The macroeconomic drivers in hedge fund beta management

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Abstract

We investigate how macroeconomic indicators alter the dynamic risk exposure of different hedge fund style strategies. We implement a multifactor model to estimate the unobservable time-varying risk exposure conditional to macroeconomic information and a VAR to measure the impact of macroeconomic predictors on different time horizons. Using monthly returns on a cross-section of 10 different style indices from February 1997 to August 2019, we find that, on average, macroeconomic indicators explain approximately 30%, 55%, and 75% variability of betas at 1-, 6-, and 36-months horizons, respectively. Although macroeconomic predictors play a critical role at every horizon, at 1-month the dominating effect comes from idiosyncratic shocks, which indicates that in the short run hedge fund managers mostly rely on their own reallocation signals. Moreover, consistent with the fundamental drivers of the smart beta factors, we find that interest rate level and GDP growth similarly impact hedge fund exposures across styles.

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Highlights:

- This paper study the relationship between macroeconomic indicators and hedge fund dynamic risk exposure.
- We use Kalman filter to estimate the unobservable beta exposure.
- In the long run: macroeconomic predictors, idiosyncratic and market shocks explain 64.42%, 33.79% and 1.79% of beta's variability, respectively.
- In the short run: the dominating effect comes from the idiosyncratic shocks.

Keywords: Kalman filter; macroeconomic indicators; factor tilting; conditional betas
JEL classification: G10; G11; G12; G23

1 Introduction

Do hedge funds shift investment strategies in response to changing market and economic conditions? The dynamic properties of hedge fund trading have been largely documented in the hedge fund literature. During the 2007-08 financial crisis, hedge funds managed to unwind part of their exposures to subprimes, contrary to banks or other institutional investors. In their Global Financial Stability Report, the International Monetary Fund (2008) indicate that hedge funds suffered only 22.8% of the total loss related to subprimes in 2006, while banks contributed to 53.3% of the total loss. The same pattern is found for 2007 (29.2% against 41.3%).

To tackle this question, we test whether hedge funds modulate the dispersion of style returns regarding economic signals. According to Bass et al. (2017), economic factors set the level of expected returns, while style factors set the dispersion around these economic factors. Our hypothesis relies on the recent literature on the economic drivers of smart beta strategies (see, for instance, the work of Dichtl et al. (2019) and Hodges et al. (2017)). We expect institutional investors and more sophisticated investors to time their exposure towards these factors by using economic variables.

Our paper contributes to the literature on time-varying beta pricing models for hedge fund returns. Racicot and Théoret (2016) investigate the cross-sectional dispersion in hedge fund betas and alphas and test whether the concentration of trades is related to macroeconomic uncertainty. We show not only that this concentration of trades occurs in times of high uncertainty but also that, more generally, hedge funds regulate their exposure to risk factors according to macroeconomic signals. Moreover, Bali et al. (2014) show that macroeconomic risk is important for modelling hedge fund returns, and Zheng et al. (2018) find evidence that hedge fund managers alter the market exposure to changes in market sentiment. We add understanding to this research by providing evidence that hedge fund managers mostly rely on changes in macroeconomic information and their own private signals for defining risk exposures. In the short run (1-month), macroeconomics plays a significant role in explaining around 30% of hedge fund managers' dynamic trades, but private signals account for 65%. The situation is almost reverse on a longer time horizon (1 year). Our analysis also shows that hedge fund managers rely on the same signals across styles. Macroeconomic information is contained in changes in interest rates, GDP growth, changes in dividend yield and changes in market uncertainty measured by the VIX impact hedge fund exposures similarly across styles. Indirectly, our paper answers a question regarding the commonality in hedge fund risk exposures and the threat to market stability. Our research also has implications regarding the commoditization of hedge fund products discussed in the media. Our research shows that a large part of their short-term dynamic trades relies on private signals. However, on an investment horizon of 6 months to 1 year, their trades are mostly driven by macroeconomic signals.

In our empirical analysis, we revisit the state-dependent approach to modelling hedge fund risk exposures by using a Kalman filter that integrates a broad set of macroeconomic variables. Mamaysky et al. (2008) already demonstrate the merit of using a Kalman filter over OLS models to estimate market timing models for mutual funds. OLS models fail to consider the timing dimension and might overestimate performance. Our approach closely follows Amisano and Savona (2017). Their approach allows fund betas towards risk factors to directly depend on the change in a broad set of macroeconomic variables such as volatility, GDP, interest rates and dividend yield. Moreover, they also use a VAR specification to allow shocks in beta due to idiosyncratic shocks (private signals), changes in the benchmark, and shocks in market benchmark return due to innovations in predictors.

Accordingly, the extant literature has mostly focused on performance analyses, such as market timing skills. Our paper also has some implications regarding market timing skills in hedge funds. We show that market shocks have a limited impact on beta dynamics. However, the aim of this paper is not to directly analyse the market timing skills of hedge fund managers or to estimate hedge fund alphas but rather to report the significance of macroeconomic factors (across styles) when defining their trades. We show that although there are different hedge fund styles, they are affected by the same macroeconomic predictors and in the same direction and that this explains 30% of their hedge fund managers' dynamic trades. However, approximately 65% of these trades are explained by private timing signals, which shows that hedge fund managers create value through their beta management skills.

Researchers have proposed numerous macroeconomic and financial risk factors to capture hedge fund risk exposure. We rely on the set of factors defined in Fung and Hsieh (2002), to which we add a value-growth factor, as in Billio et al. (2012). Our objective is not to identify new risk factors but rather to consider whether hedge fund managers control the intensity of their exposure based on economic uncertainty. Our analysis integrates the size, value, and credit spread factors, which are also factors largely traded in the market. Our results are robust to the inclusion of option-like factors, which have been extensively examined in the literature.

The remainder of this paper is organized as follows. Section 2 reviews the literature on hedge fund dynamic trades. In Section 3, we present a multifactor approach to hedge fund returns and describe our dynamic approach to hedge fund risk exposures. Section 4 estimates the time-varying exposures in hedge fund styles. Section 5 relates these dynamic exposures to macroeconomic fundamentals and presents a discussion of the main results regarding the extant literature. Section 7 concludes the paper.

2 Literature review

Business cycles and macroeconomic indicators have been shown to affect investments in small stocks, value versus growth stocks and the implementation of momentum or contrarian strategies (Griffin et al., 2003; Gulen et al., 2011; Perez-Quiros and Timmermann, 2000). With these investments being important trades for hedge fund strategies, understanding their determinants is key. The default and term spread are the usual candidates to proxy for business cycles (see Chen et al. 1986; Fama and French 1989). Moreover, in Fama and French (1989), the dividend yield is shown to be higher in periods of depression than in normal market conditions, which explains a strong positive correlation with the default spread. Moreover, by relying on the Gordon growth model, dividend yield is related to risk expectation. A high (resp. low) yield indicates that dividends have been discounted at a high (resp. low) rate Gordon (1959); Patton and Ramadorai (2013). In addition, value-growth and small-large spreads have been related to economic indicators such as GDP (see Liew and Vassalou, 2000) and to innovations in interest rates (Brennan et al., 2004; Perez-Quiros and Timmermann, 2000). Interest rates are a proxy for tighter credit constraints, especially for small firms (Perez-Quiros and Timmermann, 2000), and are adjusted by the Federal Reserve according to market conditions. In addition, Petkova (2006) relates size and value spreads to innovations in the dividend yield, term spread, default spread, and 1-month T-bill. Most of these variables appear to be significant when explaining the economics of the latter risk premia. In particular, dividend yield is positively related to the returns on small caps but is negatively related to value returns.

The recent literature has placed a special focus on value stocks. Namely, value and growth stocks display strong business cycles, and the performance of value stocks tends to be depressed when entering a recession (Petkova and Zhang, 2005). Value stock returns have indeed previously been shown to be correlated with consumption growth (Lettau and Ludvigson, 2001). On the contrary, Campbell et al. (2018) show that growth stocks protect ('hedge') investors against a possible increase in volatility or the interest rate/discount rate risk. Finally, Zhang (2005) advocates that growth stocks outperform value stocks on average in down markets due to their cost reversibility (i.e., capital can be easily downsized). Dichtl et al. (2019) expect incremental risk-adjusted returns when timing risk factors based on fundamental predictors related to the factor itself (its crowding, expected return and volatility) and technical predictors such as economic variables. In addition, Hodges et al. (2017) show that smart beta factors (style and scientific diversification) display a conditional performance on economic regimes.

The following subsections provide more details on the literature that addresses the time-varying exposures of hedge funds and the literature on the economic determinants of beta.

2.1 Dynamic pricing models

Fung and Hsieh (1997) were among the first scholars to identify the impact of dynamic trading strategies on hedge funds' return structure. Beyond market factors, their model includes proxies for the strategy component of hedge fund returns. Similarly, asset-based factors that capture option-like strategies were added to the analyses conducted by Agarwal and Naik (2004) and Fung and Hsieh (2004). On the one hand, Fung and Hsieh (2004) consider the payoffs of lookback straddles to capture the trend-following strategies in hedge funds. On the other hand, Agarwal and Naik (2004) consider investment strategies that roll over one month to maturity call and put options.

Christoffersen and Langlois (2013) observe a joint dynamic correlation among the equity factors. If this feature is reconciled with market regimes, hedge fund risk exposures could be made conditional on different levels of the mean and volatility of the equity market index. In this framework, Billio et al. (2012) show that hedge fund managers can hedge market exposures. They model volatility regime changes in the US market index by using a Markov switching model for the 1994-2009 period and find that conditional exposure to traditional location factors tends to decrease in Standard & Poor's (S&P) 500 down states relative to tranquil market states. By also relying on a Markov regime-switching process, Racicot and Théoret (2019) shows that higher moment risk is conditional on VIX.

Hasanhodzic and Lo (2007), Kuenzi and Shi (2007), and McGuire et al. (2005) use rolling-window regression-based analyses to estimate fund managers' current market exposures. Finally, the theory of structural breaks in hedge fund exposures is grounded in the work of Bollen and Whaley (2009) and Patton and Ramadorai (2013). The structural change-point regression observes two market regimes in the fund return data and estimates factor exposures separately in these two market sub-periods. Criton and Scaillet (2011) further study whether hedge fund exposures display structural breaks in turmoil periods. Siegmann and Stefanova (2017) find optimal change-points in the beta-liquidity relationship in periods that feature either market turmoil or structural changes. Accordingly, structural change-point regression best captures rapid and sharp transitions in fund exposures, while state-space models best model smooth transitions.

Bollen and Whaley (2009) considers different techniques to model the ease with which hedge funds shift asset classes, investment strategies and leverage. They compare a simple market timing model not only to a structural change-point regression with one regime switch in the data but also to a state-space model in which the factor loadings are assumed to follow a mean-reverting process. Jawadi and Khanniche (2012), on the other hand, uses a nonlinear multivariate model to study the dynamic exposure of hedge fund returns to risk factors and find an asymmetrical linkage between hedge fund and risk factors. Similarly to Bollen and Whaley (2009), we consider a hedge fund's exposure to risk factors as an unobservable state variable that follows a first-order autoregressive process (AR(1)) and use a Kalman filter to estimate it [1].

2.2 Economic variables and time-varying betas

A large literature exists on the dynamic models for hedge fund returns that incorporate economic variables. The scope of these studies is mainly on a performance analysis or is limited to the economic dependence of hedge fund market exposure. Amenc et al. (2003), Brealey and Kaplanis (2001), and Kat and Miffre (2002) propose conditioning hedge fund market exposures on certain financial indicators, such as the default spread, the implied volatility or the term spread of the US market. Cao et al. (2013) demonstrate that a hedge fund's state-dependent bets are based on volatility levels. Hedge funds are also shown to reduce risk exposure in times of scarce market liquidity. Chen et al. (2016) demonstrate hedge fund timing abilities in stocks that are sensitive to investor sentiment. Finally, Frydenberg et al. (2017) provide evidence of time-varying alphas and betas for different hedge fund strategies. With a simple moving-average regression framework, they show that market exposures and the alphas of hedge funds tend to decrease in down markets. Our research differs from their research as we provide a direct estimate of the risk exposures through time without determining ex ante the bear and bull periods. Our model is therefore more flexible.

Closer to our work, Racicot and Théoret (2009, 2010) study how a portfolio hedge fund's alphas and betas change according to market and economic variables. They use a Kalman filter to infer the dynamic exposure to risk factors. Racicot and Théoret (2012) investigates how business cycles affect hedge fund trades and provides evidence of pro-cyclicality in hedge funds' risk exposure. They demonstrate that most hedge fund styles are pro-cyclical (e.g., equity L/S and equity market neutral). An exception is made for distressed securities, which are shown to increase risk exposure during economic slowdowns. Changes in macroeconomic conditions therefore lead hedge fund managers to dynamically re-balance their asset allocations. Their study, however, only allows alpha and market beta to vary according to the state of the economy and accordingly does not relate these estimates to standard macroeconomic variables. Furthermore, they do not allow time-variability for classical hedge fund trades in small value caps, which have been shown to be related to macroeconomic conditions (see supra). More recently, using systematic tail risk measures, Gregoriou et al. (2020) investigates how downside risk across hedge fund strategies reacts to macroeconomic and financial shocks.

Furthermore, Kazemi and Islamaj (2018) study the relationship between hedge fund activeness and performance by using a Kalman filter to estimate the dynamic risk exposure of long/short (L/S)

[1] In the mutual fund literature, Swinkels and Van Der Sluis (2006) report a return-based style analysis and compare the following three different approaches to explicitly model the time-varying exposures of mutual funds: a rolling-window analysis; the Kalman filter; and the Kalman smoother.

equity hedge funds. In addition, Bali et al. (2014) demonstrate hedge funds' macro-timing ability. They show that hedge funds with strong exposure to macroeconomic uncertainty indeed outperform funds with weaker exposure. Agarwal et al. (2017) also show that uncertainty about volatility is an important determinant of hedge fund returns.

3 Multifactor model of hedge fund returns

Researchers have proposed numerous macroeconomic and financial risk factors to capture hedge fund risk exposure. We rely on the set of factors defined in Fung and Hsieh (2004), to which we add a value-growth factor, as in Billio et al. (2012).

Our objective is not to identify new risk factors but rather to consider whether hedge fund managers control the intensity of their exposure based on economic uncertainty. Our analysis covers the period from February 1997 to August 2019. The following definitions of asset-based risk factors are used in our multifactor model:

1. SP: the S&P 500 monthly return index, which characterizes the US equity market risk factor;[2]

2. SC-LC: the Small minus Big index is computed as the monthly return difference between the Russell 2000 minus the Russell 1000 indexes;[2]

3. VC-GC: the High minus Low index is computed as the monthly return difference between the Russell 1000 Value minus the Russell 1000 Growth indexes; and[2]

4. CredSpr: Moody's Baa corporate bond yield relative to the yield on 10-year Treasury constant maturity.[3]

In addition, as control variables, we include the following five option-like factors from Fung and Hsieh (2004) and their extended FH-9 model [4]:

1. PTFSBD: return of a portfolio of straddles on bond futures;

2. PTFSFX: return of a portfolio of straddles on currency futures;

3. PTFSCOM: return of a portfolio of straddles on commodity futures;

4. PTFSIR: return of a portfolio of straddles on interest rate futures; and

[2]Obtained from Thomson Financial Datastream, Inc.

[3]Time-series BAA10YM was obtained from the Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/fred2/.

[4]Available on the authors' website: http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls

5. PTFSSTK: return of a portfolio of straddles on equity futures.

As the use of a rolling window or sub-samples does not allow us to capture smooth changes and to relate them to changes in macroeconomic conditions, we use a Kalman filter to estimate the unobservable time-varying risk exposure. Our research departs from the alpha and beta estimates of Cai et al. (2018) as their research focus is on alpha and its decay. Our objective is to obtain a direct estimate of time-varying betas. We therefore perform a dynamic return-based style analysis as follows:

$$\begin{aligned} R_t - r_f &= \alpha_t + \beta_{1,t} \cdot (S\&P - r_f) + \beta_{2,t} \cdot (SC - LC) + \beta_{3,t} \cdot (VC - GC) + \beta_{4,t} \cdot CredSpr \\ &\quad + \beta_5 \cdot PTFSBD + \beta_6 \cdot PTFSFX + \beta_7 \cdot PTFSCOM + \beta_8 \cdot PTFSIR \\ &\quad + \beta_9 \cdot PTFSSTK + \epsilon_t \end{aligned} \tag{1}$$

where $\beta_{i,t}$ represents the time series of risk exposure to factor $i = 1, 2, 3, 4$, and $\epsilon_t \sim N\left(0, \sigma_\epsilon^2\right)$.

As stated before, our paper is innovative because it examines the dynamic market exposures to economic conditions. We consider that managers incorporate macroeconomic information via risk factor exposure by timing the dynamic risk exposure to different macroeconomic conditions. In contrast to Amisano and Savona (2017), we consider that beta depends on economic variations. Therefore, we assume that time-varying betas depend on the changes in macroeconomic variables as follows:

$$\begin{pmatrix} \alpha_{t+1} \\ \beta_{1,t+1} \\ \beta_{2,t+1} \\ \beta_{3,t+1} \\ \beta_{4,t+1} \end{pmatrix} = \begin{pmatrix} \alpha_t \\ \beta_{1,t} \\ \beta_{2,t} \\ \beta_{3,t} \\ \beta_{4,t} \end{pmatrix} + \begin{pmatrix} \delta_{0,1} & \delta_{0,2} & \delta_{0,3} & \delta_{0,4} & \delta_{0,5} \\ \delta_{1,1} & \delta_{1,2} & \delta_{1,3} & \delta_{1,4} & \delta_{1,5} \\ \delta_{2,1} & \delta_{2,2} & \delta_{2,3} & \delta_{2,4} & \delta_{2,5} \\ \delta_{3,1} & \delta_{3,2} & \delta_{3,3} & \delta_{3,4} & \delta_{3,5} \\ \delta_{4,1} & \delta_{4,2} & \delta_{4,3} & \delta_{4,4} & \delta_{4,5} \end{pmatrix} \times \begin{pmatrix} \Delta DIV \\ \Delta RREL \\ \Delta VIX \\ \Delta GDP \\ \Delta VIX * \Delta GDP \end{pmatrix} + \begin{pmatrix} \varepsilon_{0,t+1} \\ \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \\ \varepsilon_{3,t+1} \\ \varepsilon_{4,t+1} \end{pmatrix} \tag{2}$$

where $\varepsilon_{0,t+1} \sim N\left(0, \sigma_{\varepsilon_0}^2\right) \cdots \varepsilon_{4,t+1} \sim N\left(0, \sigma_{\varepsilon_4}^2\right)$, and we consider the following macroeconomic factors used by Bali et al. (2014):

1. DIV: the aggregate dividend yield on the S&P 500 Index;[5]

2. RREL: the relative T-bill rate, defined as the difference between the three-month T-bill rate and its 12-month backward moving average; and[6]

[5]Obtained from Robert Shiller's online data library: http://www.econ.yale.edu/shiller/data.htm.

[6]Obtained from the Federal Reserve Board: http://www.federalreserve.gov/releases/h15/data.htm.

3. VIX: the implied volatility on the S&P 500.[7]

4. GDP: the US monthly growth rate of normalized GDP;[8]

Savona (2014) shows that a performance evaluation can be distorted if the time-varying exposures of hedge funds are not considered. Hedge funds indeed exhibit time-varying betas related to changes in volatility, T-bills, term spreads and liquidity. Our analysis adds understanding to this paper by not examining performance valuations but whether commonalities exist in the way that hedge funds globally time their exposure to factors. Furthermore, the time-varying dimension is extended beyond market beta to all factors. Note that as in Agarwal and Naik (2000), because hedge funds exhibit considerable flexibility in terms of asset allocation (e.g., short selling and cash holding), there is no restriction on the negative exposure to risk factors, and we relax the constraint that style weights must sum to one.

3.1 Hedge fund data

Hedge fund returns are downloaded from the EDHEC-Risk Institute webpage for the period from February 1997 to August 2019. Table 1 reports the descriptive statistics for the main hedge fund indexes. Biases (backfill, survivorship, selection) in hedge fund data are well known in the literature. The alternative indexes published by the EDHEC are designed to provide good representation and benchmarking of the hedge fund universe. Because we do not aim to measure the performance of hedge funds but rather to understand their investment strategies, we are less concerned by the intrinsic biases in the reporting procedures.

[TABLE 1 AROUND HERE]

Among equity-focused funds, L/S equity represents the most liquid strategy. The downside risk (which is represented by negative skewness) is weaker in this strategy than in other strategies. Short selling exhibits a positive skewness but performs poorly over the sample period. The market-neutral, merger-arbitrage, fixed-income arbitrage and relative value strategies can be considered to be "short volatility" strategies. These strategies might strongly suffer in the event of market turmoil and high volatility, as represented by strong negative skewness and positive excess kurtosis. Event-driven, convertible arbitrage and distressed securities suffer from a specific downside risk (corporate events), which explains the deep negative skewness. The global macro strategy is the most diversified hedge fund strategy, which might explain its positive skewness. In our analysis, we do not consider the

[7] Obtained from the CBOE: http://www.cboe.com/micro/vix/part3.aspx.

[8] Growth rate is calculated with the time-series USALORSGPNOSTSAM, that is, normalized GDP for the United States as obtained from the Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/fred2/.

funds of funds, CTAs or emerging markets. First, CTAs require a specific asset-based approach to modelling their returns (which we do not follow here). Second, because our objective is to investigate the impact of US economic indicators on hedge fund-specific trades and hedge fund styles, we exclude emerging market-oriented strategies and funds-of-funds approaches that aggregate different hedge fund styles.

Our sample includes periods of high risk aversion and market correction that might be interesting from a macroeconomic perspective, namely, the Asian financial crisis (1997), the Russian/LTCM crisis (1998), the pre- and post-dot-com bubble (2000), and the 2007-2009 subprime market crisis related to high-risk mortgages.

4 Dynamic exposures to asset-based factors

We examine the time-varying risk exposures of 10 hedge fund styles after controlling for their option-like features. This section reports the descriptive statistics for hedge funds' exposure to asset-based factors.

Table 2 describes the hedge fund strategy exposures towards S&P, SC-LC, VC-GC and Credit Spread, that is, $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$, and $\beta_{4,t}$, respectively. The table presents the mean, standard deviation, median, minimum, and maximum of each factor exposure.

[TABLE 2 AROUND HERE]

Panel A of Table 2 shows the descriptive statistics for an L/S equity strategy. This is a widespread strategy across the hedge fund industry and the largest in terms of assets under management. The strategy displays the usual average beta on the US equity market (about 0.30). Over the period, which includes the financial crisis, exposure to equity varied between -0.09 and 0.51, i.e., a 0.60 spread. Larger spreads are observed for L/S equity funds' exposure to smart beta factors such as size, value or credit spread. The largest variation is observed for credit spread, followed by the value factor. Market-neutral strategies are a special case of L/S equity strategies that seek to be neutral regarding market conditions. A market-neutral strategy presents a very low exposure to equity risk, as shown by the average exposure to S&P, SC-LC, and VC-GC (less than 0.10 in magnitude). The exposure to US equity varies by approximately 0.25 over the period, but spreads are wider for the smart beta factors. More dynamic trades are observed for the credit spread (see Panel B).

Panels C to E of Table 2 cover the hedge fund strategies that focus on corporate events. Within this group of strategies, the event-driven strategy displays the highest exposure to S&P (around 18%) and to the size factor (around 12%) due to their indirect reliance on economic conditions and particular types of companies. Within this category fall activist hedge funds. The other corporate-driven strategies, specifically, merger-arbitrage and distressed securities, show the usual low exposure to equity strategies (inferior to 0.10). The risk involved in such strategies is indeed highly specific, and hedge funds tend to hedge on average their exposure to the market. Distressed securities are essentially a bet on a specific (micro) risk, as the success of the strategy relies primarily on the ability of the company to renegotiate its borrowing. Merger-arbitrage strategies mainly rely on an agreement made between management boards or on political risk, and the exposure to the equity market is generally hedged. Except for credit spreads, the variation in betas is slightly lower than for L/S or market neutral strategies, especially for merger arbitrage strategies. (We observe a lower variation of betas on equity factors over the period: 0.20–0.30.) As expected for a strategy that involves credit risk, the variation in credit spread exposures is the highest among the three strategies and among the highest over the 10 strategies investigated in our research.

Panels F and G in Table 2 cover fixed-income and convertible bond arbitrage funds. Fixed-income arbitrage and convertible arbitrage display very small exposures to most of the asset-based factors (inferior to 0.035 in magnitude) except for the credit spread factor. They both display an average negative exposure to the credit spread with a large variation over the period. The exposure to US equity (resp. value factor) varies widely over the period for fixed-income arbitrage (resp. convertible arbitrage).

Relative value strategies combine long and short positions to capture the price spread from mispricing between two securities. Panel H, Table 2 on relative value shows low exposures to the equity factors (S&P, SC-LC, VC-GC), but these might vary widely over the period. The highest variation is found in the credit spread and value factors. Global macro is the most diversified strategy among the hedge fund categories. Global macro funds exhibit directional exposures on the US equity factor. Their exposures to any risk factors change sharply over time.

For all "long-bias" strategies displayed from Panels A to I in Table 2, we observe an average negative exposure to the credit spread, which means that all strategies on average hedge credit risk. Moreover, they present short exposures to the value factor, as shown in Billio et al. (2012), with an important negative skew over the period. On the contrary, Panel J on the short selling strategies displays strong negative exposures to L/S funds with negative average exposures to S&P and SC-LC but positive average exposure to the value factor (with less asymmetry between the positive and negative sides). The exposure to credit spreads stays strong and negative.

Table 3 displays the exposures and significance of the five control variables for the option-like features. Most strategies display significant negative exposures to the straddle on interest rate, which shows that the strategies' performance is resilient to a small variation in interest rates. Almost all strategies exhibit positive and significant exposure to straddles on equity, which indicates the ability of these funds to earn a return from the equity market in up- and down-market conditions.

Market-neutral, fixed-income arbitrage, event-driven and distressed funds display strong nonlinearity, as shown by the significance of the three option-like factors, including straddles on bonds – which are negative, like interest rates.

[TABLE 3 AROUND HERE]

5 Time-varying betas and macroeconomic information

This section examines how macroeconomic indicators affect hedge fund dynamics. First, we examine the economic determinants of each factor trade following our methodology described in Section 3. Second, we implement a VAR specification such as in Amisano and Savona (2017) to further understand the part of beta dynamics that is related to macroeconomic signals.

5.1 Economic determinants of hedge fund betas

Table 4 displays the regression coefficients of hedge fund style exposures to the macroeconomic indicators estimated by Equation 3.

[TABLE 4 AROUND HERE]

Table 4 shows that factor exposures are highly dependent on macroeconomic information across all hedge fund styles and across risk factors. The four economic indicators are indeed significant for defining betas across all strategies. We add understanding to the extant literature by showing that macroeconomic information is an important determinant for measuring the exposures to all risk factors, not only for the US equity market factor. In addition, our results are consistent with the known economic drivers of smart beta factors. This new evidence indicates that hedge fund managers use fundamental macroeconomic information to design their dynamic strategies.

Figures 1 to 10 illustrate the conditional beta dynamics regarding the macroeconomic factors for each hedge fund style.

[Figures 1 to 10 AROUND HERE]

Panel A of Table 4 shows that the trades of L/S equity funds are highly directional and are driven by all four macroeconomic indicators, i.e., interest rates, the dividend yield, implied volatility and GDP. The exposures to the value factor depend on interest rate changes and dividend yield variation, which have both been shown to be fundamental drivers of the factor (see Campbell et al. 2018; Petkova and Zhang 2005). Moreover, a context of highly volatile markets combined with GDP growth encourages taking more growth and size risks. Again, these macroeconomic indicators have previously been related to small growth risks and to, among other things, the real options embedded in small growth stocks (see Campbell et al. 2018; Grullon et al. 2012). Fig. 1 especially emphasizes the strong relationship between the investment trades in US equity and value factor and the evolution of interest rates, as well as GDP growth and the size factor (81%).

The results displayed in Panel B of Table 4 for market-neutral funds also strongly support the hypothesis that macroeconomic information has an impact on hedge fund managers' trades. All economic indicators significantly affect the exposures of this specific hedge fund style. First, the exposure to the equity market proxied by S&P is positively related to changes in the dividend yield and interest rates such as L/S strategies. Second, exposure to the size factor is positively related to changes in implied volatility and the dividend yield. Third, exposure to value risk is negatively related to changes in dividend yield. An increase in the dividend yield has been shown to be a proxy for risk (see Section 2 and to impact the performance of the factor. These results provide evidence that hedge fund managers use these fundamental trading signals when making their asset allocation. Finally, exposures to the credit spread rely mostly on changes in interest rates, which might negatively affect low-rated stocks. Fig. 2 illustrates the strong relationship between changes in interest rates and exposure to the market factor, changes in volatility and small cap investing and, finally, GDP growth and the credit spread factor (with a multiplicative effect).

Panels C and D of Table 4 for event-driven and merger-arbitrage funds show that an increase in interest rates commands a significant increase in the exposure to the equity market, as proxied by S&P, and to the value factor. As for the previously discussed strategies, an increase in volatility and GDP growth positively impacts the exposure to the size risk, especially for event-driven strategies. Furthermore, a dividend yield increase negatively affects the exposures to the value factor. This evidence is also perfectly illustrated in Figs. 3 and 4.

Panel E of Table 4 and Fig. 5 for the distressed strategy provide similar information to Panels C and D. We observe a similar positive relationship between equity market investing and an increase in interest rates, a positive impact of volatility on both equity and small cap investing, and a negative impact of an increase in dividend yields on value factor exposure. Finally, directional bets on equity and other smart beta strategies depend on GDP growth, especially when implied volatility in the market is high.

Panel F of Table 4 and Fig. 6 on fixed-income arbitrage shows a positive impact of interest rates on global market exposure and the value factor. Dividend yields also affect the exposure to the size and value factors.

Table 4, Panel G on convertible arbitrage and Fig. 7 both show a positive relationship between exposure to the equity market (i.e., S&P, small cap) and an increase in interest rates, which posits that interest rates are a proxy for good market conditions. As previously shown, GDP growth commands higher exposure to the value factor, which benefits from economic expansion. Credit spread exposure is mostly negative, and the position depends on volatility.

Panel H of Table 4 and Fig. 8 on relative value shows the usual positive relationships recorded above between US equity and value factors and positive innovations in interest rates, as well as between GDP growth and the size and value factors. Most surprisingly, an increase in GDP commands a lower exposure to equity.

Panel I of Table 4 on global macro funds and Fig. 9 jointly show the (positive) dependence on the interest rates of hedge fund equity and value exposures and indicate the impact of GDP growth on equity and size factors. Implied volatility is also an important determinant of global macro funds' size exposure.

Finally, exposures to the risk of short selling are the least dependent strategies on macroeconomic information as shown in Panel J of Table 4 and Fig. 10.

5.2 Beta decomposition

The aim of this section is to measure how much macroeconomic predictors impact beta dynamics. In more detail, we want to determine the amount of information that DIV, RREL, VIX, and GDP (as defined in Section 3) contribute to the hedge fund's beta dynamics at different time horizons, that is, 1, 6, and 36 months. For this exercise, we use the betas' estimates obtained in Section 4 (towards our four factors) and follow Amisano and Savona (2017), who uses a structural VAR representation where the macroeconomic variables and the market benchmark (S&P 500) are also represented in the VAR. Similar to Amisano and Savona (2017), the VAR is constructed based on two assumptions: i) the unexpected part of beta depends on market shocks, and ii) the unexpected market benchmark depends on macroeconomic shocks. Following this specification, we can identify the idiosyncratic, market and macro shocks that affect beta. The VAR specification is given as follows.

$$\begin{pmatrix} 1 & -\Phi & a_{\beta m} \\ 0 & P^{zz} & 0 \\ 0 & p^{zm} & p^{mm} \end{pmatrix} \begin{pmatrix} \beta_t \\ \overline{\boldsymbol{z_t}} \\ m_t \end{pmatrix} = \begin{pmatrix} 1 & -\Phi & 0 \\ 0 & \Lambda & 0 \\ 0 & \lambda & 0 \end{pmatrix} \begin{pmatrix} \beta_{t-1} \\ \overline{\boldsymbol{z_{t-1}}} \\ m_{t-1} \end{pmatrix} + \begin{pmatrix} \Sigma_\beta & 0 & 0 \\ 0 & I_z & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \epsilon_{\beta,t} \\ \epsilon_{z,t} \\ \epsilon_{m,t} \end{pmatrix} \tag{3}$$

where $\overline{\boldsymbol{z_t}}$ is a vector of macroeconomic factors (DIV, RREL, VIX, and GDP), and Φ is a vector of the estimates obtained in state space representation (Eq. 3). To avoid collinearity issues, we eliminated the interaction effect predictor.

Table 5 presents the forecast-error variance decomposition of betas for each hedge fund index at 1-, 6-, and 36-month horizons. The results are quite conclusive: on average, macroeconomic factors play a critical role in the variability of betas and explain around 30%. In addition, the impact of macroeconomic factors increases significantly with the time horizon, and we observe an average increment of nearly 25% from 1 to 6 months and 10% from 6 to 36 months, which explains almost

65% over the long run. Market shocks explain a limited percentage of the beta dynamics in the short run (less than 10%, except for the market neutral fund exposure to small caps and short sellers' exposure to value factors). The effect of market shocks is further reduced in the long run (less than 2% on average). These results are quite similar to the results of Amisano and Savona (2017) for mutual funds. Finally, at the 1-month horizon, the dominating effect comes from the idiosyncratic variability, which indicates that in the short run, hedge fund managers mostly rely on their own reallocation signals.

Table 6 presents the forecast-error variance decomposition of betas for each hedge fund index at 1-, 6-, and 36-month horizons from January 2010 to August 2019, which excludes the Asian financial crisis (1997), the Russian/LTCM crisis (1998), the pre- and post-dot-com bubble (2000), and the 2007-2009 subprime market crisis. The results remain quite stable, but we observe an important increment, from 4.44% to 11.53%, in the market contribution to betas' variability. However, the main explanatory variables that explain beta dynamics are private signals, followed by macroeconomic information in the short run, and macroeconomic information, followed by private signals in the long run. Market shocks play a marginal role in beta dynamics.

[TABLE 5 and 6 AROUND HERE]

6 Discussion

This paper posits that if economic factors affect stock prices and investment trades in the form of factor or style investing, they should affect hedge fund investment allocations. In particular, business cycles and macroeconomic indicators have been shown to affect investments in small stocks, in value versus growth stocks and in the implementation of momentum or contrarian strategies. We examine hedge fund exposures towards the smart beta factors such as the value, size and credit spread across 10 hedge fund styles.

Our results identify commonalities in the links between the beta exposures and the macro factors across strategies. These relationships are consistent with the fundamental drivers of the smart beta factors established in the literature Brennan et al. (2004); Campbell et al. (2018); Lettau and Ludvigson (2001); Liew and Vassalou (2000); Perez-Quiros and Timmermann (2000); Petkova and Zhang (2005); Zhang (2005). We indeed show that macroeconomic information, especially the information contained in interest rates and GDP growth, similarly impact hedge fund exposures across styles. Exposure to the value, size and US equity factors are highly conditional on interest rates, GDP and volatility, and they i) tilt towards value risk with GDP and interest rates increases and 2) tilt towards growth/small cap risk during times of increased volatility (higher volatility increases the value of growth options), which supports the hedging properties of growth stocks against volatility (Campbell et al., 2018). We also observe a long bias in the small size risk across hedge fund styles, as noted by Agarwal and Naik (2004), Billio et al. (2012). This exposure is mostly influenced by volatility.

Regarding the extant literature, we contribute to Racicot and Théoret (2016), Zheng et al. (2018) and Bussière et al. (2015) by showing how hedge funds regulate their exposure to *all* risk factors according to macroeconomic signals and by providing evidence that hedge fund risk exposures rely on the same signals across styles. In contrast to the findings of Racicot and Théoret (2012), however, the exposures to S&P and smart beta premia closely follow interest rate evolution (except for short selling) across all styles.

The changes in dividend yield are mostly important for equity-based strategies (L/S and market neutral), corporate-specific strategies and relative value strategies. For equity-based strategies, an increase in dividend yield induces a decreased exposure to the market factor and value factor. For corporate-specific strategies, it commands an increased exposure to the size factor but a decreased exposure to the value factor. We observe the same impact for relative value strategies, including fixed-income arbitrage. A higher dividend yield proxies for a high discount rate risk, which benefits growth stocks according to the framework of Campbell et al. (2018).

Our paper does not draw direct conclusions on timing skills and alphas as there is a look-ahead bias (also shared by other papers) when measuring performance that uses the entire period to estimate the alpha at a point in time. However, our assumption is that if factor tilting is mainly based on pure private skills, we should not find common determinants of the changes in hedge fund risk exposures across styles. Our results show that most hedge funds trade on the same economic signals but that their private timing skill is the most important driver of their proprietary trades.

7 Conclusion

The extant literature has shown that hedge fund trades are affected by macroeconomic variables. However, the literature mostly focuses on the impact of macroeconomic uncertainty on hedge fund performance and market exposure and does not make a direct link between macroeconomic data and larger hedge fund asset allocation. Our paper addresses the time-dependency of a selected number of smart beta factors that have been shown to be common across strategies. This is particularly important, as hedge funds tend to package beta management as a form of alpha or abnormal skills.

Most strategies entail dynamic trading in alternative risk premia such as the size, value and credit spread. This paper does not investigate the full universe of risk premia but uses commonly accepted risk premia in the hedge fund industry to perform an experiment on the impact of macro-information on factor exposure. Volatility, GDP growth, innovations in interest rates and dividend yields are significantly related to factor tilts. Moreover, the fundamentals that drive this dynamic allocation can be related to previous work, including Campbell et al. (2018), Petkova (2006), Petkova and Zhang (2005), and Grullon et al. (2012) on the value and size factors. Our results therefore suggest that hedge funds perform very similar asset allocations based on public signals and use fundamental drivers of the factors to design their trades. These results are common across hedge fund managers. This suggests that hedge fund managers provide similar methods of beta management.

Finally, the conditional risk allocation across hedge fund styles described in this paper might in fact reveal trend-following and reversal patterns in the underlying risk factor. If hedge fund trades reflect trends in the underlying factors, this would affect the market timing skills of those managers. This topic is part of our future research agenda.

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Appendix of tables

Hedge fund statistics

Strategy	Mean	Median	Std	Kurtosis	Skewness	Max	Min	JB p-value
Convertible Arbitrage	0.5519	0.6500	1.6385	23.5419	-2.6392	6.1100	-12.3700	< 0.001
CTA Global	0.4358	0.2150	2.3144	2.9574	0.1488	6.9100	-5.6800	> 0.500
Distressed Securities	0.6731	0.8800	1.6946	7.7809	-1.2649	5.0400	-8.3600	< 0.001
Emerging Markets	0.6215	0.9350	3.2283	9.2408	-1.1557	12.3000	-19.2200	< 0.001
Equity Market Neutral	0.4418	0.4850	0.8046	17.2855	-2.0993	2.5300	-5.8700	< 0.001
Event Driven	0.6239	0.8350	1.6795	7.7483	-1.3604	4.4200	-8.8600	< 0.001
Fixed-Income Arbitrage	0.4276	0.5500	1.1383	30.3405	-3.9490	3.6500	-8.6700	< 0.001
Global Macro	0.5487	0.4650	1.4548	5.8055	0.9732	7.3800	-3.1300	< 0.001
Long/Short Equity	0.6243	0.7850	1.9944	4.4398	-0.3797	7.4500	-6.7500	< 0.001
Merger Arbitrage	0.5299	0.5900	0.9511	8.8137	-1.3069	2.7200	-5.4400	< 0.001
Relative Value	0.5715	0.6450	1.1373	12.1490	-1.7929	3.9200	-6.9200	< 0.001
Short Selling	-0.1881	-0.5700	4.6993	6.3144	0.7895	24.6300	-13.4000	< 0.001
Funds of Funds	0.4250	0.5200	1.5449	7.0662	-0.3592	6.6600	-6.1800	< 0.001

Table 1: This table reports some descriptive statistics for the main hedge fund indexes. Historical monthly returns (expressed in percentage terms) from the EDHEC-Risk Institute cover the period from February 1997 to August 2019 and represent a total of 272 observations.

Asset-based risk factor exposure statistics

	Panel A: Long/short equity					Panel B: Market Neutral				
	Mean	Median	Std	Max	Min	Mean	Median	Std	Max	Min
α_t	-0.2138	0.3659	1.8037	2.1025	-5.0846	0.3340	0.2568	0.7472	2.8051	-1.4074
$\beta_{1,t}$	0.2856	0.2801	0.1031	0.5107	-0.0911	0.0516	0.0527	0.0526	0.1474	-0.1283
$\beta_{2,t}$	0.1450	0.1436	0.0978	0.4779	-0.1732	0.0497	0.0283	0.0854	0.5463	-0.0674
$\beta_{3,t}$	-0.0999	-0.0891	0.1803	0.2922	-0.7003	-0.0653	-0.0705	0.0948	0.1119	-0.3763
$\beta_{4,t}$	0.1519	0.0397	0.6072	1.7636	-0.8601	0.0065	0.0586	0.2695	0.4851	-0.8109
	Panel C: Event Driven					Panel D: Merger Arbitrage				
	Mean	Median	Std	Max	Min	Mean	Median	Std	Max	Min
α_t	0.6480	0.8584	1.5871	3.9652	-4.3333	0.1144	0.1831	0.7715	1.5162	-1.8399
$\beta_{1,t}$	0.1775	0.1832	0.0929	0.3617	-0.1423	0.0773	0.0616	0.0476	0.1849	-0.0279
$\beta_{2,t}$	0.1212	0.1189	0.0818	0.4371	-0.0969	0.0698	0.0759	0.0459	0.2146	-0.0595
$\beta_{3,t}$	-0.0117	0.0025	0.1095	0.1716	-0.4565	-0.0016	0.0142	0.0676	0.1074	-0.1733
$\beta_{4,t}$	-0.1380	-0.2155	0.6415	1.7873	-1.3823	0.0652	-0.0009	0.2480	0.7443	-0.4123
	Panel E: Distressed Securities					Panel F: Fixed-Income Arbitrage				
	Mean	Median	Std	Max	Min	Mean	Median	Std	Max	Min
α_t	1.9048	2.2393	1.7793	5.5602	-3.5177	1.0600	1.0265	1.3005	4.3545	-2.1783
$\beta_{1,t}$	0.0994	0.1055	0.0922	0.2719	-0.2078	0.0034	0.0124	0.0931	0.2532	-0.4539
$\beta_{2,t}$	0.0685	0.0607	0.0726	0.3819	-0.1229	-0.0065	-0.0044	0.0421	0.1214	-0.1357
$\beta_{3,t}$	0.0166	0.0342	0.1017	0.2400	-0.4310	-0.0235	-0.0042	0.0904	0.1617	-0.3550
$\beta_{4,t}$	-0.6437	-0.8722	0.8472	1.9418	-1.8882	-0.3221	-0.3378	0.6012	1.3792	-1.8041
	Panel G: Convertible Arbitrage					Panel H: Relative Value				
	Mean	Median	Std	Max	Min	Mean	Median	Std	Max	Min
α_t	2.4958	2.3620	1.0105	5.1880	0.5706	0.2843	0.6158	1.7045	3.6215	-4.2585
$\beta_{1,t}$	0.0322	0.0447	0.0729	0.1866	-0.2193	0.0958	0.0971	0.0601	0.2101	-0.1353
$\beta_{2,t}$	0.0100	0.0094	0.0461	0.1568	-0.0997	0.0446	0.0429	0.0645	0.2321	-0.1442
$\beta_{3,t}$	-0.0030	0.0092	0.1161	0.1724	-0.5958	-0.0027	0.0060	0.0870	0.1356	-0.2984
$\beta_{4,t}$	-0.8471	-0.7325	0.6694	0.9640	-2.6237	-0.0043	-0.1429	0.6751	1.9231	-1.2819

	Panel I: Global Macro					Panel J: Short Selling				
	Mean	Median	Std	Max	Min	Mean	Median	Std	Max	Min
α_t	0.5486	0.5511	1.0912	3.5162	-2.5857	2.6405	2.6207	2.7751	9.5553	-3.5785
$\beta_{1,t}$	0.1828	0.1662	0.1296	0.4663	-0.2959	-0.5610	-0.5343	0.3922	0.5326	-1.8897
$\beta_{2,t}$	0.0010	-0.0052	0.1099	0.4447	-0.2402	-0.4304	-0.4560	0.1743	0.0910	-0.7944
$\beta_{3,t}$	-0.0182	-0.0210	0.1824	0.3970	-0.4776	0.2372	0.2315	0.1911	0.5691	-0.6504
$\beta_{4,t}$	-0.1349	-0.1548	0.3801	0.9751	-1.0936	-1.0620	-1.0993	0.9099	1.2409	-3.1165

Table 2: This table presents the statistics for each filtered time series of asset-based risk factor exposures (the time-varying risk exposures estimated through a Kalman filter). Each panel reports a different hedge fund strategy.

Control variable estimates

	Control Variables		
	Panel A: Long/short equity	Panel B: Market Neutral	Panel C: Event Driven
β_5	-0.0008 (0.4228)	-0.0024 (0.1528)	-0.0096 (0.0112)
β_6	-0.0004 (0.4555)	0.0061 (0.0007)	0.0004 (0.4481)
β_7	-0.0051 (0.1083)	-0.0028 (0.1128)	-0.0032 (0.2110)
β_8	-0.0120 (0.0001)	-0.0025 (0.0501)	-0.0114 (0.0001)
β_9	0.0115 (0.0052)	0.0053 (0.0165)	0.0068 (0.0616)
	Panel D: Merger Arbitrage	Panel E: Distressed Securities	Panel F: Fixed-Income Arbitrage
β_5	-0.0028 (0.1833)	-0.0097 (0.0113)	-0.0077 (0.0110)
β_6	0.0020 (0.2032)	0.0017 (0.3027)	-0.0020 (0.2262)
β_7	-0.0027 (0.1788)	-0.0062 (0.0604)	0.0008 (0.3917)
β_8	-0.0067 (0.0002)	-0.0095 (0.0001)	-0.0051 (0.0034)
β_9	-0.0025 (0.2206)	0.0077 (0.0422)	0.0073 (0.0188)
	Panel G: Convertible Arbitrage	Panel H: Relative Value	Panel I: Global Macro
β_5	-0.0012 (0.3641)	-0.0025 (0.1903)	0.0119 (0.0089)
β_6	-0.0020 (0.2469)	-0.0017 (0.2173)	0.0137 (0.0004)
β_7	-0.0047 (0.0804)	-0.0031 (0.1254)	0.0043 (0.1871)
β_8	-0.0092 (0.0001)	-0.0083 (0.0001)	-0.0104 (0.0004)
β_9	0.0133 (0.0004)	0.0025 (0.1939)	0.0101 (0.0279)
	Panel J: Short Selling		
β_5	0.0255 (0.0126)		
β_6	0.0064 (0.2401)		
β_7	0.0033 (0.3838)		
β_8	0.0110 (0.0516)		
β_9	-0.0127 (0.1473)		

Table 3: This table presents estimates for the option-like risk factors used as control variables (the p-values are presented in parentheses). Each panel reports a different hedge fund strategy.

Macro variable estimates

	Panel A: Long/short equity				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0059 (0.0010)	$\delta_{1,2}$ =0.1581 (0.0001)	$\delta_{1,3}$ =-0.0027 (0.0860)	$\delta_{1,4}$ =-0.2710 (0.0388)	$\delta_{1,5}$ =-0.0146 (0.1439)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0031 (0.1793)	$\delta_{2,2}$ =0.0459 (0.1066)	$\delta_{2,3}$ =0.0090 (0.0123)	$\delta_{2,4}$ =0.8082 (0.0009)	$\delta_{2,5}$ =0.0545 (0.0105)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0168 (0.0564)	$\delta_{3,2}$ =0.1361 (0.0012)	$\delta_{3,3}$ =-0.0012 (0.4096)	$\delta_{3,4}$ =-0.3134 (0.1536)	$\delta_{3,5}$ =-0.1360 (0.0207)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0617 (0.0028)	$\delta_{4,2}$ =0.1438 (0.2553)	$\delta_{4,3}$ =-0.0094 (0.2569)	$\delta_{4,4}$ =-1.1239 (0.1398)	$\delta_{4,5}$ =-0.6384 (0.0003)
	Panel B: Market Neutral				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0045 (0.0001)	$\delta_{1,2}$ =0.0666 (0.0002)	$\delta_{1,3}$ =-0.0015 (0.0898)	$\delta_{1,4}$ =-0.0839 (0.1634)	$\delta_{1,5}$ =-0.0235 (0.0012)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0038 (0.0210)	$\delta_{2,2}$ =0.0276 (0.0852)	$\delta_{2,3}$ =0.0123 (0.0001)	$\delta_{2,4}$ =-0.0864 (0.2705)	$\delta_{2,5}$ =0.0090 (0.2462)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0091 (0.0298)	$\delta_{3,2}$ =0.0317 (0.0851)	$\delta_{3,3}$ =-0.0020 (0.2419)	$\delta_{3,4}$ =0.1547 (0.1617)	$\delta_{3,5}$ =-0.0251 (0.2173)
$\beta_{4,t}$	$\delta_{4,1}$ =0.0116 (0.1580)	$\delta_{4,2}$ =0.3211 (0.0033)	$\delta_{4,3}$ =0.0154 (0.0288)	$\delta_{4,4}$ =1.3363 (0.0094)	$\delta_{4,5}$ =0.0297 (0.3814)
	Panel C: Event Driven				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0009 (0.3053)	$\delta_{1,2}$ =0.1440 (0.0001)	$\delta_{1,3}$ =0.0022 (0.1279)	$\delta_{1,4}$ =0.1371 (0.1809)	$\delta_{1,5}$ =0.0117 (0.1900)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0062 (0.0281)	$\delta_{2,2}$ =0.0102 (0.3820)	$\delta_{2,3}$ =0.0096 (0.0061)	$\delta_{2,4}$ =0.6394 (0.0053)	$\delta_{2,5}$ =0.0674 (0.0015)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0083 (0.0225)	$\delta_{3,2}$ =0.0804 (0.0070)	$\delta_{3,3}$ =-0.0054 (0.0762)	$\delta_{3,4}$ =0.2230 (0.1448)	$\delta_{3,5}$ =-0.0263 (0.2226)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0436 (0.0765)	$\delta_{4,2}$ =0.0920 (0.3487)	$\delta_{4,3}$ =-0.0025 (0.4307)	$\delta_{4,4}$ =0.9997 (0.1768)	$\delta_{4,5}$ =-0.6422 (0.0008)
	Panel D: Merger Arbitrage				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0014 (0.1479)	$\delta_{1,2}$ =0.0552 (0.0101)	$\delta_{1,3}$ =0.0020 (0.0770)	$\delta_{1,4}$ =0.0485 (0.3299)	$\delta_{1,5}$ =0.0178 (0.0358)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0036 (0.0695)	$\delta_{2,2}$ =0.0076 (0.3825)	$\delta_{2,3}$ =0.0040 (0.0756)	$\delta_{2,4}$ =0.2898 (0.0558)	$\delta_{2,5}$ =0.0450 (0.0039)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0059 (0.0272)	$\delta_{3,2}$ =0.0632 (0.0042)	$\delta_{3,3}$ =0.0005 (0.4333)	$\delta_{3,4}$ =0.0136 (0.4652)	$\delta_{3,5}$ =-0.0115 (0.3230)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0074 (0.3165)	$\delta_{4,2}$ =0.1055 (0.2449)	$\delta_{4,3}$ =0.0093 (0.1899)	$\delta_{4,4}$ =0.0562 (0.4696)	$\delta_{4,5}$ =-0.2099 (0.0598)

	Panel E: Distressed Securities				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0021 (0.1239)	$\delta_{1,2}$ =0.1309 (0.0001)	$\delta_{1,3}$ =0.0031 (0.0639)	$\delta_{1,4}$ =0.2512 (0.0536)	$\delta_{1,5}$ =-0.0029 (0.4146)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0040 (0.1036)	$\delta_{2,2}$ =0.0352 (0.1516)	$\delta_{2,3}$ =0.0107 (0.0029)	$\delta_{2,4}$ =0.5038 (0.0248)	$\delta_{2,5}$ =0.0399 (0.0388)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0072 (0.0428)	$\delta_{3,2}$ =0.0407 (0.1130)	$\delta_{3,3}$ =-0.0049 (0.1159)	$\delta_{3,4}$ =0.3909 (0.0362)	$\delta_{3,5}$ =-0.0498 (0.0786)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0776 (0.0550)	$\delta_{4,2}$ =-0.1550 (0.2913)	$\delta_{4,3}$ =-0.0223 (0.0910)	$\delta_{4,4}$ =0.9533 (0.2403)	$\delta_{4,5}$ =-0.6990 (0.0030)
	Panel F: Fixed-Income Arbitrage				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =0.0092 (0.2838)	$\delta_{1,2}$ =0.1464 (0.0007)	$\delta_{1,3}$ =0.0026 (0.1469)	$\delta_{1,4}$ =-0.0610 (0.3920)	$\delta_{1,5}$ =-0.0655 (0.1284)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0045 (0.0316)	$\delta_{2,2}$ =-0.0043 (0.4386)	$\delta_{2,3}$ =0.0039 (0.1165)	$\delta_{2,4}$ =0.2759 (0.0911)	$\delta_{2,5}$ =0.0430 (0.0059)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0078 (0.0079)	$\delta_{3,2}$ =0.0677 (0.0109)	$\delta_{3,3}$ =-0.0049 (0.0823)	$\delta_{3,4}$ =0.0780 (0.3408)	$\delta_{3,5}$ =-0.0515 (0.0284)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0540 (0.0657)	$\delta_{4,2}$ =0.2852 (0.0847)	$\delta_{4,3}$ =-0.0211 (0.0740)	$\delta_{4,4}$ =-0.2290 (0.4118)	$\delta_{4,5}$ =-0.4577 (0.0109)
	Panel G: Convertible Arbitrage				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0021 (0.0936)	$\delta_{1,2}$ =0.1056 (0.0002)	$\delta_{1,3}$ =0.0037 (0.0258)	$\delta_{1,4}$ =-0.1172 (0.2185)	$\delta_{1,5}$ =-0.0396 (0.0010)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0025 (0.1790)	$\delta_{2,2}$ =0.0559 (0.0269)	$\delta_{2,3}$ =0.0050 (0.0724)	$\delta_{2,4}$ =0.1919 (0.2017)	$\delta_{2,5}$ =0.0315 (0.0562)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0033 (0.1885)	$\delta_{3,2}$ =0.0379 (0.1085)	$\delta_{3,3}$ =-0.0044 (0.1436)	$\delta_{3,4}$ =0.7363 (0.0001)	$\delta_{3,5}$ =0.0037 (0.4543)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0601 (0.2428)	$\delta_{4,2}$ =0.0944 (0.3977)	$\delta_{4,3}$ =-0.0458 (0.0090)	$\delta_{4,4}$ =-0.6970 (0.3626)	$\delta_{4,5}$ =-0.0486 (0.4453)
	Panel H: Relative Value				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0043 (0.0002)	$\delta_{1,2}$ =0.0944 (0.0001)	$\delta_{1,3}$ =-0.0010 (0.2307)	$\delta_{1,4}$ =-0.2398 (0.0090)	$\delta_{1,5}$ =-0.0254 (0.0023)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0033 (0.0644)	$\delta_{2,2}$ =-0.0207 (0.1817)	$\delta_{2,3}$ =0.0039 (0.0616)	$\delta_{2,4}$ =0.5908 (0.0002)	$\delta_{2,5}$ =0.0489 (0.0006)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0058 (0.0184)	$\delta_{3,2}$ =0.0781 (0.0002)	$\delta_{3,3}$ =-0.0014 (0.2895)	$\delta_{3,4}$ =0.2563 (0.0352)	$\delta_{3,5}$ =-0.0215 (0.1742)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0543 (0.0086)	$\delta_{4,2}$ =0.0895 (0.2901)	$\delta_{4,3}$ =-0.0233 (0.0109)	$\delta_{4,4}$ =-0.1795 (0.4050)	$\delta_{4,5}$ =-0.7166 (0.0001)

	Panel I: Global Macro				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =-0.0063 (0.0551)	$\delta_{1,2}$ =0.1846 (0.0001)	$\delta_{1,3}$ =-0.0041 (0.0547)	$\delta_{1,4}$ =-0.4724 (0.0067)	$\delta_{1,5}$ =-0.0545 (0.0485)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0045 (0.1276)	$\delta_{2,2}$ =0.0595 (0.0912)	$\delta_{2,3}$ =0.0148 (0.0011)	$\delta_{2,4}$ =0.5317 (0.0408)	$\delta_{2,5}$ =0.0691 (0.0074)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0179 (0.0998)	$\delta_{3,2}$ =0.1205 (0.0161)	$\delta_{3,3}$ =-0.0038 (0.2605)	$\delta_{3,4}$ =-0.5156 (0.0854)	$\delta_{3,5}$ =-0.1481 (0.0383)
$\beta_{4,t}$	$\delta_{4,1}$ =-0.0283 (0.0997)	$\delta_{4,2}$ =0.3082 (0.0978)	$\delta_{4,3}$ =0.0127 (0.2260)	$\delta_{4,4}$ =0.0446 (0.4849)	$\delta_{4,5}$ =-0.3166 (0.0532)
	Panel J: Short Selling				
	ΔDIV	$\Delta RREL$	ΔVIX	ΔGDP	$\Delta VIX * \Delta GDP$
$\beta_{1,t}$	$\delta_{1,1}$ =0.0032 (0.4583)	$\delta_{1,2}$ =-0.1929 (0.0622)	$\delta_{1,3}$ =-0.0025 (0.3581)	$\delta_{1,4}$ =-0.3701 (0.2540)	$\delta_{1,5}$ =-0.2002 (0.0677)
$\beta_{2,t}$	$\delta_{2,1}$ =0.0078 (0.1890)	$\delta_{2,2}$ =-0.0259 (0.4038)	$\delta_{2,3}$ =-0.0055 (0.3119)	$\delta_{2,4}$ =-1.1678 (0.0470)	$\delta_{2,5}$ =-0.0137 (0.4142)
$\beta_{3,t}$	$\delta_{3,1}$ =-0.0068 (0.2765)	$\delta_{3,2}$ =0.0524 (0.3029)	$\delta_{3,3}$ =-0.0188 (0.0533)	$\delta_{3,4}$ =0.1192 (0.4269)	$\delta_{3,5}$ =0.0582 (0.2683)
$\beta_{4,t}$	$\delta_{4,1}$ =0.1126 (0.0119)	$\delta_{4,2}$ =0.0327 (0.4752)	$\delta_{4,3}$ =0.0167 (0.3394)	$\delta_{4,4}$ =0.8391 (0.3760)	$\delta_{4,5}$ =0.7063 (0.0511)

Table 4: This table presents the estimates for the beta's exposure to five macroeconomic variables (namely, ΔDIV, $\Delta RREL$, ΔVIX, ΔGDP and $\Delta VIX * \Delta GDP$). Each panel reports a different hedge fund strategy and the corresponding estimated coefficients, with the p-values in parentheses.

		1 month			6 months			36 months		
		Idiosyncratic	US market	Predictors	Idiosyncratic	US market	Predictors	Idiosyncratic	US market	Predictors
Long/short equity	β_1	53.36	2.32	44.32	20.22	1.25	78.53	11.19	1.34	87.47
	β_2	58.44	6.50	35.07	28.57	2.28	69.14	34.31	2.68	63.01
	β_3	74.15	0.12	25.73	51.75	0.97	47.28	26.98	1.41	71.61
	β_4	79.94	2.06	17.99	67.26	1.72	31.03	40.79	0.96	58.25
Market Neutral	β_1	62.76	2.55	34.69	36.41	1.14	62.44	19.62	1.27	79.11
	β_2	52.27	22.14	25.59	20.60	8.33	71.07	15.97	6.53	77.50
	β_3	76.59	1.48	21.92	55.99	1.50	42.51	26.42	1.25	72.33
	β_4	57.65	3.11	39.23	24.27	1.58	74.15	20.66	1.97	77.37
Event Driven	β_1	52.95	0.50	46.55	19.65	0.83	79.52	10.84	1.33	87.83
	β_2	62.20	7.62	30.17	32.91	2.38	64.71	32.03	2.31	65.65
	β_3	61.23	8.34	30.43	26.85	3.37	69.78	12.15	1.90	85.95
	β_4	91.10	0.06	8.84	86.71	2.56	10.74	67.95	1.92	30.13
Merger Arbitrage	β_1	62.29	1.68	36.03	33.01	0.90	66.09	23.21	1.45	75.33
	β_2	63.20	6.41	30.39	38.19	1.92	59.89	34.48	1.62	63.90
	β_3	56.61	0.01	43.38	21.82	0.70	77.48	10.49	1.34	88.17
	β_4	70.79	4.13	25.08	45.26	0.54	54.21	34.50	0.18	65.32
Distressed Securities	β_1	48.46	1.97	49.57	16.28	1.48	82.25	8.98	1.62	89.40
	β_2	61.53	9.88	28.59	30.15	3.99	65.86	30.00	3.99	66.01
	β_3	62.22	6.82	30.96	39.42	3.05	57.53	15.06	1.67	83.27
	β_4	83.83	1.53	14.64	79.12	3.50	17.38	64.53	2.55	32.92
Fixed-Income Arbitrage	β_1	84.16	0.01	15.83	77.70	0.03	22.27	70.93	0.10	28.97
	β_2	63.19	7.11	29.70	38.81	1.97	59.22	35.42	1.67	62.91
	β_3	67.13	6.59	26.28	46.65	2.52	50.83	27.39	2.21	70.40
	β_4	78.10	4.29	17.61	71.02	1.99	26.99	70.34	1.64	28.03

Convertible Arbitrage	β_1	60.68	1.70	37.62	29.92	0.53	69.55	19.16	0.55	80.29
	β_2	63.59	5.40	31.01	33.96	2.08	63.97	28.91	2.08	69.01
	β_3	48.51	7.99	43.50	42.93	1.71	55.36	31.51	0.80	67.68
	β_4	84.51	4.31	11.17	73.69	3.13	23.18	71.26	3.10	25.63
Relative Value	β_1	59.06	1.12	39.82	28.65	0.67	70.68	17.61	0.86	81.52
	β_2	52.06	5.50	42.44	26.98	1.41	71.60	28.83	1.24	69.93
	β_3	57.96	1.86	40.18	23.49	1.41	75.10	12.00	1.43	86.57
	β_4	79.68	3.96	16.36	68.27	3.09	28.64	63.94	2.63	33.43
Global Macro	β_1	59.49	3.35	37.17	29.05	1.39	69.56	18.87	1.40	79.74
	β_2	63.68	8.92	27.41	32.23	3.35	64.42	31.26	3.30	65.44
	β_3	78.03	0.48	21.48	57.50	1.11	41.40	41.86	1.46	56.67
	β_4	66.94	1.59	31.47	45.65	0.24	54.11	31.31	0.15	68.54
Short Selling	β_1	94.39	0.01	5.59	92.50	0.06	7.43	86.21	0.08	13.71
	β_2	49.40	5.33	45.26	61.50	2.65	35.85	64.33	2.64	33.03
	β_3	58.98	15.54	25.48	19.76	4.43	75.81	14.79	3.23	81.98
	β_4	80.05	3.20	16.75	67.33	2.90	29.77	45.58	1.65	52.77
Mean		66.03	4.44	29.53	43.55	2.02	54.43	33.79	1.79	64.42
Min		48.46	0.01	5.59	16.28	0.03	7.43	8.98	0.08	13.71
Max		94.39	22.14	49.57	92.50	8.33	82.25	86.21	6.53	89.40

Table 5: This table presents the forecast-error variance decomposition of betas by using the VAR representation described in Section 5.2 from February 1997 to August 2019

		1 month			6 months			36 months		
		Idiosyncratic	US market	Predictors	Idiosyncratic	US market	Predictors	Idiosyncratic	US market	Predictors
Long/short equity	β_1	52.06	7.46	40.48	19.11	2.65	78.25	6.95	1.17	91.87
	β_2	57.03	18.67	24.31	31.69	6.17	62.13	29.18	4.69	66.14
	β_3	90.16	0.54	9.30	70.48	0.30	29.22	20.71	0.14	79.16
	β_4	76.69	2.91	20.40	51.89	0.59	47.52	26.85	0.42	72.73
Market Neutral	β_1	61.48	7.89	30.63	21.77	1.99	76.24	5.34	0.62	94.04
	β_2	50.68	35.09	14.22	13.84	9.73	76.42	13.30	9.36	77.34
	β_3	84.41	3.11	12.47	41.82	0.79	57.38	17.83	0.36	81.80
	β_4	52.25	22.94	24.81	21.33	7.35	71.32	11.88	3.55	84.58
Event Driven	β_1	54.46	9.24	36.30	18.51	3.16	78.33	4.97	0.82	94.21
	β_2	60.33	19.65	20.02	28.69	6.67	64.63	26.58	5.67	67.75
	β_3	56.84	19.80	23.35	18.24	5.94	75.82	9.72	3.07	87.21
	β_4	89.32	0.24	10.44	83.99	0.14	15.87	77.75	0.07	22.18
Merger Arbitrage	β_1	65.32	15.65	19.03	29.08	5.87	65.05	12.86	2.57	84.57
	β_2	63.47	15.87	20.66	30.28	5.14	64.58	27.65	4.18	68.17
	β_3	57.05	2.08	40.87	16.18	0.60	83.22	2.33	0.16	97.50
	β_4	77.77	13.19	9.04	48.93	2.68	48.39	23.81	1.08	75.11
Distressed Securities	β_1	50.97	14.57	34.46	16.26	4.24	79.50	7.03	1.39	91.58
	β_2	56.79	26.28	16.93	21.82	8.72	69.46	20.30	7.74	71.96
	β_3	59.39	14.31	26.30	23.17	4.21	72.62	16.12	2.52	81.37
	β_4	83.53	1.85	14.63	70.88	1.37	27.75	64.55	1.11	34.34
Fixed-Income Arbitrage	β_1	95.18	0.51	4.31	94.16	0.32	5.52	92.22	0.31	7.46
	β_2	63.11	16.13	20.75	29.78	5.17	65.04	25.52	4.03	70.45
	β_3	65.89	16.20	17.91	25.52	4.47	70.01	11.76	2.06	86.18
	β_4	77.02	5.34	17.64	55.55	2.04	42.40	42.25	1.40	56.35

Convertible Arbitrage	β_1	63.39	13.40	23.21	21.81	3.32	74.87	5.21	0.92	93.87
	β_2	62.52	22.31	15.17	26.29	7.94	65.77	21.64	6.41	71.94
	β_3	48.91	10.86	40.23	34.54	4.12	61.34	40.05	3.48	56.48
	β_4	85.21	5.13	9.66	68.36	2.91	28.73	64.89	2.77	32.34
Relative Value	β_1	53.90	2.53	43.57	19.34	1.19	79.47	7.79	0.77	91.45
	β_2	53.78	11.58	34.64	32.83	3.38	63.79	32.49	2.08	65.43
	β_3	52.22	4.30	43.48	18.68	1.04	80.28	15.82	0.43	83.76
	β_4	73.99	6.40	19.61	43.75	1.28	54.97	42.20	0.87	56.93
Global Macro	β_1	59.97	6.45	33.58	24.05	1.70	74.26	7.46	0.73	91.81
	β_2	59.58	25.71	14.71	23.07	8.75	68.17	21.77	8.09	70.14
	β_3	85.18	1.77	13.05	52.63	0.34	47.04	8.64	0.21	91.15
	β_4	76.17	11.05	12.78	47.29	2.24	50.47	12.36	0.51	87.13
Short Selling	β_1	97.10	1.25	1.66	94.63	0.42	4.96	78.67	0.30	21.03
	β_2	51.52	12.74	35.75	54.01	2.42	43.57	40.82	1.30	57.88
	β_3	53.78	29.35	16.87	14.06	7.53	78.41	13.84	7.41	78.75
	β_4	76.47	7.01	16.52	49.48	1.17	49.34	46.34	0.58	53.07
Mean		66.37	11.53	22.09	37.69	3.50	58.80	26.44	2.38	71.18
Min		48.91	0.24	1.66	13.84	0.14	4.96	2.33	0.07	7.46
Max		97.10	35.09	43.57	94.63	9.73	83.22	92.22	9.36	97.50

Table 6: This table presents the forecast-error variance decomposition of betas by using the VAR representation described in Section 5.2 from January 2010 to August 2019

Appendix of figures

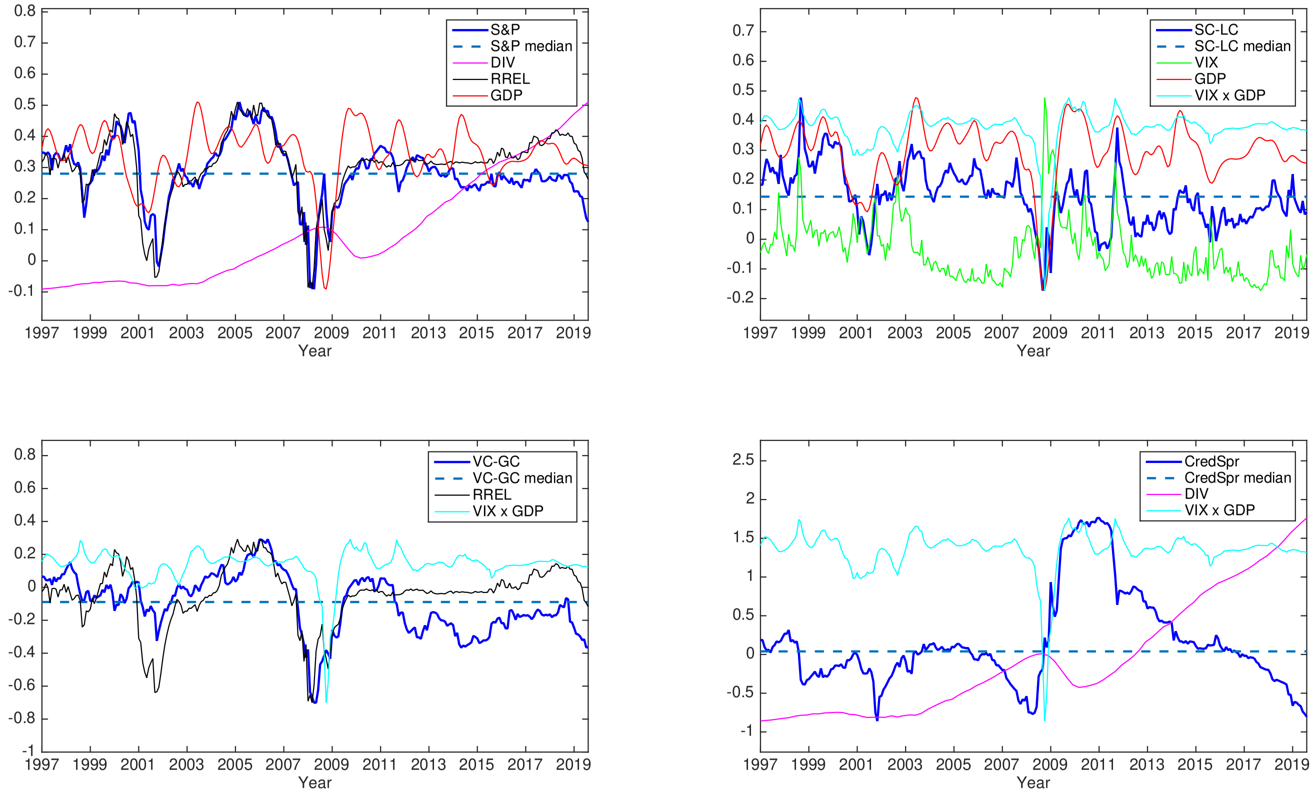

Figure 1: This figure presents the long/short equity strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

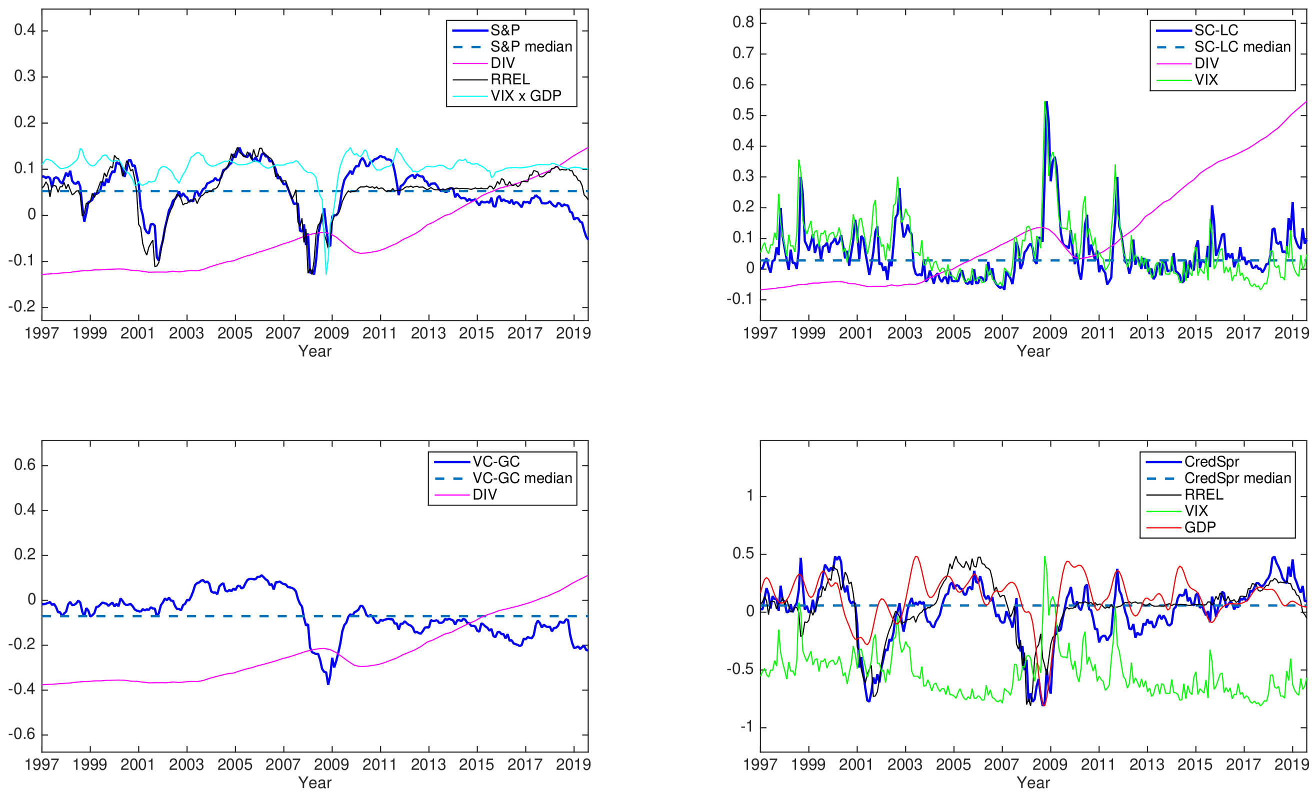

Figure 2: This figure presents the market neutral strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

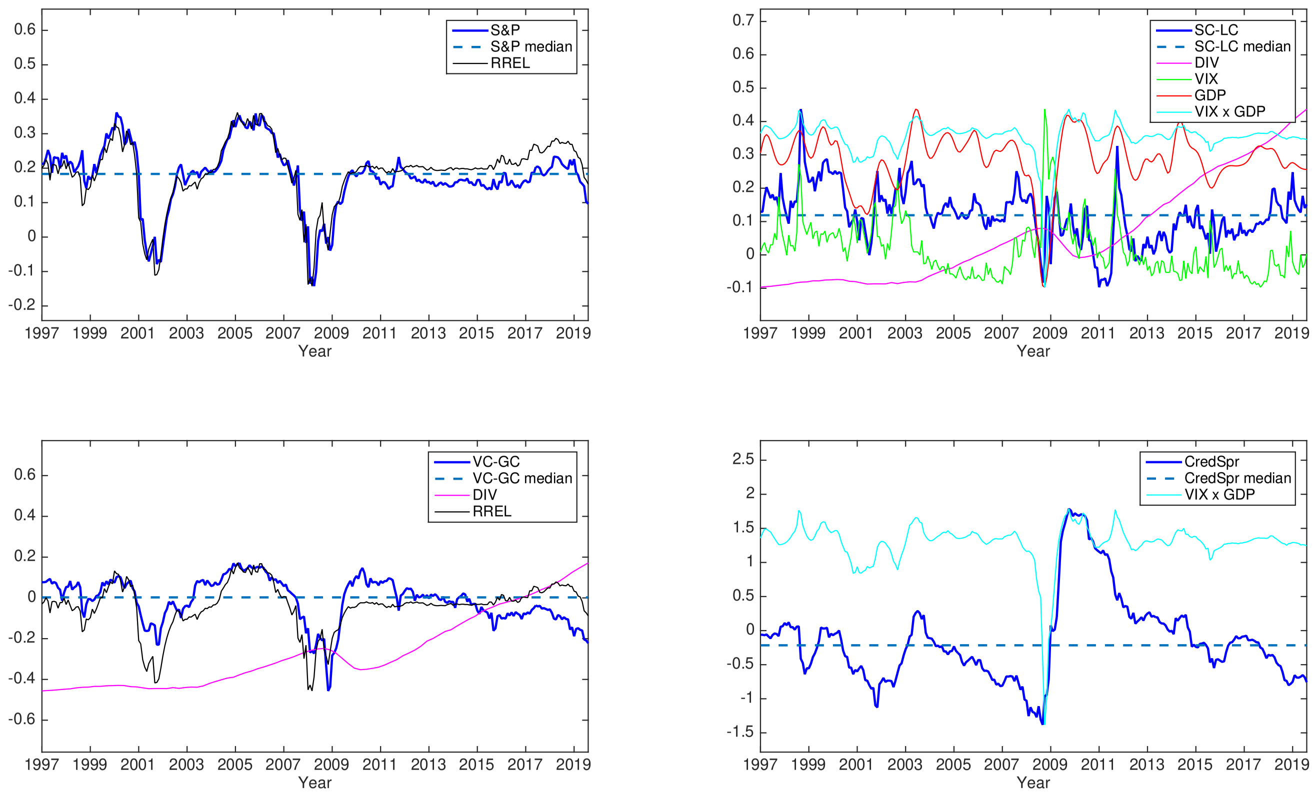

Figure 3: This figure presents the event driven strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

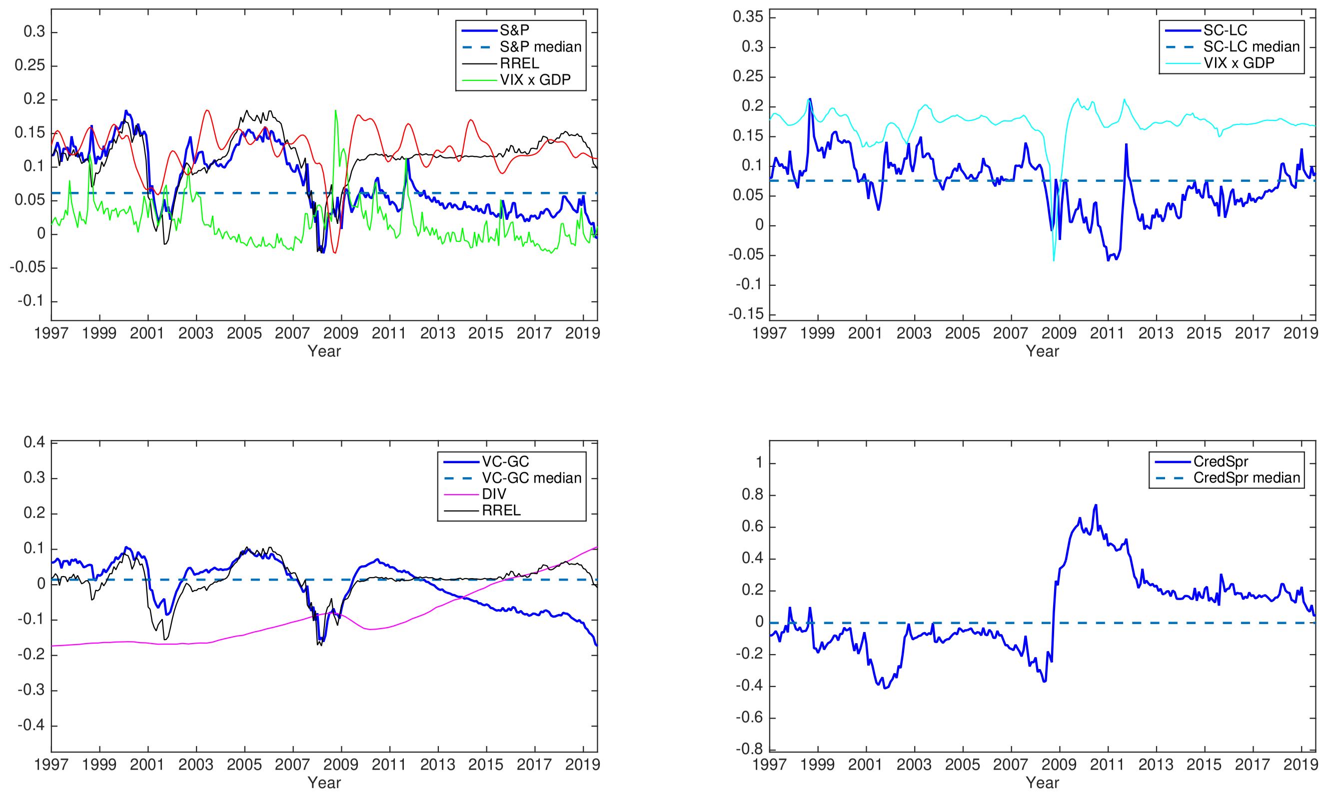

Figure 4: This figure presents the merger-arbitrage strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

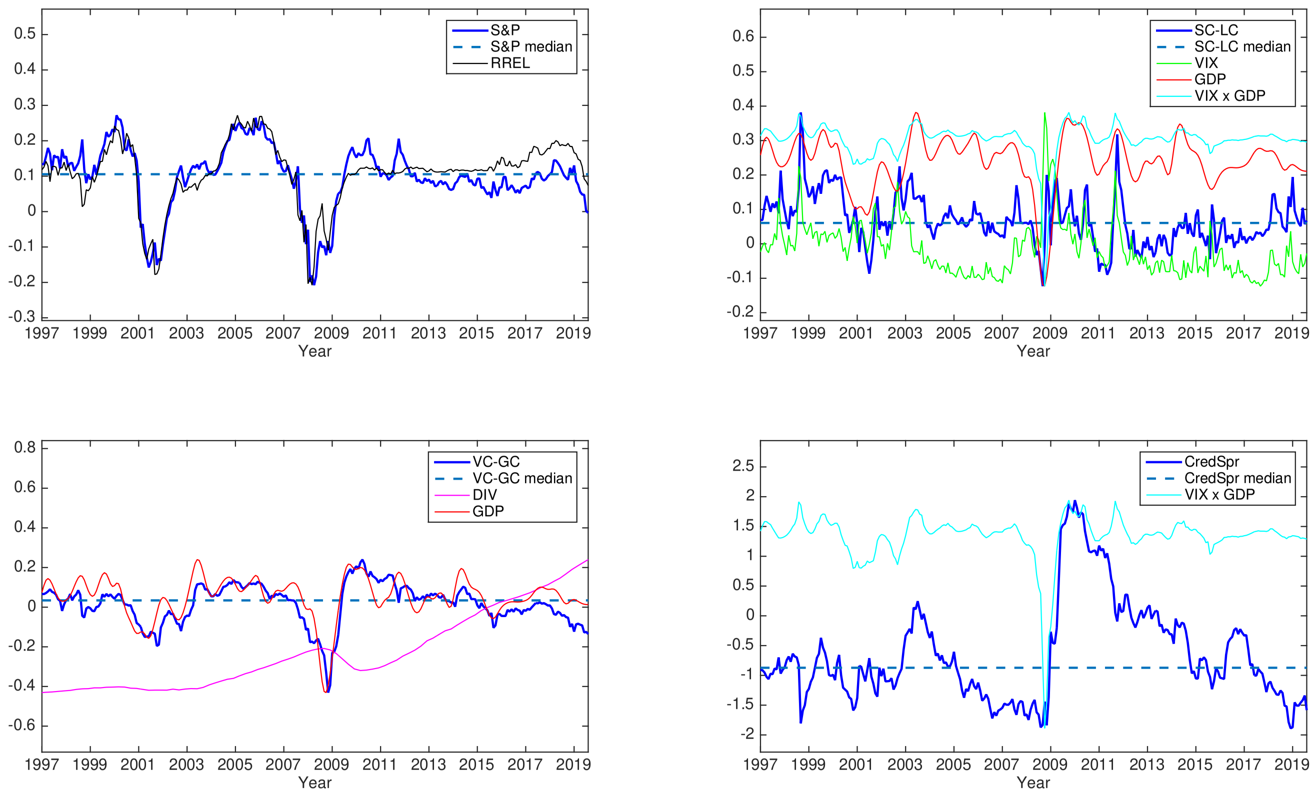

Figure 5: This figure presents the distressed securities strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

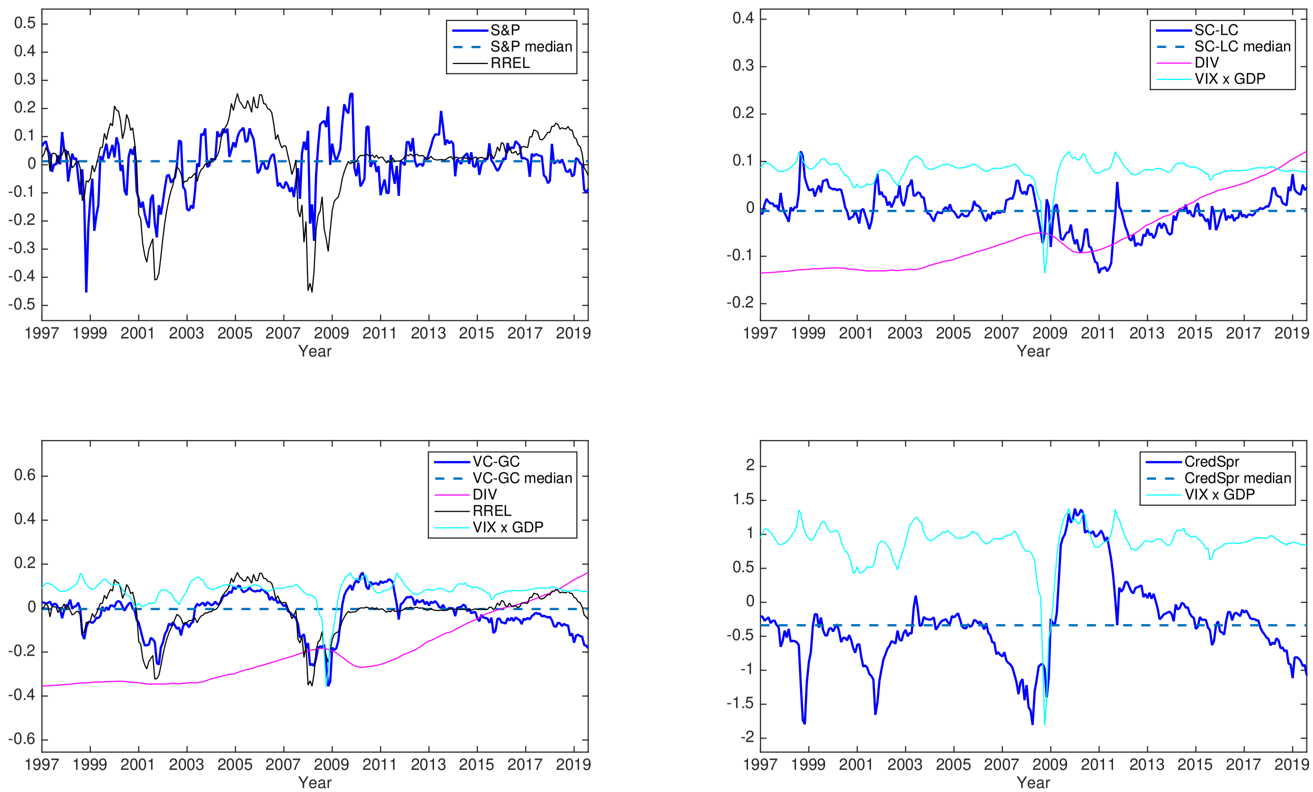

Figure 6: This figure presents the fixed income arbitrage strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

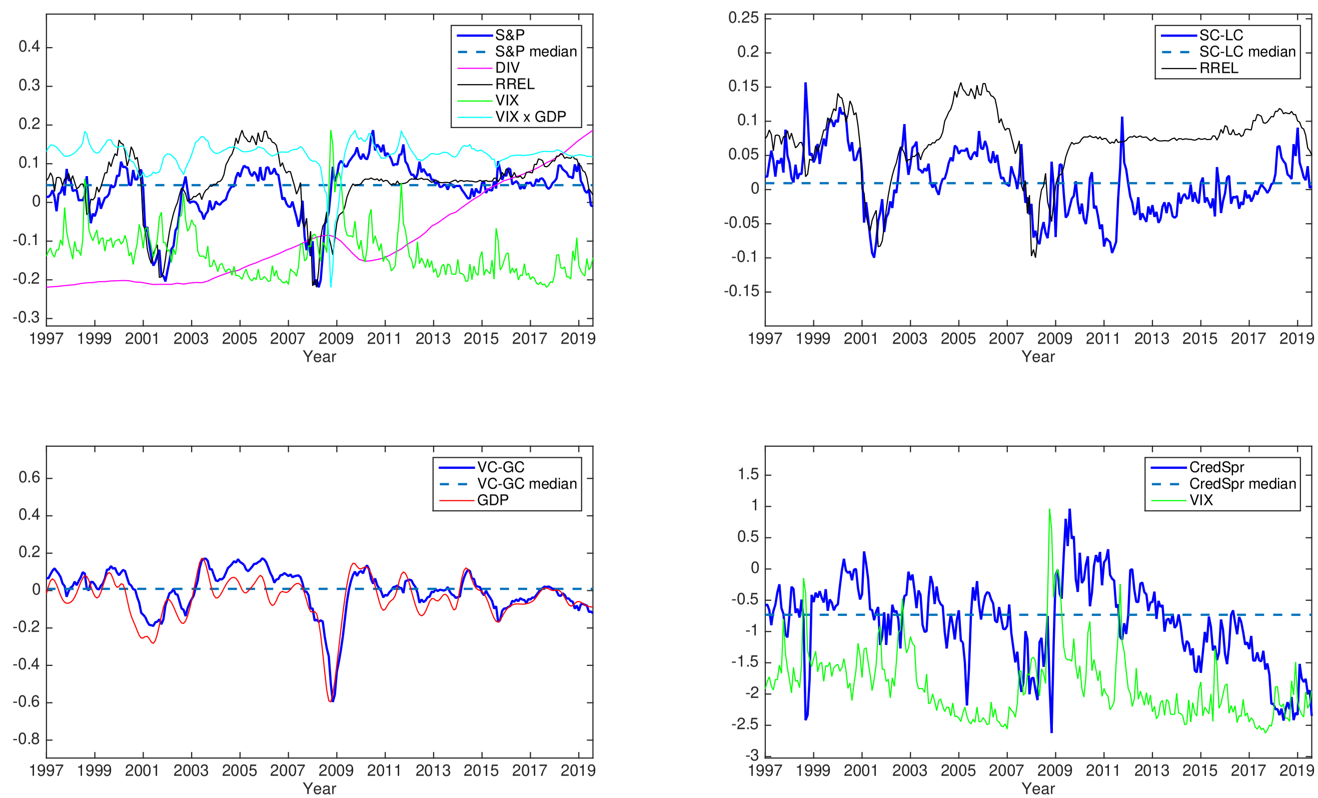

Figure 7: This figure presents the convertible arbitrage strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

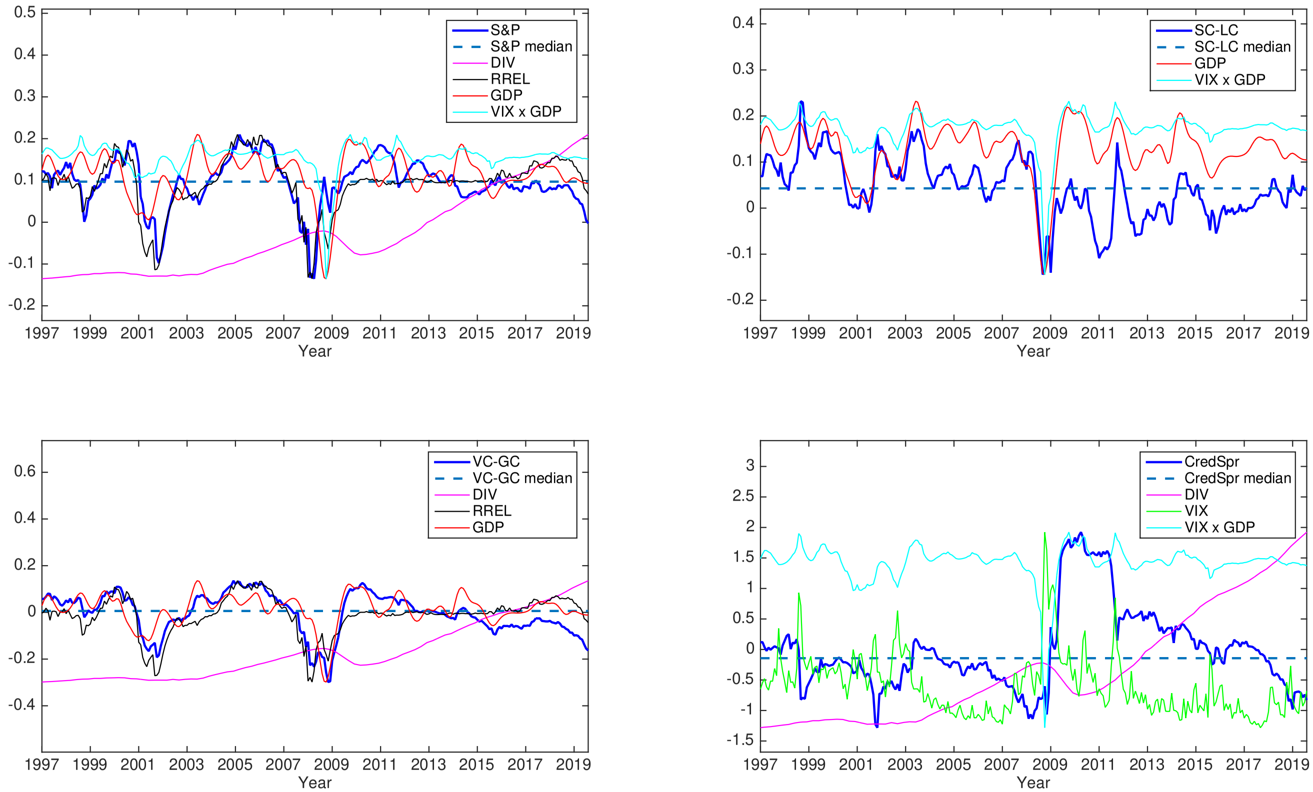

Figure 8: This figure presents the relative value strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

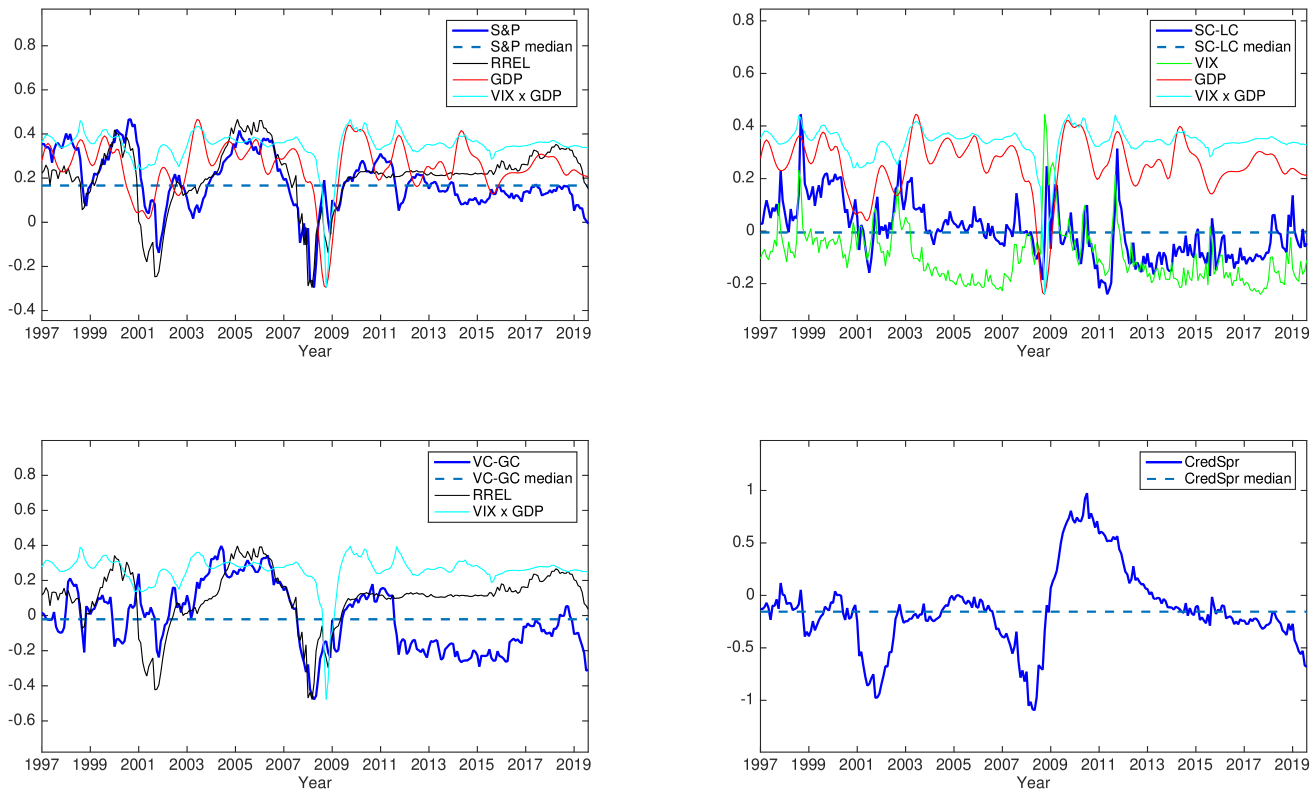

Figure 9: This figure presents the global macro strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.

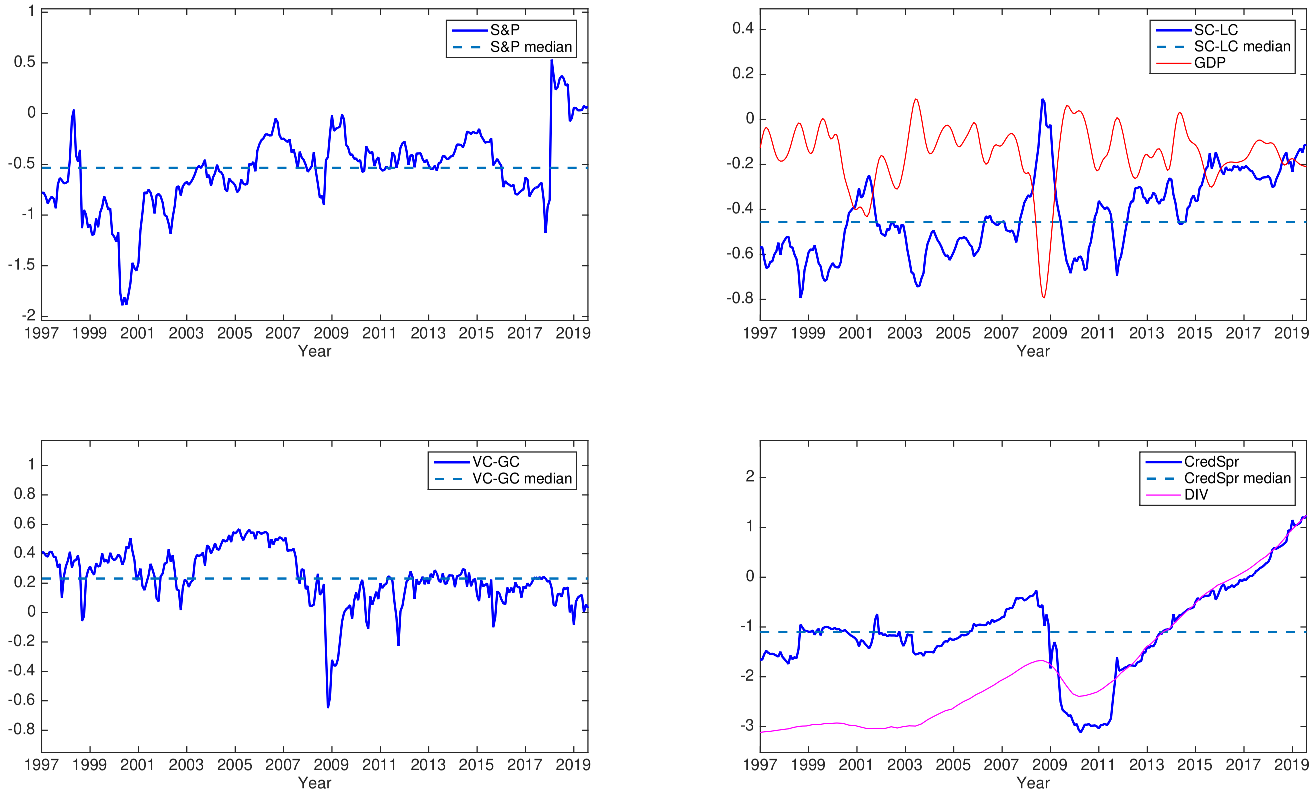

Figure 10: This figure presents the short selling strategy's time-varying exposure to risk factors (upper-left graph: S&P, upper-right graph: SC-LC, lower-left graph: VC-GC, and lower-right graph: CredSpr) obtained by the Kalman filter and the relevant macroeconomic variables from February 1997 to August 2019. Note that macroeconomic variables are scaled.