SMB_t		0.0529			0.0354
		(1.40)			(0.85)
RMW_t			-0.0547		-0.0502
			(-1.73) *		(-1.33)
CMA_t				0.0748	0.1003
				(1.96) **	(2.03) **
ΔVIX_t	0.2158	0.2232	0.2197	0.2218	0.2332
	(4.19) **	(4.34) **	(4.35) **	(4.30) **	(4.47) **
ΔTED_t	0.3541	0.3582	0.3550	0.3548	0.3585
	(13.59) **	(13.67) **	(13.76) **	(13.66) **	(13.48) **
$\Delta US\ Repo_t$	-0.0565	-0.0585	-0.0562	-0.0611	-0.0639
	(-3.18) **	(-3.12) **	(-3.09) **	(-3.40) **	(-3.46) **
$\Delta UK\ Repo_t$	-0.0843	-0.0849	-0.0859	-0.0802	-0.0808
	(-7.33) **	(-7.79) **	(-7.83) **	(-7.36) **	(-6.37) **
$\Delta JPM\ G7_t$	0.0269	0.0259	0.0297	0.0278	0.0299
	(3.51) **	(3.46) **	(3.80) **	(3.71) **	(3.78) **
$\Delta JPM\ EM_t$	-0.0243	-0.0239	-0.0264	-0.0251	-0.0269
	(-4.11) **	(-4.19) **	(-4.50) **	(-4.42) **	(-4.46) **
$\Delta illiq_{t-1}$	-0.6182	-0.6191	-0.6195	-0.6181	-0.6200
	(-41.65) **	(-41.49) **	(-41.77) **	(-41.58) **	(-41.19) **
Constant	-0.0057	-0.0016	-0.0093	-0.0077	-0.0093
	(-0.15)	(-0.04)	(-0.23)	(-0.20)	(-0.24)

Table 7: empirical result from regression equation (4): $\Delta Illiq_t = a + \beta(\Delta X_t * Dummy_t^{crisis}) + \Phi(\Delta X_t * Dummy_t^{nocrisis}) + \gamma \Delta Vol_t + \delta \Delta Illiq_{t-1} + \varepsilon_t$ where ΔX_t variables are: ΔVIX_t is the change in VIX spread, ΔTED_t is the change in TED spread, $\Delta US\ Repo_t$ is the change in US repo, $\Delta UK\ Repo_t$ is the change in UK repo, $\Delta Mkt\ Ret_t$ is the change in market excess return, and $\Delta Flows_t$ is the change in net capital flows. Vol_t is JP Morgan Volatility index (JPM) for both G7 (JPM $G7_t$) and emerging countries ($\Delta JPM\ EM_t$), and $\Delta illiq_{t-1}$ is the lag of FX market illiquidity. Dummy variable is 1 during financial crisis (March 2007 to June 2009), and 0 otherwise. The sample period is from December 1999 to December 2016. Model (1) and (3) show non-crisis period while model (2) and (4) show during the crisis period. The t-test are adjusted via Newey-West (1987) and reported in parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)	(3)	(4)
ΔVIX_t	0.1098	0.12512	0.1137	0.1029
	(1.97) **	(13.56) **	(2.05) **	(16.97) **
ΔTED_t	0.4908	0.0393	0.4851	
	(13.36) **	(0.92)	(13.55) **	
$\Delta US\ Repo_t$	-0.0992	-0.0219	-0.0963	
	(-4.45) **	(-0.39)	(-4.40) **	
$\Delta UK\ Repo_t$	-0.0210	-0.0737	-0.0211	-0.0794
	(-11.31)**	(-5.44) **	(-11.42)**	(-6.57) **
$\Delta Mkt\ Ret_t$	0.0253	0.0293	0.0255	0.0301
	(9.56) **	(7.98) **	(9.67) **	(8.56) **
$\Delta Flows_t$	0.0001	-0.0002		
	(0.69)	(-0.98)		
$\Delta JPM\ G7_t$	0.0247	0.0449	0.0247	0.0401
	(2.78) **	(3.01) **	(2.78) **	(2.83) **
$\Delta JPM\ EM_t$	-0.0297	-0.0318	-0.0299	-0.0286
	(-4.04) **	(-2.88) **	(-4.07) **	(-2.73) **
$\Delta illiq_{t-1}$	-0.6027	-0.6622	-0.6046	-0.6626
	(-44.11)**	(-22.03)**	(-45.12)**	(-24.73)**
Constant	0.0646	-0.1526	0.0660	-0.1337
	(1.05)	(-2.45) **	(1.07)	(-2.27) **

Then, the change in TED, however, does not show any explanatory power to explain the change in FX market illiquidity. This result comes as a surprise since most of the literature (see also Mancini et al., 2015, Menkhoff et al., 2012) indicate the change in TED can be used to explain the market illiquidity. The plausible explanation is that TED be observed as the supply-side factor and during the crisis period the supply for FX market liquidity is lesser than during non-financial crisis period, indicating that less supply being funded in the FX market.

The change in US repo is not statistically significant during the financial crisis period. Only UK repo can capture the change in FX market illiquidity. The funding constraint, especially in UK repo, plays a role in the impact of the change in FX illiquidity (as the coefficient is negatively related to the change in FX illiquidity).

Considering the change in volatility indexes for both G7 and emerging countries, the result is consistent with my preliminary result indicating that both indexes can be used to capture the change in FX market illiquidity. Analyzing further, the change in volatility index for G7 countries contributes to the change in FX illiquidity more during non-financial crisis period. The coefficient of 0.0449 under model (2) or during the financial crisis period is higher than coefficient of 0.0274 under model (1) or non-financial crisis period. This is also true for model (3) and (4) using only significant variables from model (1) and (2). This result suggest that G7 countries contribute to the change in FX market illiquidity especially during the financial crisis period more than emerging countries do. Then, the level of market integration (see Carrieri at el. ,2013) of developed currencies has more impact on changing market liquidity as the developed currencies are mainly accounted for trading in the FX market than emerging currencies. Furthermore, the coefficients also indicate that the contribution of the volatility index during the financial crisis is stronger than non-crisis period. For example, model (1) shows coefficient of 0.0274 while during the crisis period the coefficient is 0.0449 under model (2).

In summary, the financial crisis provides an evidence that the financial constraint issues contribute to the change in FX market illiquidity more than non-financial crisis period. In contrast to the preliminary result, the equity volatility index (VIX) can also capture the change in FX market illiquidity strongly during the financial crisis period.

6. Predictability Discussion

6.1 Liquidity predictability

Many documented literatures report the finding of liquidity predictability (see, Pastor and Stambaugh, 2003, Chordia et al., 2000a). Poti and Siddique (2013) provide an empirical evidence of the currency predictability by using carry trade approach on diversified investors and undiversified investors. They find that undiversified investors require higher liquidity due to the capital constraint than diversified investors. Their empirical finding supports that the presence of the financial constraint can induce the change in liquidity as well as some degree of currency predictability. I estimate the liquidity predictability using modification of Poti and Siddique (2013) approach as follows:

$$\Delta LIQ_t = E(\Delta LIQ_{t-1} | I_{t-1}) \tag{5}$$

The intuition behind the methodology is that the change in liquidity is determined by the expected liquidity and information set, as described by I_{t-1}, at time t-1. The information set includes the determined variables used in the previous estimation.

The analysis is based on DCC model to analyze the predictability of the FX market liquidity. The DCC model is described as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{6}$$

where H_t is covariance matrix of disturbances of market FX illiquidity, D_t is diagonal matrix conditional variances, and R_t is the matrix of conditional quasi-correlation of market FX illiquidity and control variables.

Figure 6 shows the impulse response function of the change in FX liquidity using previous information set and one-step lag of liquidity. The graph seems to support the presence of the reversals as the market FX liquidity swings between negative and positive values and gets smoothed out in the recent period. Pastor and Stambaugh (2003), and Banti et al., (2012) report similar finding as they predict the certain degree of liquidity can be predicted based on the past liquidity information.

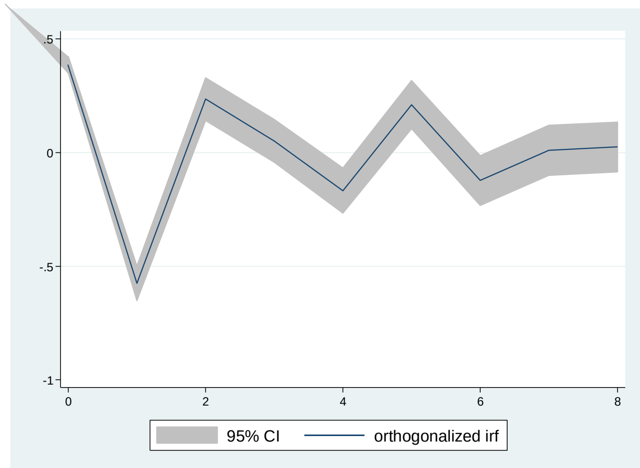

Figure 6: Impulse response function of market FX liquidity. The change in FX liquidity is estimated by the lag of FX liquidity and information set at time t-1 as described by equation (5): $\Delta LIQ_t = E(\Delta LIQ_{t-1}|I_{t-1})$.

Then, I analyze further for relationship between independent variables and FX liquidity using vector autoregressive (VAR) approach. To preserve the space for this paper, I only report using the change in FX illiquidity as dependent variables and using lags of independent variables to determine the relationship. As expected, the VAR model provides an evidence of the relationship between each proposed variable and the change in market FX liquidity as it is reported in figure 7. This evidence shows that the funding constraint and global risks can be used to predict the FX liquidity. For example, the change in FX liquidity is determined by the change in TED spread, volatility indexes for both G7 and emerging countries. However, when looking at the change in US and UK repo, they indicate a very weak predictability of the change in FX liquidity. Consistent with table (6) that the US repo does not give a significance result. In general, the proposed variables can provide a good indication of predictability power of the FX liquidity.

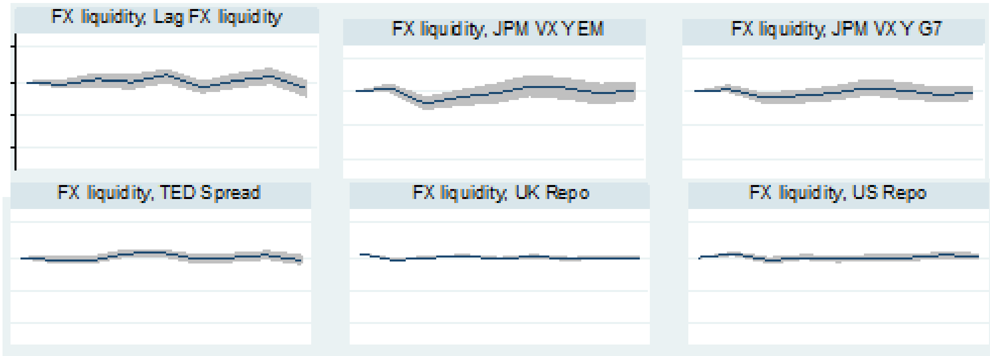

Figure 7: Vector Autoregressive (VAR) between market FX illiquidity and independent variables.

6.2 Return predictability

The previous section shows that the change in liquidity can be predicted using the proposed variables, especially the change in TED spread and volatility indexes. Now, I turn the analysis to determine the degree of return predictability. Bakshi and Panayotov (2013) and Cenedese et al. (2014) propose that the use of carry trade portfolios to predict the return predictability. To begin my analysis, I determine the excess returns of currency based on monthly excess returns as proposed by Banti et al. (2012) that the difference between the natural log of the future's spot rate and the today's forward rate[22]. Once the excess returns are determined, I follow the use of Cenedese et al. (2014) to form the conditional market variance with the decomposition form as follows:

$$MV_t = AV_t * AC_t \tag{7}$$

Where MV_t is the conditional market variance AV_t is the average of the variances of excess returns at time t, and AC_t is the average correlation of exchange rate excess returns at time t. The average variance is defined as the equally weighted average of variance of all currency excess returns while the average

[22] See. Banti et al. (2012) and Banti and Phylaktis (2015).

correlation is determined by the equally weighted average pairwise correlations of all exchange rate excess returns[23].

The average variance (AV_t) and average correlation (AC_t), as presented in equation 8, are estimated as follows:

$$AV_t = \frac{1}{N} \sum_{j=1}^{N} V_{j,t} \tag{8}$$

$$AC_t = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i}^{N} C_{ij,t} \tag{9}$$

Where $V_{j,t}$ is the realized monthly variance of excess return of currency j at time t, and $C_{ij,t}$ is the realized monthly correlation between the excess return of cross currencies i and j at time t.

Then, I construct the predictive regression as following model:

$$r_{i,t+1} = a_1 + b_1 AV_t + b_2 AC_t + \varepsilon_{t+1} \tag{10}$$

Where $r_{i,t+1}$, is the predictive excess return, AV_t is the average variance as defined by equation (8), AC_t is the average correlation as defined by equation (9), and ε_{t+1} is assumed to be i.i.d. and zero mean.

Table 8 reports the results using only market variance (MV) and decomposition model; the average correlation (AC) and average variance (AV). Consistent to Cenedese et al. (2014), I find that the market variance (MV) does not provide any explanatory power of explaining the change in currency excess returns. In fact, the average correlation and average variance can help explaining the change in the excess returns up to approximately 32% (28.91% + 4.2%). The average variance contributes the most to the change in excess returns.

[23] See. Cedenese et al. (2014)

Table 8: Predictive regression using equation (10): $r_{i,t+1} = a_1 + b_1 AV_t + b_2 AC_t + \varepsilon_{t+1}$,where $r_{i,t+1}$ is the return from time t to t+1 of the currency i, AV_t is average variance using equally weighted average of the variances of all excess returns at time t, and $AC_t$is the average correlation using equally weighted average of the pairwise correlation of all excess returns at time t. The t-test is reported using Newey-West (1987) under the parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)
Constant	0.0137	0.0157
	(2.36)**	(2.69)**
Market Variance (MV)	0.4631	
	(0.79)	
Average Variance (AV)		0.2891
		(3.81)**
Average Correlation (AC)		0.042
		(1.97)**
R-Squared	0.05	0.12

I analyze further to see whether any potential variables can be used to predict the change in return. Then, I construct the predictive regression as following model:

$$r_{i,t+1} = a_1 + b_1 AV_t + b_2 AC_t + \gamma X_t + \varepsilon_{t+1} \quad (11)$$

Where $r_{i,t+1}$, is the predictive excess return, $X_t$is the vector of proposed variables (predictive change in liquidity, change in TED spread, and change in volatility indexes), and ε_{t+1} is assumed to be i.i.d. and zero mean.

The predictive change in liquidity is the control variable as determined from the previous section. I include the change in TED spread and volatility indexes to explain possible change in the returns as the results from previous section show that these variables provide the consistency in most of the regression models. Table 9 shows my result. As expected, the result is consistent to what Cedenese et al. (2014) report what the average correlation and average variance can be used to predict the change in currency excess returns. The presence of average variance is strong for all the models ranging from 30% to 36% while the average correlation can partially explain the change in excess returns. The change in liquidity is positively correlated to the change in excess returns as investors require higher premium to a greater risk and return; however, it does not provide a strong magnitude as expected. The change in liquidity can be partially used to predict the future excess returns, but not as strong as the change in average variance since currency excess returns depends highly on their own risks rather the other currencies. The change in volatility indexes provides an interesting result since they cannot explain or used to predict the currency excess returns. Then, in general, I find that the change in excess returns depends highly on the average variance rather than other explanatory variables.

Table 9: Predictive regression using equation (11): $r_{i,t+1} = a_1 + b_1 AV_t + b_2 AC_t + \gamma X_t + \varepsilon_{t+1}$,where $r_{i,t+1}$ is the return from time t to t+1 of the currency i, AV_t is average variance using equally weighted average of the variances of all excess returns at time t, $AC_t$is the average correlation using equally weighted average of the pairwise correlation of all excess returns at time t, and $X_t$is predictive variable choices. Δ TED is the change in TED spread, Δ LIQ is the predictive change in liquidity, Δ JPM G7 is the change in JP Morgan volatility index for G7 countries, and Δ JPM EM is the change in JP Morgan volatility index for emerging countries. The t-test is reported using Newey-West (1987) under the parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)	(3)	(4)	(4)
Constant	0.0133	0.0104	0.0097	0.0108	0.0091
	(2.19) **	(2.36) **	(2.65) **	(2.25) **	(2.31) **
AV_t	0.3651	0.3087	0.3277	0.3197	0.3012
	(3.31) **	(3.15) **	(3.02) **	(3.07) **	(2.97) **
AC_t	0.0654	0.0431	0.0396	0.0412	0.0371
	(2.44) **	(2.21) **	(2.23) **	(2.25) **	(2.05) **
Δ TED_t	0.0141	0.0113			
	(6.25) **	(7.31) **			
Δ LIQ_t	0.0763		0.0817		
	(4.01) **		(4.73) **		
Δ JPM $G7_t$	0.0021			0.0032	
	(1.06)			(0.96)	
Δ JPM EM_t	-0.0063				-0.0085
	(-1.23)				(-1.01)

6.3 Robustness

I consider that the choice of the currencies in the sample may drive the estimation bias since the choice is based on Banti et al. (2012) and the most trading activities from BIS report. For my robustness check, I include 10 more currencies, both developed and emerging currencies, into the sample, namely Greece, India, Finland, Taiwan, UAE, Malaysia, Netherlands, Saudi Arabia, Spain, and Italy. The choice[24] is also based on the trading activity and data availability through Bloomberg, and Thompson and Reuters. Then, I estimate the regression based on the equation (2), (3), and (4) to observe whether including more currencies will change the preliminary results. I exclude the capital flows in the regression model since multiple tests have indicated that capital flows do not account for the change in FX liquidity.

Table 10 reports the result. Model (1) reports the result using equation (1). Consistent with table 4, the change in TED spread, repo for US and UK, volatility indexes for G7 and emerging countries, market returns and lag of FX liquidity are statistically significant and they all have the same sign as in table 4. This confirms that adding more currencies does not lower the explanatory power of the factors, funding constraints and global risks, to the change in market FX liquidity.

In Model (2), I test with 5-factor model; however, the result indicates that none of the factor is statistically significant. Unlike the finding in table 6 indicating the presence of the investment strategy of investors can account for the change in FX liquidity, model (2) does not provide a support of the claim in previous result. Mancini et al. (2013), Karnaukh et al. (2015), and Menkhoff et al. (2012) provide an explanation of excluding Taiwan currency is that the differences of the micro and macroeconomic structures of Taiwan currency to other currencies can drive the change in liquidity. Then, this result does not come as a surprise since the inclusion of Taiwan can omit the previous findings.

Then, I test for the financial crisis period. The result is reported in table 8 under model (3). The result is consistent with previous finding in table 7. All variables are statistically significant expect for TED spread. The change in VIX spread, again, becomes significant as I find in the previous regression result. The result confirms the change in VIX can capture the financial crisis shocks as resulting in the change in FX liquidity better than the change in TED spread.

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[24] Each currency must have data available through Bloomberg and Thompson and Reuter, and it must be at least 5-year spanning period.

Table 10: Robustness check of adding more currencies into the sample. ΔVIX_t is the change in VIX spread, ΔTED_t is the change in TED spread, $\Delta US\ Repo_t$ is the change in US repo, $\Delta UK\ Repo_t$ is the change in UK repo, and $\Delta Mkt\ Ret_t$ is the change in market excess return. Fama-French 5-factor model: HML, SMB, RMW, and CMA, is included under model (2). Vol_t is JP Morgan Volatility index (JPM) for both G7 (JPM $G7_t$) and emerging countries (ΔJPM EM_t), and $\Delta illiq_{t-1}$ is the lag of FX market illiquidity. Dummy variable is 1 during financial crisis (March 2007 to June 2009), and 0 otherwise. The sample period is from December 1999 to December 2016. The t-test are adjusted via Newey-West (1987) and reported in parentheses. *, ** indicate 10% and 5% level of significance.

	(1)	(2)	(3)
HML_t		-0.0012	
		(-0.75)	
SMB_t		0.0023	
		(0.85)	
RMW_t		-0.0211	
		(-1.02)	
CMA_t		0.056	
		(1.35)	
ΔVIX_t	0.0541	0.1134	0.1231
	(1.53)	(4.12) **	(12.35) **
ΔTED_t	0.3412	0.3673	0.0145
	(12.66) **	(13.18) **	(1.35)
$\Delta US\ Repo_t$	-0.0312	-0.0457	-0.0781
	(-2.78) **	(-3.21) **	(-4.41) **
$\Delta UK\ Repo_t$	-0.0254	-0.0553	-0.0124
	(-5.96) **	(-4.73) **	(-8.83) **
$\Delta JPM\ G7_t$	0.0277	0.0281	0.0359
	(3.91) **	(3.32) **	(2.75) **
$\Delta JPM\ EM_t$	-0.0265	-0.0279	-0.0326
	(-4.36) **	(-4.89) **	(-3.78) **
$\Delta Mkt\ Ret_t$	0.0101		0.0228
	(4.67) **		(6.11) **
$\Delta illiq_{t-1}$	-0.732	-0.632	-0.682
	(-24.65)**	(-23.19)**	(-18.67)**
Constant	-0.0055	-0.0081	-0.0093
	(-0.17)	(-0.26)	(-0.23)

Overall, the robustness check provides substantially supporting my initial results that the determinant variables of global risks and funding constraints can capture the change in FX liquidity. Testing with 5-

factor model is somehow need further research since currency market is different from equity market, and 5-factor is mainly used in equity market, especially in US stock market.

7. Conclusion and Remarks

Liquidity measure has been widely discussed and presented the importance of the literature in finance; however, the study of FX liquidity gets less attention from the mainstream research. This paper provides an empirical evidence of the liquidity measure in foreign exchange market, the determinants of measuring the change in market FX liquidity, as well as the predictability of the FX liquidity.

Using 20 cross currency exchange rates both developed and emerging currencies from January 1999 to December 2016, I find that the presence of the funding constraints such as repo for both US and UK, the change in TED spread, and the global risks such as volatility indexes can play an important role of the change in market FX liquidity. However, using famous 5-factor model, the result can only capture the investment risk factor loading affecting the change in FX liquidity. This result becomes even more puzzling when adding more currencies into the sample. The result does not hold anymore. There is a need of further research to explore the possibility of explanation of this puzzle.

I then test the presence of financial crisis period from 2007 to 2009. The result shows that the change in VIX plays an important role that it can capture the change in FX liquidity better than the change in TED, which is not statistically significant during the crisis period. The change in risk factor during the crisis period can contribute to the change in FX liquidity as investors face severe funding constraint and the presence of the global risks. The robustness check also confirms this result.

The test for liquidity predictability provides a consistent result. Using MGARCH and VAR to predict the determinants that contribute to the change in liquidity, the source of the predictability mostly comes from the information set of the independent variables, namely the change in TED spread, repo market, and volatility index. Then, I test further whether changing in liquidity can be used to predict the currency excess returns. Using average correlation and average variance of currency excess returns for control variables, I find that average variance contributes the most for currency predictability more than other explanatory variables.

The global risks and funding constraints play an important role of the change in FX liquidity. I, however, do not provide more variables that might contribute to the change. Moreover, the choice of currencies may depict the selection bias since there are more currencies can be added to provide clearer picture of the change in liquidity to funding constraints and global risks.

References

Galati, G., Heath, A., and McGuire, P., 2007. “Evidence of carry trade activity”. *BIS Quarterly Review*, September, pp.27 – 41.

Phylaktis, K. and Chen, L., 2010. “Asymmetric information, price discovery and macroeconomic announcements in FX market: do top trading banks know more?”. *International Journal of Finance & Economics*, *15*(3), pp.228-246.

Fama, E.F., 1998. “Market efficiency, long-term returns, and behavioral finance”. *Journal of financial economics*, *49*(3), pp.283-306.

Pasquariello, P., 2014. “Financial market dislocations”. *Review of Financial Studies*, *27*(6), pp.1868-1914.

Amihud, Y., 2002. “Illiquidity and stock returns: cross-section and time-series effects”. *Journal of financial markets*, *5*(1), pp.31-56.

Pástor, Ľ. and Stambaugh, R.F., 2003. “Liquidity risk and expected stock returns”. *Journal of Political economy*, *111*(3), pp.642-685.

Acharya, V.V. and Pedersen, L.H., 2005. “Asset pricing with liquidity risk”. *Journal of financial Economics*, *77*(2), pp.375-410.

Baker, M. and Stein, J.C., 2004. “Market liquidity as a sentiment indicator”. *Journal of Financial Markets*, *7*(3), pp.271-299.

Bekaert, G., Harvey, C.R. and Lundblad, C., 2007. “Liquidity and expected returns: Lessons from emerging markets”. *Review of Financial studies*, *20*(6), pp.1783-1831.

Stoll, H.R., 1989. “Inferring the components of the bid-ask spread: theory and empirical tests”. *The Journal of Finance*, *44*(1), pp.115-134.

Bessembinder, H., 1994. “Bid-ask spreads in the interbank foreign exchange markets”. *Journal of Financial economics*, *35*(3), pp.317-348.

Hsieh, D.A. and Kleidon, A.W., 1996. “Bid-ask spreads in foreign exchange markets: Implications for models of asymmetric information”. In *The Microstructure of Foreign Exchange Markets* (pp. 41-72). University of Chicago Press.

Mancini, L., Ranaldo, A. and Wrampelmeyer, J., 2013. “Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums”. *The Journal of Finance*, *68*(5), pp.1805-1841.

Karnaukh, N., Ranaldo, A. and Söderlind, P., 2015. “Understanding FX liquidity”. *Review of Financial Studies*, *28*(11), pp.3073-3108.

Banti, C., Phylaktis, K. and Sarno, L., 2012. “Global liquidity risk in the foreign exchange market”. *Journal of International Money and Finance*, *31*(2), pp.267-291.

Banti, C. and Phylaktis, K., 2015. “FX market liquidity, funding constraints and capital flows”. *Journal of International Money and Finance*, *56*, pp.114-134.

Menkhoff, L., Sarno, L., Schmeling, M. and Schrimpf, A., 2012. “Carry trades and global foreign exchange volatility”. *The Journal of Finance*, *67*(2), pp.681-718.

Brunnermeier, M.K., Nagel, S. and Pedersen, L.H., 2008. “Carry trades and currency crashes”. *NBER macroeconomics annual*, *23*(1), pp.313-348.

Chordia, T., Roll, R. and Subrahmanyam, A., 2000. “Commonality in liquidity”. *Journal of financial economics*, *56*(1), pp.3-28.

Adrian, T. and Shin, H.S., 2010. “Liquidity and leverage”. *Journal of financial intermediation*, *19*(3), pp.418-437.

Gorton, G. and Metrick, A., 2012. “Securitized banking and the run on repo”. *Journal of Financial economics*, *104*(3), pp.425-451.

Acharya, V.V. and Viswanathan, S., 2011. “Leverage, moral hazard, and liquidity”. *The Journal of Finance*, *66*(1), pp.99-138.

Carrieri, F., Chaieb, I. and Errunza, V., 2013. “Do implicit barriers matter for globalization?”. *Review of Financial Studies*, *26*(7), pp.1694-1739.

Fama, E.F. and French, K.R., 2016. “Dissecting anomalies with a five-factor model”. *Review of Financial Studies*, *29*(1), pp.69-103.

Brunnermeier, M.K. and Pedersen, L.H., 2009. “Market liquidity and funding liquidity”. *Review of Financial studies*, *22*(6), pp.2201-2238.

Potì, V. and Siddique, A., 2013. “What drives currency predictability?”. *Journal of International Money and Finance*, *36*, pp.86-106.

Cenedese, G., Sarno, L. and Tsiakas, I., 2014. Foreign exchange risk and the predictability of carry trade returns. *Journal of Banking & Finance*, *42*, pp.302-313.

Chapter 2

“Momentum Returns of US Equities: Diversification, Idiosyncratic Volatility, and Momentum Prediction of Industry Portfolios”

1. Introduction

Momentum refers to a motion that an object has. It can be used in broadly ways such as in sports, in physics, or even in finance. The momentum in finance, by definition, means that stocks that have performed well in the past tend to perform well in the future while stocks that performed poorly in the past are likely to continue performing poorly in the future. Jegadeesh and Titman (1993) observe and test for momentum strategy, buying stocks that have performed well (winners) and selling stock that have performed poorly (losers), of U.S stock market. Their result shows that momentum strategy can generate positive returns creating an investment opportunity for investors to exploit such trading behavior. The strategy generates a substantially size of return using a zero-investment strategy[25], short sell loser and long winner stocks. The momentum behavior has been extensively studied in many asset types such as commodity, foreign exchange market, international stock market, and so on[26]. Most of the literatures point out the same idea that there is an existence of momentum returns in most of the asset types and momentum profits tend to appear in many periods of time.

Although the momentum strategy has been widely observed, there is no well-documented literature providing a clear-cut where the momentum profit is from. Most of the literature observe the sorted-

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[25] Zero investment strategy refers to taking both short and long positions to profit from the strategy.
[26] For example, Okunev and White (2003) find the momentum in currencies, Chui, Titman, and Wei (2010) find individualism tend to extract more momentum profits than collectivism, Asness, Moskowitz, and Pedersen (2013) show that the momentum can be found in many asset classes.

momentum based on the excess return regardless any risks involved in momentum profits. This motivates my interest whether the diversification benefits may drive the existence of momentum returns. From this, I investigate the source of momentum profits whether from within or between the industries. Also, I extend further to observe the diversification benefits among industries whether combining between industries can generate greater returns. From the literature standpoint, momentum strategy is based on the previous returns, which can be in any assets types and markets. The combination of different industries may yield the profits from such strategy better than using stand-alone industry. If combining different industries provides a greater momentum profit, then there must be that some industries significantly perform as a better diversification benefit than the others.

The long-standing belief is that the higher risks will be compensated with higher returns. To receive the benefit of diversification purpose, investors should seek for stocks/assets that provide a negative correlation among them. Then, if they think momentum benefits are trading such risks for higher returns, they should be able to distract the diversification benefits of momentum strategy and, by sorting based on risks, they should be able to observe the same patterns of momentum behaviors. Motivated by this question, I explore the possibility of the source of momentum returns by using the size of volatility instead of using excess returns to sort the portfolios. Testing based on the size of volatility, I use both 3 factor and 5-factor to determine the volatility, and estimate the conditional volatility using GJR-GARCH model[27].

The objective of this paper is to provide more details according to the momentum returns sorting based on traditional, excess returns, and conditional volatility. Sorting the momentum strategy

[27] Engle and Ng (1993) test for ARCH and GARCH types and conclude that GJR is the best measure of new information of stock prices.

based conditional volatility, according to my knowledge, has not been done or documented by any paper. The closely related paper is Ang et al. (2009), who test for the return reversals of the standard idiosyncratic volatility of U.S. stock data. Their finding has been providing an importance to the literature since they show the presence of the reversals of stock returns. Motivated by their results, I test using all 48 industries as well as individual industries of the U.S. equity data to see whether the returns can be higher using conditional volatility portfolio sorting.

My initial hypotheses towards the momentum strategy are (i) using all 48 industries I should find the presence of the momentum strategy and the size of momentum profit must be high enough for investors to engage in such activities, (ii), when diving into 48 industries, some industries may provide a better return than the others, and when combining these industries, the benefits of diversification should be pronounced, and (iii), sorting based on the conditional volatility, I expect to see the size of momentum profit to be higher than that of traditional sorting portfolio.

To investigate the momentum strategy, I focus on the U.S. equity market. Using daily U.S. firm level data from 1990 to 2016, I construct the momentum return based on winner minus loser (WML) strategy[28]. The portfolios are formed based on the size of the excess returns. The top 10% of stock excess returns is grouped up ad named the winner portfolio. The bottom 10% of stock excess returns is classified as the loser portfolio[29]. To avoid potential outliers, I winzorize 1% of each tail to ensure that I screen down potential outliers. More details are discussed under data and methodology section. In general, I find that, consistent with documented literatures, there is a momentum return in U.S. equity during the recent period. Dividing my sample into 48 industries[30],

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[28] Refer to short sell loser portfolio and long winner portfolio.

[29] Top and bottom 10% sorting is suggested by many literatures such as Daniel and Moskowitz (2016), Barroso and Santa-Clara (2014).

[30] See. list of Industries at appendix T.1.

as classified based on SIC code provided through Kenneth French Website[31], the momentum profit for individual industry is also pronounced.

I also argue that the source of momentum benefits may come from diversification purpose. I run pairwise correlation based on the excess returns of all 48 industries and pair the industries that have a strong negative correlation. Choosing the strong pairs of negative correlation, I find that, however, the momentum cannot attain the highest as I find using all 48 industries. Opposite to what investors believe in, high risks are compensated with higher returns, the potential source of momentum return is purely based on excess returns rather than the correlation among industries.

This finding provides an important question whether the momentum profit can be determined based on the idiosyncratic risk. Fu (2009) documents the returns in equity markets based on idiosyncratic risk and finds that ranking portfolios based on volatilities can yield a significant gain and substantially higher than market return. Motivated by his finding, I use GJR-GARCH model[32] to determine the conditional idiosyncratic volatility, and find that both 3 and 5-factor provide similar magnitude of conditional volatility for both mean and standard deviation. Then, I sort my portfolio into five decile portfolios[33]. Sorting based on the idiosyncratic volatility, however, does not provide an ideal result as it does for sorting based on excess returns.

I then argue that using one-dimension portfolio sorting may not provide an ideal result since I need to control for factors such as volatilities and liquidity when sorting portfolios. Then, I start off by sorting portfolios based on excess returns and then sort by illiquidity (Amihud, 2002) and idiosyncratic volatility for second sorting. The double sorting can eliminate potential too high

[31] Kenneth French. U.S. Data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[32] I follow Hansen and Ng (1993) that GJR-GARCH type is most suit to measure the volatility in stock markets.
[33] Fu (2009) and Ang et al. (2009) construct the conditional volatility and divide into five decile portfolios.

momentum returns since there is no control for such returns. I find that, using double sorting can control for the momentum returns. The difference between high and low portfolio is pronounced supporting the momentum returns.

Once I determine the factors that affect the change in momentum returns, now I turn my analysis based on volatility by scaling on the excess returns using the inverse of conditional variance as suggested by Moreira and Muir (2017) to capture the potential increase and decrease risk exposure of the portfolios. I test for multiple factors to control for the size of the returns such as Fama-French 3-factor (the excess market return, size factor, and value factor), and momentum factor (MOM). Also, I include liquidity factor as well as idiosyncratic volatility as I find that they can be used to control for momentum returns. The result shows that, in fact, these factors are statistically significant to control for the returns when using by-factor regression.

The main results of the current paper are (i) I find that there is strong momentum return for all industries, but diversification benefit does not improve the momentum returns, (ii) using idiosyncratic risk to sort for loser and winner portfolio does not provide a better result than using excess return approach, and (iii) sorting portfolios based on the inverse conditional variance including multiple factors shows that the momentum returns are affected the most by the size of liquidity and the risk factors.

2. Literature Review

The study of momentum is firstly observed by Jegadeesh and Titman (1993). They provide a trading strategy buying stocks that have been performed well in the past and selling stocks that have been performed poorly in the past. The results show that the trading strategy in the U.S. stock market can provide positive returns. The positive returns, however, will not last forever since the winner stocks can become losers and vice versa. Furthermore, Jegadeesh and Titman (2001) observe U.S. equity data using 1990 to 1998 spanning period and their result show that the momentum returns can be found even using the recent data. Their findings have received a lot of attention. The presence of momentum has been expanding into many asset classes such as commodity, foreign exchange, international stock market, and so on.

The presence of momentum strategy, however, is not supported by the market efficiency hypothesis (MEH) proposed by Malkiel and Fama (1970) that the market itself can be adjusted due to the arrival of new information and the market price should reflect to the new information. De Bondt and Thaler (1985) challenge the market efficiency hypothesis (MEH). They hypothesize that if new information plays an important role for investors, then investors should overreact and such behavior can violate the MEH. Their finding provides an empirical evidence that investors do overreact to the new information resulting in selling winner stocks and buying loser stocks. Their result provides an important to finance literature is that there is a momentum in equity market that investors can exploit from.

The momentum in currency is documented by Okunev and White (2003). They test for the major currency data from 1975 to 2000. Adjusting for interest rate differential, they report that investors can extract positive returns using the momentum strategy in foreign exchange market. Menkhoff et al. (2012b) also test for the momentum returns using carry trade to form the portfolios. The portfolios are formed based on the excess returns. The top 10% currency excess returns are defined as winner portfolio while the bottom 10% excess returns are described as loser portfolio. The difference between winner and loser, winner minus loser (WML) strategy, generates approximately 10% per annum. Also, they report that the size of momentum returns is not affected by the business cycle, liquidity risk, carry trade risk, volatility risk, three-factor, or four-factor model, rather it can be explained by the country risk and transaction costs. Their findings support the presence of momentum returns in currency market and the momentum return is not affected by volatility risks contribute to the momentum returns puzzle regarding the sources of returns.

The argument of returns in momentum is explained by Chui, Titman, and Wei (2010) that the presence of individualism plays a role of positive momentum returns. They argue that individualism tend to take more risk than collectivism and result in the higher return. They, however, point out that individualism can suffer from overconfidence and result in return reversals. Their documented evidence does provide some piece of the financial behavior to explain the momentum returns.

Momentum strategy can generate substantial benefits for investors; however, the benefits tend to disappear at a longer horizon. Titman and Jegadeesh (2001) provide an empirical evidence based on the different horizon periods to use momentum strategy. They find that, in general, momentum profits tend to be higher during the first year of the strategy. The strategy, however, starts to decline until the profits become negative after 2 to 3 years of strategy period. This evidence has also been observed by Moskowitz, Ooi, and Pedersen (2012), which they test for 58 instruments and find that a strong significance of stock return predictability based on the past performance for all the instruments. They also document that the excess returns of these instruments reverse over longer horizon suggesting that momentum strategies disappear after certain period. They also test further for the position of traders; hedgers and speculators, and they conclude that speculators benefit from time series momentum at the expense of hedgers.

The recent paper of Daniel and Moskowitz (2016), using the U.S. equity data, provides an empirical evidence sorting portfolios into 10 deciles based on the excess returns. They find that the momentum portfolio (winner minus loser portfolio) provides a higher return, Sharpe ratio, and positive skewness than stand-alone portfolio. Their finding gains a lot of attention in scholar work of the presence of momentum returns. They indicate that, extending from the previous work of Barroso and Santa-Clara (2015)[34], using time-varying to manage momentum portfolio can substantially provide a greater return, lower volatility, and higher Sharpe ratio than plain momentum strategy.

The presence of international asset in momentum returns is also observed. Rouwenhorst (1998) reports the findings of momentum in international assets, using 12 European countries during the period 1980 to 1995. His finding supports the momentum strategy presented by Jegadeesh and Titman (1993). Moreover, Chan, Hameed, and Tong (2000) provide an evidence of the profitability of momentum strategies using both U.S. and international equity. They document that the presence of international assets in momentum strategies can help achieving higher returns than using only one equity market. Naranjo and Porter (2007) point out that momentum would be more beneficial if including international assets into the portfolios, especially when adding emerging markets. Using firm level data across developed and emerging countries, their finding indicates that inclusion of emerging markets provides higher returns than using purely from developed markets.

In sum, momentum strategy can generate investment opportunities for investors to engage in such strategy. The strategy is not only limited in the U.S. equity market, but also in many various asset types such as commodity, foreign exchange, and international stock markets[35]. Then, investors would receive greatly benefit of momentum strategy if they combine these asset types together.

[34] Barroso and Santa-Clara (2015) provide an evidence that momentum can be managed using constant time-varying model to forecast the momentum returns.

[35] Momentum strategy has been observed through many asset classes: FX, bond, commodities. See. Moskowitz and Grinblatt (1999), Menkhoff et al. (2012b), Rouwenhorst (1999), Okunev and White (2003), Asness, Moskowitz, and Pedersen (2013), Novy-Marx (2012).

Then, there is a gap in literature needed for the further whether the momentum returns are form within or between the industries through the diversification benefit. Also, the momentum portfolio return using inverse conditional variance is part of my interest towards this paper. I try to fill this gap and provide clearer picture of the momentum portfolio returns and the prediction of momentum portfolio.

The paper is organized as follows. Section 3 provide data and methodology used to construct portfolios and determine the momentum returns. Then, I present the empirical results in section 4. Section 5 concludes the paper.

3. Data and Methodology

3.1. Data

The primary data source is from the Center for Research in Security Prices (CRSP). I understand the potential of selection bias as well as outlier problem in CRSP database. Before I construct the portfolio, I winzorize the data for each tail at 1%. Winzorizing the data at 1% is supported by Hoberg and Phillips (2010) that winzoring at 1% will provide the most accurate data screening more than using at 5% or 10%. Also, the outliers can potentially drive too high or too low momentum portfolio returns. At the end, the sample size of all 48 industries is 1,477,518 observations. Then, I construct the momentum portfolios based on the cumulative returns[36]. The cumulative returns are formed based on the past 12 months up until 1 month before the formation date (from t-12 to t-2)[37]. Using up to the last month (t-1) can potentially generate the return reversals. Momentum strategy, as suggested by Lehman (1990), can turn winners into losers, and

[36] See. Barroso and Santa-Clara (2015), Jegadeesh and Titman, 1993).
[37] See. Daniel and Moskowitz (2016), Asness (1997), Fama and French (1996)

vice versa. To avoid this issue, I calculate the cumulative returns from t-12 up to t-2. Table 1 provides summary statistics of excess returns for each industry.

I first summarize the industry returns. Table 1 provides summary statistic based on equally weighted and value-weighted returns of 48 industries. Interestingly, the value-weighted returns provide lower returns and higher standard deviation than equally weighted approach. The plausible explanation is that value-weighted suffers from the financial crisis which attributes to a greater loss than equally weighted approach[38].

Table 1: Summary Statistics of 48 industries. The table represents the market returns based on 48 industries from January 1990 to December 2015. The market returns are based on equally weighted and value-weighted provided by the Center for Research in Security Prices (CRSP) with CRSP share code of 10 or 11. The 48 industries are divided based on the SIC Code provided by Kenneth R. French website.

		Value-weighted		Equally-weighted	
ID	Name	Mean	Stdev	Mean	Stdev
1	Agriculture	0.0432	0.1142	0.0874	0.0969
2	Food Products	0.0400	0.1183	0.0885	0.0925
3	Candy and Soda	0.0400	0.1183	0.0754	0.1025
4	Beer and Liquor	0.0457	0.1098	0.0887	0.0916
5	Tobacco Products	0.0449	0.1162	0.0810	0.0990
6	Recreation	0.0462	0.1079	0.0920	0.0897
7	Entertainment	0.0462	0.1094	0.0917	0.0916
8	Printing and Publishing	0.0436	0.1095	0.0889	0.0920
9	Consumer Goods	0.0456	0.1079	0.0923	0.0902
10	Apparel	0.0451	0.1082	0.0911	0.0907
11	Healthcare	0.0477	0.1059	0.0956	0.0881
12	Medical Equipment	0.0428	0.1119	0.0868	0.0946
13	Pharmaceutical Products	0.0389	0.1157	0.0793	0.0988
14	Chemicals	0.0433	0.1105	0.0848	0.0939
15	Rubber and Plastic Products	0.0456	0.1037	0.0957	0.0843
16	Textiles	0.0493	0.1041	0.0998	0.0857
17	Construction Materials	0.0475	0.1054	0.0951	0.0873
18	Construction	0.0451	0.1095	0.0874	0.0922
19	Steel Works Etc.	0.0445	0.1094	0.0873	0.0920
20	Fabricated Products	0.0485	0.1063	0.0910	0.0898
21	Machinery	0.0453	0.1093	0.0899	0.0916
22	Electrical Equipment	0.0460	0.1081	0.0950	0.0881

[38] See. Banz (1981), Maillard et al. (2010)

23	Automobiles and Trucks	0.0435	0.0966	0.0494	0.0898
24	Aircraft	0.0400	0.1183	0.0856	0.0940
25	Shipbuilding, Railroad Equipment	0.0427	0.1121	0.0817	0.0957
26	Defense	0.0431	0.1151	0.0811	0.0981
27	Precious Metals	0.0453	0.1125	0.0876	0.0965
28	Non-Metallic and Industrial Metal Mining	0.0475	0.1078	0.0872	0.0933
29	Coal	0.0444	0.1101	0.0782	0.0956
30	Oil	0.0421	0.1132	0.0771	0.0996
31	Utilities	0.0443	0.1104	0.0845	0.0946
32	Communication	0.0458	0.1094	0.0870	0.0933
33	Personal Services	0.0384	0.1163	0.0812	0.0981
34	Business Services	0.0434	0.1131	0.0851	0.0958
35	Computers	0.0390	0.1149	0.0831	0.0960
36	Electronic Equipment	0.0423	0.1096	0.0906	0.0914
37	Measuring and Control Equipment	0.0389	0.1149	0.0806	0.0980
38	Business Supplies	0.0421	0.1109	0.0869	0.0931
39	Shipping Containers	0.0446	0.1111	0.0881	0.0933
40	Transportation	0.0467	0.1057	0.0958	0.0870
41	Wholesale	0.0421	0.1136	0.0810	0.0971
42	Retail	0.0460	0.1086	0.0916	0.0902
43	Restaurants, Hotels, Motels	0.0444	0.1088	0.0897	0.0909
44	Banking	0.0472	0.1075	0.0913	0.0896
45	Insurance	0.0373	0.1158	0.0813	0.0982
46	Real Estate	0.0431	0.1102	0.0859	0.0937
47	Trading	0.0452	0.1079	0.0885	0.0906
48	Others	0.0435	0.1129	0.0743	0.0994

Then, I analyze further for the excess returns based on 48 industries. The industries are grouped up based on the SIC code provided by Kenneth French's website. I exclude stocks that are not traded in NYSE, AMEX, and Nasdaq. Also, I use CRSP sharecode of 10 and 11 as suggested by Daniel and Moskowitz (2016). Table 2 presents the summary statistics of excess returns of 48 industries. Most of the industries, except for Automobile and Trucks, Defense, and Oil, experience a positive return. Trading industry generates the highest return (2.44%) than any other industries. Automobile and Trucks, surprisingly, depicts the greatest volatility among industries (approximately 60% of standard deviation). Automobile and Trucks industry suffers from the recent financial crises than any other industries. The number of observation is also reported at the last column. Other industry contains the highest number of observation, which is 316,637 observations, while Utility industry has the lowest number is 215 observations.

Table 2: Excess Returns based on 48 industries. The table presents the excess returns of 48 industries from January 1990 to December 2015. The excess return is calculated by end of the day return minus the market return (Value-weighted return). The returns are adjusted with SIC sharecode of 10 or 11.

ID	Name	Mean	Stdev	Obs
1	Agriculture	0.019	0.0779	3,418
2	Food Products	0.009	0.0611	15,858
3	Candy and Soda	0.0058	0.0406	3,901
4	Beer and Liquor	0.0093	0.0594	4,962
5	Tobacco Products	0.0046	0.0647	1,751
6	Recreation	0.0074	0.0819	10,051
7	Entertainment	0.0109	0.0862	16,046
8	Printing and Publishing	0.0142	0.0642	11,638
9	Consumer Goods	0.0104	0.0675	17,077
10	Apparel	0.0154	0.0721	11,391
11	Healthcare	0.0087	0.0781	23,416
12	Medical Equipment	0.0085	0.0751	36,148
13	Pharmaceutical Products	0.0028	0.088	61,141
14	Chemicals	0.0103	0.0638	19,831
15	Rubber and Plastic Products	0.0200	0.0752	7,713
16	Textiles	0.0114	0.0716	4,927
17	Construction Materials	0.0168	0.0632	18,243
18	Construction	0.0093	0.076	13,827
19	Steel Works Etc	0.0059	0.0651	14,788
20	Fabricated Products	0.0170	0.0628	3,221
21	Machinery	0.0134	0.0625	33,356
22	Electrical Equipment	0.0164	0.0798	26,766
23	Automobiles and Trucks	-0.0038	0.6165	34,170
24	Aircraft	0.0101	0.0677	15,138
25	Shipbuilding, Railroad Equipment	0.0126	0.0637	4,838
26	Defense	-0.0013	0.0579	1,927
27	Precious Metals	0.0017	0.0495	1,845
28	Non-Metallic and Industrial Metal Mining	0.0029	0.0806	14,557
29	Coal	0.0043	0.0873	8,548
30	Oil	-0.0088	0.0762	2,663
31	Utilities	0.0104	0.0796	215
32	Communication	0.0020	0.0489	38,632
33	Personal Services	0.0028	0.0873	43,193
34	Business Services	0.0109	0.0778	12,427
35	Computers	0.0075	0.1052	151,909

36	Electronic Equipment	0.0113	0.079	36,911
37	Measuring and Control Equipment	0.0078	0.0741	64,347
38	Business Supplies	0.0169	0.0822	21,215
39	Shipping Containers	0.0073	0.0581	11,163
40	Transportation	0.0065	0.0574	3,941
41	Wholesale	0.0044	0.0668	32,662
42	Retail	0.0084	0.0755	48,068
43	Restaurants, Hotels, Motels	0.0087	0.0727	55,110
44	Banking	0.0045	0.0693	23,851
45	Insurance	0.0121	0.0792	124,213
46	Real Estate	0.0115	0.0522	38,840
47	Trading	0.0244	0.0767	11,028
48	Others	0.0040	0.0898	316,637

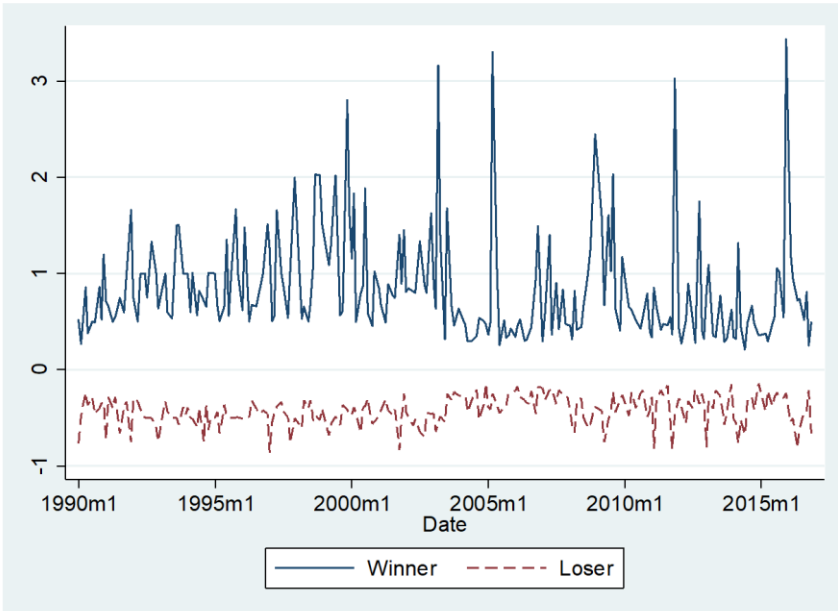
3.2. Momentum Portfolio Construction – Excess Return

Once I select my sample, I rank the portfolios based on the excess returns. The excess return is calculated using the end of the day return minus the market return (classified as valued weighted return). Top 10% of stock excess returns is classified as the winner portfolios while bottom 10% is the loser portfolio. Then, the winner minus loser (WML) is top 10% portfolio minus bottom 10% portfolio[39].

Figure 1 provides the difference excess returns between winner and loser portfolios. The winner, as expected, shows a positive excess return while loser depicts a negative return. This result is consistent with documented literature (see. Asness, 1997, Jegadeesh and Titman, 1993, Jegadeesh and Titman, 2001) that winner portfolio provides a positive return overtime while loser portfolio, on the other hand, generates a negative return.

[39] Ranking based on 10 deciles. Top 10% until bottom 10%. See. Daniel and Moskowitz (2016), Menkhoff et al. (2012b).

Figure 1: Excess returns. The figure provides the difference in excess return of top 10% and bottom 10% from January 1990 to December 2015 of all 48 industries. The solid line represents the winner return while dash line represents loser return.



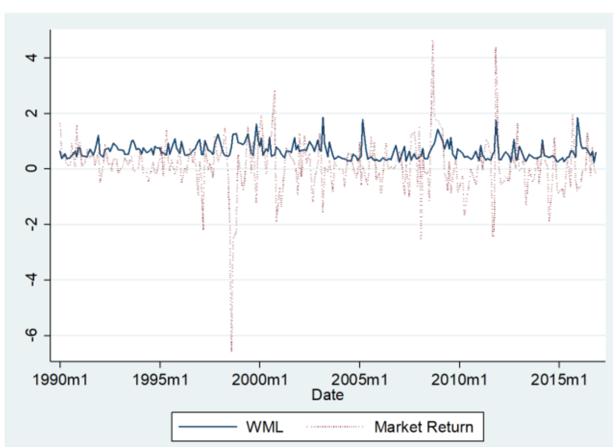
Once I sort the portfolios based on the excess returns. I have 10 portfolios where portfolio 1 is the bottom 10%, and portfolio 10 is top 10%. Table 3 presents the result. As expected, the return of loser portfolio (portfolio 1) is negative while winner portfolio (portfolio 10) is positive. The difference between standard deviation of winner and loser portfolio is pronounced, which loser portfolio (1) has a standard deviation of 12.30% compared to winner portfolio (10) with a standard deviation of 18.35%. The Sharpe ratio is also consistent with my initial finding that winner portfolio provides a substantial higher return per unit of risk than loser portfolio (-0.1608 for loser and 0.6515 for winner).

Table 3: Momentum Portfolios. The table presents the characteristics of U.S. momentum decile portfolio excess returns from January 1990 to December 2015. The primary data are from CRSP. Decile 1 portfolio is the loser portfolio, which contains the bottom 10% of the stocks with the worst losses. Decile 10 portfolio is the winner portfolio, which provides the top 10% of stocks with the largest gains. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio. V-ret is the overall value-weighted return.

Portfolio	1	2	3	4	5	6	7	8	9	10	WML	V-Ret
Mean	-7.98%	-7.46%	-3.83%	-1.38%	-0.32%	1.39%	3.29%	5.70%	9.60%	10.47%	18.45%	6.25%
Stdev.	12.30%	13.42%	8.73%	3.22%	3.40%	5.50%	6.66%	9.12%	14.90%	18.35%	19.67%	15.82%
SR	-0.16	-0.56	-0.44	-0.43	-0.10	0.25	0.49	0.62	0.64	0.65	0.94	0.40

Then, I turn my analysis into WML strategy. In comparison with value-weighted return (V-Ret), the WML strategy greatly outperforms the market return. The mean return of WML is 18.45% while the market benchmark generates only 6.2%. Sharpe ratio (SR) from WML (0.94) is also higher than market's Sharpe ratio (0.40). The return from momentum strategy helps increasing return, and higher Sharpe ratio than investing purely on the market benchmark. Menkhoff et al. (2012b) document their finding that the WML strategy increases the performance better than investing in risk-free rate, market benchmark, or bond yields. Figure 2 summarizes the difference between WML strategy and market return. As expected, WML strategy smooths the volatility of the return better than pure market return.

Figure 2: WML and Market Return. The figure represents the winner-minus-loser (WML) strategy and market return with a spanning period January 1990 to December 2015. The solid line represents the WML strategy and dash-line is market return.



3.3. Idiosyncratic Factors

In previous section, I find that my U.S. equity sample depicts the diversification benefits. Then, the plausible explanation of the relationship is the risk factor or idiosyncratic risk. The most important research in U.S. stock market is to observe the idiosyncratic risk of the stock return and can explain the change in the stock return. Idiosyncratic risk, as defined by many literatures, is the error term of the regression, which helps explain the change in the stock movement in which it is not correlated with the market risk. I am interested to test whether the idiosyncratic risk in stock returns can help predict the short-term return and improve the return from momentum strategy. I implement the strategy based on 3-factor model proposed by Fama and French[40]. Using these models, I expect to see the improvement of momentum strategy as well as the co-movement between the industries.

I specify using Fama-French model as proposed by Ang et al. (2009) as follows:

$$r_i = \alpha_i^L + \beta_i^L MKT^L + s_i^L SMB^L + h_i^L HML^L + \varepsilon_i^L$$

Where $r_i$is the daily excess U.S. dollar return of stock i, $MKT^L$is the value-weighted of local market portfolio over the one-month T-bill rate, $SMB^L$is the return of the smallest one-third of local firm minus the return of the largest one-third of local firm characterized by the market capitalization, and $HML^L$is the return of the highest one-third of book-to-market ratio minus the return of the lowest one-third of the lowest book-to-market ratio. The idiosyncratic volatility is measured by the standard deviation of the residual, ε_i^L, after the estimation from the regression model.

[40] Fama and French (2017) propose the use of five-factor to test for international assets. I exclude the use of five-factor since Fu (2009) and Ang et al. (2009) use three-factor to capture the idiosyncratic volatility from the ARCH-GARCH type model.

Fu (2009), however, points out that using the monthly stock returns with one-month lagged idiosyncratic volatilities depicts the negative relation. He argues that, different from Ang et al. (2006) and Merton (1987), that idiosyncratic volatilities are time-varying and he proposes that using exponential GARCH is more appropriate. He finds a positive significant relation between the estimated conditional volatilities and expected returns. To observe the leverage effect in volatilities, I use GJR-GACRH model (Glosten, Jagannathan, and Runkle, 1993) including asymmetric terms that can capture an important phenomenon in the conditional variance of equities. The model is estimated as follows:

$$R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$$

$$\sigma_{it}^2 = w + \sum_{i=1}^{q} [a_i + \gamma_i I_{[\varepsilon_{t-1} < 0]}] \varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$$

The equation above describes the GJR-GARCH (p,q) model, where p and q defined as the number ranging from $1 \leq p,q \leq 3$. The choice of p and q is based on Akaike Information Criteria (AIC). GJR-GARCH model is supported by Hansen and Lunde (2005) that the model can capture the leverage effect and more superior than using standard GARCH(p,q) model. They test for the IBM stock return with various conditional model and conclude that the standard GARCH is superior than using other types of conditional volatility model to predict the stock returns. The purpose of using this GJR-GARCH is to estimate the conditional variance, σ_{it}^2. The modification of the conditional variance as described in the equation is to capture the possible shocks that occur from the lagged period[41].

[41] Fu (2009) uses this modified EGARCH as to determine the leverage effect.

3.4. Portfolios sorted based on idiosyncratic volatility

I now turn my analysis of momentum strategy based on idiosyncratic volatility as determined in the previous section. Portfolios are constructed based on the level of conditional volatility as portfolio 1 is firms with the highest 20% of idiosyncratic volatility and portfolio 5 is firms with the lowest 20% of volatility. The portfolio construction is based on only 5 decile portfolios instead of 10 as I use the excess returns in the previous section. I argue that using 5 portfolios would provide more meaningful results and is more consistent with other documented literatures (see. Fu, 2009, Menkhoff et al., 2012b, Ang et al., 2009).

4. Empirical Results

4.1. Momentum in individual industries

Previous section, I estimate the momentum of all 48 industries of U.S. equity. The next question is whether momentum profits are pronounced in individual industries. We, following the same approach as provided in the previous section, estimate portfolios based on excess returns ranking from bottom 10% to top 10%. Table 4 presents 48 individual industries with 10 quintile portfolios. WML refers to the winner portfolio (portfolio10) minus loser portfolio (portfolio 1). SR is defined as the Sharpe ratio for each portfolio. The results suggest that, in general, the loser portfolio depicts a negative return in all the industries while winner portfolio shows a positive return. For example[42], the Food Products industry indicates a negative return in loser portfolio (portfolio 1) of -1.19% with the Sharpe ratio of -0.0808 and the portfolio 10 or winner portfolio shows a positive return of 3.41% with the Sharpe ratio of 0.2680. Taking long position on winner and short on loser or WML strategy, I find that most of the industries provide a greater return such as Food Products

[42] Refer to the appendix table.

with mean of 0.46% as well as an improvement in Sharpe ratio of 0.3267 under WML portfolio. I also document the similar results for other industries that WML portfolio substantially provides a better return. The Sharpe ratio, consistent with most of the industries, improves when WML strategy is estimated.

Table 4: Momentum portfolios based on 48 individual industries. The table presents the summary statistics based on individual industries of WML portfolio. The characteristics of momentum decile portfolio excess returns from January 1990 to December 2015 of all 48 industries. The table reports mean (WML) and standard deviation (Stdev) for all portfolio deciles. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio.

ID	Name	WML	Stdev	SR
1	Agriculture	0.0294	0.1508	0.1946
2	Food Products	0.0461	0.1410	0.3267
3	Candy and Soda	0.0702	0.1484	0.4728
4	Beer and Liquor	0.0570	0.1513	0.3770
5	Tobacco Products	0.1063	0.1597	0.6657
6	Recreation	0.0245	0.1420	0.1728
7	Entertainment	0.0224	0.1334	0.1681
8	Printing and Publishing	0.0426	0.1405	0.3030
9	Consumer Goods	0.0376	0.1399	0.2684
10	Apparel	0.0415	0.1342	0.3096
11	Healthcare	0.0230	0.1349	0.1704
12	Medical Equipment	0.0296	0.1330	0.2227
13	Pharmaceutical Products	0.0240	0.1319	0.1821
14	Chemicals	0.0268	0.1445	0.1858
15	Rubber and Plastic Products	0.0303	0.1414	0.2142
16	Textiles	0.0399	0.1350	0.2958
17	Construction Materials	0.0285	0.1398	0.2039
18	Construction	0.0181	0.1413	0.1278
19	Steel Works Etc	0.0156	0.1409	0.1108
20	Fabricated Products	0.0408	0.1404	0.2908
21	Machinery	0.0197	0.1385	0.1425
22	Electrical Equipment	0.0100	0.1384	0.0724
23	Automobiles and Trucks	0.0189	0.1118	0.1693
24	Aircraft	0.0260	0.1473	0.1766
25	Shipbuilding, Railroad Equipment	0.0322	0.1421	0.2263
26	Defense	0.0091	0.1616	0.0563
27	Precious Metals	0.0301	0.1328	0.2269
28	Non-Metallic and Industrial Metal Mining	0.0485	0.1314	0.3693

29	Coal	0.0218	0.1335	0.1634
30	Oil	0.0274	0.1493	0.1838
31	Utilities	0.0100	0.1341	0.0742
32	Communication	0.0885	0.1574	0.5619
33	Personal Services	0.0221	0.1425	0.1554
34	Business Services	0.0253	0.1407	0.1797
35	Computers	0.0154	0.1358	0.1134
36	Electronic Equipment	0.0132	0.1294	0.1024
37	Measuring and Control Equipment	0.0258	0.1325	0.1945
38	Business Supplies	0.0171	0.1351	0.1265
39	Shipping Containers	0.0308	0.1496	0.2060
40	Transportation	0.0376	0.1486	0.2534
41	Wholesale	0.0346	0.1428	0.2425
42	Retail	0.0209	0.1365	0.1534
43	Restaurants, Hotels, Motels	0.0187	0.1335	0.1404
44	Banking	0.0361	0.1402	0.2577
45	Insurance	0.0574	0.1478	0.3884
46	Real Estate	0.0388	0.1486	0.2607
47	Trading	0.0435	0.1448	0.3005
48	Others	0.1033	0.1575	0.6559

4.2. Relation between industries

The objective of this research is to test whether source of profit from momentum strategy is from within and/or between the industries. Therefore, if there is a diversification benefit, the source of momentum must come from between the industries rather than within the industry. I first analyze the correlation between 48 industries. The correlation is based on the relation of each industry excess return. I find, however, that, using excess returns to compute the correlation between industries, these 48 industries indicate all sign; positive, and negative correlation as the result is reported in appendix F.1. This finding is opposite to the general intuitive of the recent work of Barberis et al. (2005), which they find the strong co-movement between industries in the recent period. I find that the co-movement between the industries is, in fact, different depending on the movement of the excess return. For example, the correlation between Steel Works and Oil provides the highest negative relationship which is -0.1087. Then, this is evident that there is a diversification benefit between industries. The diversification benefit can be the greatest if the pair industries depict a perfectly negative correlation as finance textbooks and literature show.

4.3. Argument against the diversification of momentum return

This section, I analyze the possible sources of momentum returns from diversification strategy. Motivated by the fact that the momentum benefit is from taking a long position from winner and a short position from loser, I now am interested whether the combination between industries can generate a greater return than using all firms in 48 industries. The results from previous section confirms the potential diversification benefit between industries with negative correlation. The portfolio construction is the same as discussed in the previous section. I test for pair industries and expect to see greater momentum returns from industries that depict the highest negative correlation. The appendix T.2 shows my result. Using strong negative correlation between industries, I find that the result is consistent to my main results. Loser portfolio generates negative return while winner portfolio provides positive return. The WML portfolio depicts the highest return and highest Sharpe ratio. However, opposite to my initial hypothesis, the diversification benefit does not provide the strongest return as using all 48 industries. Then, the potential source of momentum return is purely based on excess returns rather than the correlation among industries. The pair between Banking and Others provides the highest momentum return which is 13.93% with the correlation between the industries of -0.0888 while the pair between Retail and Steel Work with the highest negative correlation of -0.1024 does not provide the highest WML return. The pair only generates return of 4.60%.

4.4. Idiosyncratic Factors

Table 5 shows the result from the regression based on 3-factor model. Consistent with Ang et al. (2009) that the mean of SMB is negative (-0.152%) indicating that small firms have not outperformed large firms based on recent spanning period of 1990 to 2015. The other risk loading factors are also consistent with documented literatures indicating that the market and HML are positive (0.111% and 0.349%, respectively)[43].

Figure 4 provides the idiosyncratic volatility movement from January 1990 to December 2015. As the graph shows, the idiosyncratic volatility depicts the huge swing during the financial crisis, especially during the collapse of the Lehman Brothers in 2008. The swing in idiosyncratic volatility is possibly explained by the change in country specific risks as suggested by Brooks and Del Negro (2005) that country specific risks play as the role of changing in conditional volatility. I also report the mean and standard deviation of conditional volatility based on GJR-GARCH model under the table 6. The size of conditional volatility is comparable to what Fu (2009) reports[44]. My mean of conditional volatility is 11.13% with standard deviation of 10.51%. Using the recent period from January 1990 to December 2015 can capture the presence of the conditional idiosyncratic volatility estimated by GJR-GARCH.

[43] Ang et al. (2009) report the coefficients of 0.66%, -0.08%, and 0.15% for market risk, SMB, and HML.
[44] Fu (2009) reports the mean of conditional volatility of 12.67% with standard deviation of 10.91%.

Figure 3: Idiosyncratic Volatility of 3-factor model. The figure shows the idiosyncratic volatility of 3-factor model spanning period from January 1990 to December 2015 estimated from equation: $R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$. Then, the conditional volatility is estimated by the GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i\sigma_{t-1}^2$

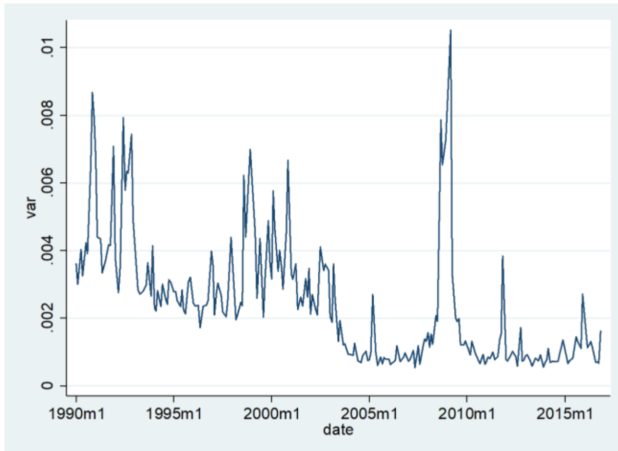


Table 5: Fama-French 3-factor model and idiosyncratic volatility. The table presents the regression from equation: $R_{it} - r_t = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, and HML_t are factor loadings as proposed by Fama-French 3-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q}[a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i\sigma_{t-1}^2$. The coefficient of factor loadings and conditional idiosyncratic volatility, E(VOL), are reported with the spanning period from January 1990 to December 2015.

	3-Factor	
Variables	Mean	Stdev.
MKT	0.111%	1.158%
SMB	-0.152%	1.908%
HML	0.346%	2.525%
E(VOL)	11.132%	10.514%

4.5. Portfolios sorted based on idiosyncratic volatility

I now turn my analysis of momentum strategy based on idiosyncratic volatility as determined in the previous section. Portfolios are constructed based on the level of conditional volatility as portfolio 1 is firms with the highest 20% of idiosyncratic volatility and portfolio 5 is firms with the lowest 20% of volatility. The portfolio construction is based on only 5 decile portfolios instead of 10 as I use the excess returns in the previous section. I argue that using 5 portfolios would provide more meaningful results and is more consistent with other documented literatures (see. Fu, 2009, Menkhoff et al., 2012b, Ang et al., 2009).

Table 6 presents the results. Ranking based on idiosyncratic volatility, however, does not yield the ideal result as presented using excess returns. Portfolio 1, as expected, provides a highest conditional volatility of 27.08% while portfolio 5 is 9.37% of conditional volatility. The return is highest for the most volatile portfolio (portfolio 1) with the mean of 1.97% while portfolio 5 depicts an average mean return of 1.23%. It is worthwhile to note that portfolio 4 has a negative return which is -1.45%. The intuition of ranking portfolios based on idiosyncratic volatility is to determine whether the volatility can play in the momentum profit. The result, however, suggests that ranking based on the conditional volatility is not better off than using plain momentum strategy as presented in table 3. The plausible reason for investors to implement this strategy is that they want to lower their risks to compensate to their returns. The WML portfolio gives 3.20% return which is higher than investing into lowest idiosyncratic volatility portfolio. Shape ratio of WML portfolio is also higher than other portfolios (0.0727 for portfolio 1 and 0.1313 for portfolio 5, and 0.1915 for WML).

Table 6: Momentum Portfolio based on idiosyncratic volatility. The table presents the characteristics of momentum decile portfolio based on idiosyncratic volatility from January 1990 to December 2015. Portfolio 1 represents the highest 20% of idiosyncratic volatility while Portfolio 5 represents the lowest 20% of idiosyncratic volatility. Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	0.0197	0.0173	0.0120	-0.0145	0.0123	0.0320
Stdev	0.2708	0.1713	0.1576	0.1173	0.0937	0.1671
SR	0.0727	0.1010	0.0761	-0.1236	0.1313	0.1915

4.6. Idiosyncratic Risk with Fama and French Five-Factor model

The presence of 5-factor model is also taken into my consideration. Fama and French (2016) test for the 5-factor model with international assets by adding profitability and investment factors to extend the 3-factor model. Their results show that adding these factors can help capture the average return patterns for both U.S. and international stocks; however, they point out the issue that the model does not fully capture the low average returns for small stocks which they behave the same way as the low profitability stocks that invest aggressively.

The 5-factor model is estimated as follows:

$$R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$$

Where CMA_i (conservative minus aggressive) is an investment factor and RMW_i (robust minus weak) is a profitability factor.

The estimation of conditional volatility is based on the GJR-GARCH model as proposed by the previous section. Table 7 indicates the results. The sizes of risk factor loadings are comparable to what I find with 3-factor model. SMB is negative confirming that the big firms have outperformed the small firms, however, the size is almost getting close to zero. CMA provides a negative mean of -0.28% indicating that firms during the recent period tend to invest more conservatively than aggressively. RMW has a mean of 0.57% providing that firms in the U.S. are more profitable in the sample period.

E(VOL) reports the conditional volatility from the GJR-GARCH estimation. The size is similar to that of 3-factor conditional volatility (mean of 12.87% with standard deviation of 15.91%). Then, using GJR-GARCH estimation with 5-factor provides a comparable estimation as I find in 3-factor model.

Table 7: Fama-French 5-factor model and idiosyncratic volatility. The table presents the regression from equation: $R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + c_i CMA_i + r_i RMW_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2)$ where MKT_t, SMB_t, HML_t, CMA_t, and RMW_i are factor loadings as proposed by Fama-French 5-factor model. The idiosyncratic volatility is measured by GJR-GARCH equation: $\sigma_{it}^2 = w + \sum_{i=1}^{q} [a_i + \gamma_i I_{[\varepsilon_{t-1}<0]}]\varepsilon_{t-1}^2 + b_i \sigma_{t-1}^2$. The coefficient of factor loadings and conditional idiosyncratic volatility, E(VOL), are reported with the spanning period from January 1990 to December 2015.

	5-Factor	
Variables	Mean	Stdev.
MKT	0.15%	1.41%
SMB	-0.04%	1.97%
HML	0.44%	2.63%
CMA	-0.28%	4.06%
RMW	0.57%	3.23%
E(VOL)	12.87%	15.91%

Then, I sort portfolio based on the 5-factor conditional idiosyncratic risk. Table 8 reports my findings. I find that, consistent with sorting based on the 3-factor conditional volatility, the return based on WML portfolio does not yield the highest return as it does for sorting based on the excess return. In fact, ranking based on 5-factor conditional volatility provides a higher return with comparable risk (3.98% mean with 15.44% standard deviation compared with 3-factor WML mean of 3.2% and standard deviation of 16.71%). Ranking based on 5-factor conditional volatility provides better return as well as the higher Sharpe ratio of 0.2578 compared to 3-factor conditional volatility Sharpe ratio of 0.1915. The result, however, cannot achieve the highest returns as I present in table 3. Then, the source of momentum returns is nothing more than purely based on excess returns

Sorting based on idiosyncratic volatility, however, does not provide a better return than using purely excess return to rank the momentum returns. Then, I confirm the evidence that the momentum returns are based on sorting based on the excess returns not from idiosyncratic risk.

Table 8: Momentum Portfolio based on idiosyncratic volatility of 5-factor model. The table presents the characteristics of momentum decile portfolio based on idiosyncratic volatility from 5-factor model from January 1990 to December 2015. Portfolio 1 represents the highest 20% of idiosyncratic volatility while Portfolio 5 represents the lowest 20% of idiosyncratic volatility. Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	0.0287	0.0187	-0.0103	0.0097	0.0111	0.0398
Stdev	0.2621	0.1673	0.1447	0.1255	0.0973	0.1544
SR	0.1095	0.1118	-0.0712	0.0773	0.1141	0.2578

4.7. Double Sorting Portfolios - liquidity and idiosyncratic volatility

Previously, I analyze the size of returns based on either excess returns or idiosyncratic volatility. Now, I move on to use double sorting which is suggested by many literatures (Fama and French, 1993, Bali and Hovakimian, 2009). Using double sorting benefits the analysis in twofold. Firstly, I can confirm whether liquidity or idiosyncratic volatility can be used as the proxy for the momentum portfolios. Second, double sorting eliminates the "too high and too low excess returns" and "too high and too low risky" stocks in portfolio construction.

The sorting begins with using excess returns of five portfolios and then I sort based on the size of liquidity and the idiosyncratic volatility. The reason of doing double sorting is that I want to see the channel that can explain the change in momentum returns.

I follow Amihud (2002) to measure the stock illiquidity as the ratio of the daily stock return and the trading volume in dollars.

$$Stock\ illiquidity = \frac{|r_{i,t}|}{Vol_{i,t}}$$

$r_{i,t}$is the return of stock i and time t and $Vol_{i,t}$ is the trading volume in dollars of stock i and time t.

Table 9 presents the result. Double sorting based on liquidity and idiosyncratic volatility depicts that I can observe, partially, the momentum returns. The momentum return (5-1 portfolio) after controlling for liquidity, as shown on panel A, provides approximately 15% return while sorting based on idiosyncratic volatility (E(Vol) in Panel B) decreases the return to 11.29%. Both are statistically significant indicating that liquidity and idiosyncratic volatility can be seen as factors that use to control for momentum returns.

Table 9: Double Sorting. The table presents the double sorting of momentum portfolio based on Amihud's liquidity (LIQ) and idiosyncratic volatility factor (E(Vol)) from January 1990 to December 2015. Portfolio 1 represents the highest 20% portfolio return while Portfolio 5 represents the lowest 20% portfolio return. 5-1 or Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

	Excess Return					
Panel A	1	2	3	4	5	5-1
LIQ	-6.50%	-2.60%	2.80%	4.80%	8.70%	15%
	Excess Return					
Panel B	1	2	3	4	5	5-1
E(Vol)	-3.80%	-1.15%	3.46%	6.78%	7.49%	11.29%

4.8. Portfolio - Inverse Conditional Volatility

In the previous section, the portfolios are formed based on the size of idiosyncratic volatility. The result, however, shows that the volatility-based portfolios cannot help determining the improvement of the momentum returns. Then, now I move on to construct portfolios based on the volatility by scaling an excess return by the inverse of conditional variance as suggested by Moreira and Muir (2017) to capture the potential increase and decrease risk exposure of the portfolios. The portfolio is constructed as following:

$$f_{t+1}^{\sigma} = \frac{c}{\widehat{\sigma_t^2(f)}} f_{t+1}$$

Where ft+1 is the one period buy-and hold portfolio excess return, $f_{t+1}^{\sigma}$is the one-period portfolio volatility, $\sigma_t^2(f)$is the proxy for the conditional variance of the portfolio, and c is a constant arbitrary number to measure the scaling conditional volatility.

To determine the proxy for portfolio conditional variance, $\sigma_t^2(f)$, I use an approximation of the previous monthly realized variance as the proxy for the conditional variance,

$$\sigma_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22})^2$$

Where $RV_t^2(f)$ is the previous month realized variance with approximation of 22 trading days.

I use both daily and monthly data from Kenneth French's website on the excess market return (Mktrf), size factor (SMB), value factor (HML), momentum factor (MOM). Time-series regression presents as follows:

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}$$

Figure 4 presents realized variance for each factor. As expected, these variables provide similar trend. Then, it is safe to conclude that these factors can be used to predict the portfolio conditional variance.

Figure 4: Realized Variance of 3-factor and momentum factor. The figure shows the size of realized variance of 3-factor and momentum factor spanning period from January 1990 to December 2015 estimated from equation: $\sigma_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22})^2$

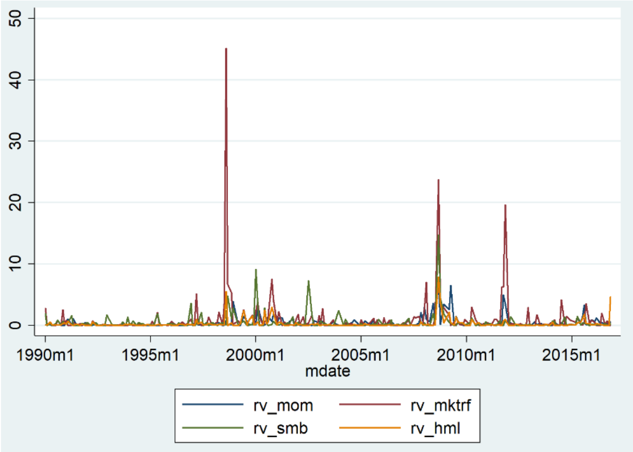


Table 10 reports regression results based on single factor, 3-factor, and 3-factor plus momentum. As expected, these factors are statistically significant as reported by p-value. Then, the portfolios can be formed based on these factors. Moreover, consistent with Moreira and Muir (2017), the alpha is positive in all the cases which reflect that investors benefit from such momentum strategy.

Table 10: Time Series Regression on 3-factor plus momentum factor. The table presents that characteristics of 3-factor and momentum factor on the portfolio construction based on inverse conditional volatility. The dependent variable is one-period portfolio volatility determined by $f_{t+1}^{\sigma} = \frac{c}{\sigma_t^2(f)} f_{t+1}$, where $f_{t+1}$is one-period buy and hold portfolio excess return, c is constant arbitrary number to measure the scaling conditional volatility, and $\sigma_t^2(f)$ is monthly realized variance. The time series regression is $f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}$.The parentheses are reported p-value.

Model	(1)	(2)	(3)	(4)	(6)	(5)
Constant	0.0031	0.0026	0.0035	0.0033	0.0019	0.0020
	(000)	(000)	(000)	(000)	(000)	(000)
MKTRF	0.0071				0.0077	0.0076
	(000)				(000)	(000)
SMB		0.0040			0.0054	0.0054
		(000)			(000)	(000)
HML			-0.0020		0.0021	0.0013
			(000)		(000)	(000)
MOM				-0.0019		-0.0016
				(000)		(000)

Then, I sort the portfolios based on the excess returns. Top 20% represent the winner portfolio while bottom 20% is loser portfolio. The difference between winner and loser portfolio is categorized as WML portfolio as I mention in the previous section. Table 11 shows the result. Using inverse conditional volatility from three factors plus momentum factor to form portfolios, in fact, helps to reduce the size of standard deviation of each portfolio. The result, however, does not show any improvement in WML portfolio return. The size of return is actually less than sorting based purely on excess return. Using this strategy helps to reduce the risk involved in the momentum investment strategy while the Sharpe ratio is 0.536, which is less than the sorting based purely on excess return with the Sharpe ratio of 0.65. We, however, can only argue that the size of return on WML portfolio is not affected by the traditional 3-factor and momentum factor. Then, in next section, I am trying to explore the WML predictability by adding economic variables.

Table 11: Portfolio based on inverse conditional variance. The table provides the portfolios based on the size of excess return by using $f_{t+1}^{\sigma} = \frac{c}{\sigma_t^2(f)} f_{t+1}$ from January 1990 to December 2015. Portfolio 1 represents the highest 20% portfolio return while Portfolio 5 represents the lowest 20% portfolio return. 5-1 or Winner minus loser (WML) is zero investment strategy which is long portfolio 5 and short portfolio 1. SR denotes for Sharpe Ratio.

Portfolio	1	2	3	4	5	WML
Mean	-1.86%	0.58%	2.14%	4.43%	6.78%	8.64%
Stdev	18.76%	20.17%	18.55%	11.67%	13.49%	16.13%
SR	-0.099	0.029	0.115	0.380	0.503	0.536

4.9. Portfolio Predictability

This section analyzes the predictability of the momentum portfolio returns. The momentum portfolio predictability has been investigated by Daniel and Moskowitz (2016). They test for the momentum return predictability using realized variance of daily returns. Their results suggest that momentum can be managed through realized variance as predicted by Barroso and Santa-Clara (2015). To predict the portfolio regression, Fama-MacBeth (1973) suggests that two-step regression is needed to determine the coefficients of risk-loading factors[45]. Once I determine the coefficients, I can run regression based on quintile portfolios. The model is presented as following:

$$r_{i,t+1} = \lambda_0 + \widehat{\beta_i}\lambda_t + \mu_i X_t + \theta_i Z_{i,t} + \alpha_{i,t+1}$$

Where $\hat{\beta} i$ is a vector of the coefficients estimated from the first step (MKTRF, SMB, HML, MOM), and Xt is a vector of economic variables, and θ_i is the vector of control variables (Idiosyncratic factor and liquidity factor).

I choose CPI, bond yield, and T-bill as economic variables. These variables are extensively studied and concluded that can present to the change in excess returns of equity markets, especially in the U.S.[46] equity. I first determine the vector of risk-loading factors coefficients from regression in the previous section. Then, I use the portfolio predictability model to determine the change in excess returns. Table 12 presents the results. As expected, all the economic variables are able to explain the change in excess returns. I also present using only beta coefficients as well as one economic variable for each model. It seems that the change in portfolio is not affected by the economic variables as I previously thought. The size of economic variables appears to be small; although they are all economically significant. The plausible explanation is that the momentum returns in fact are not driven by the economic factors since the returns are based on the previous performance of the assets themselves rather than other external forces. Using each variable to run the regression model does not worsen my initial result. Then, using economic variables do not actually impact the change in portfolio prediction since the main source of the return depends highly on the previous information from the risk-loading factors rather than other economic variables.

[45] I use MKTRF, SMB, HML, and MOM as risk-loading factors since these variables are mainly used in literatures. See. Ang et al. (2006), Ang et al. (2009), Fu (2009), Fama and French (2015).
[46] See. Bekaert and Wu (2000), Chrisoffersen et al. (2012), Menkhoff et al. (2012b).

Table 12: Portfolio Predictability. The table reports the portfolio predictability from $r_{i,t+1} = \lambda_0 + \widehat{\beta_\iota}\lambda_t + \mu_i X_t + \theta_i Z_{i,t} + \alpha_{i,t+1}$, where $\hat{\beta} i$ is a vector of the coefficients estimated from the first step (MKTRF, SMB, HML, MOM), and Xt is a vector of economic variables, and θ_i is the vector of control variables (Idiosyncratic factor and liquidity factor).

	1	2	3	4	5
Constant	0.000	0.000	0.000	0.000	0.000
	(0.66)	(-0.08)	(0.65)	(0.24)	(0.73)
MKTRF	0.320	0.226	0.375	0.234	0.369
	(2.14)	(1.99)	(2.37)	(2.01)	(2.34)
SMB	-0.169	-0.039	-0.264	-0.034	-0.299
	(-2.43)	(-2.34)	(-2.25)	(-2.29)	(-2.55)
HML	0.045	0.149	0.008	0.065	0.031
	(2.17)	(3.00)	(2.11)	(2.28)	(2.16)
MOM	0.316	0.232	0.438	0.229	0.427
	(2.54)	(2.26)	(2.84)	(2.13)	(2.76)
CPI	0.011		0.008		
	(2.35)		(2.65)		
T-Bill	0.009			0.008	
	(3.22)			(3.55)	
Bond	0.049				0.058
	(3.47)				(3.94)
Ret	0.032	0.039	0.028	0.026	0.056
	(4.39)	(5.64)	(3.96)	(3.75)	(8.13)
LIQ	-0.072	-0.066	-0.074	-0.047	-0.071
	(-0.34)	(-0.34)	(-0.36)	(-0.23)	(-0.35)
IDO	-0.046	-0.054	-0.041	-0.040	-0.071
	(-5.89)	(-7.29)	(-5.25)	(-5.29)	(-9.40)

5. Conclusion and Remarks

This paper provides a comprehensive study of momentum returns of U.S. and international assets from spanning period of January 1990 to December 2015. Using a traditional momentum portfolio construction based on excess returns, I find that loser portfolios depict negative returns while winner portfolios show positive returns. Winner minus loser (WML) portfolio provide a better return and Sharpe ratio. Dividing into 48 industries and testing for momentum returns, I find that the momentum returns are pronounced in all 48 industries.

A long-standing belief in finance that the diversification benefit comes from correlation among industries, I test for pairs of industries that provide the highest negative correlations. I find, however, that these pairs of industries cannot achieve the highest returns as I use all 48 portfolios. Then, I investigate further using GJR-GARCH to observe the conditional idiosyncratic volatility based from 3 and 5-factor models and I sort portfolios based on the level of conditional idiosyncratic volatility. My results show that, opposite to what I find in the previous section, sorting based on idiosyncratic volatility cannot help achieving the highest possible returns. In fact, using idiosyncratic volatility sorting only helps increasing Sharpe ratio.

Then, I argue that the return on WML may be affected by other factors such as idiosyncratic factor and liquidity. Then, I conduct double sorting based on liquidity and idiosyncratic volatility and find that these factors actually can control the size of the momentum return and account for other factors that might affect the WML portfolio return. In addition, I examine the predictability of these momentum portfolio by applying the approach of inverse conditional volatility proposed by Moreira and Muir (2017). The result indicates that the traditional 3-factor and momentum factor are responsible for the predictability of momentum portfolio while economic variables are small and do not contribute much to the change in WML portfolio return.

My findings confirm that the momentum return come purely from excess returns not from neither correlations nor idiosyncratic risks. This research, however, is in needs to investigate further for possible sources of momentum returns. The possibilities of returns can come in many ways such as economic variables or new sorting techniques.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), pp.31-56.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang, X., 2006. The cross-section of volatility and expected returns. *The Journal of Finance*, *61*(1), pp.259-299.

Asness, C.S., 1997. The interaction of value and momentum strategies. *Financial Analysts Journal*, *53*(2), pp.29-36.

Asness, C.S., Moskowitz, T.J. and Pedersen, L.H., 2013. Value and momentum everywhere. *The Journal of Finance*, *68*(3), pp.929-985.

Bali, T.G. and Hovakimian, A., 2009. Volatility spreads and expected stock returns. *Management Science*, *55*(11), pp.1797-1812.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of financial economics*, *9*(1), pp.3-18.

Barberis, N., Shleifer, A. and Wurgler, J., 2005. Comovement. *Journal of Financial Economics*, *75*(2), pp.283-317.

Barroso, P. and Santa-Clara, P., 2015. Momentum has its moments. *Journal of Financial Economics*, *116*(1), pp.111-120.

Barroso, P. and Santa-Clara, P., 2015. Momentum has its moments. *Journal of Financial Economics*, *116*(1), pp.111-120.

Bekaert, G. and Wu, G., 2000. Asymmetric volatility and risk in equity markets. *The review of financial studies*, *13*(1), pp.1-42.

Bekaert, G., Hodrick, R.J. and Zhang, X., 2009. International stock return comovements. *The Journal of Finance*, *64*(6), pp.2591-2626.

Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of finance*, *40*(3), pp.793-805.

Brooks, R. and Del Negro, M., 2005. Country versus region effects in international stock returns. *The Journal of Portfolio Management*, *31*(4), pp.67-72.

Chan, L.K., Jegadeesh, N. and Lakonishok, J., 1996. Momentum strategies. *The Journal of Finance*, *51*(5), pp.1681-1713.

Chordia, T. and Shivakumar, L., 2002. Momentum, business cycle, and time-varying expected returns. *The Journal of Finance*, *57*(2), pp.985-1019.

Christoffersen, P., Errunza, V., Jacobs, K. and Langlois, H., 2012. Is the potential for international diversification disappearing? A dynamic copula approach. *The Review of Financial Studies*, *25*(12), pp.3711-3751.

Chui, A.C., Titman, S. and Wei, K.J., 2010. Individualism and momentum around the world. *The Journal of Finance*, *65*(1), pp.361-392.

Daniel, K. and Moskowitz, T.J., 2016. Momentum crashes. *Journal of Financial Economics*, *122*(2), pp.221-247.

Erb, C.B. and Harvey, C.R., 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal*, *62*(2), pp.69-97.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), pp.3-56.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), pp.55-84.

Fama, E.F. and French, K.R., 2016. Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, *29*(1), pp.69-103.

Fama, E.F. and French, K.R., 2017. International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), pp.441-463.

Fama, E.F. and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), pp.607-636.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*(1), pp.24-37.

Hoberg, G. and Phillips, G., 2010. Real and financial industry booms and busts. *The Journal of Finance*, *65*(1), pp.45-86.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), pp.65-91.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance*, *56*(2), pp.699-720.

Lehmann, B.N., 1990. Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), pp.1-28.

Lesmond, D.A., Schill, M.J. and Zhou, C., 2004. The illusory nature of momentum profits. *Journal of financial economics*, *71*(2), pp.349-380.

Maillard, S., Roncalli, T. and Teïletche, J., 2010. The properties of equally weighted risk contribution portfolios. *The Journal of Portfolio Management*, *36*(4), pp.60-70.

Malkiel, B.G. and Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), pp.383-417.

Menkhoff, L., Sarno, L., Schmeling, M. and Schrimpf, A., 2012b. Currency momentum strategies. *Journal of Financial Economics*, *106*(3), pp.660-684.

Moreira, A. and Muir, T., 2017. Volatility-Managed Portfolios. *The Journal of Finance*, *72*(4), pp.1611-1644.

Moskowitz, T.J. and Grinblatt, M., 1999. Do industries explain momentum?. *The Journal of Finance*, *54*(4), pp.1249-1290.

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. *Journal of Financial Economics*, *104*(2), pp.228-250.

Naranjo, A. and Porter, B., 2007. Including emerging markets in international momentum investment strategies. *Emerging Markets Review*, *8*(2), pp.147-166.

Novy-Marx, R., 2012. Is momentum really momentum?. *Journal of Financial Economics*, *103*(3), pp.429-453.

Okunev, J. and White, D., 2003. Do momentum-based strategies still work in foreign currency markets?. *Journal of Financial and Quantitative Analysis*, *38*(2), pp.425-447.

Rouwenhorst, K.G., 1998. International momentum strategies. *The Journal of Finance*, *53*(1), pp.267-284.

Appendix T.1: 48 Industries portfolio construction. The table presents the characteristics of momentum decile portfolio excess returns from January 1990 to December 2015 of all 48 industries. Decile 1 portfolio is the loser portfolio, which contains the bottom 10% of the stocks with the worst losses. Decile 10 portfolio is the winner portfolio, which provides the top 10% of stocks with the largest gains. The table reports mean and standard deviation (Stdev) for all portfolio deciles. Winner minus loser (WML) is zero investment strategy which is long portfolio 10 and short portfolio 1. SR denotes for Sharpe Ratio.

Industry	Portfolio	1	2	3	4	5	6	7	8	9	10	WML
Agriculture	Mean	-0.01	-0.0137	-0.011	-0.003	-0.0038	0.0087	0.0248	0.0268	0.0168	0.0193	0.0294
	Stdev	0.1557	0.1182	0.1027	0.0961	0.0855	0.0682	0.1032	0.1014	0.1054	0.1412	0.1508
	SR	-0.0645	-0.116	-0.1068	-0.0311	-0.0449	0.1278	0.2406	0.2644	0.1593	0.1368	0.1946
Food Products	Mean	-0.0119	-0.0167	-0.0127	-0.0129	-0.0021	0.0061	0.0181	0.0288	0.03	0.0341	0.0461
	Stdev	0.1479	0.1251	0.1045	0.0912	0.074	0.0749	0.084	0.0967	0.1117	0.1274	0.141
	SR	-0.0808	-0.1333	-0.1212	-0.1415	-0.0278	0.0812	0.2153	0.298	0.2684	0.268	0.3267
Candy and Soda	Mean	-0.0206	-0.0219	-0.0222	-0.0107	0.0046	0.005	0.0174	0.0246	0.0302	0.0496	0.0702
	Stdev	0.1412	0.1056	0.0954	0.0772	0.08	0.0775	0.0842	0.0851	0.1077	0.1628	0.1484
	SR	-0.1456	-0.2069	-0.233	-0.1391	0.0572	0.0639	0.207	0.289	0.2803	0.3047	0.4728
Beer and Liquor	Mean	-0.0277	-0.0363	-0.0123	-0.0115	-0.0061	0.0123	0.0309	0.0335	0.0294	0.0293	0.057
	Stdev	0.1666	0.132	0.098	0.0926	0.08	0.0777	0.0876	0.0935	0.1075	0.1207	0.1513
	SR	-0.1663	-0.2752	-0.1258	-0.1246	-0.0767	0.1577	0.3529	0.3584	0.2737	0.243	0.377
Tobacco Products	Mean	-0.056	-0.0386	-0.0071	-0.0197	-0.0003	-0.0006	0.0204	0.0341	0.0601	0.0503	0.1063
	Stdev	0.1732	0.1132	0.0897	0.0776	0.0722	0.0804	0.0766	0.078	0.1194	0.1328	0.1597
	SR	-0.3233	-0.341	-0.0788	-0.2535	-0.0041	-0.0076	0.2657	0.4375	0.5037	0.3791	0.6657
Recreation	Mean	-0.008	-0.0056	-0.0139	-0.0095	-0.0038	0.0132	0.021	0.0216	0.0233	0.0166	0.0245
	Stdev	0.1411	0.1242	0.0983	0.0917	0.0773	0.0672	0.0847	0.1036	0.1124	0.1438	0.142
	SR	-0.0565	-0.0452	-0.1415	-0.1037	-0.0496	0.1959	0.2477	0.2083	0.2076	0.1152	0.1728
Entertainment	Mean	-0.004	-0.0082	-0.0167	-0.0069	-0.0107	0.0143	0.019	0.029	0.025	0.0184	0.0224
	Stdev	0.1316	0.1241	0.1103	0.0933	0.0801	0.0771	0.0955	0.1013	0.1175	0.1369	0.1334
	SR	-0.0303	-0.066	-0.1518	-0.0739	-0.1329	0.1855	0.1989	0.2865	0.2127	0.1347	0.1681
Printing and Publishing	Mean	-0.0135	-0.014	-0.0073	-0.006	0.001	0.0111	0.018	0.0212	0.0263	0.0291	0.0426
	Stdev	0.1468	0.1301	0.1062	0.0845	0.0763	0.0722	0.0839	0.0951	0.1094	0.1277	0.1405
	SR	-0.0916	-0.1077	-0.0686	-0.0712	0.0134	0.1535	0.2144	0.2224	0.2402	0.2279	0.303

Consumer Goods	Mean	-0.0109	-0.0143	-0.0076	-0.006	-0.0036	0.0076	0.0206	0.0285	0.0212	0.0266	0.0376
	Stdev	0.1398	0.1177	0.0987	0.0946	0.0883	0.0755	0.0898	0.0933	0.1053	0.1402	0.1399
	SR	-0.0782	-0.1217	-0.0768	-0.0632	-0.0403	0.1012	0.23	0.3052	0.2015	0.19	0.2684
Apparel	Mean	-0.0103	-0.0149	-0.0074	-0.0041	-0.0031	0.0097	0.0187	0.0233	0.0207	0.0312	0.0415
	Stdev	0.1417	0.1236	0.0982	0.0982	0.0765	0.0731	0.0812	0.095	0.118	0.1193	0.1342
	SR	-0.0727	-0.1208	-0.075	-0.0417	-0.0403	0.1321	0.2305	0.2458	0.1758	0.2619	0.3096
Healthcare	Mean	-0.0084	-0.002	-0.0115	-0.0057	-0.004	0.0071	0.0212	0.0221	0.0231	0.0145	0.023
	Stdev	0.1307	0.118	0.1087	0.0933	0.0856	0.0727	0.0906	0.0988	0.1056	0.1432	0.1349
	SR	-0.0646	-0.0169	-0.1053	-0.0609	-0.0463	0.098	0.2344	0.2232	0.2192	0.1016	0.1704
Medical Equipment	Mean	-0.0056	-0.0024	-0.0118	-0.0062	-0.0041	0.0117	0.0158	0.0195	0.0198	0.024	0.0296
	Stdev	0.1309	0.1108	0.1133	0.0953	0.0838	0.0813	0.1011	0.1017	0.1139	0.1372	0.133
	SR	-0.0428	-0.0219	-0.1039	-0.0647	-0.0485	0.1441	0.1559	0.1916	0.1743	0.175	0.2227
Pharmaceutical Products	Mean	-0.0051	-0.0014	-0.007	-0.0049	-0.0053	0.0106	0.0153	0.0143	0.014	0.0189	0.024
	Stdev	0.1221	0.1099	0.1117	0.0981	0.083	0.0861	0.0964	0.1027	0.1141	0.1514	0.1319
	SR	-0.0416	-0.0125	-0.0629	-0.0502	-0.0644	0.1228	0.1583	0.1393	0.1226	0.1251	0.1821
Chemicals	Mean	-0.0082	-0.0029	0.0015	-0.0036	-0.0014	0.0066	0.0117	0.0176	0.0214	0.0186	0.0268
	Stdev	0.1531	0.1208	0.1008	0.0891	0.0818	0.0769	0.0819	0.0962	0.1109	0.1272	0.1445
	SR	-0.0538	-0.0238	0.0147	-0.0406	-0.0169	0.0863	0.143	0.1833	0.1926	0.1462	0.1858
Rubber and Plastic Products	Mean	-0.0089	-0.0165	-0.0227	-0.0077	-0.0031	0.0121	0.0229	0.0334	0.0257	0.0214	0.0303
	Stdev	0.1493	0.1262	0.1092	0.0906	0.0757	0.0643	0.0801	0.0943	0.1033	0.1257	0.1414
	SR	-0.0594	-0.1311	-0.2082	-0.0855	-0.0405	0.1889	0.2856	0.3539	0.2489	0.1704	0.2142
Textiles	Mean	-0.0147	-0.0228	-0.0178	-0.0059	-0.0023	0.0143	0.0284	0.0305	0.0257	0.0252	0.0399
	Stdev	0.1377	0.1416	0.1097	0.0839	0.0739	0.0745	0.0834	0.0941	0.1059	0.1295	0.135
	SR	-0.107	-0.1613	-0.1621	-0.0699	-0.0308	0.1926	0.34	0.3236	0.243	0.1946	0.2958
Construction Materials	Mean	-0.0074	-0.0176	-0.0102	-0.0068	-0.0032	0.0091	0.0219	0.0269	0.0232	0.0211	0.0285
	Stdev	0.1453	0.1286	0.1044	0.0878	0.0782	0.0793	0.0802	0.0922	0.1115	0.1289	0.1398
	SR	-0.051	-0.1366	-0.0981	-0.0777	-0.0411	0.1144	0.2735	0.292	0.2083	0.1637	0.2039
Construction	Mean	-0.0052	0.0032	-0.0051	-0.0006	-0.0044	0.0092	0.0173	0.0124	0.0104	0.0128	0.0181
	Stdev	0.1454	0.1133	0.1082	0.0951	0.0825	0.0744	0.0887	0.1078	0.11	0.133	0.1413

	SR	-0.036	0.028	-0.0472	-0.0062	-0.0535	0.1231	0.1947	0.1152	0.0941	0.0964	0.1278
Steel Works Etc.	Mean	-0.0034	-0.0002	-0.0019	0.0003	-0.0031	0.0061	0.0166	0.0138	0.0086	0.0122	0.0156
	Stdev	0.1448	0.1272	0.1086	0.0934	0.0763	0.0883	0.0901	0.097	0.1041	0.1331	0.1409
	SR	-0.0236	-0.0012	-0.0175	0.0033	-0.0405	0.0694	0.1842	0.1424	0.0826	0.0916	0.1108
Fabricated Products	Mean	-0.0178	-0.0194	-0.0083	0.0115	-0.0102	0.0071	0.0236	0.0274	0.015	0.023	0.0408
	Stdev	0.1502	0.1346	0.0997	0.0948	0.0719	0.0669	0.0921	0.0839	0.1062	0.1207	0.1404
	SR	-0.1188	-0.1444	-0.0835	0.1213	-0.1413	0.1064	0.256	0.3261	0.1416	0.1904	0.2908
Machinery	Mean	-0.0015	-0.0049	0.0014	-0.0019	-0.0012	0.0073	0.0153	0.0166	0.0099	0.0182	0.0197
	Stdev	0.1426	0.1301	0.1066	0.0905	0.081	0.0757	0.0891	0.0979	0.1116	0.1304	0.1385
	SR	-0.0107	-0.0373	0.0128	-0.0212	-0.0152	0.096	0.1718	0.1698	0.0884	0.1397	0.1425
Electrical Equipment	Mean	-0.0048	0.0043	-0.0077	-0.0002	-0.0008	0.0104	0.0197	0.0159	0.0151	0.0052	0.01
	Stdev	0.1321	0.1222	0.1132	0.0962	0.0783	0.0809	0.0946	0.1017	0.1126	0.1511	0.1384
	SR	-0.0365	0.0348	-0.0682	-0.002	-0.0103	0.1283	0.2079	0.1561	0.1338	0.0344	0.0724
Automobiles and Trucks	Mean	-0.0032	-0.0144	-0.0184	-0.0163	-0.0107	0.0019	0.0087	0.0138	0.0086	0.0157	0.0189
	Stdev	0.107	0.1062	0.0936	0.0822	0.0765	0.0759	0.0848	0.0953	0.104	0.1213	0.1118
	SR	-0.03	-0.1358	-0.1969	-0.1979	-0.1405	0.0252	0.1027	0.1445	0.0823	0.1295	0.1693
Aircraft	Mean	-0.0017	-0.0106	0.0008	-0.0011	-0.0001	0.0107	0.0116	0.0171	0.0142	0.0243	0.026
	Stdev	0.1518	0.125	0.1047	0.089	0.0809	0.0819	0.0878	0.0919	0.1076	0.1382	0.1473
	SR	-0.011	-0.0845	0.0077	-0.0121	-0.0014	0.1311	0.1317	0.1856	0.1319	0.1761	0.1766
Shipbuilding, Railroad Equipment	Mean	-0.0066	-0.0085	-0.0035	-0.0005	-0.0076	0.011	0.0066	0.0215	0.0238	0.0255	0.0322
	Stdev	0.1453	0.1329	0.0971	0.0903	0.0743	0.0874	0.0773	0.0965	0.1143	0.1357	0.1421
	SR	-0.0456	-0.0637	-0.0356	-0.0056	-0.1016	0.1263	0.0855	0.2223	0.2077	0.1881	0.2263
Defense	Mean	-0.0063	-0.007	-0.0084	-0.0011	-0.0068	0.0058	0.0112	0.0138	0.0343	0.0028	0.0091
	Stdev	0.1653	0.1174	0.0957	0.0968	0.071	0.0841	0.0867	0.1003	0.1163	0.1543	0.1616
	SR	-0.0383	-0.0593	-0.0875	-0.0113	-0.0963	0.0687	0.1288	0.1374	0.2946	0.018	0.0563

Precious Metals Non-Metallic and Industrial Metal	Mean	-0.0008	-0.0228	0.0097	-0.0093	-0.0013	0.0092	0.0116	0.0195	0.0131	0.0293	0.0301
	Stdev	0.1251	0.1137	0.0918	0.106	0.0721	0.0935	0.0971	0.1112	0.0894	0.1483	0.1328
	SR	-0.0066	-0.2006	0.1054	-0.0877	-0.0183	0.0985	0.1194	0.1754	0.1463	0.1976	0.2269
Mining	Mean	-0.0121	-0.007	-0.0085	-0.004	-0.0089	0.0077	0.0168	0.0162	0.0149	0.0364	0.0485
	Stdev	0.1305	0.1168	0.1057	0.0947	0.0845	0.0788	0.0924	0.101	0.0988	0.1331	0.1314
	SR	-0.0926	-0.0595	-0.08	-0.0426	-0.1053	0.0983	0.1818	0.16	0.1509	0.2737	0.3693
Coal	Mean	-0.0022	-0.0039	-0.0112	-0.0034	-0.0031	0.0037	0.0084	0.0117	0.0154	0.0196	0.0218
	Stdev	0.136	0.1244	0.1098	0.0919	0.0857	0.0721	0.0869	0.1006	0.1162	0.1284	0.1335
	SR	-0.0161	-0.0314	-0.1016	-0.037	-0.0359	0.0519	0.0971	0.1167	0.1327	0.1529	0.1634
Oil	Mean	-0.0197	0.001	-0.0026	-0.0086	-0.0016	0.0055	0.0117	0.0157	0.0152	0.0077	0.0274
	Stdev	0.1594	0.1163	0.0823	0.0942	0.0793	0.076	0.0754	0.0809	0.1077	0.1291	0.1493
	SR	-0.1237	0.0084	-0.0313	-0.0914	-0.0202	0.0728	0.1548	0.1945	0.1409	0.0598	0.1838
Utilities	Mean	-0.0004	0.0005	-0.004	0.0015	-0.0031	0.007	0.0173	0.0156	0.0124	0.0096	0.01
	Stdev	0.1344	0.1187	0.1088	0.0956	0.0848	0.0771	0.0884	0.102	0.1083	0.1336	0.1341
	SR	-0.0028	0.004	-0.0368	0.0157	-0.0366	0.0912	0.1961	0.1526	0.1146	0.0718	0.0742
Communication	Mean	-0.0384	-0.0279	-0.0138	-0.0033	0.0006	0.0101	0.0194	0.0255	0.037	0.0501	0.0885
	Stdev	0.1705	0.11	0.0922	0.0813	0.0738	0.073	0.0736	0.0838	0.1007	0.1313	0.1574
	SR	-0.2251	-0.254	-0.1496	-0.0406	0.0084	0.139	0.2638	0.3043	0.3674	0.3815	0.5619
Personal Services	Mean	-0.0107	-0.0058	-0.0094	-0.0038	-0.002	0.0088	0.0155	0.0196	0.0186	0.0114	0.0221
	Stdev	0.1365	0.1145	0.1062	0.0931	0.0887	0.0804	0.095	0.1053	0.119	0.1543	0.1425
	SR	-0.0784	-0.0511	-0.0889	-0.0407	-0.0221	0.1094	0.1636	0.1865	0.156	0.0742	0.1554
Business Services	Mean	-0.0054	-0.0032	-0.0136	-0.0113	-0.0035	0.0084	0.0178	0.0222	0.0233	0.0199	0.0253
	Stdev	0.1383	0.1146	0.1122	0.0993	0.0831	0.0806	0.0851	0.1004	0.1125	0.1455	0.1407
	SR	-0.0389	-0.0282	-0.1217	-0.1142	-0.0426	0.1046	0.2091	0.2211	0.2073	0.1369	0.1797
Computers	Mean	-0.0058	-0.003	-0.0085	-0.0047	-0.0041	0.0096	0.0169	0.0161	0.0176	0.0096	0.0154

	Stdev	0.1282	0.1166	0.1125	0.0995	0.0852	0.0844	0.0951	0.1074	0.1191	0.1508	0.1358
	SR	-0.0452	-0.026	-0.0757	-0.047	-0.0479	0.1142	0.1782	0.1499	0.1476	0.0636	0.1134
Electronic Equipment	Mean	-0.0035	-0.005	-0.0031	-0.001	-0.0017	0.0126	0.0166	0.0137	0.0181	0.0097	0.0132
	Stdev	0.1239	0.1071	0.1092	0.0984	0.0832	0.0807	0.0944	0.1015	0.1099	0.1403	0.1294
	SR	-0.0282	-0.0471	-0.0283	-0.0101	-0.0208	0.1564	0.1755	0.1353	0.1648	0.0695	0.1024
Measuring and Control Equipment	Mean	-0.0155	-0.0059	-0.0018	-0.0014	-0.0017	0.0063	0.0107	0.0101	0.0083	0.0102	0.0258
	Stdev	0.126	0.1135	0.1065	0.0981	0.0816	0.0836	0.0955	0.1038	0.109	0.1453	0.1325
	SR	-0.1231	-0.0518	-0.017	-0.0144	-0.0211	0.0755	0.1125	0.0974	0.0761	0.0705	0.1945
Business Supplies	Mean	-0.0007	-0.0045	-0.0068	-0.0059	-0.0044	0.0087	0.0211	0.0185	0.0199	0.0164	0.0171
	Stdev	0.1357	0.119	0.1132	0.0966	0.0753	0.0748	0.0861	0.1048	0.1185	0.1339	0.1351
	SR	-0.0054	-0.0374	-0.0598	-0.0614	-0.0579	0.117	0.2454	0.1766	0.1681	0.1221	0.1265
Shipping Containers	Mean	-0.0084	-0.012	-0.0006	-0.0004	0.0018	0.0073	0.014	0.0183	0.0159	0.0224	0.0308
	Stdev	0.1547	0.1233	0.0982	0.0899	0.0748	0.08	0.0845	0.0944	0.116	0.1395	0.1496
	SR	-0.0546	-0.097	-0.0057	-0.0045	0.0245	0.091	0.1653	0.1943	0.1368	0.1604	0.206
Transportation	Mean	-0.0077	-0.0149	-0.0097	-0.0138	0.0006	0.0136	0.0156	0.0297	0.023	0.0299	0.0376
	Stdev	0.1551	0.1179	0.093	0.094	0.0834	0.0679	0.0837	0.0908	0.1113	0.1354	0.1486
	SR	-0.0499	-0.126	-0.1046	-0.1466	0.0072	0.2	0.1867	0.3268	0.2067	0.2209	0.2534
Wholesale	Mean	-0.0063	-0.0078	-0.0076	-0.0068	-0.0022	0.0054	0.013	0.0205	0.0211	0.0284	0.0346
	Stdev	0.1458	0.1208	0.1028	0.0949	0.0828	0.0803	0.0898	0.0991	0.1105	0.1368	0.1428
	SR	-0.0429	-0.065	-0.0738	-0.0715	-0.0262	0.0673	0.1442	0.2072	0.1912	0.2074	0.2425
Retail	Mean	-0.0043	-0.0048	-0.013	-0.0044	-0.0069	0.0089	0.0211	0.0251	0.0208	0.0166	0.0209
	Stdev	0.135	0.1194	0.1115	0.0982	0.0785	0.077	0.0892	0.1023	0.1144	0.1394	0.1365
	SR	-0.0318	-0.0398	-0.1168	-0.0445	-0.0873	0.1151	0.2366	0.2452	0.1814	0.1194	0.1534
Restaurants, Hotels, Motels	Mean	-0.0001	-0.0097	-0.0043	-0.0037	-0.0047	0.0105	0.0186	0.0211	0.0183	0.0187	0.0187
	Stdev	0.1301	0.1208	0.1008	0.0897	0.0787	0.0777	0.0877	0.1066	0.1152	0.1402	0.1335
	SR	-0.0004	-0.0803	-0.0426	-0.0409	-0.0596	0.1345	0.2123	0.1975	0.1586	0.1332	0.1404
Banking	Mean	-0.013	-0.0051	-0.0128	-0.0078	-0.0039	0.0069	0.0206	0.0212	0.0259	0.0232	0.0361

	Stdev	0.1449	0.1214	0.1092	0.0952	0.0745	0.0807	0.0859	0.1035	0.1061	0.131	0.1402
	SR	-0.0896	-0.0418	-0.1173	-0.0823	-0.0521	0.0856	0.2399	0.2049	0.2441	0.1769	0.2577
Insurance	Mean	-0.0087	-0.0232	-0.0164	-0.009	-0.0026	0.0107	0.0243	0.0308	0.0339	0.0487	0.0574
	Stdev	0.1524	0.1167	0.096	0.0829	0.0728	0.0719	0.0786	0.0911	0.104	0.1386	0.1478
	SR	-0.0572	-0.199	-0.1711	-0.1082	-0.0359	0.1494	0.3085	0.3381	0.3259	0.3513	0.3884
Real Estate	Mean	-0.0051	-0.0161	-0.0104	-0.0043	-0.0027	0.0079	0.015	0.0236	0.0276	0.0337	0.0388
	Stdev	0.1611	0.1191	0.0975	0.0909	0.0752	0.0785	0.0793	0.0893	0.102	0.1237	0.1486
	SR	-0.0316	-0.1348	-0.1071	-0.0476	-0.0356	0.1007	0.1895	0.264	0.2708	0.272	0.2607
Trading	Mean	-0.0128	-0.0231	-0.0222	-0.0143	-0.0065	0.011	0.0246	0.0356	0.0304	0.0307	0.0435
	Stdev	0.1521	0.1215	0.0998	0.0929	0.0734	0.0706	0.0753	0.0909	0.1176	0.13	0.1448
	SR	-0.0843	-0.19	-0.2221	-0.1541	-0.0888	0.1559	0.3271	0.3911	0.2587	0.236	0.3005
Others	Mean	-0.0416	-0.0327	-0.021	-0.0111	-0.0039	0.0034	0.0153	0.0285	0.0458	0.0617	0.1033
	Stdev	0.1623	0.1037	0.0867	0.0795	0.0725	0.0736	0.0755	0.0853	0.0998	0.1479	0.1575
	SR	-0.2562	-0.3151	-0.2421	-0.1401	-0.0544	0.0463	0.2032	0.3345	0.4591	0.4174	0.6559

Appendix T.2: Pair industries momentum return. The table presents the momentum returns based on the pair between industries with strong negative correlations. Portfolio 1 (loser) is defined as the bottom 10% of excess returns while portfolio 10 (winner) is top 10% of excess returns. WML is the winner minus loser or zero investment strategy taking a long position of winner and short position of loser. Correlation column presents the correlation between the industries.

Portfolio		1	2	3	4	5	6	7	8	9	10	WML	Correlation
Steel Work - Oil	Mean	-0.0317	-0.0031	-0.0029	-0.0046	-0.0078	0.0168	0.0517	0.0304	0.0234	0.0329	0.0646	-0.1087
	Stdev	0.2895	0.1266	0.1057	0.0970	0.0790	0.0876	0.0878	0.0969	0.1050	0.1306	0.2365	
	SR	-0.1095	-0.0246	-0.0278	-0.0470	-0.0984	0.1920	0.5889	0.3141	0.2232	0.2522	0.2732	
Business Service - Retail	Mean	-0.0156	-0.0118	-0.0348	-0.0147	-0.0165	0.0282	0.0621	0.0697	0.0607	0.0493	0.0649	-0.0929
	Stdev	0.2743	0.2358	0.2235	0.2001	0.1587	0.1531	0.1785	0.2039	0.2251	0.2821	0.2769	
	SR	-0.0568	-0.0500	-0.1556	-0.0737	-0.1042	0.1841	0.3478	0.3416	0.2695	0.1749	0.2344	
Retial - Steel Work	Mean	-0.0027	-0.0027	-0.0249	-0.0164	-0.0052	0.0212	0.0546	0.0462	0.0512	0.0432	0.0460	-0.1024
	Stdev	0.2817	0.2417	0.2191	0.2001	0.1566	0.1684	0.1763	0.2009	0.2204	0.2737	0.2790	
	SR	-0.0097	-0.0112	-0.1135	-0.0819	-0.0330	0.1259	0.3098	0.2298	0.2323	0.1580	0.1648	
Fabricated Products - Personal Services	Mean	-0.0312	-0.0102	-0.0224	-0.0035	-0.0090	0.0261	0.0459	0.0559	0.0446	0.0263	0.0575	-0.0878
	Stdev	0.2758	0.2340	0.2133	0.1845	0.1709	0.1534	0.1862	0.2095	0.2355	0.3034	0.2850	
	SR	-0.1133	-0.0436	-0.1048	-0.0189	-0.0525	0.1703	0.2465	0.2667	0.1894	0.0867	0.2019	
Banking - Others	Mean	-0.0600	-0.0562	-0.0265	-0.0211	-0.0075	0.0308	0.0760	0.0892	0.0640	0.0792	0.1393	-0.0888
	Stdev	0.3249	0.2549	0.2065	0.1805	0.1459	0.1471	0.1570	0.1933	0.2098	0.2598	0.3032	
	SR	-0.1847	-0.2204	-0.1283	-0.1167	-0.0513	0.2096	0.4843	0.4612	0.3050	0.3051	0.4593	
Entertainment - Transportation	Mean	-0.0072	-0.0348	-0.0395	-0.0206	-0.0236	0.0396	0.0549	0.0817	0.0664	0.0631	0.0702	-0.0905
	Stdev	0.2708	0.2527	0.2194	0.1894	0.1593	0.1481	0.1924	0.2003	0.2373	0.2694	0.2703	
	SR	-0.0264	-0.1378	-0.1798	-0.1089	-0.1483	0.2671	0.2853	0.4081	0.2800	0.2342	0.2598	
Computer - Recreation	Mean	-0.0170	-0.0071	-0.0229	-0.0111	-0.0132	0.0296	0.0513	0.0463	0.0536	0.0294	0.0464	-0.0831
	Stdev	0.2567	0.2338	0.2247	0.1989	0.1698	0.1654	0.1902	0.2153	0.2382	0.3016	0.2717	
	SR	-0.0661	-0.0303	-0.1020	-0.0560	-0.0775	0.1792	0.2697	0.2151	0.2250	0.0975	0.1707	

Appendix F.1: Correlation. The figure presents the correlations of all 48 industries. The correlation is based on the excess returns from spanning period January 1990 to December 2015.

Industry	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
1	1.0000																																															
2	0.0002	1.0000																																														
3	-0.0366	-0.0264	1.0000																																													
4	0.0526	-0.0219	0.0128	1.0000																																												
5	0.0108	0.0042	-0.0330	-0.0327	1.0000																																											
6	0.0159	-0.0075	0.0332	-0.0384	0.0242	1.0000																																										
7	0.0195	0.0084	-0.0295	-0.0176	0.0032	0.0120	1.0000																																									
8	-0.0331	-0.0630	-0.0108	-0.0181	-0.0227	0.0050	0.0881	1.0000																																								
9	0.0053	-0.0007	0.0239	0.0406	0.0110	0.0056	-0.0143	0.0066	1.0000																																							
10	-0.0394	0.0222	-0.0187	-0.0306	-0.0295	-0.0148	0.0062	0.0476	-0.0386	1.0000																																						
11	-0.0122	-0.0030	0.0006	0.0094	0.0297	-0.0005	-0.0498	-0.0203	0.0327	0.0188	1.0000																																					
12	0.0014	0.0213	0.0312	-0.0170	-0.0399	-0.0590	-0.0061	-0.0224	0.0058	0.0447	-0.0153	1.0000																																				
13	-0.0068	0.0221	0.0397	0.0792	0.0050	0.0387	0.0085	0.0031	-0.0059	-0.0408	-0.0180	-0.0174	1.0000																																			
14	0.0065	-0.0413	-0.0068	0.0108	0.0046	-0.0198	0.0036	-0.0348	-0.0057	-0.0071	-0.0173	0.0463	-0.0416	1.0000																																		
15	0.0065	-0.0413	-0.0068	0.0108	0.0046	-0.0198	0.0036	-0.0348	-0.0057	-0.0071	-0.0173	0.0463	-0.0416	0.0034	1.0000																																	
16	-0.0083	-0.0399	-0.0343	-0.0349	0.0041	0.0033	-0.0289	0.0329	0.0143	0.0636	-0.0026	0.0225	-0.0028	-0.0218	-0.0218	1.0000																																
17	-0.0025	-0.0280	-0.0139	0.0023	0.0767	-0.0557	0.0075	-0.0066	0.0269	-0.0606	-0.0040	-0.0326	0.0170	0.0317	0.0317	-0.0662	1.0000																															
18	0.0460	0.0142	0.0334	-0.0078	0.0083	-0.0167	0.0041	0.0222	-0.0342	-0.0086	-0.0095	0.0116	-0.0651	0.0106	0.0106	-0.0228	-0.0040	1.0000																														
19	-0.0214	-0.0039	-0.0169	0.0345	-0.0063	0.0044	0.0352	0.0028	-0.0247	0.0073	-0.0048	0.0111	-0.0013	-0.0504	-0.0504	-0.0115	-0.0013	0.0031	1.0000																													
20	0.0125	-0.0157	0.0180	-0.0391	-0.0241	-0.0017	0.0009	0.0216	-0.0326	-0.0484	-0.0152	-0.0335	0.1125	0.0374	0.0374	0.0252	-0.0167	-0.0223	0.0076	1.0000																												
21	-0.0405	0.0606	-0.0248	0.0014	-0.0253	-0.0004	0.0197	-0.0009	-0.0015	0.0299	0.0049	0.0036	-0.0031	0.0048	0.0048	-0.0297	0.0370	0.0199	0.0023	-0.0333	1.0000																											
22	-0.0219	-0.0484	-0.0154	0.0219	0.0490	-0.0246	0.0268	0.0265	0.0389	-0.0272	0.0089	-0.0214	0.0026	0.0340	0.0340	-0.0043	-0.0057	0.0002	-0.0260	-0.0187	0.0248	1.0000																										
23	-0.0079	0.0177	0.0432	0.0075	0.0179	-0.0490	-0.0009	-0.0094	-0.0076	-0.0123	0.0079	0.0307	0.0060	0.0312	0.0312	0.0079	-0.0270	0.0121	-0.0325	0.0055	-0.0264	-0.0007	1.0000																									
24	0.0220	0.0398	0.0082	0.0059	0.0044	-0.0093	0.0831	0.0388	-0.0090	-0.0047	-0.0524	-0.0200	0.0144	0.0435	0.0435	0.0606	-0.0205	-0.0240	-0.0199	-0.0499	-0.0210	0.0383	-0.0094	1.0000																								
25	-0.0043	-0.0065	-0.0340	-0.0306	-0.0106	-0.0193	-0.0448	-0.0340	0.0367	-0.0111	0.0012	-0.0340	0.0079	-0.0024	-0.0024	-0.0062	-0.0197	-0.0127	0.0692	-0.0196	-0.0359	-0.0176	0.0077	-0.0129	1.0000																							
26	0.0264	0.0101	0.0177	0.0146	-0.0085	-0.0564	0.0213	0.0103	0.0115	-0.0368	0.0172	-0.0093	-0.0032	-0.0011	-0.0011	0.0548	0.0351	0.0028	0.0369	0.0279	0.0147	0.0002	-0.0179	0.0023	-0.0155	1.0000																						
27	-0.0423	-0.0009	0.0133	0.0192	-0.0162	0.0095	0.0245	-0.0442	-0.0051	-0.0293	-0.0216	-0.0053	0.0427	0.0143	0.0143	0.0200	0.0349	-0.0112	0.0046	-0.0415	0.0188	0.0125	-0.0132	0.0163	-0.0030	0.0011	1.0000																					
28	-0.0206	-0.0042	0.0420	-0.0365	-0.0108	0.0050	-0.0105	-0.0188	0.0220	-0.0238	0.0725	0.0225	0.0089	-0.0139	-0.0139	-0.0146	0.0498	-0.0377	-0.0361	0.0200	0.0860	0.0320	-0.0119	-0.0508	-0.0445	0.0320	-0.0239	1.0000																				
29	-0.0109	-0.0108	-0.0049	0.0410	-0.0120	-0.0077	-0.0037	0.0243	-0.0226	-0.0119	-0.0151	-0.0130	0.0299	0.0120	0.0120	-0.0248	-0.0246	-0.0120	-0.0007	0.0231	-0.0140	-0.0364	0.0293	-0.0307	-0.0172	-0.0225	0.0665	-0.0361	1.0000																			
30	0.0114	0.0122	-0.0282	-0.0170	0.1122	0.0148	-0.0181	-0.0231	0.0208	-0.0041	-0.0234	0.0377	-0.0025	-0.0196	-0.0196	0.0055	0.0162	0.0122	-0.1087	0.0059	-0.0617	0.0312	0.0259	-0.0085	-0.0135	-0.0171	0.0321	-0.0085	0.0138	1.0000																		
31	-0.0354	0.0446	-0.0136	-0.0262	0.0061	0.0069	-0.0269	-0.0066	-0.0378	-0.0128	0.0385	-0.0279	0.0015	-0.0173	-0.0173	-0.0356	-0.0128	0.0249	0.0175	-0.0078	0.0086	0.0425	-0.0045	-0.0034	-0.0322	0.0079	0.0005	-0.0217	-0.0155	0.0219	1.0000																	
32	0.0042	-0.0492	0.0543	-0.0035	-0.0001	-0.0270	-0.0085	0.0035	-0.0373	-0.0011	-0.0011	-0.0270	0.0019	0.0206	0.0206	-0.0202	0.0242	0.0067	-0.0132	-0.0008	0.0332	0.0063	-0.0039	-0.0211	0.0270	0.0110	0.0082	0.0619	0.0217	0.0214	0.0176	1.0000																
33	-0.0103	-0.0077	0.0146	-0.0195	-0.0271	-0.0248	-0.0110	-0.0235	0.0061	-0.0400	-0.0072	-0.0144	-0.0061	-0.0041	-0.0041	0.0856	0.0847	-0.0363	-0.0195	-0.0878	-0.0151	0.0648	0.0257	0.0072	-0.0183	-0.0006	0.0100	0.0087	0.0337	0.0130	-0.0686	-0.0120	1.0000															
34	-0.0118	-0.0175	-0.0156	0.0009	-0.0126	0.0455	-0.0843	-0.0052	-0.0657	0.0595	0.0154	-0.0383	0.0515	0.0041	0.0041	0.0094	-0.0424	0.0306	-0.1024	-0.0362	-0.0315	0.0149	0.0395	-0.0079	-0.0020	-0.0063	-0.0046	-0.0010	0.0087	0.1313	0.0098	-0.0246	-0.0178	1.0000														
35	0.0139	0.0133	-0.0036	0.0248	-0.0086	-0.0831	0.0105	0.0852	-0.0631	0.0242	0.0145	0.0007	0.0280	0.0318	0.0318	-0.0268	-0.0183	-0.0040	0.0403	-0.0133	-0.0218	-0.0404	0.0182	-0.0101	-0.0578	-0.0374	0.0028	0.0339	0.0068	0.0328	-0.0029	-0.0161	-0.0049	-0.0355	1.0000													
36	-0.0293	0.0409	0.0043	-0.0269	-0.0003	0.0392	-0.0253	-0.0015	0.0064	0.0495	0.0046	-0.0252	-0.0364	0.0448	0.0448	-0.0012	-0.0220	-0.0050	-0.0213	-0.0397	0.0188	-0.0068	-0.0039	-0.0115	-0.0204	0.0384	-0.0101	0.0021	0.0320	-0.0174	0.0274	-0.0116	0.0084	0.0186	0.0022	1.0000												
37	-0.0461	-0.0074	0.0118	0.0328	0.0043	-0.0146	-0.0156	0.0016	0.0141	0.0202	0.0488	0.0137	0.0239	-0.0157	-0.0157	-0.0333	0.0435	0.0179	0.0082	-0.0559	-0.0393	0.0137	-0.0336	0.0104	0.0330	0.0062	0.0197	-0.0290	0.0047	0.0324	0.0530	0.0345	-0.0369	-0.0006	0.0267	-0.0322	1.0000											
38	0.0869	0.0055	-0.0207	0.0328	-0.0493	-0.0443	-0.0264	0.0067	0.0301	0.0061	-0.0065	0.0085	-0.0249	0.0092	0.0092	0.0066	0.0219	-0.0200	0.0141	-0.0055	0.0094	0.0333	0.0116	-0.0234	-0.0142	0.0167	0.0359	0.0352	0.0352	0.0217	0.0166	-0.0357	-0.0035	0.0105	0.0226	0.0512	0.0026	1.0000										
39	0.0061	0.0451	-0.0303	0.0104	0.1246	0.0627	-0.0160	0.0245	0.0050	-0.0175	-0.0010	-0.0180	-0.0177	-0.0156	-0.0156	-0.0004	-0.0234	-0.0029	0.0301	0.0111	-0.0615	-0.0036	-0.0378	0.0505	0.0148	-0.0143	-0.0518	-0.0171	0.0067	0.1400	-0.0037	-0.0030	-0.0199	-0.0342	0.0642	-0.0032	-0.0024	-0.0107	1.0000									
40	-0.0422	-0.0543	-0.0604	-0.0131	-0.0286	-0.0112	-0.0905	-0.0418	-0.0214	0.0373	0.0002	-0.0021	0.0425	0.0253	0.0253	-0.0091	0.0206	0.0092	0.0292	-0.0289	0.0058	0.0061	0.0110	0.0305	0.0002	0.0418	-0.0018	-0.0129	-0.0140	0.0088	0.0255	-0.0106	-0.0040	0.0231	0.0287	-0.0275	0.0471	0.0293	-0.0385	1.0000								
41	-0.0324	0.0058	-0.0022	0.0400	-0.0097	-0.0283	-0.0222	-0.0068	0.0161	0.0251	-0.0055	0.0216	-0.0360	0.0139	0.0139	-0.0375	-0.0364	-0.0596	0.0313	-0.0017	0.0311	0.0284	-0.0023	-0.0155	-0.0068	0.0146	-0.0185	-0.0271	-0.0024	-0.0050	-0.0029	0.0118	0.0023	-0.0088	0.0367	-0.0420	0.0017	-0.0063	-0.0524	0.0561	1.0000							
42	-0.0068	0.0230	0.0052	-0.0273	0.0377	0.0136	0.0047	-0.0116	0.0651	-0.0057	0.0233	0.0026	-0.0283	-0.0438	-0.0438	0.0025	0.0285	-0.0271	0.0267	-0.0713	0.0238	-0.0054	-0.0445	0.0371	-0.0365	-0.0229	0.0059	0.0253	-0.0037	0.0035	0.0268	-0.0166	-0.0110	-0.0929	-0.0059	-0.0220	0.0273	0.0034	0.0262	0.0113	-0.0173	1.0000						
43	-0.0125	0.0293	-0.0419	-0.0058	0.0128	0.0444	-0.0209	-0.0148	-0.0092	-0.0127	-0.0150	0.0010	0.0078	-0.0138	-0.0138	0.0294	0.0001	-0.0673	0.0358	0.0095	-0.0303	-0.0326	0.0449	-0.0525	-0.0188	0.0203	0.0009	-0.0117	0.0109	-0.0241	0.0141	0.0139	0.0567	0.0253	-0.0418	0.0329	-0.0098	-0.0258	-0.0649	-0.0152	0.0453	0.0105	1.0000					
44	0.0061	-0.0246	-0.0013	-0.0200	0.0171	0.0533	-0.0220	-0.0171	-0.0424	-0.0361	0.0252	0.0424	0.0447	-0.0169	-0.0169	0.0115	-0.0190	-0.0040	0.0041	0.0842	-0.0063	-0.0437	0.0176	-0.0502	-0.0033	0.0262	-0.0805	0.0044	-0.0100	-0.0181	0.0334	-0.0387	-0.0327	-0.0253	0.0180	0.0215	0.0029	-0.0242	-0.0198	0.0368	0.0010	-0.0083	-0.0148	1.0000				
45	-0.0341	0.0314	-0.0372	0.0137	-0.0123	0.0401	0.0265	0.0169	-0.0224	-0.0313	-0.0374	0.0326	-0.0314	-0.0607	-0.0607	0.0182	-0.0243	-0.0094	0.0142	-0.0053	-0.0028	-0.0047	0.0122	0.0254	-0.0164	-0.0006	-0.0204	-0.0202	0.0323	0.0159	0.0119	-0.0193	0.0065	-0.0002	0.0059	0.0279	0.0227	-0.0225	0.0205	-0.0189	0.0154	-0.0209	-0.0113	-0.0268	1.0000			
46	-0.0096	-0.0221	0.0085	0.0054	0.0023	0.0029	0.0023	0.0161	0.0310	0.0162	-0.0236	-0.0363	0.0175	0.0126	0.0126	0.0259	-0.0007	-0.0313	-0.0250	-0.0057	-0.0282	0.0071	0.0042	-0.0358	0.0482	-0.0121	0.0373	-0.0234	0.0061	0.0262	-0.0602	0.0281	0.0432	-0.0044	0.0027	-0.0128	-0.0131	-0.0138	0.0291	0.0473	0.0338	-0.0346	0.0279	-0.0083	-0.0371	1.0000		
47	0.0525	-0.0286	-0.0270	-0.0522	-0.0128	0.0409	-0.0099	-0.0699	-0.0503	0.0240	-0.0097	0.0019	-0.0389	0.0004	0.0004	-0.0254	0.0274	-0.0189	0.0025	0.0570	-0.0129	-0.0262	0.0081	0.0024	0.0053	0.0199	-0.0621	0.0328	-0.0407	0.0210	-0.0313	0.0126	0.0178	-0.0012	-0.0126	-0.0106	0.0079	0.0448	-0.0089	-0.0155	0.0184	-0.0231	0.0270	0.0466	-0.0120	0.0142	1.0000	
48	0.0380	0.0189	0.0054	0.0583	0.0062	-0.0096	0.0184	-0.0167	-0.0469	-0.0140	-0.0204	-0.0243	-0.0103	0.0410	0.0410	-0.0652	-0.0178	-0.0114	0.0262	-0.0134	-0.0055	0.0289	0.0093	0.0109	-0.0426	0.0489	0.0159	0.0013	-0.0027	-0.0099	-0.0017	-0.0220	-0.0010	-0.0348	0.0190	0.0014	-0.0056	-0.0219	0.0126	0.0492	-0.0092	0.0189	-0.0034	-0.0888	0.0068	-0.0217	0.0100	1.0000

Vita

This author received the Bachelor's Degree in Business Administration majoring in Marketing from Assumption University, Thailand. After that, he pursued the higher education and began his studies at the University of Dallas where he received MBA in Finance and Accounting in 2012, and the University of Tampa where he received M.S. in Finance in 2014. He decided to study at the Ph.D. level at the University of New Orleans. While studying at the University of New Orleans, he taught courses in Economics and Finance as the Teaching Associate. This dissertation is the last requirement for the Ph.D. program.