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ESSAYS ON EMPIRICAL ASSET PRICING

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Abstract

This thesis focuses on empirical asset pricing, and it contains the following three essays:

The first essay derives a U.S. government bond market volatility index (GBVX) based on the Arrow-Debreu state-contingent pricing methodology. We show that GBVX is an unbiased predictor for the next 30-day realized volatility of the Treasury note futures return. GBVX also subsumes the information of GARCH, EWMA and historical volatility measures. Furthermore, GBVX serves as an effective predictor for the future realized volatilities of a wide class of fixed income portfolios. The results suggest GBVX served as a powerful instrument for volatility forecasting in the fixed income markets.

The second essay shows that the innovation in GBVX delivers statistically and economically significant in-sample and out-of-sample predictive power for U.S. equity risk premium over the recent 2000-2015 sample period. It yields a sizable increase in terminal wealth growth, Sharpe ratio, and utility gains. In addition, the predictive ability of the innovation in GBVX is comparable to, and in a majority of cases, surpasses those of conventional predictors commonly used in the literature, as well as a range of historical and other implied volatility indices. The strong predictive ability of the innovation in GBVX stems from its anticipation of cash flow news.

In the third essay, we test the hypothesis that liquidity and pricing efficiency causally affect each other. As a response to the 2015 Chinese stock market crash, regulators prohibited arbitrage activities in the index futures and cash markets. Based on this natural experiment, we find that the absence of arbitrage activities led to the breakdown of the two-way causality relation between liquidity and the absolute futures-cash basis. We thus confirm that the relation between liquidity and the absolute futures-cash basis is not driven by the omitted variable bias, but is indeed due to arbitrage.

Declaration by Author

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Chapter 1

Introduction

This thesis is on empirical asset pricing and covers two important topics: bond market volatility and market efficiency. In this chapter, we give a brief introduction of the research in this thesis, including the motivation, empirical design and results, contributions, and the organization of the thesis.

1.1 Topic 1: bond market volatility

Understanding volatility generates continuing interest for both market and academic, especially after the recent financial crisis. For instance, the CBOE VIX index (also dubbed the investors' fear index) is believed to be a good proxy of aggregate uncertainty or risk aversion in the U.S. market. The VIX index is also shown to be a good predictor for the cross-section of stocks (Ang et al., 2006), corporate credit spreads (Collin-Dufresne et al., 2001) and bond excess returns (Baele et al., 2010). In contrast, given this extensive literature for equity markets, it is rather surprising that less effort has been devoted to measure and understand the volatility risk of fixed income securities, a market whose aggregate size is more than 2.5 times of the stock market in the end of 2015 (SFIMA 2016 report),[1] and a market that also serves as a bridge between the financial market and the real economy.

To fill this void, in Chapter 2, we focus on deriving an implied volatility index for the Treasury bond market, akin to VIX for the stock market. We focus on the Treasury bond market as it serves as a source of collateral for financing as well as a preliminary instrument to conduct monetary policy. Interest rate volatility, as reflected by the Treasury price fluctuations, thereby encodes valuable

[1] `http://www.sifma.org/factbook/`.

information in relation to the financial markets and the state of macro economy.[2] Construction of this index involves the state-pricing theories of Arrow (1964) and Debreu (1959) under the Black (1976) assumptions, relying on the approach of Breeden and Litzenberger (1978).[3] We generate market state prices for the 10-year Treasury note futures market and then use these prices to construct a volatility index for the U.S. government bond market. We call this index as "GBVX", and by nature, it is a measure of the expectation towards the future 30-day volatility of the 10-year government bond market.

We then explore the volatility forecasting ability of the GBVX in the fixed income markets. We first find that GBVX is an unbiased predictor for the 30-day realized volatility of the 10-year Treasury note futures returns, while the recently available CBOE TYVIX is a biased one.[4] We also show that GBVX subsumes the information of GARCH, EWMA and historical volatility measures. We further compare the forecasting abilities of GBVX and VIX in the fixed income markets. We show that GBVX outperforms VIX in forecasting the future volatilities of investment-grade corporate bonds portfolio and Commercial Mortgage-Backed Securities (CMBS) portfolios. Our results suggest that the information content of GBVX and VIX is non-overlapping and one is hardly a proxy for the other. Finally, we also demonstrate how GBVX can be effectively replicated by market makers, using a hedge portfolio comprising options on the 10-year Treasury note futures. Overall, our results in Chapter 2 suggest that GBVX index is a valuable tool for investors in the fixed income markets.

Next, in Chapter 3, we explore the predictive power of bond market volatility against the monthly equity risk premium. There are two motivations for this chapter. First, a sizeable literature shows that the information contained in the bond market is valuable in predicting aggregate stock market returns.[5]

[2]Regulators have paid special attention to the Treasury volatility in the era of unconventional monetary policy after the 2008 financial crisis. For instance, IMF (2013) surmises that the Fed's exit from its asset purchases could cause "excessive interest-rate volatility that could have adverse global implications".

[3]Recent applications of the state preference approach in the asset pricing area include deriving volatility indices for stock markets and mutual funds (Liu and O'Neill, 2015, 2016; O'Neill et al., 2015), stock valuations (Barraclough, 2007), and measuring tail risks in the stock markets (Liu and Faff, 2017; Nguyen, 2015; O'Neill and Liu, 2016).

[4]The TYVIX index, which was introduced by the CBOE in 2013 but is backdated to 2003, also measures the expected percentage volatility of the 10-year Treasury note futures price over a 30-day horizon. The construction method of TYVIX lies on the "model free" method of VIX. See more comparisons between GBVX and TYVIX in Section 2.2.2 of Chapter 2.

[5]For instance, the slope of the Treasury yield curve (Campbell, 1987; Fama and French, 1989), one-month Treasury bill rate (Fama and Schwert, 1977; Campbell, 1991; Hodrick, 1992) and corporate bond default spread (Keim and Stambaugh, 1986; Fama and French, 1989) are all popular stock return predictors.

The existing studies, however, mainly focus on the information extracted from the level of bond yields and pay less attention to its volatility, though dating back to Longstaff and Schwartz (1992), interest rate volatility has been proposed as an important state variable. Second, volatility in Treasuries encodes valuable information about the state of the macro economy or financial markets, and monetary policy uncertainty (Mueller et al., 2013). In line with its informational role, recent studies document a strong negative relation between bond market volatility and real economy(Fernández-Villaverde et al., 2011; Creal and Wu, 2014; Bretscher et al., 2016; Istrefi and Mouabbi, 2016). The price of the aggregate stock market, as a reflection of investors' expectation of future discounted aggregate cash flows, is closely linked with the expectation of future economic conditions (Fama, 1990). In this spirit, we examine the information content of the Treasury yields volatility by testing how the change of bond yield volatility affects the change in stock market prices.

As evidenced in Chapter 2, GBVX well captures the dynamics of Treasury volatility and is also available in real time, we use GBVX as the proxy for the bond market volatility. We test the forecasting ability of the monthly innovation of GBVX ($\Delta GBVX$) towards the next-month U.S. equity risk premium. We find a one standard deviation increase of $\Delta GBVX$ predicts a 87 basis points (bps) decrease of the one-month-ahead excess S&P 500 index returns. In addition, this predictability is robust in out-of-sample tests and when controlling for commonly used return predictors in Welch and Goyal (2008) and other volatility measures. We also show that such predictability has a strong economic implication: an investor who allocates between equity and risk-free assets based on the prediction of $\Delta GBVX$ achieves a terminal growth of 70% higher than the initial wealth and a Sharpe ratio of 0.48. Finally, we explore the source of the strong predictive power of $\Delta GBVX$. The vector autoregressive (VAR) return decomposition results suggest that the predictive power of $\Delta GBVX$ for stock excess returns lies primarily in its ability to anticipate cash flow news. This is consistent with the empirical evidence that bond market volatility negatively relates to the real economic activities.[6]

Collectively, the empirical findings in Chapters 2 and 3 suggest that GBVX contains valuable and unique predictive information regarding the future volatility in the fixed income market and the equity risk premium in the stock market. These findings, together with the fact that GBVX can be easily constructed under the state-preference asset pricing framework, offers practitioners an appealing tool in their investment decisions.

[6]Fama (1990) and Gourio (2012) argue that the level of fundamental cash flows in the economy is closely linked to economic activities.

1.2 Topic 2: market efficiency

In Chapter 4, we turn our attention to market efficiency. The Law of One Price states that two traded or synthesized instruments with the same future cash flows should trade at the same price due to arbitrage forces. In practice, the effectiveness of arbitrage in enhancing pricing efficiency should depend on liquidity. This notion has been tested by Roll et al. (2007) in the context of the index futures/cash markets. They find that that the innovations to the absolute futures-cash basis and spreads are positively correlated, and there is a positive two-way Granger causality relation between these two variables. The results thereby suggest that liquidity plays an important role in moving markets toward an efficient outcome. Same findings have been documented in the international markets as well (e.g., Lee, Chien and Liao, 2012; Kadapakkam and Kumar, 2013).

However, in terms of identification, the conclusions in Roll et al. (2007) may suffer from the “omitted variable bias". The results on Granger causality could be spurious or measure wrong feedback relations, if as is likely, there are omitted variables (such as interest rates, market volatility, and market sentiment in this context) that simultaneously affect liquidity and the absolute futures-cash basis. To address this “omitted variable bias", in this essay, we employ a novel approach. As a response to the 2015 Chinese stock market crash, regulators prohibited arbitrage activities in the index futures and cash markets. We use this natural experiment, which “shuts down" the driving force (arbitrage activities), to test the hypothesis that liquidity and pricing efficiency causally affect each other.

We find that in the pre-restriction period, results are in line with the findings in Roll et al. (2007) that the absolute futures-cash basis and market illiquidity have a positive two-way causality relation, both statistically and economically. However, during the restriction period, we find the resulting absence of arbitrage activities led to the breakdown of this two-way causality relation. To alleviate the concern that the market crash effect could provide explanatory power for our results, we use the Hong Kong market as a control group. The Hong Kong market also experienced several turmoil during the 2015 Chinese market crash, but there is no trading restrictions imposed on either the futures or cash markets. We find that positive two-way relation prevails in both pre-restriction and restriction periods in the Hong Kong market, indicating that there is no market effect driving the results.

Overall, our findings suggest that arbitrage is the force to be reckoned with in shaping the interplay between liquidity and market efficiency. Our results also imply that the regulations triggered arbitrage constraint has an adverse effect on market efficiency by shutting down its interaction with liquidity.

Finally, we conclude the thesis in Chapter 5.

Chapter 2

A State-Price Volatility Index for the U.S. Government Bond Market

2.1 Introduction

Understanding volatility generates continuing interest for both market participants and academics. In the past two decades, an extensive body of literature has focused on the measurement and utilizing/taming of volatility in the equity market. Especially, the Chicago Board Options Exchange (CBOE) VIX index has long been recognised as a proxy for aggregate uncertainty in the stock market (Whaley, 2009) and a useful tool of volatility forecasting (Carr and Wu, 2006). Surprisingly, although the U.S. Treasury bond market is one of most liquid markets in the world and functions as a bridge between the real economy and financial markets,[1] measuring its volatility has received much less attention. The Treasury bond market serves as a source of collateral for financing as well as a preliminary instrument to conduct monetary policy. The interest rate volatility, as reflected by the Treasury price fluctuations, thereby encodes valuable information towards the financial markets and the state of macro economy.

In this chapter, we derive a forward-looking interest rate volatility index (GBVX) for the U.S. government bond market (10-year Treasury note futures), akin to VIX for the stock market. We

[1] James Carville, political advisor to President Clinton, once commented that "I used to think that if there was reincarnation, I wanted to come back as the president or the pope or as a 400 baseball hitter. But now I would like to come back as the bond market. You can intimidate everybody." - Bloomberg, "Bond Vigilantes Push U.S. Treasuries Into Bear Market", February 10, 2009.

target the 10-year Treasury bond volatility since among all the options of different tenors, the 10-year Treasury options are the most widely used tool for trading and hedging volatility in fixed income markets.[2] Construction of this index involves the state-pricing theory of Arrow (1964) and Debreu (1959) under the Black (1976) assumptions, relying on the approach of Breeden and Litzenberger (1978). We generate market state prices from the 10-year Treasury note futures options market and then use these to construct a volatility index for the U.S. government bond market. We call this index "GBVX", and by nature, it is a measure of the expectation of the next 30-day volatility in the 10-year Treasury note futures return.

The TYVIX index, which was introduced by the CBOE in 2013 but is backdated to 2003, also measures the expected percentage volatility of the 10-year Treasury note futures price over a 30-day horizon. It is interesting to note that both GBVX and TYVIX reflect the 30-days implied volatility of the same underlying asset âĂŞ the 10-year Treasury note futures. Due to this fact, these two indices are highly correlated (with a correlation coefficient of 0.993), and they have close adjusted R^2 values when forecasting the 30-day realized volatility of the 10-year Treasury note futures returns. However, the $Wald$ test demonstrates that GBVX is an unbiased predictor for the next 30-day realized volatility, while TYVIX is a biased one. This striking difference is consistent with the concern that the inclusion of thinly traded out-of-money (OTM) options in calculating the volatility index, as the TYVIX's construction method does, would overestimate the future volatility (Liu and O'Neill, 2015).[3] The importance of using unbiased estimators of volatility for the purpose of pricing and hedging has been emphasized by Bakshi and Kapadia (2003) and O'Neill and Liu (2015) among others. From this perspective, the advantage of being an unbiased volatility measure would support GBVX to be superior to TYVIX.

Moreover, we also compare the forecasting ability of GBVX with other widely used volatility predictors in the literature (see e.g. Carr and Wu, 2006; Wang, 2010; Liu and O'Neill, 2015), including the GARCH volatility, EWMA volatility and the historical volatility. The forecasting results show that GBVX subsumes the information from other volatility measures in predicting the next 30-day realized volatility of the Treasury note futures return. This provides compelling evidence of the strong forecasting power of GBVX.

[2]The variation of 10-year Treasury yields is also found to be a good measure of monetary policy shocks in the zero-lower bound episode (Rogers et al., 2014).

[3]The GBVX index, instead, only relies on the at-the-money (ATM) implied volatility, which is found to be an unbiased predictor in the literature (see e.g. Canina and Figlewski, 1993; Christensen and Prabhala, 1998).

We further examine the forecasting ability of GBVX towards the future volatilities of other two popular asset classes in the fixed income markets: corporate bond and Commercial Mortgage-Backed Securities (CMBS).[4] We also include VIX for comparison to test whether GBVX contains distinct information from that of VIX, which is a standard measure of uncertainty in the financial market.

As corporate bonds are hybrid assets that are sensitive to both bond market and equity market news (Hong et al., 2012; Luo and Dash, 2011), we first test the different information content between GBVX and VIX in the corporate bond market. The results show that GBVX largely subsumes the information of VIX regarding the future volatility of bond-like investment-grade corporate bond portfolios, while VIX is more informative against the future volatility of stock-like high-yield corporate bond portfolios. These results suggest that information content of GBVX and VIX is not overlapping in the corporate bond market. Our findings at the volatility level also confirms and extends the conclusions in Hong et al. (2012) that the stock market return is a stronger predictor for the returns of high-yield bonds than for the returns of investment-grade bonds.

Finally, we explore the predictive ability of GBVX in the CMBS market. Since the key determinate of the value of CMBS is interest rate (Sundaresan, 2009), it is natural to expect implied interest rate volatility to be related with the future realized volatility of the CMBS portfolios returns.[5] We confirm this prediction by showing that GBVX consistently forecasts the next 30-day realized volatility of Barclays CMBS indices across all credit ratings. In contrast, VIX is found to be an insignificant predictor. The evidence in both corporate bond market and CMBS market indicates that GBVX, as a measure of interest rate volatility, is a useful tool for volatility forecasting in the fixed income markets and its important role cannot be simply substituted by VIX.

This chapter contributes to two strands of the literature. Frist, this paper draws on the recent emerging literature on constructing bond market volatility indices. Based on the same model-free methodology of constructing the VIX index, CBOE (2013), Mele and Obayashi (2013) and Mueller et al. (2013) develop a set of implied volatility indices for the U.S. Treasury bond market. Different from their approach, this study applies the easy-to-implement state-preference framework to construct

[4]CMBS are securitizations of pools of mortgage loans on commercial properties, typically including apartment buildings, shopping or strip malls, office properties and industrial properties. For more details on CMBS, we refer readers to Lancaster et al. (2015).

[5]Another possible channel to support the predictive ability of GBVX is hedging. The Treasury bond options are commonly used to hedge the risk of CMBS portfolios (Duarte, 2008), as a result, the movements of GBVX partially reflects investors' hedging demand, which sources from their perception on the future volatility of CMBS portfolios.

GBVX. The comparison between GBVX and TYVIX indicates the superior performance of GBVX as an unbiased volatility measure. This chapter also extends and complements the studies that employ the state-preference approach to construct the volatility indices in the stock market (see e.g. Liu and O'Neill, 2015, 2016; O'Neill, Wang and Liu, 2015) to the Treasury bond market. Different from their results in the stock market, I find that the state-preference volatility in the bond market is an unbiased volatility estimator.

Furthermore, this is the first study that examines the forecasting ability of Treasury bond market volatility towards the realized volatilities in the fixed income markets. It is also the first time in the literature that the bond market volatility is found to subsume the information content of VIX in predicting the volatility of investment-grade corporate bond and CMBS portfolios.

The rest of the chapter proceeds as follows. Section 2.2 discusses the method used to construct the GBVX index. Section 4.3 details the data source and variable construction methods. Section 2.4 presents the volatility forecasting results. Finally, Section 2.5 concludes.

2.2 Methodology

2.2.1 Construction of GBVX

As the bond derivatives market is the most developed of all derivatives markets, following Martin and Ross (2013), we assume that the bond market is complete. Hence, all the assets in the market can be spanned by a unique matrix of Arrow-Debreu state prices.

A state-contingent claim is defined in the form:

$$P_t = \sum_s \Phi_{s,t+T} D_{s,t+T} \tag{2.1}$$

where P_t is the price of an asset at time t,$\Phi_{s,t+T}$ is the state-price for an unit payoff at state s and time $t+T$, and $D_{s,t+T}$ is the payoff of the asset at state s and time $t+T$. In this study, different levels of 10-year Treasury note futures price represent different possible states in the bond market.[6]

We set the asset payoff $D_{s,T}$ at future calendar date $T = 30$ as $D_{s,T} = log(\frac{F_s}{f_0})^2$, which is equal to the log of the square of the ratio of the 10-year Treasury note futures price at state $s(F_s)$ to that at its current state (F_0). We define states in the bond market using the daily levels of futures prices.

[6] It is one of the common approaches to use the level of prices (returns) to represent the states(Ross, 2015). Liu and O'Neill (2015) and O'Neill et al. (2015) apply the same strategy in the stock market.

To understand this, a state of 100 indicates the bond futures price will be at 100 after one month. As such, one can regard $D_{s,T}$ as the payoff of the future variance of the 30-day Treasury note futures in different states in a month's time. The price of this asset (P_t), therefore, is the price of the future variance of bond futures in a comparable way to the theoretical derivation of VIX, where the fair value of future variance is replicated (Whaley, 1993).

We now consider the specification of the state price, $\Phi_{s,T}$. Breeden and Litzenberger (1978) prove that the second derivative of the call price (C) and put price (P) relative to the strike price (K) can be used to price the elementary claim of an asset. Specifically, we define the state price $\Phi_{s,T}$ in continuous time as $\Phi_{s,T} = \frac{\partial^2 C}{\partial K^2}|_{K=F_s}$. Since the asset in our context is futures price, instead of the cash price, we extend the approach in Breeden and Litzenberger (1978) under the assumption of Black (1976), who proposes a pricing formula for European options written on futures contract. As illustrated in Section2.6,the second derivative of the call option is proved to be:

$$\frac{\partial^2 C}{\partial K^2}|_{K=F_s} = \frac{e^{-\gamma T}\phi(d_2)}{K\sigma\sqrt{T}} \tag{2.2}$$

where $d_2 = \frac{log(\frac{F_0}{K})-0.5\sigma^2 T}{\sigma\sqrt{T}}$, $\phi()$ denotes the standard normal probability density function evaluated at d_2; T is the time to maturity, which is set to be 30/365; r and σ refer to the annualized risk-free rate and volatility of the Treasury note futures;[7] and K is the strike price of the futures options (i.e., the level of the Treasury futures at which the state price is required).

The value of the contingent claim that generates the unit payoff if the price of the underlying asset is greater than or equal to F_s is estimated as:

$$\Phi(F_s, F_{s+1}) = e^{-rT}\Big\{N\big[d_2(K = F_s)\big] - N\big[d_2(K = F_{s+1})\big]\Big\} \tag{2.3}$$

Taken together, the GBVX index or the one-month-ahead government bond volatility index can be

[7]In a spirit similar to Yan (2011), we estimate the volatility ÏČ as the average of the implied volatilities of one at-the-money call option and one at-the-money put option, each with a maturity nearest to the 30-day period. Options on Treasury futures traded in the Chicago Mercantile Exchange (CME) are American style. Thus the implied volatility is calculated using the binomial tree method of Cox et al. (1979). Although we calculate the state prices based on Black (1976)'s formula for the hypothetical European options written on futures contract, and use the at-the-money (ATM) implied volatility from the American options, it should not cause any inconsistency. Theoretically, according to Merton (1973), the European and American options should be closely priced for assets without dividends (like the futures in this context), and hence, the early exercise premium is negligible. Empirically, Mueller et al. (2013) show that the exercise premium is close to zero for ATM Treasury bond futures options.

expressed as:

$$GBVX_t = \sqrt{\sum_s \Phi(F_s, F_{s+1}) log(\frac{F_s}{F_0})^2} \tag{2.4}$$

Since the minimal tick size (i.e, state level) for the Treasury note futures is 1/128, and the state price is calculated within two adjacent states in Equation 2.4, we re-define Equation 2.4 as:

$$GBVX_t = \sqrt{\sum_s \Phi(F_s, F_{s+1}) log(\frac{F_s + 0.5 \times 1/128}{F_0})^2} \tag{2.5}$$

2.2.2 GBVX and TYVIX

Since May 23, 2013, CBOE has published an implied volatility index from 10-year Treasury futures options, labelled TYVIX. TYVIX measures the expected percentage volatility of the 10-year Treasury Notes futures price over a 30-day horizon. As such, TYVIX is the expected future volatility to the Treasury bond market as VIX is to the stock market.[8]

It is interesting to note that both GBVX and TYVIX reflect the implied volatility of the same underlying asset (the 10-year Treasury note futures). Despite their similarities regarding what they measure, there are three subtle, yet important, differences. First, the TYVIX index is constructed using a methodology similar to that adopted to formulate the VIX index (i.e., the model-free implied volatility technique), whereas the formation of GBVX is traced to the state-preference asset pricing theory of Arrow (1964) and Debreu (1959). Recent studies propose that the VIX methodology is not actually model-free. Du and Kapadia (2012) argue that VIX is a biased estimator of the quadratic variation of the stock return when there are discontinuities in the stock price process. Andersen et al. (2015) reaches the same conclusion when studying the high frequency behaviour of VIX. Such issues may prevent TYVIX from being a qualified volatility measure.

Second, the TYVIX index is constructed using both out-of-the-money (OTM) and at-the-money (ATM) futures options data, whereas GBVX relies only on the ATM futures options data. Taylor et al. (2010) cast doubt on whether OTM options provide incremental power to ATM options in explaining the dynamics of the volatility index. Liu and O'Neill (2015) propose that the inclusion of the thinly traded OTM options would lead to over-estimation for future volatility, and the value of TYVIX could be affected by artificial or stale bids for deep OTM options. These problems are less concerned for

[8]Choi (2016) studies the dependence between VIX with TYVIX. Interested readers can refer to the CBOE's website (`http://www.cboe.com/micro/volatility/tyvix/pdf/tyvixguidepart1.pdf`) for further details on the construction of TYVIX.

GBVX as only the implied volatility from the ATM options are used. In Section 2.4.2, we document strong evidence that TYVIX is a biased volatility estimator, while GBVX as proposed by this study is an unbiased one.

Third, since GBVX is defined as the price of future payoffs (payoffs here are the squared log returns), it is flexible to develop other indices based on GBVX to meet investors' customized needs. For instance, the partial volatility index can be constructed by setting the payoffs for positive (negative) returns as zero. Indices of higher moments, e.g. skewness and kurtosis, are also easy to obtain by changing the squared returns to higher moments. GBVX can also serve as an input to construct volatility indices for assets, including the investment-grade corporate bond and CMBS, whose volatilities are believed to be strongly associated with the government bond market.

2.2.3 GBVX and MOVE

The Bank of America/Merrill Lynch Option Volatility Estimate index (MOVE) is a yield curve weighted index of the normalized Black (1976)'s implied volatility of one-month Treasury options traded over-the-counter (OTC). This index weights 2-, 5-, 10-, and 30-year contracts as follows: 20% for 2-year contracts, 20% for 5-year contracts, 40% for 10-year contracts, and 20% for 30-year contracts.[9] As such, by construction, the MOVE index (which is expressed in basis points) reflects the market expectations of future Treasury bond yield volatility, whereas GBVX (quoted in percentages) measures the variations in the Treasury Notes futures prices. Furthermore, GBVX reflects the relatively medium-term implied volatility since it is constructed based on the 10-year Treasury note futures options, whereas the MOVE index reflects the weighted average of short-term, medium-term and long-term implied volatilities, since it is formulated based on Treasury options with different tenors (i.e., 2-, 5-, 10-, and 30-year maturities).

It is notable that MOVE is included in the Statistical Appendix of the International Monetary FundâĂŹs Global Financial Stability Report and is also a key component used to construct the Financial Stress Index of the Federal Reserve Bank of St. Louis. In addition, it is conveniently available and can be accessed through financial database platforms such as DataStream and Bloomberg.[10] Despite its popularity and advantages, MOVE has three significant drawbacks relative to GBVX.

[9]Since the MOVE index is the weighted average of the volatilities of different maturities and MOVE and GBVX have different underlying assets, we have not compared the forecasting abilities between MOVE and GBVX.

[10]Recent empirical studies that examine the properties of the MOVE index include, for example, Zhou (2014).

First, as we noted above, MOVE is estimated using Black (1976)'s implied volatility, which is typically hindered by its troubling assumption of deterministic volatility. In contrast, GBVX is constructed from the more robust state-preference framework, which, we believe, provides a solid theoretical asset pricing foundation underpinning the volatility index.

Second, the construction of GBVX relies on Treasury note futures options, which are more liquid compared to the OTC options market used to estimate MOVE.[11] This distinction is important because liquidity plays a significant role in determining the performance of a volatility measure (Taylor et al., 2010).

Third, Mueller et al. (2013) surmise that, given MOVE is a weighted implied volatility of options on bonds with different tenors, it is debatable as to what the volatility index is actually proxying, since traders in different clienteles are likely to hold bonds with varying tenors. Moreover, the fact that MOVE is a weighted implied volatility index also makes it hard to be hedged/replicated by a market marker.

2.3 Data and variable definitions

In this section, we introduce the data used in this chapter. The first dataset contains the inputs used to construct GBVX. The second dataset includes the currently available bond and stock volatility indices and other commonly used economic and financial condition measures. The last dataset consists of corporate bond and CMBS indices. Definitions and construction methods for main variables are also illustrated.

2.3.1 State prices inputs

Underlying asset (F): The underlying asset is the 10-year Treasury note futures contract continuous series available in DataStream. Consistent with the common approaches to dealing with futures contract, this series starts at the nearest contract month, which forms the first price values for the continuous series until either the contract reaches its expiry date or until the first business day of the notional contract month, whichever is sooner. At this point, prices from the next trading contract month are taken and no adjustment for price differentials is made.

[11] Deuskar et al. (2011) show that the OTC interest rate options market is highly illiquid, where interest rate derivatives typically trade at a discount, presumably due to a lack of demand.

Volatility input (σ): The implied volatility for the 10-year Treasury note futures options is the continuous series of one month constant maturity ATM implied volatility in DataStream. This data is available since August 8, 2000, which thus defines the starting point of the sample period in this study.

Risk-free rate (r): To be consistent with the construction method of TYVIX, daily risk free rate used to calculate the state prices is the one month constant to maturity Treasury bill rates posted by the U.S. Department of Treasury.[12] This data is available only since July 31, 2001. Before that, the daily risk free rate obtained from the Kenneth French's online data library is used as a proxy.[13]

2.3.2 Alternative volatility measures and financial/economy uncertainty indicators

Bond market volatility indices: The historical data of TYVIX since January 2, 2003 is obtained from CBOE. The MOVE index is sourced from DataStream.

Stock market volatility index: The historical data of VIX is obtained from CBOE.

Other data: We source the Cleveland Financial Stress Index (CFSI), the Chicago Fed National Activity Index (CFNAI), and the Moody BAA and AAA bond yields from the Federal Reserve Bank of St. Louis. The daily economic policy uncertainty index of U.S. is from Baker et al. (2016), available at `http://www.policyuncertainty.com/`. Term spread (TERM) is defined as the difference between 10-years and 2-years yields and the data source is the constant to maturity Treasury bill rates posted by the U.S. Department of Treasury.

2.3.3 Corporate bond and CMBS indices

Corporate bond indices: Bank of America/Merrill Lynch US Corp Master Total Return Index and Bank of America/Merrill Lynch US High Yield Master II Total Return Index from the Federal Reserve Bank of St. Louis are used as proxies for the investment-grade and high-yield corporate bond portfolios in respective.

CMBS indices: Following Li and Song (2015), the Barcalys indices of AAA-, AA-, and A- rated CMBS are used as proxies for the CMBS market. The data is obtained from Bloomberg.

[12] `https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield`

[13] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary.html.`

2.3.4 Variable definitions and construction methods

$RVol_{t,t+30}$: The 30-day realized volatility of 10-year Treasury note futures return. It is calculated by the close-to-close volatility measure and expressed in annualized basis points:

$$RVol_{t,t+30} = \sqrt{(\frac{365}{30} \times \sum_{i=1}^{i=22} R^2_{t+i})} \tag{2.6}$$

where R_{t+i} denotes the log return based on close-to-close prices.

$GARCH_i$: The GARCH (1,1) volatility of asset class i. Following Carr and Wu (2006), the GARCH return volatility is calculated based on assumptions of a GARCH(1,1) process on the asset return innovation and an AR(1) process for the return. It is then annulized and expressed in annualized basis points. To avoid the forward-looking bias, our estimation is based on a 6-month rolling window.

$EWMA_i$: The Exponentially Weighted Moving Average (EWMA) volatility of asset class i. EWMA volatility is calculated according to Riskmetrics (1996) by setting the smoothing factor as 0.94, and it is then transformed to annulized basis points.

$Historic_i$: The 30-day historical volatility of asset class i. It is defined as the realized volatility 30 days before.

2.4 Empirical results

2.4.1 Historical behaviour of GBVX

Figure 2.1 plots the historical behaviour of GBVX and VIX from 2000 to 2015. It is evident that GBVX reflects the various economic states of the market. In particular, during periods of economic upturn (such as the period from 2004 to 2006), GBVX tends to stay at a low level. Nevertheless, during economic downturns, such as those coinciding with the 2008-2009 U.S. subprime crisis and the Euro crisis, the index exhibits a sharp, but relatively short-lived, increase in level, which reflects the investors' heightened uncertainty on interest rate during the period. Moreover, as GBVX and VIX are the implied volatility measures for two asset classes that are impacted by different factors, these two indices share some common trends during the crisis period but behave distinctly in normal market.

Figure 2.2 further demonstrates that one is hardly a proxy for the other. The one-year rolling correlations (rho) between GBVX and VIX change substantially over time from 2001 to 2015. Before

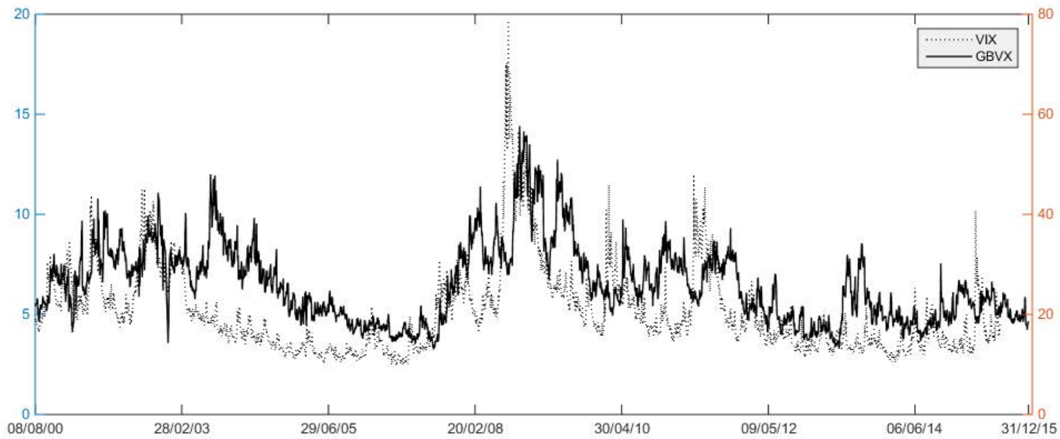

FIGURE 2.1: The historical behaviour of GBVX and VIX

In this figure, we plot the historical observations of the government bond market volatility index GBVX and the CBOE volatility index VIX. The left $Y-axis$ represents GBVX and the right $Y-axis$ represents VIX. The series are from August 8, 2000 to December 31, 2015.

the financial crisis, the correlation is low and even negative in some episodes. During the 2008-2009 financial crisis, the correlation peaks at 0.91, probably driven by concerns about tail events. However, in 2010 and 2011, when the market's focus shifted from the private section to the public (Mele and Obayashi, 2013), we see again the marked divergences between these two indices. The correlation, however, turns back to be high again during the Euro crisis period.

This dynamic correlation seeks an economic interpretation. As a preliminary analysis, we calculate the correlations between ρ and several economic indicators of financial market stress and business conditions: the Cleveland Financial Stress Index (CFSI), the default spread which is measured as the difference between Moody BAA and AAA bond yields, and the Chicago Fed National Activity Index

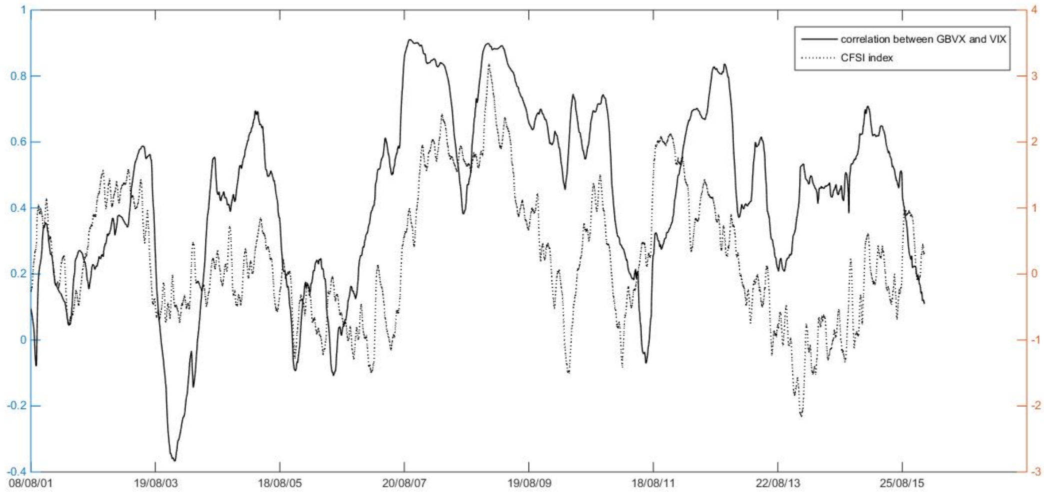

FIGURE 2.2: Moving correlation between GBVX and VIX

In this figure, we plot the moving correlation (rho) between the government bond volatility index GBVX and the CBOE volatility index VIX. Each correlation is calculated over the previous one year of data, and the sample period is from August 8, 2001 to December 31, 2015. We also plot the daily observations of the Cleveland Financial Stress Index (CFSI). The left Y-axis represents the correlation between GBVX and VIX, and the right Y-axis represents CFSI.

(CFNAI).[14] The correlations are 0.460 (with CFSI), 0.378 (with default spread) and -0.390 (with CFNAI). This result suggests that the dynamic correlation between GBVX and VIX is state-dependent: it surges when the economic conditions deteriorate and the financial market stress increases, but declines when the economy booms and the financial markets are stable. To vividly demonstrate this, we plot the CFSI together with the values of ρ in Figure 2.2. It shows that CFSI largely captures the trends of ρ in a consistent way. Overall, this preliminary analysis posits that GBVX contains more distinct information from VIX in “good" times than does in “bad" times.[15]

[14]The CFSI incorporates information from a number of financial markets, including credit, equity, foreign exchange and interbank, to provide a measure of financial system stress on a continuous basis. The default spread is an indicator of perceived business conditions in the general economy (Zhou, 2014). Higher default spread indicates a higher probability of the economy to be poor. The CFNAI index, which is measured as a weighted average of 85 indicators to capture four main aspects of overall macroeconomic activities including production and income, employment, unemployment and hours; personal consumptions and housings; and sales, orders, and inventories, is found to be a useful real-time gauge on current and future economy activity and inflation in the U.S. As the CFNAI index is a monthly measure, we assign the same CFNAI index for the daily observations within one month when calculating the correlation.

[15]The analysis here is preliminary. To conduct a more formal test, we need to adopt a structural model to model

Table 2.1 presents the summary statistics for the levels and daily changes of the implied volatility indices and realized volatility measure for the 10-year Treasury note futures market from August 8, 2000 to December 31, 2015. We also include the VIX index for comparison. It is clearly shown that the stock market volatility is more than 3 times as high as the bond market volatility. When overlapping GBVX with TYVIX from January 3, 2003 to December 31, 2015, we can see that they share a very close distribution. It is also noticeable that all the volatility series are highly persistent. Though the levels of the bond volatility indices show only moderate skewness and excess kurtosis, the excess kurtosis for the daily differences is much larger, indicating potential jumps in the volatility process for the bond futures return.[16]

Panel A of Table 2.2 shows the cross-correlations between the two volatility indices (GBVX and TYVIX) and the subsequent realized volatility (RVol) from January 3, 2003 to December 31, 2015, at both levels and daily differences. The two volatility indices, though based on different methodologies, are highly correlated in both levels (0.993) and daily differences (0.871). The two volatility indices are also highly correlated with their corresponding subsequent realized volatility in levels (0.791 and 0.796), but the correlation values become close to zero in daily differences (-0.071 and -0.051).

In Panel B of Table 2.2, we report the cross-correlations between the GBVX index and other commonly used indicators that capture the financial market/economy uncertainty, including the MOVE index, VIX, TERM (difference between the US 10-year and 2-year Treasury bond yields), the Cleveland Financial Stress Index (CFSI), and the economic policy uncertainty index (EPU) in Baker et al. (2016).[17] The pair-wise correlations are examined at daily levels in overlapping periods from August 8, 2000 to December 31, 2015. GBVX is found to be highly correlated with the MOVE index (0.938), despite having different underlying assets and construction principles. We can also observe that GBVX is also significantly associated with other uncertainty measures. Overall, these results indicate that the GBVX index can be viewed as a sound proxy for financial and economic uncertainty.

two indices jointly (see for example the regime switching model in (Zhou, 2014)) and incorporate more economic state variables, especially those capturing the conditions of worldwide economy and financial markets.

[16] Unlike the jumps at the price level, jumps at the volatility level has not been widely studied in the literature, and the limited studies so far all focus on the stock market, see e.g. Eraker (2004) and Wang et al. (2015).

[17] Besides these daily measures, we also calculate the correlation between the end-of-month GBVX and the monthly macro uncertainty measure in Jurado et al. (2015). The correlation value is significantly positive at 0.687.

TABLE 2.1: Summary statistics of volatility indices and realized volatilities

This table reports the summary statistics on levels and daily differences of the government bond volatility index GBVX, CBOE Treasury note volatility index (TYVIX), and the 30-day realized volatility (RVol) on 10-year Treasury note futures return. CBOE volatility index VIX index is also included for comparison. GBVX, RVol and VIX are from August 8, 2000 to December 31, 2015. $GBVX_{03-15}$ and TYVIX are from January 3, 2003 to December 31, 2015. All series are represented in percentage volatility points.

	Levels					Daily Differences				
Moments	GBVX	$GBVX_{03-15}$	TYVIX	RVol	VIX	GBVX	$GBVX_{03-15}$	TYVIX	RVol	VIX
Mean	6.552	6.394	6.982	6.588	20.562	0.000	-0.001	-0.001	0.000	0.000
Stdev	2.004	2.060	2.069	2.646	8.983	0.373	0.349	0.334	0.422	1.722
Min	3.254	3.254	3.620	2.162	9.890	-3.316	-2.199	-2.900	-6.514	-17.360
Max	14.413	14.410	14.720	18.031	80.860	2.971	2.972	3.300	4.893	16.540
Skew	0.891	1.082	1.067	1.170	2.075	0.099	0.142	0.262	-0.497	0.609
Excess Kurt	0.716	1.052	0.994	1.584	6.585	10.625	7.457	8.199	32.430	18.155
AC(1)	0.983	0.985	0.987	0.987	0.982	-0.069	-0.041	-0.018	0.073	-0.127

TABLE 2.2: Correlation matrix

Panel A reports the contemporaneous cross-correlation between government bond volatility index GBVX, the CBOE Treasury note volatility index TYVIX, and 10-year Treasury note futures realized volatility (RVol) from January 3, 2003 to December 31, 2015, both in levels and daily differences. Panel B reports the contemporaneous cross-correlation in levels between GBVX and other commonly used financial/economic uncertainty indicators at daily levels. MOVE is the Merrill Lynch Option Volatility index. VIX is the CBOE volatility index. TERM is the difference between the US 10-year and 2-year Treasury bond yields. CFSI is the Cleveland Financial Stress Index from the Federal Reserve Bank at St. Louis. EPU is the economic policy uncertainty index from Baker et al. (2016). GBVX, MOVE, VIX, TERM, CFSI and EPU are all from August 8, 2000 to December 31, 2015. Pair-wise correlations are based on the overlapping periods. *** indicate statistical significances at the 1% level.

Panel A: Cross-correlations between bond volatility indices and subsequent realized return volatility

Correlation	$GBVX_{03-15}$	TYVIX	RVol	$GBVX_{03-15}$	TYVIX	RVol
		Levels			Daily Differences	
GBVX03-15	1			1		
TYVIX	0.992***	1		0.872***	1	
RVol	0.791***	0.796***	1	-0.071	-0.051	1

Panel B: Cross-correlations between GBVX and commonly used financial/economy uncertainty indicators

Correlation	GBVX	MOVE	VIX	TERM	CFSI	EPU
GBVX	1					
MOVE	0.938***	1				
VIX	0.734***	0.764***	1			
TERM	0.471***	0.337***	0.267***	1		
CFSI	0.529***	0.609***	0.674***	0.130***	1	
EPU	0.333***	0.306***	0.484***	0.278***	0.404***	1

2.4.2 Volatility forecasting: in comparison with TYVIX

The primary goal of a volatility index is to serve as a measure of the 30-day expected volatility (CBOE, 2003). In this section, we compare the information content of the GBVX index and the TYVIX index in predicting subsequent 30-day realized volatility of 10-year Treasury note futures return from January 3, 2003 to December 31, 2015. The forecasting equation is:

$$RVol_{t,t+30} = \alpha + \beta GBVX(TYVIX)_t + \epsilon_{t,t+30} \tag{2.7}$$

where $RVol_{t,t+30}$ denotes the realized volatility in next 30 days. Unbiasedness of coefficients is tested in univariate regressions by performing a *Wald* test, imposing the joint hypothesis of α being equal to zero and β being equal to one. For an unbiased model we should not be able to reject the underlying hypothesis.

From Panel A of Table 2.3, the forecasting results show that GBVX and TYVIX have similar explanatory power for the next 30-day realized volatility (adjusted R^2s are 62.5% and 63.5%). The *Wald* test cannot reject the unbiasedness hypothesis for GBVX at conventional significance levels; however, the unbiasedness hypothesis for TYVIX is rejected by the $Wald$ test at the 5% significance level, confirming the concerns discussed in Section 2.2.2 that TYVIX may not be an unbiased measure for volatility due to its “model free" methodology and the fact that it uses the OTM options as inputs.

In Panel A, the realized volatility measure is constructed with overlapped observations. To avoid the inference problems associated with overlapping observations (see e.g. Richardson and Smith, 1991; Hodrick, 1992; Ang and Bekaert, 2007), we also check the robustness by using a monthly sample that contains only the end of month observations. The results, in Panel B, confirm the strong predictive abilities of GBVX and TYVIX with adjusted R_s^2 of 65.4% and 65.3%. The *Wald* test still reaches the same conclusion that GBVX is an unbiased predictor while TYVIX is a biased one.

According to Bakshi and Kapadia (2003) and O’Neill and Liu (2015), it is important to use an unbiased volatility estimator for the purposes of pricing and hedging. GBVX has this advantage over TYVIX as volatility measured for the fixed income market and can for example be used as a direct input to calculate the *Value at Risk*.

2.4.3 Volatility forecasting: in comparison with commonly used volatility measures

Following Carr and Wu (2006) and Wang (2010), we also compare the ability of GBVX to forecast the next 30-day realized volatility of 10-year Treasury note futures with other commonly used volatility predictors, e.g. GARCH (1, 1) volatility, EWMA volatility and 30-day historical volatility, for which the definitions have been introduced in Section 2.3.4. A common way to evaluate the prediction performances of multiple predictors is the Mincer and Zarnowitz (1969) regression. We

TABLE 2.3: Forecasting 10-year Treasury note futures realized volatility with GBVX and TYVIX (2003-2015)

This table presents the OLS estimates (and the t-statistics in parentheses) of the following equation:

$$RVol_{t,t+30} = \alpha + \beta GBVX_t(TYVIX_t) + \epsilon_{t,t+30}$$

$RVol_{t,t+30}$ denotes the realized volatility of Treasury note futures returns in next 30 days. We use the government bond volatility index GBVX and the CBOE Treasury note volatility index TYVIX as predictors. The data is from January 3, 2003 to December 31, 2015. Panel A reports the results when all the observations are used for the forecasting regression. Panel B reports the results when only the end-of-month non-overlapping observations are used. $Wald$ is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$, and the associated p-value is reported in parentheses. To correct for autocorrelation and heteroskedasticity, we use the Newey-West estimator for covariance matrix. ** represents statistical significance at the 5% level.

Panel A: Full sample analysis

	α	t_α	β	$t_{1-\beta}$	$AdjR^2$	*Wald*
GBVX	-0.046	(-0.113)	1.009	(0.118)	0.625	0.014
TYVIX	-0.374	(-0.838)	1.013	(0.166)	0.635	6.510**

Panel B: Non-overlapping sample analysis

	α	t_α	β	$t_{1-\beta}$	$AdjR^2$	*Wald*
GBVX	-0.189	(-0.617)	1.026	(0.590)	0.654	0.382
TYVIX	-0.480	(-1.579)	1.021	(0.511)	0.653	8.846**

therefore regress the 30-day realized volatility on the different volatility measures in the following way:

$$RVol_{t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 Alternative_{i,t} + \epsilon_{t,t+30} \tag{2.8}$$

where $RVol_{t,t+30}$ denotes the realized volatility in next 30 days, and $Alternative_{i,t}$ denotes the time-t estimates of one of the three volatility measures (GARCH, EWMA and 30-day historical) in annualized basis points. The sample period spans from August 8, 2000 to December 31, 2015.

Informational efficiency can be tested in encompassing regressions by constraining the slope parameters of alternative estimators to zero, thereby determining if the respective approaches contain information beyond that of a baseline model. If, in encompassing regressions, one estimator is to be more informative, it must have a significant slope estimate and the explanatory power must rise compared to the restricted model. Additionally, we test the joint hypothesis of the first slope parameter β_1 being equal to one and the second slope parameter β_2 being equal to zero.

Panel A of Table 2.4 presents the results of the univariate regressions for each estimation approach. It is then evident that GBVX generates an adjusted R^2 more than 15 percentage points higher than any other predictor does. More importantly, in the regression of using GBVX as the single predictor, the intercept (α) is close to zero (0.151), and the slope (β_1) is close to 1 (0.983). A joint null hypothesis that $\alpha = 0$ and $\beta_1 = 1$ cannot be rejected by the *Wald* test. The results show strong evidence again that GBVX is an unbiased predictor for the future realized volatility in an extended sample from 2000 to 2015. The unbiasedness hypotheses for the other three measures, however, have all been rejected by the *Wald* tests.

For the results of the encompassing regressions in Panel B of Table 2.4, we can see that the adjusted R^2 s in the two predictors' regressions are almost as same as the one using GBVX as the single predictor. Further, as indicated by the $Wald$ test, the assumption that GBVX subsumes all information contained in, e.g., GARCH, EWMA or HIST, cannot be rejected. Collectively, the Mincer and Zarnowitz (1969) regression results show that GBVX outperforms the other predictors in volatility forecasting. This finding also highlights the superior forecasting ability of the implied volatility measure.

2.4.4 Forecasting corporate bond portfolio realized volatility with GBVX and VIX

In the last section, we demonstrate sound evidence that GBVX is a qualified conditional volatility measure for the government bond market. We further explore the ability of GBVX to forecast the realized volatilities of the other asset classes in the fixed income markets. We include VIX for comparison. Although GBVX and VIX are reasonably correlated (0.734), their dependence structure is time varying as shown in Figure 2 and they also have different interpretations. By nature, GBVX is a proxy for the conditional interest rate volatility while VIX serves as a fear gauge for the stock market

TABLE 2.4: Forecasting 10-year Treasury note futures realized volatility with GBVX and alternative volatility measures (2000-2015)

This table presents the OLS estimates (and the t-statistics in parentheses) of the following equation:

$$RVol_{t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 Alternative_{i,t} + \epsilon_{t,t+30}$$

$RVol_{t,t+30}$ denotes the realized volatility of Treasury note futures returns in next 30 days, GBVX denotes the government bond volatility index, and $Alternative_{i,t}$ denotes the time-t estimates of one of the three volatility measures: GARCH, EWMA and 30 days historical. GARCH return volatility is based on assumptions of a GARCH(1,1) process on the portfolio return innovation and an AR(1) process for the return. EWMA is calculated following the method of Riskmetrics (1996) by setting λ as 0.94. The data is from August 8, 2000 to December 31, 2015. In Panel A, $Wald$ is an asymptotic $Wald$ test of the joint null that $\alpha = 0$ and $\beta_1 = 1$. In the bivariate regressions in Panel B, $Wald$ is an asymptotic $Wald$ test of the joint underlying hypothesis that the first slope coefficient (β_1) is equal to one and the second slope coefficient (β_2) is equal to zero. To correct for autocorrelation and heteroskedasticity, we use the Newey-West estimator for covariance matrix. *** represents statistical significance at the 1% level.

Panel A: Univariate Regressions

	α	t_α	β_{GBVX}	$t_{1-\beta_{GBVX}}$	β_{GARCH}	$t_{1-\beta_{GARCH}}$	β_{EWMA}	$t_{1-\beta_{EWMA}}$	β_{HIST}	$t_{1-\beta_{HIST}}$	$Adj R^2$	*Wald*
GBVX	0.151	(0.329)	0.983	(-0.214)							0.553	0.172
GARCH	1.232	(1.302)			0.672***	(-2.348)					0.410	12.898***
EWMA	2.104***	(4.167)					0.579***	(-5.489)			0.408	33.611***
HIST	2.796***	(3.742)							0.577***	(-2.894)	0.335	15.162***

Panel B: Bivariate Regressions

	α	t_α	β_{GBVX}	$t_{1-\beta_{GBVX}}$	β_{GARCH}	$t_{1-\beta_{GARCH}}$	β_{EWMA}	$t_{1-\beta_{EWMA}}$	β_{HIST}	$t_{1-\beta_{HIST}}$	$Adj R^2$	*Wald*
GBVX+GARCH	0.221	(0.475)	1.041***	(7.442)	-0.055	(-0.590)					0.553	0.471
GBVX+EWMA	0.166	(0.355)	1.023***	(7.620)			-0.035	(-0.503)			0.533	0.425
GBVX+HIST	0.311	(0.275)	1.076***	(9.468)					-0.089	(-1.289)	0.555	1.872

uncertainty (Whaley, 2000, 2009). In this section, we further investigate how this difference in nature leads to their different information content in the corporate bond market.

Corporate bonds are an ideal asset class for this test as it can be viewed as a hybrid of risk-free bonds and stocks, and is therefore exposed to both interest rate risk and market systematic risk. High-yield bonds typically have high default risk, tying their expected cash flows more closely to the valuation changes of firm values. As such, high-yield corporate bonds exhibit equity-like properties (Ramaswami, 1991; Luo and Dash, 2011), and we can expect that the conditional stock market volatility (VIX) will contain more information about the future volatility of the high-yield bond portfolios than does GBVX. Investment-grade bonds have relatively stable expected cash flows due to small default risk. Hence, the return variations of investment-grade bonds would be less sensitive to news about firmsâĂŹ valuations. Instead, these safer bonds would be more sensitive to interest rate changes and behave more like government bonds. Therefore, this hypothesis asserts that compared to VIX, the conditional bond market volatility (GBVX) will be more informative against the future realized volatility of investment-grade bond returns.

We test the above hypotheses by comparing the relative information content of GBVX and VIX in forecasting the next 30-day realized return volatilities of corporate bond portfolios. The predictability is examined by the following regression model:

$$RVol_{t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 VIX_{,t} + \epsilon_{t,t+30} \tag{2.9}$$

We use two well-known public corporate bond indices from the Bank of America/Merrill Lynch, namely the BofA Merrill Lynch US Corp Master Total Return Index and BofA Merrill Lynch US High Yield Master II Total Return Index to represent the investment-grade and high-yield bond portfolios in respective.

Panel A of Table 2.5 presents the regression results for the case of investment-grade portfolio. When we use GBVX as the single predictor, the slope estimate is statistically significant and the adjusted R^2 is as high as 51.0%. For the case of using VIX as the predictor, the slope is also significant, but the adjusted R^2 is considerably lower (37.2%). More importantly, when both predictors are combined together, the slope estimate for VIX is much smaller, while the slope for GBVX still remains of a similar magnitude. Meanwhile, the adjusted R^2 in the multivariate regression (52.4%) is close to the one using GBVX as the single predictor. Overall, the above results suggest that GBVX is an effective (though biased) predictor for the subsequent investment-grade corporate bond volatility and

VIX does not provide material information beyond that in the GBVX index.

In Panel B of Table 2.5, it is found that GBVX cannot significantly forecast the realized volatility of high-yield bond portfolio returns, while VIX is statistically significant. In the multivariate regression model, only VIX is significant and the adjusted R^2 only increases marginally from 41.3% (VIX as the single predictor) to 41.6%. In line with our hypothesis, stock market conditional volatility is more informative for the future variations of high-yield bond portfolio returns.

Overall, the results above support the hypotheses that GBVX and VIX are informative for the future realized volatilities of the investment-grade bond portfolio and high-yield bond portfolio respectively. To the best of our knowledge, this is the first study that explores the volatility predictability of the corporate bond market with the conditional stock market and bond market volatilities. Our findings are also consistent with Hong et al. (2012) that the stock market return is a stronger predictor for the returns of high-yield bonds than for the returns of investment-grade bonds.

2.4.5 Forecasting CMBS portfolio realized volatility with GBVX and VIX

In this section, we further investigate the ability of GBVX to forecast another important asset class: CMBS, which has currently become one of the premier investments in the fixed income markets (Lancaster et al., 2015). The forecasting ability is examined based on the following regression model:

$$RVol_{i,t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 VIX_{,t} + \epsilon_{t,t+30} \tag{2.10}$$

where $RVol_{i,t,t+30}$ denotes the realized volatility of either one of the returns of the Barclays AAA-, AA-, and A- rated CMBS indices. The sample period is from August 8, 2000 to December 31, 2015.

Table 2.6 reports the results. For the AAA- rated index, it is evident from the table that higher GBVX forecasts higher realized volatility of CMBS portfolio returns. In sharp contrast, VIX has not shown any forecasting ability at any conventional significance level. The adjusted R^2 of the regression is as high as 49.3%. Given the insignificance of VIX, the strong explanatory power stems primarily from GBVX.

For AA- and A- rated indices, we can find a similar pattern: the coefficients before GBVX (β_1) is positive and significant while the coefficients before VIX (β_2) are statistically indifferent from zero. Thereby, we can conclude that GBVX subsumes the information content of VIX in predicting the CMBS portfolios volatility. Another interesting pattern is that the values of adjusted R^2 increase along the credit ratings: 32.7% (A), 35.0% (AA) and 49.3% (AAA). This is consistent with the

TABLE 2.5: Information content in GBVX and VIX in forecasting future corporate bond portfolio realized volatility (2000-2015)

This table presents the OLS estimates (and the t-statistics in parentheses) of the following equation:

$$RVol_{t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 VIX_t + \epsilon_{t,t+30}$$

$RVol_{t,t+30}$ denotes the realized volatility in next 30 days of one of the alternative corporate bond portfolios. We use the government bond volatility index GBVX and the CBOE volatility index VIX as predictors. The data is from August 8, 2000 to December 31, 2015. To correct for autocorrelation and heteroskedasticity, we use the Newey-West estimator for covariance matrix. *** represents statistical significance at the 1% level.

Panel A: BofA Merrill Lynch US Corp Master Total Return Index

	α	t_α	β_{GBVX}	$t_{\beta_{GBVX}}$	β_{VIX}	$t_{\beta_{VIX}}$	$AdjR^2$
GBVX	0.795***	(2.819)	0.623***	(12.886)			0.510
VIX	2.402***	(13.343)			0.120***	(12.734)	0.372
GBVX+VIX	0.826***	(2.981)	0.507***	(8.563)	0.035***	(3.389)	0.524

Panel B: BofA Merrill Lynch US High Yield Master II Total Return Index

	α	t_α	β_{GBVX}	$t_{\beta_{GBVX}}$	β_{VIX}	$t_{\beta_{VIX}}$	$AdjR^2$
GBVX	-1.572	(-0.613)	0.821	(1.765)			0.260
VIX	-0.957	(-1.632)			0.231***	(5.640)	0.413
GBVX+VIX	-1.377	(-0.986)	0.133	(0.554)	0.209***	(8.940)	0.416

intuition that the variation of highest rated CMBS portfolios is primarily driven by the movements in interest rates, while other factors, e.g., the default risk, also play a role in the valuation of relatively lower rated CMBS products (Sundaresan, 2009).

2.4.6 Replicating (Hedging) GBVX as a market maker

Investors who seek to replicate/hedge against changes in the bond market volatility can take positions in the options market. This section illustrates how GBVX can be replicated or hedged by a market maker using options on the 10-year Treasury note futures. The replicating portfolio is constructed by using DataStream pricing data from 2011 to 2014, a period in which the interest rate uncertainty is a big concern in the market due to the Federal Reserve's serial unconventional monetary programs (see e.g. Breeden and Litzenberger, 2014; Rogers, Scotti and Wright, 2014). Following

TABLE 2.6: Information content in GBVX and VIX in forecasting future CMBS realized volatility (2000-2015)

This table presents the OLS estimates (and the t-statistics in parentheses) of the following equation:

$$RVol_{t,t+30} = \alpha + \beta_1 GBVX_t + \beta_2 VIX_t + \epsilon_{t,t+30}$$

$RVol_{t,t+30}$ denotes the realized volatility in next 30 days of one of the alternative Bayclays CMBS portfolios. We use the government bond volatility index GBVX and the CBOE volatility index VIX as predictors. The data is from August 8, 2000 to December 31, 2015. To correct for autocorrelation and heteroskedasticity, we use the Newey-West estimator for covariance matrix. *** represents statistical significance at the 1% level.

	α	t_α	β_{GBVX}	$t_{\beta_{GBVX}}$	β_{VIX}	$t_{\beta_{VIX}}$	$AdjR^2$
AAA-CMBS	-6.393	(-0.932)	0.799***	(3.915)	0.292	(0.717)	0.493
AA-CMBS	-5.979	(-0.760)	0.973***	(3.862)	0.246	(0.536)	0.350
A-CMBS	-6.382	(-0.817)	1.077***	(3.752)	0.255	(0.551)	0.327

Whaley (1993), we construct a dynamic hedge of volatility risk by using $delta$ and $vega$ hedging.

A "volatility spread" is a hedge portfolio with $delta$ equal to zero and $vega$ equal to one. Here the assumption is that GBVX is delta neutral and has a unit exposure to the volatility risk. A replicating portfolio is constructed using the two closest to the money put and call options at the closet maturity date to 30 days.[18] Two simultaneous equations are solved day-by-day:

$$\begin{aligned} n_c delta_c + n_p delta_p &= 0 \\ n_c veta_c + n_p vega_p &= 1 \end{aligned} \tag{2.11}$$

where n_c is the number of call options and n_p is the number of put options, $delta$ is the sensitivity of option value to the price of underlying asset, and $vega$ is the sensitivity of option value towards volatility. *Delta* and *vega* for these American-style options are calculated using the binomial tree method of Cox et al. (1979).

The procedure above results in a delta-neutral portfolio rebalanced daily with a unit exposure to changes in volatility. To account for the bid-ask spread, the mid-quotes of options are used. Since the

[18]In the selection procedure, for both put and call options, we first require that the absolute value of option strike be within 2% of the underlying asset price, and then choose the maturity close to 30 days. If more than one option satisfies the criteria, we further choose the one with the strike price most close to the underlying price.

options are closest-to-the-money, volatility exposure can be treated linearly (Feinstein, 1989; Whaley, 1993). As a result, *delta* and *vega* hedging is likely to be effective against the GBVX index.

In line with O'Neill et al. (2015), we assess the “performance" of the replicated portfolio using a linear regression of daily changes in the value of the replicated portfolio versus the daily changes in GBVX, across different sample periods in the following form:

$$\Delta GBVX_t = \alpha + \beta \Delta Portfolio_t + \epsilon_t \tag{2.12}$$

TABLE 2.7: Linear regression of changes in the hypothetical replicating portfolio against changes in GBVX (2011 to 2014)

This table presents the OLS estimates (and the t-statistics in parentheses) of the following equation:

$$\Delta GBVX_t = \alpha + \beta \Delta Portfolio_t + \epsilon_t$$

$\Delta Portfolio_t$ denotes the daily change of the market price of the hedging portfolio, and$\Delta GBVX_t$ denotes the daily change of the government bond volatility index GBVX. The data is from January 4, 2011 to December 31, 2014. $Wald$ is an asymptotic *Wald* test of the joint null that $\alpha = 0$ and $\beta = 1$. To correct for autocorrelation and heteroskedasticity, we use the Newey-West estimator for covariance matrix. * and ** represent statistical significance at the 10% and 5% levels respectively.

	α	t_α	β	$t_{1-\beta}$	$AdjR^2$	*Wald*
2011	-0.003	(-0.393)	1.039	(0.572)	0.692	0.773
2012	-0.001	(-0.249)	0.878**	(-2.589)	0.822	6.745**
2013	-0.002	(-0.240)	0.857*	(-1.926)	0.692	3.326
2014	-0.001	(-0.225)	0.900*	(-2.152)	0.812	4.967*
2011-2014	-0.002	(-0.596)	0.922**	(-2.350)	0.731	5.627*

The results reported in Table 2.7 show that over the 2011-2014 period, the adjusted R^2 is as high as 0.731, suggesting most of the variation in the change of portfolio values can be attributed to the change in GBVX. We further test the joint null hypothesis of that $\alpha = 0$ and $\beta = 1$. The *Wald* test statistic can only reject the null hypothesis marginally at 10%. The year-by-year regression experiments confirm that results from the whole sample and in years 2011 and 2013, the results strongly support the unbiasedness. Overall, the results demonstrate that the hypothetical portfolio tracks the index well across a four-year period over which volatility varies widely, suggesting that the GBVX index represents a useful tool that the market makers can construct a simple and effective hedging strategy.

2.5 Concluding remarks

This chapter is novel in that it uses the state-pricing methodology to derive a volatility-index for the U.S. government bond market. Results presented here support the empirical application of state-pricing methodology in the construction of volatility indices. This is evidenced by the strong performance of GBVX in forecasting realized volatilities across the fixed income asset classes: the government bond, corporate bond portfolios and CMBS portfolios, and the fact that GBVX is an unbiased predictor for future realized volatility of its underlying asset while the recently available TYVIX index is a biased one. By comparing the forecasting abilities of GBVX and VIX in the fixed income markets, the current study shows that their information is non-overlapping and one is hardly a proxy for the other. Finally, this paper also demonstrates how the index can be effectively replicated by market makers, using a hedge portfolio comprising options on the 10-year Treasury note futures. As a conclusion, the GBVX index is a valuable tool for investors in the fixed income markets.

2.6 Appendix: Second derivative of call (put) options in Black (1976)

The Black (1976) formula for a plain vanilla European call written on the futures contract with time to maturity T, strike, K, current futures price, F_t, is given by:

$$C(K,t) = e^{-rT}[F_t \int_{-\infty}^{\frac{log(\frac{F_t}{K})+\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\mu^2} du - K \int_{-\infty}^{\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}} \mu^2 du] \tag{2.13}$$

Now differentiate with respect to K:

$$\begin{aligned} \frac{dC(K,t)}{dK} &= -\frac{F_t e^{-rT}}{K\sigma\sqrt{T}}[\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{log(\frac{F_t}{K})+\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}})^2}] - e^{-rT}[\int_{-\infty}^{\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}} \mu^2 du] \\ &+ \frac{e^{-rT}}{\sigma\sqrt{T}}[\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}})^2}] \end{aligned} \tag{2.14}$$

Now we show that the first term and the third term in Equation (2.14) sum to zero and that

$$\frac{F_t e^{-rT}}{K\sigma\sqrt{T}}[\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{log(\frac{F_t}{K})+\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}})^2}] = \frac{e^{-rT}}{\sigma\sqrt{T}}[\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}})^2}] \tag{2.15}$$

To see this, on the left-hand side, use the substitution

$$\frac{F_t}{K} = e^{-log\frac{F_t}{K}} \tag{2.16}$$

and then rearrange the exponent in the exponential function.

Thus, we are left with

$$\frac{dC(K,t)}{dK} = -e^{-rT}[\int_{-\infty}^{\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}} \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}}\mu^2 du] \tag{2.17}$$

Once the first derivative (*delta* of strike) is obtained, the second derivative will be

$$\frac{\partial^2 C(K,t)}{\partial K^2} = -e^{-rT}\frac{1}{K\sigma\sqrt{T}}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{log(\frac{F_t}{K})-\frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}})^2} = e^{-rT}\frac{1}{K\sigma\sqrt{T}}n(d_2^{Black}) \tag{2.18}$$

with

$$d_2^{Black} = \frac{log(\frac{F_t}{K}) - \frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}} \tag{2.19}$$

Chapter 3

A new government bond volatility index predictor for the U.S. equity premium

3.1 Introduction

A vast amount of recent literature focuses on the out-of-sample predictability of the U.S. equity premium and the empirical evidence is mixed. Some studies find little evidence of the role of conventional predictors such as dividend yield and earnings price ratio in predicting the equity premium out-of-sample (see, in particular, the study by Welch and Goyal (2008)), whereas others find that new predictors such as technical indicators and short interest play a strong role (Neely et al., 2014; Rapach et al., 2016).

The current essay makes a significant contribution to the literature by formulating a new predictor termed as the government bond volatility index or GBVX, to forecast the U.S. monthly equity premium. Effectively, GBVX reflects the implied volatility of the 10-year Treasury Notes futures options. We use several tests to show that over the recent sample period spanning between 2000:09 and 2015:12, the change or innovation in the monthly GBVX (i.e., $\Delta GBVX$) performs as well as âĂŞ and in a majority of instances, better than âĂŞ a host of other popular predictors to forecast the U.S. monthly equity premium. More importantly, the predictive ability of $\Delta GBVX$ is significant, both statistically and economically. This suggests that $\Delta GBVX$ contains valuable information that is substantially different from that found in conventional predictors used to forecast the U.S. excess stock returns.

The current essay is not the first to scrutinize the extent to which information extracted from the bond market is related to equity premium. Keim and Stambaugh (1986), Campbell (1987), Campbell and Thompson (2008), Welch and Goyal (2008), and Rapach et al. (2010) examine various bond-related variables, such as the term spread, default spread, and Treasury bill rate. These variables, however, exclusively reflect information concerning the level of bond yield. In stark contrast, the novel GBVX predictor proposed in this study captures information related to the volatility of the Treasury bond. Numerous studies have shown that Treasury bond volatility encodes valuable information regarding the state of the economy and financial markets. Creal and Wu (2014), for example, find that higher Treasury bond volatility leads to higher unemployment rate. Bretscher et al. (2016) find that Treasury bond volatility is positively associated with the slowdown of future economic activities at the market and firm levels.[1] Our research extends these studies by showing that the information embedded in the volatility of the Treasury Notes is relevant and useful for forecasting excess stock returns.

We also assess the predictive capacity of the levels of the monthly GBVX. Banerjee et al. (2007) find that both levels and innovations of volatility indices are important proxies for volatility risk. From a statistical viewpoint, the standard predictive regression based on the level of GBVX yields consistent point estimates (Ericsson et al., 2009). However, the first differencing or innovation of GBVX is more appropriate if both the dependent and independent variables in the predictive regression are integrated (and the resulting regression coefficient estimates are more efficient (Ericsson et al., 2009)), but unit root tests may lack power owing to the small sample size considered in the current study. The results show that the innovation of GBVX is a superior predictor.

In addition, we evaluate the predictive abilities of several other historical and implied volatility indices of the stock and bond markets, including, among others, realized stock volatility, realized Treasury bond volatility, and the popular forward-looking Bank of America Merrill Lynch Option Volatility Estimate index (MOVE). The results point to the continual dominance of the innovation in GBVX. This represents a novel finding, since previous studies pay relatively little attention to comparing the abilities of backward-looking and forward-looking measures of bond and stock market volatility to forecast equity premium.

We summarize the empirical findings of the current study as follows. First, the in-sample results

[1] Fernández-Villaverde et al. (2011) demonstrate that a significant change in bond market volatility triggers a fall in output, consumption, and investment in emerging markets, whereas Istrefi and Mouabbi (2016) find that interest rate uncertainty has large and persistent negative effects on the economies of the Group of Ten (G10) countries.

reveal that the U.S. monthly equity premium increases by a 87 basis points (bps), on average, following a unit decrease in the standardized $\Delta GBVX$ in the preceding month. The adjusted R^2 ($\bar{R}^2$) of the in-sample predictive regression based on $\Delta GBVX$ is high, estimated at 3.41%. To ensure the robustness of our finding against small sample bias, we perform an extensive bootstrap simulation procedure and compare the actual $\bar{R}^2$ estimated from the observed data with the cut-off $\bar{R}^2$ benchmark derived from the bootstrap procedure. The result shows that the actual $\bar{R}^2$ estimate of 3.41% is significantly higher than can be attributed to chance. We then assess the predictive performance of the level of GBVX. It is relatively weaker. Similarly, only 4 of the 14 commonly used predictors of Welch and Goyal (2008) (log dividend yield, book-to-market ratio, Treasury bill rates, and long term yields) generate comparable quantitative in-sample predictive findings to the $\Delta GBVX$. When we study the predictive abilities of other historical and implied volatility indices, their in-sample $\bar{R}^2$ estimates are lower than 3.41%, and they are also considerably lower than their respective cut-off $\bar{R}^2$ benchmarks derived from the bootstrap procedure.

We use the popular out-of-sample R^2 statistic of Campbell and Thompson (2008) or R^2_{oos} as the ultimate stock return predictability test. The results show that $\Delta GBVX$ continues to outperform many other predictors in the out-of-sample setting. In particular, the predictive regression for $\Delta GBVX$ yields the highest statistic, and this estimate is statistically and economically significant. By contrast, most of the 14 conventional predictors of Welch and Goyal (2008) and other volatility predictors fail to convincingly beat the historical average benchmark at the usual significance levels. While the standard predictive regression model, in theory, can forecast excess returns of any sign, practitioners are primarily interested in the positive equity premium forecasts. As such, we re-analyze the out-of-sample findings by restricting the negative equity premium forecasts to zero, as suggested by Campbell and Thompson (2008). In any case, imposing Campbell and Thompson (2008)'s restriction accentuates the support for using the $\Delta GBVX$ predictor.

Next, we explore the economic value of using the variables to predict future stock returns. The results demonstrate that an investor who allocates between equity and risk-free assets based on the prediction of $\Delta GBVX$ achieves a terminal growth of 70% higher than the initial wealth. By contrast, the naïve “buy-and-hold" strategy merely increases the investor's terminal wealth by 46%. In terms of the Sharpe ratio, the asset allocation strategy based on the $\Delta GBVX$ predictor generates a hefty annualized estimate of 0.48, whereas the sample mean Sharpe ratio estimate generated by all other predictors is merely 0.15. The final exercise involves the calculation of the utility for a mean-variance investor (with a relative risk coefficient of three) who allocates between equity and risk-free assets using the equity premium forecasts. The result shows that the aforementioned asset allocation strategy based on the $\Delta GBVX$ predictor delivers massive utility gains of 411bps to the investor over the "buy-and-hold" strategy. On the other hand, the asset allocation strategies based on most of other predictors typically generate utility gains of less than 300bps.

Given the above empirical findings, a natural question ensues: What drives the strong predictive ability of the innovations in GBVX? Fernández-Villaverde et al. (2011), Creal and Wu (2014), and Bretscher et al. (2016) show that high bond market volatility shock leads to lower future real economic outputs. Given that the level of fundamental cash flows in the economy is closely linked to economic activities (Fama, 1990; Gourio, 2012), we conjecture that the innovations in bond volatility (i.e., $\Delta GBVX$) are likely to affect the change in investors' expectations towards future cash flows. To examine this hypothesis, we adopt the vector autoregressive (VAR) decomposition methodology of Campbell (1991) and Campbell and Ammer (1993). The results show that the predictive power of $\Delta GBVX$ for stock excess returns lies primarily in its ability to anticipate cash flow news, thus providing support to our hypothesis.

This chapter proceeds as follows. Section 3.2 begins by discussing the model specification that researchers generally use to assess stock return predictability. This is followed by the data description, including the construction of GBVX. Section 3.3 presents the in-sample and out-of-sample predictive results, as well as the findings of the analyses based on various asset allocation strategies and utility gains. Section 4.4 discusses the VAR decomposition to examine the source of the predictive ability of $\Delta GBVX$ Finally, Section 3.5 concludes.

3.2 Model specification and equity premium predictions

3.2.1 Model specification

The analyses in this study rely on the familiar predictive regression specification:

$$r_{t+1} = \alpha + \beta x_t + \epsilon_{t+1} \tag{3.1}$$

where r_{t+1} is the log return on the U.S. stock market index in excess of the Treasury risk-free rate (i.e., equity premium) for month $t+1$, and x_t refers to the respective predictor variables defined below. Following recent related studies (see e.g. Rapach, Strauss and Zhou, 2010; Rapach, Ringgenberg and

Zhou, 2016), we use the S&P 500 index (including dividends) to measure the U.S. stock market index.[2]

3.2.2 Predictors

We compare the predictive power of the volatility predictors described above to the 14 monthly predictors of Welch and Goyal (2008).[3] These 14 predictors, which are also the subject of interest in recent studies by Rapach et al. (2010), Rapach et al. (2016) and Neely et al. (2014) on stock return predictability, are as follows: 1. Log dividendâĂŞprice ratio (DP): The log of 12-month moving sums of dividends paid on the S&P 500 index minus the log of the S&P 500 index.
2. Log dividend yield (DY): The log of 12-month moving sums of dividends paid on the S&P 500 index minus the log of one-month lag of the S&P 500 index.
3. Log earnings-price ratio (EP): The log of 12-month moving sums of earnings on the S&P 500 index minus the log of the S&P 500 index.
4. Log dividend-payout ratio (DE): The log of 12-month moving sums of dividends paid on the S&P 500 index minus the log of 12-month moving sums of earnings on the S&P 500 index.
5. Book-to-market ratio (BM): Book-to-market ratio of the Dow Jones Industrial Average.
6. Net equity expansion (NTIS): The ratio of 12-month moving sums of net equity issues by stocks listed on the New York Stock Exchange (NYSE) to the total end-of-year market capitalization of NYSE stocks.
7. Realized stock volatility (SVOL): Following Neely et al. (2014) and Rapach et al. (2016), we estimate the monthly realized stock volatility based on a 12-month moving standard deviation estimator of Mele (2007), which is computed as $SVOL_t = \frac{\sqrt{(\frac{\pi}{2})}\sum_{i=1}^{12}|r_{t+1-i}|}{12}$, where r_t is the t-month excess

[2]Nonetheless, the switching strategies discussed in Section 3.3.3 rely on the tradable S&P 500 futures. The continuous futures series are constructed based on contracts with the nearest month to maturity.

[3]With the exception of the SVOL variable, we extract the remaining 13 monthly predictors from Amit Goyal's website at `http://www.hec.unil.ch/agoyal/`. Goyal's dataset is updated through to 2015.12. Welch and Goyal (2008) show that in addition to these 14 conventional predictors, the Percent Equity Issuing (labelled as âĂIJeqisâĂİ), which is the ratio of equity issuing activity to the fraction of total issuing activity, has strong predictive ability on monthly stock excess returns. Nonetheless, we follow recent literature on U.S. stock return predictability (see, e.g., Rapach et al., 2010, 2016; Neely et al., 2014) and exclude the monthly âĂIJeqisâĂİ variable from our final analysis since its monthly data (which are available from Jeffrey WurglerâĂŹs website at `http://people.stern.nyu.edu/jwurgler/`) only extends to 2008. Our (unreported) experiment reveals that "eqis" yields strong explanatory power (its in-sample $\bar{R}^2$ = 2.75%) in predicting the U.S. equity premium over a narrower sample period that covers from 2000:09 to 2008:04.

return on the stock market index.[4]

8. Treasury bill rates (TBL): Interest rate on the three-month Treasury bill security.

9. Long-term yield (LTY): Yield on long-term government bonds.

10. Long-term return (LTR): Return on long-term government bonds.

11. Term spread (TMS): The difference between LTY and TBL.

12. Default yield spread (DFY): The difference between MoodyâĂŹs Baa and Aaa rated corporate bond yields.

13. Default return spread (DFR): The returns on long-term corporate bond minus the returns on long-term government bond.

14. Inflation (CPI): Consistent with Welch and Goyal (2008), we proxy CPI using the lagged consumer price index for all urban consumers, since the monthly report on inflation information for month t is typically released in the subsequent month $t+1$.

Besides these commonly used predictors, we also include a set of volatility predictors: monthly innovation of VIX (ΔVIX), monthly innovation of MOVE ($\Delta MOVE$), monthly innovation of TYVIX ($\Delta TYVIX$) and the realized bond volatility of the excess returns on the 10-year Treasury note futures (BVOL), which is defined using Mele's estimator.

3.2.3 Descriptive statistics

Table 3.1 reports the summary statistics of the monthly equity premium (r_{t+1}), which has a mean of 0.24% and a standard deviation of 4.39%. The panel also presents the corresponding statistics for all the predictors used in the current study, and these include both the level and innovation of the monthly GBVX. The level of GBVX has a mean of 6.6 and a standard deviation estimate of nearly 2.0, whereas the mean and standard deviation estimates of $\Delta GBVX$are 0.002 and 1.0, respectively.

Table 3.2 reports the Pearson correlation matrix for all the variables. The finding for $\Delta GBVX$ is of particular interest. While most of Welch and Goyal (2008)'s predictors are strongly correlated with one another, $\Delta GBVX$ appears to be unrelated to them. $\Delta GBVX$ is also among a handful

[4] Welch and Goyal (2008) define SVOL as the sum of squared daily returns on the S&P 500 index for a particular month. Nonetheless, Neely et al. (2014) and Rapach et al. (2016) note that this estimation procedure tends to yield extreme outliers, especially during severe financial crisis periods such as the DotCom bubble burst, and the 2008-2009 U.S. subprime crisis. The Mele's moving standard deviation estimator overcomes this issue.

TABLE 3.1: Summary statistics of returns and predictors

This table reports summary statistics (sample mean, sample standard deviation, skewness, kurtosis and first order autocorrelation coefficient) for the monthly equity premium (r_{t+1}), which is expressed in percentages i.e., multiplied by 100), the 14 commonly used predictors of Welch and Goyal (2008), and the various bond volatility predictors described in Section 3.2.2. The in-sample period for the $\Delta TYVIX$ spans a narrower sample period from 2003:02 to 2015:11, whereas the in-sample period for all other predictors covers from 2000:09 to 2015:11. The sample period for r_{t+1} covers from 2000:10 to 2015:12.

Variable	Mean	Std.Dev	Skewness	Kurtosis	AC(1)
r_{t+1} (%)	0.237	4.993	-0.763	1.426	0.148
DP	-3.983	0.191	0.461	2.162	0.954
DY	-3.981	0.193	0.209	1.996	0.950
EP	-3.134	0.442	-2.019	4.359	0.976
DE	-0.848	0.517	2.751	7.729	0.981
BM	0.290	0.067	-0.773	0.375	0.929
NTIS	-0.001	0.019	-1.048	0.977	0.969
SVOL	0.060	0.025	0.744	0.135	0.971
TBL	0.015	0.018	0.969	-0.399	0.976
LTY	0.042	0.011	-0.417	-0.942	0.957
LTR	0.006	0.033	0.077	2.228	-0.031
TMS	0.027	0.013	-0.711	-0.535	0.963
DFY	0.011	0.005	2.829	9.326	0.955
DFR	0.000	0.020	-0.472	5.330	0.008
CPI	0.002	0.003	-1.310	8.607	0.435
BVOL	0.017	0.005	0.668	-0.368	0.939
GBVX	6.602	1.984	0.928	0.822	0.868
$\Delta GBVX$	-0.002	1.009	1.081	4.896	-0.161
$\Delta MOVE$	-0.052	15.898	1.720	10.715	-0.165
ΔVIX	-0.004	4.686	0.700	3.649	-0.022
$\Delta TYVIX$	-0.017	1.054	1.237	5.645	-0.194

of predictors that have the highest correlation coefficient (in absolute terms) to r_{t+1}. These results foreshadow our subsequent empirical findings that $\Delta GBVX$ contains important and new information not embedded in the existing popular predictor variables of Welch and Goyal (2008) in predicting the U.S. equity premium. Not surprisingly, the panel also shows that $\Delta GBVX$ is highly correlated with both $\Delta MOVE$ and $\Delta TYVIX$, presumably because all three variables measure volatility shocks in the Treasury bond market.

3.3 Empirical results

3.3.1 In-sample test results

We begin our empirical analyses by reporting the in-sample predictive results of Equation 3.1 in Table 3.3. A few remarks are in order before we discuss the results.

First, we standardize the respective x_t variables prior to running the regression to control for differences in units of measurement across the predictors. This facilitates the comparison of the estimated regression coefficients (β). Second, similar to Rapach et al. (2016), we estimate the heteroscedasticity and autocorrelation consistent (HAC) t-statistic for the estimated β to obtain a more reliable inference. Third, we follow Rapach et al. (2016) and test the null hypothesis of no reaction ($H_0 : \beta = 0$) against the alternative hypothesis of a positive reaction ($H_A : \beta > 0$), since the theory often provides the reasonable expected sign for β.[5] As such, we multiply TBL, LTY, DFY, and all the implied volatility predictors by -1 prior to estimating Equation 3.1, as indicated in the second column of Table 3.3 (see also the sample Pearson correlation matrix result reported in Table 3.2 in the current study and Table 3 of (Rapach et al., 2016)). Fourth, it is highly probable that the standard errors of Equation 3.1 suffer from small sample bias. In addition, in reviewing the work by Inoue and Kilian (2005), Kilian and Vega (2011) note that the conventional asymptotic Student t-test tends to reject the null hypothesis of no predictability more often than it should when the same regression model is tested using different regressors. To alleviate these concerns, we closely follow the recommendation of Rapach et al. (2016) and perform a wild bootstrap procedure based on 10,000 simulations to assess the statistical significances of the coefficient estimates of Equation 3.1.

Table 3.3 shows that only 4 of the 14 commonly used predictors of Welch and Goyal (2008)-DY, BM, TBL, and LTY-yield statistically significant β estimates at the 10% level. Of these predictors,

[5] Inoue and Kilian (2005) show that the one-sided t-test considerably improves the power of tests of predictability.

TABLE 3.2: Correlations

This table reports the Pearson correlation coefficients of the monthly equity premium (r_{t+1}), which is expressed in percentages i.e., multiplied by 100), the 14 commonly used predictors of Welch and Goyal (2008), and the various bond volatility predictors described in Section 3.2.2. The in-sample period for the $\Delta TYVIX$ spans a narrower sample period from 2003:02 to 2015:11, whereas the in-sample period for all other predictors covers from 2000:09 to 2015:11. The sample period for r_{t+1} covers from 2000:10 to 2015:12. The correlations are calculated based on overlapping sample periods.

	r_{t+1}	DP	DY	EP	DE	BM	NTIS	SVOL	TBL	LTY	LTR	TMS	DFY	DFR	CPI	BVOL	GBVX	$\Delta GBVX$	$\Delta MOVE$	ΔVIX	$\Delta TYVIX$
r_{t+1}	1																				
DP	0.16	1																			
DY	0.20	0.97	1																		
EP	0.06	-0.21	-0.21	1																	
DE	0.01	0.55	0.54	-0.93	1																
BM	0.16	0.63	0.62	0.43	-0.13	1															
NTIS	0.11	-0.48	-0.45	0.15	-0.31	0.01	1														
SVOL	0.05	0.25	0.24	-0.7	0.69	-0.18	0.03	1													
TBL	-0.15	-0.55	-0.57	0.05	-0.25	-0.51	-0.09	-0.36	1												
LTY	-0.20	-0.58	-0.61	-0.31	0.05	-0.67	0.2	0.1	0.68	1											
LTR	0.05	0.04	-0.02	0.04	-0.02	0.07	0.04	0.01	0	-0.09	1										
TMS	0.04	0.26	0.27	-0.32	0.37	0.13	0.29	0.56	-0.79	-0.09	-0.08	1									
DFY	-0.05	0.69	0.66	-0.6	0.77	0.17	-0.51	0.56	-0.27	-0.12	0.03	0.27	1								
DFR	0.08	-0.04	0.08	-0.21	0.17	-0.09	0.08	0.2	-0.05	0.03	-0.46	0.09	0.11	1							
CPI	0.08	-0.21	-0.21	0.13	-0.19	-0.12	0.03	-0.13	0.2	0.22	-0.07	-0.08	-0.33	-0.14	1						
BVOL	0.06	0.21	0.21	-0.62	0.6	-0.08	0.18	0.6	-0.22	0.3	0	0.54	0.44	0.14	-0.03	1					
GBVX	-0.16	0.25	0.19	-0.58	0.59	-0.16	-0.17	0.61	-0.24	0.29	-0.01	0.56	0.61	-0.01	-0.19	0.58	1				
$\Delta GBVX$	-0.20	-0.06	-0.1	0.07	-0.08	-0.01	-0.06	-0.06	0.08	0.06	-0.19	-0.05	-0.07	-0.09	-0.12	-0.1	0.26	1			
$\Delta MOVE$	-0.18	-0.06	-0.12	0.09	-0.1	-0.01	-0.06	-0.08	0.09	0.06	-0.15	-0.07	-0.09	-0.19	-0.09	-0.1	0.2	0.88	1		
ΔVIX	-0.14	0.01	-0.16	0.12	-0.1	0.05	-0.04	-0.1	0.09	0.06	0.16	-0.07	-0.1	-0.52	0.14	-0.08	0.08	0.27	0.35	1	
$\Delta TYVIX$	-0.19	-0.04	-0.1	0.09	-0.08	0.03	-0.07	-0.08	0.05	0.03	-0.09	-0.04	-0.04	-0.13	-0.13	-0.1	0.23	0.94	0.88	0.26	1

β_{LTY} has the largest estimate at 0.873. The estimated β for the level of GBVX is statistically insignificant, but the slope coefficient estimate for $\Delta GBVX$ is statistically significant at the 5% level. In fact, $\beta_{\Delta GBVX}$ =0.872, and the magnitude of this estimate matches that of β_{LTY}. In other words, upon a unit decrease in the standardized $\Delta GBVX$ in month t, the equity premium in the following month $t+1$ increases considerably by 87 bps (recall that we multiply the standardized $\Delta GBVX$ with -1 prior to running the regression). The slope coefficient estimates of the remaining bond implied volatility predictors ($\Delta MOVE$ and $\Delta TYVIX$) are also statistically significant, but their estimated β_s are lower than $\beta_{\Delta GBVX}$. On the other hand, the estimated β of the predictive regression based on the realized bond volatility predictor (BVOL) is insignificant.

It is interesting to examine whether both the level and innovation of GBVX offer complementary predictive abilities on equity premium. To investigate this issue, we estimate the following joint predictive regression:

$$r_{t+1} = \alpha + \beta \Delta GBVX_t + \gamma GBVX_t + \epsilon_{t+1} \tag{3.2}$$

The result shows that β = 0.745 (its HAC-robust t-statistic is 1.846, which is statistically significant at the 5% level using the wild bootstrapped p-value), whereas the estimated γ remains insignificant. This suggests that the innovation of GBVX plays a leading role in predicting the U.S. excess stock returns.

Does $\Delta GBVX$ provide new and incremental information beyond that accorded by the 14 conventional predictors of Welch and Goyal (2008) in forecasting in-sample equity premium in the sample period considered in the current study? To address this question, we begin by deploying principal component analysis (PCA) to reduce the large number (14) of standardized predictors to a smaller set of uncorrelated components. Following the recommendation of Neely et al. (2014), we extract the first three components, which account for a cumulative value of 62% of the variation. We then estimate the following joint predictive regression:

$$r_{t+1} = \alpha + \beta \Delta GBVX_t + \sum_{j=1}^{3} \gamma \hat{F}_{j,t} + \epsilon_{t+1} \tag{3.3}$$

where $\hat{F}_{1,t}$,$\hat{F}_{2,t}$,$\hat{F}_{3,t}$ are the first, second, and third estimated principal components, respectively.[6]

[6]Since years of time series data are required to obtain statistically meaningful principal components, we follow Neely et al. (2014) and use the 1951-2015 sample period to estimate the principal components. The estimated principal components from 2000:09 to 2015:11 are then used as explanatory variables in Equation 3.3. Consistent with Neely et al. (2014), the plots show that financial ratio variables such as DP, DY, EP, and BM load heavily and positively on $\hat{F}_{1,t}$, and thus,

TABLE 3.3: In-sample predictive regression results

The table reports the estimated β and corresponding heteroscedasticity and autocorrelation adjusted t-statistic (in bracket) of the in-sample predictive regression Equation 3.1. The results are reported for the 14 predictors of Welch and Goyal (2008), and the various volatility predictors discussed in Section 3.2.2. We multiply the respective predictors with +1 or -1 (see the 'Sign' column) before running the regression to test the null hypothesis $H_0 : \beta_i = 0$ against the alternative hypothesis that $H_A : \beta_i > 0$. The last three columns shows the adjusted R^2 ($\bar{R}^2$) of the actual data, and the 90% and 95% cut-off levels of the estimated from 10,000 wild bootstrap simulations. The in-sample period for the $\Delta TYVIX$ spans a narrower sample period from 2003:02 to 2015:11, whereas the in-sample period for all other predictors covers from 2000:09 to 2015:11. *, ** and *** indicate statistical significances at the 10%, 5% and 1% levels, respectively, according to the wild bootstrapped p-values.

Variable	Sign	β	(t-stat)		$\bar{R}^2$ (%)	90 % $\bar{R}^2$ (%)	95 % $\bar{R}^2$ (%)
DP	+1	0.722	(1.205)		2.17	2.66	3.83
DY	+1	0.861	(1.788)	*	3.31	2.08	3.09
EP	+1	0.243	(0.403)		-0.24	3.25	5.89
DE	+1	0.060	(0.106)		-0.53	2.37	3.58
BM	+1	0.691	(2.343)	**	1.93	1.43	2.26
NTIS	+1	0.463	(0.807)		0.56	2.36	3.39
SVOL	+1	0.226	(0.646)		-0.29	0.79	1.33
TBL	-1	0.654	(2.219)	**	1.68	0.66	1.18
LTY	-1	0.873	(3.420)	***	3.42	0.62	1.11
LTR	+1	0.236	(0.326)		âĂŞ0.26	1.67	2.56
TMS	+1	0.164	(0.495)		âĂŞ0.41	0.61	1.11
DFY	-1	0.212	(0.356)		âĂŞ0.32	3.15	4.54
DFR	+1	0.372	(0.251)		0.17	4.31	5.87
CPI	+1	0.332	0.738		0.02	1.46	2.22
BVOL	+1	0.246	(0.679)		âĂŞ0.24	1.14	1.87
GBVX	-1	0.688	(1.308)		1.91	2.14	3.09
$\Delta GBVX$	-1	0.872	(1.837)	**	3.41	3.05	4.22
$\Delta MOVE$	-1	0.801	(1.879)	**	2.79	3.95	5.56
ΔVIX	-1	0.594	(1.410)		1.29	3.25	4.62
$\Delta TYVIX$	-1	0.785	(1.605)	**	3.10	5.09	7.08

The qualitative and quantitative findings regarding the predictive ability of $\Delta GBVX$ remain unchanged, with $\beta_{\Delta GBVX}$ = 0.816 and statistical significant at the 5% level.

Table 3.3 also reports the in-sample adjusted R^2 ($\bar{R}^2$) estimates. At first glance, the values of $\bar{R}^2$ for the 14 conventional predictors reported in the current study appear to be several orders of magnitude higher than those obtained by Welch and Goyal (2008). It is probable that our high $\bar{R}^2$ estimates are artefacts of the recent 2000-2015 sample period that we consider, whereas Welch and Goyal (2008) examine a relatively longer sample period (1927-2004). To provide a meaningful analysis, we compare the actual $\bar{R}^2$ estimated using the observed data with the 90% and 95% cut-off levels of $\bar{R}^2$ estimated from the 10,000 wild bootstrap simulation procedure (see the final two columns of Table 3.3). In accordance with the earlier results concerning $\hat{\beta}$, only DY, BM, TBL, and LTY have values of $\bar{R}^2$ that are higher than the 90% simulated cut-off benchmark. Among these predictors, LTY has the largest $\bar{R}^2$ at 3.42%, and it is over the 95% cut-off $\bar{R}^2$ value. The main object of interest in the current study, $\Delta GBVX$, has a comparable $\bar{R}^2$ at 3.41%, and this estimate also exceeds the 90% cut-off $\bar{R}^2$ benchmark.[7] In contrast, the $\bar{R}^2$ estimates for the other remaining volatility predictors, BVOL, $\Delta MOVE$, ΔVIX, and $\Delta TYVIX$, are well below the 90% simulated cut-off benchmarks.

As a further analysis, we compute the $\bar{R}^2$ statistic separately for positive and negative volatility shocks using a specification modified from Neely et al. (2014). The statistic, which is labelled as the modified $\bar{R}^2_z$ statistic, is defined as:

$$modified\bar{R}^2_z = 1 - \frac{\sum_{t=1}^{T} D^z_t \hat{\epsilon}^2_t}{\sum_{t=1}^{T} D^z_t (r_t - \bar{r})^2} \tag{3.4}$$

where $D^{z=+}_t$ is a dummy variable equalling to 1 if $\Delta GBVX \geq 0$ (i.e., if there is a zero or positive volatility shock in month t) and 0 otherwise, $D^{z=-}_t$ is a dummy variable equalling to 1 if $\Delta GBVX < 0$ (i.e., if the volatility shock is negative in month t) and 0 otherwise, $\hat{\epsilon}^2_t$ refers to the fitted residual of Equation 3.1, $\bar{r}$ is the full-sample mean of r_t, and T is the full sample observations. The result shows that the modified $\bar{R}^2_{z=+}$ = 2.09%, and $\bar{R}^2_{z=-}$ =3.62%, which is suggestive that the

$\hat{F}_{1,t}$ reflects the dynamics in financial ratios. $\hat{F}_{2,t}$, which is loaded heavily and positively by SVOL, LTY, TMS, and DFY, is volatile and increases dramatically during financial crisis periods such as the 2008-2009 subprime crisis. Finally, $\hat{F}_{3,t}$ contains information pertaining to various variables, with positive loadings by DP, DY, DE, NTIS, and DFR, and negative loadings by TBL, LYT, LTR, and CPI.

[7] The in-sample test results of Table 3.3 reveal that while the $\bar{R}^2$ statistic of LTY exceeds the 95% cut-off value, the $\bar{R}^2$ statistic of $\Delta GBVX$ merely exceeds the 90% cut-off value. However, as Table 3.4 shows, the $\Delta GBVX$ predictor substantially outperforms all other variables (including the LTY predictor) in the out-of-sample test, which is the ultimate test for forecasting equity premiums.

equity premium predictability concentrates more over periods of negative bond volatility shocks than positive shocks.

In summary, the in-sample test results presented in Table 3.3 , together with the joint predictive regression finding of Equation 3.3, demonstrate that the innovation in GBVX possesses different and incremental information over the conventional predictors in forecasting the U.S. equity premium over the sample period considered in the current study.

3.3.2 Out-of-sample test results

The “gold standard" for stock return predictability is the out-of-sample test, which addresses issues related to data mining that tend to impede the validity of the in-sample test. With this in mind, we adopt the methodology similar to that used in prior related studies (see e.g. Campbell and Thompson, 2008; Welch and Goyal, 2008; Rapach, Strauss and Zhou, 2010; Rapach, Ringgenberg and Zhou, 2016) to analyze the out-of-sample U.S. equity premium predictability. In particular, we rely on an expanding estimation window to generate the one-month-ahead out-of-sample forecasts of $\hat{r}_{t+1}$. This necessitates the division of the full T sample period into an in-sample estimation period with m observations and an out-of-sample portion with Tm observations. The first out-of-sample forecast of $\hat{r}_{m+1}$ is given by:

$$\hat{r}_{m+1} = \hat{\alpha}_m + \hat{\beta}_m x_m, \tag{3.5}$$

where $\hat{\alpha}_m$ and $\hat{\beta}_m$ refer to the least square estimates of Equation 3.1, which are computed by regressing $\{r_{t+1}\}_{t=0}^{m-1}$ on a constant and $\{x_t\}_{t=0}^{m-1}$. The next out-of-sample forecast of $\hat{r}_{m+2}$ is computed as:

$$\hat{r}_{m+2} = \hat{\alpha}_{m+1} + \hat{\beta}_{m+1} x_{m+1}, \tag{3.6}$$

where $\hat{\alpha}_{m+1}$ and $\hat{\beta}_{m+1}$ are generated by regressing $\{r_{t+2}\}_{m}^{t=0}$ on a constant and $\{x_{t+1}\}_{t=0}^{m}$, and so on. We use data from 2000:09-2005:09 (i.e., one-third of the full sample period) to forecast the first $\hat{r}_{m+1}$, and the out-of-sample forecasting period spans from 2005:10-2015:12.

Then, we use Campbell and Thompson (2008)'s out-of-sample R^2 (R^2_{oos}) to compare the $\{r_{t+1}\}_{t=m}^{T-1}$ recursive forecasts with the $\{r_{t+1}^{HA}\}_{t=m}^{T-1}$ historical average forecasts, which are also estimated recursively using an expanding estimation window but are devoid of any x predictors. The R^2_{oos} statistic is computed as:

$$R^2_{oos} = 1 - \frac{\sum_{k=1}^{T-m}(r_{m+k} - \hat{r}_{m+k})^2}{\sum_{k=1}^{T-m}(r_{m+k} - \hat{r}^{HA}_{m+k})^2} \tag{3.7}$$

We test the null hypothesis of $H_0 : R^2_{oos} \leq 0$ against the alternative hypothesis $H_A : R^2_{oos} > 0$, using the McCracken (2007) mean square error (MSE)-F test statistic. The rejection of the null hypothesis in favor of the alternative hypothesis implies that the x predictor provides significant out-of-sample explanatory power over the historical average model in predicting excess returns.

In addition, we re-estimate the R^2_{oos} statistic Equation 3.7 by imposing appropriate restriction to the equity premium forecasts as suggested by Campbell and Thompson (2008). In particular, we constrain negative equity premium forecasts to zero since practitioners are mainly interested in positive equity premium forecasts. Campbell and Thompson (2008) show that such restriction tends to enhance the out-of-sample forecast performance of the individual predictors.

Panel A of Table 3.4 reports the results with no restriction imposed, whereas Panel B of the table presents the result after imposing Campbell and Thompson (2008)'s restriction on the equity premium forecasts. At first impression, the R^2_{oss} statistics of some of the 14 conventional predictors reported especially in Panel B of Table 3.4 appear to be considerably higher than the estimates obtained by Welch and Goyal (2008), and we surmise in earlier Section 3.3.1 that our results could be sensitive to the recent (and shorter) sample period. To address this issue, we compare the MSE-F test statistic against the one-sided critical values computed from 10,000 simulations that are obtained from the bootstrap procedure.

The out-of-sample forecasting results reported in Panel A of Table 3.4 reveal that none of Welch and Goyal (2008)'s 14 conventional predictors beat the historical average benchmark at the usual significance levels. In contrast, the monthly R^2_{oos} for the GBVX level is significantly positive at 1.04%. The best out-of-sample predictive performance, however, belongs to the $\Delta GBVX$ predictor, since it yields the highest monthly R^2_{oos} of 2.69% and is statistically significant at the 1% level. Further note that this R^2_{oos} estimate is also statistically significant because it exceeds the 95% cut-off benchmark estimate of 1.27% generated from the bootstrap procedure (the benchmark cut-off value is not tabulated in the table to save space).

It is also interesting to examine if the $\Delta GBVX$ predictor contains useful out-of-sample predictive information beyond what is already embedded in the other predictors. The test metric commonly used to study this premise is the encompassing regression model of:

$$r^*_{m+k} = (1-\lambda)\hat{r}_{m+k,i} + \lambda\hat{r}_{m+k,\Delta GBVX} \tag{3.8}$$

where r^*_{m+k} refers to the combined equity premium forecast over the sample period from k = 1 to $T - m$, $\hat{r}_{m+k,\Delta GBVX}$ is the out-of-sample equity premium forecast based on $\Delta GBVX$, and $\hat{r}_{m+k,\Delta GBVX}$ refers to the out-of-sample equity premium forecast based on other individual predictors with $i \neq \Delta GBVX$. The $\Delta GBVX$ predictor is deemed to encompass the predictive forecast of variable i if the estimated λ equals unity; otherwise, the predictive forecast of variable i encompasses the predictive forecast based on $\Delta GBVX$ (i.e., if $\lambda = 0$).

The final column in Panel A of Table 3.4 reports the estimated λ for equity premium forecasts with no restriction. Notably, all the λ estimates are positive with sizable magnitudes (12 of 19 variables have a $\hat{\lambda}$ of no less than 0.8), and Harvey et al. (1998)'s test reveals that they are all significantly different from 0 at the 5% level. To summarize, the forecast provided by $\Delta GBVX$ cannot possibly be encompassed by any of the other variables; instead, the $\Delta GBVX$ forecast encompasses the predictive forecasts made by the other variables.[8]

We now turn to the findings reported in Panel B of Table 3.4. In any case, imposing Campbell and Thompson (2008)'s restriction provides stronger support for using the $\Delta GBVX$ predictor, since its R^2_{oos} estimate is even higher (and still the largest) at 3.45%, and it is also statistically and economically significant (versus the 95% cut-off benchmark estimate of 1.71%). By contrast, the next best variable, TBL, has a statistically significant R^2_{oos} estimate of only 2.39%.

In summary, the out-of-sample R^2_{oos} statistic and encompassing test results presented in this section reiterate the earlier in-sample test findings, namely, that the innovation in GBVX contains valuable information on future U.S. excess stock returns, especially in predicting monthly stock excess returns.

3.3.3 Switching strategies and utility gains

This section investigates the economic value of using various predictors to forecast monthly equity premiums. Consider first an investor who switches between equity and risk-free assets using equity premium forecasts. In particular, as in Guo and Qiu (2014) and Guo et al. (2014b), we presume the investor invests 100% of the investment to the equity market if the out-of-sample predicted excess market return is positive; otherwise, the investor prefers investing totally in the risk-free asset.[9]

[8] In untabulated results, we also test whether $(1 - \lambda)$ is significantly different from zero. Harvey et al. (1998)'s test indicates that the null hypothesis, namely, $(1 - \lambda = 0)$, cannot be rejected at the usual significance levels.

[9] Another possible strategy to be used is the asset allocation strategy in which an investor with a certain utility function splits the investment between equity and risk-free rate based on the predictions of equity return and volatility. We have

TABLE 3.4: Out-of-sample predictive regression results

The table reports the out-of-sample test results for the 14 predictors of Welch and Goyal (2008), and the various volatility predictors discussed in Section 3.2.2. The R^2_{oss} statistic is estimated based on Equation 3.7. MSE-F refers to the McCracken (2007) test statistic, which examines the null hypothesis of $H_0 : R^2_{oss} \leq 0$ against the alternative hypothesis of $H_A : R^2_{oss} > 0$. We obtain the MSE-F critical values from 10,000 bootstraps. The λ column reports the estimated λ for the encompassing test, and the corresponding statistical significance asterisk indicator (the significant value is determined based on Harvey et al. (1998) test on the null hypothesis that $\lambda = 0$). Panel A reports the results without Campbell and Thompson (2008)'s restriction, whereas Panel B reports the analogous results after imposing Campbell and Thompson (2008)'s restriction which set negative equity premium forecasts to zero. The out-of-sample period for the $\Delta TYVIX$ spans a narrower sample period from 2007:05 to 2015:12, whereas the out-of-sample period for all other predictors covers from 2005:10 to 2015:12. *, ** and *** indicate statistical significances at the 10%, 5% and 1% levels, respectively.

	Panel A: Without restriction					Panel B: With restriction				
Variable	R^2_{oss} (%)	MSE-F		λ		R^2_{oss} (%)	MSE-F		λ	
DP	âĂŞ7.69	âĂŞ8.78		0.98	***	âĂŞ5.49	âĂŞ6.40		1.00	***
DY	âĂŞ4.84	âĂŞ5.68		0.87	***	âĂŞ3.53	âĂŞ4.20		1.00	***
EP	âĂŞ7.15	âĂŞ8.21		0.87	***	1.20	1.49		0.82	*
DE	âĂŞ7.25	âĂŞ8.32		0.80	***	1.14	1.42		1.00	**
BM	0.42	0.52		0.67	**	2.07	2.60	*	0.82	*
NTIS	âĂŞ1.06	âĂŞ1.29		0.75	**	0.39	0.48		1.00	**
SVOL	âĂŞ1.15	âĂŞ1.40		0.81	**	0.84	1.05		0.93	**
TBL	âĂŞ1.38	âĂŞ1.67		0.77	**	2.39	3.01	**	0.77	
LTY	âĂŞ4.67	âĂŞ5.49		0.70	***	âĂŞ4.52	âĂŞ5.32		0.89	***
LTR	âĂŞ1.39	âĂŞ1.69		0.91	***	1.01	1.26		1.00	**
TMS	âĂŞ1.48	âĂŞ1.79		0.87	**	1.08	1.35		1.00	**
DFY	âĂŞ5.50	âĂŞ6.41		0.74	***	1.23	1.53	*	1.00	**
DFR	âĂŞ7.62	âĂŞ8.71		1.00	***	âĂŞ2.67	âĂŞ3.20		1.00	***
CPI	âĂŞ1.44	âĂŞ1.75		0.86	**	0.70	0.87		1.00	**
BVOL	âĂŞ0.93	âĂŞ1.13		0.84	***	1.41	1.76	*	0.98	*
GBVX	1.04	1.29	**	0.61	**	2.06	2.58	**	0.84	*
$\Delta GBVX$	2.69	3.40	***	N/A		3.45	4.40	***	N/A	
$\Delta MOVE$	âĂŞ0.70	âĂŞ0.86		1.00	***	1.38	1.72	*	1.00	***
ΔVIX	âĂŞ2.15	âĂŞ2.58		0.76	**	âĂŞ2.94	âĂŞ3.51		1.00	***
$\Delta TYVIX$	âĂŞ1.01	âĂŞ1.04		1.00	***	âĂŞ0.81	âĂŞ0.83		1.00	***

Figure 3.1 plots the cumulative growth of the asset allocation strategies based on several individual predictors, each of which begins with an initial investment of $100 in 2005:09. For ease of readability, the figure only plots the strategies based on three predictors that yield the highest out-of-sample R^2_{oos} estimates based on Campbell and Thompson (2008)'s restriction,[10] as reported in Panel B of Table 3.4 $\Delta GBVX$, TBL, and BM. We compare these strategies to the naïve "buy-and-holdâĂİ strategy. A striking finding emerges from Figure 3.1 âĂŞ the $\Delta GBVX$-based strategy clearly dominates the others, with the terminal investment reaching $170 in 2015:12 (i.e., the terminal growth is 70% more than the initial wealth). By contrast, the TBL, BM, and naïve strategies deliver terminal growths that ended with a 46% to 66% increase over the initial wealth during the same period.

Compared with the naïve "buy-and-holdâĂİ strategy, the outstanding performance of the switching strategy sources from the fact that our prediction model with $\Delta GBVX$ successfully predicts the negative equity premium in the future and avoids the loss by switching to the risk free rate. Among the 47 monthly negative equity risk premium observations, our switching strategy is correct (we have invested 100% in the risk free rate to avoid loss) for 34 times and wrong (we have invested 100% in the stock index futures) for 13 times. It indicates that in a majority of time (72.34%), our strategy protects us from the loss due to market decline. In contrast, among the 76 monthly positive equity risk premium observations, our switching strategy has a much lower success ratio of 39.47%.

We also calculate the annualized Sharpe ratios for all the strategies. We adjust the annualized Sharpe ratios for potential first-order serial correlation in monthly stock returns using the technique suggested by Lo (2002).[11] The first column of Table 3.5 presents the results. The performance of the asset allocation strategy based on the $\Delta GBVX$ predictor clearly stands out, since it yields a sizable annualized Sharpe ratio of 0.482. On the other hand, six other predictors âĂŞ EP, BM, TBL, DFY, BVOL and GBVX âĂŞ generate Sharpe ratios ranging between 0.25 and 0.48, and the remaining predictors have Sharpe ratios below 0.18. Overall, the sample mean Sharpe ratio estimate of all the predictors (excluding $\Delta GBVX$) is considerably lower at 0.15.

Another channel that we employ to assess the economic value afforded by the various predictors is from the perspective of a mean-variance investor who attempts to maximize utility gains by allocating

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not applied this strategy as it requires a prediction of volatility as well.

[10] Under Campbell and Thompson (2008)'s restriction, we set the out-of-sample negative equity premium forecast to zero. This is analogous to investing in risk-free assets in our switching strategy.

[11] Rather than reproducing Lo (2002)'s adjustment technique, we refer interested readers to his seminal paper, especially to Equation (22), page 41.

TABLE 3.5: Sharpe ratio and CER gain

The table reports the out-of-sample annualized Sharpe ratio estimates and certainty equivalent return (CER) gains for the 14 predictors of Welch and Goyal (2008) and the various volatility predictors discussed in Section 3.2.2. The CER gain (expressed in basis points) is for a mean-variance investor assuming a relative risk-aversion coefficient (γ) of three and who allocates between the S&P 500 futures and risk-free asset using the out-of-sample predictive regression Equation 3.7, relative to the naÃŕve “buy-and-holdâĂİ passive strategy. The out-of-sample period for the $\Delta TYVIX$ spans a narrower sample period from 2007:05 to 2015:12, whereas the out-of-sample period for all other predictors covers from 2005:10 to 2015:12.

Variable	Sharpe ratio	CER
DP	âĂŞ0.017	âĂŞ103
DY	0.023	âĂŞ78
EP	0.478	285
DE	0.136	151
BM	0.254	211
NTIS	âĂŞ0.019	12
SVOL	0.060	122
TBL	0.439	384
LTY	0.175	86
LTR	âĂŞ0.135	34
TMS	0.000	115
DFY	0.360	193
DFR	âĂŞ0.154	âĂŞ93
CPI	âĂŞ0.092	81
BVOL	0.465	207
GBVX	0.358	280
$\Delta GBVX$	0.482	411
$\Delta MOVE$	0.174	181
ΔVIX	0.167	163
$\Delta TYVIX$	0.127	294

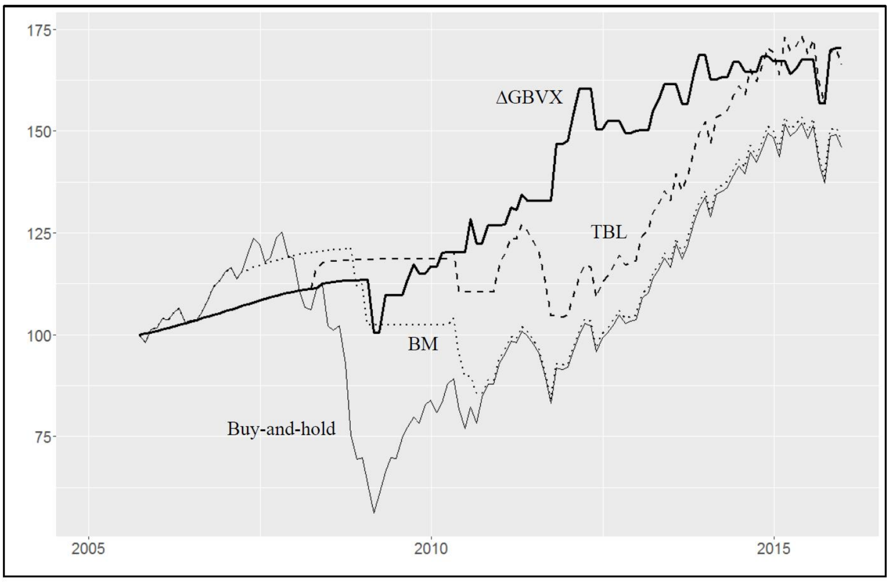


FIGURE 3.1: Cumulative values of various trading strategies

The figure plots the monthly cumulative values of trading strategies constructed using the $\Delta GBVX$, TBL and BM predictors, as well as the naïve “buy-and-hold" strategy. Each strategy starts with a \$100 initial investment. The out-of-sample period is from 2005:10 to 2015:12.

across equity and risk-free assets, using various equity premium forecasts. Specifically, in a spirit similar to Campbell and Thompson (2008) and Rapach et al. (2010, 2016), we assume the investor has the following mean-variance utility function:

$$U = R_p - 0.5\gamma\sigma_p^2, \tag{3.9}$$

where R_p and σ_p^2 respectively are the mean and variance of the portfolio returns, and γ refers to the coefficient of the investorâĂŹs relative risk aversion. We set γ to a realistic estimate of 3, as recommended by Rapach et al. (2016). We then calculate the certainty equivalent return (CER) gain of investing in a portfolio based on the aforementioned asset allocation strategy relative to that of the naÃŕve “buy-and-hold" strategy:

$$CER = (R_p - 0.5\gamma\sigma_p^2) - (R_{naive} - 0.5\gamma\sigma_{naive}^2). \tag{3.10}$$

In other words, the CER gains of Equation 3.10 are the “incremental management fees" that the investor is willing to pay to invest in the asset allocation strategies based on the equity premium forecasts over the "buy-and-hold" strategy. The results, which are reported in the second column of Table 3.5, reveal that the investor is prepared to pay a hefty incremental annual management fee of 411bps to have access to predictive regression based on $\Delta GBVX$ instead of the "buy-and-hold" strategy. In sharp contrast, most of other predictors command less than 300bps as incremental annual management fees (except for TBL, which has CER gains of 384bps).

Finally, we investigate the extent to which $\Delta GBVX$ contributes additional CER economic gains to the entire set of the 14 predictors of Welch and Goyal (2008). The economic gains of these 14 variables are succinctly captured by the first three principal components, which are recursively estimated to avoid problems related to "forward-looking bias" in constructing the out-of-sample asset allocation. The results reveal that the mere three principal components generate annualized CER gains of 410bps, whereas the inclusion of $\Delta GBVX$ increases the CER gains substantially to 588bps (this represents substantial CER incremental gains of 178bps).

3.4 Source of $\Delta GBVX$'s predictive ability

This section investigates the source of $\Delta GBVX$'s predictive ability. To address this issue, we follow Rapach et al. (2016) and utilize the vector autoregressive (VAR) methodology of Campbell (1991) and Campbell and Ammer (1993) to measure whether the predictive ability of $\Delta GBVX$ stems from its ability to anticipate cash flow and/or discount rate news. Here, a brief description of the VAR methodology is suffice, and we refer interested readers to the studies by Campbell (1991) and Campbell and Ammer (1993) for further technical discussions.

Consider the following first-order VAR specification:

$$y_{t+1} = \begin{bmatrix} r_{t+1} \\ DP_{t+1} \\ \hat{F}_{1,t+1} \\ \hat{F}_{2,t+1} \\ \hat{F}_{3,t+1} \end{bmatrix} = Ay_t + \mu_{t+1}, \tag{3.11}$$

where r_{t+1} is the log stock return, and A is a 5×5 matrix of slope coefficients. We include the log dividend-price ratio (i.e., DP) in Equation 3.11, since Engsted et al. (2012) emphasize the importance of accounting for this variable to properly estimate the cash flow and discount rate news components. We also include the first three principal components ($\hat{F}_{1,t+1}$, $\hat{F}_{2,t+1}$, and $\hat{F}_{3,t+1}$) extracted from 13 of the 14 conventional predictors of Welch and Goyal (2008), that is, we exclude the DP variable from the PCA analysis.[12]

The log stock return is decomposed as:

$$r_{t+1} = E_t r_{t+1} + \eta_{CF,t+1} - \eta_{DR,t+1}, \tag{3.12}$$

where $E_t r_{t+1}+$ refers to the expected log stock return at time $t+1$ based on the information obtained at time t, and $\eta_{CF,t+1}$ and $\eta_{DR,t+1}$ respectively are the cash flow and discount rate news components of the stock return innovations. Section 3.6 discusses the empirical estimation of the respective components of $E_t r_{t+1}$, $\eta_{CF,t+1}$, and $\eta_{DR,t+1}$.

We then regress the log stock return on $\Delta GBVX$ using the predictive regression Equation 3.1, which is restated here as:

$$r_{t+1} = \alpha + \beta \Delta GBVX_t + \epsilon_{t+1} \tag{3.13}$$

The following regressions ensue:

$$\hat{E}_t r_{t+1} = \alpha_{\hat{E}} + \beta_{\hat{E}} \Delta GBVX_t + \epsilon_{\hat{E},t+1} \tag{3.14}$$

$$\hat{\eta}_{DR,t+1} = \beta_{DR} \Delta GBVX_t + \epsilon_{DR,t+1} \tag{3.15}$$

$$\hat{\eta}_{CF,t+1} = \beta_{CF} \Delta GBVX_t + \epsilon_{CF,t+1} \tag{3.16}$$

By construction, Equations 3.13 to 3.16 are related through their estimated slope coefficients:

$$\hat{\beta} = \hat{\beta}_{\hat{E}} + \hat{\beta}_{\hat{CF}} - \hat{\beta}_{\widehat{DR}} \tag{3.17}$$

Altogether, each of the slope coefficient estimates in Equation 3.17 reveals the extent to which the ability of $\Delta GBVX$ to predict log stock returns is attributed to its ability to forecast $\hat{E}_t r_{t+1}$, $\hat{\eta}_{CF,t+1}$, and/or $\hat{\eta}_{DR,t+1}$.

Table 3.6 reports the results. It is evident from the table that the strong predictive ability of $\Delta GBVX$ emanates from its anticipation of future cash flows. To explain, note that both $\hat{\beta}_{\hat{E}}$ and $\hat{\beta}_{\widehat{DR}}$

[12] Chen and Zhao (2009) suggest using the PCA approach to minimize the effect related to the choice of state variables in the return decomposition analysis.

are statistically significant at the 10% level, but their respective contributions to the magnitude of are relatively muted. By contrast, $\hat{\beta}_{\hat{CF}}$ contributes a sizable amount to $\hat{\beta}$, and it is also statistically significant at the 1% level. Recent studies by Fernández-Villaverde et al. (2011), Creal and Wu (2014), and Bretscher et al. (2016) provide evidence suggesting that high bond volatility is significantly associated with lower real economic activities. Garrett and Priestley (2012) and Chen et al. (2013) emphasize the key role of cash flow news in driving stock price movements. Our current result that $\Delta GBVX$'s strong predictive ability is sourced primarily from the cash flow channel is thus consistent with these empirical findings.

TABLE 3.6: Predictive regression estimation results for stock return decomposition

This table reports the estimation results for Equations 3.13 to 3.16. The $\hat{E}_t r_{t+1}$,$\hat{\eta}_{DR,t+1}$ and $\hat{\eta}_{CF,t+1}$ variables are empirical estimates from the vector autoregressive (VAR) model, which is estimated from 2000:09 to 2015:11. The intercept terms for Equations 3.15 and 3.16 are supressed to zero since $\hat{\eta}_{DR,t+1}$ and $\hat{\eta}_{CF,t+1}$, by construction, have zero means. The significance of regression slope coefficient is determined by the one-sided test and wild bootstrapped p-value. *, ** and *** indicate statistical significances at the 10%, 5% and 1% levels, respectively.

Dependent Var.	Equation	β	(t-stat)		$\bar{R}^2$ (%)
r_{t+1}	(3.13)	âĂŞ0.851	(âĂŞ1.808)	**	3.33
$\hat{E}_t r_{t+1}$	(3.14)	âĂŞ0.117	(âĂŞ1.618)	*	0.51
$\hat{\eta}_{DR,t+1}$	(3.15)	âĂŞ0.533	(âĂŞ1.553)	*	2.12
$\hat{\eta}_{CF,t+1}$	(3.16)	âĂŞ1.267	(âĂŞ2.046)	***	9.34

3.5 Concluding remarks

The essay presented in this chapter advances the literature on stock return predictability by proposing a novel predictor to forecast the U.S. monthly equity premium. We show that over the recent sample period spanning from 2000:09 to 2015:12, the change or innovation in monthly GBVX (i.e., $\Delta GBVX$) has statistically and economically significant power in predicting in-sample and out-of-sample monthly stock excess returns. $\Delta GBVX$'s predictive ability matches or exceeds those of other conventional predictors commonly used in the asset pricing literature, as well as the predictive ability of several other historical and implied volatility indices. It also clearly stands out in terms of investment wealth growth, and it yields a considerably higher Sharpe ratio and a sizable increase in utility gains. Finally, the return decomposition result reveals that $\Delta GBVX$ anticipates future cash flows.

Overall, the empirical findings in the current study suggest that innovation in GBVX contains valuable and unique predictive information that many other predictors do not possess. This finding, together with the fact that GBVX can be easily constructed under the state-preference asset pricing framework, offers practitioners an appealing alternative means to predict the U.S. monthly equity premium.

3.6 Appendix: Empirical estimation of return components

We estimate $E_t r_{t+1}$, $\eta_{DR,t+1}$ and $\eta_{CF,t+1}$ as follows:

$$E_t r_{t+1} = e^{'} A y_t \tag{3.18}$$

$$\eta_{DR,t+1} = e^{'} \rho A (I - \rho A)^{-1} \mu_{t+1} \tag{3.19}$$

$$\eta_{CF,t+1} = e^{'} \mu_{t+1} + \eta_{DR,t+1} \tag{3.20}$$

where I is an 5 x 5 identity matrix, μ_{t+1} is the matrix for residuals, e is an 5-vector with one as its first element and zeros for other remaining elements, $\rho = \frac{1}{1+exp(\overline{d-p})}$ and $\overline{d-p}$ refers to the sample mean of $d_t - p_t$ in Campbell and Shiller (1988) log-linear approximation of the log stock return (with d_t and p_t refer to the log dividend and log stock price, respectively).

Chapter 4

On the relation between liquidity and the futures-cash basis: evidence from a natural experiment

4.1 Introduction

The Law of One Price is the economic theory that two traded or synthesized instruments with the same future cash flows should trade at the same price due to arbitrage trades. The effectiveness of arbitrage in enhancing pricing efficiency should depend on liquidity. Roll, Schwartz and Subrahmanyam (2007) test this notion by comprehensively investigating the intertemporal association between stock market liquidity and the absolute futures-cash basis in the context of the New York Stock Exchange (NYSE) index futures/cash markets. Using a vector autoregressions (VAR) approach, they find that the innovations to the absolute futures-cash basis and spreads are positively correlated, and there is a positive two-way Granger causality relation between them. The underlying mechanism of this phenomenon, as surmised by Roll, Schwartz and Subrahmanyam (2007), is that a liquid market would facilitate arbitrage trades and then eliminate market mispricing, while the arbitrage triggered trades in response to a wide futures-cash basis could also reduce liquidity due to order imbalances.[1] This two-way relation also exists in the international markets (e.g., Lee, Chien and Liao, 2012; Kadapakkam and Kumar, 2013).

However, there remains one potential issue in Roll, Schwartz and Subrahmanyam (2007) and other relevant studies, which is the "*omitted variable bias*". Testing if and how market liquidity and the absolute futures-cash basis interacts with each other poses a tricky identification challenge. According to Granger (1980), Lütkepohl (1982), and Stock and Watson (2001), among others, the results on Granger causality could be spurious or measure wrong feedback relations, if as is likely, there are omitted variables (such as interest rate, market volatility, and market sentiment, etc. in our context)[2] that simultaneously affect liquidity and the absolute futures-cash basis. In our context, to overcome the potential for omitted variable bias, the commonly used approaches in the ordinary least squares (OLS) regression, i.e., instrument variables or exogenous shocks to independent variable(s), can prove difficult since we have two series of lagged independent variables.[3]

In this essay, we formally test whether the interplay between liquidity and the absolute futures-cash basis is caused by the forces of arbitrage. We employ a natural experiment to "shut down" the driving force (arbitrage activities) and test whether the two-way relation between liquidity and the futures-cash basis still holds or not. Specifically, recent trading restrictions on short sales and index futures trading in the Chinese financial markets provide us with an ideal laboratory setting for such an identification strategy.[4] As a response to the Chinese stock market crash starting in the middle

[1]The interplay between market efficiency and liquidity is an enduringly important research question in the financial economics literature. For instance, Kumar and Seppi (1994) point out, arbitrage activities, and hence, the futures-cash basis, may be affected by liquidity. In the reverse direction, market-wide order imbalances resulting from arbitrage trades may have a contemporaneous and a persistent impact on liquidity (e.g., Stoll, 1978a; O'Hara and Oldfield, 1986; Chordia, Roll and Subrahmanyam, 2002).

[2]For instance, numerous theoretical and empirical studies have demonstrated the role volatility plays in driving illiquidity (e.g., Stoll, 1978b, 2000; Amihud and Mendelson, 1989; Chordia, Roll and Subrahmanyam, 2001; Chordia, Sarkar and Subrahmanyam, 2005), while Chen, Cuny and Haugen (1995) document that stock market volatility is a key determinant of the index futures-cash basis.

[3]Roll, Schwartz and Subrahmanyam (2007) mention the possible existence of the omitted variable bias and control for volatility and signed index returns, the possible common drivers, in the VAR estimation. However, as it is impossible to control for all the known and unknown factors in one system, we adopt a different identification strategy based on the economic mechanism behind the statistical relation.

[4]Stock and Watson (2001) also suggest that, although not commonly used in the literature, the natural experiment approach could be a remedy for the omitted variable bias problem in the Granger causality test.

of June 2015, since July 2015, regulators successively restricted the positions for the "speculation or arbitrage" purpose in the index futures market by limiting the number of trades and sharply increasing the transaction costs and margin rates. Regulators also de facto banned short positions in the stock market.[5] Under these restrictions, arbitrage trades, which need to set up simultaneous positions in both markets and are sensitive to transaction costs, are in fact infeasible(Han and Liang, 2016). Hence, in this restriction experiment, the positive two-way relation between the absolute futures-cash basis and illiquidity should break down if their relation is indeed due to the arbitrage activities other than the endogeneity problem.

We first investigate the relation between the Chinese Securities Index 300 (CSI 300) absolute futures-cash basis and the aggregate liquidity of the CSI 300 using the VAR approach and impulse response analysis for the sample period from January 2, 2012 to May 29, 2015 (a half month before the market crash). In this pre-restriction period, results are in line with the findings in both U.S. and international markets: the absolute futures-cash basis and market illiquidity have a positive two-way causality relation both statistically and economically, and the results are stronger for the effective spread measure compared to the quoted spread measure, possibly due to the fact that the effective spread is a more accurate estimate of arbitrage cost (Blume and Goldstein, 1997).

We next examine the sample period that covers the quasi-natural experiment (July 7, 2015 to June 30, 2016). We find that the significant two-way causality relation in the pre-restriction period disappears in this restriction period for all the futures contracts. The impulse response analyses also show that shocks to spreads (bases) are uninformative towards the future movements of bases (spreads) and the mean values of response are statistically different from those in the pre-restriction period. The insignificant impulse responses also reveal that the economic significance of the cross-effects between liquidity and the futures-cash basis is negligible. To ensure the robustness, we also use a more strict definition for the restriction period (August 3, 2015 to June 30, 2016), and the results are qualitatively unaltered. Moreover, we use the Z-test to statistically compare the VAR coefficients in the two sample periods (pre-restriction and restriction) and the results indicate that the coefficients are significantly different between these two sample periods. Overall, our results confirm the hypothesis that arbitrage is the underlying mechanism that drives the interplay between spreads and the futures-cash basis.

One remaining concern for our central conclusion is the market crash effect. Lien et al. (2013) argue that when market liquidity decreases and the absolute futures-cash basis increases (a typical

[5] We provide a more detailed introduction of this restriction experiment in Section 2 and Section 4.6.

phenomenon during the 2015 Chinese market crash), the dependence structure between these two variables may break down. Since our restriction period overlapped the Chinese market crash period, our treatment effect (restriction) might therefore be confounded by the market crash effect that can potentially provide explanatory power for our results. To alleviate this concern, we first conduct a Granger causality test in the post-crash sample period from September 1, 2015 to June 30, 2016. The relation between spreads and the absolute futures-cash basis, however, is still insignificant for this stable period in the market. Second, we use the Hang Seng China Enterprise Index (HSCEI)[6] in the Hong Kong Stock Exchange (HKEx) as a control group. Since the variation in “H" shares' stock prices reflects operating information in mainland China, the HSCEI is highly integrated with the mainland China stock markets. As a result, during the 2015 Chinese stock market crash, the HSCEI also experienced severe turmoil. However, in contrast to mainland China, there is no trading restriction imposed on either the futures or cash markets in Hong Kong. We find that a positive two-way relation prevails in both pre-restriction and restriction periods in the Hong Kong market. Collectively, our findings effectively rule out the likelihood that the treatment effect in the restriction period is driven by the market crash effect.

Our study contributes to two strands of literature. First, this essay complements and extends, both methodologically and substantively, a rigorous analysis of the relation between liquidity and the futures-cash basis. To the best of our knowledge, this is the first study that formally addresses the omitted variable bias problem in the bulk of the literature on this topic. Based on a novel identification strategy, we conclude that the interplay between liquidity and pricing efficiency is “casual" other than “correlated" and confirm that arbitrage is indeed the underlying mechanism.

Second, our essay also joins the literature on the consequences of regulations during a market crash. Using the 2007-2009 global financial crisis as a natural experiment, researchers have mainly focused on the impact of short selling bans on liquidity and pricing efficiency separately across different markets (e.g., Boulton and Braga-Alves, 2010; Beber and Pagano, 2013; Boehmer, Jones and Zhang, 2013; Trebbi and Xiao, 2015). Focusing on the recent 2015 Chinese market crash, we tackle the real effects of regulations on liquidity and market efficiency jointly. We utilize the restrictions in both futures and stock markets in China and document that the regulations triggered arbitrage constraint shuts down the interaction between liquidity and market efficiency during and after the 2015

[6]The HSCEI was established on October 3, 2001, based on companies listed in Hong Kong but registered in mainland China (“H" shares). This index comprises the 40 largest and most liquid H shares.

Chinese market crash.

The rest of the chapter proceeds as follows. We provide the institutional background in Section 4.2. In Section 4.3, we describe the variable construction methods and outlines our data. In Section 4.4, we present the empirical results. Concluding remarks are given in Section 4.5.

4.2 Institutional background

In this section, we focus on introducing the institutional background of the natural experiment, including the 2015 Chinese market crash, the short sale bans in the stock market and the trading restrictions in the index futures market, and the uniqueness of this Chinese regulatory experiment comparing to the regulation shocks in other markets.

As shown in Figure 4.1, after a sharp rise from the middle of March to the middle of June, the Chinese stock market started to crash on June 15, 2015 and in the consecutive 17 trading days, the CSI 300 index dropped from 5335.11 to 3663.04, or 31.34%. After three stable weeks, the CSI 300 index collapsed again on August 24, falling 8.49%, marking the largest decline since 2007, and continued to drop by 7.63% on August 25.[7] Since September 1, the market started to improve and became steady. By the end of December 2015, the CSI 300 index had recovered from the crash and outperformed the S&P 500 Index for 2015. In the first week of 2016, on both January 4 (Monday) and January 7 (Thursday), trading in the Chinese stock market and index futures market was halted after a 7% drop in the CSI 300 index from the time markets opened because of the newly issued circuit-breaker rule.[8] Regulators suspended the circuit-breaker rule on January 8.[9] In January, the CSI 300 index decreased by 17.74%. Beginning in February, the Chinese stock market slowly recovered from the panic caused by the circuit-breaker rule and the CSI 300 index has remained around 3,200. As of October 24, 2016, the CSI 300 index is at the level of 3367.58.

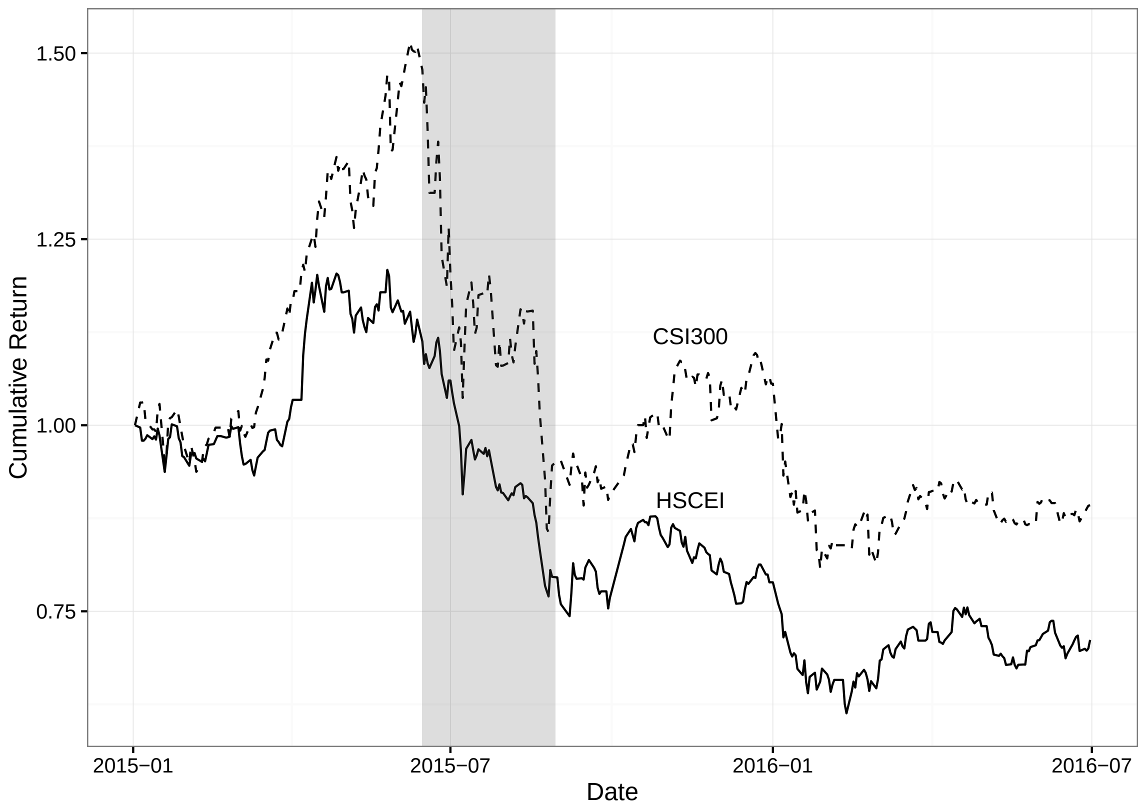
During the 2015 Chinese crash period (June 15, 2015 to August 31, 2015), the index futures

[7] These two days are known as “Black Monday and Tuesday." Since there is a 10% downside limit in the Shanghai and Shenzhen stock markets, a drop of 8.49% means that the majority of the stocks in the market had hit the limit ban.

[8] The complete trading session on Thursday lasted only 29 minutes, including a 15-minute halt in trading that was triggered after an initial 5% drop in the index. See a related report at: `http://www.bloomberg.com/news/articles/2016-01-07/china-s-29-minutes-of-chaos-stunned-brokers-and-a-race-to-sell`.

[9] We remove the first week of January 2016 from our sample due to the consideration that the measurement of futures-cash basis and spreads would be inaccurate in these extremely short-ended sessions.

FIGURE 4.1: Cumulative returns of CSI 300 and HSCEI



In this figure, we plot the cumulative returns of the CSI 300 and HSCEI. The time period is from January 2, 2015 to June 30, 2016.

trading was commonly blamed by the public as the catalyst for the market decline.[10] Beginning on July 7, 2015, a bundle of policies were implemented by regulators to restrict speculative contracts in index futures and other shorting behaviors.[11] In the Chinese index futures market, all the futures positions are divided into two groups: hedging positions and speculative positions. To open hedging positions, investors should apply to the China Financial Futures Exchange (CFFEX), and the number of contracts they can open is limited to cover their long-term stock investments. Typically, hedging positions are opened by institutional investors such as mutual funds and brokers. All other positions are classified by the regulators as speculative positions, which include positions for arbitrage and speculative purposes.

[10] See a related report at: `http://english.caixin.com/2015-09-09/100847961.html`.

[11] See related reports at: `http://english.gov.cn/news/top_news/2015/07/07/content_281475142013234.htm` and `http://www.reuters.com/article/china-markets-futures-idUSB9N0VJ02P20150826`.

The policies for the futures market are designed to primarily restrict speculative positions, while hedging positions are only slightly influenced (increasing margin rate from 10% to 20%). Currently, the restrictions on speculative positions include limiting the number of opening contracts to no more than 10 per day per investor, increasing the margin rate to 40% (which was 10% before) and increasing transaction cost to 0.230% (which was 0.005% before). In Section 4.6, we further discuss these policies.

Without official announcements, short selling is de facto frozen in the Chinese stock market. In Figure 4.2, we plot the daily volume of short selling, with the data obtained from Shanghai and Shenzhen Stock Exchanges. Since July 7, 2015, the trading volume dropped dramatically. On August 4, 2015, regulators changed the trading rule for short sales from "T+0" to "T+1", which the market interpreted as a signal to comprehensively restrict short selling. It is evident that starting from that date, trading volume is negligible compared to the pre-restriction period. Trading restrictions for both markets dramatically increase the cost of arbitrage and make them infeasible, which provides an ideal quasi-natural experiment to identify the channel underlying the relation between liquidity and the futures-cash basis.

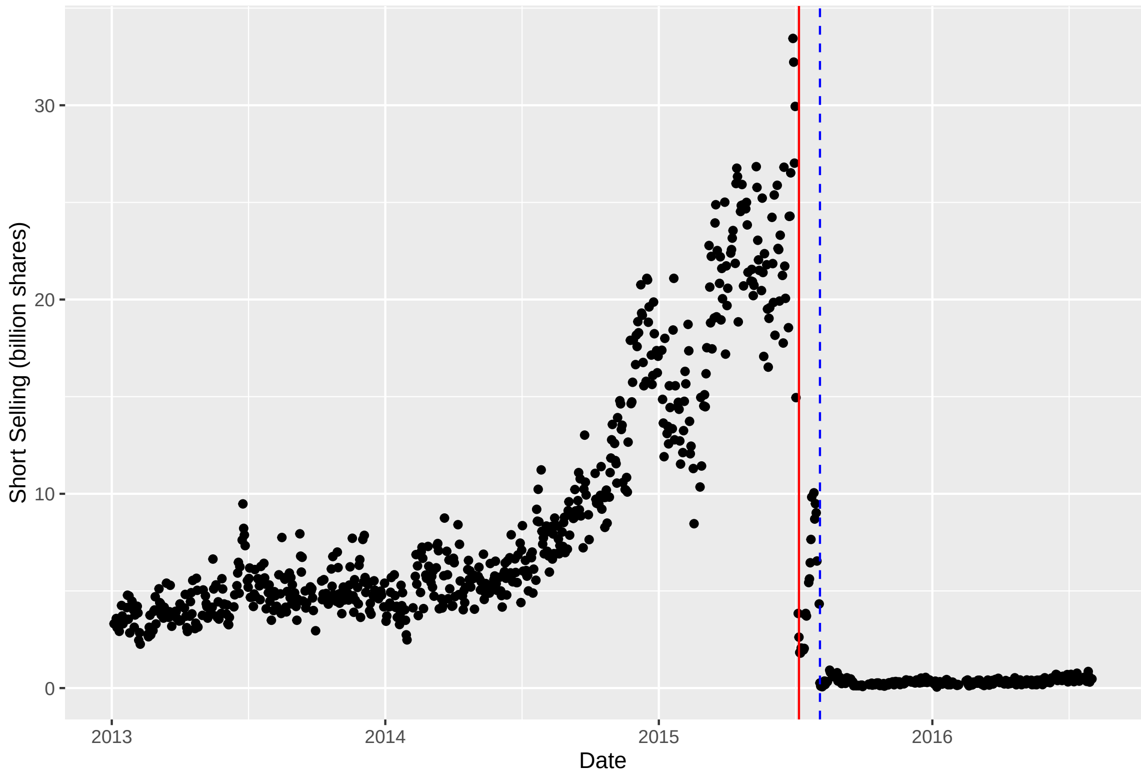
During the 2007-2009 global financial crisis, most regulators around the world imposed bans or constraints on short sales, either for financial stocks only or for the entire stock market (Beber and Pagano, 2013). As recently as 2011 and 2012, Belgium, France, Italy, and Spain imposed renewed short selling restrictions on stocks. Even though without restrictions on the index futures market, restrictions on short sales in the cash market would also prohibit the arbitrage trades in the presence of negative futures-cash basis, thus making our testing strategy possibly feasible in these markets. However, compared to other markets, the Chinese stock and futures markets provide a better laboratory setting for our research question.

First, the index futures market in China is active and has a large trading volume. In 2014, the trading volume of the CSI 300 futures contracts was more than 216 million and ranked in the top-10 worldwide Equity Index Futures & Options Contracts by the Futures Industry Association.[12] In July 2015, the China Financial Futures Exchange was ranked by the World Federation of Exchanges as the most active market for index futures.[13] Among all the markets that issued short selling bans, only the U.S. and Japanese markets have comparable futures trading volumes. Second, the restrictions in the Chinese market are comprehensive. Since July 2015, regulators in China restricted transactions

[12] https://fimag.fia.org/.

[13] http://www.world-exchanges.org/.

FIGURE 4.2: Short sale volume



In this figure, we plot the daily volume of aggregate short selling (billion shares) in the Chinese stock market from January 2, 2013 to June 30, 2016. The solid vertical line denotes the date of July 7, 2015. The dashed vertical line denotes the date of August 4, 2015.

on both the futures and stock markets. In other markets, the index futures trading was unaffected. For short sales in the stock market, some market restrictions only applied to financial stocks (e.g., U.S., U.K., Canada, and South Korea) instead of the entire market or were only in the form of a naked ban other than a covered ban (e.g., Japan, Spain, Switzerland, and Italy). Under these circumstances, arbitrage in the futures/stock market is still possible. For instance, Karmaziene and Sokolovski (2015) show that short selling equity ETFs was a viable method of circumnavigating the ban in the U.S. market and they estimated that close to $5.5 billion new short positions were established using the ETFs. Third, the trading restriction period in China is long and covers both a market crash period and a more settled period, thus alleviating the concern that our results may be driven by a market crash. In summary, to the best of our knowledge, China might be the only market that can satisfy all three conditions: (i) active with large trading volume, (ii) incurring comprehensive restrictions, and (iii) having a sufficiently long restriction period. All these three conditions are crucial for our identification strategy to be feasible and effective.

4.3 Data

In this section, we introduce the data sources and explain the methods used to construct the futures-cash basis and liquidity measures. Our analysis focuses on the CSI 300 cash index and the CSI 300 index futures. The CSI 300 index was initiated by the China Securities Index Company Ltd on April 8, 2005 to measure the performance of the aggregate Chinese stock market. It consists of the top 300 stocks with the largest market capitalization from the Shanghai Stock and Shenzhen Stock Exchanges, the total value of which accounts for 70% of the total market capitalization of these two markets. To provide investors with a hedging instrument, the China Financial Futures Exchange introduced index futures against the CSI 300 index on April 16, 2010.[14]

4.3.1 Futures-cash basis

Following MacKinlay and Ramaswamy (1988), the absolute value of the relative index futures basis (henceforth, ABAS) can be defined as:

$$ABAS = \frac{|Fe^{-(r-\delta)t} - S|}{S}, \tag{4.1}$$

where F is the index futures price; S is the cash stock market index; r is the risk-free rate over the remaining life of the contract; t is the time to contract expiration; and δ is the dividend yield over the contract's remaining lifetime.

Specifically, the absolute futures-cash basis is empirically constructed with the following components: F is the daily closing futures price on the CSI 300 index futures contract, while S is the daily closing value of the CSI 300 index.[15] The risk-free rate r is the Shanghai Interbank Offered Rate

[14]For details about the CSI 300 index and the CSI 300 index futures market, see Yang, Yang and Zhou (2012).

[15]There is a slight asynchronicity between the hours of operation of the Shanghai and Shenzhen Stock Exchanges and the China Financial Futures Exchange (where the futures contracts trade). Specifically, while both the Shanghai and Shenzhen Stock Exchanges operate from 9:30 a.m. to 11:30 a.m., and then from 1:00 p.m. to 3:00 p.m.(Beijing time), the trading hours of the China Financial Futures Exchange are from 9:15 a.m. to 11:30 a.m., and from 1:00 p.m. to 3:15 p.m. (Beijing time). According to Roll, Schwartz and Subrahmanyam (2007), although this asynchronicity will introduce some measurement errors in the basis, it should not affect the statistical inferences. To ensure the robustness, we also use

(SHIBOR) maturing as close to the futures expiration date as possible.[16] The dividend yield δ is the (continuously compounded) difference between the CSI 300 total return index and the CSI 300 index. All the data used in constructing the absolute futures-cash basis are obtained from DataStream.

The expiration day of the CSI 300 index futures contracts is the third Friday of the contract (delivery) month. Contract (delivery) months include the current month, next month, and the final months of next quarter and next two quarters, which are called quarter-months. We plot the smoothed daily trading volumes of these four contracts from January 2, 2012 to June 30, 2016 in Figure 4.3. As clearly shown, the current-month contract has the highest trading volume and the contracts for the final months of next quarter and next two quarters are inactively traded with volumes negligible compared to the other two contracts. Therefore, we focus only on the first two contracts in the following analysis.

We construct two absolute futures-cash basis series by starting with a contract with certain months to maturity and rolling over into a successive contract at the reset date with the same original time to maturity. We name these two basis series as current-month basis (*ABAS1*) and next-month basis (*ABAS2*).

4.3.2 Liquidity measures

Following Roll, Schwartz and Subrahmanyam (2007), we use two cost-based liquidity measures for each stock, quoted spread and effective spread, and these spreads are not scaled by price to avoid attributing variations in stock prices to variations in liquidity (i.e. the common divisor problem in Powell et al. (2009)). These are two widely used liquidity measures in both short-horizon and long-horizon liquidity research.[17]

For a given stock, the quoted spread for the s^{th} time interval is defined as:

$$Quoted\,Spread_s = Ask_s - Bid_s, \tag{4.2}$$

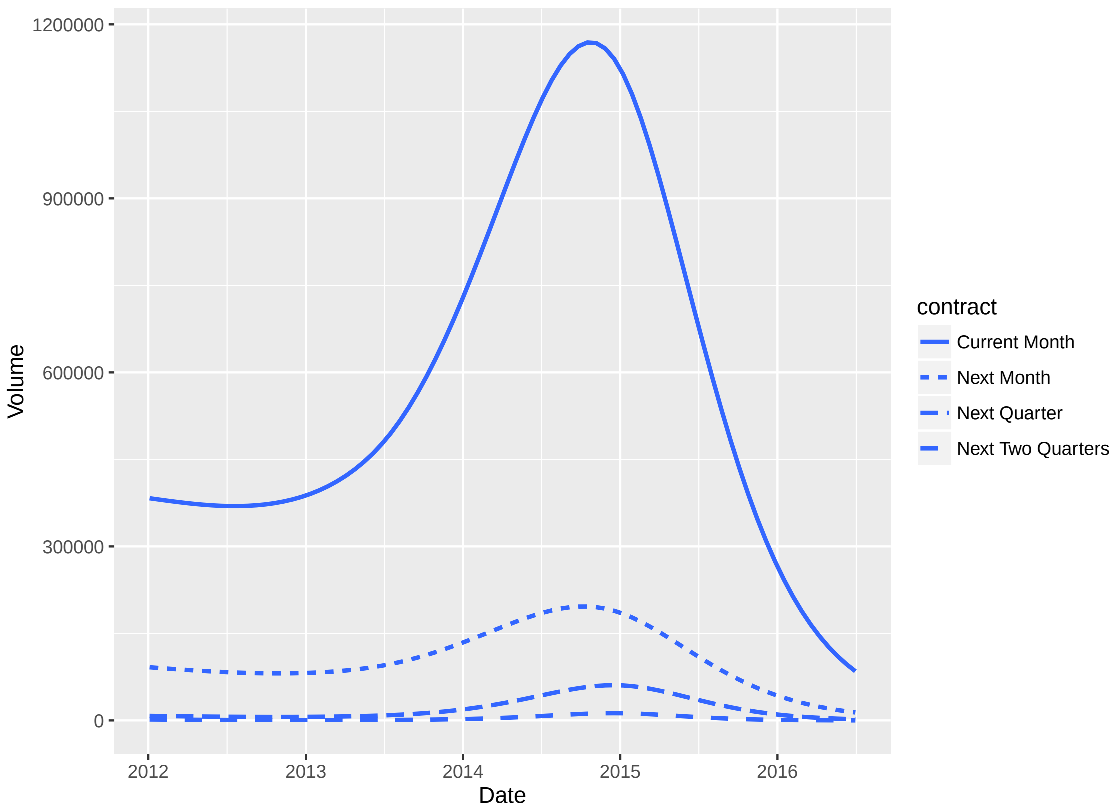
where Ask_s and Bid_s are the best ask and bid quotes for the s^{th} time interval. The daily quoted

the intraday trading data of the CSI 300 index futures contracts from TRTH to obtain the futures price at 3:00 pm. The untabulated results show that our conclusion remains the same.

[16]The maturities for SHIBOR we use are overnight, 1 week, 2 weeks, 1 month, and 3 months.

[17]Since our study focuses on a daily basis, we do not use the other commonly used liquidity measures, including the price impact measure of Amihud (2002), which typically measures liquidity over a relatively long time period. For recent comprehensive surveys on liquidity measures, see Holden, Jacobsen and Subrahmanyam (2014) and Benson et al. (2015).

FIGURE 4.3: Trading volume of CSI 300 futures contracts



In this figure, we plot the smoothed trading volumes for four contracts of CSI 300 index futures: current month, next month, next quarter month and next two quarters month. The time period is from January 2, 2012 to June 30, 2016.

spread, $Quoted\,Spread_i$, is the time-weighted average of $Quoted\,Spread_s$ computed over all the time intervals within trading day i.

For a given stock, the effective spread for the k^{th} trade is defined as:

$$Effective\ Spread_k = 2\left|P_k - M_k\right|, \tag{4.3}$$

where P_k is the price of the k^{th} spread and M_k is the midpoint of the consolidated Best Bid Offer (BBO) prevailing immediately prior to the time of the k^{th} trade. Daily effective spread, $Effective\ Spread_i$, is the volume-weighted average of $Effective\ Spread_k$ computed over all the trades within trading day i.

Daily spread measures are averaged and value-weighted, across stocks (with weights proportional to market capitalizations of the tradable shares at the end of last month[18]) to obtain the aggregate market illiquidity measures.

[18]Here we use the market value of tradable shares other than the total market value as it is hard to measure the market

To construct these two liquidity measures, we obtain intraday trades and quotes data of all the constituents of the CSI 300 index from the Thomson Reuters Tick History (TRTH) database, which is supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). TRTH is a survivor-bias-free database that contains historical Reuters data feeds beginning January 1996 on over 5 million instruments from various exchanges. Fong, Holden and Trzcinka (2016) documents that TRTH is a comparable database for the international markets to that of the Trade and Quote (TAQ) for the U.S. market in terms of liquidity research.

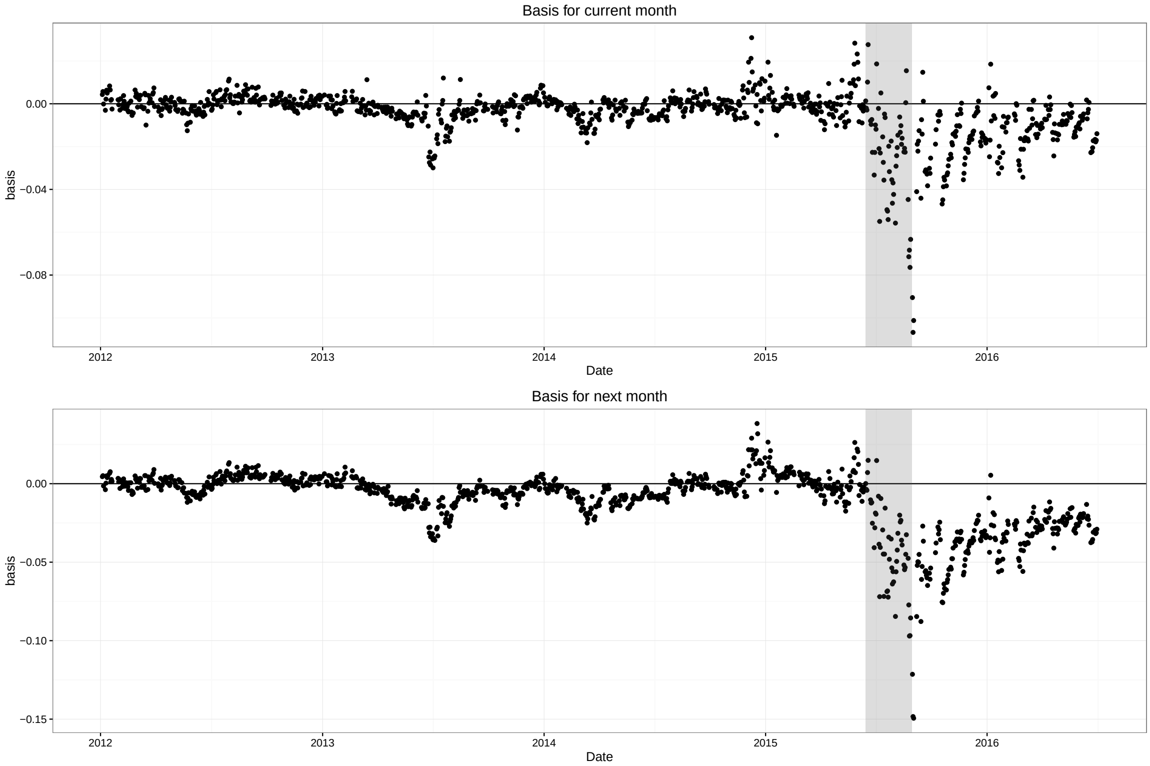
We collect the CSI 300 index composition information from TRTH and adjust the sample of individual stocks for the aggregate liquidity measures whenever there is any adjustment in the CSI 300 index composition.

4.3.3 Summary statistics

We report the summary statistics of the absolute futures-cash bases and spreads in Table 4.1. In Panel A, we find that in the pre-restriction period, the mean values of the absolute futures-cash bases increase monotonically along the maturities, indicating the possible presence of arbitragers in the Chinese market as short-term contracts are more actively traded. The mean value of quoted spread (0.014 CNY (Chinese yuan)) is lower than that of effective spread (0.020 CNY). This is because in China the security trading scheme is order driven instead of market making. As shown in Panel B, in the restriction period, the mean values of the absolute futures-cash bases increased dramatically for both the current-month and next-month futures contracts. For instance, for the current month contract, the mean percentage absolute basis in the pre-restriction period is close to zero (0.407%), reflecting the effectiveness of arbitrage activities, while in the restriction period, it is as high as 2.083%. The high level of absolute basis is consistent with our argument that in the restriction period, arbitrage activities were prohibited and the pricing gap thereby cannot be closed. Consistent with the observations in the other markets, market liquidity strains during a market crash. Comparing Panel A with Panel C, it is evident that the spread measures increased dramatically during the 2015 Chinese stock market crash period. For instance, the mean value of the effective spread rises 35% from 0.020 CNY to 0.027 CNY. Considering that the CSI 300 index dropped more than 36% in the crash period, the percentage-based spread measures increased even more. In Panel D, we can observe that the level of market liquidity

value of non-tradable shares accurately. See Li et al. (2011) for more detailed discussions on the tradable and non-tradable shares in China.

FIGURE 4.4: Futures-cash bases for the CSI 300



In this figure, we plot the CSI 300 index futures-cash bases for the current month and next month contracts. The series are from January 2, 2012 to June 30, 2016. The shaded area denotes the 2015 Chinese stock market crash period, which is from June 15, 2015 to August 30, 2015.

recovers to some extent after the market crash with mean values of spread measures close to those in the pre-restriction period.

We also plot the dynamics of the futures-cash bases and two spread measures in Figures 4.4 and 4.5. During the restriction period, the futures-cash bases were generally negative and with large magnitudes, and spreads increased sharply. In the restriction period, the least restricted position in the futures market was the hedging position and short selling in the cash market was frozen. As a result, the high magnitude of negative futures-cash bases as shown in Figure 4.4 might largely reflect the premiums investors were willing to pay in the futures market to hedge their long positions in the cash market.

Futures-cash basis and spread measures show calendar regularities and time trends (e.g., Gallant, Rossi and Tauchen, 1992). To address this issue, following Roll, Schwartz and Subrahmanyam (2007) and Kadapakkam and Kumar (2013), we adjust the raw absolute futures-cash bases and spreads by

TABLE 4.1: Summary statistics for CSI 300 futures-cash bases and liquidity measures

Summary statistics are for the absolute futures-cash bases (in percentages relative to the cash index value), and (in CNY) for the CSI 300 value-weighted quoted and effective spreads. *ABAS1* and *ABAS2* represent unadjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the unadjusted quoted bid-ask spread. *ESPR* represents the unadjusted effective spread .

Panel A: Pre-restriction Period (January 2, 2012 - May 29, 2015)

Variables	Mean	Median	Std. Dev.
ABAS1	0.407%	0.297%	0.425%
ABAS2	0.652%	0.480%	0.167%
QSPR	0.014	0.014	0.002
ESPR	0.020	0.020	0.004

Panel B: Restriction Period (July 7, 2015 - June 30, 2016)

Variables	Mean	Median	Std. Dev.
ABAS1	2.083%	1.536%	1.893%
ABAS2	4.225%	3.584%	2.330%
QSPR	0.016	0.016	0.002
ESPR	0.021	0.020	0.002

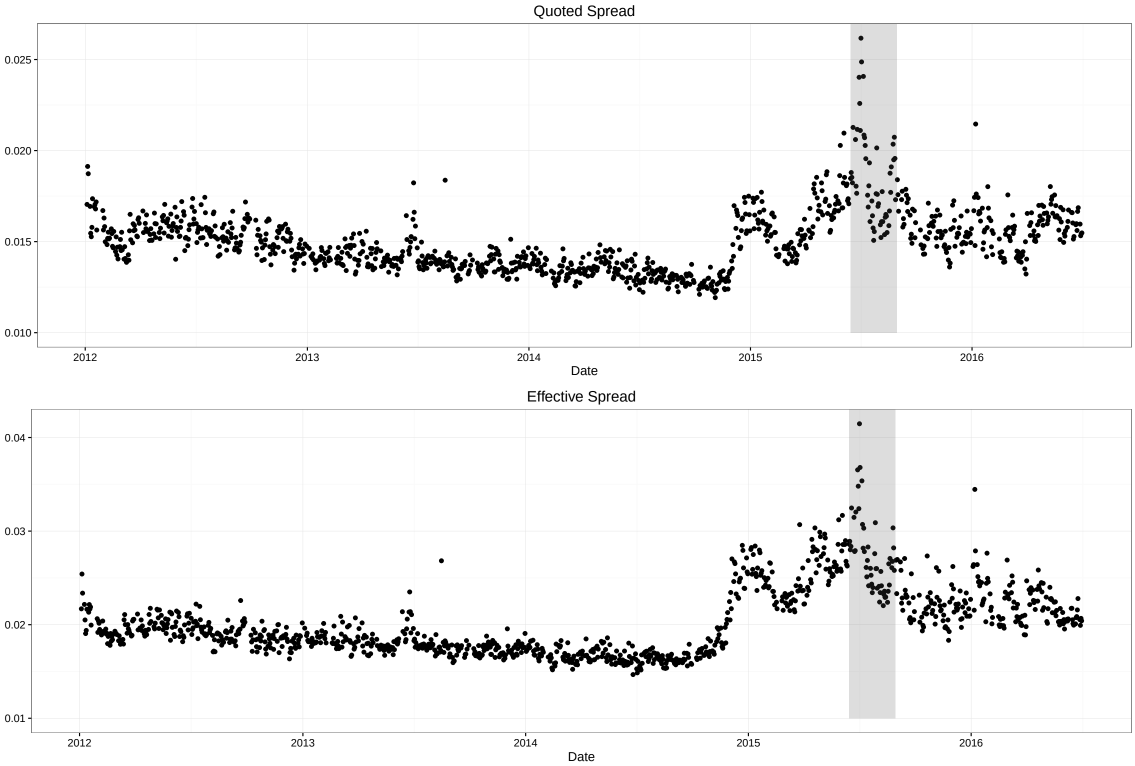
Panel C: Crash Period (June 15, 2015 - August 30, 2015)

Variables	Mean	Median	Std. Dev.
ABAS1	2.940%	2.232%	2.480%
ABAS2	4.752%	4.484%	3.241%
QSPR	0.019	0.018	0.003
ESPR	0.027	0.027	0.004

Panel D: Post-crash Period (September 1, 2015 - June 30, 2016)

Variables	Mean	Median	Std. Dev.
ABAS1	1.629%	1.342%	1.384%
ABAS2	3.784%	3.140%	1.963%
QSPR	0.015	0.015	0.001
ESPR	0.020	0.019	0.003

FIGURE 4.5: Spread measures for CSI 300



In this figure, we plot the CSI 300 index quoted spread and effective spread. The series are from January 2, 2012 to June 30, 2016. The shaded area denotes the 2015 Chinese stock market crash period, which is from June 15, 2015 to August 30, 2015.

controlling for the weekday effect, monthly effect, pre- and post- holiday effects, and linear and quadratic time trends. For bases, we also control for the time to maturity. The residuals from these regressions are then used in the analysis.

Table 4.2 reports the pair-wise correlation matrix among two adjusted futures-cash basis measures (*ABAS1* and *ABAS2*) and two spread measures (*QSPR* and *ESPR*) in the pre-restriction period and restriction period in Panels A and B respectively. In the pre-restriction period, all correlations are positive and significant at the 1% level. The two absolute basis measures are highly correlated, and the two spread measures are also significantly related. In addition, the correlations of the bases with spreads are all positive. In contrast, we find that in Panel B, the positive correlations of the bases with spreads disappear. This finding indicates a potential structural break during the restriction period.

TABLE 4.2: Correlation matrix

ABAS1 and *ABAS2* represent adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the quoted bid-ask spread (adjusted by calender effects and time trends). *ESPR* represents the effective spread (adjusted by calender effects and time trends). * and *** denote statistical significance at the 10% and 1% levels, respectively.

Panel A: Normal Period (January 1, 2012 - May 29, 2015)				
	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1				
ABAS2	0.89***			
QSPR	0.30***	0.27***		
ESPR	0.30***	0.26***	0.97***	
Panel B: Restriction Period (July 7, 2015 - June 30, 2016)				
	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1				
ABAS2	0.91***			
QSPR	0.08	-0.12		
ESPR	0.14*	-0.03	0.90***	

4.4 Results

In this section, we first show that the general pattern of the relation of the futures-cash basis and liquidity in the pre-restriction period (January 2, 2012 to May 29, 2015). Then, to address the omitted variable bias, we adopt a natural experiment identification design and test their relation in the restriction period (July 7, 2015 to June 30, 2016). Finally, to provide further evidence that our conclusion is not driven by the market crash effect, we also conduct a sub-sample analysis and use the Hong Kong market as a control group.

4.4.1 Results in the pre-restriction period

In this section, the sample period is from January 2, 2012 to May 29, 2015. Our analysis mainly relies on the vector autoregressions (VAR) model, which provides evidence with a rich dynamic structure. The vector we use mainly includes two variables: adjusted absolute bases and adjusted quoted spread (or adjusted effective spread). The number of lags is chosen as the minimum of the values selected by Akaike and Schwarz information criteria, which is four in our case. Four VARs are estimated, pairing each of the two adjusted absolute bases (two futures contracts for current month and next month) with two spread measures (adjusted quoted spread and adjusted effective spread).

The VAR model that captures the joint dynamics of bases and spread measures can be expressed as:

$$y_t = \sum_{i=1}^{4} \alpha_i y_{t-i} + \sum_{j=1}^{4} \beta_j x_{t-j} + \epsilon_t, \tag{4.4}$$

where y represents the column variable, while x represents the row variable and ϵ denotes the residuals. The null hypothesis is that row variable does not Granger-cause the column variable. Hence, it is a joint test of whether all β_j equal to 0.

Panel A in Table 4.3 reports the F-statistics of all the pairwise Granger causality tests. The results show that *ABAS1* and *ABAS2* highly significantly Granger-cause *QSPR* and *ESPR*, suggesting that arbitrage forces, triggered by the futures-cash bases, lead to inventory imbalance and strain the liquidity in the stock market. In the other direction, *ESPR* also Granger-causes the absolute bases, especially for the next-month contract, indicating that illiquidity does impede pricing efficiency. The stronger effect for the longer-term contracts is consistent with the findings in Roll, Schwartz and Subrahmanyam (2007), in which they argue that liquidity concerns are more relevant for arbitrageurs in longer-term, relatively less-active contracts. In contrast to *ESPR*, the effects of *QSPR* on bases are not found to be significant. This observation is largely in parallel with Roll, Schwartz and Subrahmanyam (2007), suggesting that effective spread, which accounts for transactions executing within and outside the quotes (Blume and Goldstein, 1997), is a more relevant estimate of arbitrage cost.

To have a clear picture of the Granger causality relation, we also conduct impulse response analyses. An impulse response function (IRF) depicts the current and future responses of endogenous variables to a one-time, unit standard deviation, positive shock to one of the variables. We use the inverse of the Cholesky decomposition of the residual variance-covariance matrix to orthogonalize the impulses. Figures 4.6 and 4.7 present the impulse responses of the cross effects between the absolute futures-cash basis and spread. Monte Carlo simulations (1,000 replications) are applied to get the 95% confidence intervals of the responses.

In Figure 4.6, for the responses of *QSPR* to *ABAS1*, consistent with the Granger causality result, a shock to the current-month absolute futures-cash basis has a significantly positive and persistent

TABLE 4.3: Granger causality tests

ABAS1 and *ABAS2* represent adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the quoted bid-ask spread (adjusted by calender effects and time trends). *ESPR* represents the effective spread (adjusted by calender effects and time trends). F-statistics are reported with the p-values in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Pre-restriction Period (January 2, 2012 - May 29, 2015)

	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1			4.830***	6.318***
			(0.001)	(0.000)
ABAS2			2.279*	3.422***
			(0.058)	(0.008)
QSPR	1.527	1.770		
	(0.197)	(0.138)		
ESPR	2.411**	2.831**		
	(0.050)	(0.027)		

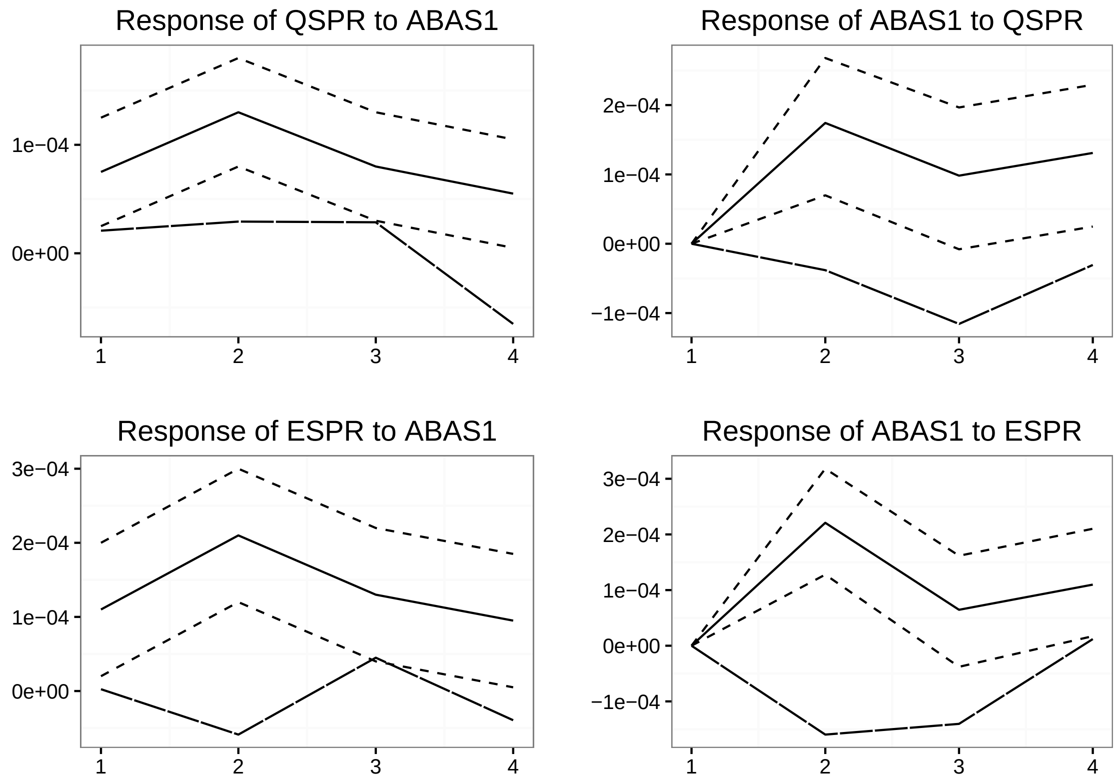
Panel B: Restriction Period I (July 7, 2015 - June 30, 2016)

	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1			0.444	1.713
			(0.776)	(0.147)
ABAS2			0.514	1.322
			(0.725)	(0.262)
QSPR	0.555	0.023		
	(0.457)	(0.980)		
ESPR	0.743	0.256		
	(0.389)	(0.613)		

Panel C: Restriction Period II (August 1, 2015 - June 30, 2016)

	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1			0.951	1.061
			(0.435)	(0.376)
ABAS2			0.943	1.010
			(0.439)	(0.402)
QSPR	1.535	0.343		
	(0.216)	(0.558)		
ESPR	0.648	0.229		
	(0.421)	(0.633)		

FIGURE 4.6: Impulse responses comparsion I: current-month futures contract



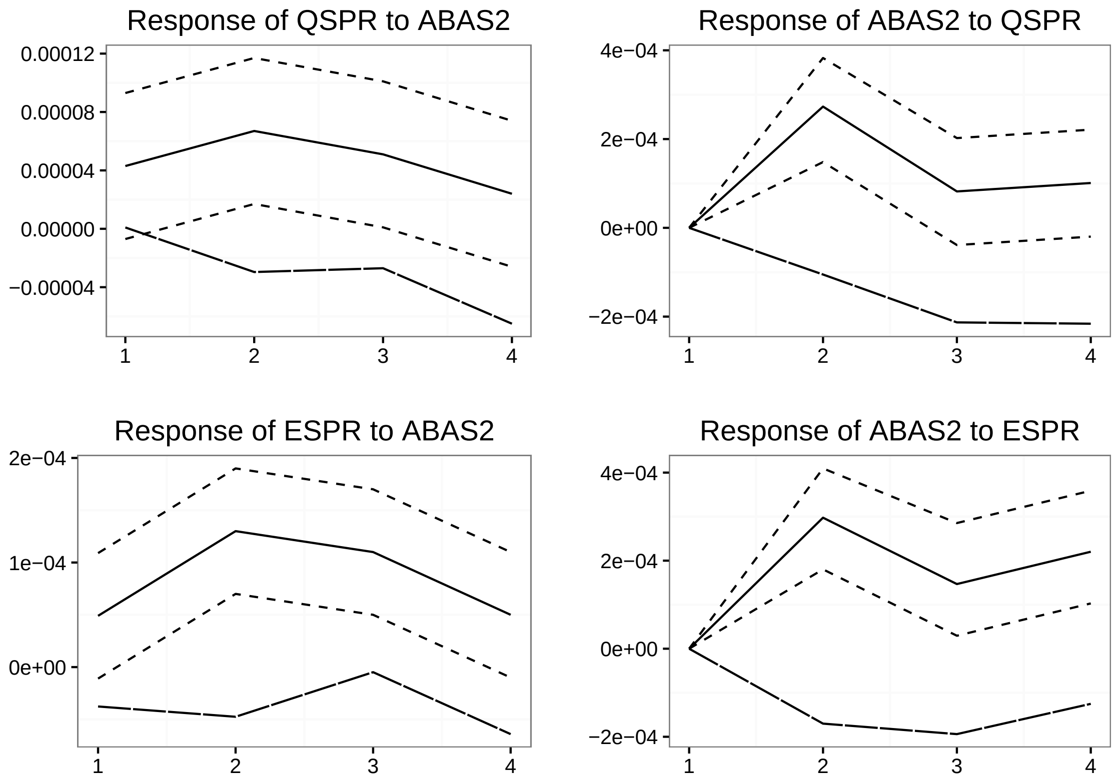
In this figure, we plot the impulse responses of *ABAS1* and *QSPR* (*ESPR*) in the pre-restriction period (January 2, 2012 to May 29, 2015) and the restriction period (July 7, 2015 to June 30, 2016). The solid lines denote the mean response values in the pre-restriction period, and the short dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The long dashed lines represent the mean response values in the restriction period.

effect on the adjusted quoted spread. Meanwhile, even though *QSPR* does not Granger-cause absolute bases, after accounting for the joint dynamics by including the persistence of the absolute basis and liquidity variables, a shock to *QSPR* also leads to a higher absolute futures-cash basis. As shown in Figure 4.6, the cross-effect of *ESPR* and *ABAS1* exhibits a similar pattern. For the next month contract (Figure 4.7), we find both spreads (bases) shocks are informative towards future movements of bases (spreads). The results in the impulse response analysis reinforce our findings in the Granger causality test.

Next, we gauge the economic significance in a similar way to that of Roll, Schwartz and Subrahmanyam (2007).[19] Specifically, we measure economic significance using both CNY value and

[19]By doing so, we can also compare the results in the pre-restriction period and the restriction period economically.

FIGURE 4.7: Impulse responses comparsion II: next-month futures contract



In this figure, we plot the impulse responses of *ABAS2* and *QSPR* (*ESPR*) in the pre-restriction period (January 2, 2012 to May 29, 2015) and the restriction period (July 7, 2015 to June 30, 2016). The solid lines denote the mean response values in the pre-restriction period, and the short dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The long dashed lines represent the mean response values in the restriction period.

percentage. When the response variable is *QSPR* (or *ESPR*), the economic significance in terms of CNY value is the annualized extra trading cost of a daily round-trip trade of one million shares in the basket of CSI 300 stocks caused by a one standard deviation shock from *ABAS1* (or *ABAS2*); the economic significance in terms of percentage for spread is measured as extra trading cost over the average total trading cost. When the response variable is *ABAS1* (or *ABAS2*), the economic significance in terms of CNY value is the annualized extra divergence between the futures and its cash value for a trade of one million shares of a 40 CNY stock, caused by a one standard deviation shock from *QSPR* (or *ESPR*); the economic significance measured in percentage is the extra divergence value over the average total divergence value. The specific formulas for these measures are in the Note portion of Table 4.4. Information used to calculate these measures is from Panel A in Table 4.1 and Figures 4.6

and 4.7.

TABLE 4.4: Economic significance

This table presents economic significance in million CNY value and percentages. When the response variable is $QSPR$ (or $ESPR$), the economic significance in terms of CNY value is measured as: $Value(Spread) = Response(Spread) \times 1million \times 250$, where $Response(Spread)$ is the sum of the four response coefficients for spread in Figured 4.6 and 4.7, and 250 is the total trading days per year. The economic significance in terms of percentage is measured as: $Percentage(Spread) = \frac{Response(Spread) \times 1million \times 250}{AverageSpread \times 1million \times 250}$, where $AverageSpread$ is the average spread as reported in Panel A of Table 4.1. When the response variable is $ABAS1$ (or $ABAS2$), the economic significance in terms of CNY value is measured as: $Value(Basis) = Response(Basis) \times 1million \times 40 \times 250$, where $Response(Spread)$ stands for the sum of the four response coefficients for basis in Figure 4.6; the economic significance in terms of percentage can be expressed as: $Percentage(basis) = \frac{Response(basis) \times 1million \times 40 \times 250}{AverageBasis \times 1million \times 40 \times 250}$, where $AverageSpread$ refers to the average absolute futures-cash basis as reported in Panel A of Table 4.1.

	Response Variables:			
	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1			0.085	0.1375
			(1.70%)	(2.75%)
ABAS2			0.047	0.085
			(0.93%)	(1.70%)
QSPR	4.030	4.600		
	(9.87%)	(11.27%)		
ESPR	4.000	6.500		
	(9.80%)	(15.93%)		

We summarize the results with respect to the economic significance of the IRFs in Table 4.4. As shown, for a daily round-trip trade of one million shares of CSI 300 stocks, a one standard deviation shock from *ABAS1* impacts *ESPR* and aggregates to an annualized extra trading cost of 0.1375 million CNY (or 2.75% of the average total trading cost). A value of 2.75% is non-trivial and close to the effect of three-month absolute basis on the *ESPR* in the U.S. market (3%) as reported in Roll, Schwartz and Subrahmanyam (2007, p. 2022). The effect is stronger for the other way around. When the response variable is *ABAS1*, a one standard deviation shock from *ESPR* can bring extra an annualized 4 million CNY divergence between the futures and cash value for a trade of one million shares of a 40 CNY stock. This is equivalent to 9.8% of the average total divergence value, which is about 1.67 times of the effect of *ESPR* on the three-month absolute basis in the U.S. case. In line with the findings in Table 4.3, when *ABAS2* is considered, the percentage value can increase to around 16%, reflecting that arbitragers in longer-term (less active) contracts suffer more from the liquidity shock.

Overall, our results indicate that there exists a two-way positive relation between spreads and the absolute futures-cash bases in the Chinese market both statistically and economically, and are thus consistent with the findings in Roll, Schwartz and Subrahmanyam (2007) and Kadapakkam and Kumar (2013) for the U.S. and Indian markets.

4.4.2 Results in the restriction period

We define two restriction periods with different starting points. First, although the official announced restriction polices on the CSI 300 index futures trading took place on August 3, 2015, on July 7, 2015 it was reported that opening speculating positions on CSI 300 index futures may be rejected without any notification.[20] Moreover, arbitragers need to hold opposing positions in both markets. Restrictions that sharply increase the cost of arbitrage in one market would largely impede the arbitrage activities. Since the restrictions on the short selling of stocks started July 7, 2015, we define the first restriction period as being from July 7, 2015 to June 30, 2016.[21]

Second, August 3, 2015 is the day that regulators announced the restrictions on futures trading for the CSI 300 index futures. One day later (August 4, 2015), it was announced that the short selling scheme was switched from "T+0" to "T+1." Henceforth, we use a more strict definition of restriction period (August 3, 2015 to June 30, 2016) to ensure our central conclusion is robust.

Our hypothesis is that in the restriction period, since the arbitrage activities are frozen, the absolute futures-cash bases should have no causal effects on liquidity and vice versa. We test this hypothesis using the Granger causality test, together with the impulse response analysis. Panel B of Table 4.3 reports the F-statistics and p-values for all the tests pairing two absolute bases and two spread measures for the restriction period from July 7, 2015 to June 30, 2016. In contrast to Panel A, all the F-statistics

[20] For example, on July 13, 2015, after 3 p.m., all opening long position orders in the futures market were rejected. See news at: `http://cn.reuters.com/article/2015/07/13/cn-drv-idCNKCS0PN11H20150713`.

[21] June 30, 2016 is the last date in our sample. The restrictions on these two markets are as of October 24, 2016.

are insignificant in both directions for both current-month and nex-month futures contracts. The results in the second restriction period (August 3, 2015 to June 30, 2016), as presented in Panel C, further reinforce the evidence that the interplay between absolute futures-cash bases and spreads is absent under restriction. Overall, the Granger causality tests indicate that the absolute futures-cash bases do not Granger cause liquidity and vice versa when arbitrage activities are prohibited.[22]

In Figures 4.6 and 4.7, we plot the impulse responses for the VAR models estimated using the sample data in the first restriction period for the current-month and next-month contracts, together with the IRFs in the pre-restriction period. First, it is evident that in the restriction period, the responses of *ESPR* (*QSPR*) to shocks of *ABAS1* (*ABAS2*) are not significantly different from zero.[23] The shocks of *ESPR* (*QSPR*) also contain no information about the future movements of *ABAS1* (*ABAS2*). All these results are consistent with the breakdown of Granger causality, as documented in Panel B of Table 4.3. Second, we compare the IRFs in the restriction period with the confidence intervals in the pre-restriction period. The underlying null hypothesis in this comparison is that the IRFs in the restriction period are indifferent from the ones in the pre-restriction period. However, we can find that the lines for restriction period are out of the confidence intervals of responses for the pre-restriction period for most cases, especially for the next-month contract in Figure 4.7, indicating rejection of the null hypothesis. This evidence that the impulse response patterns in these two periods are distinctly different. Third, as shown in Table 4.4, the IRFs in the pre-restriction period are economically significant and comparable to the findings for the U.S. market as reported in Roll, Schwartz and Subrahmanyam (2007). However, in the restriction period, since the mean values of IRFs are indifferent from zero and significantly different from those in the pre-restriction period, the economic meaning thereby is negligible.

As a further test, we also compare the coefficients in the VAR models across two regimes (pre-restriction and restriction) using the Z-test. Considering that the regressors in the VAR model with four lags are likely to be highly collinear, we test the coefficient differences based on the VAR model

[22]As the restriction period has more than 230 observations, the likelihood that insignificance is due to the power issue of small sample size is trivial.

[23]We have not plotted the confidence intervals for the IRFs in the restriction period here to make the presentation of results clear. The results show that the lower confidence intervals are always below zero and the upper confidence intervals are always above zero.

TABLE 4.5: Z-test for regime differences

This table reports the Z-test results for the coefficients difference in the VAR models with only one lag. The VAR model is $Y_t = \alpha_i Y_{t-1} + \beta_i X_{t-1} + \epsilon_t$. The VAR models are estimated for the pre-restriction period, which is from January 2, 2012 to May 29, 2015, and the restriction period, which is from July 7, 2015 to June 30, 2016. The pair-wise estimates of β and associated t-statistics are reported. Z-statistic denotes statistic for testing the difference between two coefficients in two sample periods, and the associated p-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Spread measures as dependent variables

	Pre-restriction Period		Restriction Period		Difference Tests	
	QSPR	*ESPR*	*QSPR*	*ESPR*	*QSPR*	*ESPR*
Independent Variable	Coefficient	Coefficient	Coefficient	Coefficient	Z-Statistic (p-value)	Z-Statistic (p-value)
Lag(ABAS1)	0.022***	0.057***	-0.003	0.004	9.652***	4.431***
	(4.213)	(4.055)	(-0.490)	(0.190)	(0.000)	(0.000)
Lag(ABAS2)	0.014***	0.037***	-0.005	-0.006	12.952***	6.195***
	(4.473)	(4.274)	(-1.176)	(-0.404)	(0.000)	(0.000)

Panel B: Absolute basis measures as dependent variables

	Pre-restriction Period		Restriction Period		Difference Tests	
	ABAS1	*ABAS2*	*ABAS1*	*ABAS2*	*ABAS1*	*ABAS2*
Independent Variable	Coefficient	Coefficient	Coefficient	Coefficient	Z-Statistic (p-value)	Z-Statistic (p-value)
Lag(QSPR)	0.207***	0.170***	-0.008	-0.204	13.830***	1.525*
	(3.971)	(2.961)	(-0.320)	(-0.686)	(0.000)	(0.064)
Lag(ESPR)	0.109***	0.094***	0.015	-0.041	3.807***	1.727**
	(4.134)	(3.239)	(0.372)	(-0.416)	(0.000)	(0.042)

with only one lag[24] as follows:

$$y_{t,j} = \alpha_j y_{t-1,j} + \beta_j x_{t-1,j} + \epsilon_{t,j}, \tag{4.5}$$

where j denotes the sample periods (i.e., $j = 1$ denotes the pre-restriction period and $j = 2$ denotes the restriction period), y represents the column variable, x represents the row variable, and ϵ denotes the residuals. We are particularly interested in testing whether the βs are different in the two regimes for the same set of y and x variables. This can be achieved by the Z-test, with the statistic equals to $\frac{\beta_1-\beta_2}{\sqrt{(SE(\beta_1))^2+(SE(\beta_2))^2}}$, where $SE(\beta_i)$ denotes the standard deviation of β_i.

Table 4.5 reports the testing results. At first glance, the patterns are in sharp contrast in two sample periods: the estimates of β, which measure the cross effect between spreads and absolute based, are all significantly positive in the pre-restriction period, but non of them are significant in the restriction period. This confirms again our previous findings in the Granger casualty tests in Table 4.3. The last two columns report the Z statistics and the associated p values for the Z-test. For instance, when the y variable is *QSPR*, and the x variable is *ABAS1*, the estimates of β are 0.022 and -0.003 in the pre-restriction period and restriction period, respectively. The statistic of Z-test turns out to be 9.652, which is positively significant at 1% level. This indicates that compared to the restriction period, the effect of lagged *ABAS1* on *QSPR* is statistically larger in the pre-restriction period. The columns show that all of the other Z statistics are positive and significant at conventional levels. As a result, we can conclude that the coefficients in two regimes are statistically different and the coefficients in the pre-restriction regime are predominately larger than the ones in the restriction regime.

Taken together, the evidence suggests that the two-way positive relation breaks down both statistically and economically in the restriction period. We thus confirm the hypothesis that the arbitrage

[24]Since all the absolute futures-cash basis and spread measures are highly autocorrelated, the independent variables would have the multicollinearity issue, making the Z-test lacking of power (see e.g. Enders, 2015, p.290). In order to test whether the coefficients in the two regimes are different, we have also used an augmented VAR model with 4 lags that uses dummy variables to distinguish two regimes. We use the F-test to test whether the coefficients of the interaction terms jointly equal to zero. Since multicollinearity influences the individual parameter estimates but not the overall level of variance accounted for, the F-test is reliable even in the presence of multicollinearity. The results confirm that the coefficients in the two regimes are statistically different. The drawback of this F-test approach, however, is that it cannot tell the directions of the differences i.e., we cannot know whether the coefficients are statistically larger in the restriction period or in the pre-restriction period. With this in mind, we mainly rely on the simple version of VAR model with 1 lag to test the regime differences by the Z-test.

force is the underlying mechanism that drives the interplay between liquidity and the absolute futures-cash basis.

4.4.3 Controlling the market crash effect

The results show that during the restriction period, the significant two-way positive relation between market illiquidity and the absolute futures-cash basis no longer exists. One remaining concern for this interpretation is the effect of the 2015 Chinese market crash. Lien et al. (2013) show that when the market liquidity decreases and the absolute basis increases, the dependence structure between these two variables may break down in an extreme case. After the Chinese stock market crash in 2015, market liquidity significantly dropped. Table 4.1 shows that the effective bid-ask spread increased from 0.020 CNY in the pre-restriction period to 0.027 CNY in the crash period and to 0.021 CNY in the whole restriction period. Given that the market index significantly dropped (around 37%) during the market crash, the percentage spreads experienced a larger increase while the market liquidity significantly decreased. As a result, since the first one-six of the restriction period overlaps the crash period, the relation between the absolute futures-cash basis and liquidity could dissipate due to the significant decrease in market liquidity, not the absence of arbitrage activities.

To ensure our findings in the restriction period are not confounded by the market crash effect, we conduct two robustness checks. We first conduct a Granger causality test using the post-crash sample period. From September 1, 2015 to June 30, 2016, market conditions became relatively stable and were much less noisy, as shown in Figure 4.1. However, from Table 4.6, the F-statistics indicate that we cannot reject the null hypothesis that spreads (absolute futures-cash bases) contain information towards future absolute bases (spreads) movements for both current month and next month contracts. We draw a similar conclusion from unreported results on impulse response analyses. Henceforth, our results for a more settled market alleviate concerns regarding the market crash effect.

Furthermore, we use the index futures/cash markets in Hong Kong as a control group.[25] The Hong Kong financial market is increasingly integrated with the mainland China market, especially as a growing number of Chinese enterprises go public in the Hong Kong stock market (e.g., Wang and Jiang, 2004; Wang, Miao and Li, 2013).[26] For firms listed in Hong Kong but registered in mainland

[25]Our analysis is in the spirit of a difference-in-difference (DID) approach, but not a formal one. We do not employ a formal DID analysis as the typical DID analysis is used to test the difference in means while we care about the change of joint coefficients in a VAR system, making the DID approach methodologically difficult.

[26]By the end of 2015, there were 229 H share companies listed in the Hong Kong stock market, including the Big

TABLE 4.6: Robustness: Granger causality tests in the post-crash period

ABAS1 and *ABAS2* represent the daily adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the daily quoted bid-ask spread (adjusted by calender effects and time trends). *ESPR* represents the daily effective spread (adjusted by calender effects and time trends). F-statistics are reported with the p-values in parentheses. The time period is from September 1, 2015 to June 30, 2016.

Post-crash period (September 1, 2015 - June 30, 2016)				
	ABAS1	*ABAS2*	*QSPR*	*ESPR*
ABAS1			0.651	1.760
			(0.527)	(0.138)
ABAS2			0.130	1.258
			(0.971)	(0.288)
QSPR	0.643	1.128		
	(0.633)	(0.345)		
ESPR	0.109	0.666		
	(0.979)	(0.617)		

China (H shares), their share prices reflect operating information in mainland China, and therefore have close proximity to mainland China stock markets. From January 2, 2012 to December 31, 2015, the correlation between the HSCEI, which captures the performance of the 40 largest H share stocks, and the CSI 300 index is 50.9% in terms of return and 63.2% in terms of realized volatility.[27]

Four state-owned banks in mainland China. The market capitalization of H share companies was HK $ 5,157 billion, 21.11% of the total market capitalization in the Hong Kong stock market. When “Red chips" stocks, stocks of mainland China companies incorporated outside China and listed in Hong Kong, are also counted in, the China-related stocks had a market share of 42.15% in the Hong Kong market. Source: HKEx Monthly Market Highlights (`https://www.hkex.com.hk/eng/stat/smstat/chidimen/cd_mc.htm`) and HKEx Securities Market Statistics (`https://www.hkex.com.hk/eng/stat/smstat/chidimen/cd_mc.htm`).

[27]We use 5-minute CSI 300 index and HSCEI data from TRTH to construct the simple realized volatility measures at a daily frequency by taking a square root of the summation of all the 5-minute return squares within a trading day.

During the Chinese market crash period in 2015, as we can see in Figure 4.1, the HSCEI also collapsed, dropping from 13,984 to 9,741.41 (46%). In contrast to the mainland China markets, however, regulators in Hong Kong did not impose any restrictions on the HSCEI futures/cash markets.[28] Different regulations in these two markets, thereby, provide us with an institutional setting to address the market crash effect further. If the disappearance of the two-way positive relation is a result of the market crash instead of the arbitrage restrictions, we should also observe a structural break in the HSCEI futures/cash market after the Chinese market crash, given the high similarity between the mainland China market and H share stocks. Otherwise, the crash effect is unlikely to be the main driving force for the breakdown of the interaction between spreads and the absolute futures-cash bases.

To test this hypothesis, we construct spreads and the absolute futures-cash basis measures for the HSCEI futures/cash markets in a similar way as for the CSI 300 futures/cash markets.[29] Similar to the CSI 300 index futures contracts, the delivery months for the HSCEI futures also include current month, next month, and the final months of the next quarter and the next two quarters.[30] To be consistent, we only include the first two contracts in the analysis and denote these two basis series as *HKABAS1* and *HKABAS2*.

In line with the analysis for the mainland China market, we estimate the VAR model for the Hong Kong market in two sample periods: one from January 2, 2012 to May 29, 2015, and the other from July 7, 2015 to June 30, 2016. Table 4.7 presents the estimation results for these two sample periods. Panel A shows that in the pre-restriction period, in the HSCEI futures/cash markets, there is a two-way Granger causality relation between stock market illiquidity and the absolute futures-cash bases for both the current-month and the next-month contracts. As in the Chinese and U.S. markets, the spreads have stronger effects on the bases for the longer-term contracts. The evidence in Panel B

[28]In practice, the Hong Kong Stock Exchange manages a shortable list and updates it quarterly. Short selling is permitted only for specific stocks on the list. However, during our sample period, the ETFs on the HSCEI were always shortable.

[29]The risk-free rate is the Hong Kong Interbank Offer Rate (HIBOR), with maturities including overnight, 1-week, 2-week, 1-month, 2-months, and 3-months. The dividend yield is the difference between the (continuously compounded) difference between the HSCEI total return index and the HSCEI index. For liquidity measures, we weight the quoted spreads/effective spreads for the individual firms in the HSCEI by their market value in the last month.

[30]The H-shares index futures were introduced on December 8, 2003. Its underlying asset is the HSCEI. It is a top-10 derivatives market product in the Hong Kong market and has a trading volume comparable to the Hang Seng Index futures. For more details on the futures contracts, we refer readers to: `https://www.hkex.com.hk/eng/prod/drprod/hshares/hhifut.htm`.

TABLE 4.7: Granger causality tests in the Hong Kong market

HKABAS1 and *HKABAS2* represent the daily adjusted absolute bases for two futures contracts (current month and next month) for HSCEI index of Hong Kong market. *HKQSPR* represents the daily quoted bid-ask spread (adjusted by calender effects and time trends). *HKESPR* represents the daily effective spread (adjusted by calender effects and time trends). F-statistics are reported with the p-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pre-restriction period (January 1, 2012 - May 29, 2015)

	HKABAS1	*HKABAS2*	*HKQSPR*	*HKESPR*
HKABAS1			2.566*	2.750**
			(0.053)	(0.041)
HKABAS2			2.205*	3.495**
			(0.086)	(0.015)
HKQSPR	2.101*	7.156***		
	(0.085)	(0.000)		
HKESPR	2.466*	3.369**		
	(0.061)	(0.018)		

Panel B: Restriction period (July 7, 2015 - June 30, 2016)

	HKABAS1	*HKABAS2*	*HKQSPR*	*HKESPR*
HKABAS1			2.381*	2.870**
			(0.069)	(0.036)
HKABAS2			2.152*	3.201**
			(0.093)	(0.023)
HKQSPR	2.174*	6.480***		
	(0.090)	(0.000)		
HKESPR	1.853	4.908***		
	(0.137)	(0.002)		

for the restriction period is striking: wider bases still lead to larger spreads for both contracts due to the arbitrage-triggered order imbalance and larger spreads also cause wider absolute futures-cash bases, at least for the next month contract, as illiquidity impedes arbitrage and thereby the pricing efficiency.[31] Considering that the HSCEI experienced a larger drop than the CSI 300 index during the market crash, our results provide strong evidence that arbitrage activities are still the driving force for the interplay between liquidity and pricing efficiency even during market upheaval.

4.5 Conclusion

In this paper, we explore the relation between the absolute futures-cash basis and liquidity in the Chinese CSI 300 index futures/cash market from 2012 to 2016. Our main purpose is to address the omitted variable bias. We first use the restrictions on the futures trading and stocks short sales imposed by the regulators as a response to the 2015 Chinese market crash as a natural experiment. We find that during this restriction period, in which the arbitrage channel is shut off, the significant two-way relation between the absolute futures-cash basis and liquidity in the pre-restriction period dissipates both statistically and economically. Using the Hong Kong market as a control sample, we confirm that there is no market crash effect driving the results. Our results suggest that the two-way positive causality relation between the absolute futures-cash basis and liquidity is indeed casual through the arbitrage channel, and is not due to endogeneity. Our evidence indicates that arbitrage is the force to be reckoned with in shaping the interplay between liquidity and market efficiency.

4.6 Appendix: Restrictions on futures trading

In this Appendix, we briefly summarize the restrictions on index futures trading issued by the China Financial Futures Exchange. We obtain these announcements from the official weibo (Chinese version of Twitter) of the China Financial Futures Exchange.[32] We introduce these restrictions based on the time line of announcement dates.

July 6, 2015

[31]The results for the F-test with dummy variables, as reported in the Online Appendix Table A6, show that the F-statistics are all insignificant, indicating that we cannot reject the null that the coefficients are indifferent in two regimes in the Hong Kong market.

[32]`http://weibo.com/cffexfabu`.

Starting from July 7, 2015, transactions on the China Security Index 500 (CSI 500)[33] futures is limited to 1,000 contracts per client per day for one direction of trading (either long or short).

July 8, 2015

Starting from July 8, 2015, the margin rate for CSI 500 index futures increases from 10% to 20% (except for the hedging position). Since July 9, 2015, the margin rate for CSI 500 index futures has increased to 30%.

July 31, 2015

Starting from August 3, 2015, for clients with speculative positions (including arbitrage and speculation) in all the index futures (including the CSI 300 index futures), for a single contract, cancelling more than 400 orders for a single contract or more than five trades a day would be considered as "irregular trading."

August 25, 2015

On August 26, 2015, the margin rates for speculative positions in the CSI 300 and SSE 50[34] index futures increased from 10% to 12%. Since August 27, 2015, the margin rates for speculative positions in the CSI 300, SSE 50 index futures increased to 15%, while the margin rate for the long (speculative) positions in the CSI 500 index futures is increased to 15%. Starting from August 28, 2015, the margin rates for speculative positions in the CSI 300, SSE 50 index futures increased to 20%, while the margin rate for the long (speculative) positions in the CSI 500 index futures increased to 20%.

Starting from August 26, 2015, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 600 contracts per day per client for speculative positions on each futures product.

Starting from August 26, 2015, the transaction fee for the intraday delivery (opening and closing position in the same day) increased from 0.05‰ to 0.115‰.

August 28, 2015

Since August 31, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 100 contracts per day per client for speculative positions on each futures product. Since August 31,

[33]CSI 500 was launched on January 15, 2007, and it is designed to capture the aggregate performance of the small-cap stocks in the Chinese stock market. The index futures (CSI 500 index futures) was launched on April 16, 2015 by the China Financial Futures Exchange.

[34]SSE 50 index was launched on January 2, 2004, and it is designed to capture the aggregate performance of the 50 stocks with the largest market capitalizations in the Shanghai stock market. The index futures (SSE 50 index futures) was launched on April 16, 2015 by the China Financial Futures Exchange.

2015, the margin rates for speculative positions increased to 30%.

September 2, 2015

Since September 7, 2015, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 10 contracts per day per client for speculative positions on each futures product.

Since September 7, 2015, the margin rates in the CSI 300, SSE 50, and CSI 500 index futures increased from 30% to 40% for the speculative positions and 20% for the hedging positions.

Since September 7, 2015, the transaction fee for the intraday delivery (opening and closing position in the same day) increased from 0.115‰ to 2.30‰.

Chapter 5

Conclusion and future work

5.1 Conclusion

This thesis comprises three essays on empirical asset pricing. The first two essays focus on deriving a novel government bond volatility index for the U.S. market and exploring its connections with the fixed income and stock market. The last essay tests the notion that “the effectiveness of arbitrage in enhancing pricing efficiency should depend on liquidity" in the Chinese market.

In Chapter 2, we employ the state-pricing methodology to derive a volatility index (GBVX) for the U.S. government bond market. Our results support the empirical application of the state-pricing methodology in the construction of volatility indices. This is evidenced by strong performance of GBVX in forecasting realized volatilities in the government bond, corporate bond portfolio and CMBS portfolio returns. By comparing the forecasting abilities of GBVX and VIX in the fixed income markets, we show that their information is non-overlapping and one is hardly a proxy for the other. Finally, we also demonstrate how the index can be effectively replicated by market makers, using a hedge portfolio comprising options on the 10 year Treasury note futures. Overall, the GBVX index is a valuable tool for investors in the fixed income markets.

In Chapter 3, we uncover significant effects of bond yield volatility risk on the equity risk premium. This novel risk factor, i.e. the innovation of GBVX ($\Delta GBVX$) largely outperforms popular return predictors and other volatility predictors in both in-sample and out-of-sample forecasting tests for the monthly S&P 500 excess return. Using $\Delta GBVX$ as the market timing indicator can also generate promising utility gains for risk averse investors in a sample period that covers the recent Global Financial Crisis. Finally, we show that the strong predictive power of $\Delta GBVX$ sources from the cash flow channel. Our findings, together with the fact that GBVX can be easily constructed under the state-preference asset pricing framework, offer market practitioners an appealing alternative means to predict the U.S. monthly equity premium.

The findings in these two chapters are relevant for the investment industry. We show that the investors can use the bond volatility index as a new tool to forecast the future volatility of fixed income markets and the equity risk premium in the stock market.

In Chapter 4, we explore the relation between the futures-cash basis and liquidity. Our main purpose is to address the “omitted variable bias". We first use the restrictions on the futures trading and stocks short sales in the Chinese market as a natural experiment. We find that during this restriction period, in which the arbitrage channel is shut off, the significant two-way relation between basis and illiquidity in the pre-restriction period disappears both statistically and economically. Using the Hong Kong market as a control sample, we confirm that there is no “market crash effect" driving the results. All of these tests suggest that the two-way positive causality relation between the futures-cash basis and liquidity is not due to endogeneity, but is indeed casual through the arbitrage channel. By doing so, we prove and highlight the significant of liquidity in moving markets towards an efficient outcome.

The results also indicate that the regulations prohibit arbitrage and thereby shuts off the interaction between liquidity and price discovery. The policy implication is that the regulators should be cautious of the adverse effects due to the trading bans.

5.2 Future work

There are a number of future research topics that can be extended from this thesis:

- While the GBVX index is focused on the U.S. Treasuries, the state pricing methodology applies to any bond market as long as the bond options are available and liquid, e.g. the European government bonds traded on Eurex, Japanese government bonds traded on the Osaka Exchange and the Australian government bonds traded on the ASX. When these indices are available, it is also interesting to explore the interactions of the bond market volatility measures in the international context. The state prices generated from GBVX can also be easily applied to construct the partial volatility indices, the higher moments, and the forward looking volatility indices for corporate bond and CMBS portfolios, in which there are no liquidly traded options.[1]

[1]For these applications in the stock market, I refer readers to Liu and O'Neill (2016),O'Neill and Liu (2015) and Liu

- The GBVX index only focuses on the volatility of options with a maturity of 30 days. The methodology can be easily extended to other maturities. By doing so, we can construct the term structure of the bond implied volatility and explore its connections with the real economic activities and potentially the bond risk premium.[2]

- A risk factor should normally possess both cross-sectional and time series pricing abilities under consistency consideration (Campbell and Cochrane, 2000; Maio and Santa-Clara, 2012). In future research, it is worth exploring the cross-sectional pricing ability of the $\Delta GBVX$ and comparing it with that of VIX, whose cross-sectional pricing ability is well documented by Ang et al. (2006) and Guo and Qiu (2014) among others, and those of interest rate, monetary policy and macro uncertainty variables (Lioui and Maio, 2014; Maio, 2013; Bali et al., 2016).

- In Chapter 4, we document that the linear Granger-causality between liquidity and the index futures-cash basis disappears due to the shut-down of the arbitrage channel. Our testing procedure can also be extended to include the possible nonlinear relationship (Hiemstra and Jones, 1994; Lien et al., 2013). Moreover, starting from February 17, 2017, the China Financial Futures Exchange has slightly eased the restrictions on stock index futures trading.[3] It is interesting to see whether the relation between liquidity and the futures-cash basis would reappear if all the restrictions were finally removed.

and Faff (2017).

[2]Using a term structure model, Creal and Wu (2016) documents strong evidence that the estimated term structure of bond yields conveys promising information on the economic fluctuations. In the stock market, Guo et al. (2014a) find that the term structure of implied volatility can be well captured by the Nelson-Siegel model; Bakshi et al. (2011) and Luo and Zhang (2016) show that the forward variances are predictive of real economic activity and asset returns.

[3]See a related report and more details in `http://news.xinhuanet.com/english/2017-02/17/c_136062352.htm`

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