Effects of Uncertainty and Risk Aversion on the Exposure of Investment-Style Factor Returns to Real Activity

Mariano González-Sánchez
(mariano.gonzalez@cee.uned.es)
National Distance Education University (UNED)

Juan Nave
(juan.nave@uclm.es)
University of Castilla La Mancha

Gonzalo Rubio
(gonzalo.rubio@uch.ceu.es)
CEU Cardenal Herrera University

Abstract

How do uncertainty and risk aversion affect the behavior of investment-style factors? We argue that a significant channel through which both uncertainty and risk aversion impact aggregate risk factors is the exposure of factor returns to real activity. We analyze this issue using mixed data sampling decomposition of the sensitivity of factor returns to real activity into high- and low-frequency components. We find a positive and significant relation between uncertainty and risk aversion for the low-frequency component of the sensitivity of factor returns to economic activity. More importantly, risk aversion significantly amplifies the effects of uncertainty on real activity exposure. The quality-based factor is an important exception to these findings.

This version: April 2, 2020

Keywords: real activity beta; low-frequency component; high-frequency component; uncertainty; risk aversion; investment-style factors

JEL classification: G12; C32; E32; E44

Mariano González-Sánchez and Juan Nave acknowledge financial support from the Spanish Ministry of Economy and Competitiveness through grant MINECO/FEDER ECO2015-65826-P, and Mariano González-Sánchez acknowledges financial support from the Cátedra Universidad CEU San Pablo-Mutua Madrileña. Gonzalo Rubio acknowledges financial support from Generalitat Valencia through grant Prometeo/2017/158 and from the Spanish Ministry of Science, Innovation, and Universities through grant PGC2018-095072-B-I00. We thank an anonymous reviewer for a very helpful suggestion. Any errors are entirely our own.
Corresponding author: Gonzalo Rubio (gonzalo.rubio@uch.ceu.es)

1. Introduction

We study the effects of uncertainty and risk aversion on the exposure of investment-style factor returns, including the stock market excess return, with respect to real activity. Overall, our paper contributes to the macro-finance literature by identifying a relevant channel through which uncertainty and risk aversion affect the relation between factor returns and the real economy. Furthermore, our results help understand the economic sources of previous factor-based anomalies. Can small, value, and momentum risk premiums be at least partially explained by the impact of uncertainty and risk aversion on the exposure of their returns to real activity? We argue that the effects of uncertainty and risk aversion on the exposure of factor returns to economic activity clarify the time-varying behavior of investment-style factors.

The motivation underlying our research is based on the macro-finance literature. Recent evidence provided by Rossi and Timmermann (2015) in the context of Merton's (1973) 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 describe the time-varying opportunity set. Following the logic of the ICAPM, Rossi and Timmermann 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, as a proxy for consumption and investment opportunities, plays a significant role in explaining the time-varying behavior of expected market excess returns.

At the same time, stimulated by the impact of the Great Recession and the (relatively new) availability of empirical proxies measuring uncertainty, considerable macroeconomic research about the effects of uncertainty on the real economy has been carried out in the last decade. In this context, Bloom, Bond and Van Reenen (2007), Bloom (2009), Jurado, Ludvigson and Ng (2015), Baker, Bloom and Davis (2016), Ludvigson, Ma and Ng (2019), Carriero, Clark and Marcellino (2018), and Bloom, Floetotto, Jaimovich, Saporta, and Terry (2018), among others, show the significant effects of alternative flavors of uncertainty on economic growth, investment and consumption. In other words, uncertainty affects the realizations of the state variables underlying the intertemporal risk in the ICAPM framework.

On the other hand, there is increasing interest in distinguishing between uncertainty and risk aversion. As pointed out by Bekaert, Engstrom, and Xu (2019), economic uncertainty can be understood as the amount of risk, whereas risk aversion is the price of risk. This distinction is consistent with the research of Bekaert and Hoerova (2014, 2016), who argue that uncertainty can be proxied for by the conditional expected variance, and risk aversion by the variance risk premium. Moreover, in the external habit model of Campbell and Cochrane (1999), time-varying risk aversion 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 (2019) using a theoretical framework with recursive preferences and habit formation, show that risk aversion amplifies the effects of uncertainty shocks on the economy.

These alternative settings justify the separate and simultaneous analysis of the impact of uncertainty and risk aversion on the exposure of factor returns to real economic activity. Moreover, given that we combine the data of several uncertainty proxies, risk aversion, macroeconomic activity, and daily stock returns, we argue that the mixed data sampling regression (MIDAS) developed by Ghysels, Santa-Clara, and Valkanov (2003) is particularly appropriate for our research. Econometric methods involving data sampled at different frequencies have been shown to be useful for forecasting the volatility of equity returns (Ghysels, Santa-Clara, and Valkanov, 2006), as well as for explaining the relation between conditional variance and expected market returns (Ghysels, Santa-Clara, and Valkanov, 2005). The success of MIDAS lies in the additional statistical power that mixed data frequency regressions incorporate from the use of daily data in estimating conditional variances and covariances. In addition, in explaining current volatility, MIDAS allows for a very flexible functional form for the weights applied to past squared returns. In this paper, we work within the MIDAS setting and take advantage of the mixed frequency conditional stock market beta framework proposed by González-Sánchez, Nave, and Rubio (2018) to decompose the exposure of factor returns to real activity into high- and low-frequency components.

Our empirical results show that both uncertainty and risk aversion significantly affect the low-frequency component of the exposure of factor returns to real activity. For most investment-style factors, including the stock market excess return, there is a positive and significant relation between both uncertainty and risk aversion, and the sensitivity of returns with real activity. Moreover, risk aversion has a strong amplifying effect over and above the reported uncertainty impact. The significance of these effects starts to increase at the beginning of recessions, with stronger effects at the end of recessions. Although these overall results remain rather stable throughout the two alternative subperiods into which we divide the full sample period, the effects of both uncertainty and risk aversion are especially important during the second subperiod from June 2003 to June 2017. Indeed, the uncertainty effects are mainly driven by the second subperiod, whereas the effects of risk aversion remain statistically significant across both subperiods.

Relative to classic investment factors, the Quality Minus Junk (QMJ) factor of Asness, Frazzini, and Pedersen (2019) presents completely different behavior. Higher uncertainty and risk aversion are associated with the significantly decreased sensitivity of

QMJ returns to real activity. The QMJ factor is a defensive factor relative to the real economy, not only to the market portfolio. The channels in which we demonstrate the defensive behavior of the QMJ factor are aggregate uncertainty and risk aversion.

This paper proceeds as follows. Section 2 describes the statistical research design, while Section 3 presents the data. Section 4 discusses the individual effects of uncertainty and risk aversion, and Section 5 describes the simultaneous impact of uncertainty and risk aversion. Finally, Section 6 presents our conclusions.

2. Research Design

Henceforth, to be precise and to employ the usual financial notation, we refer to the exposure of factor returns to real activity as real activity betas. Therefore, we are concerned with the effects of uncertainty and risk aversion on real activity betas, defined as the regression coefficient between factor returns and real economic activity. More specifically, we estimate the mixed frequency conditional real activity beta as a weighted average of the high- and low-frequency components of the exposure of factor returns to economic activity. In this context, uncertainty and/or risk aversion are the drivers of the conditional real activity beta through the low-frequency component.

The mixed frequency real activity beta framework is given by

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

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

where $R_{p,t+1}$ is the monthly excess market portfolio return or any of the investment-style factor returns, $\beta^{MF}_{pRA,t}$ is the mixed frequency real activity beta, which is a weighted average of the high-frequency beta component, $\beta^{H}_{pRA,t}$, and the low-frequency beta component, $\beta^{L}_{pRA,t}$, and ω_p is the high-frequency weight of the conditional real activity beta. Thus, we can distinguish between the impacts of uncertainty and risk aversion on the low-frequency (monthly) component and the high-frequency (daily) component of the real activity beta.

The high- and low-frequency components are given by

$$\beta^{H}_{pRA,t} = \frac{\sum_{d=1}^{D} \Psi\left(d, \kappa_{p1}, \kappa_{p2}\right)\left(r_{p,t-d} \times ra_{t-d}\right)}{\sum_{d=1}^{D} \Psi\left(d, \kappa_{p3}, \kappa_{p4}\right) \times ra^{2}_{t-d}} , \tag{3}$$

$$\beta^{L}_{pRA,t} = \lambda_{p,0} + \lambda_{p,X} \sum_{j=1}^{J} \Psi\left(h, \kappa_{p5}, \kappa_{p6}\right) \times X_{t-j} , \tag{4}$$

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 daily change in the real activity index up to month *t*, and X_{t-j} denotes each of the lagged measures of uncertainty or risk aversion 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 following beta function weighting scheme:

$$\Psi\left(s, \kappa_{pa}, \kappa_{pb}\right) = \frac{\left(\frac{s}{S}\right)^{\kappa_{pa}-1}\left(1-\frac{s}{S}\right)^{\kappa_{pb}-1}}{\sum_{d=1}^{S}\left(\frac{d}{S}\right)^{\kappa_{pa}-1}\left(1-\frac{d}{S}\right)^{\kappa_{pb}-1}} , \tag{5}$$

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, κ_{pa} and κ_{pb}.[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

$$\Phi = \left(\beta_0, \lambda_{p,0}, \lambda_{p,X}, \omega_p, \kappa_{p1}, \kappa_{p2}, \kappa_{p3}, \kappa_{p4}, \kappa_{p5}, \kappa_{p6}\right), \tag{6}$$

obtained by minimizing the expression,

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

We use nonlinear least squares to estimate the parameters and the corresponding standard errors are obtained as described by Judge, Griffith, Hill, and Lutkepohl (1985). A potential concern with the estimation is that it relies on the sensitivity of the results to the initial conditions. The initial parameters are therefore obtained by simulated annealing, a global optimization method that reasonably approximates the global optimum of a given function in a large search space. Then, we apply the usual quasi-Newton optimization techniques, and employ then the BFGS method.[2]

---

[1] See Ghysels, Sinko, and Valkanov (2007) for a discussion and comparison among alternative weighting schemes.

[2] The methodology of Broyden, Fletcher, Goldfarb, and Shanno, described in Fletcher (1987), uses the numerical gradient to choose the direction in which the parameter values change and the numerical Hessian to estimate the size of the change. We finally obtain standard errors using the information matrix; that is, the variance-covariance matrix of the parameters is estimated as the inverse of the numerical Hessian for the optimal values.

Finally, it is important to note that we simultaneously estimate the effects associated with uncertainty and risk aversion and both real activity beta components, rather than use a multi-step estimation procedure.

3. Data

We analyze the effects of uncertainty and risk aversion on the three-factor risks of the popular three-factor model of Fama and French (1993), with excess market return, size (SMB) and value (HML) factors.[3] Moreover, since the authors 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 also consider this factor in our analysis. We collect these monthly data from Kenneth French's website (http://mba.tuck.darmouth.edu).

In addition, we use the QMJ factor of Asness et al. (2019), 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. (2019) 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 US market, but also in 24 other countries. The QMJ factor is downloaded from the AQR Capital Management database (www.aqr.com).

As a proxy for risk aversion, we employ the measure provided by the European Central Bank (ECB), available on monthly basis since December 1998. It is the first

[3] Fama and French (2015) expand this model with profitability (robust minus weak, RMW) and investment (conservative minus aggressive, CMA) factors. Since these factors are related to profitability and management efficiency, we employ instead the QMJ factor described below.

principal component of five currently available risk aversion indicators, namely, Commerzbank's Global Risk Perception, UBS's FX Risk Index, Westpac's Risk Appetite Index, Bank of America's Risk Aversion Indicator, and Credit Suisse's Risk Appetite Index. A rise in the first principal component denotes an increase in risk aversion. We extend the data by projecting the ECB risk aversion measure on the Chicago Fed National Financial Conditions Index. The estimated coefficients are employed to construct a synthetic measure of risk aversion from April 1988 to November 1998. The data series are downloaded from the ECB at https://www.sdw.ecb.europe-eu and the Federal Reserve Bank of Chicago at https://www.chicagofed.org/publications/nfci/index.

As the first measures of uncertainty, we employ the macroeconomic and financial uncertainty indexes 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. The data are collected from https://www.sydneyludvigson.com/data-and-appendixes. As a second proxy for uncertainty, we use the Economic Policy Uncertainty (EPU) indicator of Baker et al. (2016), which counts the frequency of articles containing the words *uncertain* or *uncertainty*, *economy* or *economics*, and one or more of *Congress*, *deficit*, *Federal Reserve*, *legislation*, *regulation*, or *White House*. The data are downloaded from https://www.policyuncertainty.com. There is an increasingly popular literature on the relation and transmission mechanism between uncertainty and economic growth. Overall, there is consensus that higher uncertainty leads to lower growth.[4]

In addition, as uncertainty proxies, we employ the monthly risk-neutral equity and Treasury volatilities, estimated with daily data for a given month. The Chicago Board

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

Options Exchange Volatility Index (VIX) is the risk-neutral one-month expected stock market volatility for the US Standard & Poor's 500 (S&P 500) index. It is computed by averaging the weighted prices of puts and calls on the S&P 500 index over a wide range of strike prices. It has become an extremely popular and useful measure of near-term market volatility. The Merrill Lynch Option Volatility Estimate (MOVE) Index is a term structure-weighted index of the normalized implied volatility on one-month Treasury options, weighted on the two-, 5-, 10-, and 30-year contracts. It is therefore the equivalent of the 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 increases in the MOVE suggest that the market is willing to pay more to hedge against unexpected movement in interest rates. González-Urteaga, Nieto, and Rubio (2019) show that the MOVE is a net sender of volatility to the VIX. Although this result holds for most of their sample period between 1988 and 2017, it is especially true during bad economic times. The authors also show that net connectedness between the MOVE and the VIX is explained by monetary and economic drivers. This empirical finding suggests that the MOVE is an important economic indicator and, therefore, its volatility is a powerful candidate to proxy for uncertainty. Data for the VIX and the MOVE are obtained from the Fed at https://www.fred.stlouisfed.org and Bloomberg at https://www.bloomberg.com/professional, respectively.

Using data from April 1988 to June 2017, we show in Table 1 the pairwise correlation coefficients among all the proxies for uncertainty and risk aversion described above.[5] As expected, all the signs are relatively high and positive. The larger correlations are between macroeconomic and financial uncertainty, between risk aversion and

[5] The availability of some measures of uncertainty and risk aversion naturally defines our sample period.

financial uncertainty, and between risk aversion and the volatility of the VIX. The correlation between macroeconomic uncertainty and risk aversion is also high, but not as high as the previous correlations. Finally, EPU and the volatility of the MOVE are the least correlated measures of uncertainty with respect to the rest of the uncertainty proxies and risk aversion.

As discussed previously, our analysis makes it convenient to use a combination of daily and monthly frequency data. Therefore, we employ the ADS real activity index of Aruoba, Diebold, and Scotti (2009), which is designed to track real economic conditions at high frequency. The average value of the index is zero. Positive values indicate above-better conditions, whereas negative values represent below average conditions. Data are downloaded from the Federal Bank of Philadelphia at https://www.philadelphia.org.

To conclude, we explore the effects of uncertainty and risk aversion on the exposure (conditional real activity beta) of the market portfolio return and four investment-style factors, namely, size, value, momentum, and quality to economic activity, proxied for by the ADS real activity index. Note that the four chosen factors are probably the most popular strategies in the factor investing and beta smart industry.

4. Uncertainty, Risk Aversion, and Real Activity Betas

The availability of alternative uncertainty measures opens the door to questioning the sources of uncertainty and, therefore, their effects on any economic variable. Rossi, Sekhposyany, and Souprez (2019) 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, whereas macroeconomic uncertainty is a stronger proxy for ex-post uncertainty. These differences have consequences in understanding the recessionary effects of the alternative proxies for uncertainty. The results reported by González-Urteaga et al. (2019) suggest that the volatility of the MOVE is also connected with ex-ante rather than ex-post uncertainty, even more than the volatility of the VIX. These different timing effects make it convenient to use the principal component of the five series to capture an overall proxy of uncertainty. The first principal component explains 79.2% of the variability of the variance-covariance matrix of the five uncertainty approximations. Figure 1 displays the time-varying behavior of the principal component and ECB risk aversion. As expected, both measures are strongly counter-cyclical, with high spikes during recessions. The temporal behavior suggests that both measures are reasonably proxies for uncertainty and risk aversion.

In Table 2, we report the results of estimating equation (4) by analyzing the effects of the first principal component of the five uncertainty measures. Panel A shows the impact of uncertainty on the low-frequency real activity beta of the market risk premium and the four risk factors for the full sample period from April 1988 to June 2017. In all cases, except for the QMJ factor, an increase in uncertainty significantly raises the real activity beta. In other words, an adverse uncertainty shock increases the beta of these long-short portfolios. This result is consistent with that obtained by Maio and Philip (2018) regarding the behavior of the momentum factor. These authors show that the momentum premium arises because past winners have larger real activity risk than past losers. Our evidence suggests that uncertainty is an important source of the economic risk embedded in the winner's leg of the MOM factor. A similar result holds for the market portfolio, small, and value stocks.[6] The quality-based QMJ factor, however, behaves

[6] Our results could also provide a macroeconomic justification for the findings reported by Bali, Brown, and Tang (2017), who show that economic uncertainty is priced in the cross-section of stock returns. The

differently. On average, it seems to capture a flight-to-quality phenomenon during times of rising uncertainty. This result also suggests that the QMJ factor is a powerful hedging factor that presents potential real diversification effects when combined with the HML or MOM factors. It is also interesting to note that the short-term beta component of these three factors have similar weights and that the QMJ factor presents the lowest root mean squared error (RMSE) across all five portfolios.

Panels B and C of Table 2 show the results from the first subperiod, from April 1988 to May 2003, and the second subperiod, from June 2003 to June 2017, respectively. The first subperiod is characterized by two official National Bureau of Economic Research (NBER) recessions, from July 1990 to March 1991 and from March 2001 to November 2001. During this subperiod, the effects of uncertainty are clearly less significant across the alternative investment factors. Only the SMB factor with a positive effect and the QMJ factor with the negative impact remain statistically different from zero. On the other hand, the results for the second subperiod, from May 2003 to June 2017, confirm the significant effects we report for the full sample period. The results of the second subperiod, which includes the Great Recession, are very similar to those for the full sample period. Moreover, the RMSE values are consistently lower for the second subperiod relative to the first. The consequences of the Great Recession seem to have a very relevant effect on the impact that uncertainty has on the exposure of investment factor returns to real activity.

Panels A to C of Table 3 shows the results with respect to risk aversion for the full sample period and the first and second subperiods, respectively. The results are similar, but stronger than in the case of uncertainty. The estimated coefficients are consistently

effects of uncertainty on real activity betas could be a key driver of the available empirical results relating economic activity and expected excess returns.

larger than those reported in Table 2. During the full sample period, the first four factors have a positive and significant relation between risk aversion and their real activity beta. An adverse risk aversion shock increases the real activity beta of these factor risks. As before with uncertainty, risk aversion is a significant source of economic risk reflected through the impact on real activity betas. The QMJ factor maintains its hedging behavior, even with respect to risk aversion. Short-term weights are similar across all five factors, with the SMB portfolio presenting the highest short-term weight. Contrary to the case of uncertainty, the results are more consistent throughout both subperiods. From April 1988 to May 2003, the magnitudes of the coefficients are lower than in Panel A, but all coefficients are statistically different from zero except for the MOM factor. Additionally, it is the case that the second subperiod dominates the effects of risk aversion on the estimated exposure to real activity. The coefficients are even larger than for the full sample period, are always estimated with precision, and have the expected sign. Finally, the RMSE values are always lower than in the first subperiod.

To conclude, using the concepts of uncertainty and risk aversion as the underlying sources of real activity effects, our results identify a channel through which uncertainty and especially risk aversion impact the stock market. More precisely, the channel is the low frequency exposure that the market and aggregate dynamic portfolios have with respect to real activity. These complementary results between uncertainty and risk aversion motivate the following bivariate estimation, where 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 estimated model is

$$\beta^{L}_{pRA,t} = \lambda_{p,0} + \lambda_{p,UNC} \sum_{j=1}^{J} \Psi\left(h, \kappa_{p9}, \kappa_{p10}\right) \times UNC_{t-j}$$
$$+ \lambda_{p,RA} \sum_{j=1}^{J} \Psi\left(h, \kappa_{p11}, \kappa_{p12}\right) \times ARAV_{t-j} \ . \quad (8)$$

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 the regression of the ECB risk aversion on the financial uncertainty proxy of Jurado et al. (2015).[7]

Panels A to C of Table 4 report the bivariate effects of the first principal component of uncertainty and the adjusted risk aversion on the low-frequency component of real activity betas of factor risks, using equation (8). During the full sample period displayed in Panel A, the simultaneous estimation shows that increases in uncertainty impacts positively and significantly on the real activity beta of the excess market return, SMB, and MOM investment-style factor risks. The effects are negative for the HML and QMJ factors. On the other hand, sensitivity with respect to risk aversion is positive for the market, SMB, and HML factors. Interestingly, risk aversion affects negatively the low-frequency component of the real activity beta for the momentum- and quality-based factors. The negative sensitivity of the low-frequency real activity momentum beta with respect to risk aversion is important. Note that risk aversion positively affects 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, while the momentum strategy consists of buying stocks that are becoming expensive. The shorter time horizon associated with the momentum strategy could

[7] We choose financial uncertainty to extract the adjusted proxy for risk aversion because it is the uncertainty measure with the highest correlation coefficient with respect to risk aversion, as shown in Table 1.

explain the different response of value and momentum to the risk aversion effects on the low-frequency real activity beta. The economic source of the real economic effects on winners is associated with uncertainty shocks, while the economic source of economic effects on losers seems to be related to risk aversion. However, the economic source of real economic effects on value goes through risk aversion, while uncertainty seems to be the source of real effects on growth stocks.

Regarding the QMJ factor, both uncertainty and risk aversion are negatively associated with its real activity beta. The reaction of the real activity beta of the QMJ factor implies hedging behavior against bad real economic times simultaneously characterized by uncertainty and risk aversion. These results, associated with sensitivity with respect to the real economy, have important implications for understanding the behavior of quality stocks.

Panels B and C of Table 2 show the results for the first and second subperiods, respectively. The findings resemble those reported in Tables 2 and 3 for the separate effects of uncertainty and risk aversion, respectively. During the first subperiod, uncertainty tends to present non-significant results, although it has a significant and positive impact on the real activity market beta. On the hand and for both subperiods, the results regarding risk aversion replicate those reported for the full sample period. Additionally, it is the case that the empirical results during the second subperiod are highly significant, with stronger and larger coefficients than during the first subperiod and lower RMSE values.

Panels A and B of Figure 2 display the time-varying behavior of the low-frequency component of the real activity betas associated with the uncertainty principal component and risk aversion for the market and the QMJ factor, respectively. In the case of the excess return of the market portfolio, these low-frequency components tend to increase from the very beginning of recessions, with peaks at the end or immediately afterwards. The exception is the behavior of the real activity market beta during the recession of the 1990s in Panel A, which shows a decrease rather an increase with respect to risk aversion. The behavior of the real activity beta relative to uncertainty is precisely the opposite during those years. On the hand, the time-varying behavior of the low-frequency real activity beta of the QMJ factor with either uncertainty or risk aversion, shown in Panel B, is consistent with the results reported in Tables 2 and 3. Not only is it negative for most of the sample period, but also the real activity beta turns out to decrease 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.

6. Conclusions

The analysis of uncertainty and risk aversion, as drivers of the sensitivity of the market and investment-style dynamic factors, clarifies the characteristics of these popular factors during bad macroeconomic and financial times. The overall market portfolio return shows a significant increase in sensitivity to real activity whenever uncertainty and/or risk aversion rises. It seems that an important channel by which uncertainty and/or risk aversion negatively affects the market portfolio excess return is the exposure of returns to real activity shocks.

The real activity market beta is significantly and positively related to uncertainty, but the effect is much stronger with respect to risk aversion. In terms of absolute value, the larger impact of risk aversion relative to uncertainty is a constant result across alternative dynamic factor risks. However, the sign of the uncertainty and/or risk aversion effects on the sensitivity of the factors to real activity differs across the investment factors. The HML factor reacts negatively (positively) with respect to uncertainty (risk aversion), suggesting that risk aversion is the main driver of the risky behavior of this factor in terms of real activity. It is well known that the MOM and HML factors work at different frequencies. This could explain the very different impacts of uncertainty and risk aversion on the sensitivity of the MOM factor to real activity, because, unlike in the HML portfolio, the MOM factor reacts negatively (positively) with respect to risk aversion (uncertainty).

When we divide the full sample period into two non-overlapping subperiods, the results remain strong, with highly significant effects of risk aversion on the exposure of factor returns to real activity. However, the relevant effects of uncertainty on the factor real activity beta are clearly stronger during the second subperiod. As with previous recessions, the effects of the Great Recession are very important in explaining the effects of risk aversion, but they become a key issue for understanding how uncertainty affects the exposure of factor returns to real activity.

Finally, Asness et al. (2019) show that their QMJ factor, which buys high-quality stocks and shorts low-quality (junk) stocks, earns significant risk-adjusted returns in 25 stock market exchanges around the world. 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. The authors plot the risk-adjusted returns of the QMJ factor against market excess returns and show that the quality factor presents mild positive convexity, which suggests that the QMJ factor benefits from flight-to-quality stock market declines. In this research, we show complementary evidence for the QMJ factor. The sensitivity of the QMJ factor returns to real activity significantly decreases with uncertainty and risk aversion, and these effects occur at the beginning of recessions, with the highest negative impact at the end of recessions. The QMJ investment factor is a very important hedging investment-style factor against increasing uncertainty and risk aversion. Moreover, risk aversion amplifies the effects of uncertainty on the sensitivity of stock market returns to the business cycle behavior of the real economy. The results associated with the QMJ factor remain important for both subperiods.

References

Aruoba, S., F. Diebold, and C. Scotti (2009), Real-Time Measurement of Business Conditions, *Journal of Business and Economic Statistics* 27, 417-427.

Asness, C., A. Frazzini, and L.H. Pedersen (2019), Quality Minus Junk, *Review of Accounting Studies* 24, 34-112.

Asness, C., A. Frazzini, R. Israel, T. Moskowitz, and L.H. Pedersen (2018), Size Matters, If You Control Your Junk, *Journal of Financial Economics*, 129, 479-509.

Baker, S., N. Bloom, and S. Davis (2016), Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics* 131, 1593-1636.

Bali, T., S. Brown, and Y. Tang (2017), Is Economic Uncertainty Priced in the Cross-Section of Stock Returns? *Journal of Financial Economics* 126, 471-489.

Bekaert, G., and M. Hoerova (2014), The VIX, the Variance Premium and Stock Market Volatility, *Journal of Econometrics* 183, 181-192.

Bekaert, G., and M. Hoerova (2016), What Do Asset Prices Have to Say about Risk Appetite and Uncertainty? *Journal of Banking and Finance* 67, 103-118.

Bekaert, G., E. Engstrom, and N. Xu (2019), The Time Variation in Risk Appetite and Uncertainty, Working Paper, Columbia University Business School.

Bloom, N. (2009), The Impact of Uncertainty Shocks, *Econometrica* 77, 623-685.

Bloom, N. (2014), Fluctuations in Uncertainty, *Journal of Economic Perspectives* 28, 153-176.

Bloom, N., S. Bond, and J. van Reenen (2007), Uncertainty and Investment Dynamics, *Review of Economic Studies* 74, 391-415.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta, and S. Terry (2018), Really Uncertain Business Cycles, *Econometrica* 86, 1031-1065.

Bretscher, L., A. Hsu, and A. Tamoni (2018), Risk Aversion and the Response of the Macroeconomy to Uncertainty Shocks, Working Paper, London School of Economics.

Campbell, J., and J. Cochrane (1999), By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107, 205-251.

Carhart, M. (1997), On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

Carriero, A., T. Clark, and M. Marcellino (2018), Measuring Uncertainty and its Impact on the Economy, *The Review of Economics and Statistics* 100, 799-815.

Cochrane, J. (2017), Macro-Finance, *Review of Finance* 21, 945-985.

Fama, E., and K. French (1993), Common Risk Factors in the Return of Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E., and K. French (2015), A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1-22.

Fletcher, R. (1987), Practical Methods of Optimization, 2nd. Edition, New York, John Wiley & Sons.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2003), The MIDAS Touch: Mixed Data Sample Regression Models, Working Paper, Rady School of Management, University of California San Diego.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2005), There is a Risk-Return Trade-off After All, *Journal of Financial Economics* 76, 509–548.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2006), Predicting Volatility: Getting the Most out of Return Data Sampled at Different Frequencies, *Journal of Econometrics* 131, 59–95.

Ghysels, E., A. Sinko, and R. Valkanov (2007), MIDAS Regressions: Further Results and New Directions, *Econometric Reviews* 26, 53-90.

González-Sánchez, M., J. Nave, and G. Rubio (2018), Macroeconomic Determinants of Stock Market Betas, *Journal of Empirical Finance* 45, 26-44.

González-Urteaga, A., B. Nieto, and G. Rubio (2019), An Analysis of Connectedness Dynamics between Risk-Neutral Equity and Treasury Volatilities. Working Paper, University CEU Cardenal Herrera, Department of Business and Economics, Spain.

Judge, G., W. Griffith, R. Hill, and H. Lutkepohl (1985), The Theory and Practice of Econometrics, 2nd. Edition, Wiley.

Jurado, K., S. Ludvigson, and S. Ng (2015), Measuring Uncertainty, *American Economic Review* 105, 1177-1216.

Ludvigson, S., Ma, Ng (2019), Uncertainty and Business Cycle: Exogenous Impulse or Endogenous Response, *American Economic Journal: Macroeconomics*, forthcoming.

Maio, P., and D. Philip (2018), Economic Activity and Momentum Profits: Further Evidence, *Journal of Banking and Finance* 88, 466-482.

Merton, R. (1973), An Intertemporal Capital Asset Pricing Model, *Econometrica* 41, 867-887.

Rossi, A., and A. Timmermann (2015), Modelling Covariance Risk in Merton's ICAPM, *Review of Financial Studies* 28, 1428-1461.

Rossi, B., T. Sekhposyany, and M. Souprez (2019), Understanding the Sources of Macroeconomic Uncertainty, Barcelona GSE Working Paper nº 920.

Table 1
Correlation Coefficients Among Uncertainty and Risk Aversion Measures: April 1988 to June 2017

	Macro Uncertainty	Financial Uncertainty	EPU	Risk Aversion	Volatility MOVE	Volatility VIX
Macro Uncertainty	1	0.688	0.269	0.614	0.406	0.452
Financial Uncertainty		1	0.358	0.722	0.435	0.557
EPU			1	0.470	0.318	0.479
Risk Aversion				1	0.464	0.696
Volatility MOVE					1	0.496

This table contains the pairwise correlation coefficients for a set of uncertainty and risk aversion measures. The Macro and Financial Uncertainty measures are provided by Jurado, Ludvigson, and Ng (JLN) (2015); EPU is the (log) of the economic policy uncertainty index of Baker, Bloom, and Davis (BBD) (2016); Risk Aversion is the ECB measure of risk aversion; volatility MOVE is the monthly volatility of the MOVE, and volatility VIX is the monthly volatility of the VIX. The VIX is the risk-neutral one-month expected stock market volatility for the S&P 500 index. It is computed by averaging the weighted prices of puts and calls on the S&P 500 index over a wide range of strike prices. The MOVE is a term structure-weighted index of the normalized implied volatility on one-month Treasury options, which are weighted on the two-, 5-, 10-, and 30-year contracts.

Table 2
Uncertainty Effects on the Low-Frequency Component of the Real Activity Betas
of Investment-Style Risk Factors: April 1988 to June 2017

Panel A: Full Sample Period, April 1988 to June 2017
First Principal Component of Uncertainty Proxies

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	-0.164 (-7.32)	-0.083 (-5.01)	-0.153 (-3.07)	-0.035 (-2.73)	0.274 (3.54)
$\hat{\lambda}_{p,PC\_UNC}$	0.052 (7.46)	0.023 (5.16)	0.047 (3.10)	0.017 (4.80)	-0.084 (-3.87)
Beta High-frequency Weight	0.443 (3.72)	0.453 (4.79)	0.717 (2.41)	0.712 (5.39)	0.751 (6.06)
RMSE %	4.152	3.059	3.001	4.688	2.803

Panel B: First Subperiod, April 1988 to May 2003
First Principal Component of Uncertainty Proxies

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	-0.078 (-1.96)	-0.157 (-9.07)	0.051 (1.31)	-0.091 (-2.56)	0.390 (5.68)
$\hat{\lambda}_{p,PC\_UNC}$	0.016 (1.29)	0.041 (8.16)	-0.017 (-1.39)	0.025 (0.54)	-0.118 (-4.75)
Beta High-frequency Weight	0.562 (2.49)	0.513 (5.41)	0.715 (2.92)	0.749 (2.48)	0.708 (3.29)
RMSE %	4.474	3.064	3.155	4.911	2.904

Panel C: Second Subperiod, June 2003 to June 2017
First Principal Component of Uncertainty Proxies

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	-0.231 (-7.83)	-0.056 (-3.02)	-0.296 (-4.90)	-1.122 (-8.28)	-0.094 (-7.82)
$\hat{\lambda}_{p,PC\_UNC}$	0.067 (3.84)	0.016 (2.02)	0.091 (5.57)	0.149 (7.28)	-0.080 (-5.69)
Beta High-frequency Weight	0.416 (6.79)	0.414 (2.84)	0.723 (8.49)	0.755 (4.83)	0.771 (4.16)
RMSE %	3.772	2.361	2.859	4.264	2.754

This table reports the estimated impact of uncertainty on the low-frequency component of the real activity betas of the three Fama-French risk factors (excess market, SMB, HML) and the momentum (MOM) and quality (QMJ) factors. We employ the first principal component of the five available uncertainty proxies described in Section 3. Panels A to C use data for the full sample period, the first subperiod, and the second subperiod, respectively. The *t*-statistics are reported in parentheses, and the RMSE values are presented as percentages.

Table 3
Risk Aversion Effects on the Low-Frequency Component of the Real Activity Betas of Investment-Style Risk Factors: April 1988 to June 2017

Panel A: Full Sample Period, April 1988 to June 2017
Risk Aversion

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	0.035 (5.92)	-0.012 (-9.36)	0.006 (2.77)	0.023 (5.13)	-0.004 (-10.88)
$\hat{\lambda}_{p,RAV}$	0.455 (6.75)	0.266 (2.13)	0.275 (2.49)	0.414 (9.88)	-1.297 (-2.96)
Beta Low-frequency Weight	0.747 (4.49)	0.801 (5.79)	0.699 (2.37)	0.745 (5.15)	0.690 (8.90)
RMSE %	4.160	3.041	3.000	4.686	2.795

Panel B: First Subperiod, April 1988 to May 2003
Risk Aversion

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	0.026 (2.87)	-0.021 (-3.59)	0.007 (4.46)	-0.002 (-3.18)	-0.006 (-2.47)
$\hat{\lambda}_{p,RAV}$	0.055 (1.98)	0.249 (4.41)	0.256 (3.38)	0.032 (0.94)	-0.776 (-2.67)
Beta Low-frequency Weight	0.766 (2.62)	0.776 (2.87)	0.697 (3.08)	0.713 (3.31)	0.708 (2.05)
RMSE %	4.247	3.117	3.149	4.740	2.896

Panel C: Second Subperiod, June 2003 to June 2017
Risk Aversion

	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	0.057 (2.72)	-0.010 (-5.31)	0.012 (3.44)	0.037 (3.11)	-0.021 (-1.99)
$\hat{\lambda}_{p,RAV}$	0.562 (3.77)	0.648 (5.24)	0.259 (2.05)	0.815 (6.95)	-1.077 (-3.24)
Beta Low-frequency Weight	0.726 (4.33)	0.823 (4.17)	0.711 (2.59)	0.747 (3.07)	0.683 (2.83)
RMSE %	3.977	2.954	2.843	4.266	2.615

This table reports the estimated impact of risk aversion on the low-frequency component of the real activity betas of the three Fama-French risk factors (excess market, SMB, HML) and the momentum (MOM) and quality (QMJ) factors. Risk aversion is approximated by the ECB's measure of risk aversion. Panels A to C use data for the full sample period, the first subperiod, and the second subperiod, respectively. The *t*-statistics are reported in parentheses, and the RMSE values are presented as percentages.

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

Panel A: Full Sample Period	Excess Market	SMB	HML	MOM	QMJ
$\hat{\lambda}_{p,0}$	-0.091 (-3.33)	-0.057 (-2.38)	0.136 (5.76)	-0.207 (-4.39)	0.127 (5.74)
$\hat{\lambda}_{p,PC\_UNC}$	0.029 (3.52)	0.015 (2.27)	-0.047 (-6.20)	0.069 (5.49)	-0.038 (-5.72)
$\hat{\lambda}_{p,ARAV}$	0.391 (3.74)	0.219 (5.62)	5.862 (8.46)	-2.184 (-3.39)	-1.056 (-4.62)
Beta Low-frequency Weight	0.159 (2.32)	0.168 (5.35)	0.881 (7.39)	0.642 (3.14)	0.597 (7.12)
RMSE %	4.142	3.005	2.945	4.651	2.776
Panel B: April 1988 to May 2003	**Excess Market**	**SMB**	**HML**	**MOM**	**QMJ**
$\hat{\lambda}_{p,0}$	-0.189 (-4.19)	-0.064 (-4.81)	-0.458 (-2.27)	-0.396 (-2.96)	0.400 (3.47)
$\hat{\lambda}_{p,PC\_UNC}$	0.011 (3.18)	0.009 (2.47)	-0.035 (-0.18)	0.022 (0.71)	-0.011 (-1.08)
$\hat{\lambda}_{p,ARAV}$	0.058 (2.77)	0.017 (4.16)	0.421 (2.18)	-0.117 (-2.11)	-0.121 (-3.56)
Beta Low-frequency Weight	0.187 (3.38)	0.096 (7.69)	0.914 (2.21)	0.798 (3.22)	0.688 (2.46)
RMSE %	4.245	3.136	3.094	4.721	2.890
Panel C: June 2003 to June 2017	**Excess Market**	**SMB**	**HML**	**MOM**	**QMJ**
$\hat{\lambda}_{p,0}$	0.233 (7.70)	-0.004 (-2.83)	-0.495 (-8.11)	-0.646 (-3.55)	-0.257 (-4.32)
$\hat{\lambda}_{p,PC\_UNC}$	0.076 (8.76)	0.248 (3.13)	-0.070 (-3.18)	0.131 (6.97)	-0.056 (-3.24)
$\hat{\lambda}_{p,ARAV}$	0.682 (5.97)	0.000 (1.47)	4.686 (7.13)	-2.537 (-3.07)	-1.271 (-5.85)
Beta Low-frequency Weight	0.154 (2.55)	0.147 (5.04)	0.911 (4.38)	0.727 (3.36)	0.644 (3.63)
RMSE %	3.738	2.346	2.577	4.243	2.534

This table reports the simultaneously estimated impacts 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 the real activity betas of the three Fama-French (excess market, SMB, HML) risk factors and the momentum (MOM) and quality (QMJ) factors. The proxies for uncertainty are macroeconomic uncertainty, financial uncertainty, EPU, the volatility of the MOVE, and the volatility of the VIX. Risk aversion is the ECB's risk aversion measure. However, given the high correlation between this proxy of risk aversion and the alternative uncertainty approximations, we measure risk aversion as the residuals of the regression of the ECB's risk aversion on financial uncertainty. The *t*-statistics are reported in parentheses, and RMSE values are presented as percentages. Panels A to C use data for the full sample period, the first subperiod, and the second subperiod, respectively.

Figure 1

First Principal Component (PC1) of Five Uncertainty Proxies (Macroeconomic Uncertainty, Financial Uncertainty, EPU, the Volatility of the MOVE, and the Volatility of the VIX and Risk Aversion: April 1988 to June 2017

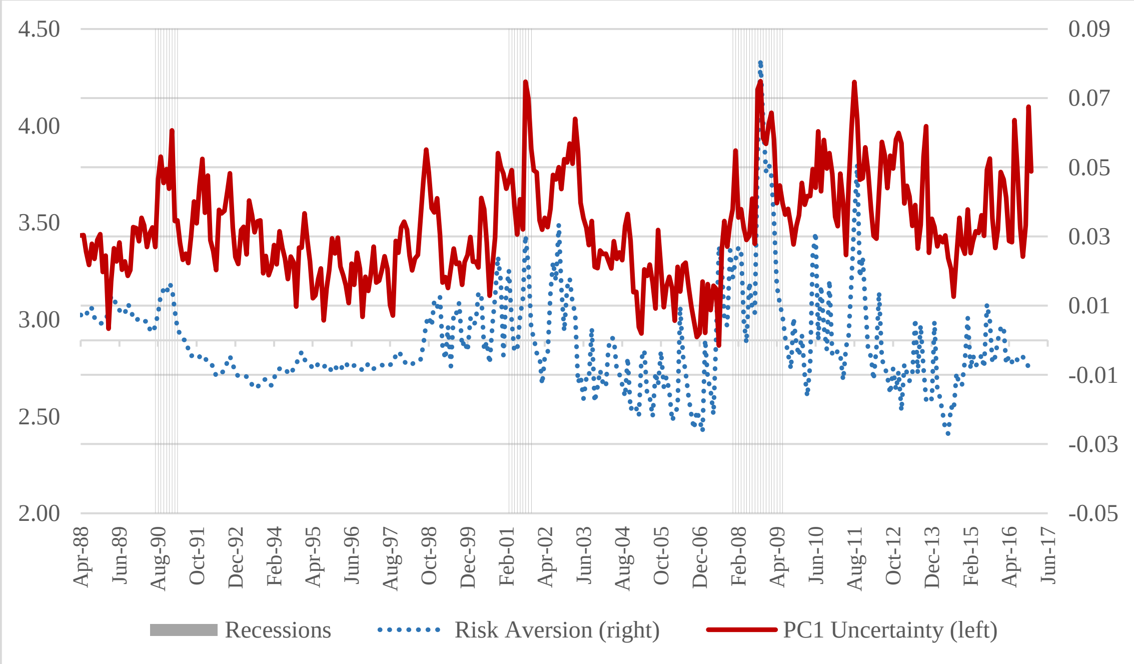
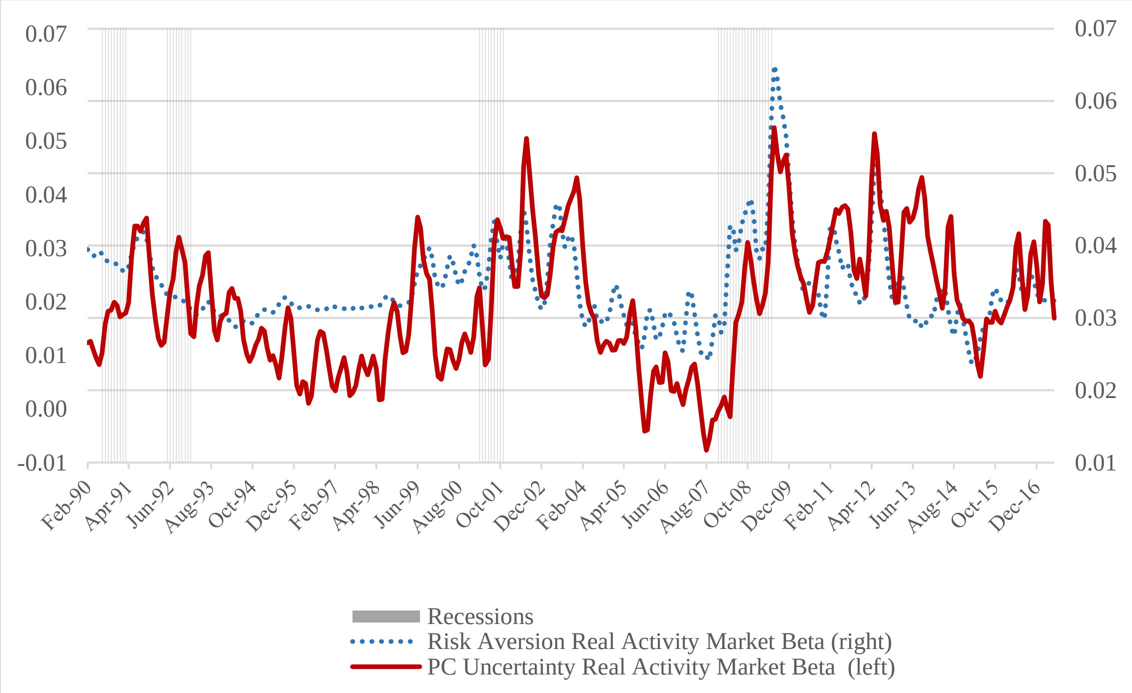


Figure 2

Panel A:

Low-Frequency Components of the Real Activity Market Betas of the First Principal Component (PC) of Five Uncertainty Proxies (Macroeconomic Uncertainty, Financial Uncertainty, EPU, the Volatility of the MOVE, and the Volatility of the VIX and Risk Aversion: February 1990 to June 2017



Panel B:

Low-Frequency Components of the Real Activity QMJ Betas of the First Principal Component (PC) of Five Uncertainty Proxies (Macroeconomic Uncertainty, Financial Uncertainty, EPU, the Volatility of the MOVE, and the Volatility of the VIX and Risk Aversion: February 1990 to June 2017