Market frictions and hedge fund trading strategies

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Abstract

Implied moments extracted from options have been shown to conduct forward-looking information for the stock markets. Stock and option markets can thus at specific times reflect differing information, called 'disagreement periods'. We first define these events over the period January 1997-December 2015. We then investigate the role that hedge funds, a proxy for sophisticated investors, play in the price discovery process between stock and option markets during disagreement/agreement periods. We investigate timing ability of hedge funds by relating the discrepancy between options and stock markets to fund performance. We observe that hedge fund managers time efficiently their portfolio around periods of high disagreement and high economic policy uncertainty (EPU). A threshold regression analysis reiterates the same conclusion for higher levels of the disagreement rate. Further analysis shows that hedge funds performance gets stronger in higher levels of EPU.

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1 Introduction

Hedge funds are commonly perceived to employ dynamic trading strategies as opposed to the buy-and-hold strategy, predominant in the mutual fund industry. A great deal of the literature emphasizes the use of adaptive trading strategies by hedge funds in response to changing market conditions (see Fung and Hsieh (1997) Agarwal and Naik (2004), Kuenzi and Shi (2007), Bollen and Whaley (2009), Christoffersen and Langlois (2013), Billio et al. (2012)). In short, hedge fund managers attempt, generally with success to time the financial markets.

As evidenced in the recent literature, hedge fund managers identify periods of mispricing to exploit accordingly the prospective returns. Ma et al. (2022) investigate hedge fund managers' abilities to seek mispriced assets and to improve subsequently market efficiency. Fund managers also analyze the information flow having implications to assets future prices. Brandt et al. (2019) use an index summarizing the real time information flow about macroeconomic aggregates estimated by principal component analysis to evaluated hedge funds market timing. Chen et al. (2020) investigate the use of continuously evolving information by skilled investors including hedge funds to adapt their trading strategies.

A key question about market timing is: what type of information can hedge fund managers exploit? A number of the works address the ability of fund managers to process superior information on indicators such as market volatility, liquidity risk, or macroeconomic data. Cao et al. (2013) explore liquidity timing by hedge funds and find that market exposure is positively associated with market liquidity. Lambert and Platania (2020) implement a factor model in which unobservable factor loadings depend on the macroeconomic variables including GDP, implied volatility index, the relative T-bill rate and aggregate dividend yield. They find that macroeconomic variables significantly explain exposures variation. A recent literature goes further in sophistication in general in signal processing and focuses on market sentiments. Zheng et al. (2018) examine hedge funds ability to time market sentiment by disentangling high sentiment and low sentiment periods and relating market beta to an investor sentiment index. Chen et al. (2021) analyze sentiment timing skill and find high sentiment beta and alpha for sentiment timer funds. Patton and Ramadorai (2013) investigate high frequency dynamics in hedge funds exposure and evidence significant intra-month variation in the exposures.

We believe that, before trying to extract relevant information from very complex analytics based on interpretations, hedge fund managers would be naturally inclined to reap the "low hanging fruits" signaling informational inefficiencies. The link between option and stock markets is a natural candidate for this purpose. This route has already been adopted with some success in the hedge fund literature. Based on the method of Bakshi et al. (2003) to retrieve the intrinsic values of the risk-neutral variance, skewness, and kurtosis payoffs from option prices, Hübner et al. (2015) develop a conditional higher-moment asset pricing model that is shown to complement the leading specification applied to hedge funds. Shin et al. (2019) further explore the timing of the option-implied tail risk by hedge funds. They use four proxies for the option-implied tail risk factors including skewness, kurtosis and two other factors measured as the slope of the regression of out-of-money put-implied volatility on option moneyness.

In this paper, we focus on observable discrepancies between options and stock markets, and investigate whether hedge fund managers account for such information to time their strategies. Even though one may anticipate that relative mispricing of options compared to their underlying would represent valuable information about the foreseeable market evolution, this question surprisingly represents an unexplored dimension of market timing. This can probably be explained by the fact that, even though it makes intuitively sense, the technical requirements in order to faithfully ascertain the dynamics of the option-stock distortions, that we call here "disagreement rate", are still underdeveloped. We approach the issue in two steps. First, we capture the dynamics of our factor model for each hedge fund trading strategy by an unrestricted state-space modeling of the pricing equation in which factor loading follow a random walk.

In the second step, we relate the hedge funds' market timing behavior to the information sent from the options markets. To this end, we obtain the factor loadings adjusted by the market disagreement rate, then evaluate hedge funds performance through the returns explained by the adjusted factor loadings. The important merit of our proposed state-space modeling compared to the methodologies usually employed in the literature is that we do not restrict the varying factor loadings by relating them to a priori known indices. It is common practice in the literature to approximate varying exposure by a first order Taylor expansion series expressed in terms of the supposedly timing variable. The exposure is in fact reduced to a linear model in terms of the underlying timing variable. This modelling approach can cause serious biases because not only the complex nonlinearities hidden in the variation of the factor loading are ignored but also other timing skills that might be used by fund managers are ignored. The random walk modeling of the exposures overcomes these shortcomings by capturing the dynamics of the timing strategies without inclusion of any hypothetically timing variable.

In parallel with examination of the disagreement rate, we use the economic policy uncertainty (EPU) index developed by Baker et al. (2016) to examine if fund managers efficiently rebalance their exposures during periods of uncertain market conditions. The literature on EPU timing abilities of hedge funds is scarce. Liang et al. (2020) and Dragomirescu-Gaina et al. (2021) find that hedge fund managers react to innovations in the EPU indicators to time their trading strategies. The fact that during periods of bear market, both EPU and the disagreement rate to rise, motivates us to consider impact of uncertainty associated with economic policy on fund managers' decisions.

We find that option implied disagreement rates contain information about contemporaneous and future market volatility and thus can be used by informed traders to anticipate future market return. Our analysis on the estimated varying factor loadings and the contemporaneous relation to the disagreement rate reveals that market frictions are an important source of information that are efficiently used by hedge funds in their market timing strategies. We also add to the literature on the EPU timing abilities of hedge funds by finding that higher levels of EPU is associated with stronger performance of hedge funds.

The remainder of the paper is organized as follows: Section 2 reviews the literature regarding the connection and information flow between stock and option markets. Section 3 describes the data on options and hedge funds used in the empirical study. Section 4 explains the methodology employed to detect times of disagreement between stock and option markets and provides some economic insights regarding those specific periods. Section 4 describes the methodology used to infer hedge funds' trades in location factors. Section 6 analyses the global impact of the disagreement rate. Finally, Section 7 concludes.

2 Information flows between stock and options market

When markets are complete, option trades should not transmit any new information in particular they can be replicated through a portfolio of stocks and bonds. However, when market frictions appear, a price discovery process might occur between option and stock markets, with the result that both markets transmit different information.

There is a common perception that informed investors might first trade in the options market in order to benefit from the limited downside and the leverage effect. There is pervasive evidence that supports the close connection between the option and stock markets (Black, 1975; Mayhew et al., 1995; Easley et al., 1998; Arnold et al., 2000; Cao et al., 2005; Pan and Poteshman, 2006; Lee et al., 2021). For example, the levels of the expected market volatility, skewness, and kurtosis for the next 30 trading days could be extracted from a cross-sectional series of out-of-the-money option prices Bakshi et al. (2003). These parameters are interpreted as follows. Option-implied volatility levels are powerful predictors of future realized volatility, while a decrease (resp. an increase) in the skewness (resp. kurtosis) of the market portfolio suggests an increase in the probability of experiencing strongly negative (resp. extreme) returns.

Information about general market conditions could have hence an effect on the expected market risk related to both an investment or a company. On the one hand, these risk estimates implied by options market have been shown to be able to anticipate asset allocation and thus risk exposures of fund managers (Hübner et al., 2015). Investors with private information will preferably trade in option markets (lower short-selling costs, highly leveraged bets). On the other hand, changes in option prices may therefore reveal information about the underlying asset that are not incorporated in earnings expectation disclosures. Diavatopoulos et al. (2012) have shown the predictive power of changes in expected skewness and kurtosis as implied in option prices on stock returns prior to earnings announcements. These changes in implied moments reflect anticipated information of informed investors or analysts which, therefore, have predictive power for future returns. Besides, Chang et al. (2012) express their forward-looking measure of beta as a function of the variance and the skewness of the underlying distributions. They demonstrate the ability of option-implied moments to anticipate changes in future betas. Furthermore, Chang et al. (2012) show the significance of option-implied moments for explaining the cross-section of stock returns. Gharghori et al. (2017) evaluate the future stock return and volatility predictability by option traders around stock split periods and find that option traders anticipate volatility and stock returns because of information leakage.[1]

Chakravarty et al. (2004) investigate price discovery by introducing a measure of information share as contribution of either of the markets to the total variance of the common trend component of the cointegrated spot and implied price series. They also relate the information share to market characteristics including volume, volatility, price spread and excess return and find evidence supporting the fact that options market is more informative during periods of high volume. Lee et al. (2021) examine the information content of options order imbalances and find evidence of predictive power of order imbalances in particular that of the foreign investors has longer time and more significant predictive power.

In times of high volatility, noise trading can be important and make stock prices deviate from their fundamental values as shown by De Long et al. (1990). This could push informed investors to perform sophisticated investment trades in the option markets in order to benefit from leveraged bets. The information content of their trades will therefore be transmitted first into the option prices and create a disagreement event between the two markets. A disagreement day is defined as an event in which the stock and option market disagree about the price of the stock.

Hedge fund dynamic trading around dates of disagreement provides indeed a natural experiment as these managers trade volatility and convexity (Fung and Hsieh, 1997, 2001; Agarwal and Naik, 2004; Chen and Liang, 2007; Agarwal et al., 2017). Besides, there is strong evidence supporting the ability of hedge funds to exploit mispricing caused by noise traders. This is supported by Giannetti and Kahraman (2016) who qualify hedge funds as "rational arbitrageurs" or in Jank and Smajlbegovic (2017) who show that short sellers, especially hedge

[1]For further readings about information content of risk estimates implied by options, see Goncalves-Pinto et al. (2020), Fodor et al. (2017)

funds, trade against mispricing. Large hedge funds appear to trade on private fundamental information (see Irwin and Holt, 2004). If indeed they first trade in options market, as would informed traders, those markets should be the first to reflect the information, thereby creating a disagreement.

Some recent works argue against the dominance of the informed trading on the information content of the options market. Goncalves-Pinto et al. (2020) document that disagreement between options and stock market arise as a results of the price pressure in the stock market. According to Hiraki and Skiadopoulos (2021), disagreement between two markets arise as a result of market friction rather than the informed trading in the options markets. Patel et al. (2020) relate the disagreement in both markets to the differential speed of information propagation and prosecuted insider trading. Thus, having laid aside the causes of the disagreement between option and stock markets, we raise the question that whether or not the disagreement between option and stock market can be a source of information that hedge fund managers can use to anticipate future market performance.

3 Data

3.1 Options data

We collect options data from OptSum. This dataset provides end-of-day index option summary (bid, ask, volume and price of the options as well as price of the underlying asset) for CBOE traded options in SPX from May 1990 to November 2015. To calculate the option closing prices, we follow the methodology recommended by the data supplier[2]. Following Muravyev et al. (2013), we adopt three conditions need to be satisfied for the options to be included in the study.

1) Liquidity condition: There needs to have been at least one transaction for both the call and the put option of corresponding strike and maturity. If trading volume is nil for

[2]To calculate the option closing prices we look at three components, the last bid, last ask and the last sale of an option: (i) If the last sale is between the last bid and last ask the close is on the last sale; (ii) If the last sale is less than or equal to the last bid the option series is closed on the last bid and similarly if the last sale is greater than or equal to the last ask, the close is on the last ask; (iii) In the case where there is no last sale for an option series the previous day's close is looked at as if it were the last sale and the same rules are applied; (iv) In the case of a newly listed series having no last sale the close is on the last ask.

either, both options are eliminated.

2) Moneyness condition: $|log(S/K)| < 0.1$, where S is the underlying price and K denotes the strike price.

3) Maturity condition: All options must have a remaining maturity of between 7 days and 90 days.

3.2 Hedge funds data

We are interested in market-wide disagreement rates whose dynamics are estimated using state-space estimation techniques. Even though using individual hedge funds data would enable us to gain granularity in the results, their aggregation at the index level might lead us to lose a substantial part of the information as the sum of the parts -whatever the technique uses- does not necessarily represent the true connection between their associated strategy and the disagreement rate on option and stock markets. Thus, using indices appears here to provide a better warranty of a meaningful set of results. The empirical part is conducted on EDHEC alternative indices: Long Short Equity, Market Neutral, Event Driven, Merger Arbitrage, Distressed Securities, Relative Value, Fixed Income, Convertible Arbitrage, CTAs, Global Macro, Emerging Markets, Short Selling. We excluded Funds of Funds as these funds do not directly trade in the markets. Table 1 shows the descriptive statistics of the 226 monthly observations for each of the 12 trading strategies.

The data are retrieved from EDHEC Risk Institute. Contrary to other hedge fund indices, they are neither equally or value weighted. The indices come from a Principal Component Analysis, which extracts co-movements within hedge fund styles from several databases. This does not only avoid style drift from individual hedge funds when they report to databases but also selection biases from using one single dataset. The databases used differ for each hedge fund style according to coverage and representativity of the datasets. This methodology is called the "indices of indices" as first used in Amenc et al. (2003).

Table 1: Descriptive statistics of the hedge fund trading strategies

	mean	median	max	min	std.	skewness	kurtosis	obs.
convertible arbitrage	0.006	0.008	0.061	-0.124	0.018	-2.63	21.68	226
CTA	0.005	0.004	0.069	-0.054	0.024	0.17	2.86	226
distressed securities	0.007	0.009	0.050	-0.084	0.018	-1.36	7.92	226
emerging markets	0.007	0.010	0.123	-0.192	0.034	-1.18	8.72	226
equity market neutral	0.005	0.006	0.025	-0.059	0.008	-2.38	19.32	226
event driven	0.007	0.009	0.044	-0.089	0.017	-1.45	7.94	226
fixed income arbitrage	0.005	0.006	0.037	-0.087	0.012	-3.86	27.47	226
global macro	0.006	0.005	0.074	-0.031	0.015	0.90	5.33	226
long/short equity	0.007	0.009	0.075	-0.068	0.021	-0.39	4.27	226
merger arbitrage	0.006	0.006	0.027	-0.054	0.010	-1.39	8.59	226
relative value	0.006	0.008	0.039	-0.069	0.012	-1.89	11.78	226
short selling	0.000	-0.005	0.246	-0.134	0.049	0.73	5.98	226

4 Disagreement events

4.1 Identifying disagreement rates

Since SPX options present no early exercise, that is European-style exercise, we use the Put-Call parity relation to compute daily estimates of the S&P 500 implied stock price:

$$\varepsilon_j = C(K,\tau) - P(K,\tau) - e^{-q\tau} S_{implied,t} + e^{-rt} K, \tag{1}$$

where we incorporate the dividend yield (q) of the S&P 500 in the call-put parity relation. The dividend yield is obtained from Damodaran's webpage at NYU[3]. This approach has been widely used in the academic literature (see for instance, Muravyev et al., 2013).

With daily implied price estimates, we define a disagreement day when the S&P 500 index price and the estimated implied price differ by more than 0.2%. A similar relative threshold has been used in Muravyev et al. (2013).

Furthermore, we define monthly disagreement rate as the ratio of the disagreement days to the total number of the trading dates in the month, that is:

$$Disagreement\ rate = \frac{Disagreement\ days}{Total\ days\ in\ a\ month}. \tag{2}$$

[3]http : //pages.stern.nyu.edu/ adamodar/NewH omeP age/datafile/spearn.htm

We count 11 months with a disagreement rate more than 50% for the period ranging from January 1997 to July 2015 (see Figure 1). We also count 25, 43, 68 and 98 months with a disagreement rate more than 40%, 30%, 20%, and 10% respectively. This methodology leads to the identification of September 2008 as having the maximum disagreement rate of 87.0% across the time horizon. The preceding and the succeeding months record 76.2% and 84.2% disagreement rates. During the recession in early 2000s and the European sovereign debt crisis the disagreement rate spikes. We observe a disagreement rate of 60% during November 2000, and 52.2% during July 2011 following the rating downgrade of Greek banks and Portugal bond by Moody's. We might relate this mixed evidence to times of high risk aversion (bearish markets), which command less price discovery as informed investors actively trade within the spot markets and therefore commands less disagreement between the information content of the two markets.

4.2 Robustness of the disagreement methodology

Different alternatives could have been considered for defining the disagreement rate: use of intraday data and use of bid-ask prices. We rejected the use of intraday data as we infer hedge fund trades on a monthly basis. Capturing a disagreement day whose disagreement resolves at the end of the day would not be relevant for understanding the hedge fund rebalancing on a monthly basis. We have therefore decided to stick to last prices.

We could also have defined disagreement by using implied (last) bid and ask prices. A spot price outside of implied bid-ask range would define a disagreement day. The problem occurs in times of high volatility in the market, where gamma traders could widen the bid-ask spread as they do not want to carry gamma risks overnight in such risky conditions. This method would therefore be biased by the conservative strategies implied by these trades.

Our objective is to find disagreement dates, which make sense economically and which are consistent with other implied measures such as the VIX. We therefore compare the evolution of the disagreement rates using the last prices or last bid-ask spread methodologies and the evolution of the VIX in Figure 1.

Figure 1 shows the evolution of the VIX and the disagreement rate. We can visually observe some similarities in the evolution of both time series when defining disagreement

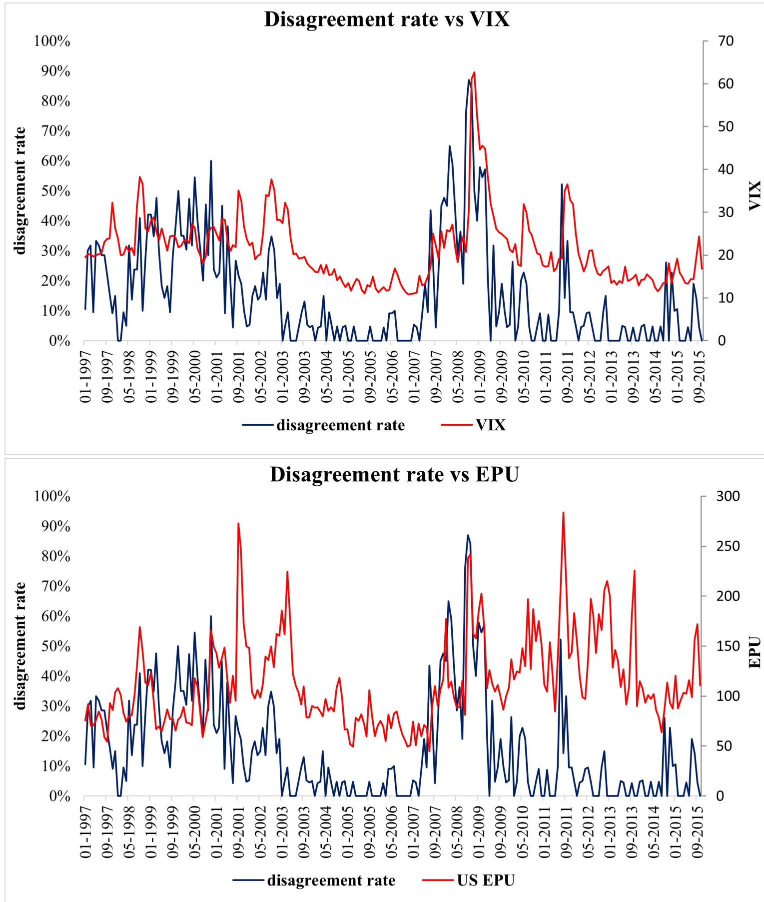

Figure 1: The disagreement rate and uncertainty indices

events based on deviation from the implied bid-ask spread.

The joint behavior of the two measures during the early months of the global financial crisis and the European sovereign debt crisis is of special interest. It seems that the information content of our disagreement rate has a predictive power on the subsequent market crash. This finding is not surprising as Diavatopoulos et al. (2012) find that implied moments can predict future market volatility. Our disagreement rate represents the anticipated information of the informed investors in options markets. The finding around the two important dates is also in line with Gharghori et al. (2017), who argue option traders anticipate future return and volatility ahead of earnings announcement.

As Table 2 shows, there is a significant relation between the volatility index and the disagreement rate. We performed a unit root test on both variables in order not to end up with a spurious relation. Both series reject the null hypothesis of a unit root. We estimate a

Table 2: Information content of the disagreement rate

regressor	D_t	p-value	D_t	p-value	VIX_t	p-value
C	0.0270	0.2961	0.0519	0.0256	2.8938	0.0000
D_t					5.3164	0.0049
D_{t-1}	0.4344	0.0000	0.4786	0.0000	14.9203	
D_{t-2}	0.3362	0.0000	0.3326	0.0000	-3.7632	0.0937
D_{t-3}					-7.0569	0.0004
VIX_t	0.0057	0.0157				
VIX_{t-1}	-0.0053	0.0171			0.7950	0.0000
EPU_t			0.0005	0.0376		
EPU_{t-1}			-0.0008	0.0054		
R-squared	0.5666		0.5700		0.8439	
Adjusted R-squared	0.5587		0.5621		0.8403	
F-statistic	71.5782	0.0000	72.5687	0.0000	234.5550	0.0000

The VIX and EPU are used in separate ARDL models to predict the disagreement rate (D_t). The disagreement rate is used to predict VIX. The lags are chosen according to BIC.

Table 3: Granger causality test

	Model 1 $VIX_t \nrightarrow D_t$	Model 2 $D_t \nrightarrow VIX_t$	Model 3 $EPU_t \nrightarrow D_t$	Model 4 $D_t \nrightarrow EPU_t$	Model 5 $EPU_t \nrightarrow VIX_t$	Model 6 $VIX_t \nrightarrow EPU_t$
lags=2						
F-statistic	0.3128	39.9616	3.1024	8.6699	3.9167	0.6273
p-value	0.7317	0.0000	0.0469	0.0002	0.0213	0.5350
lags=3						
F-statistic	1.9469	29.6129	2.4187	8.0779	2.5374	0.4513
p-value	0.1232	0.0000	0.0672	0.0000	0.0567	0.7167
lags=4						
F-statistic	1.4071	23.5491	1.9918	7.7607	2.0507	0.8772
p-value	0.2327	0.0000	0.0969	0.0000	0.0885	0.4784

number of autoregressive distributed lag models (ARDL) to examine predictive power of the uncertainty indicators for the disagreement rate. We also estimate an ARDL to examine the disagreement rate in predicting the implied volatility. Table 2 evidences the disagreement rate can predict the future implied volatility. The adjusted R squared of the column predicting the VIX becomes stronger, indicating the implication of the information content of options market for future market volatility. We use the two exogenous and the endogenous uncertainty indices in separate ARDL models to predict the disagreement rate. To ensure that the results are not contaminated by the problem of spurious regression, we also performed a unit root test on the EPU. The results strongly rejected the null hypothesis of a unit root. As Table 2 shows, both VIX and EPU predict the disagreement rate with the EPU delivering adjusted R-squared.

The findings in Table 2 that the uncertainty indicators predict the disagreement rate and in a stronger relation, the disagreement rate predicts VIX, motivate us to perform Granger causality test between the variables. As Table 3 shows the null hypothesis of the model 2 is strongly rejected, whereas the p-values of the model 1 remain high in different lags. This finding implies that the disagreement rate is the cause of VIX which is in line with Table 2 where the ARDL model of VIX on the disagreement rate delivers the highest R-squared. Between the models 3 and 4, we observe stronger rejection of the null hypothesis in model 4. And finally Granger causality tests between EPU and VIX in models 5 and 6 imply that EPU predicts the VIX and not vise versa. These findings motivates us to examine EPU in market timing of hedge funds.

5 State-space modeling of hedge funds trading strategies

In this section, we obtain time-varying exposures toward certain set of risk factors. For this endeavor, we use the set of factors presented in Billio et al. (2012), which has been widely used in the hedge fund literature, see for instance Fung and Hsieh (2002) and Agarwal and Naik (2004), among others. Each factor is defined as follows:

1. SP: The S&P 500 index, characterizing the US equity market risk factor.

2. SMB: Small minus Big index is computed as the monthly return difference between the MSCI world small minus MSCI world large.[4]

3. HML: High minus Low index is computed as the monthly return difference between the MSCI world value minus MSCI world growth.[4]

4. UMD: The Carhart momentum factor or the relative performance of winner over loser stocks.[5]

5. EM: MSCI Emerging markets.[4]

6. DVIX: first difference in the implied volatility of the US equity market.[6]

7. GSCI: S&P Goldman Sachs Commodity Index.[4]

[4]Obtained from Thomson Financial Datastream Inc.
[5]Obtained from K. French's website
[6]Obtained from CBOE website

8. Term: term spread measured as the difference between yields on 10-year and 3-month Treasury bill.[6]

9. DEF: default spread measured by the difference between yields on Moody's Seasoned Aaa rated and Baa rated corporate bond yield.[7]

Trend following strategies have payoffs that are nonlinear functions of the risk factors. Fung and Hsieh (2001) show that these nonlinearities can be replicated by lookback straddles. Since these factors are sought to capture nonlinearities in exposures to risk factors, we assume a constant exposure to these factors, which are referred to as option-like factors. We add five option-like factors that are of growing popularity in the literature during last years. These are five trend-following factors consisted of lookback straddles on bond futures (PTFSBD), on currencies (PTFSFX), on commodity futures (PTFSCOM), on short term interest rate (PTFSIR) and on the stock market (PTFSSTK). (For further theoretical and empirical discussions about option-like factors see Fung and Hsieh (2001), Agarwal and Naik (2004), Fung and Hsieh (2007), Fays et al. (2018), Chen et al. (2021)). All factors range from February 1997 to August 2015. Table 4 shows the descriptive statistics of the 226 monthly observations for each of the 14 risk factors.

We rely on Kalman filter to dynamically estimate the unobservable time-varying risk

Table 4: Descriptive statistics of the risk factors

	mean	median	max	min	std.	skewness	kurtosis	obs.
SP	0.006	0.010	0.157	-0.168	0.048	-0.50	4.22	226
EM	0.005	0.007	0.222	-0.273	0.072	-0.41	4.46	226
GSCI	0.001	0.004	0.195	-0.295	0.068	-0.41	4.18	226
Mom	0.005	0.007	0.184	-0.344	0.055	-1.45	11.76	226
SMB	0.003	0.003	0.112	-0.091	0.025	-0.08	5.23	226
HML	-0.001	-0.003	0.081	-0.071	0.022	0.44	5.49	226
CS	0.018	0.020	0.037	-0.007	0.012	2.90	13.48	226
TS	0.010	0.009	0.034	0.005	0.004	-0.27	1.94	226
DVIX	0.000	-0.004	0.205	-0.153	0.047	0.84	7.02	226
PTFSBD	-0.019	-0.040	0.689	-0.266	0.151	1.38	5.68	226
PTFSFX	-0.005	-0.041	0.692	-0.300	0.185	1.25	4.82	226
PTFSCOM	0.000	-0.029	0.648	-0.247	0.146	1.08	4.60	226
PTFSIR	-0.015	-0.067	2.219	-0.351	0.270	4.33	30.04	226
PTFSSTK	-0.049	-0.075	0.666	-0.302	0.147	1.62	7.44	226

SP, EM, GSCI, Mom, CS, TS and DVIX stand for S&P 500, emerging markets, Goldman Sachs commodity index, momentum, credit spread, term spread and the change in VIX respectively.

[7]Obtained from FRED (Federal Reserve Bank of St. Louis) database.

exposures. In more detail, we assume a state-space representation, where the observation equation describes the dynamic evolution of each hedge fund's returns, and the state equation defining the unobservable risk exposure evolution is given as a random walk:

$$R_t = \alpha + \sum_{i=1}^{N} \beta_{i,t} F_{i,t} + \sum_{i=1}^{M} \gamma_i H_{i,t} + \epsilon_t, \tag{3a}$$

$$\beta_{1,t+1} = \beta_{1,t} + \varepsilon_{1,t+1}, \tag{3b}$$

$$\vdots$$

$$\beta_{N,t+1} = \beta_{N,t} + \varepsilon_{N,t+1}, \tag{3c}$$

where $\beta_{i,t}$ represents the time series of risk exposure to factor i, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, $\varepsilon_{1,t+1} \sim N(0, \sigma_{\varepsilon_1}^2)$, $\ldots$, $\varepsilon_{N,t+1} \sim N(0, \sigma_{\varepsilon_N}^2)$ in which we assume that the initial weight is equally distributed among the factors, that is $\beta_{i,0} = 1/NumberofFactors = 1/9\ \forall i$ and calibrated via an optimization routine, where the log-likelihood function is maximized. α is the intercept, $F_{i,t}$ represents the time series of returns to factor i, and R_t the time series of returns for a given hedge fund strategy. $H_{i,t}$ represents option-like factors and γ_i denotes the time invariant exposures to the option like factors. Also, as in Agarwal and Naik (2000), since hedge funds exhibit a great deal of flexibility in terms of asset allocation (i.e., shortselling, cash holding, etc) we allow for negative exposure to risk factors and relax the constraint that the style weights have to add up to one.

We perform an analysis on a selection of the time-varying factor loadings. We used the variable selection information criterion (VIC) developed by Zhang and Wu (2012) to select the risk factors to which the exposures are varying. The estimated factor loadings in Equation 3a are, to some extent, robust in the sense that applying the variable selection procedure according to VIC leads to more or less the same evolution of the exposures. Table 5 exhibits the factors to which the exposures are selected by the VIC to vary. In the model chosen for each hedge fund style in Table 5, the exposures to the other risk factors including the intercept are constant.

A number of the estimated factor loadings in Equation (3a) have very small variances.

Table 5: Robustness check of the time-varying risk loadings according to VIC

	The selected factor with time-varying exposure	VIC
convertible arbitrage	EM-CS	-6.90
CTA	EM-GSCI	-2.41
distressed securities	SP-EM-SMB- CS	-3.97
emerging markets	EM-CS	-3.15
equity market neutral	SP -EM-HML-CS	-5.77
event driven	SP-EM-SMB-CS	-3.96
fixed income arbitrage	EM-GSCI-CS	-9.01
global macro	SP-EM- SMB -CS	-3.67
long/short equity	SP- EM-SMB- HML -CS	-4.20
merger arbitrage	SP-EM- SMB -CS	-4.64
relative value	SP-EM-CS	-5.82
short selling	SP-SMB-HML	-1.92

SP, EM, GSCI, Mom, CS, TS and DVIX stand for S&P 500, emerging markets, Goldman Sachs commodity index, momentum, credit spread, term spread and the change in VIX respectively.

Most of these factor loadings are not selected in the variable selection procedure using VIC. However, we include these factor loadings in the state-space because it causes no problem to our objective as we aim at investigating the impact of the disagreement rate on the time-varying exposures.

6 Examining hedge fund individual dynamic asset allocation

These new perspectives on stock and option market joint equilibrium have the potential to give insightful explanations about hedge fund dynamic trades. We infer hedge fund positions from their dynamic beta. In this section, we examine whether hedge fund managers significantly alter their trades, when there is an imbalance between the information content of option and stock markets.

6.1 Testes hypotheses

In section 5, we assumed a state-space representation, where the unobserved risk exposure to each factor follows a random walk as in Equations 3b and 3c, and the filtered coefficients at time $t+1$ are optimally computed by Kalman filter. Such representation provides crucial information about the β's distribution and statistical properties in particular. We formulate two hypotheses tests. The first one concerns the dynamic portfolio management by fund managers. The second one aims to test the implications of the information content of the options market for the fund managers. In the second hypothesis, we test for the impact of the disagreement on portfolio rebalancing. Hence, we define the following set of hypotheses to be tested.

Hypothesis 1:

- Null hypothesis $H1_0$: Hedge fund managers do not dynamically rebalance their portfolio.

- Alternative hypothesis $H1_a$: Hedge fund managers dynamically rebalance their portfolio resulting in a factor model in which each exposure follows a random walk.

In order to perform the instability test on the factor loadings, we first regress each strategy on a constant and the option-like factors. Then the residuals of these regression are examined in a second regression for possible dynamic instability. We use the L_c test statistic developed by Hansen (1992) to test for varying exposures.

Hypothesis 2:

- Null hypothesis $H2_0$: A disagreement has no impact on hedge fund trades.

- Alternative hypothesis $H2_a$: A disagreement triggers an unexpected reallocation hedge fund

Given the state-space model, the abnormal or unexpected allocation to factor i is defined as

$$AA_i = |\beta_{i,t} - E[\beta_{i,t}]| = |\beta_{i,t} - \beta_{i,t-1}|. \tag{4}$$

These values are then projected on the disagreement rates to investigate the contribution of the information in the options market in anticipating future stock market performance.

We further investigate whether hedge fund managers can time their trading using the information content of the disagreement rate. We perform a two-step analysis on the filtered factor loadings.

First, we simply relate the absolute change in the factor loadings to the disagreement rate. This analysis aims to reveal whether there is any significant relation between the information stemming from the options market and the trading strategies performed by fund managers.

Second, we investigate whether hedge fund managers can strategically time their trades to realize returns outperforming market. To this end, we obtain the explained time-varying exposures after having projected them on the disagreement rates. The explained exposures are then used in the pricing Equation 3a to yield the returns attributable to the disagreement rates.

6.2 Empirical findings

The L_c statistic is calculated from the cumulative first order condition of the ordinary least squares (OLS). In the simple univariate regression, the L_c statistic is calculated as the ratio of the average sum of squares of the cumulative first order condition to the sum of squares of the first order condition. The test statistic can be generalized to test for joint instability of the coefficients. The asymptotic distribution of the test statistic depends on the number of the parameters under the instability test.

We first regress the series of each trading strategy on a constant and five option-like

Table 6: Hansen instability test

strategy	convertible arbitrage	CTA	distressed securities	emerging markets
L_c	2.53^{*}	1.88	3.15^{***}	3.96^{***}
strategy	equity market neutral	event driven	fixed income arbitrage	global macro
L_c	3.96^{***}	2.57^{**}	1.84	3.40^{***}
strategy	long/short equity	relative value	short selling	merger arbitrage
L_c	2.58^{**}	3.98^{***}	2.67^{**}	5.06^{***}

The critical values at 1%, 5% and 10% significance levels are 3.05, 2.54 and 2.29 respectively. First, we regress the series of each trading style on a constant and the option-like factor. Then we use the residual series and the risk factors to perform the Hansen instability test. The superscripts *,** and *** represent respectively the significance at 10%, 5% and 1% levels.

factors to obtain residuals. Then we use the residuals in a second regression on the nine risk factors to test for joint instability of the coefficients. As noted by Hansen (1992), if the model includes numerous regressors, the L_c test statistic for the individual instability tests is a small number, whereas the test statistic of the joint instability test would be large. In that case, as indicated by Hansen (1992), the joint test is more reliable than the individual tests. Table 6 shows the results of applying Hansen instability test on the null hypothesis of the joint stability of the 9 factor loadings. In the individual stability test, the null hypothesis on stability of each factor is not rejected for either of the factor loadings. However, we observe evidence of joint instability for most of the trading strategies.

As Table 7 shows, the exposures to S&P 500 factor is reallocated significantly during periods of disagreements between options and stock market. Exposure to the credit spread is also significantly adjusted during markets disagreement in four trading strategies. The only risk factor to which fund managers do not significantly rebalance their exposure is the SMB factor. Momentum factor is the factor to which fund managers across most strategies do not adjust their exposure. In one single long short strategy, we observe a varying exposure and also the significant impact of the disagreements on the adjustments to the exposure. The exposures to the SMB factor are varying across two strategies of merger arbitrage and global macro, however the varying exposures is not significantly adjusted over the disagreement rate. The emerging market is the only strategy having varying exposure to the term spread factor, however there is no significant relation between changes in the exposure and the disagreement rate.

Table 7: Regression of the absolute change in time-varying exposures on the disagreement rate

	convertible arbitrage		CTA		distressed securities		emerging markets	
	C	coefficient	C	coefficient	C	coefficient	C	coefficient
SP	1.3×10^{-12}	2.5×10^{-12}	4.3×10^{-2}	3.5×10^{-2}	6.7×10^{-3}	9.3×10^{-3}	3.7×10^{-2}	5.1×10^{-2}
	1.7×10^{-4}	8.1×10^{-5}	6.5***	1.2	5.5***	1.8*	6.0***	2.0**
EM	1.3×10^{-11}	1.1×10^{-11}	1.5×10^{-11}	1.9×10^{-12}	1.4×10^{-11}	-1.9×10^{-12}	1.4×10^{-12}	1.0×10^{-12}
	7.4×10^{-4}	1.4×10^{-4}	5.3×10^{-4}	1.6×10^{-5}	6.8×10^{-4}	-2.2×10^{-5}	1.8×10^{-4}	3.1×10^{-5}
GSCI	1.8×10^{-3}	1.6×10^{-3}	1.1×10^{-2}	7.6×10^{-3}	3.4×10^{-3}	1.2×10^{-3}	1.1×10^{-12}	-5.1×10^{-14}
	5.7***	1.2	5.7***	9.7×10^{-1}	6.1***	5.3×10^{-1}	1.8×10^{-4}	-2.0×10^{-6}
Mom	2.2×10^{-13}	6.3×10^{-13}	1.5×10^{-11}	1.3×10^{-11}	9.7×10^{-12}	6.5×10^{-12}	1.1×10^{-12}	2.2×10^{-12}
	8.4×10^{-5}	5.6×10^{-5}	5.1×10^{-4}	1.0×10^{-4}	5.7×10^{-4}	9.1×10^{-5}	1.4×10^{-4}	6.8×10^{-5}
SMB	3.6×10^{-11}	-7.5×10^{-12}	7.1×10^{-12}	-4.5×10^{-12}	3.2×10^{-11}	-1.4×10^{-11}	1.1×10^{-11}	1.9×10^{-12}
	8.6×10^{-4}	-4.3×10^{-5}	2.7×10^{-4}	-4.0×10^{-5}	7.7×10^{-4}	-8.1×10^{-5}	3.3×10^{-4}	1.4×10^{-5}
HML	7.8×10^{-12}	1.6×10^{-11}	1.5×10^{-11}	1.7×10^{-11}	2.1×10^{-11}	3.0×10^{-11}	3.6×10^{-2}	5.4×10^{-2}
	3.2×10^{-4}	1.5×10^{-4}	3.1×10^{-4}	8.4×10^{-5}	5.0×10^{-4}	1.7×10^{-4}	5.4***	1.9*
CS	3.9×10^{-1}	3.5×10^{-1}	3.8×10^{-11}	-6.8×10^{-12}	2.2×10^{-1}	9.9×10^{-2}	3.6×10^{-11}	6.9×10^{-11}
	7.9***	1.7*	4.7×10^{-4}	-2.0×10^{-5}	8.1***	8.6×10^{-1}	3.3×10^{-4}	1.5×10^{-4}
TS	1.1×10^{-10}	-2.8×10^{-11}	1.3×10^{-11}	-1.6×10^{-11}	7.9×10^{-12}	-6.8×10^{-12}	8.4×10^{-3}	1.3×10^{-3}
	6.4×10^{-4}	-4.0×10^{-5}	4.2×10^{-4}	-1.3×10^{-4}	2.1×10^{-4}	-4.4×10^{-5}	5.7***	2.1×10^{-1}
DVIX	1.9×10^{-2}	4.2×10^{-2}	3.0×10^{-12}	1.5×10^{-12}	1.8×10^{-12}	2.2×10^{-12}	9.0×10^{-15}	2.5×10^{-14}
	5.5***	2.9***	2.0×10^{-4}	2.2×10^{-5}	2.1×10^{-4}	2.8×10^{-5}	1.1×10^{-5}	7.0×10^{-6}

	equity market neutral		event driven		fixed income arbitrage		global macro	
	C	coefficient	C	coefficient	C	coefficient	C	coefficient
SP	4.5×10^{-3}	1.2×10^{-2}	9.7×10^{-3}	2.0×10^{-2}	1.5×10^{-12}	7.0×10^{-12}	1.3×10^{-2}	1.9×10^{-2}
	1.7×10^{-4}	8.1×10^{-5}	6.5***	1.2	5.5***	1.8*	6.0***	2.0**
EM	2.7×10^{-3}	4.6×10^{-3}	6.2×10^{-13}	2.4×10^{-13}	1.9×10^{-12}	9.3×10^{-13}	2.3×10^{-2}	2.4×10^{-2}
	4.9***	1.9*	1.5×10^{-4}	1.4×10^{-5}	3.0×10^{-4}	3.6×10^{-5}	6.2***	1.5
GSCI	2.1×10^{-13}	4.0×10^{-13}	1.5×10^{-3}	2.3×10^{-3}	6.0×10^{-4}	2.0×10^{-3}	1.1×10^{-15}	-1.5×10^{-16}
	1.2×10^{-4}	5.2×10^{-5}	5.0***	1.8*	3.5***	2.8***	7.1×10^{-6}	-2.4×10^{-7}
Mom	4.8×10^{-12}	1.5×10^{-11}	5.1×10^{-12}	2.6×10^{-12}	2.0×10^{-12}	4.7×10^{-12}	5.5×10^{-12}	7.8×10^{-12}
	4.8×10^{-4}	3.5×10^{-4}	4.3×10^{-4}	5.3×10^{-5}	2.8×10^{-4}	1.6×10^{-4}	4.2×10^{-4}	1.4×10^{-4}
SMB	2.5×10^{-13}	2.3×10^{-13}	1.5×10^{-12}	-5.6×10^{-14}	4.5×10^{-12}	2.7×10^{-12}	1.6×10^{-2}	1.1×10^{-2}
	8.0×10^{-5}	1.7×10^{-5}	1.7×10^{-4}	-1.5×10^{-6}	3.0×10^{-4}	4.3×10^{-5}	6.0***	9.4×10^{-1}
HML	2.9×10^{-2}	3.9×10^{-2}	6.5×10^{-12}	2.2×10^{-11}	2.2×10^{-12}	6.8×10^{-12}	3.3×10^{-2}	5.8×10^{-2}
	5.2***	1.6	2.7×10^{-4}	2.1×10^{-4}	1.8×10^{-4}	1.3×10^{-5}	5.6***	2.3***
CS	1.9×10^{-2}	2.3×10^{-2}	1.1×10^{-1}	7.2×10^{-2}	1.1×10^{-1}	2.7×10^{-1}	8.8×10^{-3}	3.7×10^{-3}
	5.8***	1.7*	7.9***	1.3	5.6***	3.3***	5.4***	5.3×10^{-1}
TS	2.6×10^{-12}	-2.0×10^{-12}	1.5×10^{-11}	-7.8×10^{-12}	1.3×10^{-11}	5.6×10^{-12}	1.0×10^{-11}	-1.4×10^{-11}
	2.3×10^{-4}	-4.1×10^{-5}	3.6×10^{-4}	-4.5×10^{-5}	2.9×10^{-4}	2.9×10^{-5}	3.9×10^{-4}	-1.2×10^{-4}
DVIX	8.8×10^{-3}	1.9×10^{-2}	7.1×10^{-12}	1.3×10^{-11}	3.2×10^{-2}	9.7×10^{-2}	6.2×10^{-4}	1.0×10^{-3}

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	4.6***	2.3**	4.1e-4	1.8e-4	4.4***	3.1***	3.0***	1.2
	long/short equity		relative value		short selling		merger arbitrage	
	C	coefficient	C	coefficient	C	coefficient	C	coefficient
SP	1.2×10^{-2}	2.7×10^{-2}	4.1×10^{-3}	5.9×10^{-3}	2.2×10^{-2}	7.9×10^{-2}	6.3×10^{-12}	3.8×10^{-12}
	5.3***	2.9***	5.6***	1.9*	3.9***	3.3***	4.4×10^{-4}	6.4×10^{-5}
EM	5.8×10^{-3}	5.5×10^{-3}	1.9×10^{-3}	9.9×10^{-4}	2.2×10^{-2}	5.4×10^{-2}	1.1×10^{-2}	8.9×10^{-3}
	5.8***	1.3	6.2***	7.4×10^{-1}	4.7***	2.7***	5.9***	1.2
GSCI	8.3×10^{-13}	4.8×10^{-13}	1.3×10^{-3}	-3.6×10^{-4}	7.6×10^{-14}	4.0×10^{-14}	1.5×10^{-11}	-6.0×10^{-12}
	2.0×10^{-4}	2.7×10^{-5}	6.7***	-4.3×10^{-1}	3.2×10^{-5}	4.1×10^{-6}	1.1×10^{-3}	-9.8×10^{-5}
Mom	1.0×10^{-3}	2.7×10^{-3}	8.7×10^{-12}	1.8×10^{-12}	4.7×10^{-12}	2.1×10^{-11}	7.2×10^{-12}	7.1×10^{-12}
	3.4***	2.2**	7.9×10^{-4}	3.9×10^{-5}	1.8×10^{-4}	1.9×10^{-4}	5.4×10^{-4}	1.2×10^{-4}
SMB	1.3×10^{-11}	8.2×10^{-12}	4.6×10^{-16}	-4.7×10^{-17}	2.8×10^{-11}	2.0×10^{-11}	1.1×10^{-2}	6.4×10^{-3}
	4.7×10^{-4}	7.3×10^{-5}	3.9×10^{-6}	-9.4×10^{-8}	3.6×10^{-4}	6.1×10^{-5}	5.7***	7.5×10^{-1}
HML	5.1×10^{-2}	5.3×10^{-2}	5.4×10^{-12}	4.9×10^{-12}	1.8×10^{-2}	6.2×10^{-2}	3.3×10^{-12}	4.5×10^{-12}
	8.4×10^{-5}	5.6×10^{-5}	5.1×10^{-4}	1.0×10^{-4}	5.7×10^{-4}	9.1×10^{-5}	1.4×10^{-4}	6.8×10^{-5}
CS	5.5×10^{-2}	1.7×10^{-2}	8.0×10^{-2}	3.4×10^{-2}	2.0×10^{-2}	3.5×10^{-2}	3.7×10^{-2}	1.2×10^{-2}
	7.7***	5.7×10^{-1}	8.5***	8.5×10^{-1}	4.2***	1.7*	7.2***	5.4×10^{-1}
TS	6.9×10^{-11}	-6.0×10^{-11}	1.4×10^{-10}	-1.3×10^{-10}	1.8×10^{-10}	-1.1×10^{-10}	2.8×10^{-11}	-2.5×10^{-11}
	9.1×10^{-4}	-1.9×10^{-4}	1.5×10^{-3}	-3.2×10^{-4}	8.3×10^{-4}	-1.2×10^{-4}	5.8×10^{-4}	-1.2×10^{-4}
DVIX	6.0×10^{-12}	8.4×10^{-12}	2.6×10^{-2}	1.9×10^{-2}	3.7×10^{-12}	1.9×10^{-11}	9.3×10^{-13}	2.3×10^{-13}
	1.9×10^{-10}	6.5×10^{-11}	2.4**	4.1×10^{-1}	1.3×10^{-4}	1.6×10^{-4}	1.9×10^{-4}	1.1×10^{-5}

SP, EM, GSCI, Mom, CS, TS and DVIX stand for S&P 500, emerging markets, Goldman Sachs commodity index, momentum, credit spread, term spread and the change in VIX respectively. The superscripts *,** and *** represent respectively the significance at 10%, 5% and 1% levels.

Overall, we can conclude that most of the hedge funds use the disagreement rate to change their exposure to the market risk. This analysis indicates the importance of the information associated with the options market for the fund managers, nevertheless it entails no implication on favorable use of the information by the fund managers.

6.3 Performance measurement

In this section, we present the main findings on the disagreement between the information content of option and stock markets and investigate the efficient use of this information by fund managers. We examine if the information implied by the options market is used by fund managers to anticipate future market return and to improve their performance. As the results in Table 2 and Table 3 indicate, hedge funds performance in different levels of uncertainty is also worthy of investigation. We examines funds performance by projecting the estimated factor loadings on the estimated disagreement rate or the uncertainty index. We use the projected factor loadings to predict hedge funds returns. The two step estimation is given by:

$$\hat{\beta}_{i,t} = c + b\hat{D}_t + \eta_t, \tag{5a}$$

$$\hat{\beta}_{i,t} = c + bEPU_t + \eta_t, \tag{5b}$$

$$\hat{R}_t = \hat{\alpha} + \sum_{i=1}^{N} \hat{\hat{\beta}}_{i,t} F_{i,t} + \sum_{i=1}^{M} \hat{\gamma}_{i,t} H_{i,t}, \tag{6}$$

where $\eta_t \sim N(0, \sigma_\eta^2)$, $\hat{\beta}_{i,t}$ denotes the estimate time-varying loading on i-th factor, $\hat{D}_t$ and EPU_t denote the estimated disagreement rate and the EPU index respectively. $\hat{\hat{\beta}}_{i,t}$ stands for the projected $\hat{\beta}_{i,t}$ on $\hat{D}_t$ or EPU_t as predicted by Equations (5a) or (5b). $\hat{\gamma}_{i,t}$ denotes the estimated time-invariant loading on the option-like factors by Equation (3a). $F_{i,t}$ and $H_{i,t}$ are as in Equation (3a) and c, b are scalars and $\hat{\alpha}$ is the estimated intercept in Equation (3a). $\hat{R}_t$ in Equation (6) represents the hedge fund return predicted by the disagreement rate or the EPU indicator. $\hat{R}_t$ involves information on the way fund managers use either of the disagreement rate or the EPU to time their trading strategies.

There has recently been interest in investigating EPU timing of hedge funds. Liang et al. (2020) find that orthogonalised (with respect to macroeconomic fundamentals) EPU is negatively priced by a large number of hedge funds in the sense that portfolios with higher exposure to the orthogonolised EPU earn lower average returns. Dragomirescu-Gaina et al. (2021) examine the impact of generalised shocks to a number of uncertainty indicators including EPU on continuously varying as well as regime dependent betas and find that regime dependent betas react faster to the uncertainty shocks.

If hedge fund managers care about disagreement between options and stocks markets, their reaction should differ depending on the extent to which the two markets disagree. This fact motivates us to obtain $\hat{R}_t$ using threshold regression on the data set for which the disagreement rate exceeds equally distanced levels. We also obtain $\hat{R}_t$ associated with the data for which the EPU exceeds equally distanced thresholds.

Table 8 shows the performance of each strategy across different thresholds on the disagreement rate. Since the disagreement rate barely exceeds the 50% level (with only 11 months exceeding 50% out of the 226 months), we include the thresholds until this level. The shortselling strategy realizes a Sharpe ratio of -0.10, whereas that of the market return is roughly 0.02. The performance of this strategy is improved across a number of higher thresholds. Although most of the trading strategies outperform market index, the performance is considerably improved after exclusion of lower values of the disagreement rate. CTA fails to outperform market, neither the disagreement is efficiently used by fund managers. However, the null of stable factor loadings in Table 6 is not rejected for CTA. The results of the threshold regression for the disagreement rate higher than 10% unanimously imply favorable use of the disagreement rate by fund managers. The projected return series of the Global macro strategy has a Sharpe ratio of -0.04, whereas that of the realized returns is 0.09. We obtain hedge funds performance associated with the lagged values of the disagreement rate. As Table 8 shows the Sharpe ratios associated with the concurrent disagreement rate slightly outperforms those of the lagged disagreement rate.

As results in Tables 2 and 3 suggest, the uncertainty associated with economic policy can motivate hedge funds to rebalance portfolio exposures. EPU is found to be the cause of the VIX and the disagreement rate, whereas VIX does not affect the EPU. We obtain Sharpe ratios associated with the projected hedge fund returns on the factor loading that are themselves projected on the EPU index. As Figure 2 shows the Sharpe ratios of the explained hedge fund returns are close to those explained by the disagreement rate when the threshold equals the minimum value of the EPU index. During periods of low uncertainty, hedge funds performance, as Table 8 and Fagure 2 show, remains close to the performance during periods of low disagreement. We observe two strategies having negative projected Sharpe ratios when the EPU threshold is small. That of the global macro is less than the Sharpe ratio of the projected return on the disagreement rate, however it remain positive. The projected Sharpe ratios of these strategies cross that of the projected returns on the disagreement rate in higher threshold values. In the EPU threshold of 100, the predicted returns of all the hedge fund indices have higher Sharpe ratios when the factor loadings are predicted by the EPU index. Hedge funds performance dramatically increases in higher levels of uncertainty. After the uncertainty level of 150, hedge funds performance slightly falls and then it improves in higher values. It seems that the concurrent EPU index outperforms the lagged EPU, as Figure 2 displays.

Table 8: Sharpe ratio of the hedge fund returns attributable to the disagreement rate

	convertible arbitrage			CTA			distressed securities		
	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B
S_0	0.07	0.07	0.07	-0.16	-0.13	0.01	0.16	0.17	0.15
S_1	0.65	0.66		-0.10	-0.08		0.54	0.55	
S_2	0.66	0.65		-0.07	-0.07		0.35	0.34	
S_3	1.60	1.59		0.10	0.06		0.59	0.55	
S_4	0.79	0.63		0.42	0.42		0.79	0.73	
S_5	3.01	3.18		1.00	1.39		2.55	2.98	

	emerging markets			equity market Neutral			event driven		
	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B
S_0	0.06	0.06	0.06	0.17	0.18	0.04	0.16	0.17	0.11
S_1	0.22	0.23		1.03	1.07		0.49	0.50	
S_2	0.08	0.08		0.76	0.75		0.37	0.37	
S_3	0.18	0.17		1.05	0.96		0.56	0.52	
S_4	0.15	0.13		2.16	2.03		0.69	0.64	
S_5	0.38	0.49		2.82	3.23		2.07	2.35	

	fixed income arbitrage			Global macro			Long/short equity		
	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B
S_0	0.23	0.23	-0.01	-0.04	-0.02	0.09	0.16	0.16	0.10
S_1	0.93	0.93		0.30	0.32		0.46	0.47	
S_2	0.50	0.43		0.21	0.21		0.35	0.35	
S_3	0.80	0.68		0.46	0.42		0.54	0.50	
S_4	0.42	0.25		0.65	0.55		0.57	0.55	
S_5	3.80	3.69		0.97	1.32		1.10	1.29	

	merger arbitrage			relative value			short selling		
	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B	$lags = 0$	$lags = 1$	B
S_0	0.27	0.29	0.09	0.33	0.34	0.12	-0.09	-0.09	-0.10
S_1	0.96	0.99		0.88	0.90		-0.06	-0.05	
S_2	0.90	0.93		0.76	0.75		0.04	0.04	
S_3	1.17	1.13		1.13	1.06		0.01	0.01	
S_4	1.27	1.31		0.80	0.63		0.05	0.01	
S_5	3.72	4.53		2.93	3.25		0.37	0.45	

The two first panels represent Sharpe ratios associated with the explained factor loadings by the concurrent and lagged disagreement rates respectively. time-varying factor loadings are projected threshold regressions. S_is stand for different thresholds of the disagreement rate. The thresholds satisfy $0.1 \times i \leq S_i$ where $i = 0, \ldots, 5$. Thus S_i in panel A includes all data and S_5 excludes the dates in which the disagreement rate is less than 0.5. Panel B represents Sharpe ratios of the realized hedge fund returns.

7 Concluding remarks

Our paper thesis is that if implied-moments conduct looking-forward information, there should be active trading, which makes implied prices coming from options deviate from stock prices. We assumed an inclusive factor model comprising both option-like factors and nine widely used risk factors in the literature. Having assumed time invariant exposures to the option-like factors we examined instability of the risk exposures through Hansen instability test.

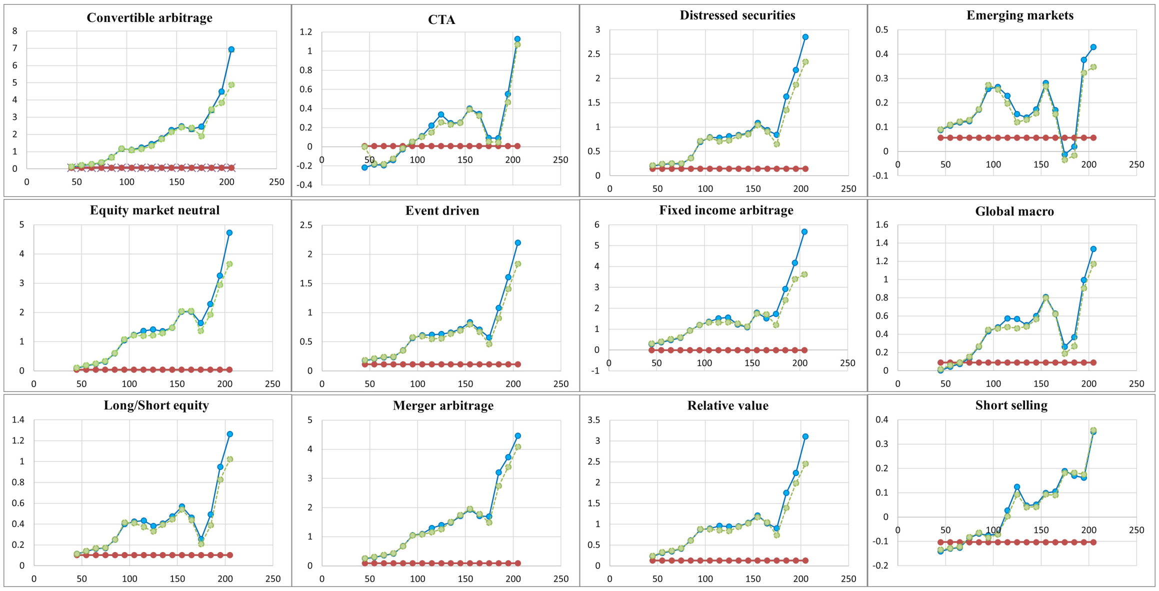

Figure 2: Sharpe ratios of the hedge fund returns attributable to the US EPU. The solid line represents Sharpe ratios attributable to the concurrent EPU, and the dashed line represents those of the lagged EPU. The horizontal line represents Sharpe ratio attributable to the concurrent disagreement rate. The vertical axis represents the Sharpe ratio and the horizontal axis represents the EPU threshold used in the threshold regression.

We related the asset positions (inferred from a time-varying multifactor model on hedge fund returns) to the disagreement between implied prices between option and stock prices. Therefore this assumption implies that a price discovery takes place and a flow of information comes from one market to the other.

This paper also considers specific events, where we observe market frictions in the information transmission between option and stocks markets. We identified the periods that are associated with rising information imbalance between the two markets. Such disagreement or inefficient events are more likely to occur in times of high volatility and noise trading as well as in times of active gamma trading. Such events have significant implications in portfolio management by creating opportunities for traders who implement reversal strategies and tactical style allocation between small, large, value and growth stocks. The disagreement rate predicts the implied volatility of the market. Thus it can be used to hedge against future volatility. We implemented an analysis of the impact of the disagreement rate on hedge fund abnormal trades. Our analysis shows that imbalance of information between the stock and option markets, which we qualify of disagreement, is contemporaneously and positively correlated with abnormal portfolio rebalancements. Our work relates to Bernales et al. (2020) who recently demonstrated not only strong herding behavior in times of high market volatility or macroeconomic events in the underlying stock markets, but also in the most sophisticated option markets. In our framework, we show that such events, mostly related to macroeconomic events, cause disagreement between the two markets. Trading on market factor is by far the most dynamic strategy across all hedge fund styles. The reallocation in this strategy is positively associated with market frictions, which escalates during periods of economic slowdown. Active trades depending on the disagreement are also found in credit spread strategies.

We raised the question if hedge fund managers time the disagreement between options and stock markets and then adjust their exposures accordingly. Using the projected time-varying exposures on the disagreement rate, we obtained a series of hedge fund returns that can be used to evaluate market timing of fund managers. The Sharpe ratios of the returns obtained from a threshold regression reveals that market frictions are of paramount importance for the managers as they contain information that predict future market returns. The threshold of 10% for the disagreement rate is considered as an important signal by fund managers to initiate portfolio rebalancing.

Likewise, we obtained the returns predicted by time-varying projected exposures on the US EPU. The results of threshold regression indicated that during periods of higher uncertainty, fund managers are inclined to time their strategies according to the EPU level. This finding in periods of low uncertainty is not as strongly as evident in comparison with high uncertainty periods.

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