The Dynamic Effects of Uncertainty and Risk Aversion on Real Activity Betas of Stock Markets Factor Risks

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Abstract

This paper employs a MIDAS decomposition of real activity betas into a high- and low frequency components to study how uncertainty and risk aversion affects the relation between investment-style factor returns and the real economy. For most investment-style factors, including the stock market excess return, there is a positive and significant relation between uncertainty and risk aversion and the beta of returns with real activity. Moreover, these effects start increasing at the beginning of recessions, with stronger effects occurring at the end of recessions. However, exactly the opposite effects are found for the quality/profitability-based factors.

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1. Introduction

This paper studies how uncertainty and risk aversion affect the conditional beta of the stock market portfolio, and the most popular dynamic factor risks with respect to real activity. In other words, what is the sensitivity of the real activity betas of investment-style factor risks to uncertainty and risk aversion shocks? Overall, our paper contributes to the macro-finance literature by clarifying the channel through which uncertainty and risk aversion affect the relation between stock returns and the real economy.

Our research connects two strands of literature on finance and macroeconomics by putting together two separate pieces of available empirical evidence. First, from the finance point of view, the recent evidence provided by Rossi and Timmermann (2015) in the context of the intertemporal capital asset pricing model (ICAPM), shows that high frequency real economic activity contains significant information about the state of the economy and indeed, it helps describing the time-varying opportunity set. Following the logic of the ICAPM, they show that the conditional covariance of returns with real economic activity presents a strongly positive and significant relation with the expected market risk premium. Thus, real economic activity plays a significant role in explaining the time-varying behavior of expected market excess returns.

Second, from the macroeconomic point of view, Bloom (2009), Bloom, Bond, and Van Reenen (2007), Bloom, Floetotto, Jaimovich, Saporta, and Terry (2018), Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016), Ludvigson, Ma, and Ng (2017), and Carriero, Clark, and Marcellino (2017), among others, show significant effects of uncertainty on economic growth, investment, and consumption. The impact of the Great Recession, and the relatively new availability of empirical proxies to measure uncertainty have stimulated a considerable amount of research on uncertainty.

Our research puts together these two pieces of evidence on asset pricing and macroeconomic uncertainty by studying how important uncertainty is in explaining the conditional real activity beta of stock market factor risks. Thus, we analyze whether uncertainty is a significant driver of the real activity beta not only of the excess market portfolio return, but also of a set of popular dynamic factor risks, which are the key components of the so-called factor investing. If, indeed, uncertainty significantly affects the conditional real activity beta, it would suggest that uncertainty is a major driver of the positive relation between the expected market risk premium and the conditional covariance of returns with real activity as found by Rossi and Timmerman (2015). This would clarify the role of uncertainty in the financial markets, and the source of real effects on stock returns. It would imply that uncertainty has significant effects on the behavior of the time-varying opportunity set. Moreover, it would provide a macroeconomic justification of the findings reported by Bali, Brown, and Tang (2017) who show that economic uncertainty is priced in the cross-section of stock returns.

At the same time, there is an increasing interest in distinguish between uncertainty and risk aversion. As pointed out by Bekaert, Engstrom, and Xu (2018), economic uncertainty can be understood as the amount of risk, while risk aversion is the price of risk. This distinction is consistent with the research of Bekaert and Horeova (2014, 2016) who argue that uncertainty can be proxied by the conditional expected variance, and risk aversion by the variance risk premium. Moreover, time-varying risk aversion under the external habit model of Campbell and Cochrane (1999) has become a key idea to explain the time-varying behavior of expected returns. In addition, as pointed out by Cochrane (2017), risk aversion is a fundamental driver of business cycles and, more importantly, of recessions. Indeed, Bretscher, Hsu, and Tamoni (2018) using a theoretical framework with recursive preferences and habit, show that risk aversion amplifies the effects of uncertainty shocks on the macroeconomy. For all these reasons, we also analyze the separate and simultaneous impact of uncertainty and risk aversion on the real activity betas of factor risks and the aggregate stock market.

We employ a Mixed Data Sampling Regression (MIDAS) framework and the decomposition of conditional betas into high- and low-frequency components proposed by González-Sánchez, Nave, and Rubio (2018), where the mixed frequency conditional beta is the weighted average of both components. Econometric methods involving data sampled at different frequencies have been shown to be useful for forecasting volatility in equity assets as well as for explaining the relation between conditional variance and expected market returns.[1] The success of MIDAS lies in the additional statistical power that mixed data frequency regressions incorporate from using daily data in estimating conditional variances. In addition, MIDAS allows for a very flexible functional form for the weights to be applied to past squared returns as a way of explaining current volatility.

Under this framework, we study the effects of uncertainty and risk aversion on the low frequency component of real activity betas of investment-style factors. It is important to note that we simultaneously estimate both real activity beta components and the effects of uncertainty and risk aversion rather than using a multiple step estimation procedure. It is also important to point out that we are especially concerned with the low frequency effects of uncertainty and risk aversion on the beta of returns with real activity and not with the stock market portfolio.

We show that both uncertainty and risk aversion significantly affect the behavior of stock market returns with respect to real activity. For most investment-style factors,

[1] See Ghysels, Santa-Clara, and Valkanov (2005, 2006), and González-Sánchez, Nave, and Rubio (2012), respectively.

including the stock market excess return, there is a positive and significant relation between uncertainty and risk aversion and the covariability of returns with real activity. Moreover, these effects start increasing at the beginning of recessions, but the stronger effects occur at the end of recessions. However, this is not true for some of the investment-style factors. More precisely, the Quality Minus Junk (QMJ) factor of Asness, Frazzini, and Pedersen (2014) presents a completely different behavior. Higher uncertainty and risk aversion are associated with a decreasing sensitivity of the QMJ returns with real activity. The QMJ is a defensive factor relative to the real economy, and not only to the market portfolio. The channels through which we show the defensive behavior of the QMJ factor are aggregate uncertainty and risk aversion. The Betting against Beta (BAB) factor of Frazzini and Pedersen (2014) also presents a different behavior. The effects of uncertainty and risk aversion on the BAB real activity is negative and positive with respect to uncertainty and risk aversion, respectively. Hence, the BAB factor is a defensive real activity factor relative to overall uncertainty but not with respect to risk aversion.

This paper proceeds as follows. Section 2 describes the econometrics, while Section 3 presents the data employed in the analysis. In Section 4, we discuss the individual effects of alternative uncertainty proxies and risk aversion, while Section 5 contains the simultaneous impacts of uncertainty and risk aversion. Finally, Section 6 presents our conclusions.

2. The Econometric Setting

We employ the mixed frequency conditional beta proposed by González-Sánchez et al. (2018). Hence, we estimate real activity betas as a weighted average of a high- and low frequency components. In this context, uncertainty (and/or risk aversion) is the driver of the conditional real activity beta through the low frequency component.

The mixed frequency real activity beta framework is given by,

$$R_{p,t+1} = \beta_0 + \beta_{pRA,t}^{MF} RA_{t+1} + u_{p,t+1} \,, \tag{1}$$

$$\beta_{pRA,t}^{MF} = \omega_p \beta_{pRA,t}^{H} + \left(1-\omega_p\right) \beta_{pRA,t}^{L} ;\; 0 \le \omega_p \le 1 \,, \tag{2}$$

where $R_{p,t+1}$ is the monthly excess market portfolio return or any of the investment-style factor risks return, $\beta_{pRA,t}^{MF}$ is the mixed frequency real activity beta, which is a weighted average of the high, $\beta_{pRA,t}^{H}$, and low, $\beta_{pRA,t}^{L}$, frequency beta components, and ω_p is the high frequency weight of the conditional beta.

The high and low frequency components are given by

$$\beta_{pRA,t}^{H} = \frac{\sum_{d=1}^{D} \Psi\left(d, \kappa_{p,1}, \kappa_{p,2}\right)\left(r_{p,t-d} \times ra_{t-d}\right)}{\sum_{d=1}^{D} \Psi\left(d, \kappa_{p,3}, \kappa_{p,4}\right) \times ra_{t-d}^{2}} \,, \tag{3}$$

$$\beta_{pRA,t}^{L} = \lambda_{p,0} + \lambda_{p,UNC} \sum_{h=1}^{H} \Psi\left(h, \kappa_{p,5}, \kappa_{p,6}\right) \times UNC_{t-h} \,, \tag{4}$$

where $r_{p,t-d}$ is the daily lagged excess return of factor risk *p* using data up to month *t* and associated with the following month, ra_{t-d} is the lagged of the daily change in the real activity index up to month *t*, and UNC_{t-h} denotes each of the lagged uncertainty measure relative to month *t*. The number of lags for both the daily returns and the monthly state variables are optimally estimated within the MIDAS procedure according to the beta function weighting scheme given by

$$\Psi\left(s,\kappa_{p,\delta},\kappa_{p,\delta+1}\right)=\frac{\left(\frac{s}{S}\right)^{\kappa_{p,\delta}-1}\left(1-\frac{s}{S}\right)^{\kappa_{p,\delta+1}-1}}{\sum_{d=1}^{S}\left(\frac{d}{S}\right)^{\kappa_{p,\delta}-1}\left(1-\frac{d}{S}\right)^{\kappa_{p,\delta+1}-1}} \quad , \tag{5}$$

which provides many potential shapes to accommodate various lag structures associated with either (past) daily returns, real activity or (past) monthly uncertainty. The beta function can represent a monotonically increasing or decreasing weighting scheme depending on the values of the two parameters, $\kappa_{p,\delta}$ and $\kappa_{p,\delta+1}$.

To estimate the mixed frequency conditional betas and the effects of the uncertainty proxies, we assume that the monthly return generating process for each portfolio is given by expression (1). The set of parameters to be estimated for each portfolio and for a given uncertainty measure is given by

$$\Phi=\left(\beta_0,\lambda_{p,0},\lambda_{p,UNC},\omega_p,\kappa_{p,1},\kappa_{p,2},\kappa_{p,3},\kappa_{p,4},\kappa_{p,5},\kappa_{p,6}\right), \tag{6}$$

where they obtained by minimizing the following expression[2]:

$$\min_{\{\Phi\}} MSE \equiv \min_{\{\Phi\}}\left[\frac{1}{T}\sum_{t=1}^{T}\left(R_{p,t+1}-\hat{R}_{p,t+1}\right)^2\right]. \tag{7}$$

Similarly, we employ this framework to analyze the effects of risk aversion on real activity betas using a proxy for risk aversion instead the uncertainty measure. The model becomes,

$$\beta^L_{pRA,t}=\lambda_{p,0}+\lambda_{p,RAV}\sum_{h=1}^{H}\Psi\left(h,\kappa_{p,7},\kappa_{p,8}\right)\times RAV_{t-h} \tag{8}$$

[2] See González-Sánchez et al. (2018) for additional details of the estimation procedure.

where *RAV* is the risk aversion proxy presented in Section 3.

3. Data

As measures of uncertainty, we employ the macroeconomic and financial uncertainty indices of Jurado et al. (2015), defined as the combined conditional volatility of the unforecastable component of a large number of macroeconomic and financial variables, respectively. As an alternative proxy for uncertainty, we use the Baker et al. (2016) Economic Policy Uncertainty (EPU) indicator, which counts the frequency of articles containing the words uncertain or uncertainty, economy or economics, and the following six policy words, Congress, deficit, central bank, legislation, regulation, and government. There is an increasingly popular literature on the relation and transmission mechanism between uncertainty and economic growth. Overall, there is a consensus that higher uncertainty leads to lower growth.[3]

In addition, as uncertainty proxies, we employ the monthly volatility of VIX and MOVE estimated with daily data for a given month. The VIX index is the risk-neutral one-month expected stock market volatility for the U.S. S&P500 index. It is computed by averaging the weighted prices of puts and calls on the S&P500 index over a wide range of strike prices. It has become an extremely popular and useful measure of near-term market volatility. The MOVE index, which is the Merrill Lynch Option Volatility Estimate Index, as the Treasuries implied volatility. It is a term structure weighted index of the normalized implied volatility on one-month Treasury options, which are weighted on the 2, 5, 10, and 30-year contracts. It is therefore the equivalent of VIX for Treasury bond returns and reflects the market-based measure of uncertainty about the composite future behavior of interest rates across different maturities of the yield curve. Current

[3] See Bloom (2014) for a review article on uncertainty and real activity growth.

increases in MOVE suggests that the market is willing to pay more for hedging against unexpected movement in interest rates. González-Urteaga, Nieto, and Rubio (2018) show that MOVE is a net sender of volatility to VIX. Although this result holds for most of their sample period between 1988 and 2017, it is especially true during bad economic times. They also show that net connectedness between MOVE and VIX is explained by monetary and economic drivers. This empirical finding suggests that MOVE is an important economic indicator and, therefore, the volatility of MOVE is a powerful candidate to proxy for uncertainty.

As a proxy for risk aversion, we employ the measure provided by the European Central Bank (ECB), which is available on monthly basis since December 1998. It is the first principal component of five currently available risk aversion indicators, namely Commerzbank Global Risk Perception, UBS FX Risk Index, Westpac's Risk Appetite Index, Bank of America Risk Aversion Indicator, and Credit Suisse Risk Appetite Index. A rise in the indicator denotes an increase in risk aversion. We extend the data by projecting the ECB risk aversion on the Chicago Fed National Financial Conditions Index (NFCI).[4] The estimated coefficients are employed to construct a synthetic measure of risk aversion from April 1988 to November 1998.

Table 1 contains the pairwise correlation coefficients among all proxies for uncertainty and risk aversion described above. As expected, all signs are relatively high and positive. The larger correlations are between macroeconomic and financial uncertainty, risk aversion and financial uncertainty, and risk aversion and the volatility of VIX. The correlation between macroeconomic uncertainty and risk aversion is also high, but not as high as the previous correlations. Finally, EPU and volatility of MOVE are the

[4] Data are downloaded from the Federal Reserve Bank of Chicago at https://www.chicagofed.org/publications/nfci/index

less correlated measure of uncertainty with respect to the rest of uncertainty proxies and risk aversion.

Note that our analysis requires a combination of daily and monthly frequency data. For this reason, we employ the ADS real activity index of Aruoba, Diebold, and Scotti (2009), which is designed to track real economic conditions at high frequency.[5] The average value of the index is zero. Positive values indicate better-than-average conditions, whereas negative values represent worse-than-average conditions.

We analyze the effects of uncertainty and risk aversion on the three factor risks of the popular Fama and French (1993) three-factor model, with the excess market return, size (SMB) and value (HML) factors.[6] Moreover, given that they are not able to explain the cross-sectional variability of momentum portfolios unless Carhart's (1997) momentum factor (MOM) is included in the cross section, we consider this factor in our analysis. We collect these monthly data from Kenneth French's website (http://mba.tuck.darmouth.edu).

We use the Quality minus Junk (QMJ) factor of Asness et al. (2014), further explored by Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018). These authors define a quality stock as an asset for which an investor would be willing to pay a higher price. These are stocks that are safe (low required rate of return), profitable (high return on equity), growing (high cash flow growth), and well managed (high dividend payout ratio). Asness et al. (2014) show that the QMJ factor, which buys high-quality stocks and shorts low-quality (junk) stocks, earns significant risk-adjusted returns not only in the

[5] Data are downloaded from the Federal Reserve Bank of Philadelphia at https://www.philadelphiafed.org.
[6] Fama and French (2015) expand this model with the profitability (robust minus weak, RMW) and investment (conservative minus aggressive, CMA) factors. In this research, given that these are factors related to profitability and management efficiency, we employ instead the Quality minus Junk factor described below.

U.S. market but also in 24 other countries. The QMJ factor is downloaded from the AQR Capital Management Database (www.aqr.com).

Finally, recent empirical evidence supports the presence of funding liquidity across a wide range of securities. Frazzini and Pedersen (2014) show that leverage constraints are strong and significantly reflected in the return differential between leveraged low-beta stocks and de-leveraged high-beta stocks. The authors argue that the positive and highly significant risk-adjusted returns relative to traditional asset pricing models shown by portfolios sorted by the level of market beta are explained by shadow cost-of-borrowing constraints.[7] The authors illustrate their argument by proposing a market neutral BAB factor consisting of the difference between long-leveraged low-beta stocks and short de-leveraged high-beta securities. This factor is also downloaded from the AQR Capital Management Database.

To conclude, we explore the effects of five uncertainty measures and a proxy for risk aversion of the conditional real activity beta of the market portfolio return, and five factor risks, namely size, value, momentum, quality and low beta risk investment-style factors. These five factors have probably become the most popular strategies in the factor investing and beta smart industry.

4. Individual Uncertainty Measures, Risk Aversion, and Real Activity Betas

We next estimate the models from April 1988 to June 2017. We employ this sample period due to the availability of data for some of the measures of uncertainty and risk aversion. We analyze the effects of macroeconomic and financial uncertainty, economic policy uncertainty, the volatilities of MOVE and VIX, and the ECB risk aversion proxy.

[7] See also Asness, Frazzini, Gormsen, and Pedersen (2018) for additional evidence supporting this argument.

Moreover, we also estimate these effects using the first principal component of the five uncertainty measures. The estimated models are given by expressions (4) and (8), where we employ the uncertainty proxies and risk aversion, respectively.

In Table 2, we report the results for our sample period analyzing individually the effects of the five uncertainty measures, the first principal component and the risk aversion proxy. Note that the first principal component explains 79.2% of the variability of the variance-covariance matrix of the five uncertainty approximations. Panels A through E of Table 2 show the results for the five uncertainty proxies. Panel F contains the results using the first principal component of the five uncertainty measures, and Panel G displays the results with respect to risk aversion. The results show intriguing discrepancies among the five uncertainty proxies regarding the sensitivity of real activity betas to uncertainty. This motivates the analysis based on the first principal component, and it helps understanding how close a given measure of uncertainty is related to the principal component. Rossi, Sekhposyany, and Souprez (2017) propose a framework to understand the macroeconomic effects of the alternative measures of uncertainty discussed in literature. They show that EPU spikes earlier than the macroeconomic uncertainty measure of Jurado et al. (2015) and argue that EPU is driven relatively more by ex-ante uncertainty, while the macroeconomic uncertainty proxy more for ex-post uncertainty. These differences have consequences for understanding the recessionary effects of the alternative proxies for uncertainty. The results reported by González-Urteaga et al. (2018) suggest that the volatility of MOVE is also connected with ex-ante rather than ex-post uncertainty, even more than the volatility of VIX. Following this logic, the positive sensitivity of the market portfolio excess return shown in Panel F of Table 2, where we employ the principal component, is better explained by EPU and the volatility of the risk-neutral Treasury volatility, which seems to better capture the idea of ex-ante uncertainty. On the other hand, the quality/profitability-based factor risk, namely QMJ, respond negatively to overall uncertainty, and this negative sign is explained by the negative sign of financial uncertainty and the volatility of VIX, which are pure measures of financial uncertainty. A similar negative and significant sensitivity is also obtained for the BAB factor risk for most of the uncertainty proxies with the exception of macroeconomic uncertainty for which is not statistically different from zero. Recall that this latter factor is constructed going long on low beta stocks, which suggests a defensive real activity behavior against uncertainty. The traditional SMB, HML, and MOM factors responds positively to overall uncertainty. However, the HML factor is positively related to uncertainty measures with a macroeconomic flavor, and negatively associated with pure financial uncertainty proxies. Finally, the positive overall respond of the SMB factor is basically due to macroeconomic uncertainty and the volatility of MOVE while, as expected, the sensitivity of the SMB factor is negatively related with pure financial uncertainty measures.

Panel G of Table 2 contains the results for risk aversion. Except for the QMJ factor, the sensitivity of all other factors to risk aversion, including the market portfolio excess return, is positive and statistically different from zero. Higher risk aversion is accompanied by higher covariability of their returns with real activity. As with uncertainty, the higher risk aversion, the lower the covariance between the QMJ factor and real activity is. It is also relevant to point out that the signs of the overall uncertainty, represented by the first principal component, and risk aversion is the same for all factor risks except for the BAB factor. The correlation between the principal component of uncertainty and risk aversion is 0.49. This high correlation makes reasonable to expect, as observed in most cases, that the signs of uncertainty and risk aversion are the same. However, even more important is to note that the magnitudes of the sensitivities associated with risk aversion are always higher (including for the QMJ factor in absolute terms) than for the uncertainty principal component. Risk aversion seems to play an amplifying role in the effects of uncertainty on the sensitivity of returns with the real economy.

To conclude, using the concepts of uncertainty and risk aversion as the underlying sources of real activity effects, our results clarify which are the economic and financial characteristics that distinguish the popular factor risks so heavily employed in financial economics. Moreover, we also clarify the channel through which uncertainty and risk aversion impact on the stock market. It is through the low frequency exposure that the market and aggregate dynamic portfolios have to real activity.

These complementary results that we find using uncertainty and risk aversion motivate the following bivariate estimation in which we simultaneously analyze the effects of both uncertainty and risk aversion proxies.

5. Simultaneous Effects of Uncertainty and Risk Aversion on Real Activity Betas

In the bivariate estimation, the low-frequency real activity beta includes not only a proxy for uncertainty but also a measure of risk aversion. The model is now given by

$$\begin{aligned}\beta^{L}_{pRA,t} &= \lambda_{p,0} + \lambda_{p,UNC} \sum_{h=1}^{H} \Psi\left(h, \kappa_{p,9}, \kappa_{p,10}\right) \times UNC_{t-h} \\ &+ \lambda_{p,RA} \sum_{h=1}^{H} \Psi\left(h, \kappa_{p,11}, \kappa_{p,12}\right) \times ARAV_{t-h}\end{aligned} \tag{9}$$

Due to the high correlation between the measures of uncertainty and the risk aversion provided by the ECB, we employ an adjusted proxy for risk aversion, denoted by *ARAV*, which is the residual of regressing the European Central Bank (ECB) risk aversion on the financial uncertainty proxy of Jurado et al. (2015).

Figure 1 displays the time-varying low frequency real activity market beta for the five uncertainty proxies estimated from the bivariate model that employs simultaneously a given measure of uncertainty and the adjusted risk aversion from the ECB. Independently of the uncertainty proxy, all resulting betas present a very similar time-changing pattern. The striking exception is the behavior of the low frequency real activity market beta when we use the volatility of MOVE as a proxy for uncertainty. Table 3 contains summary statistics of these low frequency real activity market betas estimated for each uncertainty proxy. On average, the low frequency beta associated with the volatility of MOVE is much more volatile than the rest of the low frequency betas. The difference between the maximum and minimum values is also much larger for the volatility of MOVE. This is consistent with the higher peaks of the time-varying beta shown in Figure 1. It seems that the low frequency component of the marker real activity beta reacts much more to changes in the volatility of MOVE than to other uncertainty proxies, including the volatility of VIX. This is consistent with the findings of González-Urteaga et al. (2018) suggesting how important MOVE is as an economic indicator during bad economic times.

Panels A through E of Table 4 show the sensitivities of the market and dynamic factor risks to uncertainty and risk aversion simultaneously. Regarding the market portfolio return, risk aversion is positive and significantly associated with the real activity market beta for all measures of uncertainty. However, a significant positive relation with respect to uncertainty is only found when we employ the volatilities of MOVE and VIX as proxies for uncertainty. Similarly, the SMB dynamic factor shows that risk aversion is positive and significantly associated with the real activity SMB beta, but the results with respect to uncertainty are only positive and statistically significant with the volatility of MOVE and EPU. As in the case of the market, there is a larger positive impact of risk aversion relative to average uncertainty. The HML factor risk displays basically the same results as the SMB factor. Once again, risk aversion is positively related with the real activity HML beta, but this is not always the case for all measures of uncertainty. Interestingly, the uncertainty coefficient is positive and significant when we employ a measure of uncertainty more closely related to macroeconomic measures rather than to financial proxies. Hence, the positive relation shows up if we employ macroeconomic, EPU, and the volatility of MOVE as approximations for uncertainty. As before, for the market and the SMB factor, the effect is larger for risk aversion than for uncertainty.

The momentum factor presents a negative and consistent results with respect to risk aversion, and a positive and significant evidence regarding the uncertainty proxies given by the macroeconomic and financial measures of Jurado et al. (2015), and the volatility of VIX. The negative sensitivity of the low-frequency real activity momentum beta with respect to risk aversion is important. Note that risk aversion impacts positively on the real activity HML beta and recall that value and momentum work at different frequencies. Value strategies pay attention to stocks that have been falling during a relatively long period of time, while the momentum strategy consists of buying stocks that are becoming expensive. The shorter time horizon associated with the momentum strategy may explain the different response of value and momentum to the risk aversion effects on the low frequency real activity beta.

The QMJ factor of Frazzini et al. (2014) shows a very different behavior. The risk aversion coefficient of their real activity beta is always negative and statistically significant. At the same time, the uncertainty coefficient is only positive and statistically different from zero when we employ macroeconomic uncertainty. As previously discussed, the behavior of this factor can be explained by noting that it is a hedging factor against bad real economic times. Hence, we should expect negative rather than positive coefficients for the QMJ factor. Indeed, this is what we find in our empirical exercise using the volatilities of risk-neutral equity and Treasury volatilities. These results, associated with the sensitivity with respect to the real economy, have important implications for the understanding of the behavior of quality stocks.

Finally, the BAB factor has very consistent results across all measures of uncertainty employed in the analysis. The sensitivity with respect to risk aversion is always positive suggesting that the real activity beta increases with risk aversion. The extremely opposite reaction of the BAB against uncertainty and risk aversion is an intriguing result. If we accept that the BAB is closely related with funding liquidity, as discussed by Frazzini and Pedersen (2014), the results suggest that risk aversion affects negatively the sensitivity of funding liquidity with the real economy. Funding liquidity needs the amplifying effects of higher risk aversion over and above the uncertainty impact before reacting negatively.

As pointed out before, we extract a summary of these effects across the five uncertainty measures using the first principal component of the five proxies. Figure 2 displays the time-varying behavior of the principal component and the ECB risk aversion. As expected, both measures are strongly counter-cyclical with high spikes during recessions. Table 5 reports the bivariate effects of uncertainty, represented by the first principal component, and the adjusted risk aversion on the low frequency component of real activity betas of factor risks using equation (9). Overall, the simultaneous estimation shows that increases in uncertainty impacts positively on the real activity beta of the excess market return, SMB, and MOM investment-style factor risks. The effects are negative for the rest of the factors. On the other hand, the sensitivity with respect to risk aversion is positive for the market, SMB, HML and BAB factors. Risk aversion affects negatively on momentum and the quality-based factors. Indeed, for this latter factor both uncertainty and risk aversion are negatively associated with the beta between real activity and the QMJ returns. Risk aversion is therefore more important than uncertainty, in the sense of increasing real activity beta, for the HML and BAB factors, and the positive coefficient is higher than the uncertainty coefficient for the market and the SMB factor. The opposite is true for the MOM and quality-based factors.[8]

Figures 3.A through 3.E displays the time-varying behavior of the low frequency component of real activity betas associated with the uncertainty principal component and risk aversion for the market and the five representative factor risks. These low frequency components tend to increase from the very beginning of recessions with peaks at the end or immediately after recessions. This is the case for the market, SMB, HML and MOM factors. The exception is the behavior of the real activity market beta during the recession of the nineties in Figure 3.A that shows a decrease rather an increase with respect to risk aversion. In fact, the behavior of the beta relative to uncertainty is precisely the opposite during those years. The time-varying behavior of the low frequency real activity beta of the QMJ with either uncertainty or risk aversion is striking. It is not only negative for most of the sample period, it turns out that the real activity beta decreases during recessions. The QMJ factor becomes more defensive with respect to the real economy during bad economic times. The strong decline in the real activity beta during the Great Recession is certainly impressive. The BAB real activity beta shows a similar behavior with respect to uncertainty but a very strong positive reaction during recessions when we consider the effects of risk aversion. All these results are consistent with the average estimated sensitivity coefficients shown in Table 5.

[8] On average, the RMSE of the bivariate model with the uncertainty principal component decreases 1.17% relative to the univariate uncertainty case, while diminishes 1.02% for risk aversion.

6. Conclusions

The analysis of uncertainty and risk aversion, as drivers of the sensitivity of the market and investment-style dynamic factors, clarify the characteristics of these popular factors during bad macroeconomic and financial times. The overall market portfolio return shows a significant increase in the sensitivity to real activity whenever uncertainty and/or risk aversion goes up. It seems that the channel by which uncertainty and/or risk aversion negatively affect the market portfolio excess return is through the exposure of returns to real activity shocks. The real activity market beta is significant and positively related to uncertainty, but the effect is much stronger with respect to risk aversion. In absolute value, the larger impact of risk aversion relative to uncertainty is a constant across alternative measures of uncertainty and dynamic factor risks. However, the sign of the uncertainty and/or risk aversion effects on the sensitivity of the factors to real activity is different across the investment factors. The HML and BAB factors react negatively (positively) with respect to uncertainty (risk aversion), suggesting that risk aversion is the main driver of risky behavior of these factors relative to real activity. It is well known that the MOM and HML factors work at differently frequencies. This may explain the very different impact of uncertainty and risk aversion to the sensitivity of the MOM factor to real activity. Contrary to the HML and BAB factor, the MOM factor reacts negatively (positively) with respect to risk aversion (uncertainty). Finally, Asness et al. (2014) show that their QMJ, that buys high-quality stocks and shorts low-quality (junk) stocks, earns significant risk-adjusted returns not only in the U.S. market, but also in 24 other countries. In addition, their striking finding is that the QMJ factor displays large realized returns during stock market downturns, which suggests that the quality-based factor does not exhibit bad-times risk. They plot the risk-adjusted returns of the QMJ factor against market excess returns and show that the quality factor presents a mild positive convexity, which suggests that the QMJ factor benefits from flight-to-quality stock market declines. In this paper we show a complementary evidence of the QMJ factor. The sensitivity of the QMJ returns to real activity strong and significantly decreases with uncertainty and risk aversion, and these effects occur from the beginning of recessions reaching the highest negative impact at the end of recessions. The QMJ investment factor is a very important hedging investment-style factors against uncertainty and risk aversion.

Overall, risk aversion amplifies the effects of uncertainty on the sensitivity of stock market returns to the business cycle behavior of the real economy.

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Table 1
Correlation Coefficients Among Uncertainty and Risk Aversion Measures. April 1988-June 2017

	MACRO UNC	FIN UNC	EPU	RISK AVERSION	VOL MOVE	VOL VIX
MACRO UNC	1	0.688	0.269	0.614	0.406	0.452
FIN UNC		1	0.358	0.722	0.435	0.557
EPU			1	0.470	0.318	0.479
RISK AVERSION				1	0.464	0.696
VOL MOVE					1	0.496

This table contains the pairwise correlation coefficients for a set of uncertainty and risk aversion measures. MACRO UNC is the macroeconomic uncertainty of Jurado, Ludvigson, and Ng (JLN) (2015); FIN UNC is the financial uncertainty of JLN (2015); EPU is the (log) of the economic policy uncertainty Index of Baker, Bloom, and Davis (BBD) (2016); RISK AVERSION is the European Central Bank measure of risk aversion; VOL MOVE is the monthly volatility estimated with daily data within the given month of the MOVE Index. VOL VIX is the similar monthly volatility of VIX. The VIX index is the risk-neutral one-month expected stock market volatility for the US S&P500 index. It is computed by averaging the weighted prices of puts and calls on the S&P500 index over a wide range of strike prices. The MOVE index is the Merrill Lynch Option Volatility Estimate Index. It is a term structure weighted index of the normalized implied volatility on one-month Treasury options, which are weighted on the 2, 5, 10, and 30-year contracts.

Table 2
Individual Uncertainty and Risk Aversion Effects on the Low Frequency Component of the Real Activity Betas of Investment-Style Factor Risks: April 1988-June 2017

Panel A: Macro Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.069 (9.68)	-0.028 (-6.63)	-0.067 (-2.09)	-0.576 (-3.83)	-0.023 (-3.17)	-0.004 (-0.10)
$\hat{\lambda}_{p,MUNC}$	-0.048 (-8.88)	0.032 (5.33)	0.107 (2.28)	0.864 (3.69)	0.011 (1.19)	0.054 (0.84)
Beta Short-term Weight	0.721 (6.68)	0.713 (6.28)	0.679 (10.39)	0.738 (2.69)	0.685 (10.67)	0.806 (3.02)
RMSE %	4.166	3.052	2.998	4.534	2.817	3.685
Panel B: Financial Uncertainty	**Excess Market**	**SMB**	**HML**	**MOM**	**QMJ**	**BAB**
$\hat{\lambda}_{p,0}$	0.095 (2.64)	0.066 (4.00)	0.027 (2.57)	-0.327 (-7.70)	0.035 (7.85)	0.296 (9.24)
$\hat{\lambda}_{p,FUNC}$	-0.055 (-10.85)	-0.074 (-3.31)	-0.021 (-9.32)	0.366 (1.66)	-0.021 (-7.07)	-0.267 (-9.16)
Beta Short-term Weight	0.766 (9.13)	0.708 (5.62)	0.676 (11.88)	0.709 (2.34)	0.696 (6.75)	0.841 (7.82)
RMSE %	4.164	3.046	3.002	4.439	2.816	3.652
Panel C: Economic Policy Uncertainty	**Excess Market**	**SMB**	**HML**	**MOM**	**QMJ**	**BAB**
$\hat{\lambda}_{p,0}$	0.006 (4.87)	-0.002 (-1.16)	-0.037 (-4.01)	-0.001 (-0.09)	-0.035 (-3.80)	0.071 (6.74)
$\hat{\lambda}_{p,EPU}$	0.599 (12.15)	-0.077 (-1.25)	0.961 (4.89)	0.512 (3.73)	0.414 (2.69)	-0.795 (-2.23)
Beta Short-term Weight	0.705 (7.55)	0.709 (5.95)	0.678 (4.36)	0.705 (9.26)	0.701 (4.57)	0.810 (3.38)
RMSE %	4.164	3.054	3.001	4.469	2.819	3.685
Panel D: Volatility of MOVE	**Excess Market**	**SMB**	**HML**	**MOM**	**QMJ**	**BAB**
$\hat{\lambda}_{p,0}$	-0.043 (-10.54)	-0.043 (-3.85)	-0.006 (-3.81)	0.050 (3.33)	-0.027 (-3.73)	0.041 (3.27)
$\hat{\lambda}_{p,VMOVE}$	3.250 (9.72)	1.522 (6.18)	0.546 (5.27)	-1.291 (-2.81)	0.415 (2.46)	-0.016 (-2.82)
Beta Short-term Weight	0.736 (6.40)	0.717 (7.10)	0.682 (5.54)	0.625 (3.39)	0.713 (3.20)	0.843 (7.28)
RMSE %	4.127	3.037	2.999	4.684	2.827	3.680

Panel E: Volatility of VIX	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.038 (2.78)	0.001 (0.35)	0.015 (5.15)	0.020 (3.65)	0.019 (5.85)	0.057 (4.57)
$\hat{\lambda}_{p,VVIX}$	-0.060 (-3.46)	-0.108 (-2.07)	-0.123 (-2.29)	0.155 (2.17)	-0.671 (-5.79)	-0.264 (-7.98)
Beta Short-term Weight	0.715 (1.99)	0.712 (2.26)	0.682 (10.89)	0.770 (3.97)	0.783 (12.16)	0.846 (4.09)
RMSE %	4.166	3.053	3.003	4.687	2.807	3.680

Panel F: First Principal Component Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	-0.164 (-7.32)	-0.083 (-5.01)	-0.153 (-3.07)	-0.035 (-2.73)	0.274 (3.54)	0.191 (2.62)
$\hat{\lambda}_{p,PC\_UNC}$	0.052 (7.46)	0.023 (5.16)	0.047 (3.10)	0.017 (4.80)	-0.084 (-3.87)	-0.049 (-8.88)
Beta Short-term Weight	0.443 (3.72)	0.453 (4.79)	0.717 (2.41)	0.712 (5.39)	0.751 (6.06)	0.701 (5.87)
RMSE %	4.152	3.059	3.001	4.688	2.803	3.679

Panel G: Risk Aversion	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.035 (5.92)	-0.012 (-9.36)	0.006 (2.77)	0.023 (5.13)	-0.004 (-10.88)	0.019 (6.33)
$\hat{\lambda}_{p,RAV}$	0.455 (6.75)	0.266 (2.13)	0.275 (2.49)	0.414 (9.88)	-1.297 (-2.96)	1.341 (8.40)
Beta Short-term Weight	0.747 (4.49)	0.801 (5.79)	0.699 (2.37)	0.745 (5.15)	0.690 (8.90)	0.785 (5.62)
RMSE %	4.160	3.041	3.000	4.686	2.795	3.672

This table reports the individually estimated impact of uncertainty and risk aversion on the low frequency component of real activity betas of the three Fama-French risk factors (Excess Market, SMB, HML), and the momentum (MOM), quality (QMJ), and beta against beta (BAB) factors. Panels A through E show the individual evidence regarding uncertainty using either the macroeconomic, financial, economic policy, volatility of MOVE, or volatility of VIX as measures of uncertainty, respectively. Panel F displays the results using the first principal component of the five uncertainty proxies employed individually in previous panels. Panel G contains the impact of risk aversion, which is approximated by the European Central Bank Risk Aversion. MOVE is the one-month Merrill Lynch Option Risk-Neutral Treasury Volatility. VIX is the one-month CBOE Option Risk-Neutral Equity Volatility. In parentheses we report the *t*-statistic.

Table 3
Summary Statistics of the Low Frequency Real Activity Market Beta from the Bivariate Model with Uncertainty and Risk Aversion: February April 1988-June 2017

Low frequency Betas	Macro Uncertainty	Financial Uncertainty	Economic Policy Uncertainty	Volatility of MOVE	Volatility of VIX
Average	0.0294	0.0296	0.0226	0.0223	0.0256
Standard Deviation	0.0129	0.0181	0.0140	0.0255	0.0154
Coefficient of Variation	0.4386	0.6116	0.6190	1.1472	0.6004
Maximum	0.0746	0.0920	0.0867	0.1872	0.1153
Minimum	-0.0029	-0.0152	-0.0051	-0.0171	-0.0001

This table reports simple statistics of the low frequency real activity market beta estimated under the bivariate model with alternative proxies for uncertainty and risk aversion. The proxy of risk aversion is the European Central Bank Risk Aversion. Given the high correlation between this proxy of risk aversion and the alternative uncertainty approximations, we measure risk aversion as the residuals of regressing the European Central Bank risk aversion on financial uncertainty. MOVE is the one-month Merrill Lynch Option Risk-Neutral Treasury Volatility, and VIX is the one-month CBOE Option Risk-Neutral Equity Volatility.

Table 4
Uncertainty and Risk Aversion Bivariate Effects on the Low Frequency Component of the Real Activity Betas of Investment-Style Factor Risks: April 1988-June 2017

Panel A: Macroeconomic Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.061 (8.16)	-0.023 (-1.97)	-0.067 (-5.74)	-0.610 (-3.10)	-0.021 (-6.84)	0.016 (5.11)
$\hat{\lambda}_{p,MUNC}$	-0.048 (-3.40)	0.022 (1.28)	0.011 (5.77)	0.943 (3.09)	0.020 (4.80)	0.001 (0.03)
$\hat{\lambda}_{p,ARAV}$	1.472 (3.07)	0.589 (9.03)	0.164 (4.92)	-2.831 (-2.94)	-1.774 (-5.16)	5.386 (5.82)
Beta Short-term Weight	0.719 (2.33)	0.653 (5.33)	0.679 (3.58)	0.743 (2.24)	0.725 (6.50)	0.854 (4.39)
RMSE %	4.152	3.040	2.996	4.498	2.783	3.603

Panel B: Financial Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.046 (1.44)	0.049 (5.20)	0.021 (6.13)	-0.359 (-2.44)	0.009 (0.32)	0.288 (4.52)
$\hat{\lambda}_{p,FUNC}$	-0.017 (-0.57)	-0.061 (-0.25)	-0.016 (-4.27)	-0.398 (-2.46)	-0.017 (-0.58)	-0.273 (-4.61)
$\hat{\lambda}_{p,ARAV}$	1.991 (4.95)	0.666 (5.31)	0.360 (7.40)	0.739 (2.90)	-1.966 (-7.86)	1.770 (5.97)
Beta Short-term Weight	0.762 (3.81)	0.732 (4.17)	0.692 (5.15)	0.709 (1.69)	0.752 (6.47)	0.841 (4.21)
RMSE %	4.156	3.040	2.999	4.456	2.782	3.638

Panel C: Economic Policy Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	-0.030 (-0.88)	-0.052 (-5.43)	-0.040 (-6.09)	0.048 (5.33)	0.018 (0.72)	0.035 (0.73)
$\hat{\lambda}_{p,EPU}$	1.159 (1.41)	0.960 (5.19)	0.961 (6.72)	-0.060 (-0.35)	-0.541 (-1.12)	-0.571 (-0.56)
$\hat{\lambda}_{p,ARAV}$	1.373 (5.31)	0.569 (1.60)	0.569 (8.67)	-2.735 (-12.15)	-1.839 (-3.00)	3.861 (2.50)
Beta Short-term Weight	0.674 (3.82)	0.678 (3.82)	0.678 (5.90)	0.768 (9.33)	0.738 (2.34)	0.798 (2.24)
RMSE %	4.165	3.052	2.994	4.466	2.780	3.638

Panel D: Volatility of MOVE	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	-0.022 (-3.54)	-0.023 (-7.04)	-0.013 (-2.26)	0.084 (9.08)	0.028 (6.26)	0.069 (5.99)
$\hat{\lambda}_{p,VMOVE}$	2.250 (4.77)	0.546 (3.76)	0.546 (2.62)	-0.907 (-7.92)	-1.587 (-8.06)	-2.099 (-6.04)
$\hat{\lambda}_{p,ARAV}$	0.711 (6.17)	0.710 (2.54)	1.171 (1.98)	-3.311 (-8.14)	-1.126 (-3.19)	5.124 (8.02)
Beta Short-term Weight	0.736 (6.34)	0.678 (2.88)	0.678 (1.99)	0.843 (5.20)	0.737 (6.10)	0.845 (5.27)
RMSE %	4.140	3.053	3.001	4.466	2.773	3.602

Panel E: Volatility of VIX	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	0.013 (7.40)	0.020 (2.74)	0.025 (8.45)	-0.052 (-2.88)	0.004 (5.68)	0.109 (10.20)
$\hat{\lambda}_{p,VVIX}$	0.222 (7.96)	-0.539 (-3.70)	-0.343 (-7.82)	2.126 (3.81)	-0.257 (-5.11)	-1.802 (-9.90)
$\hat{\lambda}_{p,ARAV}$	1.065 (5.56)	1.338 (3.84)	0.664 (5.59)	-6.554 (-4.71)	-2.364 (-6.46)	6.554 (10.16)
Beta Short-term Weight	0.677 (6.10)	0.673 (4.38)	0.683 (4.98)	0.850 (4.30)	0.809 (3.19)	0.838 (9.33)
RMSE %	4.155	3.040	2.998	4.644	2.784	3.625

This table reports the simultaneously estimated impact of each individual uncertainty proxy denoted by ($\hat{\lambda}_{p,\{MUNC,FUNC,EPU,VMOVE,VVIX\}}$) and (adjusted) risk aversion ($\hat{\lambda}_{p,ARAV}$) on the low frequency component of real activity betas of the three Fama-French risk factors (Excess Market, SMB, HML), and the momentum (MOM), quality (QMJ), and beta against beta (BAB) factors. Panels A through E show the simultaneous evidence using macroeconomic, financial, economic policy, volatility of MOVE, and volatility of VIX as measures of uncertainty, respectively. Risk aversion is the European Central Bank Risk Aversion. However, given the high correlation between this proxy of risk aversion and the alternative uncertainty approximations, we measure risk aversion as the residuals of regressing the European Central Bank risk aversion on financial uncertainty. MOVE is the one-month Merrill Lynch Option Risk-Neutral Treasury Volatility. Risk aversion is the European Central Bank Risk Aversion. VIX is the one-month CBOE Option Risk-Neutral Equity Volatility. In parentheses we report the *t*-statistic.

Table 5
Overall Uncertainty and Risk Aversion Bivariate Effects on the Low Frequency Component of the Real Activity Betas of Investment-Style Factor Risks: April 1988-June 2017

Panel A: Macroeconomic Uncertainty	Excess Market	SMB	HML	MOM	QMJ	BAB
$\hat{\lambda}_{p,0}$	-0.091 (-3.33)	-0.057 (-2.38)	0.136 (5.76)	-0.207 (-4.39)	0.127 (5.74)	0.150 (6.70)
$\hat{\lambda}_{p,PC\_UNC}$	0.029 (3.52)	0.015 (2.27)	-0.047 (-6.20)	0.069 (5.49)	-0.038 (-5.72)	-0.043 (-6.60)
$\hat{\lambda}_{p,ARAV}$	0.391 (3.74)	0.219 (5.62)	5.862 (8.46)	-2.184 (-3.39)	-1.056 (-4.62)	1.132 (7.57)
Beta Short-term Weight	0.159 (2.32)	0.168 (5.35)	0.881 (7.39)	0.642 (3.14)	0.597 (7.12)	0.225 (1.99)
RMSE %	4.142	3.005	2.945	4.651	2.776	3.627

This table reports the simultaneously estimated impact of the first principal component of the five uncertainty proxies ($\hat{\lambda}_{p,PC\_UNC}$) and risk aversion ($\hat{\lambda}_{p,ARAV}$) on the low frequency component of real activity betas of the three Fama-French (Excess Market, SMB, HML) risk factors, and the momentum (MOM), quality (QMJ), and beta against beta (BAB) factors. The uncertainty proxies are macroeconomic, financial, economic policy, volatility of MOVE, and volatility of VIX as measures of uncertainty. Risk aversion is the European Central Bank Risk Aversion. However, given the high correlation between this proxy of risk aversion and the alternative uncertainty approximations, we measure risk aversion as the residuals of regressing the European Central Bank risk aversion on financial uncertainty. MOVE is the one-month Merrill Lynch Option Risk-Neutral Treasury Volatility. VIX is the one-month CBOE Option Risk-Neutral Equity Volatility. In parentheses we report the *t*-statistic.

Figure 1
Low Frequency Real Activity Market Beta of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX): February 1990-June 2017

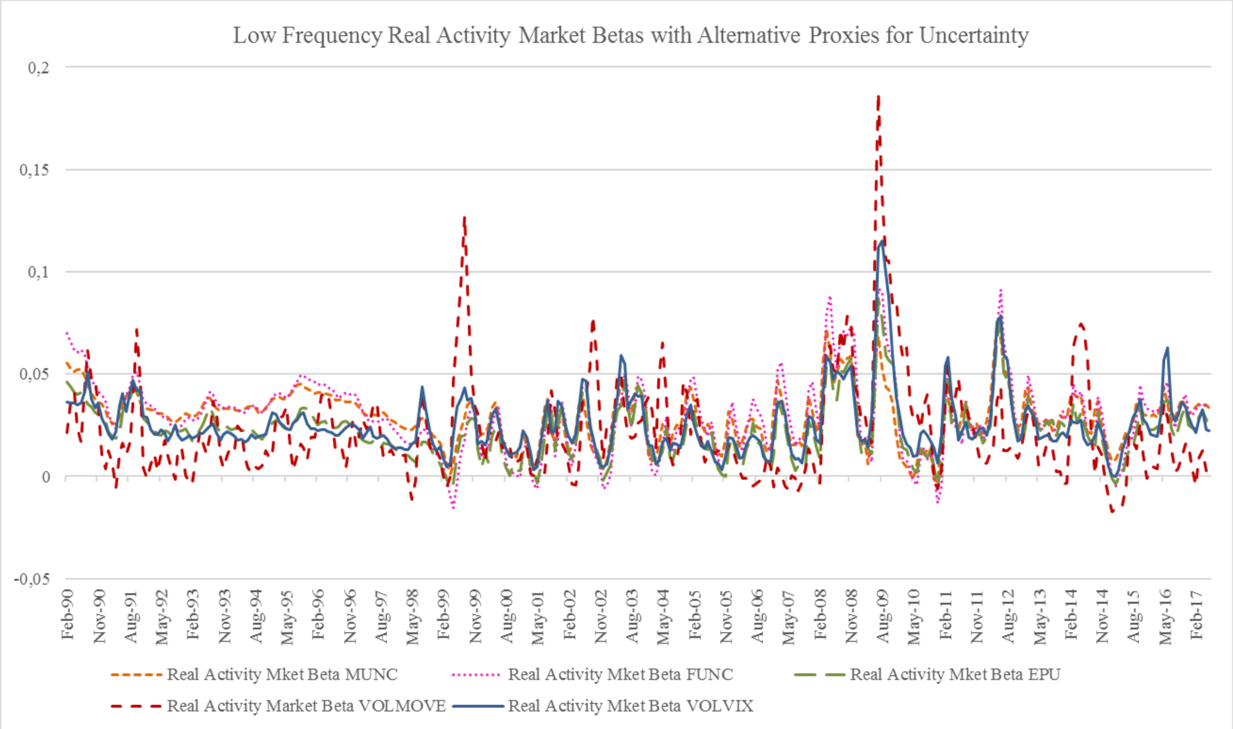

Figure 2
First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: April 1988-June 2017

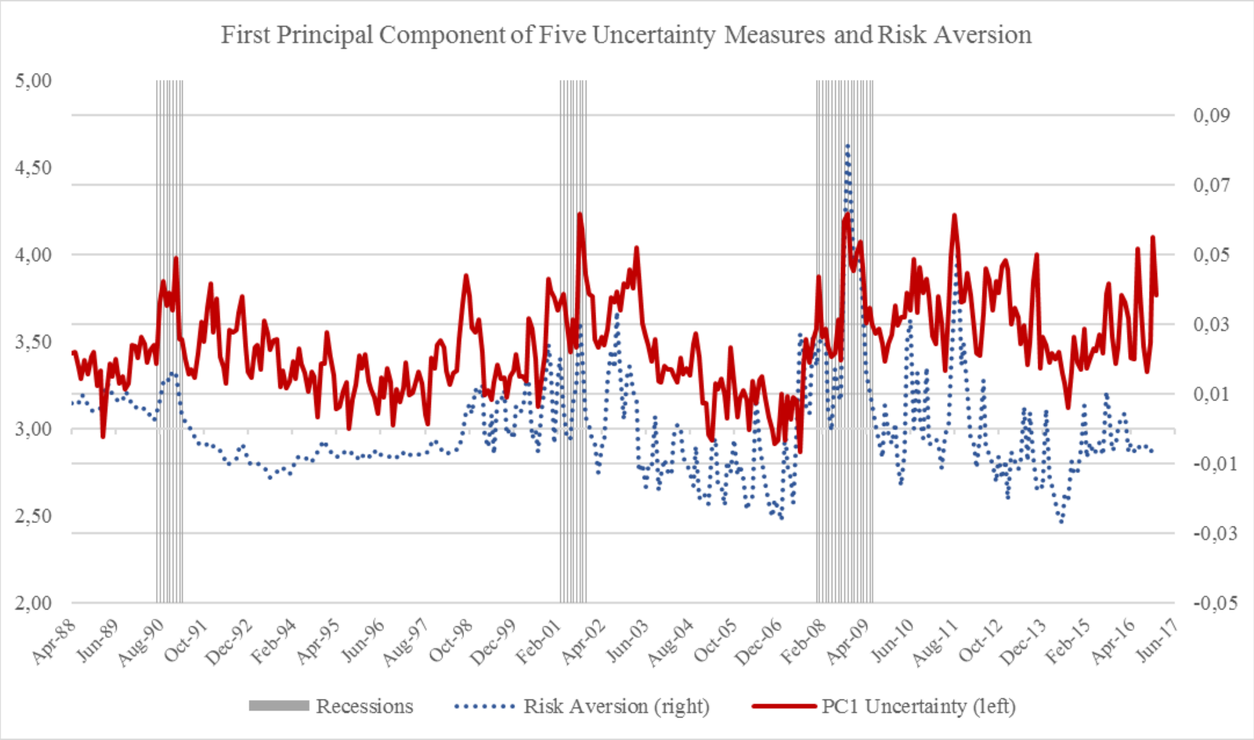

Figure 3.A
Low-Frequency Components of Real Activity Market Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017

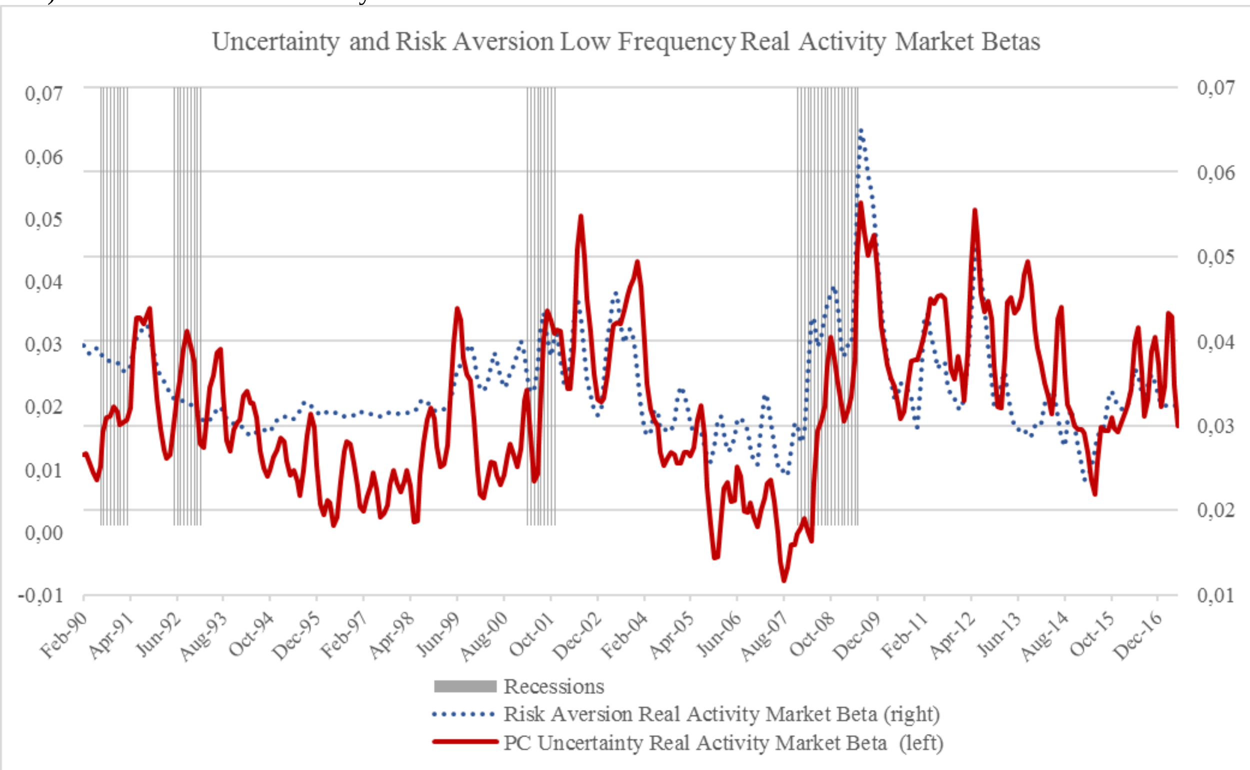

Figure 3.B
Low-Frequency Components of Real Activity SMB Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017

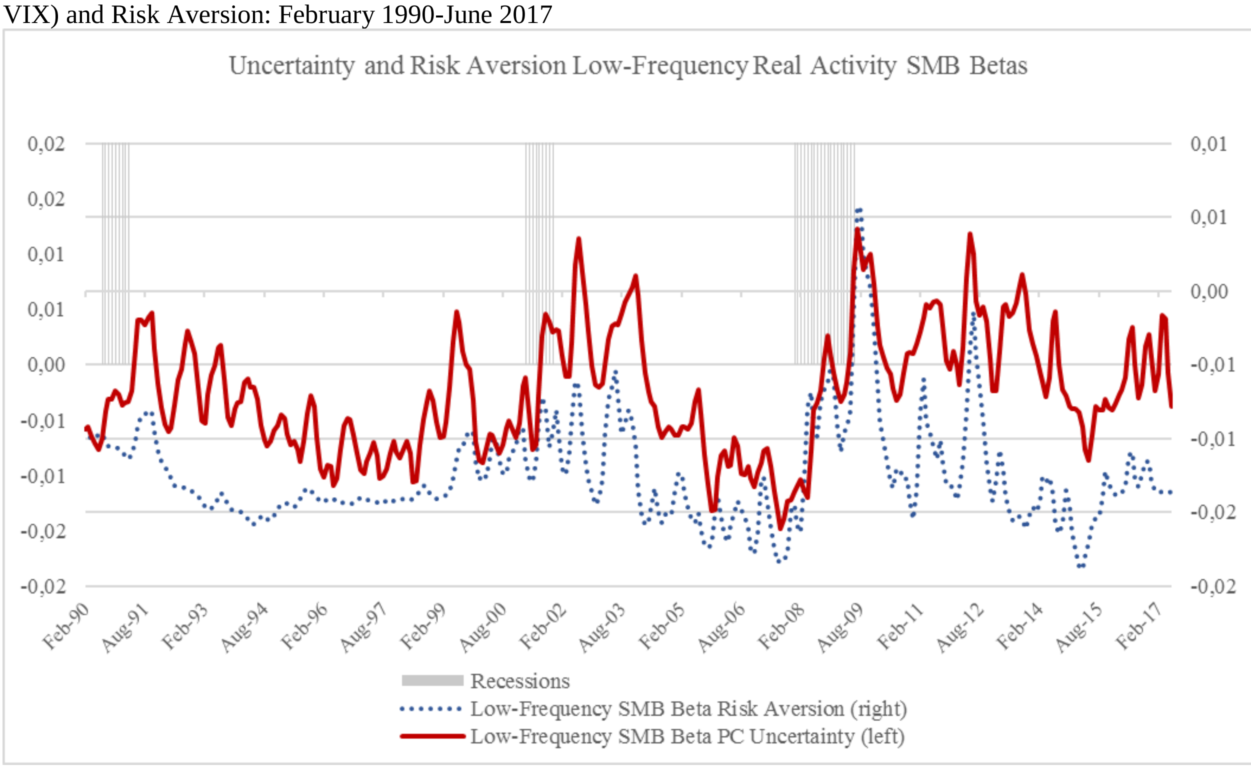

Figure 3.C
Low-Frequency Components of Real Activity HML Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017

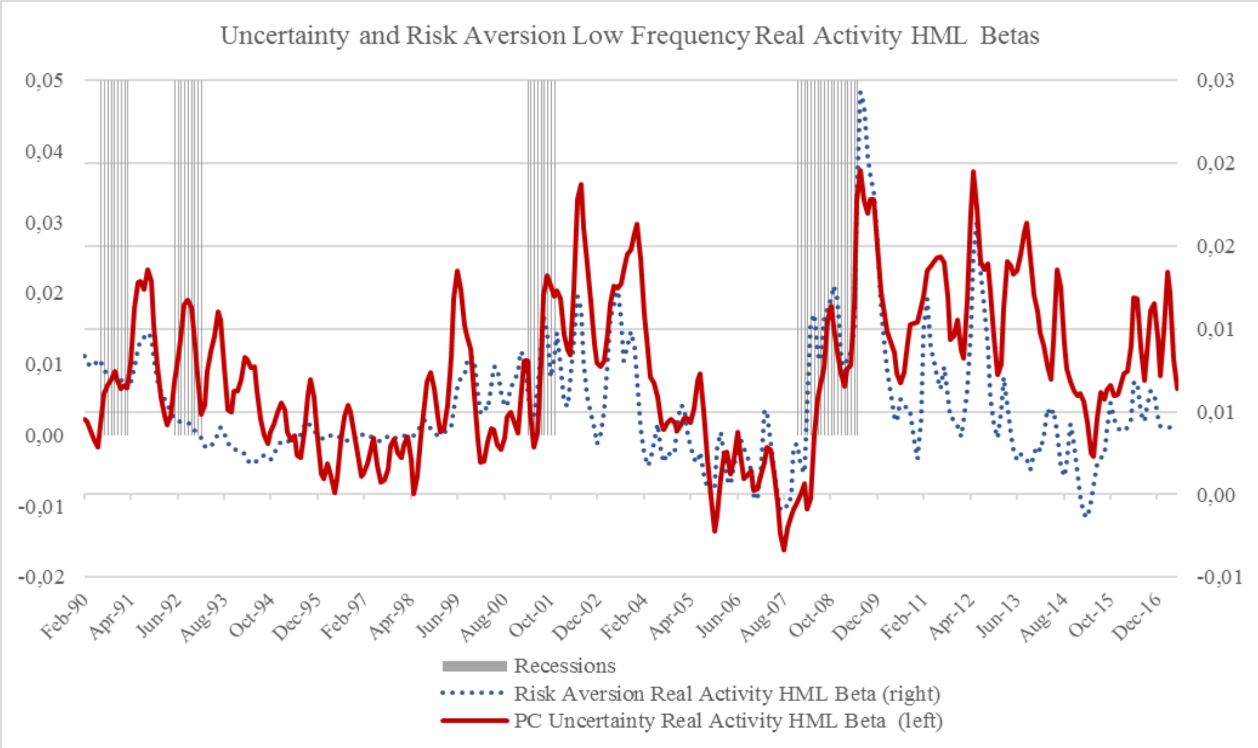

Figure 3.D
Low-Frequency Components of Real Activity MOM Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017

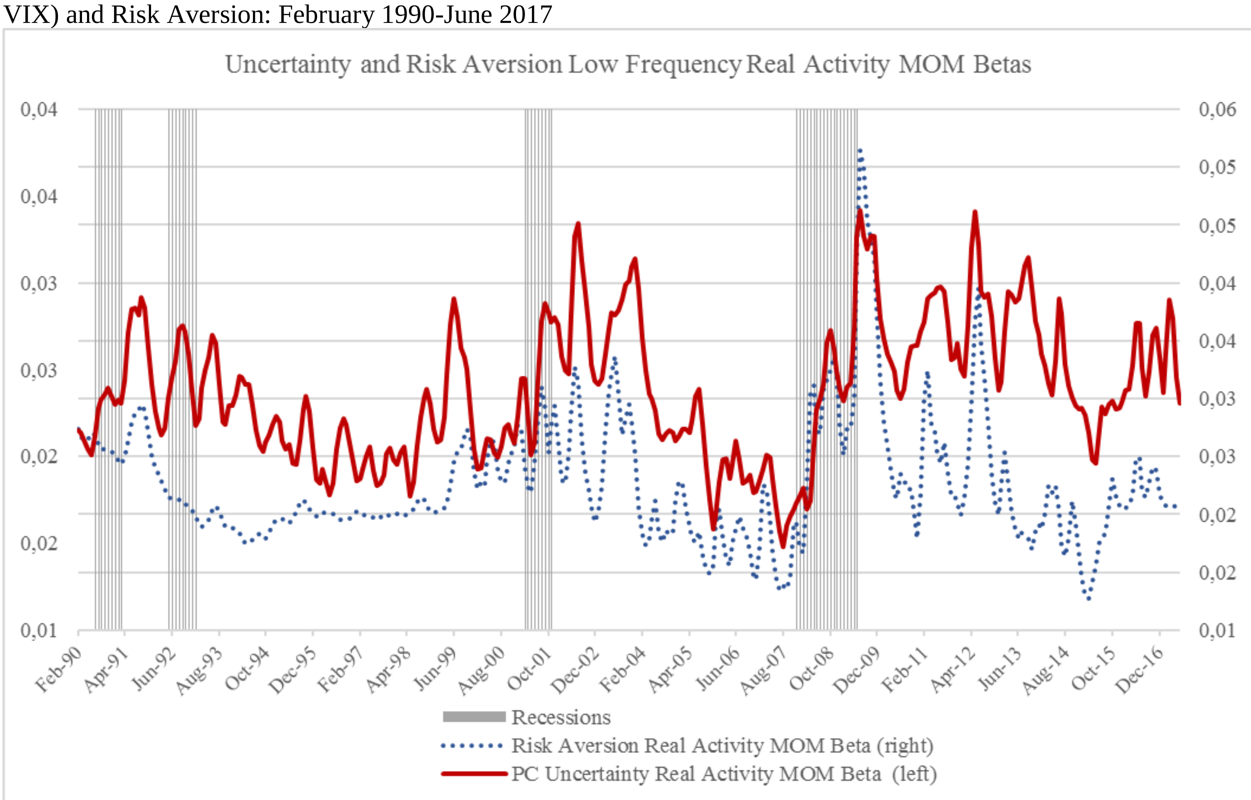

Figure 3.E
Low-Frequency Components of Real Activity QMJ Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017

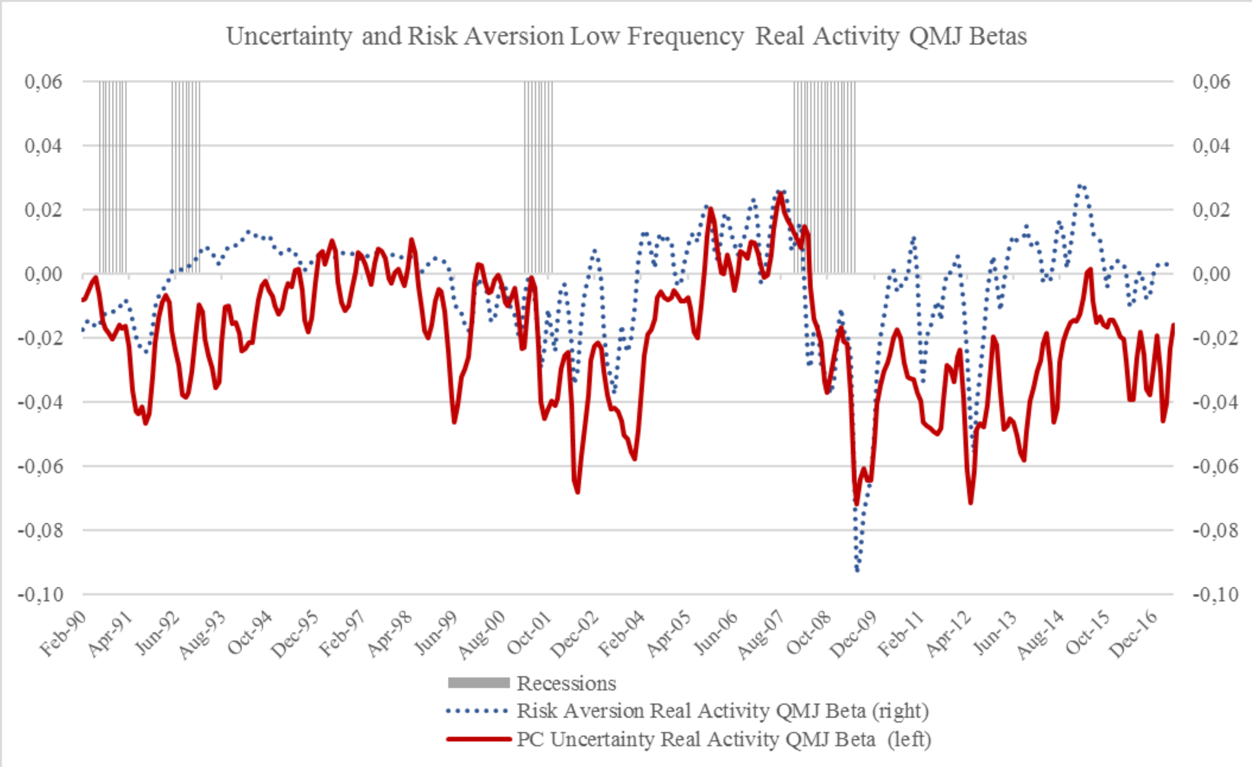

Figure 3.F
Low-Frequency Components of Real Activity BAB Betas of the First Principal Component of Five Uncertainty Proxies (Macroeconomic, Financial, Economic Policy, Volatility of MOVE, and Volatility of VIX) and Risk Aversion: February 1990-June 2017