Do higher moments risk premia compensate for macroeconomic risk? *

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Abstract

In this paper I investigate whether the risk premia associated with higher moments such as variance, skewness and kurtosis bears compensation for macroeconomic risk. I introduce a new measure for kurtosis risk premia and show that the higher moment risk premia are related to macroeconomic risk. In particular, the results suggest that (i) different risk premia compensates for different macroeconomic risks; (ii) there is asymmetrical relationship with macroeconomic risks and (iii) the risk premia is driven by two common factors, which are related to VIX and financial constraints

Higher moment risk premia is the cost investors need to pay to get protection against variance, skewness or kurtosis. The rising demand for such protection got wide media coverage[1] and is of a particular interest from academic perspective. On one hand, there is an evidence that it can be traded in the market and is time-varying (see for instance, Bollerslev, Tauchen, and Zhou (2009), Kozhan, Neuberger, and Schneider (2013) and Harris and Qiao (2017)). On the other hand, little is known what determines the size of the premia.

Kozhan et al. (2013) and Schneider (2015) suggest that the size of higher moment risk premia is determined by some common risk factor, which is related to risk aversion. However, it is not clear what this factor is; whether any other factors exist and whether they affect all types of higher moment risk premia or just a specific one. Finally, due to evidence that higher moments such as variance, skewness and kurtosis are linked to macroeconomic conditions (see for example, Perez-Quiros and Timmermann (2001), Flannery and Protopapadakis (2002) and Ghysels, Plazzi, and Valkanov (2011)), the relevant question is whether factors that determine the cost of insurance[2] against higher moment risk are also related to macroeconomy.

From a practitioners point of view such knowledge is valuable for both buyers and sellers of the protection. On buy side, investors are willing to buy such insurance due to higher moment preferences (see for example, crash aversion in Rubinstein (1994), preferences for positive skewness in Barberis and Huang (2008) and disaster risk aversion Gourio (2012)), whereas on sell side profits from selling such insurance are positively related to hedge funds alphas as indicated by Bondarenko (2004). Vague understanding of what determines the cost of such insurance and how it behaves in different macroeconomic environments may result in poor risk management and subsequent losses.

To identify factors that determine size of higher moment risk premia and its relation to macroeconomic conditions, I investigate whether macroeconomic variables can explain the cost of protection against variance, skewness and kurtosis. In particular, I introduce a new measure to estimate

[1] Relevant news pages include:
"Investors demand extreme risk protection", *Financial Times, 2009* https://www.ft.com/content/0c0b6734-ecc6-11de-8070-00144feab49a
"Pimco Sells Black Swan Protection as Wall Street Markets Fear", *Bloomberg, 2010* https://www.bloomberg.com/news/articles/2010-07-20/pimco-sells-black-swan-protection-as-wall-street-profits-from-selling-fear
"Investors Boost Stock Hedges at Fastest Pace in More Than a Year", *Bloomberg, 2017* https://www.bloomberg.com/news/articles/2017-09-12/investors-boost-stock-hedges-at-fastest-pace-in-more-than-a-year

[2] Here and further in the paper words "insurance" and "protection" are used interchangeably

kurtosis risk premia (KRP) by extending Neuberger (2012) and Kozhan et al. (2013) models, who show that higher moment risk premia can be approximated with a swap contract that exchanges the variability in higher moments risk. I construct monthly measures of moments risk premia for variance (VRP), skewness (SRP) and kurtosis (KRP) with daily data on options on S&P 500 futures from OptionMetrics for the period from January 1996 to December 2017.

The choice of macroeconomic variables is based on previous evidence that higher moments are related to tight financial constraints, hedging and tail risk (Gennotte and Leland (1990), Yuan (2005), Adrian and Rosenberg (2008) and Bali, Brown, and Caglayan (2012)). The list of macroeconomic variables is close to the one in Beber, Brandt, and Luisi (2015) and divided in groups for Inflation, Output, Employment and Sentiment. In addition, I introduce variables related to cost of borrowing in the economy, which I group as Financial Constraints. All of the data was taken from St.Louis FRED and spans the period from 1980 to 2017. For every sample day I extract the first principal component for each category, while making adjustments for different series lengths and persistence as discussed in Beber et al. (2015). In addition, I include VIX due to evidence that it has forecasting power over higher moments as in Neumann and Skiadopoulos (2013).

I use ordinary and quantile regressions to investigate the relationship between higher moment risk premia (VRP, SRP and KRP) and macroeconomic components. The results confirm that higher moment risk premia are related to macroeconomic risk, but such relationship is not symmetric. In particular, the compensation for macroeconomic risks are the most pronounced in times, when higher moment risk premia is the most positive (i.e. when investor gets compensated for higher moment risk), but is weak in times of more negative premia (i.e. when investor bears costs of hedging). Moreover, the results suggest that there are two common factors: VIX and Financial Constraints that drive the variation in higher moment risk premia, while only SRP and KRP appear to provide compensation for low Sentiment and Inflation. The first finding complements previous suggestions by Kozhan et al. (2013) and Schneider (2015), who suggest that common variation is due to risk aversion. The second, on the other hand, is interesting as it suggest that even though there are common factors, each higher moment is related to other macroeconomic components and such relation appears to be more related to the size of compensation for the higher moment risk tan to hedging costs. Finally, the results confirm previous findings of Kozhan et al. (2013) and Harris and Qiao (2017) that investors pay premia to hedge the exposure for higher moment risk.

The paper has twofold contribution to the literature on higher moments risk premia. First, I introduce the measure of KRP by extending the models of Neuberger (2012) and Kozhan et al. (2013). Unlike previous measures of KRP as in Zhao, Zhang, and Chang (2013), Chang, Christoffersen, and Jacobs (2013) and Harris and Qiao (2017), the newly introduced measure has a straightforward interpretation of a trading strategy as well as it grows with time horizon, which is alongside Bansal and Yaron (2004) long-run risk. Second, I show that higher moment risk premia bears compensation for macroeconomic risk and that such compensation is not the same across different types of premia. To author's best knowledge, it is the first paper to investigate the link between higher moment risk premia and macroeconomy. In addition, I extend the results of Kozhan et al. (2013), Chang et al. (2013) and Schneider (2015) by showing that there are not one but two common factors that drive higher moment risk premia (Market risk and Financial constraints).

1 Methodology

Assume that at a certain time t investor is unsure about future moments value, which he or she will observe at some time in future, T. This uncertainty prompts the investor to hedge the exposure to higher moment's risk and enter the swap contract to fix the level of expected future moment and hedge the time-varying risk. In such swap the investor is compensated for if the realized moment is higher than the fixed expected one, which implies that the investor goes long in realized moment and short in expected moment.[3]

Equation (1) presents the definition of the higher moments risk premia used in this paper and can be interpreted as an excess return of the swap contract. Such definition is alongside Kozhan et al. (2013) and implies that higher moments risk premia is the difference between the ex-post realization of a higher moment (variance, skewness or kurtosis) between time t and T and its ex-ante future expectation at time t for this period. The measure is standardized by the future expectation for comparison reasons. Negative sign of the premia implies that investors have to pay for the protection, whereas a positive sign implies that investors are compensated for the risk.

[3]The relationship flips in case of skewness though, because investors have preference for positive skewness and are averse of negative skewness

$$
\begin{aligned}
VRP_{t,T} &= \frac{\textit{Realized variance}_{t,T}}{\textit{Implied variance}_{t,T}} - 1 \\
SRP_{t,T} &= \frac{\textit{Realized skewness}_{t,T}}{\textit{Implied skewness}_{t,T}} - 1 \\
KRP_{t,T} &= \frac{\textit{Realized kurtosis}_{t,T}}{\textit{Implied kurtosis}_{t,T}} - 1
\end{aligned} \tag{1}
$$

It has to be noted that Bollerslev et al. (2009) provides similar definition for the moment risk premia, however, the main difference between their measure and Kozhan et al. (2013) is the way they define implied and realized moments. In particular, Kozhan et al. (2013) show that one can define realized and implied moments in such a way that the whole swap can be seen as a zero-cost market-neutral portfolio.

In the following subsections I provide brief overview for the theoretical framework of Kozhan et al. (2013), who show that the risk premia can be constructed from a set of the out-of-money (OTM) options by using the spanning theorem of Bakshi and Madan (2000). Then I present my extension of their method, which allows to estimate KRP. Finally, I outline the approximation procedure used in estimation of the risk premia used in this paper.

1.1 Variance and Skewness risk premia

In this section, I briefly outline the main setup and results of Kozhan et al. (2013), which are essential for further estimation of KRP. First, consider the economy with a single risky asset, a forward contract with fixed maturity T and a risk-free bond of a same maturity. Let the forward price at some time t be $F_{t,T}$; the log-price be $f_{t,T}$ and the log-return be $r_{t,T} = f_{T,T} - f_{t,T}$. Finally, assume the bond price at any time t as $B_{t,T}$ with $B_{T;T} = 1$.

In the previous example, there was an investor, who wanted to make a bet on the risk of the higher moment of the risky asset. For now, assume that the moment yields some arbitrary payoff g, which is a function of the underlying return $r_{t,T}$. Moreover, assume that $g(r_{t,T})$ is twice-differentiable and $g(0) = 0$. The last assumption implies that there is no uncertainty at time T. Kozhan et al. (2013) show that in order to make a bet on a risk of g, the investor can enter the delta-hedged g-swap, where portfolio with payoff g is hedged in a forward market. Such position implies that the swap is equivalent to taking a long position in the realized moment (floating leg) and short the implied moment (fixed leg).[4] The fixed leg is known at the beginning of a trading month at time t and is a forward looking measure, whereas the floating leg is only known at the end of the trading month at time T and hence is a backward looking measure.

However, the higher moments are not tradable and hence the payoff g may be not easily attainable. For this reason the investor has to create a replicating portfolio with the same payoff g. The results of Bakshi and Madan (2000) and Carr and Madan (2001) show that using the whole universe of options one can create a replicating portfolio with any payoff. Kozhan et al. (2013) use this property to approximate the payoff g with a portfolio of the out-of-the-money (OTM) options. In particular, let $G^V_{t,T}$ and $G^S_{t,T}$ stand for the fixed legs for the variance and skewness swaps respectively and Q be the forward pricing measure, then the functional forms for the fixed legs are as follows.

$$\begin{aligned}
G^V_{t,T} &= \frac{2}{B_{t,T}}\left\{\int_0^{F_{t,T}} \frac{P_{t,T}(K)}{K^2}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{K^2}dK\right\} \\
G^S_{t,T} &= \frac{6}{B_{t,T}}\left\{\int_{F_{t,T}}^{\infty} \frac{(K-F_{t,T})C_{t,T}(K)}{K^2 F_{t,T}}dK - \int_0^{F_{t,T}} \frac{(F_{t,T}-K)P_{t,T}(K)}{K^2 F_{t,T}}dK\right\} \\
&\text{and} \\
G^S_{t,T} &= 3(G^E_{t,T} - G^V_{t,T}), \text{ where} \\
G^E_{t,T} &= E^Q_t\left[\frac{F_{T,T}}{F_{t,T}} ln \frac{F_{T,T}}{F_{t,T}}\right]
\end{aligned} \tag{2}$$

In equation (2) $P_{t,T}(K)$ and $C_{t,T}(K)$ stand for the prices of OTM put and call options with respective strike K. The entropy, $G^E_{t,T}$, is first introduced by Neuberger (2012) and is a variance of the futures contract with a payoff $F_{T,T}ln(F_{T,T})$. The introduction of entropy allows to rewrite the fixed leg of SRP as a zero cost portfolio, which takes long position in entropy, $G^E_{t,T}$, and short position in fixed leg of VRP. Further, it is shown that entropy is used in estimation of the floating leg of SRP as well as kurtosis risk premia (KRP) as well.

The case of fixed leg is simple since the expectations are formed at the beginning at time t and are fixed up until T. On the other hand, the floating leg needs to be continuously readjusted to ensure perfect hedge. It may not be always possible and hence, Kozhan et al. (2013) show how the hedge can be locally approximated given discrete rebalancing. If the rebalancing happens within

[4]For more detailed specification of the detla-hedged g-swap refer to Kozhan et al. (2013)

equal time intervals δt in $[t, T]$, then periodic change in short leg can be defined as $\delta Y_{t,T}^V$ and $\delta Y_{t,T}^S$ for case of variance and skewness as in equation (3).

$$
\begin{aligned}
\delta Y_{t,T}^V &= 2(e^{\delta f_{t,T}} - 1 - \delta f_{t,T}) \\
\delta Y_{t,T}^S &= 3\delta G_{t,T}^E (e^{\delta f_{t,T}} - 1) + 6(2 - 2e^{\delta f_{t,T}} + \delta f_{t,T} + \delta f_{t,T} e^{\delta f_{t,T}}), \\
&\text{where} \\
\delta f_{t,T} &= f_{t+\delta t,T} - f_{t,T} = r_{t,T} - r_{t+\delta t,T} \\
\delta G_{t,T}^E &= G_{t+\delta t,T}^E - G_{t,T}^E
\end{aligned} \tag{3}
$$

With the aggregation property of Neuberger (2012), $\delta Y_{t,T}^V$ and $\delta Y_{t,T}^S$ can be aggregated over the whole period $[t, T]$ to find the floating leg for VRP and SRP as $\sum \delta Y_{t,T}^V$ and $\sum \delta Y_{t,T}^S$. Finally, Kozhan et al. (2013) show how equation (2) and (3) can be approximated using the observable options data. Before presenting the approximation, I extend their model and show how fixed and floating legs for KRP can be calculated in the subsection below.

1.2 Kurtosis risk premia

As was noted before Kozhan et al. (2013) do not show how to estimate KRP, so in this section I extend the framework of Kozhan et al. (2013) and introduce the fixed and floating legs as in equation (1) for estimation of KRP.

I introduce a contract which pays $g^K(r_{t,T}) = 6(e^{2r_{t,T}} - 2r_{t,T} - 5 + 4e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}})$ and later show that it indeed represents kurtosis. First, I call the fixed leg of a risk premia, $G_{t,T}^K$, and show that it is related to the entropy and fixed leg of VRP.

$$
\begin{aligned}
G_{t,T}^K &= E_t^Q \left[6 \left(\left(\frac{F_{T,T}}{F_{t,T}} \right)^2 - 2ln\frac{F_{T,T}}{F_{t,T}} - 5 + 4\frac{F_{T,T}}{F_{t,T}} - 4\frac{F_{T,T}}{F_{t,T}} ln\frac{F_{T,T}}{F_{t,T}} \right) \right] \\
&= 6\left(G_{t,T}^Z + G_{t,T}^V - 2G_{t,T}^E \right), \text{ where} \\
G_{t,T}^Z &= E_t^Q \left[\left(\frac{F_{T,T}}{F_{t,T}} \right)^2 - 1 \right] = E_t^Q \left[e^{2r_{t,T}} - 1 \right]
\end{aligned} \tag{4}
$$

For the ease of interpretation and further calculations, I introduce additional contract with payoff $g^Z(r_{t,T}) = e^{2r_{t,T}} - 1 = \left(\frac{F_{T,T}}{F_{t,T}}\right)^2 - 1$.[5] The $g^Z(r_{t,T})$-contract is a zero cost portfolio with a long

[5] Neuberger (2012) uses similar contract to describe variance.

position in a variance of forward prices and a short one in a risk-free asset and then $G^Z_{t,T}$ is an implied variance of such portfolio. In what follows I refer to $G^Z_{t,T}$ as a quadratic variance.

As there is no instrument with a payoff $g^K(r_{t,T})$ in the market, investor needs to approximate such payoff with a portfolio of OTM options. Then the fixed leg of KRP, $G^K_{t,T}$, can be replicated approximated by following

$$G^K_{t,T} = \frac{12}{B_{t,T}} \left\{ \int_0^{F_{t,T}} \frac{(F_{t,T} - K)^2 P_{t,T}(K)}{K^2 F^2_{t,T}} dK + \int_{F_{t,T}}^{\infty} \frac{(K - F_{t,T})^2 C_{t,T}(K)}{K^2 F^2_{t,T}} dK \right\} \tag{5}$$

Finally, I present the floating leg for continuous and discrete rebalancing in equation (6). It has to be noted that though only discrete rebalancing is used in this paper, the functional form for continuous case is presented for intuition purposes. $dY^K_{t,T}$ and $\delta Y^K_{t,T}$ refer to floating leg of KRP in case of continuous and discrete rebalancing respectively. The derivations for discrete and continuous floating leg of KRP can be found in Appendix A.1

Continuous case:

$$dY^K_{t,T} = 12d(G^Z_{t,T} - G^E_{t,T})df_{t,T} + 6G^Z_{t,T}(df_{t,T})^2$$

Discrete case:

$$\begin{aligned} \delta Y^K_{t,T} &= 6(G^Z_{t+\delta t,T}(e^{\delta f_{t,T}} - 1)^2 + 2(e^{\delta f_{t,T}} - 1)(\delta G^Z_{t,T} - \delta G^E_{t,T})) \\ &+ 6(e^{2\delta f_{t,T}} - 2\delta f_{t,T} + 4e^{\delta f_{t,T}} - 4\delta f_{t,T} e^{\delta f_{t,T}} - 5) \end{aligned} \tag{6}$$

where

$$\delta G^Z_t = G^Z_{t+\delta t,T} - G^Z_{t,T}$$

As is shown in Proposition 1 below, $G^K_{t,T}$ locally approximates the fourth central moment of returns. To obtain more commonly used measure of kurtosis, I scale both the fixed and floating legs by the $(G^V_{t,T})^2$. In particular, the implied measure of kurtosis is defined as

$$kurt_{t,T} = \frac{6(G^Z_{t,T} + G^V_{t,T} - 2G^E_{t,T})}{(G^V_{t,T})^2} \tag{7}$$

Proposition 1. *The scale measure $kurt_{t,T}$ is equal to the kurtosis of the distribution of log returns on the asset under forward pricing measure, Q*

Proof. Proof can be found in Appendix A.2 □

1.3 Risk premia construction

Using the methodology from previous section, I apply the approximation procedure of Kozhan et al. (2013), who show that the risk premia can be calculated with a span of out-of-the-money (OTM) European options. First, order N+1 options of different strikes maturing at the end of the trading period, T, from the lowest strike, K_0, to the highest strike, K_N, and define the option prices $P_{t,T}$ and $C_{t,T}$ as the midpoints of the bid and ask quotes. Given these assumptions Bakshi and Madan (2000) formula for log, entropy and squared contracts can be approximated in the following way.

$$\Delta I(K_i) = \begin{cases} \frac{K_{i+1}-K_{i-1}}{2}, & \text{for } 0 \leq i \leq N \text{ with } K_{-1} \equiv 2K_0 - K_1,\ K_{N+1} \equiv 2K_N - K_{N-1} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Then empirical estimates of fixed legs for variance($v^L_{t,T}$), entropy ($v^E_{t,T}$) and quadratic variance($v^Z_{t,T}$) can be obtained with the following formulas

$$\begin{aligned} v^L_{t,T} &= 2\sum_{K_i \leq F_{t,T}} \frac{P_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i) + 2\sum_{K_i > F_{t,T}} \frac{C_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i) \\ v^E_{t,T} &= 2\sum_{K_i \leq F_{t,T}} \frac{P_{t,T}(K_i)}{B_{t,T}F_{t,T}K_i}\Delta I(K_i) + 2\sum_{K_i > F_{t,T}} \frac{C_{t,T}(K_i)}{B_{t,T}F_{t,T}K_i}\Delta I(K_i) \\ v^Z_{t,T} &= 2\sum_{K_i \leq F_{t,T}} \frac{P_{t,T}(K_i)}{B_{t,T}F_{t,T}^2}\Delta I(K_i) + 2\sum_{K_i > F_{t,T}} \frac{C_{t,T}(K_i)}{B_{t,T}F_{t,T}^2}\Delta I(K_i) \end{aligned} \tag{9}$$

According to equations (2) and (4) the fixed legs for skewness and kurtosis can be estimated with $s_{t,T} = 3(v^E_{t,T} - v^L_{t,T})$ and $k_{t,T} = 6(v^L_{t,T} + v^Z_{t,T} - 2v^E_{t,T})$. Now assuming that rebalancing happens every δ periods (for example, every day), floating legs for VRP, SRP and KRP are respectively as follows

$$\begin{aligned}
rv_{t,T} &= \sum_{i=1}^{T-1} 2(e^{r_{i,i+1}} - 1 - r_{i,i+1}) \\
rs_{t,T} &= \sum_{i=1}^{T-1} \left[3\delta v_{i,T}^{E}(e^{r_{i,i+1}} - 1) + 6(2 - 2e^{r_{i,i+1}} + r_{i,i+1} + r_{i,i+1}e^{r_{i,i+1}})\right] \\
rk_{t,T} &= \sum_{i=1}^{T-1} 6\left[v_{i+1,T}^{Z}(e^{r_{i,i+1}} - 1)^2 + 2(e^{r_{i,i+1}} - 1)(\delta v_{i,T}^{Z} - \delta v_{i,T}^{E})\right] \\
&+ \sum_{i=1}^{T-1} 6\left[e^{2r_{i,i+1}} - 2r_{i,i+1} + 4e^{r_{i,i+1}} - 4r_{i,i+1}e^{r_{i,i+1}} - 5\right]
\end{aligned} \tag{10}$$

Having the estimates of fixed and floating legs the risk premia can be found with equation (1). It has to be noticed that the sum in equations (10) comes from Neuberger (2012) aggregation property. The property implies that the estimate of a realized moment over the trading period is an aggregation of the realized values observed at every point of rebalancing. For example, when one tries to estimate the realized moment over a month using daily rebalancing, the monthly estimate of a realized moment is a sum of daily estimates.

$$\begin{aligned}
skew_{t,T} &= \frac{s_{t,T}}{(v_{t,T}^{L})^{\frac{3}{2}}} \quad & rskew_{t,T} &= \frac{rs_{t,T}}{(v_{t,T}^{L})^{\frac{3}{2}}} \\
kurt_{t,T} &= \frac{k_{t,T}}{(v_{t,T}^{L})^{2}} \quad & rkurt_{t,T} &= \frac{rk_{t,T}}{(v_{t,T}^{L})^{2}}
\end{aligned} \tag{11}$$

To empirically illustrate that risk premia also tracks the dynamics of higher moments, equation (11) can be used to estimate implied and realized skewness and kurtosis by standardizing fixed and floating legs with implied variance. $skew_{t,T}$ and $kurt_{t,T}$ are implied skewness and kurtosis, whereas $rskew_{t,T}$ and $rkurt_{t,T}$ are realized skewness and kurtosis respectively. It is easy to see that the implied moments are forward looking measures and are known at the beginning of trading period, whereas the realized moments are backward looking and are only known at the end of trading period.

2 Data

2.1 Risk premia estimates

To estimate the higher moment risk premia I use the daily data on European options written on the S&P 500 spot index, which is taken from OptionMetrics. The dataset covers the period between January 1996 and December 2017 and includes bid and ask quotes as well as implied volatilities, strike prices, maturities and interest rates. Since the calculation of moments depends on quality of the data I filter out the options with zero bid and/or ask quotes and options with non-standard settlements.

Similar to Kozhan et al. (2013) I assume daily rebalancing and use options that mature every trading month, which I define as a time from the first trading day after options' expiration up to the next month expiration. As option expirations do not coincide with end of the calendar months, it is naturally that trading months do not coincide with calendar as well. In what follows, words "trading months" and "months" are used interchangeably, unless stated otherwise.

Table 1 suggests that higher moment risk premia has negative mean of -0.26, -0.61 and -0.54 for VRP, SRP and KRP respectively. It suggests that investor on average pays 26, 61 and 54 basis points to hedge variance, skewness and kurtosis risk of 1 dollar. As is also documented by previous literature (see for example, Bollerslev et al. (2009), Chang et al. (2013), Kozhan et al. (2013) and Zhao et al. (2013)), on average it is profitable for the insurance provider (for example, hedge fund) to sell the protection against higher moment risk in the market, whereas on buy side, it costs to hedge high moment risks for investors.

However, it can be seen from Figure 1, which plots the time varying high moment risk premia, that the risk premia is subject to jump risk and becomes positive in certain times. The observation is alongside previous evidence of Zhao et al. (2013) and Bollerslev, Todorov, and Xu (2015), who argue that jump risk is one of the components of higher moments risk premia. Intuitively, such jumps correspond to times when investors are compensated for high moment risk and insurance providers (for example, hedge funds) pay such compensation. It is interesting that the positive jumps are pronounced the most in high moment risk premia.

Table 1 also suggests that higher moment risk premia are correlated with the coefficient varying

Table 1.
Descriptive statistics

Panel A: Descriptive statistics

	Mean	SD	Skewness	Kurtosis	Q1	Median	Q3	Phillips-Perron
$v^L \times 100$	0.36	0.45	6.30	57.23	0.15	0.25	0.40	0.0
$rv \times 100$	0.26	0.39	6.31	51.90	0.08	0.15	0.30	0.0
$skew$	-2.40	1.09	-1.26	2.14	-2.99	-2.17	-1.64	0.0
$rskew$	-0.86	1.71	-3.89	20.06	-0.98	-0.38	-0.12	0.0
$kurt$	18.84	15.19	2.28	6.79	9.01	13.78	23.82	0.0
$rkurt$	6.61	13.03	6.10	46.87	1.59	3.03	6.47	0.0
VRP	-0.26	0.61	3.50	17.63	-0.59	-0.41	-0.13	0.0
SRP	-0.61	0.80	3.65	17.06	-0.95	-0.80	-0.58	0.0
KRP	-0.54	0.94	6.72	59.82	-0.88	-0.78	-0.54	0.0

Panel B: Correlations

	rv	$skew$	$rskew$	$kurt$	$rkurt$	VRP	SRP	KRP
v^L	0.54***	0.28***	0.01	-0.30***	-0.08	-0.05	0.05	0.02
rv		0.22***	-0.31***	-0.23***	0.22***	0.57***	0.42***	0.40***
$skew$			0.07	-0.95***	-0.11	0.04	0.09	0.15**
$rskew$				-0.04	-0.90***	-0.65***	-0.91***	-0.79***
$kurt$					0.08	-0.03	-0.10	-0.15**
$rkurt$						0.69***	0.75***	0.82***
VRP							0.64***	0.66***
SRP								0.86***

The table shows descriptive statistics and correlations for calculated variables. v^L is monthly implied variance of the log contract on S&P 500 index options, rv is monthly realized variance, $skew$ is monthly implied skewness, $rskew$ is monthly realized skewness, $kurt$ is monthly kurtosis, $rkurt$ is monthly realized kurtosis, VRP is monthly variance risk premia, SRP is monthly skewness risk premia and KRP is monthly kurtosis risk premia. In Panel A, the values under columns Mean, SD, Q1, Median, Q3 and Phillips-Perron report sample averages, standard deviations, 25th percentile, median, 75th percentile values and p-values for the Phillips-Perron unit roote test respectively. Panel B shows the correlations between the variables; *,** and *** indicate the value is statistically different from zero at 10%, 5% and 1% levels respectively. The data are for nonoverlapping monthly periods from January 1996 to December 2017

around 0.6 for coefficients between VRP and other higher moment risk premia and reaching 0.86 in case of SRP and KRP pair. High correlation between the risk premia is along side previous finding of Kozhan et al. (2013), who suggest that there is some common factor, which drive the higher moment risk premia. On the other hand, it appears that the correlation is pronounced more between SRP and KRP than with VRP. It may mean that there is high similarity between SRP and KRP comparing to SRP and VRP. The notion can be explained by evidence of Chang et al. (2013), who show high correlation between skewness and kurtosis and argue that pronounced kurtosis is usually associated with more negative skewness.

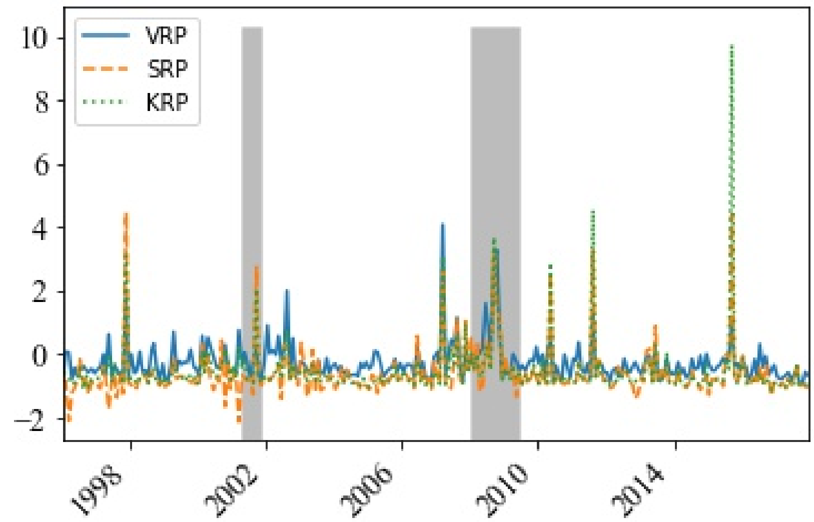

Figure 1.
Risk premia of statistical moments
The figure shows monthly time series of the risk premia associated with statstical moments of S&P 500 index. VRP, SRP and KRP stand for variance risk premia, skewness risk premia and kurtosis risk premia respectively. The shaded areas represent the NBER recession periods. The data range is from January 1996 to December 2017.

2.2 Macroeconomic variables

Before selecting a set of macroeconomic variables, which are going to be used in regression analysis later, some issues with the data itself need to be solved. In particular, the frequency and even time when macroeconomic variables become public do not coincide with trading months of the premia. For example in case of GDP, the values are published with one quarter lag and it may be published sometimes before and sometimes after the positions in options are rolled over. One of the straightforward idea is to use reference periods and link the observed higher moment risk premia with each reference period. However, such approach has a pitfall as it induces forward looking bias, because simply the information was not published and market participants do not observe it. On the other hand, it is reasonable to assume that market participants use all of the available information to imply the state of the economy and update their beliefs as new information comes out.

For the reason described above, I follow Beber et al. (2015) in creation of the set of macroeconomic variables. Their main idea is that at any arbitrary time t investor uses all of the available information to create a timely estimate of macroeconomic conditions. In particular, I collect the data from St.Louis FRED from 1980 to 2017 and the announcement days of the macroeconomic variables from the archives of each governmental agency that is responsible for issuing the data. The full list of variables is presented in Appendix B. All of the data is grouped in five broad categories: Inflation, Employment, Output, Sentiment and Financial Constraints. The first four groups were taken from Beber et al. (2015), while Financial Constraints group was constructed from variables that usually are associated with cost of leverage and discount rate such as Ted rate, Term spread, Commercial paper spread and Default yield.

Beber et al. (2015) show that first principal component of each group gives a good timely estimate of the underlying macroeconomic phenomenon, for example Inflation for Inflation group.

Extraction of first principal components on such data is problematic for two reasons. First, the series have different lengths. To account for this feature I adjust the correlation matrix used in PCA in a spirit of Stambaugh (1997). Second, the data itself is highly persistent, in the sense that it is highly autocorrelated due to its low frequency. Beber et al. (2015) show that it can be accounted for by subsampling the data on a relatively lower frequency, when the persistence is not pronounced as much. In addition, I correct the correlation matrix with Newey-West procedure. The more detailed procedure on adjusting the data can be found in Beber et al. (2015).

Having the above mentioned adjustments in mind, I extract the first principal components for each group for the period from 1996 to 2017. I use period from 1980 to 1996 to obtain my initial estimate of corrected correlation matrix Ω_0, then at every other day t, I use the all available data from 1980 up to time t to get a timely- estimate of the corrected correlation matrix Ω_t. With these correlation matrices I extract the value of the first principal component for each group at time t. The resulted series of the macroeconomic PCAs are plotted in on the left hand side of Figure 2 and their descriptive statistics are shown in Table 2

The selection of these five groups is based on previous empirical evidence on macroeconomic variables and higher moments. Inclusion of Inflation, Output and Employment is due to evidence of Hong and Stein (2003), who state that the negative news about economy go hand in hand with the negative skewness. The inclusion of Sentiment group is motivated by behavioural finance literature, which shows that sentiment has influence on stock prices, see for example, Stambaugh, Yu, and Yuan (2012). Moreover, there is evidence that skewness and sentiment are linked through gambling preferences (Han (2008) and Byun and Kim (2016)). Finally, Yuan (2005) and Adrian and Rosenberg (2008) claim that the skewness is an indicator of the financial constraints and that crises propagate through them. In addition, as higher moment risk premia is a profit for selling protection against higher moment risk by sophisticated investors (for example, hedge funds as in Bondarenko (2004)), it may be affected by liquidity spirals of Brunnermeier and Pedersen (2009).

Table 2.
Descriptive statistics

Panel A: Descriptive statistics

	Mean	SD	Skewness	Kurtosis	Q1	Median	Q3	Phillips-Perron
Employment	0.08	0.64	-2.50	14.00	-0.12	0.17	0.43	0.0
Inflation	-0.00	0.83	-0.60	7.22	-0.33	0.02	0.37	0.0
Output	-0.07	1.57	-0.98	2.51	-0.86	0.16	0.81	0.0
Sentiment	-0.08	1.08	-1.02	3.86	-0.64	-0.01	0.59	0.0
F. Constraints	-0.19	0.79	3.82	21.33	-0.62	-0.38	-0.10	0.0
xm	0.00	0.04	-0.29	3.95	-0.02	0.00	0.03	0.0
VIX	20.55	9.12	2.36	9.29	13.96	18.68	24.24	0.0

Panel B: Correlations

	Inflation	Output	Sentiment	F. Constraints	VIX
Employment	0.23***	0.43***	0.08	-0.38***	-0.48***
Inflation		0.32***	0.11*	-0.13**	-0.26***
Output			0.17***	-0.42***	-0.51***
Sentiment				-0.24***	-0.26***
F. Constraints					0.58***

The table shows descriptive statistics and correlations for the extracted principal components for macroeconomic variables. The captions of Employment, Inflation, Output, Sentiment, F. Constraints stand for the first principal components for groups of Employment, Inflation, Output, Sentiment and Financial constraints, whereas xm and VIX stand for excess return of S&P 500 index and VIX. In Panel A, the values under columns Mean, SD, Q1, Median, Q3 and Phillips-Perron report sample averages, standard deviations, 25th percentile, median, 75th percentile values and p-values for the Phillips-Perron unit roote test respectively. Panel B shows the correlations between the variables; *,** and *** indicate the value is statistically different from zero at 10%,5% and 1% levels respectively. The data are for nonoverlapping monthly periods from January 1996 to December 2017

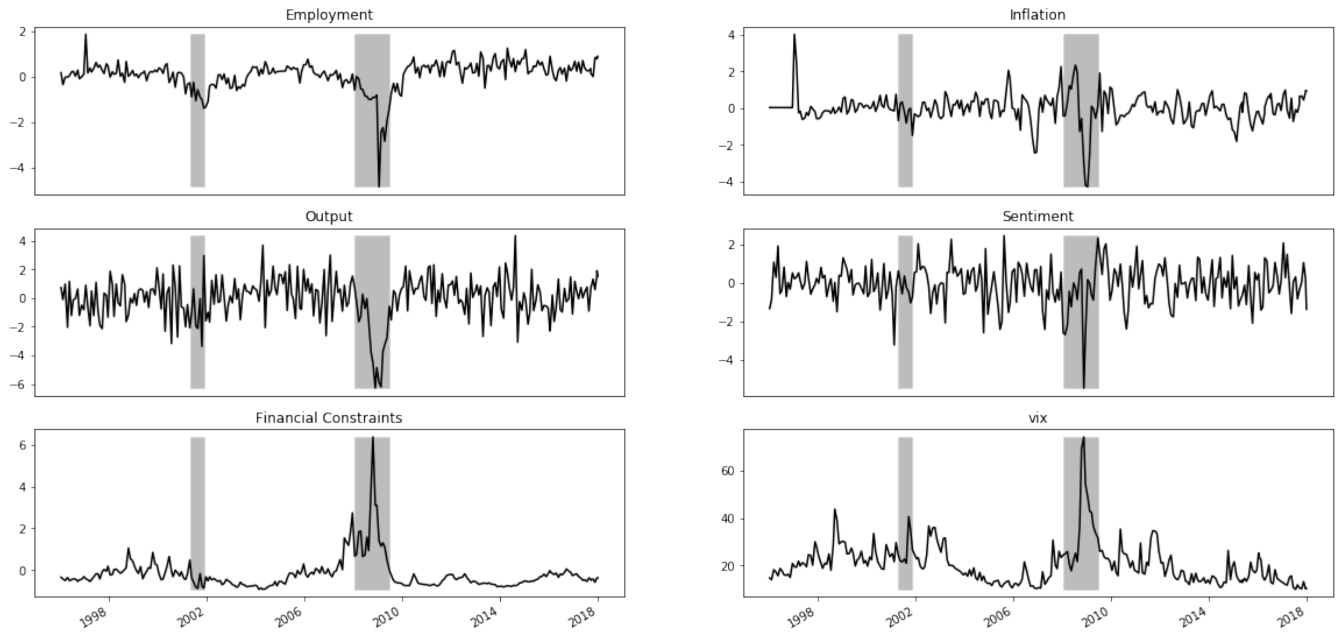

Figure 2.
Macroeconomic PCAs
The figure shows monthly time series of the extracted first principal component for Employment, Inflation, Output, Sentiment and Financial Constraints. In addition, VIX was added for comparison. The shaded areas represent the NBER recession periods. The data range is from January 1996 to December 2017.

3 Empirical results

3.1 Linear regression

Panel B of Table 1 shows that all of the higher moment risk premia are highly correlated. Such correlation is alongside previous findings of Hong and Stein (2003), Kozhan et al. (2013) and Chang et al. (2013). To account for such correlation structure I run separate regressions of the following form on VRP, SRP and KRP.

$$RP_t = \alpha + \beta RP_{t-1} + \gamma X_t + \omega X_{t-1} + e_t \tag{12}$$

In the formula above the left hand side, RP_t, is the respective higher moments risk premia such as VRP, SRP or KRP at time t. On the right hand side, RP_{t-1} is the respective lagged value of the higher moment risk premia, whereas X_t and X_{t-1} are the contemporaneous and lagged values

Table 3.
Regression results

	Explanatory			Predictive			Joint		
	VRP	SRP	KRP	VRP	SRP	KRP	VRP	SRP	KRP
Intercept	-0.24***	-0.65***	-0.57***	-0.2***	-0.61***	-0.53***	-0.24***	-0.67***	-0.58***
	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.06)	(0.04)	(0.05)	(0.05)
VIX	0.06***	0.08***	0.09***				0.06***	0.08***	0.09***
	(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.01)
F. Const.	0.35***	0.3***	0.3***				0.37***	0.31***	0.31***
	(0.08)	(0.08)	(0.1)				(0.08)	(0.08)	(0.09)
Inflation	-0.05	-0.17***	-0.17**				-0.06	-0.17***	-0.18**
	(0.04)	(0.06)	(0.08)				(0.04)	(0.06)	(0.09)
Sent.	-0.04	-0.12***	-0.11**				-0.03	-0.11***	-0.11**
	(0.03)	(0.04)	(0.05)				(0.03)	(0.04)	(0.05)
Employ.	-0.04	-0.02	0.08				-0.03	-0.03	0.08
	(0.07)	(0.1)	(0.1)				(0.08)	(0.12)	(0.11)
Output	0.02	0.03	0.02				0.02	0.04	0.03
	(0.02)	(0.03)	(0.03)				(0.02)	(0.04)	(0.04)
VIX_{t-1}				-0.02	0.0	-0.0	-0.01	0.01	0.0
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$F.\ Const._{t-1}$				0.23**	0.21**	0.26***	0.15*	0.04	0.07
				(0.11)	(0.1)	(0.09)	(0.09)	(0.1)	(0.12)
$Inflation_{t-1}$				0.08*	-0.0	-0.0	0.08	-0.01	-0.02
				(0.05)	(0.07)	(0.09)	(0.05)	(0.07)	(0.11)
$Sent._{t-1}$				0.03	0.03	0.03	0.01	0.0	-0.01
				(0.04)	(0.05)	(0.06)	(0.03)	(0.04)	(0.05)
$Employ._{t-1}$				-0.18**	-0.13	-0.18*	-0.12**	-0.05	-0.07
				(0.08)	(0.1)	(0.1)	(0.06)	(0.08)	(0.06)
$Output_{t-1}$				-0.05*	-0.04	-0.04	-0.02	0.0	0.0
				(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)
RP_{t-1}	0.06	-0.06	-0.05	0.2	0.0	0.01	0.05	-0.09*	-0.07**
	(0.06)	(0.04)	(0.03)	(0.14)	(0.06)	(0.04)	(0.08)	(0.05)	(0.03)
$Adj.R^2$	0.37	0.30	0.27	0.08	0.00	-0.00	0.38	0.28	0.25
F-stat	0.00	0.00	0.00	0.02	0.03	0.00	0.00	0.00	0.00
N. Obs.	263	263	263	263	263	263	263	263	263

The table shows the results of the regressions as in equation (12) of VRP, SRP and KRP on macroeconomic principal components. The values in brackets stand for standard errors and stars indicate statistical significance from zero with *, ** and *** standing for 10%, 5% and 1% significance level. F. Const. stands for Financial Constraints; Sent. stands for Sentiment and Employ. stands for Employment. Explanatory tab means that the lagged values of components were excluded from the regression; Predictive tab implies that the lagged values were included, but the contemporaneous values were excluded; and Joint tab runs the regression together with contemporaneous and lagged realization of macroeconomic components. RP_{t-1} stands for the lagged higher moment risk premia such as VRP, SRP or KRP; whereas $t-1$ in the bottom of component name indicates lagged value. $Adj.R^2$ shows the *Adjusted* R^2 for each of the regressions; *F-stat* is the p-value for the F-statistic with null hypothesis that all of the regressors are jointly equal to zero and *N. Obs.* stands for number of observations used in each regression.

for the macroeconomic components. The significance of γ will indicate that higher moment risk premia compensates for the changes in macroeconomic conditions, whereas ω will show whether current compensation for higher moment risk is related to macroeconomic conditions in previous month. Finally, β will suggest that there is autocorrelation in higher moment risk premia.

With a specification as in equation (12), I run three sets of regressions. The first set of regressions excludes X_{t-1}, while only keeping the contemporaneous values of macroeconomic components, X_t, and is referred to as explanatory set. Second set, predictive set, looks at the predictability and hence includes the lagged values, X_{t-1}, but excludes the contemporaneous values of the components. Finally, I run the joint regression as is specified in equation (12). Table 3 presents the results of these regressions. The values in parentheses are the t-statistics, which are estimated from Newey-West errors with adjustment for 12 lags (12 months).

The first line of Table 3 indicates that the unconditional expectation of higher moment risk premia is significantly negative, as the coefficients for Intercept is significant and varies around -0.24, -0.65 and -0.57 for VRP, SRP and KRP respectively. These findings are alongside the empirical evidence presented in Kozhan et al. (2013), Chang et al. (2013) and Harris and Qiao (2017) and stand for the average cost of hedging the exposure to higher moment risk. It means that from January 1996 to December 2017, average investor pays 24 (65 or 57) basis points to protect one dollar from variance (skewness or kurtosis) risk.

The explanatory set of regressions from Table 3 shows that VIX is highly significant and positive for all of the higher moments premia. The positive sign of the coefficients means that investors get compensated in times of more pronounced market risk, but have to pay in times of low risk. Similarly to VIX, the coefficients for Financial Constraints appear to be positive and highly significant as well. The result means that by buying the protection from higher moment risk investors also get the protection in times of more severe financial constraints. For example a single unit increase in financial constraints measured by the first principal component gives investor compensation of 35 basis points in case of VRP and 30 basis points in case of SRP and KRP. The finding is interesting as it can be related to the concept of liquidity spirals of Brunnermeier and Pedersen (2009), which usually appears when the financial constraints become more tight and financial institutions try to fire-sale their assets. During such events high market volatility, more negative skewness as well as higher probability of tail events are observed, which makes the protection against moment risk more valuable for investors.

Interesting finding is that it appears that different higher moment risk premia compensates for different macroeconomic risks. For example, SRP and KRP appear to provide protection against low inflation and negative sentiment unlike VRP. The negative and significant coefficients for Inflation suggest that a unit increase in the first principal component in Inflation group is associated with 17 basis points decrease in SRP and KRP, while similar increase in the first principal component for Sentiment group is associated with 12 and 11 basis points decrease in SRP and KRP. The result for Sentiment and Inflation are alongside expectations, because the stock market is considered to be a hedge against inflation; while the result for Sentiment is alongside the evidence of previous literature that skewness is related to sentiment. In particular, Barberis and Huang (2008) show that skewness is usually related to gambling preference which are more pronounced in times of high sentiment as suggested by Fong and Toh (2014) and Byun and Kim (2016).

The second set of regressions, which consists of predictive regressions, suggest that there is one month predictability in higher moment risk premia as the results of F-test reject the null hypothesis that all of the coefficients are jointly equal to zero. In particular, it seems that lagged first principal components for Financial constraints, Inflation, Employment and Output have in sample predictive power over future higher moment risk premia. For example, the positive coefficients of 0.23, 0.21 and 0.26 for VRP, SRP and KRP that more tight financial constraints in previous trading month are translated in more positive higher moment risk premia next month. Similarly, the lagged values of first principal component for Employment seem to be negative predictor of VRP and KRP. Finally, lagged values for Output appear to be negative predictor for VRP. However, most of the predictability disappears once the joint regression is performed with the minor exception of lagged values of components for Financial Constraints and Employment in case of VRP. Though significant at 10% level, the coefficients suggest that there is lagged values of Financial Constraints and Employment are positive and negative predictors of VRP.

In general, the results suggest that the higher moment risk premia prices macroeconomic risk. While VIX and Financial Constraints appear to be compensated for by all types of higher moment risk premia, only SRP and KRP bear significant compensation for Inflation and Sentiment risk. On the other hand, it appears that there is limited evidence of predictability from macroeconomic components to higher moment risk premia. In unreported results, I perform various tests for multicollinearity and do not find any multicollinearity issues in the regressions. In addition, I find that the results are robust to inclusion of lagged realization of macroeconomic components as well as exclusion of lagged realization of premia.

Table 4.
Squared regressions

	Squared-only			Joint		
	VRP	SRP	KRP	VRP	SRP	KRP
Intercept	-0.31***	-0.78***	-0.67***	-0.26***	-0.71***	-0.57***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)
VIX^2	0.00*	0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Financial Constraints^2	0.26***	0.18	0.19	0.18***	0.06	0.07
	(0.05)	(0.13)	(0.15)	(0.05)	(0.09)	(0.11)
Inflation^2	0.01	0.01	0.03	0.01	0.03	0.04
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Sentiment^2	-0.01	0.01	0.00	-0.01	0.02	-0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Employment^2	-0.03***	0.02	-0.02	-0.02	0.04	0.01
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Output^2	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
VIX				0.05***	0.07***	0.09***
				(0.01)	(0.02)	(0.02)
Financial Constraints				0.17*	0.29***	0.25**
				(0.10)	(0.11)	(0.11)
Inflation				-0.02	-0.16***	-0.18*
				(0.05)	(0.06)	(0.1)
Sentiment				-0.03	-0.11***	-0.11**
				(0.03)	(0.04)	(0.05)
Employment				-0.03	0.04	0.10
				(0.10)	(0.11)	(0.10)
Output				0.03	0.04	0.02
				(0.02)	(0.03)	(0.04)
RP_{t-1}	-0.02	-0.10**	-0.08	0.02	-0.08**	-0.06**
	(0.06)	(0.05)	(0.05)	(0.07)	(0.04)	(0.03)
$Adj.R^2$	0.29	0.17	0.13	0.39	0.30	0.26
F-stat	0.00	0.00	0.00	0.00	0.00	0.00
N. Obs.	263	263	263	263	263	263

The table shows the results of the regressions as in equation (13) of VRP, SRP and KRP on macroeconomic components. $Squared - only$ column stands for the regression, where only squared components are accounted for; *Joint* shows the result of pooled regression of macroeconomic components and their squared counterparts. RP_{t-1} stands for the lagged higher moment risk premia such as VRP, SRP or KRP; whereas square indicates squared component.$Adj.R^2$ shows the *Adjusted* R^2 for each of the regressions and *F-stat* is the p-value for the F-statistic with null hypothesis that all of the regressors are jointly equal to zero. Finally, N. Obs. stands for number of observations used in each regression.

3.2 Non-linear relationship

In the previous section, I showed that there is a compensation for macroeconomic risk assuming that there is only linear relationship between the macroeconomic components and higher moment risk premia. However, as is shown in Ang and Chen (2002) the concept of risk in finance may be not straightforward and various non-linear relationships may arise. Existence of non-linearity may just not be captured by regression as in equation (12). To address such critique I control for non-linear dependency by running the following regressions:

$$RP_t = \alpha + \beta RP_{t-1} + \gamma X_t + \rho X_t^2 + e_t \tag{13}$$

In the equation above RP_{t-1} stands for lagged value of respective risk premia such as VRP, SRP and KRP; X_t is the matrix of macroeconomic components and X_t^2 is the respective matrix of squared components. Results of two sets of regressions are reported in Table 4. First one omits the linear part X_t, whereas the second set includes all of the variables outlined in equation (13).

The main results suggest that the conclusions of previous section hold and that only in case of VRP there is a non-linear effect coming from Financial Constraints. Table 4 shows that the squared macroeconomic component for Financial Constraints appears to be positive and significant even after inclusion of linear components. It means that higher uncertainty about access to capital is associated with more positive values of VRP. For investor, it means that she receives compensation for high variability in Financial Constraints only when she buys protection against second moment, but not against skewness or kurtosis.

3.3 Quantile regressions

Given graphs presented in Figure 1 and 2, relevant question is how sensitive the conclusions drawn from Table 3 to outliers and whether there is a symmetric relation between risk premia and macroeconomic components. For this reason I run the set of quantile regressions for 5%, 25%, 50%, 75% and 95%[6].

$$RP_t^q = \alpha + \beta X_t + e_t \tag{14}$$

[6] In unreported results I ran regressions for every 5th quantile in interval [5;95] the results and conclusions are quantitatively similar and do not add anything to the discussion

In the formula above RP_t^q stands for the q-quantile of the risk premia such as VRP, SRP or KRP, whereas X_t is the matrix of macroeconomic components and e_t is the error term. The results of such regressions are presented in Table 5

The very first result of quantile regressions suggest that pseudo R^2 increases in quantiles, which means that observed variables explain higher quantiles of higher moment risk premia better than lower quantiles. It means that the variables in regression explain the times investors gets compensated for higher moment risk better than times when investor has to pay for protection. Intuitively, the investor gets compensated in times of increasing higher moment risk and has to pay when the higher moment risk is low, which means that lower quantiles of higher moment risk premia correspond to times of highest costs of hedging or lowest higher moment risk, while higher quantiles of risk premia correspond to times when higher moment risk is high and investor got compensated for such risk.

The results of 50th quantile represents median regressions and show how the relationship between median values of higher moment risk premia and macroeconomic conditions. In particular, it can be seen that the most robust relationship is between VIX and Financial Constraints as the coefficients are positive and significant at 1% level. Interesting observation is that the coefficients for VIX are all highly significant and positive for all quantile levels, except for SRP at 5th quantile, where it is negative. The result suggest that in times when it is expensive to hedge Skewness risk such as rising stock market increases in VIX increase the costs of hedging. On the other hand, in case of VRP and KRP, increases in VIX are associated with higher compensation to investor. Another interesting finding from the table is that the coefficients of VIX increase in quantiles from lowest to highest quantile. It means that higher quantiles appear to be more sensitive to VIX than lower quantiles of higher moments risk premia.

The results for Financial Constraints are also interesting as unlike VIX, the results appear the most significant for median regressions, but the significance declines as one moves closer to 5th or 95th quantile. The results suggests that even though Financial Constraints affect median value of higher moment risk premia, they do not explain jumps in higher moment risk premia, while VIX does.

As for other macroeconomic components, the results for Sentiment appears to be pronounced the most for SRP, where the coefficients are significant and negative for all quantiles except for

Table 5.
Quantile regressions

Panel A. VRP

Quantile	Intercept	Employ.	Inflation	Output	Sentiment	F.Const.	VIX	*Pseudo*-R^2
0.05	-0.76***	0.02	-0.07**	0.01	0.01	0.27***	0.03***	0.09
	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.00)	
0.25	-0.54***	0.04	-0.01	0.01	0.00	0.18***	0.04***	0.11
	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.04)	(0.00)	
0.50	-0.36***	-0.07	0.01	0.03	0.01	0.32***	0.05***	0.16
	(0.02)	(0.06)	(0.03)	(0.02)	(0.02)	(0.06)	(0.01)	
0.75	-0.11***	-0.08	0.02	-0.01	-0.02	0.29***	0.07***	0.21
	(0.03)	(0.07)	(0.05)	(0.02)	(0.03)	(0.11)	(0.01)	
0.95	0.52***	-0.43***	-0.02	0.06	-0.12	0.49	0.08***	0.35
	(0.08)	(0.15)	(0.15)	(0.05)	(0.07)	(0.37)	(0.02)	

Panel B. SRP

Quantile	Intercept	Employ.	Inflation	Output	Sentiment	F.Const.	VIX	*Pseudo*-R^2
0.05	-1.25***	0.05	-0.01	0.01	-0.01	0.03	-0.04***	0.09
	(0.03)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.01)	
0.25	-0.91***	0.01	-0.03	-0.01	-0.03*	0.03	0.01***	0.02
	(0.02)	(0.04)	(0.03)	(0.01)	(0.02)	(0.04)	(0.00)	
0.50	-0.72***	0.02	-0.05	-0.01	-0.04*	0.25***	0.04***	0.10
	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.00)	
0.75	-0.44***	-0.09	-0.05	-0.03	-0.10***	0.30***	0.07***	0.20
	(0.03)	(0.1)	(0.06)	(0.03)	(0.03)	(0.11)	(0.01)	
0.95	0.35***	0.18	-0.25**	-0.02	-0.25**	0.11	0.15***	0.41
	(0.09)	(0.54)	(0.11)	(0.07)	(0.1)	(0.19)	(0.03)	

Panel C. KRP

Quantile	Intercept	Employ.	Inflation	Output	Sentiment	F.Const.	VIX	*Pseudo*-R^2
0.05	-0.97***	0.01	0.01	-0.00	0.01	0.10***	0.01***	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	
0.25	-0.85***	0.00	-0.01	-0.01	-0.01	-0.00	0.02***	0.06
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)	(0.00)	
0.50	-0.70***	-0.04	-0.02	-0.01	-0.02	0.27***	0.04***	0.12
	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.00)	
0.75	-0.43***	-0.01	-0.05	0.01	-0.09***	0.19*	0.07***	0.21
	(0.03)	(0.09)	(0.05)	(0.02)	(0.03)	(0.1)	(0.01)	
0.95	0.35***	0.23	-0.34	0.05	-0.20*	0.33	0.14***	0.36
	(0.1)	(0.55)	(0.25)	(0.07)	(0.11)	(0.47)	(0.04)	

The table shows the results of quantile regressions as in equation (14) for 5%, 25%, 50%, 75% and 95% of risk premia on macroeconomic components. Panel A, B and C presents the results of such regressions for VRP, SRP and KRP respectively. The labels on top show the respective macroeconomic components with Employ for Employment and F.Const for Financial Constraints. The far left column stands for respective quantile of risk premia; the numbers in parentheses list standard errors; while *, ** and *** depict significance at 10%, 5% and 1%

the 5th one, whereas the coefficients for KRP appears to be only significant for higher quantiles. The highest significance is observed at 75th quantile for both SRP and KRP and the estimated coefficients increase in quantile. On the other hand, the results for Inflation and Employment appear to be only pronounced in the highest and lowest quantiles for VRP and SRP, but not KRP. In particular, the highest (95th) quantile of SRP is negatively related with Inflation, while in case of VRP the same negative relationship is observed in the lowest (5th) quantile. Finally, Employment appears to be pronounced in 95th quantile of VRP, with the coefficient being negative and significant 1% level. The results suggest that in times when investors get compensated for variance risk, the compensation increases if the employment is low. Similarly, when investors get compensated for skewness risk, the compensation is lower the higher the Inflation. In case of VRP, when investors have highest variance hedging costs, these costs increase the higher the Inflation.

Overall these results shows that though the main conclusions of previous sections hold, the relationship between macroeconomic components and higher moment risk premia appears to be asymmetric. The effect of macroeconomic components are pronounced for higher quantiles of higher moment risk premia, when its the most positive, than for lower quantiles, when it is the most negative.

4 Conclusion

The paper investigates the role of the macroeconomic variables in the dynamics of the higher moment risk premia on the example of variance, skewness and kurtosis risk premia. The paper extends the model of Kozhan et al. (2013) and employs the extensive set of macroeconomic variables that are grouped in five broad categories: Inflation, Employment, Output, Sentiment and Financial Constraints. Then the first principal component is extracted for each group.

By running the set of separate ordinary and quantile regressions on higher moments risk premia, I find that higher moments risk premia is related to macroeconomic risk and relationship appears to be stronger in times when investors are compensated for higher moment risk. Moreover, it appears that SRP and KRP provide protection against Inflation and Sentiment risks with the relationship been pronounced the most in higher quantiles of the risk premia. Finally, I document that there are two components that drive the variability in higher moment risk premia: VIX and Financial

Constraints, which adds to evidence of Kozhan et al. (2013) and Schneider (2015), who speculate about existence of the common factor. The paper also confirms the previous findings that investors pay the premium to hedge the higher moments risk.

The results of the paper have a particular interest from practitioner point of view. First, it compares the hedging abilities of different higher moment risk premia. Second, the results are interesting for investors, who sell the protection against higher moment risk premia, by showing that in times when they have to compensate for higher moment risk the size of the compensation is highly related to macroeconomic risk in the market. Such information is of a particular use for hedging and risk management purposes.

Finally, as the paper investigates the higher moments risk premia associated with S&P 500 futures, it is interesting whether the similar conclusions hold in cross-section of stock returns. Moreover, the results of the regressions suggest that there can be other factors that explain the variability in higher moments risk premia. All these questions are left for future research.

An Appendix

A Proofs

A.1 Derivation of realized kurtosis formulas

I start by showing that the payoff can be replicated by Bakshi and Madan (2000). To do so define $H[F_{T,T}] = 6\left(\left(\frac{F_{T,T}}{F_{t,T}}\right)^2 - 2\ln\frac{F_{T,T}}{F_{t,T}} - 5 + 4\frac{F_{T,T}}{F_{t,T}} - 4\frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}}\right)$, and apply the formula to find

$$\begin{aligned} H'[F_{t,T}] &= 6(2\frac{F_{T,T}}{F_{t,T}^2} - 2\frac{1}{F_{T,T}} + 4\frac{1}{F_{t,T}} - 4\frac{1}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}} - 4\frac{1}{F_{t,T}}) = 0 \\ H''[F_{t,T}] &= 6(2\frac{1}{F_{t,T}^2} + 2\frac{1}{F_{T,T}^2} - 4\frac{1}{F_{t,T}}\frac{1}{F_{T,T}}) = 0 \end{aligned} \tag{15}$$

From Bakshi and Madan (2000) and Carr and Madan (2001):

$$
\begin{aligned}
H[F_{T,T}] &= H[F_{t,T}] + H'[F_{t,T}](F_{T,T} - F_{t,T}) \\
&\quad + \int_0^{F_{t,T}} H''[K]P_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} H''[K]C_{t,T}(K)dK \\
&= \int_0^{F_{t,T}} H''[K]P_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} H''[K]C_{t,T}(K)dK \\
&= 12\int_0^{F_{t,T}} \frac{(F_{t,T}-K)^2}{K^2F_{t,T}^2}P_{t,T}(K)dK + 12\int_{F_{t,T}}^{\infty} \frac{(F_{t,T}-K)^2}{K^2F_{t,T}^2}C_{t,T}(K)dK
\end{aligned}
\tag{16}
$$

By plugging it back to the equation (4) and taking the expectation, I obtain exactly the formula as in equation (5)

In addition, I calculate the fixed leg for the contract $g^Z(r_{t,T}) = e^{2r_{t,T}} - 1 = \left(\frac{F_{T,T}}{F_{t,T}}\right)^2 - 1$. By applying the same Bakshi and Madan (2000) formula I can find

$$
\begin{aligned}
H[F_{t,T}] &= \left(\frac{F_{T,T}}{F_{t,T}}\right)^2 - 1 = 0 \\
H'[F_{t,T}] &= 2(\frac{F_{T,T}}{F_{t,T}}) = 2\frac{F_{T,T}}{F_{t,T}^2} = 2\frac{1}{F_{t,T}} \\
H''[F_{t,T}] &= 2\frac{1}{F_{t,T}^2} = 2\frac{1}{F_{t,T}^2} \\
H[F_{T,T}] &= H[F_{t,T}] + H'[F_{t,T}](F_{T,T} - F_{t,T}) \\
&\quad + \int_0^{F_{t,T}} H''[K]P_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} H''[K]C_{t,T}(K)dK \\
&= 2\frac{1}{F_{t,T}}(F_{T,T} - F_{t,T}) + 2\int_0^{F_{t,T}} \frac{1}{F_{t,T}^2}P_{t,T}(K)dK + 2\int_{F_{t,T}}^{\infty} \frac{1}{F_{t,T}^2}C_{t,T}(K)dK \\
&= 2\left(\frac{F_{T,T}}{F_{t,T}} - 1 + \int_0^{F_{t,T}} \frac{P_{t,T}(K)}{F_{t,T}^2}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{F_{t,T}^2}dK\right)
\end{aligned}
\tag{17}
$$

In what follows, I use $G_t^Z = E_t^Q[e^{2r_{t,T}} - 1]$ and $\delta G_t^Z = G_{t+\delta t}^Z - G_t^Z$. To calculate the floating leg formulas, I am going to make use of Proposition 1 in Kozhan et al. (2013) again and estimate the floating leg for both continuous and discrete times. First, the floating leg can be found with

$$
dY_{t,T} = dG'_{t,T}df_{t,T} + \frac{1}{2}(G''_{t,T} - G'_{t,T})(df_{t,T})^2 \tag{18}
$$

Then lets find the values for the derivatives can be calculated as follows

$$\begin{aligned} G'_{t,T} &= E_t^Q[g'(r_{t,T})] = E_t^Q[6(2e^{2r_{t,T}} - 2 - 4r_{t,T}e^{r_{t,T}})] \\ &= 12E_t^Q[e^{2r_{t,T}} - 1] - 12G_t^E = 12G_t^Z - 12G_t^E \\ G''t,T &= E_t^Q[g''(r_{t,T})] = E_t^Q[6(4e^{2r_{t,T}} - 4e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}})] \\ &= 24E_t^Q[e^{2r_{t,T}}] - 24 - 12G_t^E = 24G_t^Z - 12G_t^E \end{aligned} \tag{19}$$

Then plugging the expressions in equation (18) gives the following:

$$\begin{aligned} dY_{t,T}^K &= dG'_{t,T}df_{t,T} + \frac{1}{2}(G''_{t,T} - G'_{t,T})(df_{t,T})^2 \\ &= 12d(G_t^Z - G_t^E)df_{t,T} + 6G_t^Z(df_{t,T})^2 \end{aligned} \tag{20}$$

As for the discrete time case, I recall the result of Proposition 1 from Kozhan et al. (2013). In particular, the floating leg in the discrete time setting can be found with the following formula

$$\begin{aligned} \delta Y_{t,T}^K &= E_{t+\delta t}^Q\left[g(r_{t,t+\delta t} + \delta f_{t,T}) - g(r_{t,t+\delta t}) - (e^{\delta f_{t,T}} - 1)E_t^Q[g'(r_{t,T})]\right] \\ &- E_{t+\delta t}^Q\left[g(r_{t,t+\delta t}) - (e^{\delta f_{t,T}} - 1)E_t^Q[g'(r_{t,T})]\right] \\ &= 6E_{t+\delta t}^Q[e^{2r_{t,t+\delta t}}](e^{2\delta f_{t,T}} - 1) + 6(-2\delta f_{t,T} + 4e^{\delta f_{t,T}} - 4\delta f_{t,T}e^{\delta f_{t,T}} - 4) \\ &- 12G_{t,t+\delta t}^E(e^{\delta f_{t,T}} - 1) - (e^{\delta f_{t,T}} - 1)(12G_t^Z - 12G_t^E) \\ &= 6G_{t+\delta t}^Z(e^{\delta f_{t,T}} - 1)^2 + 12(e^{\delta f_{t,T}} - 1)(\delta G_t^Z - \delta G_t^E) + 6(e^{2\delta f_{t,T}} - 2\delta f_{t,T} + 4e^{\delta f_{t,T}} - 4\delta f_{t,T}e^{\delta f_{t,T}} - 5) \end{aligned} \tag{21}$$

A.2 Proposition proof

To illustrate it we will make use of Taylor expansion around 0. Here we will calculate all of the powers up to the fourth:

$$
\begin{aligned}
g^K(r_{t,T}) &= 6(e^{2r_{t,T}} - 2r_{t,T} - 5 + 4e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}}) \\
g'^K(0) &= 6(2e^{2r_{t,T}} - 2 + 4e^{r_{t,T}} - 4e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}}) \\
&= 6(2e^{2r_{t,T}} - 2 - 4r_{t,T}e^{r_{t,T}}) = 0 \\
g''^K(0) &= 6(4e^{2r_{t,T}} - 4e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}}) = 0 \\
g'''^K(0) &= 6(8e^{2r_{t,T}} - 8e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}}) = 0 \\
g''''^K(0) &= 6(16e^{2r_{t,T}} - 12e^{r_{t,T}} - 4r_{t,T}e^{r_{t,T}}) = 24
\end{aligned}
\tag{22}
$$

Then using Taylor expansion and applying it on equation (4) it can be shown that

$$
\begin{aligned}
E_t^Q[g^K(r_{t,T})] &= E_t^Q\left[\frac{2 \times 3 \times 4}{4!} r_{t,T}^4 + O(r_{t,T})^5\right] \\
&= E_t^Q\left[r_{t,T}^4 + O(r_{t,T})^5\right]
\end{aligned}
\tag{23}
$$

B List of Macroeconomic variables

Table 6 shows the macroeconomic variables used to construct the groups. The financial constraints group consists of the following variables:

- Ted spread
- Commercial paper spread = Commerical paper yield - Three month T-bill
- Term spread = Ten years treasury yield- Three month T-Bill
- Default yield = Moody's BAA 10year yield - Moody's AAA 10 year yield

Table 6.
List of macroeconomic variables

Variable	Economic release	Group	Adjustment
US Import Price Index	U.S. Import and Export Price Indexes	Inflation	1
PPI Finished Goods Total	Producer Price Index	Inflation	1
PPI Finished Goods Less Food and Energy	Producer Price Index	Inflation	1
CPI for All Urban Consumers	Consumer Price Index	Inflation	1
CPI for All Urban Consumers Less Food and Energy	Consumer Price Index	Inflation	1
ECI Civilian Workers	Employment Cost Index	Inflation	1
GDP Chain-type Price Index	Gross Domestic Product	Inflation	1
Personal Consumption Expenditure (Core) Excluding Food and Energy	Personal Income and Outlays	Inflation	1
Nonfarm Real Output per hour	Productivity and Costs	Inflation	1
ADP National Employment report	ADP Employment	Employment	1
Initial Jobless Claims	Jobless Claims	Employment	1
Continued Jobless Claims	Jobless Claims	Employment	1
Employees Total Nonfarm Payroll	Employment Situation	Employment	1
Employees Total Nonfarm Payroll	Employment Situation	Employment	1
Civilian Unemployment Rate	Employment Situation	Employment	1
Average Weekly Hours of All Employees	Employment Situation	Employment	1
Manufacturers' New Orders: Durable Goods	"Full Report - Manufacturers' Shipments, Inventories and Orders	Output	1
Manufacturers' New Orders all industries	"Full Report - Manufacturers' Shipments, Inventories and Orders	Output	1
Total Consumer Credit	G.19 Consumer Credit	Output	1
Merchant Wholesalers Inventories	Advance Monthly Sales for Retail and Food Services	Output	0
Advance Real Retail and Food Services Sales	Advance Monthly Sales for Retail and Food Services	Output	1
Advance Retail Sales: Retail and Food Services Excluding Motor Vehicles	Advance Monthly Sales for Retail and Food Services	Output	0
Industrial Production Index	G.17 Industrial Production and Capacity Utilization	Output	1
Capacity Utilization	G.17 Industrial Production and Capacity Utilization	Output	1
Real Manufacturing and Trade Inventories	"Advance Report on Durable Goods – Manufacturers' Shipments, Inventories, and Orders	Output	1

Table 6.
List of macroeconomic variables(continued)

Variable	Economic release	Group	Adjustment
New Orders for Consumer Goods: Consumer Durable Goods	"Full Report - Manufacturers' Shipments, Inventories and Orders	Output	1
New Orders for Consumer Goods: Durable Goods Excluding Transportation	"Full Report - Manufacturers' Shipments, Inventories and Orders	Output	1
GDP rate	Gross Domestic Product	Output	0
Personal Consumption Expenditures	Gross Domestic Product	Output	1
Personal Income	Personal Income and Outlays	Output	1
Personal Consumption Expenditures Nominal	Personal Income and Outlays	Output	1
Michigan Sentiment	Michigan Sentiment	Sentiment	1
Empire State Business Conditions	Empire State Manufacturing Survey	Sentiment	1
Texas Outlook Business	Dallas Fed Manufacturing Business Outlook	Sentiment	1
Phil Fed Business Outlook	Philadelphia Fed Business Outlook	Sentiment	1
Ted spread	-	Financial Constraints	0
BAA yield	-	Financial Constraints	1
AAA yield	-	Financial Constraints	1
Three month T-bill	-	Financial Constraints	1
Ten years Treasuries	-	Financial Constraints	1
Commercial paper	-	Financial Constraints	1

The table shows the variables used for construction the groups. The column Variable shows the names of the variables used; the column Economic release lists the release, where the variable is published; the column Group identifies the respective group such Output, Inflation, Sentiment, Employment or Financial Constraint; and the column Adjustment indicates whether the adjustment for stationarity is needed, where 1 stands for the need of adjustment by taking the first difference and 0 for no adjustment.

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