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On the Behavior of the Spanish Capital Market

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Working paper

No. 80

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Abstract

This paper analyzes the performance of various asset classes traded in the Spanish Capital Market. We compare the relative behavior of stock and corporate bond market indices, risk factors, and option-based expected market risk premia of the IBEX-35 at alternative horizons. We finally discuss the spillover volatility connections between the stock market portfolio, the general index of corporate bonds, the long-term government bond, and risk-neutral volatility and skewness. The stock market index is a net sender of volatility to the rest of asset classes, especially during the Great Recession and the Eurozone debt crises. The government bond is a net sender of volatility to corporate bonds and risk-neutral volatility and skewness. In fact, during stressed periods, the returns of the government bond have a positive exposure to the market stock return, which suggests that the Spanish long-term bond is a risky asset rather than being a hedging asset. This fact, together with the strong counter-cyclical behavior of the expected market risk premium at any horizon, suggests that the Spanish corporations are badly affected during recessions with a negative impact on investment and output growth. It is not surprising how rapidly the Spanish economy deteriorates at the beginning of recessions. Note that the ultimate objective is to learn about the Spanish real economy through the lens of financial markets

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Content

1 Introductory Comments

This paper analyzes the behavior and performance of the main asset classes in the Spanish capital market. More precisely, we study the stock market indices, the equity sectors, the corporate bond indices, the 10-year government bond, and a portfolio that replicates selling positions in market volatility to take advantage of reasonable economic times. In addition, we analyze the performance of popular risk factors that are widely used by the industry under factor or style investing strategies, and the behavior and characteristics of the Spanish expected market risk premia at alternative horizons over the business cycle extracted from option prices on the IBEX 35 index. We also analyze the time-varying behavior of the risk-neutral volatility, risk-neutral skewness as a proxy for tail risk, and the variance risk premium to show how important the buying and selling market variance strategies are. Finally, we discuss the connected dynamics across asset classes in the sense of volatility spillovers from one asset to the others and to the full system. By spillovers we mean measures of how much future unexpected variation in one asset is explained by current shocks to the other assets. Hence, this approach allows us to learn how the new information embedded in one asset is transmitted to the others.

Our main objective is to learn about the Spanish real economy through the lens of the Spanish capital markets. During stressed periods, the returns of the government bond have a positive exposure to the market stock return, which suggests that the Spanish long-term bond is a risky asset rather than being a hedging asset. This fact, together with the strong counter-cyclical behavior of the expected market risk premium at any horizon, suggests that the Spanish corporations are badly affected during recessions with a negative impact on investment and output growth. Hence, it is not surprising how rapidly the Spanish economy deteriorates at the beginning of recessions. The key signals extracted from the behavior of the Spanish capital markets about the Spanish real economy denotes a rather pessimistic view.

Our results have not only investment implications, but also policy connotations. This is especially the case for the industrial structure of Spanish companies, and for BME Clearing since central clearing counterparties require appropriate collateral when standing between buyers and sellers to avoid future counterparty defaults and potential propagation through the financial system. Any decision must equilibrate the need to maintain a proper risk-based default fund in the Spanish Clearing entity, but also to avoid systematic negative spillover effects to the system. In this regard to have an overall performance evaluation of the Spanish capital markets seems to be appropriate and helpful. Our sample period, which is defined by the availability of risk-neutral moments, goes from January 2, 2007, to June 30, 2021. It includes the Great Recession, the Eurozone Debt Crisis, and the exogenous COVID-19 pandemic.

2 A Brief International Perspective

Before describing the empirical results regarding asset classes, sectors, and risk factors in the Spanish market, it is convenient to provide a brief comparison of the performance of the Spanish stock market relative to other major exchanges. Table 1 contains the descriptive statistics of four European stock exchanges and the U.S. market using monthly data from January 2007 to June 2021. Data are obtained from the web page of AQR Capital Management at www.aqr.com. Since the original data available at AQR is given in U.S. dollars, we first convert dollars to euros using the exchange rates available at the Federal Reserve Bank of St. Louis at https://fred.stlouisfed.org. For the Spanish stock market, rather than using the data provided by AQR, we use the returns of the IBEX 35 Total Index (with dividends).[1] Data are provided in excess returns over the U.S. 3-month Treasury bill as the proxy for the risk-free rate. Therefore, the results displayed in Table 1 are average statistics for market risk premia in all five markets relative to the same risk-free rate converted into euros.[2]

The results in Panel A of Table 1 show a very clear and distinct pattern in the performance across the five stock markets. The U.S. market shows an impressive performance with a high average excess returns and low volatility that explain the high Sharpe ratio of 0.63. Interestingly, it is also true that the U.S. market has the most negative skewness among the five markets. Overall, the European stock markets present significantly poorer results, although a clear message rises from the average statistics. Germany and France have similar results with a good relative performance given by Sharpe ratios of 0.36 and 0.34, respectively. On the other hand, Spain and Italy present bad and similar results, at least relative to the other markets, with Sharpe ratios of 0.13 and 0.15, respectively. The correlation coefficients given in Panel B of Table 1 show that Spain and Italy have the lower correlations with the U.S. market compared to the other two European markets. To understand these results, it is very important to notice that the sample period starts approximately seven months before the initial signals of the Great Recession, and it includes the Eurozone debt crisis and the pandemic. Figure 1 shows the cumulative monthly excess returns of investing 100 euros at the beginning of the sample period in January 2007. Grey bars correspond to recession dates of the Spanish economy given by the Spanish Business Cycle Dating Committee of the Spanish Economic Association available at http://www.asesec.org. The cumulative performance clearly

1 The Spanish market data provided by AQR is the general index of the Madrid stock market (IGBM) with dividends. Although we also employ the IGBM in this research for comparison purposes, most of the analyses are based on either the IBEX 35 Index or the IBEX 35 with dividends. This justifies why we employ the IBEX 35 Total Index in this initial analysis. All market indices from AQR include dividend payments.

2 The results are very similar using local risk-free rates or alternative market indices.

illustrates the results reported in Table 1. The distinct three groups arising in Figure 1 suggest how dramatic the consequences of the Great Recession have been for the southern European countries. Despite that performance is obviously negatively affected by economic crises across all markets, the global sample results suggest that both Spain and Italy suffer relatively more than other countries given their lower productivity growth and its plausible consequences for future growth. Labor and educational regulations together with relatively low resources invested in R&D&I as a percentage of GDP, the questionable institutional quality, and problematic fiscal accounts could explain the behavior of the Spanish and Italian markets compared to other competing economies.[3] Given that stock prices reflect expectations about future discounted cash flows, these results suggest that markets have serious doubts about the future potential growth of the Spanish economy.

International excess market returns in euros for the Eurozone (Spain, Germany, France, and Italy) and the U.S. market: Monthly data from January 2007 to June 2021

TABLE 1

Panel A Descriptive Statistics	SPAIN IBEX 35 TOTAL	USA	GERMANY	FRANCE	ITALY
Annualized Average	0.027	0.082	0.059	0.058	0.029
Annualized Volatility	0.208	0.131	0.164	0.168	0.196
Global Market Beta	0.954	0.759	0.924	0.933	1.016
Skewness	0.105	-0.611	-0.454	-0.359	-0.207
Excess Kurtosis	2.603	2.159	0.873	1.417	1.205
Monthly Maximum	0.253	0.124	0.134	0.178	0.206
Monthly Minimum	-0.222	-0.140	-0.157	-0.167	-0.192
Autocorrelation	0.029	0.073	0.080	0.078	0.045
SHARPE	0.130	0.628	0.359	0.343	0.147
Panel B Correlations	**SPAIN IBEX 35 TOTAL**	**USA**	**GERMANY**	**FRANCE**	**ITALY**
SPAIN IBEX 35 TOTAL	1	0.691	0.768	0.840	0.871
USA		1	0.874	0.843	0.773
GERMANY			1	0.913	0.866
FRANCE				1	0.947

Panel A of this table reports descriptive statistics of the excess returns of the Spanish stock market index (IBEX 35 TOTAL), and the excess returns of the U.S., German, French, and Italian stock markets provided by AQR Capital International. These excess returns and the global market portfolio are originally given in U.S. dollars, and they are transformed into euros, using the euro/dollar exchange rate in the last day of each month in the sample. All excess returns are obtained relative to the 3-month Treasury bill rate from the U.S. market, which is also transformed into euros to calculate excess returns. Market betas of each stock market are estimated with respect to the excess return of the global market portfolio. We report the 1-month lagged autocorrelation. Panel B contains the correlation coefficients between the five stock market indices during the full sample period.

3 The extraordinary resources compromised by the NEXT GENERATION EU, which are approximately 1.8% of the Spanish GDP over three years, represent a historical opportunity to modernize the Spanish economy.

The cumulative monthly excess returns of investing 100 euros in January 2007 in the Stock Market Indices of Spain, the U.S.A., Germany, France, and Italy: Monthly data from January 2007 to June 2021

FIGURE 1

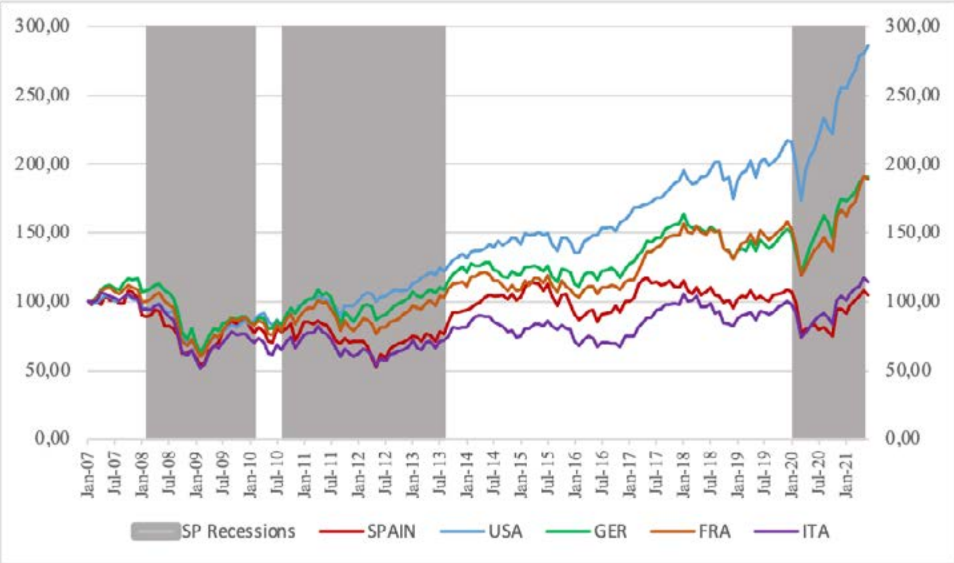
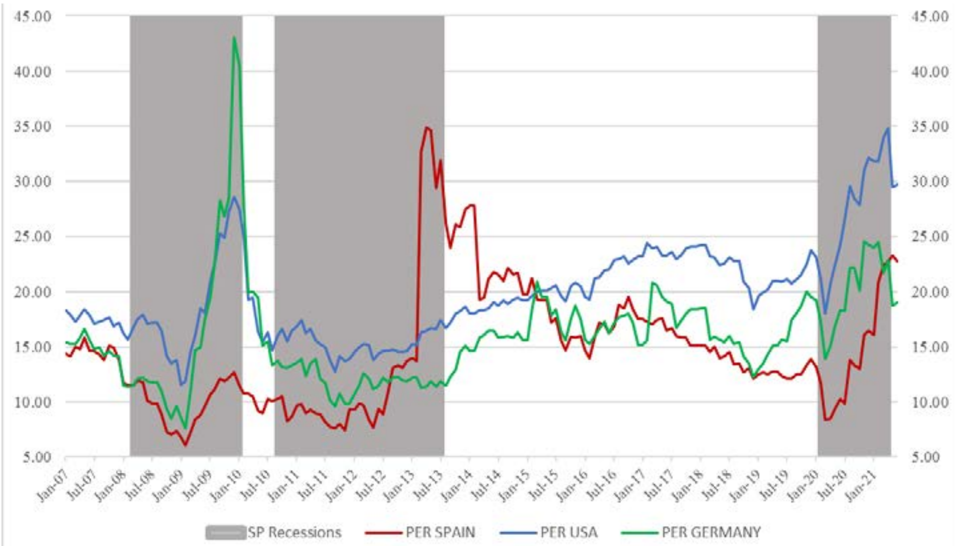


Figure 2 shows the price earnings ratio (PER) of the Spanish, U.S., and German stock market. Data are from MSCI at https://www.msci.com. Overall, the stock market in Spain tends to be valued below the other two markets. The Spanish PER is most of the time below the ratio of the U.S. and German markets. This is consistent with the previous poor performance of the stock market in Spain. However, it is interesting to observe that at the end of the Great Recession and Eurozone debt crises, there is a strong and rapidly increasing rally in the Spanish PER. In fact, the valuation of Spanish shares was above the PER of the other two countries from March 2013 through the beginning of 2015. The problem is the lack of persistence of the initial positive shocks. It is also consistent with the GDP growth experienced by the Spanish economy at the end of bad times. Spain tends to have a very volatile GDP growth showing big drops, but also strong initial growth rates after the recessions, which is usually higher than other European countries. A similar pattern is observed during the health crisis, although this time the Spanish PER is slightly above the German PER just at the end of the sample period, but below the extraordinary valuation of the U.S. stocks.

Price earnings ratios (PER) of Spain, Germany, and the U.S.A. provided by MSCI: Monthly data from January 2007 to June 2021

FIGURE 2



In addition, we would like to point out that the relations between the real and financial economies are of great importance. Over the last two decades, we have learnt how important financial crises are for the fluctuations of the real economies and for the impact on GDP growth around the globe (Muir, 2017) and (Cochrane, 2017). Adverse uncertainty shocks have long-lasting negative effects on aggregate investment and output (Baker, Bloom, and Davis, 2016). These effects of uncertainty shocks are amplified by increases in risk aversion associated with financial markets in bad times and its impact on the expected market risk premia (and the cost of equity capital of firms), which largely explains the channel between financial and real economic crises.

Related to this insight, recent work by Greenwald, Lettau, and Ludvigson (2021), and Lettau, Ludvigson, and Ma (2019) shows that the real market value of equities in the U.S. stock market experienced an unprecedent growth reaching an average 7.5% per annum from 1989 to 2017. This is consistent with the evidence provided by our Figures 1 and 2. During the same years, real output growth was 2.6%. On the other hand, from 1966 to1988 the average annual growth rate of the stock market was just 1.6%, whereas output growth was 3.9%. Therefore, there has been an extremely significant widening between the stock market and the real economy. The question of course is how we can explain this empirical fact. From 1989 to 2017, Greenwald et al. (2021) show that 43% of the increase in the equity wealth can be attributable to reallocation of rewards to shareholders at the expense of labor compensation. In addition, economic growth explained 25%, a lower market risk premium accounted for 24%, and lower interest rates for only 8%. However, from 1966 to 1988 much less wealth was created but economic growth accounted for more than 100%. A consistent explanation with the previous evidence has been provided by Acemoglu and Restrepo (2022) who show that between 50% and 70% of the wage structure over the last decades in the U.S. are accounted for by the relative declines in workers associated with routine tasks in industries experiencing rapid automation related to artificial intelligence.[4]

4 In a related work, Gabaix and Koijen (2021) argue that institutional investments are fairly constrained in their operating decisions, which significantly reduces the scope of changing their strategies in response

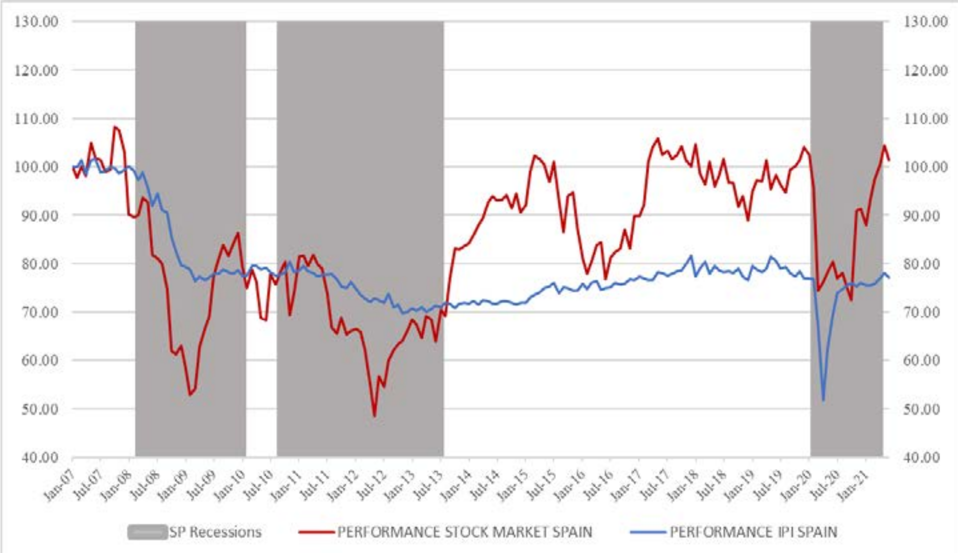
In Figures 3.A through 3.C, we provide simple evidence supporting the previous findings for the U.S. Economy and illustrate related findings for the Spanish and German markets.[5] In Figure 3.A, we show the cumulative excess return of the IBEX 35 Total Index, and the cumulative growth of the industrial production index (IPI) for Spain. Before the pandemic, the gap between the stock market and the IPI cumulative growth rates was approximately 25.5 points and, at the end of the period, the gap reached a similar value of 24.3 points. In between, there was a parallel big drop in both the stock market and IPI cumulative growth rates. In Figure 3.B, we display similar evidence for the German market. However, the gap between the two indicators of the financial and real economies is larger in this case relative to the Spanish market. Before the pandemic, the gap reached 43.5 points and, at the end of the sample period, we observe a double gap of 90.5 points. As before, we find a rapid increase in financial wealth after the outbreak of the pandemic. Finally, Figure 3.C illustrates the striking evidence from the U.S. economy. This is consistent with the formal results provided by Greenwald et al. (2021), and Acemoglu and Restrepo (2021). The gaps between the two cumulative growth rates were 115.0 and 185.7 points before the COVID-19 and at the end of the sample, respectively.

This explanation may also be valid globally, although the evidence of the Spanish economy is weaker compared to the German and U.S. cases. Whether the results for the Spanish case reflect either good or bad news is a difficult question with social implications. Although it may imply that the labor share has not been so negatively affected in Spain compared to other countries, it may also suggest that the actual structure of the industrial economy in Spain is not technological competitive relative to other industrialized countries. Even worse, it may imply that international investors are rather pessimistic about the future evolution of the competitiveness and productivity growth of the Spanish economy. The results of Table 1 and Figure 1 are consistent with this view.

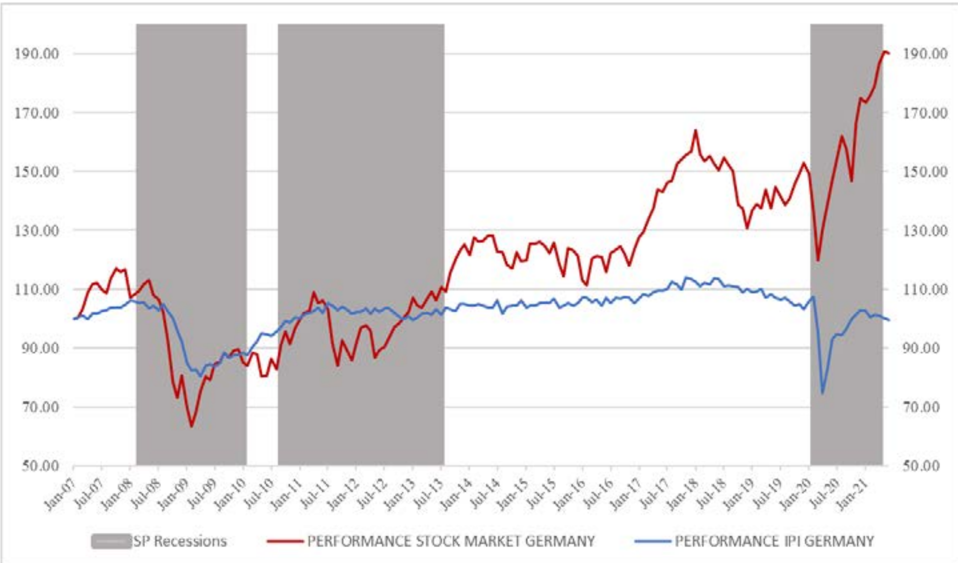
to changing market conditions. A relevant consequence is that the price elasticity of demand of the aggregate stock market is small causing that relatively low volume has large impact on prices.

5 The three following figures use the real growth of industrial production. Although the stock market returns are in nominal values, note that we employ excess returns over the risk-free rate. Therefore, this is like using real stock market rates of returns, and both series are perfectly comparable.

Cumulative excess returns of the Spanish Stock Market (IBEX 35 TOTAL) and cumulative growth of the Industrial Production Index (IPI) for the Spanish Economy: Monthly data from January 2007 to June 2021 FIGURE 3.A

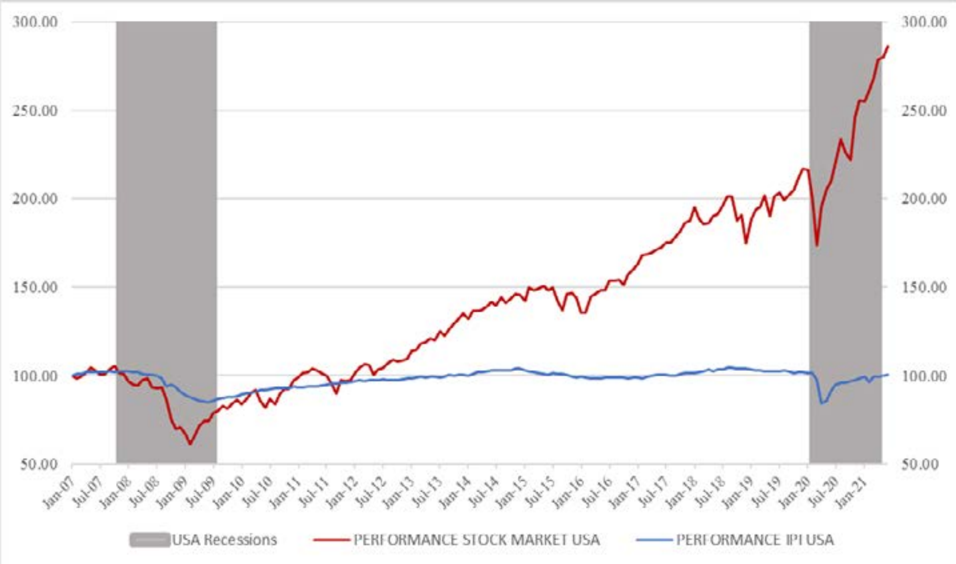


Cumulative excess returns of the German Stock Market and cumulative growth of the Industrial Production Index (IPI) for the German economy: Monthly data from January 2007 to June 2021 FIGURE 3.B



Cumulative excess returns of the U.S. Stock Market and cumulative growth of the Industrial Production Index (IPI) for the U.S. economy: Monthly data from January 2007 to June 2021

FIGURE 3.C



To conclude this section, we present additional evidence regarding the exposure of the Spanish 10-year government bond return to the stock market over the business cycle. More precisely, we show how monetary policy during our sample period has affected the exposure of long-term government bonds to the stock market not only in Spain, but also in the U.S. and German markets. Important differences in that exposure between the Spanish and the other two markets are reported next.

Campbell, Pflueger, and Viceira (2020) show that the exposure of the U.S. Treasury bonds to the equity market has changed considerably over time and that this time varying behavior is partly driven by the U.S. monetary policy. Campbell et al. (2020) split the sample in two non-overlapping sub-periods, the first from the third quarter of 1979 to the first quarter of 2001, and the second from the second quarter of 2001 to the fourth quarter of 2011. They find that the average Treasury market beta is positive in the first sub-period (0.31) while negative in the second (-0.19). The positive beta or market exposure is attributed by the authors to the strong anti-inflationary U.S. monetary policy followed during the first sub-period, and the negative beta of the second sub-period to the focus of monetary policy on output fluctuations and the non-conventional monetary policy, which made Treasury bonds act as hedgers of stock market declines. The long-term U.S. government bonds are seen as safe heaven assets.

We estimate market betas of 10-year government bonds of the Spanish, the U.S., and the German economies using rolling windows of non-overlapping 12 monthly returns and the following ordinary least squares regressions:

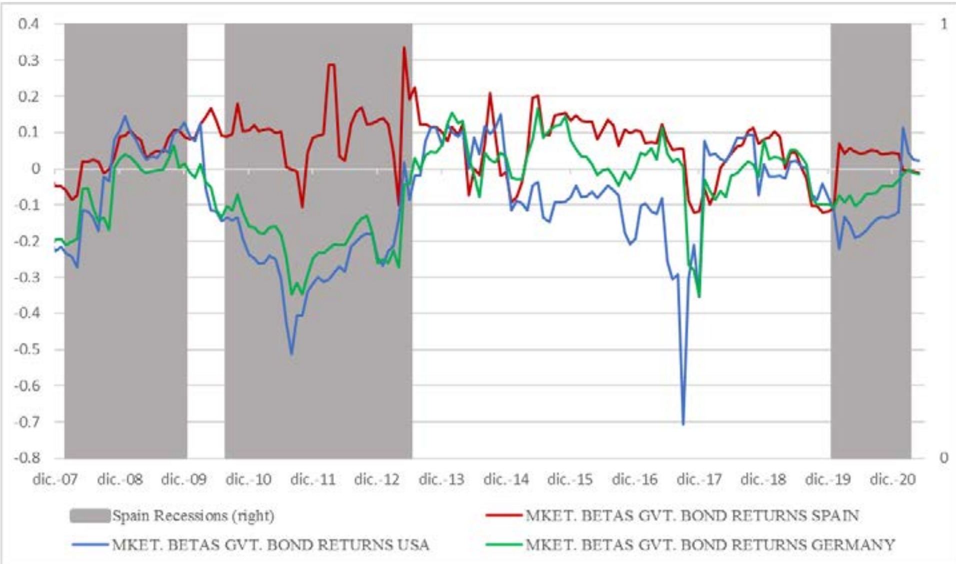
$$LGvt_{bt}^{j} = \beta_0 + \beta_1 R_{mt}^{j} + \varepsilon_t \text{ ; } j = \textit{Spain, U.S., Germany}, \tag{1}$$

where $LGvt_{bt}^{j}$ is the 10-year government bond return for country *j*, and R_{mt}^{j} is the stock market return for country *j*. The results are shown in Figure 4 together with the Spanish recessions. As expected, given the previous results of Campbell et al. (2020), we find that for most of the sample period, the market exposures of the long-term government bonds of the U.S. and German markets are negative. Average market betas for the full sample period are -0.09 and -0.06 for the U.S and German markets, respectively. Moreover, average market exposures during the recession months are -0.16 and -0.13 for both markets, respectively. In other words, during the full sample period under a non-conventional monetary policy focused on production, government bonds are hedgers with respect to the stock markets for both the U.S. and German economies. Even more important, government bonds become stronger hedgers relative to the stock markets during especially bad economic times. Market betas double during the recession months with respect to the exposures over the full sample.

The Spanish case is precisely the opposite. Average market betas during the full sample and the recession months are positive and equal to 0.08 and 0.09, respectively. The Spanish long-term government bonds are risky assets moving positively with respect to the Spanish stock market returns. Average betas are even more positive during the Spanish recession associated with the sovereign debt crisis. Not even under the enormous support of the European Central Bank during the pandemic, the Spanish government bonds became hedgers.[6] The protection received by government bonds does not seem to be completely effective for Spain. This result resembles the previous evidence about the Spanish markets and signals a worrisome lack of confidence in the Spanish economy.

Market betas of the Spanish, German, and U.S. 10-year government bond returns relative to the market stock returns of the Spanish, German, and U.S. stock market indices. Market betas are estimated using rolling windows of non-overlapping 12 monthly returns: Monthly data from January 2007 to June 2021

FIGURE 4



6 This result also holds when we estimate market government bond betas with daily data using a rolling-window with non-overlapping periods of 30 days. The Italian government bond shows a similar pattern during the stressed periods of the Eurozone.

3 The Performance of Asset Classes

We now compare the average and cumulative performance of five asset classes traded in the Spanish Capital Market.

We analyze two stock market indices: the IBEX 35 made up by the 35 most liquid companies traded on the Spanish market, which is a price index that is weighted by market capitalization and adjusted according to the free float of each company in the index, and the IBEX 35 TOTAL Index that includes dividend payments.

In addition, we include the PUTWRITE Index that is a systematic selling position of put options on the IBEX 35 with one month to expiration. The price received by selling the options and the nominal (the strike price times the multiplier associated with the index) are invested at the overnight risk-free rate or euro short-term rate (€STR). It is important to point out that this index is perfectly replicable. One key insight to understand the strategy associated with the PUTWRITE index is that the correlation between the realized market volatility and the rate of return of the IBEX 35 TOTAL estimated with monthly data is -0.38 during our sample period. The PUTWRITE selling strategy is an attractive investment vehicle with potentially good results whose returns have a positive correlation with the market index returns of 0.81. Given the asymmetric behavior between the realized market volatility and the market portfolio return, the PUTWRITE strategy can be understood as selling variance to take advantage of periods with positive, close to zero or even slightly negative market returns or relatively low variance. The buyer of the put options does not exercise the options when the market rises, and the seller keeps the put prices received. On the other hand, the buyers of the PUTWRITE are hedging against strong declines in the market or times of high market volatility. If we understand this strategy as taking positions on the market variance, it is also important to point out that this strategy is a one directional strategy. A long position using straddles would take exposures to variance associated with large up and down movements of the stock market index. The potential problem with these positions is that the right way to hedge variance risk is to isolate the variance completely. In other words, the ideal way of having exposure to variance would be to construct a synthetic pure position such that the value of the synthetic changes only when variance changes. This position would not be sensitive to movements in variables other than the underlying volatility. In practice this is possible using variance swaps. We will come back to this discussion later in the paper.

Finally, we use two additional rates of returns from fixed income products. First, we employ the AIAF General Index of Corporate Bonds, which is an index of corporate bonds issued at medium (between 3- and 5- year maturities) and long horizons (between 5- and 10- year maturities). The average duration of the index during our sample period is 4.78 years. It is an index of total returns that includes price variations and coupon payments. The index weights all individual issues by the market value of the outstanding balances rather by trading volume. The last asset employed in the analysis is the rate of returns of the 10-year government bond, which is the reference long-term bond to calculate the sovereign risk premium for the Spanish economy.[7]

Panel A of Table 2 shows the descriptive statistics for the monthly rates of returns of the five asset classes. The results confirm the poor performance of the Spanish stock market, especially when we employ the IBEX 35 without dividends. The impact of dividend payments is clearly relevant. The Sharpe ratio is 0.16 and -0.06 for the IBEX 35 TOTAL and the IBEX 35, respectively. It is surprising that both indices have a small positive skewness and as expected, the one-lagged autocorrelations are very small. The PUTWRITE strategy presents better results with low average return, but low volatility relative to the stock market indices, although it has large excess kurtosis and negative skewness. The Sharpe ratio is 0.24, although the correlation with the indices is approximately 0.81 (Panel B of Table 1). This suggests very little diversification benefits from a portfolio combining the stock market and the PUTWRITE portfolio, although, on average, it provides an additional gain to the stock market returns. Moreover, note that long positions in the PUTWRITE is a powerful hedging vehicle against adverse stock market shocks as it is also implied by its high negative skewness.

The fixed income results are striking, especially the performance statistics of the index of Corporate Bonds. The average return is 5.5%, which is higher than the average return of the stock market even with dividends. Given that its volatility is much lower than market volatility, the Sharpe ratio of the General Index of Corporate Bonds is an impressive 1.62. In addition, the corporate bond returns have low correlation with the market portfolio returns. However, we should be careful with the interpretation of these results given the low levels of liquidity that the individual components of the index have. In other words, this corporate bond portfolio has high illiquidity risk that probably explains a large percentage of the average return. Unfortunately, we do not have data to confirm this conjecture. Moreover, the sample period is characterized by a continuous decline of interest rates. This fact also explains another significant portion of not only the average return, but also the low volatility associated with the corporate bond returns. In addition, it is not clear how credit risk across corporate bond portfolios affects these results. In any case, the well-known pattern of low interest rates and the corresponding persistent increase in bond prices may explain their extraordinary performance. Note the high autocorrelation of corporate bond returns. Finally, the long-term government bond performance is also impressive. The Sharpe ratio is 0.33, although the returns show a high negative skewness.

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7 The stock market indices, the PUTWRITE index, and the Corporate Bond Index are from BME at https://www.bolsasymercados.es/esp/Sobre-BME/Historico/Indices. AIAF es the reference Spanish market of fixed income bonds issued by corporations. In addition, BME manages the MARF market, which is the alternative market of corporate bonds for companies of medium size. Data of the Government bond are downloaded from https://fred.stlouisfed.org.

Descriptive Statistics of the rates of returns across asset classes in the Spanish capital market: Monthly data from February 2007 to June 2021 TABLE 2

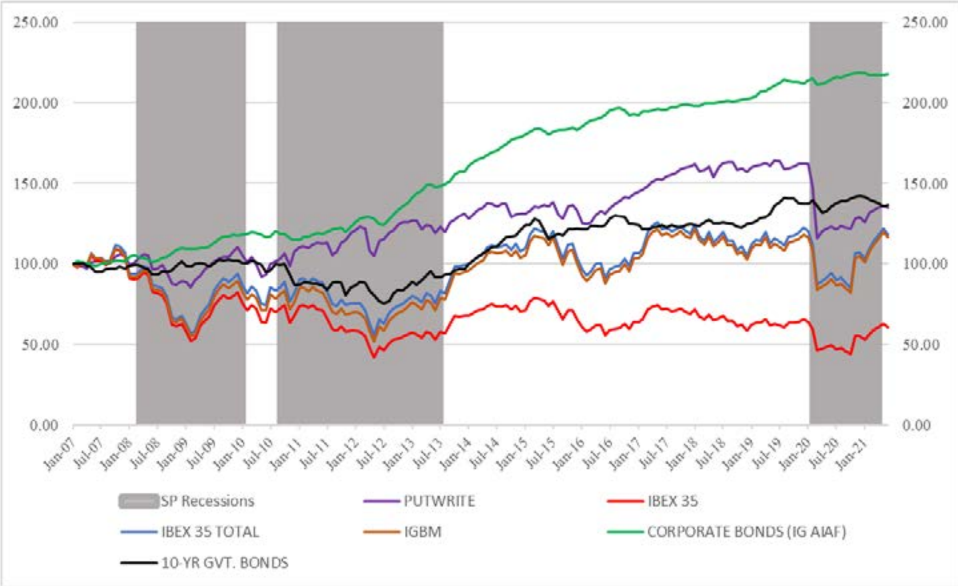
Panel A Descriptive Statistics	IBEX 35 TOTAL	IBEX 35	PUTWRITE	Corporate Bonds (AIAF)	10-year Government Bonds
Annualized Average	0.033	-0.013	0.028	0.055	0.025
Annualized Volatility	0.208	0.208	0.119	0.034	0.075
Skewness	0.105	0.080	-1.952	-0.104	-0.733
Excess Kurtosis	2.580	2.621	9.655	0.508	2.460
Monthly Maximum	0.253	0.252	0.091	0.028	0.065
Monthly Minimum	-0.221	-0.222	-0.215	-0.027	-0.089
Autocorrelation	0.028	0.027	0.084	0.379	0.201
SHARPE	0.160	-0.063	0.238	1.622	0.326

Panel B Correlations	IBEX 35 TOTAL	IBEX 35	PUTWRITE	Corporate Bonds (AIAF)	10-year Government Bonds
IBEX 35 TOTAL	1	0.998	0.809	0.117	0.210
IBEX		1	0.805	0.121	0.218
PUTWRITE			1	0.080	0.128
Corporate Bonds (AIAF)				1	0.717

Panel A of this table reports descriptive statistics of the rates of returns of five asset classes in the Spanish capital market, namely, the IBEX 35 TOTAL index that includes dividends, the IBEX 35 index, the PUTWRITE index that represents selling volatility positions in the IBEX 35 index estimated from option prices on the market, the general index of corporate bonds (AIAF) that contains corporate bonds with medium (between 3- and 5- year maturities) and long term (between 5- and 10- year maturities) corporate bonds with average duration of 4.78 years, and the 10-year government bonds. We report the 1-month lagged autocorrelation. Panel B contains the correlation coefficients between the five asset classes during the full sample period. Both stock market indices, the AIAF corporate bond index, and the PUTWRITE index are from BME. Given that the first available observation for the PUTWRITE index is January 2007, we report all return statistics from February 2007.

Figure 5 shows the cumulative returns from investing 100 euros in January 2007 in the alternative asset classes. The pattern of performance is consistent and clarifies the results reported in Table 2. The corporate bonds are the winners. The PUTWRITE strategy also has a good performance, but this investment vehicle suffers considerably when there is a big drop in the stock market. The large decline experienced by the PUTWRITE portfolio at the outbreak of the pandemic makes this strategy to end up having the same final value as the long-term government bond. The two fixed income assets have a much better behavior during bad economic times. The obvious losers are the stock market indices including the IGBM, which shows a very similar behavior with respect to the IBEX 35 TOTAL Index.

The cumulative monthly returns of investing 100 euros in January 2007 in six asset classes in the Spanish capital market. Cumulative performance is displayed for the IBEX 35 TOTAL, IBEX 35, and the IGBM (General Stock Market Index) market indices, the PUTWRITE index, the AIAF corporate bond general index, and the 10-year government bond: Monthly data from January 2007 to June 2021 FIGURE 5



4 The Performance of Corporate Bonds Across Maturities

Given the surprising performance of the General Index of Corporate Bonds, this section further investigates this asset class by extending the previous analysis to alternative corporate bond indices in which the individual issues are classified by maturity. BME provides data on short-term bonds with maturities of less than 3 years and average duration of 1.9 years; medium-term bonds with maturities between 3- and 5- years and duration of 3.7 years; long-term bonds with maturities between 5- and 10- years and duration of 6.2 years, and the very long maturity corporate bonds with maturities higher than 10 years and average duration of 11.2 years.[8]

Panel A of Table 3 shows the descriptive statistics of the corporate bond indices. We observe a strong positive relation between the average rate of returns of these corporate bonds and their risks as measured by duration. Interestingly, if we measure risk by the corporate bond betas with respect to the return of the General Index of Corporate Bonds (or even by the volatility of returns), we find the same pattern between average returns and risk than with duration. Corporate bond betas are positive, statistically significant, and increase monotonically with maturity. The same pattern is found with respect to the return of the IBEX 35 Total Index. However, these market betas are low, and they are estimated with very low precision. As we already pointed out in Section 2, the market beta of the long-term government bond is also positive and statistically different from zero during the sample period. In fact, it is equal to 0.076; this is to say, higher than the market beta of long-term corporate bond returns. In addition, and as expected, the short-term corporate bonds present high positive skewness, excess kurtosis, and autocorrelation relative to longer maturity bonds. Finally, the Sharpe ratios are certainty impressive, and despite the increasing average returns, we report a monotonically decreasing pattern with maturity given the impact of higher volatilities for longer duration bonds. Again, as we pointed out when describing the General Index performance relative to other asset classes, one should be very careful with the interpretation of these extraordinary results.

Panel B of Table 3 show correlation coefficients among corporate bond indices. These correlations are high, especially between corporate bonds with longer maturity. The highest correlation reported is between the returns of the General Index and the returns of the long-term corporate bonds, while the lowest is between the short-term and very long-term corporate bonds.

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8 Unfortunately, data on credit ratings of the components of these indices are not available.

Descriptive statistics of corporate bond returns for alternative maturities (AIAF): Monthly data from January 2007 to June 2021

TABLE 3

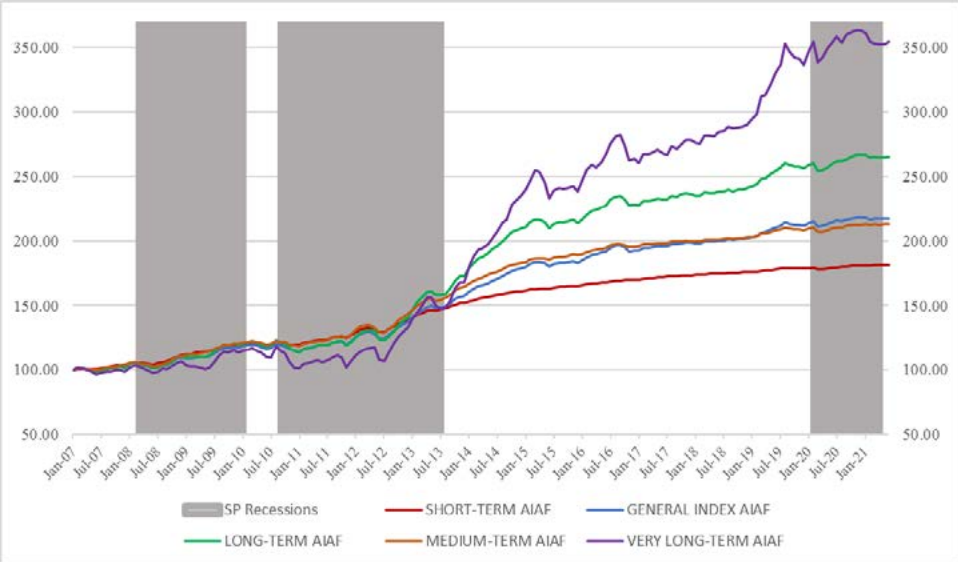
Panel A Descriptive Statistics	GENERAL INDEX	SHORT-TERM	MEDIUM-TERM	LONG-TERM	VERY LONG-TERM
Annualized Average	0.054	0.042	0.053	0.068	0.090
Annualized Volatility	0.034	0.017	0.030	0.048	0.087
Average Duration	4.8	1.9	3.7	6.2	11.2
Beta General Index AIAF	1.000	0.426	0.849	1.393	2.410
Market Beta	0.018	0.008	0.025	0.026	0.038
Skewness	-0.092	0.608	0.139	-0.127	-0.162
Excess Kurtosis	0.487	2.591	1.430	1.542	1.308
Monthly Maximum	0.028	0.020	0.029	0.042	0.081
Monthly Minimum	-0.027	-0.014	-0.026	-0.049	-0.078
Autocorrelation	0.372	0.528	0.447	0.385	0.289
SHARPE	1.600	2.471	1.766	1.426	1.034
Panel B Correlations	**GENERAL INDEX**	**SHORT-TERM**	**MEDIUM-TERM**	**LONG-TERM**	**VERY LONG-TERM**
GENERAL INDEX	1	0.854	0.957	0.981	0.928
SHORT-TERM		1	0.944	0.811	0.670
MEDIUM-TERM			1	0.938	0.824
LONG-TERM				1	0.937

Panel A of this table reports descriptive statistics of the rates of returns of five maturity-sorted corporate bonds from AIAF, namely, the general corporate bond index with maturities between 3- and 10- years; the short-term index with maturities of less than 3 years; the medium-term index with maturities between 3- and 5- years; the long-term index with maturities between 5- and 10- years; the very long-term index with maturities higher than 10 years. Average duration in years over the full sample period. Betas of corporate bond returns are estimated with respect to the returns of the AIAF General Index, while market corporate bond betas are with respect to the IBEX 35 Total Index. We report the 1-month lagged autocorrelation. Panel B contains the correlation coefficients between the five corporate bond return indices during the full sample period. The five AIAF corporate bond indices are from BME.

Figure 6.A contains the performance of the alternative corporate bond indices. It is measured by the cumulative returns of investing 100 € in January 2007. The results clearly show the continuously increasing pattern of corporate bonds returns, especially for the very long-term maturities. They experienced very mild declines at the beginning of the Great Recession and the pandemic, and they also seem to be affected by politically stressed times.

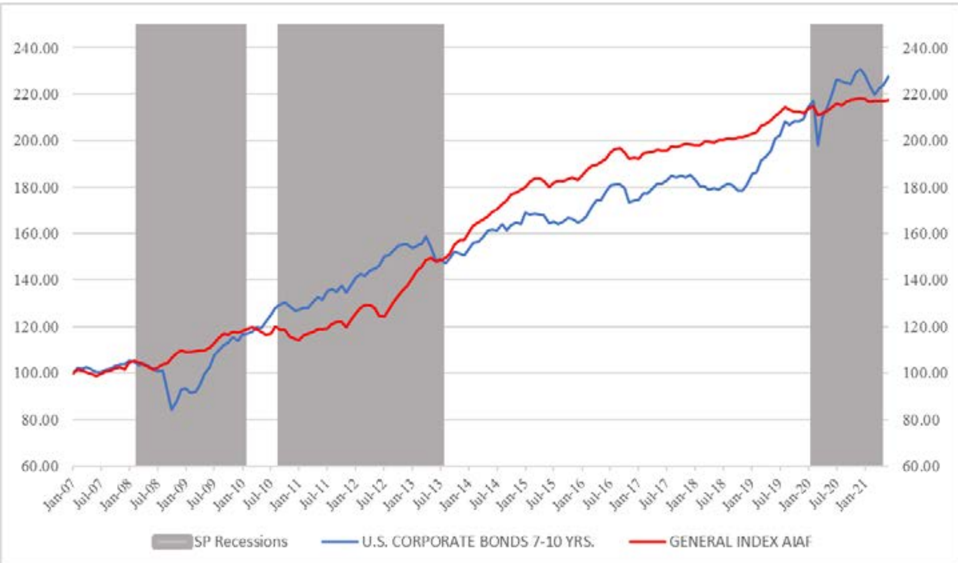
The cumulative monthly returns of investing 100 euros in January 2007 in five maturity-sorted corporate bonds from AIAF, namely, the general corporate bond index the short-term index, the medium-term index, the long-term index, and the very long-term index: Monthly data from January 2007 to June 2021

FIGURE 6.A



The cumulative monthly returns of investing 100 euros in January 2007 in the U.S. corporate bonds with 7 to 10 years to maturity and in the general corporate bond index from AIAF: Monthly data from January 2007 to June 2021

FIGURE 6.B



The apparently striking performance of Spanish corporate bond returns should not be taken as an international anomaly. It is very important to keep in mind that they are much more illiquid securities than stocks or long-term government bonds. Moreover, these results are strongly sample-dependent. From January 2007 to the end of our sample period, interest rates have been not only historically low in levels, but they have experienced a continuous decrease over time that explains the increasing behavior of bond prices. Figure 6.B shows the cumulative performance of the AIAF General Index and the long-term corporate bond for the U.S. market. The pattern over time is very similar, although the U.S. corporate bonds are more volatile than the similar Spanish bonds.

5 The Performance of Equity Sectors

We next analyze the returns of six industry portfolios provided by BME. These portfolios are associated with the Spanish General Index (IGBM) that contains all stocks traded in the Spanish Stock Exchange. In addition, this sector classification incorporates more sectors than the alternative available sectors, which only include stocks from the IBEX 35 Index.

Panel A of Table 4 shows the descriptive statistics of the IGBM Index, and the six available sectors. We can extract three distinct groups in terms of either average performance or cumulative returns as displayed in Figure 7. On the negative side, we find the Financial Services sector. The extreme adverse shocks suffered by the Spanish banks during the Great Recession and the European debt crisis, together with very low interest rates and the corresponding impact on financial margins, makes this sector to have not only the average most negative return across all sectors, but it is also the sector with the highest volatility. The obvious implication is a large and negative Sharpe ratio of -0.15. The equity wealth lost by investors in this sector is clearly appreciated in Figure 7. The very high average market beta with respect to the IGBM Index, which is equal to 1.41 summarizes these characteristics all together. Such a high beta in bad overall economic times for the stock market during the sample period is totally consistent with the bad performance of the financial sector. On the opposite side, we find the Consumer Goods Sector. It has simultaneously the highest average return and the lowest volatility across sectors, including the IGBM Index. Its Sharpe ratio and the equity wealth created by investing in this sector as shown in Figure 7 are striking.[9] Moreover, contrary to the case of the Financial Services sector, the Consumer Goods sector has the lowest average beta among all six analyzed sectors. This sector is a highly quality, defensive, and profitable sector. In Panel B of Table 4, we show the correlation coefficients among these six sectors. It is also interesting to point out that the Consumer Goods sector tends to have the lower correlations with the IGBM and with the rest of the sectors. This of course has relevant implications for potential diversified investment strategies. Finally, on the middle, we have the performance shown by the other four sectors, namely Petroleum & Power, Basic Materials and Construction, Consumer Services, and Technology and Telecommunications. Their cumulative returns in Figure 7 and the Sharpe ratios are below the statistics associated with the IGBM. All four sectors lost equity wealth at the end of the sample period, and the Basic Materials and Construction and Technology and Telecommunications sectors present negative Sharpe ratios.

9 It is important to recall that INDITEX is one of the companies that belong to this sector. Its annualized risk-adjusted return or alpha (independently of the asset pricing model employed) is approximately 8.5% during the sample period. This company may have a great influence on the results.

Descriptive statistics of the rates of return of six sectors of the Spanish Stock Market together with the General Stock Market Index (IGBM): Monthly data from January 2007 to June 2021

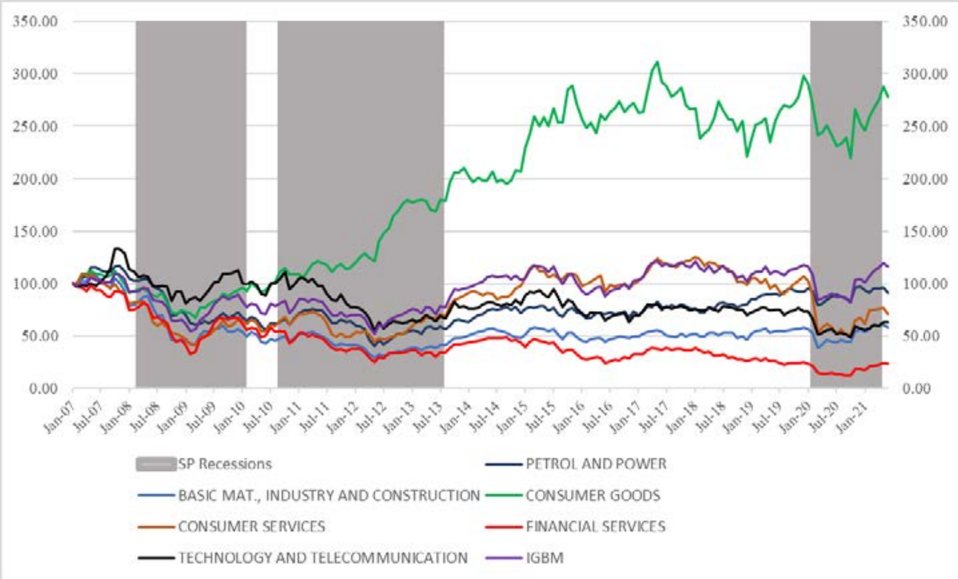
TABLE 4

Panel A Descriptive Statistics	IGBM	PET. & POWER	MAT.& CONS.	CONS. GOOD.	CONS. SERV.	FINAN. SERV.	TECH &TELEC
Annual. Avg.	0.035	0.012	-0.008	0.090	0.011	-0.048	-0.006
Annual. Vol.	0.209	0.185	0.226	0.177	0.252	0.314	0.213
Market Beta	1.003	0.738	0.953	0.587	0.995	1.406	0.847
Skewness	0.121	-0.282	-0.309	0.315	-0.693	0.839	-0.102
Exc. Kurtosis	2.869	1.078	2.292	1.330	6.062	5.087	1.656
Month Max.	0.265	0.158	0.220	0.210	0.298	0.467	0.223
Month Min.	-0.227	-0.173	-0.263	-0.131	-0.398	-0.320	-0.230
Autocorrel.	0.036	0.009	0.091	-0.030	0.056	0.062	-0.109
SHARPE	0.167	0.063	-0.037	0.512	0.045	-0.152	-0.026
Panel B Correlations	**IGBM**	**PET. & POWER**	**MAT.& CONS.**	**CONS. GOOD.**	**CONS. SERV.**	**FINAN. SERV.**	**TECH. &TELEC**
IGBM	1	0.825	0.866	0.683	0.819	0.934	0.824
PET. & POWER		1	0.764	0.541	0.617	0.651	0.719
MAT.& CONS.			1	0.688	0.812	0.752	0.687
CONS. GOOD.				1	0.653	0.564	0.546
CONS. SERV.					1	0.760	0.668
FINAN. SERV.						1	0.663

Panel A of this table reports descriptive statistics of the rates of returns of six industrial and financial sectors of the Spanish Stock Market: Petroleum & Power (PET. & POWER), Basic Materials and Construction (MAT. & CONS.), Consumer Goods (CONS. GOOD.), Consumer Services (CONS. SERV.), Financial Services (FINAN. SERV.), and Technology and Telecommunications (TECH. & TELEC.). We also report the statistics for the General Stock Market Index (IGBM) that includes all stocks traded in the Spanish continuous stock market. Market betas are obtained by regressing the total returns of the IGBM and the sectors on the total returns of the IBEX 35 TOTAL index. We report the 1-month lagged autocorrelation. Panel B contains the correlation coefficients between the returns of the six industrial and financial sectors during the full sample period. All indices are from BME.

The cumulative monthly returns of investing 100 euros in six industrial and financial sectors of the Spanish Stock Market, and in the General Stock Market Index (IGBM): Monthly data from January 2007 to June 2021

FIGURE 7



6 The Performance of Risk Factors and the Risk-Adjusted Returns of Corporate Bonds and Equity Sectors

6.1 Factor Investing and the Research-Oriented Selection of Risk Factors

A classic portfolio selection strategy based on a combination of the stock market portfolio and government bonds tends to have a very high correlation with a full investment in the stock market. Given the extremely painful investment records of the market return during financial crises, especially during the Great Recession, the so-called *factor investing* is becoming popular and expanding rapidly among institutional investors. As Asness, Ilmanen, Israel, and Moskowitz (2015) point out, institutional investors have turned their interest to strategies carrying alternative sources of return with relatively little correlation to the traditional market return. Factor investing consists of taking positions in systematic risk factors and thus being long and short in opposite characteristics. For example, a value investment style implies to long value firms (those with the highest book-to-market ratio) and to short growth firms (those with the lowest book-to-market ratio). This strategy replicates the return on the value factor of Fama and French (1993). A factor investment strategy is defined by Asness et al. (2015) as the simultaneous long-short systematic and disciplined strategy that delivers long-term positive average returns across markets and asset classes, with overall low correlation with long-only portfolios.

The asset pricing literature has shown an enormous number of variables that supposedly explain the cross-sectional variation of average equity returns. Therefore, investors who want to follow a factor investment strategy are invaded by dozens of proposals claiming success by assuring positive and significant risk-adjusted returns or alphas. However, on the one hand, this proliferation of factors is certainly disturbing because theory shows that risk factors should be pervasive across assets and markets (Harvey, Liu, and Zhou, 2016; Clarke, 2021; and Jensen, Kelly, and Pedersen, 2021). On the other hand, these positive alphas are disguised into large portfolios that are exposed to the market. This implies that investors willing to pay fees to obtain alphas end up paying for market exposure or beta. For this reason, financial research conducting analyses of investment performance must be particularly careful in choosing risk factors. The selected factors should not only be economically motivated, but they should have also proven sounded out-of-sample success across many asset classes and stock markets around the world.

The previous discussion points towards a well-founded selection of risk factors in any analysis related with the performance of investment strategies. The factors used in this research about the Spanish Stock market are the classic Fama-French

(1993) three factors, namely, the excess market return, the size or small minus big (SMB), and the value minus growth (HML) factors,[10] together with the momentum (MOM) factor proposed by Carhart (1997), and two factors inspired by popular investing strategies based on quality and low risk: the quality minus junk (QMJ) factor of Asness, Frazzini, and Pedersen (2019), and the betting against beta (BAB) factor of Frazzini and Pedersen (2014), also known as the low-risk or defensive factor. Data for these Spanish factors are obtained from the web page of AQR Capital Management at www.aqr.com. The exception is the excess market return, which we take as the excess return between the IBEX 35 Index return and the yield of the 3-month Spanish Treasury bill.

It is convenient to explain further the QMJ and BAB risk factors given that they are relatively new compared with the classic size and value factors and the momentum factors. Quality pricing and the associated investment strategies are receiving increasing attention among practitioners and academics.[11] A recent line of research undertaken by Asness et al. (2019) identifies a quality stock as an asset for which investors would be willing to pay a high price, which means that these stocks are simultaneously safe (low beta), profitable (high return on equity), growing (high cash flow growth), and well managed (high dividend payout ratio). As Alquist, Frazzini, Ilmanen, and Pedersen (2020) point out when discussing the facts and fictions of low-risk strategies, Asness et al. (2019) focus on a broad composite or umbrella series of three subgroups, namely profitability, growth, and safety to construct a risk factor using the Fama and French (1993) dollar-neutral weighting scheme. The authors' QMJ factor, which 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, the striking finding of Asness et al. (2019) is that the QMJ factor displays large, realized returns during downturns, which suggests that the quality-based factor does not exhibit bad-times risk. The surprising and extremely good performance of the QMJ factor in bad economic times implies that high-quality stocks are hedging assets, and consequently, they should have relatively low average returns during long sample periods. On the contrary, in the U.S. market, the factor displays positive Fama-French (1993) three- and four-factor alphas, the latter including Carhart's (1997) momentum factor (MOM), and a positive Fama-French (2015) five-factor alpha with relatively low idiosyncratic risk. As Asness et al. (2019) argue, this evidence presents a very serious challenge to rational risk-based explanations of asset pricing.[12] In any case, which

10 Size for the small and big companies is measured by market capitalization. Value firms are stocks with high book equity to market equity ratio, and growth firms are the ones with low book equity to market equity ratio.

11 Interestingly, this is the case even though, as shown by Frazzini, Kabiller, and Pedersen (2018), quality investing is one the key factors behind Warren Buffet's extraordinary historical performance. At least since Graham (1973), there has been a long industry tradition regarding quality strategies. However, there are multiple ways of understanding quality and, consequently, several practical and competing quality strategies. For example, Novy-Marx (2013) shows that gross profitability, a simple quality definition, which is the difference between a firm's total revenues and the costs of goods sold, scaled by assets is a powerful metric predicting the relative average return behavior of stocks. The Fama-French (2015) profitability factor is operating profitability, which is revenues minus the costs of goods sold, minus selling (general and administrative) expenses, minus interest expenses, divided by book equity.

12 See Bouchard, Ciliberti, Landier, Simon, and Thesmar (2016), and González-Urteaga and Rubio (2021) for additional complementary evidence explaining the performance of the QMJ factor.

does not present any doubt is the success that quality-based strategies are having among practitioners. Finally, the betting against beta (BAB) factor of Frazzini and Pedersen (2014) is defined as the return differential between leveraged low-beta stocks and deleveraged high-beta stocks. Frazzini and Pedersen (2014) show that leverage constraints are strong and significantly reflected in the return provided by this factor. Indeed, the authors argue that the positive and highly significant risk-adjusted returns relative to the traditional asset pricing models shown by portfolios sorted by the level of market beta are explained by shadow cost-of-borrowing constraints. In other words, the BAB factor captures funding liquidity, which implies that it becomes negative in bad liquidity times.[13]

The selection of these factors responds to three criteria. First, the selected factors must be sensitive to real activity. Rossi and Timmermann (2015) show that real activity, as a proxy for consumption and investment opportunities, plays a significant role in explaining the time-varying behavior of expected market risk premia. Given that expected excess returns are the product of the price of risk and the quantity of risk, and that uncertainty and risk aversion are embedded in the price of risk, the chosen factors must be exposed to shocks in both uncertainty and risk aversion as the key channel connecting the expected risk premia with the real economy. González-Sánchez, Nave, and Rubio (2018) and González-Sánchez, Nave, and Rubio (2020) show that value, momentum, quality, and defensive factors present strong economic foundations given their relationship with uncertainty and risk aversion. Moreover, Maio and Philip (2018) show that economic activity plays a key role in explaining the anomalies associated with momentum, and Kelly, Moskowitz, and Pruitt (2021) show that momentum captures time-varying risk compensation. Zhang (2005) shows that value stocks are riskier because during bad times they are burdened with more unproductive capital and, when these firms want to disinvest, they face higher adjustment costs. In fact, the market beta of value stocks tends to increase relative to growth betas during industrial/financial related economic crises. On the contrary, growth firms can better deal with a downturn by deferring investments. Moreover, as already pointed out, Asness et al. (2019) show that the quality factor is a powerful hedging strategy against bad times, and Frazzini and Pedersen (2014) argue that the defensive factor reflects funding liquidity. The size factor is also included given the relevance of this style if investors control by junk (Asness, Frazzini, Israel, Moskowitz, and Pedersen, 2018).[14] Third, the selected factors must hold up across a multitude of asset classes, stock markets, and time periods. The papers by Asness, Moskowitz, and Pedersen (2013), Israel and Maloney (2014), Asness et al. (2015), Asness, Frazzini, Israel, and Moskowitz (2015a, 2015b), Asness et al. (2018), and Clarke (2021) discuss the risk factors that are proven to be pervasive styles across asset classes and markets.[15] Moreover, these papers also identify those factors that successfully explain not only the unconditional, but also the conditional time-varying expected risk premia. The value, momentum, quality, and low risk factors, together with the carry factor

13 See Asness, Frazzini, Gormsen, and Pedersen (2020), and Chen and Lu (2019) for additional detailed discussion on the BAB factor and funding liquidity. See Schneider, Wagner, and Zechner (2020), for a skewness-based explanation of the BAB factor.

14 Regarding the size effect, see also Alquist, Israel, and Moskowitz (2018).

15 See Nieto and Rubio (2022) for a comparison of the performance of risk factors between the Great Recession and the COVID-19 crises using a representative set of stock markets around the world.

(higher-yielding assets show higher returns than lower-yielding assets) that is especially popular in currency investing, are the more relevant examples satisfying these characteristics.

A conceptual clarification about value, momentum, and quality risk factors is important. First, value and momentum strategies work at differently frequencies. Value identifies cheap or expensive stocks as those whose price have been falling or rising for several years, while momentum require buying the stocks that are becoming expensive and selling those that are becoming cheap, before they actually become expensive or cheap. This suggest that value strategy means buying losers and selling winners over a period of two to six years, while momentum imply buying winners and selling losers over the past year, but beyond that these stocks start to reverse as the value effect becomes predominant. Therefore, a stock that has favorable value and momentum characteristics is a cheap stock on the rise. Second, when doing value investing, an important question is whether the stock looks cheap because it is cheap or because it deserves to be cheap. The risk that a value investor ends up with economically bad companies is known as the value trap. If the mean-reversion of the book-to-equity ratio is driven by a rising price, then the value strategy is correct. However, if mean-reversion is driven by a falling book value because of negative earnings then the value strategy will fail. Quality investment corrects these potential problems. The idea is to buy firms that are cheap relative to the expected quality of the stock, something known as the quality at a reasonable price or QARP strategy. This strategy buys high quality firms at a discounted price.[16]

6.2 Factor Performance in the Spanish Stock Market

Panel A of Table 5 shows the descriptive statistics of the excess market return and six risk factors. Two of them are the value-growth factors, namely the HML factor of Fama and French (1993), and HMLD or the HML Devil factor proposed by Asness and Frazzini (2013). The HML Devil is the value-growth factor with monthly price updates in the book-to-market ratio rather than the original Fama and French HLM factor proposal, where they update value and growth once a year, on June 30. This implies that in the original calculation, the book and price data used to form the book-to-price ratio are always 6 to 18 months old. The results show two very distinct performance among risk factors in Spain. The size (SMB), value (HML, HMLD), and defensive-funding liquidity (BAB) factors present either negative or close to zero average returns. Note that these factors take simultaneously long and short positions that reduces their volatility. All of them have lower volatility than the excess market return. Surprisingly, however, the MOM and BAB factors have a relatively high volatility during our sample period. The autocorrelation of monthly returns tends to be low except for the value factors, but especially for the HML factor, which shows an autocorrelation of 0.28. Note that the monthly updates of the HMLD reduces the autocorrelation to 0.19. The Sharpe ratio among factors follows the same differences shown for average returns. The striking feature of the reported unconditional statistics is the high Sharpe ratio of the MOM factor that equals 0.69, while the market portfolio has a Sharpe ratio of 0.12. Indeed, the MOM factor

16 These important issues are discussed in more detail by Pedersen (2015).

shows an extraordinary performance since the summer of 2015 and even during the COVID-19 associated recession as shown in Figure 8, where we show the cumulative excess returns of the excess market return and the six factors.[17] Despite the correction in performance of the MOM factor from October 2020 onwards, this factor has a remarkably performance during the problematic first months of the health crisis. Finally, given that the sample period includes three dramatics crises, it is not surprising the excellent behavior of the QMJ factor. It has a relatively high Sharpe ratio of 0.39, and in Figure 8 the cumulative performance of the QMJ factor almost double the equity wealth invested in this hedging factor.

Panel B of Table 5 shows the correlation coefficients among risk factors. First, the correlation between the market and the value factors is relatively high and positive. Second, the correlation between the market and the MOM, QMJ, and BAB factors is negative and high. Third, the MOM factor has positive correlation with the QMJ and BAB factors. Fourth, and even more important, there is a negative correlation between both, the QMJ and MOM factors with respect to value and size factors. These negative correlations have important implications for potential advantages of diversification when following factor investing strategies.

To summarize the performance of factors, we perform the following regression of each factor against the rest:[18]

$$F_{jt} = \alpha_j + \beta_{j,m} R^e_{mt} + \sum_{\substack{k=1 \\ k \neq j}}^{K} \beta_{j,k} F_{kt} + \varepsilon_{kt}, \tag{2}$$

where F_{jt} is one of the six factors used in the analysis, and R^e_{mt} is the excess market return. None of the factors shows an either a positive or negative statistically significant alpha, except for the MOM factor. The annualized alpha is 8.4%. The MOM factor is the absolute winner in the Spanish stock market during the past fifteen years. In addition, by looking at the exposures (betas) of the MOM factor to the other factors, we note that MOM is explained by growth, high quality, and defensive firms.

Given the impressive performance of the MOM risk factor in Spain, we may want to check whether this is an idiosyncratic phenomenon or, on the contrary, it is also observed in other countries. Figure 9 shows the performance of the MOM risk factor for the Spanish, German, and U.S. stock markets, where al returns are in euros. The performance of the German market is even more impressive than the Spanish case, basically because the MOM risk factor in Germany does not suffer as much as the MOM factor in Spain during the second part of the COVID-19 crisis. There is also a drop in the cumulative return at the outbreak of the pandemic, but the decline is smaller than in the Spanish market because it is stabilized during the last six months of the sample period. The Spanish is not a rare phenomenon. Regarding the poor relative performance of the MOM factor in the U.S. market, we must recall

17 See Nieto and Rubio (2020) for an analysis of the performance of Spanish risk factors during the outbreak of the COVID-19.

18 When the dependent variable is any of the two value factors, we do not employ the other as an additional explanatory variable.

that over a long sample period spanning 90 years and compared to other factors, momentum has offered investors the highest Sharpe ratio. However, as shown by Barroso and Santa Clara (2015), the MOM factor in the U.S. has also had the worst crashes that take decades to recover from. This is a worrisome property for investors who dislike negative skewness and high excess kurtosis. This is exactly the pattern we observe in Figure 9 for the U.S. stock market since the Great Recession.

Descriptive statistics of the excess market return (IBEX 35 TOTAL) and six risk factors of the Spanish Stock Market: Monthly data from January 2007 to June 2021 TABLE 5

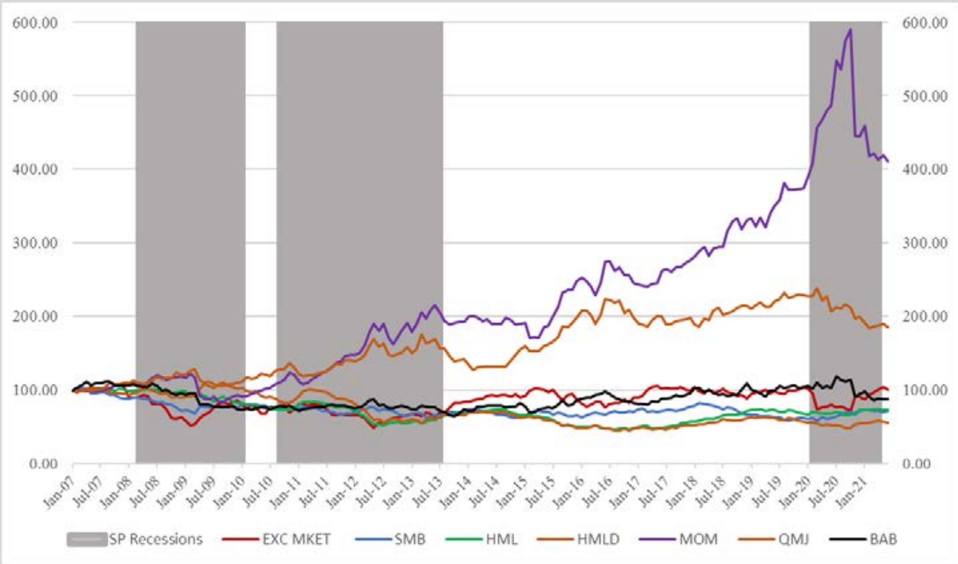
Panel A Descriptive Statistics	EXCESS MARKET	SMB	HML	HMLD	MOM	QMJ	BAB
Annualized Average	0.025	-0.015	-0.014	-0.030	0.114	0.051	0.004
Annualized Volatility	0.208	0.102	0.100	0.119	0.164	0.131	0.152
Skewness	0.086	0.572	-0.264	0.266	-1.431	-0.238	-0.547
Excess Kurtosis	2.585	1.621	0.088	0.615	6.758	1.295	3.146
Monthly Maximum	0.254	0.132	0.072	0.112	0.125	0.136	0.149
Monthly Minimum	-0.221	-0.074	-0.093	-0.104	-0.246	-0.126	-0.199
Autocorrelation	0.031	0.060	0.280	0.187	0.120	-0.002	-0.086
SHARPE	0.118	-0.145	-0.142	-0.257	0.693	0.391	0.024
Panel B Correlations	**EXCESS MARKET**	**SMB**	**HML**	**HMLD**	**MOM**	**QMJ**	**BAB**
EXCESS MARKET	1	-0.059	0.375	0.480	-0.616	-0.619	-0.570
SMB		1	0.022	0.049	-0.137	-0.275	-0.055
HML			1	0.812	-0.413	-0.558	-0.264
HMLD				1	-0.616	-0.592	-0.392
MOM					1	0.646	0.569
QMJ						1	0.481

Panel C Risk-Adjusted Returns (Alphas)	SMB	HML	HMLD	MOM	QMJ	BAB
REST FACTORS	0.0014 (0.63)	0.0011 (0.60)	0.0014 (0.69)	0.0070 (3.01)	0.0019 (1.05)	-0.0024 (-0.87)

Panel A of this table reports descriptive statistics of monthly returns of the excess market return (IBEX 35 TOTAL), and six risk factors of the Spanish Stock Market: size (SMB), value Fama-French (HML), value with monthly updating (HML Devil), momentum (MOM), quality (QMJ), and low risk (BAB) factors: Monthly data from January 2007 to June 2021. The excess market return of the IBEX 35 TOTAL is calculated relative to the monthly 3-month Spanish Treasury bill. We report the 1-month lagged autocorrelation. Panel B contains the correlation coefficients between the excess market return and the six risk factors during the full sample period. Panel C shows the alphas of each of the factors given in the first row against the rest of the factors. *t*-statistics in parentheses.

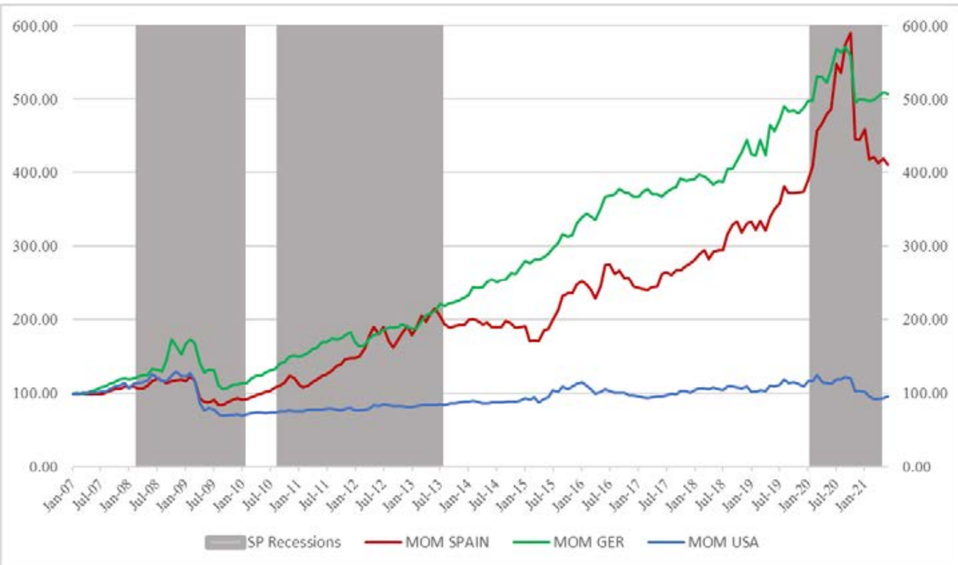
The cumulative monthly returns of investing 100 euros on January 2007 in the excess market return (IBEX 35 TOTAL), and six risk factors of the Spanish Stock Market. Cumulative performance is displayed for the size (SMB), value (HML and HMLD), momentum (MOM), quality (QMJ), and low risk (BAB) factors: Monthly data from January 2007 to June 2021

FIGURE 8



The cumulative monthly returns of investing 100 euros on January 2007 in the momentum (MOM) risk factors of the Spanish, German, and U.S. stock markets. All returns in euros: Monthly data from January 2007 to June 2021

FIGURE 9



6.3 Risk-Adjusted Returns of Corporate Bonds and Equity Sectors in the Spanish Capital Market

Next, we take advantage of the availability of data for Spanish risk factors to analyze the risk adjusted returns (alphas) of corporate bond indices sorted by maturity, and the equity sectors associated with the IGBM. All excess returns used below to analyze the performance of corporate bonds, and equity sectors are calculated with respect the 3-month Treasury bill.

Panel A of Table 6 shows the alpha of each Corporate Bond Index using either a two-factor model alpha that includes the excess market return and the excess long-term government bond return, an alpha estimated with the equity six-factor model and the excess long-term government bond return, or a model with only the excess returns of the AIAF General Index of corporate bonds as the explanatory variable: [19]

$$R^e_{cbt} = \alpha_j + \beta_{j,m} R^e_{mt} + \beta_{j,lgvtb} LGvt^e_{bt} + \varepsilon_{jt}, \tag{3}$$

$$R^e_{cbt} = \alpha_j + \beta_{j,m} R^e_{mt} + \beta_{j,lgvtb} LGvt^e_{bt} + \sum_{k=1}^{F} \beta_{j,k} F_{kt} + \varepsilon_{jt}, \tag{4}$$

$$R^e_{cbt} = \alpha_j + \beta_{j,gicb} R^e_{gicbt} + \varepsilon_{jt}, \tag{5}$$

where R^e_{cbt} is the excess return of each of the Corporate Bond Indices *j* at time *t*, F_{kt} is the return of risk factor *k* at time *t*, and R^e_{gicbt} is the excess return of the AIAF general index of corporate bonds. Alphas across all corporate bonds and model specifications tend to be positive and estimated with high precision. The annualized alpha for the Corporate Bond General Index is 3.3% and 3.8% for models given by equations (3) and (4), respectively. The alphas monotonically increase in both specifications with maturity, and the same pattern is found for the *R*-squared statistic. The very long-term corporate bond presents an annualized alpha of 7.0%. Importantly, when we control exclusively for the AIAF General Index in regression (5), we find positive and significant alphas for the short- and medium-maturity bonds, but a negative a significant alpha for the longest maturity bond. This is due to the higher duration and beta risks of long-term corporate bonds reported previously. These results are consistent with the descriptive statistics reported in Table 3, and the cumulative returns shown in Figure 6.A.

Panel B of Table 6 shows similar results with respect to the equity sectors. We report the CAPM alpha, and the alpha obtained from the six-factor model. Once again, the risk-adjusted returns are consistent with the descriptive results of Table 4 and Figure 7. The model specifications are given by the following regressions:

19 The six-factor model is estimated using the Fama and French (1993) HML factor.

$$R_{st}^{e} = \alpha_{j} + \beta_{j,m} R_{mt}^{e} + \varepsilon_{jt}, \tag{6}$$

$$R_{st}^{e} = \alpha_{j} + \beta_{j,m} R_{mt}^{e} + \sum_{k=1}^{F} \beta_{j,k} F_{kt} + \varepsilon_{jt}, \tag{7}$$

where R_{st}^{e} is the excess return of sector *s* at time *t*. The Consumer Goods sector presents a positive and (weakly) statistically significant CAPM annualized alpha of 6.5%, while the Financial Services sector has a negative and statistically significant alpha of 9.3%. The *R*-squared statistics of Consumer Good are the lowest among the equity sectors. Interestingly, when we add risks supported by the main risk factors, both alphas lose their statistical significance. However, Basic Materials and Construction, and the Technology and Telecommunications have now negative and (weakly) statistically significant alphas. Note that the six-factor model consistently explains better the variability of the sectors' returns than the CAPM. The additional risks embedded in the six-factor model are important to explain the behavior of the realized returns of the equity sectors in Spain. This is especially the case for the Consumer Goods sector where the increase in the *R*-squared value from the CAPM to the multi-factor model is the highest among all sectors. This explains that the positive alpha generated by the sector losses the statistical significance when we control for additional risk factors. In addition, given the exposures of this sector to the alternative risk factors, it is important to point out that the Consumer Goods sector is characterized by including growth and high-quality stocks. In other words, the beta of this sector is negative with respect to the HML factors, and highly positive relative to the QMJ factor. Its positive exposure to growth and quality stocks reduces the alpha relative to the CAPM model. Similarly, during our sample period, banks are value, losers, and junk stocks. Given the bad performance of these types of stocks, the negative performance of the financial sector is alleviated when we employ a multi-factor model relative to the CAPM.

Risk-adjusted returns (alphas) for stock market sectors and maturity-sorted corporate bond returns: Monthly data from January 2007 to June 2021

TABLE 6

Panel A: Corporate Bonds (AIAF)	GENERAL INDEX	SHORT-TERM	MEDIUM-TERM	LONG-TERM	VERY LONG-TERM
Alpha: Excess Market + Government Bond	0.00328 (6.425)	0.00243 (8.650)	0.00322 (6.891)	0.00436 (5.824)	0.00584 (4.401)
Adjusted-R^2	0.534	0.403	0.493	0.501	0.529
Alpha: Six-Factor Model + Government Bond	0.00320 (6.044)	0.00252 (8.614)	0.00323 (6.623)	0.00416 (5.362)	0.00537 (3.875)
Adjusted-R^2	0.538	0.404	0.495	0.508	0.529
Alpha: AIAF General Index	-	0.00104 (5.493)	0.00046 (2.338)	-0.00021 (-0.985)	-0.00205 (-2.769)
Adjusted-R^2	-	0.760	0.920	0.963	0.871

Panel B: Market Sectors	PET. & POW.	MAT. & CONS.	CONS. GOOD.	CONS. SERV.	FINAN. SERV.	TECH. & TELEC.
Alpha: CAPM	-0.00143 (-0.627)	-0.00355 (-1.469)	0.00544 (1.944)	-0.00199 (-0.623)	-0.00776 (-3.025)	-0.00309 (-1.169)
Adjusted-R^2	0.684	0.764	0.477	0.668	0.862	0.680
Alpha: Six-Factor Model	-0.00362 (-1.990)	-0.00476 (-2.138)	0.00295 (1.240)	-0.00200 (-0.691)	-0.00244 (-1.098)	-0.00523 (-1.971)
Adjusted-R^2	0.816	0.816	0.654	0.740	0.904	0.704

Panel A of this table reports the risk-adjusted returns (alphas) of monthly excess returns of five maturity-sorted corporate bonds from AIAF, namely, the general corporate bond index with maturities between 3 and 10 years and average sample duration of 4.8 years; the short-term index with maturities of less than 3 years and average sample duration of 1.9 years; the medium-term index with maturities between 3 and 5 years and average sample duration of 3.7 years; the long-term index with maturities between 5 and 10 years and average sample duration of 6.2 years; the very long-term index with maturities higher than 10 years and average sample duration of 11.2 years. Panel B of this table reports the risk-adjusted (alphas) of the monthly excess returns of six industrial and financial sectors of the Spanish Stock Market: Petroleum & Power (PET. & POWER), Basic Materials and Construction (MAT. & CONS.), Consumer Goods (CONS. GOOD.), Consumer Services (CONS. SERV.), Financial Services (FINAN. SERV.), and Technology and Telecommunications (TECH. & TELEC.). The excess returns of the corporate bond indices and sectors are calculated relative to the monthly 3-month Spanish Treasury bill. The excess market return is the excess return of the IBEX 35 TOTAL, and the six risk factors of the Spanish Stock Market are the following: size (SMB), value Fama-French (HML), value with monthly updating (HML Devil), momentum (MOM), quality (QMJ), and low risk (BAB) factors. For corporate bonds, we employ as an additional factor the excess return of the 10-year government bond return. *t*-statistics are given in parentheses.

7 The Expected Market Risk Premium in the Spanish Stock Market

7.1 Estimation and the Time-Varying Counter Cyclical Behavior of the Expected Market Risk Premium

The term structure of the expected market risk premium, which is the difference between the expected market return for a given future horizon and the risk-free rate at the same horizon, plays a fundamental role in many financial decisions. Any real or financial investment with a specific expiration or maturity date requires a discount rate with the same maturity. In fact, the expected market risk premium is the key input of the equity cost of capital used by corporations to discount future cash flows. However, the empirical implementation of this basic idea is a complex task. Although it is well known how evasive it is to estimate the conditional expected risk premium, it is also widely accepted that the expected market risk premium is not only time-varying and counter-cyclical, but it is also different for alternative horizons.

We next analyze the time-varying behavior of the Spanish equity term structure by focusing on the expected market risk premium at different horizons of the IBEX 35 Index. We employ the option-based approach developed by Martin (2017) rather than the alternative approach based on dividend strips. As pointed out by Cochrane (2011), most of the variation in prices is due to changes in expected returns. Therefore, by using expected market returns, this study learns about changes in discount rates driven by risk aversion and/or uncertainty. Moreover, Gormsen and Koijen (2020) employ data from the dividend futures market to estimate growth expectations by maturity and find that the information of dividends is insufficient to explain the big drop in the stock market during the outbreak of the COVID-19.[20] Therefore, we obtain the expected market risk premium for the Spanish stock market by extracting forward-looking information from option prices on the IBEX 35 and, more specifically, from the risk-neutral variance of the Spanish stock market index. Our sample period is from October 11, 2006, to April 30, 2020.

Employing the fundamental asset pricing equation, Martin (2017) shows that the expected market risk premium can be written as follows:[21]

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20 Similar conclusions are obtained for other economic or financial crises (Muir, 2017) and (Cochrane, 2017). See Binsbergen (van) and Koijen (2017), Bansal, Miller, Song, and Yaron (2021), Chabi-Yo and Loudis (2020), Bakshi, Crosby, Gao, and Zhou (2020), and Gormsen (2021), for recent evidence on the term structure of the expected market risk premium under alternative procedures and data on either dividend futures or option prices.

21 Appendix A provides the foundations and a simple proof of the following equation.

$$E_t^P\left(R_{m,T}\right)-R_{f,t}=\frac{1}{R_{f,t}}Var_t^Q\left(R_{m,T}\right)-Cov_t^P\left(M_T R_{m,T},R_{m,T}\right), \tag{8}$$

where $R_{m,T}$ is the gross market return between t and T, M_T is the stochastic discount factor (SDF) at time T, $R_{f,t}$ is the gross risk-free rate from t to T available at time t, $E_t^P\left(\cdot\right)$ and $Cov_t^P\left(\cdot\right)$ are the expectation operator and the conditional covariance under the physical probability at time t, and $Var_t^Q\left(\cdot\right)$ is the risk-neutral conditional variance at time t.[22] It is crucial to understand that the variance under the risk-neutral probability adjust for risk by weighting bad states more than good states, whereas the realized variance symmetrically weights both states. Moreover, and in contrast to realized variances, risk-neutral variances are ex-ante or forward-looking measures that can be extracted form option prices. Therefore, the information content of these risk-neutral measures reflects expectations about risk and thus they should be closely related to expected risk premia.

Martin (2017) points out that if the relative risk aversion and the elasticity of intertemporal substitution are greater than one under recursive preferences, then the following negative correlation condition (NCC) holds for the market portfolio return:

$$Cov_t^P\left(M_T R_{m,T},R_{m,T}\right)\leq 0. \tag{9}$$

Thus, under this condition, the risk-neutral variance normalized by the risk-free rate constitutes a lower bound for the expected market risk premium:

$$E_t^P\left(R_{m,T}\right)-R_{f,t}\geq\frac{1}{R_{f,t}}Var_t^Q\left(R_{m,T}\right). \tag{10}$$

Therefore, Martin's lower bound and follow-up research depend crucially on the NCC condition.[23] Our estimation of the Spanish expected market risk premium employs equation (10). Appendix B describes the details of the estimation procedure of the right-hand side of expression (10) using option prices on the IBEX 35.

22 Section 9 discusses the risk-neutral moments available for the Spanish Stock Market. In any case, it is important to point out that we employ the model-free variance estimator proposed by Martin (2017), which is different from the estimation procedures used to estimate the risk-neutral volatility by BME, and even by the Chicago Board Options Exchange (CBOE) when estimating the well-known U.S. risk-neutral market volatility or the VIX. See Appendix B for details.

23 Martin and Wagner (2019) extend Martin's (2017) market risk premium lower bound approach to study expected excess returns at the individual level. Their new expression does not depend on the NCC condition but instead requires an estimate of the expected market return. To obtain this estimate, Martin and Wagner (2019) assume that the covariance in the NCC condition is equal to zero. Moreover, Kadan and Tang (2020) derive a sufficient condition under which the prices of options written on a given stock can be aggregated to estimate a lower bound on the expected risk premium of that stock. Moreover, Chabi-Yo and Loudis (2020) extend Martin's approach by deriving lower and upper bounds on the expected market risk premium using not only risk-neutral variance but also risk-neutral skewness and kurtosis. Their conclusions support the use of expression (10) as a reasonable approximation to the true unobservable expected market risk premium. Rubio, Serrano, and Vaello-Sebastiá (2022) show that the lower bound is reasonably tight. Using U.S. data and a non-parametric and out-of-sample SDF, they show that the root mean squared percentage error is on the range between 1.61% and 1.31% depending on the data employed. Back, Crotty, and Kazempour (2022) cannot reject the validity of the lower bound when forecasting future realized excess returns, but they do argue against tightness.

Descriptive statistics of the estimated daily time series of the annualized expected market risk premia at alternative horizons are reported in Panel A of Table 7. Given the typical magnitudes of the unconditional market risk premium using past long-term average realized values, or estimates obtained using popular predictors like the dividend yield or the earnings price ratio, the average estimates present reasonable values for all horizons. The expected premium for the 1-month horizon is 6.26%, and for the 1-year horizon is 5.03%.

The results also show that the average expected market risk premium decreases monotonically with the horizon. Similarly, the standard deviation also declines monotonically, with lower standard deviations than the average expected market risk premium for all horizons. The expected market risk premium is right-skewed and fat-tailed, especially at the shorter horizons. Both the skewness and kurtosis are unconditionally decreasing reproducing the pattern of the mean and standard deviation. Interestingly, the median shows a decreasing pattern from the 3-month horizon onwards, but it is lower at the 1- compared with the 3-month horizon.[24] The takeaway is that volatility, skewness, and kurtosis of the expected market risk premium are key elements for understanding the unconditional level of the expected market risk premium in Spain across horizons.

Panel B of Table 7 shows the average (mean) slope of the term structure of the expected market risk premium using the differences between the 3-, 6-, 9-, 12-, 18-and 24-month horizons relative to the 1-month horizon. The slope is, in all cases, downward sloping and increases (in absolute value) monotonically with the horizon. An important characteristic of the slope, as observed in other countries, is that the slope becomes significantly more negative during recessions, and it becomes especially negative for longer horizons. This result is consistent with the pattern observed for the minimum values of the slope across horizons.

Figures 10.A and 10.B show the time-varying behavior of the expected market risk premium and the time-varying slope of the term structure for the Spanish market, respectively. The slope of the term structure is obtained as the difference between the 3-, and 12-months with respect to the 1-month horizon. We also show the difference between the 12- and the 3-month horizons. As in other sections, the bars represent official recessions for the Spanish economy. The results show a very consistent time-varying behavior for both the expected market risk premium and the slope of the term structure. The expected market risk premia are extremely sensitive to bad economic times. Indeed, the slope of the term structure becomes dramatically downward sloping in all stressed cases, although the effects is especially strong for longer horizons. The time-varying behavior of the expected market risk premia seems to be strongly affected by recessions, showing a well-defined countercyclical variation over the business cycle.

24 Using data for the S&P 500, the EURO STOXX 50, and the NIKKEI 225, Rubio et al. (2022) find a decreasing pattern for the average market risk premia, but an inverted U-shape for the median. The median for the FTSE 100 is slightly increasing, but practically flat across horizons.

Descriptive Statistics of the IBEX 35 Expected Market Risk Premia for Alternative Horizons: Daily Data from October 11, 2006 to April 30, 2020

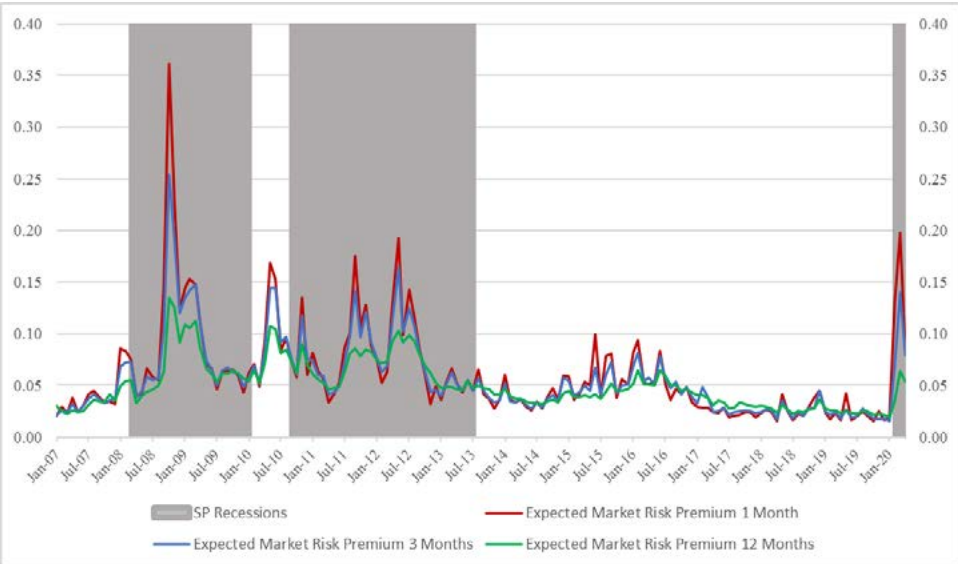
TABLE 7

Panel A. Expected Market Risk Premium IBEX 35											
Horizon	**Mean**	**Vol.**	**Skew.**	**Kurt.**	**Min.**	**5%**	**25%**	**50%**	**75%**	**95%**	**Max.**
1m	0.0626	0.0569	3.380	17.597	0.0112	0.0162	0.0291	0.0468	0.0724	0.1660	0.6048
3m	0.0579	0.0412	2.235	7.397	0.0085	0.0187	0.0302	0.0472	0.0685	0.1422	0.3735
6m	0.0540	0.0316	1.544	2.669	0.0084	0.0206	0.0307	0.0465	0.0648	0.1224	0.2362
9m	0.0518	0.0273	1.302	1.497	0.0095	0.0216	0.0314	0.0456	0.0627	0.1108	0.1782
12m	0.0503	0.0247	1.204	1.179	0.0099	0.0225	0.0321	0.0452	0.0661	0.1030	0.1490
24m	0.0458	0.0203	1.259	1.680	0.0094	0.0228	0.0311	0.0409	0.0572	0.0878	0.1348
Panel B. The Average Term Structure of the Expected Market Risk Premium IBEX 35											
Horizon	**Mean**	**Vol.**	**Skew.**	**Kurt.**	**Min.**	**5%**	**25%**	**50%**	**75%**	**95%**	**Max.**
3 – 1	-0.005	0.011	-5.621	45.165	-0.276	-0.031	-0.006	0.000	0.003	0.009	0.042
6 – 1	-0.009	0.031	-5.366	40.399	-0.382	-0.050	-0.010	-0.000	0.005	0.012	0.072
9 – 1	-0.011	0.036	-5.139	37.403	-0.427	-0.062	-0.013	-0.001	0.006	0.014	0.038
12 – 1	-0.012	0.039	-4.985	35.663	-0.460	-0.071	-0.015	-0.002	0.006	0.014	0.030
24 – 1	-0.017	0.043	-4.582	31.111	-0.513	-0.085	-0.021	-0.005	0.005	0.013	0.035

Panel A of this table reports the descriptive statistics of the lower bound expected market risk premia for the IBEX 35. These lower bounds are obtained daily from option prices on the IBEX 35 market index. The estimation procedure follows Martin (2017). Panel B present the descriptive statistics for the average term structure as the differences between the expected market risk premia for the 3-, 6-, 9-, 12-, and 24-month horizons and the 1-month horizon.

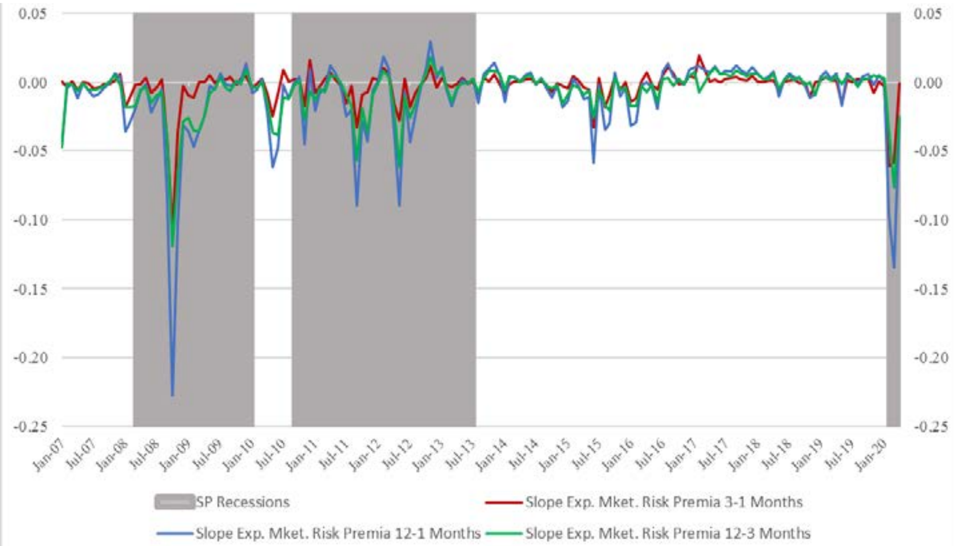
Expected Market Risk Premia of the Spanish Market for the 1-, 3-, and 12-month horizons: Monthly Data from January 2007 to April 2020

FIGURE 10.A



Slope of the Expected Market Risk Premia of the Spanish Market for the 3 minus 1, 12 minus 1, and 12 minus 3-month horizons: Monthly Data from January 2007 to April 2020

FIGURE 10.B



7.2 Economic Implications of the Time-Varying Behavior of the Expected Market Risk Premium

Once, we have characterized not only the expected market risk premium, but also the slope of the equity term structure, it is important to emphasize the economic implications of the expected market risk premium. This described behavior over the business cycle for the Spanish market is common across the main stock exchanges around the world. Globally, expected market risk premia display a strong counter cyclical variation with highly positively correlations with recessions. A low (high) stock price implies a high (low) expected return. The rising expected excess returns in responsible for the widespread decline in realized returns and prices during the initial stages of recessions. Hence, during recessions prices will continue to go down until the expectation of a financial gain will be high enough to compensate the investment risk. One of the key results of financial economics is that time-varying expected returns move prices, and not the other way around (Cochrane, 2011).

In addition, risk premia are strongly coordinated across alternative risk asset classes. This striking coordinated risk associated with expected market risk premia (the collapse of stock prices, the extraordinary increases in credit spreads, or the mismatches in derivative pricing) is the central phenomenon of the economic and financial recessions.[25] We also know that risk aversion and economic uncertainty are key drivers of the expected risk premia around the world.[26] As Cochrane (2017)

25 See Cochrane (2017) for a detailed elaboration of these crucial ideas. Rubio et al. (2022) show that the statistical and economic integration of expected market risk premia around the world increases significantly during recessions.

26 See Rubio et al. (2022) for the international evidence using four major stocks around the world, Nieto and Rubio (2022) for the U.S. market using not only expectations from options prices, but also from

explicitly argues, the main lesson of Finance to Macroeconomics is that counter-cyclical risk aversion, the related counter cyclical expected risk premia, and precautionary savings are the central features of recessions in modern economies. We should recognize that investments do not fall because (risk-free) interest rates rise. Similarly, investments and output growth do not fall due to changes in the elasticity of intertemporal substitution (the sensitivity of consumption to changes in interest rates). The key aspect to understand recessions is to fully understand risk aversion and the expected market risk premia across asset classes.[27] In addition, given the positive interaction between risk aversion, economic uncertainty, and the expected market risk premium, policy authorities should avoid generating uncertainty in their fiscal, monetary, or structural decisions. The consequences for the real activity growth are very serious and the negative channel from the financial markets comes through increases in the expected market risk premium.

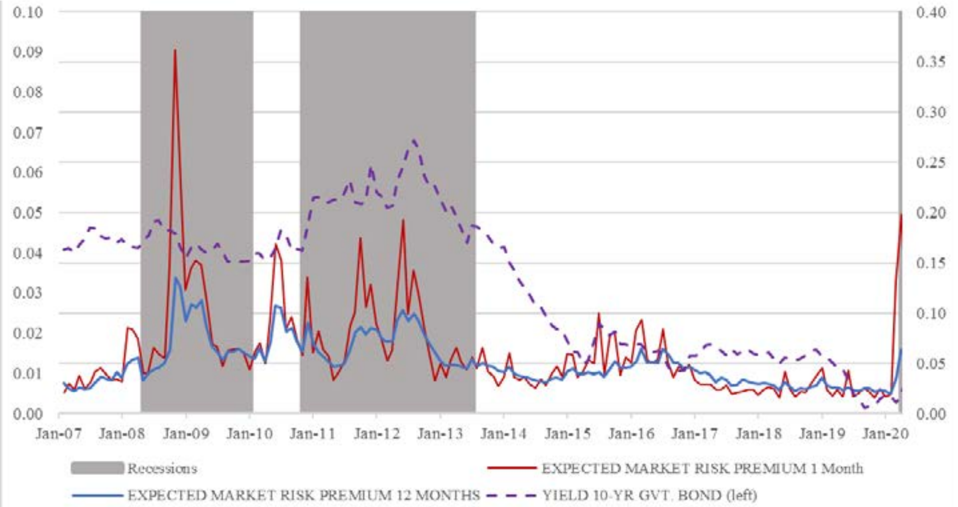
These ideas are illustrated in Figure 11.A and Figure 11.B for the Spanish and the U.S. markets, respectively. The U.S. long-term government bond yield declines substantially during the early stages of the Great Recession. Note the drop in the U.S. government bond yield from approximately 4% to 2%. However, the real impact on investment and output came though the rapid and large increase in the expected market risk premia at both horizons. Similar findings are observed for the COVID-19 outbreak. The crisis associated with the Eurozone sovereign debts, which represented a second big recession in Spain, but not in the U.S., is different because both the yield of the Spanish debt and the expected market risk premia rose, while in the U.S. the negative impact on corporate investments came mainly through another increase in the expected market risk premia at both the 1- and 12-month horizons.

financial and economic predictors, and Grau (2022) for an application to the Spanish economy. These research studies employ the model of time-varying risk aversion with habit preferences of Campbell and Cochrane (1999). See also the evidence provided by Bretscher, Hsu, and Tamoni (2020), who showed that risk aversion amplifies the real economic responses to uncertainty shocks.

27 Increases in aggregate risk aversion under consumption-based macro-finance models is not the only way to understand the importance of financial crises on the real economy. The so-called intermediary asset pricing models is a complementary and powerful specification. These models shift attention from measuring the stochastic discount factor of the representative household as the marginal rate of substitution of consumption to the growth rate of the marginal value of wealth of financial intermediaries. See Adrian, Etula, and Muir (2014), and Haddad and Muir (2021).

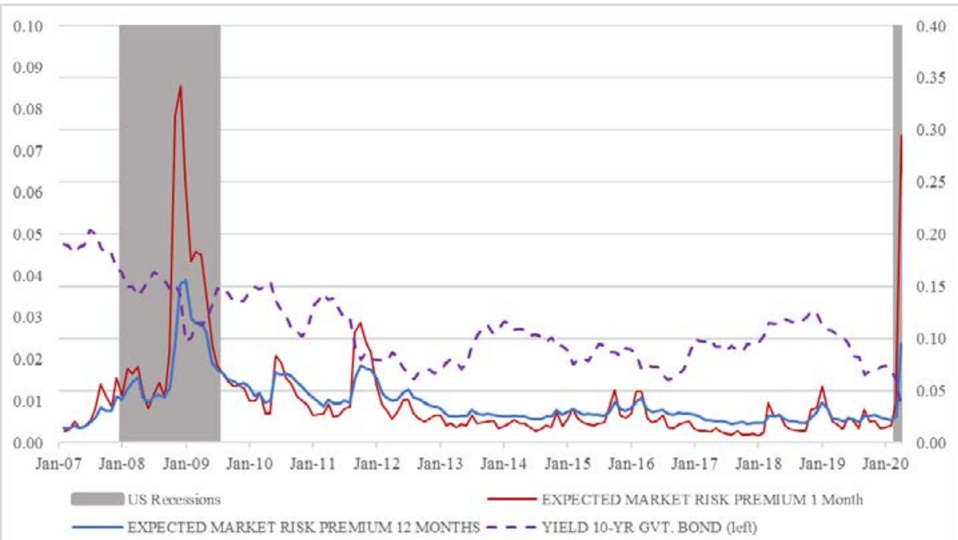
The Spanish Expected Market Risk Premium and the Spanish 10-Year Government Bond Yield: Monthly Data January 2007 to April 2020

FIGURE 11.A



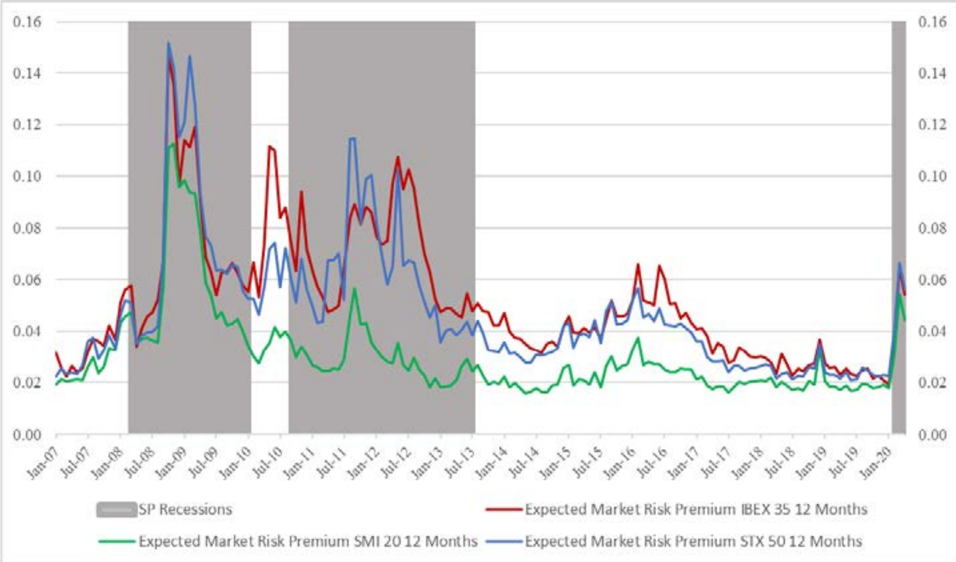
The U.S. Expected Market Risk Premium and the U.S. 10-Year Government Bond Yield: Monthly Data January 2007 to April 2020

FIGURE 11.B



The following relevant implication is related to the international comparison of the expected market risk premium across European stock markets. Figure 12 shows the time-varying counter cyclical variation of the expected market risk premia for the IBEX 35, the Swiss SMI 20, and the EURO STOXX 50 stock market indices. First, the main message is that investors clearly signal the Swiss market as having much lower risk than the other two markets. The expected market risk premium associated with the SMI 20 is consistently below the Spanish and European markets. The average expected market risk premia during the sample period are 3.01%, 5.03%, and 4.68% for the SMI 20, IBEX 35, and EURO STOXX 50, respectively. The behavior over time of the risk premia for the Spanish and European markets also show how the different phases of the different crises affect both economies. It is especially important the increase of the Spanish risk premium observed between the two crises associated with the Great Recession. It clearly suggests that financial markets were advancing a second strong recession for Europe, but especially for Spain.

The Expected Market Risk Premia for the IBEX 35, SMI 20, and Euro Stoxx 50 Market Indices: Monthly Data January 2007 to April 2020 for the 1-Year Horizon FIGURE 12



A final economic implication discusses the information contained in the expected market risk premium at different horizons regarding the future growth of industrial production. Therefore, we analyze whether the Spanish expected market risk premium forecasts future real activity growth.

We perform the following OLS predicting regressions with HAC standard errors:

$$\Delta IPI_{t,T} = \beta_0 + \beta_1 E_t\left(R^e_{m,T}\right) + \beta_2 \Delta IPI_{t-T,t} + \beta_3 TERM_t + \varepsilon_{t,T}, \tag{11}$$

where $\Delta IPI_{t,T}$ is the growth of industrial production over the horizon between today and future months T = 1, 3, 6, and 12, $E_t\left(R^e_{m,T}\right)$ is the expected market risk premium over the same future horizons T as provided by option prices today, and *TERM* is the slope of the term structure of interest rates measured by the difference between the yield of the Spanish 10-year government bond and the 3-month Treasury bill. As usual with this type of forecasting regressions, we control for the lagged values of real activity, and for the slope of the term structure of interest rates, which is a well-known and powerful predictor of future real activity. Increases in the slope of the term structure have been shown to predict higher future growth rates of economic activity (Stock and Watson, 2003).

Table 8 shows the results. Increases today in the expected market risk premia signal future bad economic times at the horizon for which the expectation has been taken. Therefore, we expect a negative relation between future real activity growth and the expected market excess return. The results are significantly consistent with this hypothesis at the 1- and 3-month horizons. Thus, market expectations for the near future contain significant information about future growth of industrial production. This is the case even controlling for the lagged changes in real activity and the slope of the term structure of interest rates, which shows a positive and statistically slope coefficient at the 6-months horizon, and a weakly forecasting ability at the rest of the horizons. Note that the three predictors explain 17% and 22% of the variability of future real activity at the 1- and 3-month horizons, respectively. However, the explanatory power decay rapidly for longer horizons.[28]

The Expected Market Risk Premia Predictability of the Future Growth of Industrial Production for Alternative Horizons: Monthly Data October 2006 to April 2021

TABLE 8

Horizons in Months	β_0	β_1	β_2	β_3	Adj. R^2
1	0.227 (0.62)	-0.255 (-2.15)	-0.401 (-2.28)	0.483 (1.81)	0.174
3	-0.839 (-0.53)	-0.432 (-2.41)	-0.740 (-1.88)	1.148 (1.89)	0.222
6	-1.883 (-0.66)	-0.573 (-1.41)	-0.426 (-0.86)	1.797 (2.26)	0.101
12	-0.486 (-0.34)	-0.599 (-1.74)	0.001 (0.81)	0.601 (1.75)	0.033

This table reports the expected market risk premia predictability of the industrial production growth for the 1-, 3-, 6-, and -12 months horizons using the following forecasting regressions:

$$\Delta IPI_{t,T} = \beta_0 + \beta_1 E_t\left(R^e_{m,T}\right) + \beta_2 \Delta IPI_{t-T,t} + \beta_3 TERM_t + \varepsilon_{t,T},$$

where $\Delta IPI_{t,T}$ is the future growth rate of industrial production between *t* and *T*, $E_t\left(R^e_{m,T}\right)$ is the expected market risk premia for future horizons *T* = 1, 3, 6, and 12 months, and *TERM* is the slope of the term structure of interest rates given by the difference between the yields of the 10-year government bond and the 3-month Treasury bill. HAC-based *t*-statistics are given in parenthesis.

7.3 The Expected Market Risk Premium and Risk Factors in the Spanish Market

As discussed in the previous sub-section, expected returns move prices and not the other way around. This is one of the key results of modern financial economics. The question now is how sensitive the realized excess market return and risk factors are to shocks in the expected market risk premium at different horizons. In other words, the punchline of this section is to learn whether Spanish risk factors move throughout economic cycles due to changes in the expectations embedded in the market excess returns. An affirmative answer to this question would help institutional investors to properly understand which factor strategies should be implemented throughout the peaks and valleys of the business cycle.

To be precise, we select the same risk factors employed in Section 6, namely the excess market return, and the size (SMB), value (HML), momentum (MOM), quality (QMJ), and low-risk investment (BAB) factors. Our hypothesis is that SMB, HML, and BAB are expected to do well when the prospects of the economy are good (when the expected market risk premium is low). This implies a negative exposure (betas) between the factors and the expected market risk premium. Using a similar

28 See Martin (2017), and Back et al. (2021) for a comprehensive discussion about the forecasting ability of the lower bound of the U.S. expected market risk premium regarding future market excess returns.

argument, QMJ has been shown to be a good investment hedger, so institutional investors may benefit from looking protection when the outlook of the economy is bad. We would therefore expect a positive coefficient in the regressions. Finally, it may seem reasonable to think that the MOM factor does not respond to market expectations about the state of the economy. However, it may easily be the case that losers, relative to winners, perform worse during bad economic times. If this is the case, the slope coefficient in the regression could be positive. On the other hand, as already point out, Barroso and Santa Clara (2015) show that the MOM factor experiences very large drops during economic crises showing a significant negative skewness over long sample periods. If this were the dominant effect, then the slope coefficient would be negative. Hence, for MOM we would expect either a positive or a zero coefficient.

Using the logic discussed above on expectations being the drivers of realized returns, we run the following OLS regressions of risk factors on the expected market risk premia at the 1-, 3-, 6-, and 12-month horizons with HAC-based standard errors:

$$F_{kt} = \beta_0 + \beta_1 E_t\left(R^e_{m,T}\right) + \varepsilon_t \tag{12}$$

for $T = 1, 3, 6, 12$ and where F_{kt} is the return of risk factor k at time t.

Panels A, B, C, and D of Table 9 present the results for the alternative horizons. The negative slope coefficients associated with the market risk premia for all horizons illustrate that the realized market risk premia decrease (prices drop) when market expectations signal bad times (when the expected market risk premium increases). This is especially the case for shorter horizons. Moreover, negative significant slope coefficients are found for the HML/HMLD factors, which suggests that value stocks tend to fall more than growth stocks when the expected market risk premium goes up. Moreover, the slope coefficients increase monotonically (in absolute value) with the horizon. Value investment performs especially bad when the increase in the expected market risk premium remains high for long horizons. On the opposite side, we find that the QMJ factor shows a positive and significant slope coefficient for the shorter horizons, which implies that junk stocks tend to decrease more than high-quality stocks when market expectations are bad. Hence, the QMJ factor acts as a hedger when market expectations are poor for the next 1- and 3-month horizons. This hedging effect disappears for longer horizons.

The BAB factor presents a negative slope coefficient, but it is only weakly statistically different from zero at the longest horizon. Leveraged low-beta stocks do worse than unlevered high-beta assets when market expectations are bad for the next year. Finally, the SMB and MOM factors do not show statistically significant slope coefficients. These factors do not seem to react with enough precision to shocks in market expectations over the business cycle.

To conclude, value and quality factors are the risk factors that, with different signs, react more to the time-series dynamics of the expected market risk premium. These exposures of popular risk factors to the expected market risk premia are an important source of information for properly executed factor investing. In any case, as expected and even at the one-year horizon, the realized excess market return is the portfolio with a stronger reaction to negative signs in market expectations. At the shortest horizon, the expected market risk premium explains 18% of the variability of the realized market risk premium in Spain.

The Relation between Risk Factors and the Expected Risk Premia: Monthly Data January 2007 to April 2020 TABLE 9

Panel A. EMRP 1H	Excess Market	SMB	HML	HMLD	MOM	QMJ	BAB
Intercept	0.032	0.001	0.008	0.006	0.004	-0.003	0.003
	(5.84)	(0.21)	(1.87)	(1.70)	(0.99)	(-0.68)	(0.61)
Slope	-0.530	-0.049	-0.159	-0.156	0.105	0.135	-0.027
	(-5.77)	(-1.26)	(-2.54)	(-2.42)	(1.22)	(2.75)	(-0.43)
Adj. R^2	0.177	-0.000	0.059	0.040	0.007	0.022	-0.005
Panel B. EMRP 3H	**Excess Market**	**SMB**	**HML**	**HMLD**	**MOM**	**QMJ**	**BAB**
Intercept	0.030	0.001	0.010	0.007	0.006	-0.002	0.005
	(5.04)	(0.15)	(2.48)	(1.61)	(1.15)	(-0.56)	(1.13)
Slope	-0.526	-0.049	-0.211	-0.182	0.087	0.138	-0.076
	(-4.24)	(-0.86)	(-3.49)	(-2.00)	(0.79)	(2.24)	(-1.05)
Adj. R^2	0.107	-0.002	0.066	0.033	-0.001	0.012	-0.001
Panel C. EMRP 6H	**Excess Market**	**SMB**	**HML**	**HMLD**	**MOM**	**QMJ**	**BAB**
Intercept	0.027	-0.001	0.013	0.009	0.008	-0.002	0.009
	(3.65)	(-0.13)	(2.49)	(1.57)	(1.16)	(-0.33)	(1.64)
Slope	-0.495	-0.030	-0.278	-0.222	0.060	0.134	-0.138
	(-2.98)	(-0.36)	(-2.90)	(-2.44)	(0.41)	(1.57)	(-1.60)
Adj. R^2	0.056	-0.005	0.071	0.030	-0.005	0.005	0.004
Panel D. EMRP 12H	**Excess Market**	**SMB**	**HML**	**HMLD**	**MOM**	**QMJ**	**BAB**
Intercept	0.023	-0.001	0.015	0.010	0.009	-0.000	0.011
	(2.58)	(-0.13)	(2.41)	(1.41)	(1.22)	(-0.05)	(1.87)
Slope	-0.452	-0.029	-0.326	-0.259	0.032	0.120	-0.193
	(-2.13)	(-0.28)	(-2.74)	(-1.62)	(0.19)	(0.94)	(-1.82)
Adj. R^2	0.027	-0.006	0.062	0.025	-0.006	-0.001	0.006

This table reports the results from regressions of the excess market return of the IBEX 35 TOTAL, that is calculated relative to the monthly 3-month Spanish Treasury bill, and six risk factors of the Spanish Stock Market: size (SMB), value Fama-French (HML), value with monthly updating (HML Devil), momentum (MOM), quality (QMJ), and low risk (BAB) factors on the expected market risk premia at different horizons. The expected market risk premia are obtained daily from option prices on the IBEX 35 market index. The estimation procedure follows Martin (2017). Panels A to D report the regression for the 1-, 3-, 6-, and 12-month horizons, respectively. Heteroskedasticity- and autocorrelation-adjusted standard (HAC) errors are used to estimate the *t*-statistics given in parenthesis.

8 Conditional Variances of Equities and Bonds, and the Relation between the Expected Market Risk Premium and the Conditional Stock Market Variance

We next estimate the conditional volatility of daily returns for the three major asset classes of the Spanish capital market: the stock market index proxied by the IBEX 35 Total Index, the corporate bond index given by the AIAF General Corporate Bond Index, and the 10-year government bond return.

We estimate a simple generalized autoregressive conditional heteroskedasticity (GARCH) model of dynamic variance given by,[29]

$$\sigma_{t+1}^2 = \omega + \alpha R_t^2 + \beta \sigma_t^2, \tag{13}$$

where σ_{t+1}^2 is the conditional time-varying variance of the returns of each of the three asset classes used in this Section, and R_t^2 represents the daily realized variance, given that the daily average return is assumed to be zero. It is important to note that the model requires that $(\alpha + \beta) < 1$.

Mean-reversion is a key property of time-varying variance for asset returns. By taking the unconditional expectation in expression (13), it is easy to show that long-run variance in the GARCH model is given by $\sigma^2 = \dfrac{\omega}{(1-\alpha-\beta)}$ Then, by substituting the intercept ω in equation (13), the GARCH model can be written as

$$\sigma_{t+1}^2 = \sigma^2 + \alpha\left(R_t^2 - \sigma^2\right) + \beta\left(\sigma_t^2 - \sigma^2\right). \tag{14}$$

In words, the conditional future variance under the GARCH model is a weighted average of the long-run variance, today's squared return (the shock from new information), and today's conditional variance.

Note that the RiskMetrics model, widely used in industry and known as the exponentially weighted moving average (EWMA) model, can be viewed as a special case of the simple GARCH (1, 1) model. It turns out that in the EWMA model, there is only one parameter λ that defines the dynamics of the conditional variance, which is known as the decay parameter. If we force $\alpha = 1 - \lambda$ and $\beta = \lambda$, so that $\alpha + \beta = 1$, and $\omega = 0$, we get the RiskMetrics model. It is then easy to understand that the long-run variance is not defined in the EWMA model, which implies that the industry model does not allow for mean-reversion in the variance dynamics. Although, the

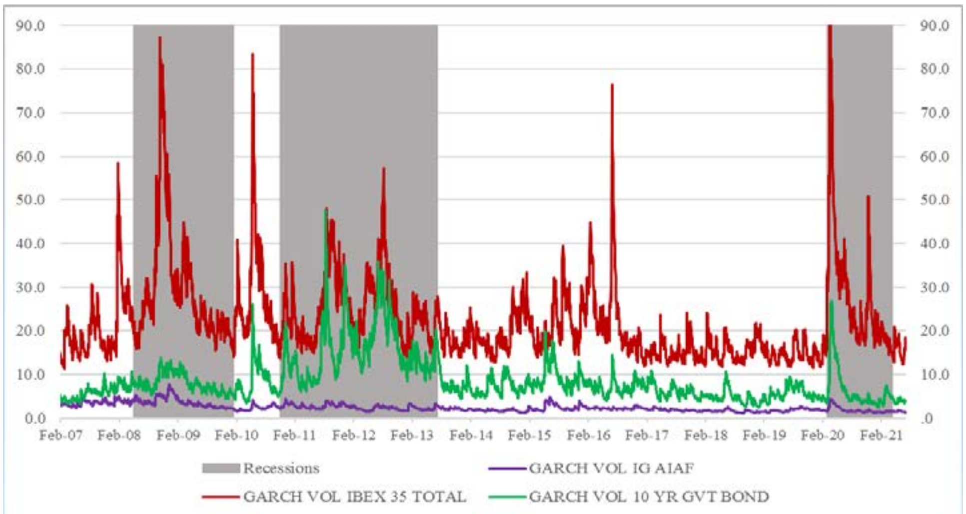
29 Alternative GARCH models, that incorporate the stylized fact through which negative returns increase variance by more than positive returns of the same magnitude, produce similar results. Note that these models require nonlinear parameter estimation. See Christoffersen (2012) for a description of the alternative GARCH family specifications.

EWMA is very popular and it depends only on one parameter, one must be very careful in imposing the same λ over the business cycle. It may significantly underestimate the estimation of conditional volatilities during stressed time periods.

Figure 13 shows the conditional annualized volatility estimated from expression (13) for the daily returns of the stock market, corporate bonds, and the long-term government bond. As expected, the conditional volatility of the IBEX 35 shows a strong time-changing behavior with high peaks during recessions and other problematic geopolitical times. The mean-reversion characteristic is also observed. A shock may push variance away from its long-run average, but eventually will come back to the long-run average, which tends to be relatively stable over time. This feature is observed for the three asset classes in the sample. This property is clearly reflecting the mean-reversion of conditional volatility that can be seen in the alternative way of writing the GARCH model in equation (14).

It is also important to point out the strong time-varying behavior of the conditional volatility of the long-term government bond. The parallel behavior of the variance for both, the Spanish bond and the stock market is consistent with the positive market betas of long-term government bonds reported in Section 2. The Spanish bond shows high peaks during recessions replicating the pattern of the stock market. This is especially important during the Eurozone crisis. During the middle of August of 2011, the conditional volatility of the government bond was even higher than the volatility of the IBEX 35. Recall that the well-known diabolical loop between sovereign and bank credit risk was a distinctive feature of the sovereign risk crisis not only in Spain but also in the rest of southern European countries. On the contrary, the conditional volatility of corporate bonds is much smoother with much smaller peaks during bad economic times. This suggest that the extraordinary Sharpe ratio of corporate bonds shown in Table 2, which was due to the low average volatility is not only an unconditional property of corporate bonds. Once again, this calls for a careful interpretation of the corporate bond returns extracted from the available corporate bond indices.

Annualized GARCH Volatilities of the Returns of the IBEX 35 Total Index, the General Index of Corporate Bonds (AIAF), and the 10-year Government Bond: Daily Data from January 2, 2007 to June 30, 2021 FIGURE 13



Finally, there is vast literature studying the positive relationship between the expected excess market return and its conditional variance or market risk. This fundamental trade-off is the core foundation of financial economics. Merton (1973) shows that when the investment opportunity set is constant or, alternatively, when the rates of returns are independent and identically distributed, the market relation between the conditional expected excess return and the conditional variance is given by

$$E_t\left(R^e_{m,t+1}\right) = \gamma\sigma^2_t\left(R^e_{m,t+1}\right), \tag{15}$$

where, theoretically, the parameter γ reflects aggregate risk aversion, which must be positive. Interestingly, it has proved difficult from an empirical perspective to find a positive relationship between expected market return and market risk. Among others, Glosten, Jagannathan, and Runkle (1993), and Brandt and Kang (2004) report a negative relation, while Ghysels, Santa-Clara, and Valkanov (2005), and Bali (2008) find a positive relationship for the U.S. market. In addition, León, Nave, and Rubio (2007) also document a positive relation for several European countries. The studies finding a positive relation employ either a mixed data sampling regression analysis (MIDAS) to estimate the coefficient of risk aversion or exploit the information contained in the cross-section of asset returns when studying the intertemporal relationship between risk and expected return. These studies use past realized market returns as a proxy for future market returns and employ complex econometric estimations.

Instead, we employ our expected market risk premium estimated from options using Martin's (2017) procedure over the 1-month horizon and the GARCH conditional variance estimated from (13) as a proxy for the conditional variance. Note that we combine data from the option and stock markets.

The Relation between the Expected Market Return and Risk (GARCH Volatility of the IBEX 35 Return): Daily Data January 2, 2007 to April 30, 2020 FIGURE 14

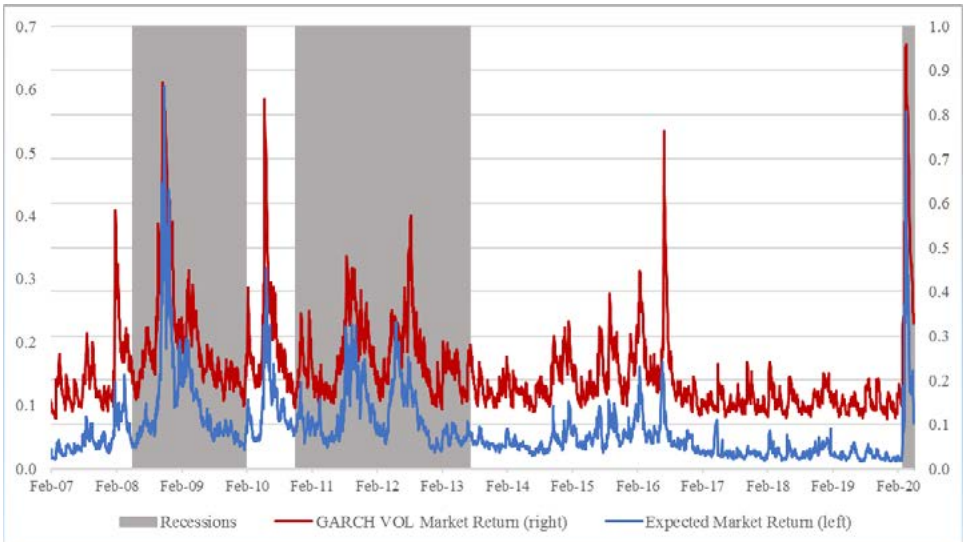


Figure 14 shows both estimated series for our sample period.[30] The results strongly confirm the positive relation between conditional expected return and conditional risk in the Spanish stock market. A simple OLS regression with HAC standard errors of the expected market risk premium on the GARCH conditional market variance show a positive and highly significant slope coefficient of 1.47 and a *R*-squared value of 67.4%.[31]

30 Figure 14 employs the annualized conditional volatility rather than the estimated conditional variance.

31 The theoretical interpretation of the slope coefficient implies that 1.47 is the level of risk aversion. This is a lower level that the estimated risk aversion using Spanish consumption data and the habit preference model with time-varying risk aversion of Campbell and Cochrane (1999). This difference may be explained by noting that the estimated coefficient increases when we allow the simple model in (15) to incorporate a stochastic opportunity set captured with an additional conditional covariance term between market returns and a predictor of real activity rather than the simple implicit myopic framework of expression (15).

9 The VIBEX, the SKEW, and the Market Variance Risk Premium

Risk-neutral volatilities, widely used in financial markets, are directly associated with fears embedded in investor expectations about the future economic outlook. In other words, relative to realized volatilities, risk-neutral volatilities adjust for risk by weighting bad states more than good states.[32] Moreover, and in contrast to realized volatilities, risk-neutral volatilities are ex-ante or forward-looking measures that can be extracted form option prices. Therefore, the information content of these risk-neutral measures reflects expectations about risk and thus they are closely related to expected risk premia. This is precisely the intuition behind the expected market risk premium employed in this paper. These insights have guided our decision of discussing next not only the risk-neutral volatility for the Spanish market, but also the risk-neutral skewness.

Risk-neutral volatilities are computed by averaging weighted prices of puts and calls on stock market indices. In the case of the VIX, which the risk-neutral volatility of the S&P 500 Index, 1-month maturity options are weighted by the inverse of the squared of strikes over a wide range of exercise prices. Hence, puts out-of-the-money are especially relevant for the VIX, which explains why this volatility index is associated with expected fears embedded in the U.S. market. On the contrary, the VIBEX, the Spanish risk-neutral volatility of the IBEX 35, is estimated by weighting 1-month maturity at-the-money options. In any case, the Spanish risk-neutral volatility reflects a forward-looking measure or the expectation of volatility over the options expiration period. Data for the VIBEX are available at daily frequency from January 2, 2007, to June 30, 2021.[33] On average, the VIBEX is 23.11% and it is characterized by a high volatility of volatility of 8.98% and positive skewness of 1.68. The coefficient of variation is 0.39 and it reflects that our sample period is characterized by the Great Recession, the Eurozone crisis, and the COVID-19. Using the same sample period, the average VIX is 20.0% with a higher volatility of volatility of 9.62%, which implies a higher coefficient of variation of 2.39. This suggests that the VIX is more volatile than the VIBEX, probably because of the estimation procedure of both indices. Note that the average Spanish conditional volatility

32 Expression (A.11) in Appendix A shows mathematically this insight, which is one of the most important ideas of financial economics. Intuitively, these probability measures assign a higher probability to bad events like pandemics, earthquakes, or climate changes than the physical probabilities. The usual physical probability associated with these events is relatively small. However, risk-neutral probabilities incorporate the high-risk aversion of consumers related to the bad economic consequences of those events. The higher the risk aversion, the higher weight will be assigned by risk-neutral probabilities to those events. Indeed, economic, monetary, and political authorities should start thinking in terms of risk-neutral probabilities instead of paying attention to physical probabilities.

33 Data are from BME at https://www.bolsasymercados.es/esp/Sobre-BME/Historico/Indices.

from the GARCH model is 22.36%. Figure 15.A shows the asymmetric behavior between the IBEX 35 Total Index and the VIBEX, reflecting the well-known leverage effect that is generated by the loss of equity wealth when the stock market drops, and the corresponding financial risk associated with risky positions that increases the level of absolute risk aversion. The correlation is highly negative and equals to -0.75.

The SKEW Index, also available at daily frequency from BME since January 2, 2007, signals the tail risk of the IBEX 35 or, in other words, the probability that the market assigns to a big drop in the Spanish stock exchange index. The Spanish SKEW Index is estimated from the relative demand of 1-month maturity puts-out-of-the money with respect to all other options. This is related to VIBEX, since an increase in the SKEW Index corresponds to an increase in the slope of the smirk of risk-neutral volatilities across strikes indicating higher tail risk. Recall that the volatility smirk is the asymmetric relation between implied volatilities and moneyness, with out-of-the-money puts being more expensive than either at-the-money or in-the-money puts.

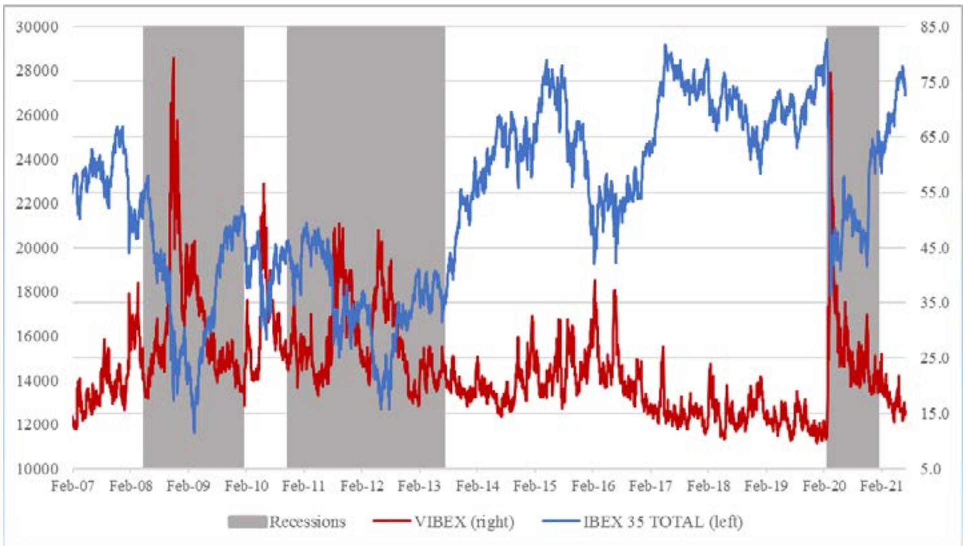
Figure 15.B shows the simultaneous time-varying behavior of the VIBEX and the SKEW. The correlation between the VIBEX and the SKEW indices is 0.25 over the full sample period, and 0.29 during recession months of the Spanish economy. Both indices show high peaks during the Great Recession and during the sovereign crisis of the Eurozone.[34] Also note that the highest level of the SKEW index was reached during the month of September of 2007, as a clear signal of the outbreak of the Great Recession. Further note that approximately since the beginning of 2017 until the COVID-19 outbreak, we simultaneously observe a very calm volatility period and an increasing tendency of the SKEW Index, suggesting an accumulation of fears towards the Spanish economy. In fact, the low levels of market volatilities was a characteristic of the stock markets around the world during this period. Finally, note that the Spanish SKEW index is much less volatile than the VIBEX with a coefficient of variation of only 0.25 compared to the 0.39 of the VIBEX.[35]

34 The SKEW Index of the U.S. market is estimated from the relative demand of puts out-of-the money with respect to at-the-money options. As in the case of the VIX, this estimation procedure is different from the one employed in Spain. Over the same sample period, and contrary to the Spanish case, the correlation between the VIX and the U.S. SKEW Index is negative and equal to -0.31. However, during the recession dates of the U.S. economy, this correlation becomes positive and equal to 0.36. See Gormsen and Jensen (2019) for a comprehensive analysis about higher-moment risks in the U.S. market.

35 See Castellanos (2017) for the estimation details regarding both the VIBEX and the SKEW indices.

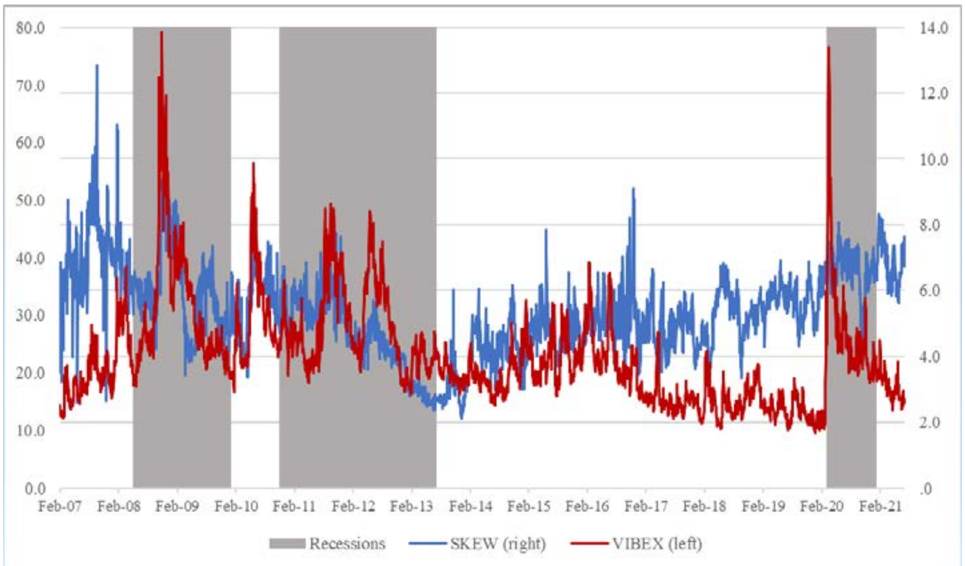
The Asymmetric Behavior between the IBEX 35 TOTAL and the VIBEX: Daily Data from January 2, 2007 to June 30, 2021

FIGURE 15.A



The VIBEX and the SKEW: Daily Data from January 2, 2007 to June 30, 2021

FIGURE 15.B



The last point discussed in this section analyzes simultaneously the market realized variance and the risk-neutral variance for the Spanish market. We know that the market risk premium is the difference between the market portfolio return and the risk-free rate. On average, the market risk premium is positive to compensate risky investment positions. Recall that expected market return under the risk-neutral probability measure must be equal to risk-free rate. This implies that the market risk premium is the average market return under the physical probability minus the return under the risk-neutral probability or risk-free rate. The same reasoning holds for the market variance risk premium. It is defined as the difference between the expected market realized variance of returns under the physical probability measure and the risk-neutral variance:

$$VRP_{mt,T} = E_t^P\left(VAR_{mt,T}\right) - E_t^Q\left(VAR_{mt,T}\right), \quad (16)$$

where $VRP_{mt,T}$ is the market variance risk premium.[36] The variance risk premium has been reported to be negative on average during alternative sample periods and for stock exchanges around the world. In practice, investors can take either long or short positions using variance swaps. Since the payoff of a variance swap contract is the difference between the realized variance and the variance swap rate, which is approximated by the risk-neutral variance, negative returns to long positions on variance swap contracts means that investors are willing to accept negative returns on average for purchasing realized variance. It implies that long positions in variance can be interpreted as a hedging position against stock markets crashes. Therefore, to accept on average negative returns of long variance positions can be rationale, since the correlation between volatility shocks and market returns, as shown in Figure 15.A, is known to be strongly negative and investors may want protection against stock market crashes. Equivalently, investors who are sellers of variance providing insurance to market participants, require substantial positive average returns. However, when the stock market experiences a large decline, volatility jumps and investors selling volatility suffer losses, which represents gains to those who have bought volatility insurance.[37] The PUTWRITE portfolio discussed in Section 3 represents an indirect way of approximately taking buying and selling positions in the Spanish market variance. Investors obtain average positive returns from purchasing the PUTWRITE portfolio (selling variance) if there are not large negative returns in the market index. On the other hand, whenever there is a big negative shock in the stock market, short positions in the PUTWRITE portfolio (buying variance) would experience positive hedging results.

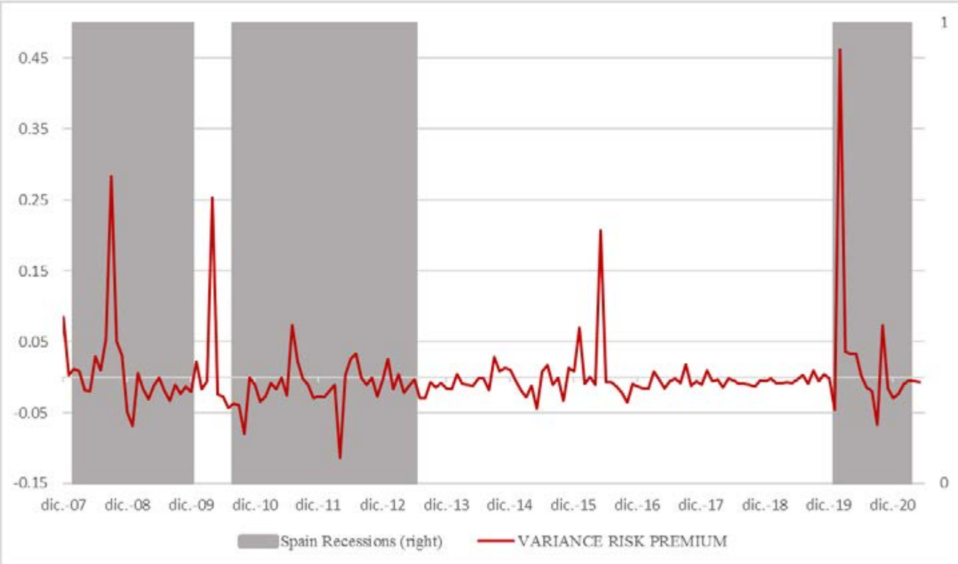
Figure 15.C shows the Spanish variance risk premium over the sample period at the monthly frequency. It is estimated as the difference between the realized market variance of each month estimated with daily returns over each month, and the square of the VIBEX. Not that this is the ex-post variance risk premium, or the payoff of the variance swap rather than the theoretical ex-ante variance risk premium given by expression (16). Surprisingly, on average, the variance risk premium over our sample period is small but positive and equal to 0.037%. The behavior of the variance risk premium over time is strongly counter cyclical showing high peaks during bad economic times. There is also a big jump between the Great Recession and the Eurozone crisis, and another jump in June 2016 that coincides with the Spanish elections and the Brexit referendum. In other words, long investment positions in market variance are a powerful hedging asset. The highest peak of the variance risk premium is observed in the outbreak of the pandemic in March 2020. It is a positive 0.46%. The average variance risk premium without that specific

36 See Carr and Wu (2009) and Bollerslev, Tauchen, and Zhou (2009) for excellent discussions of the variance risk premium. Zhou (2018) reviews the evidence regarding the powerful short-term forecasting ability of the variance risk premia and provides the macroeconomic foundation of the existence of the variance risk premium beyond the negative correlation between stock returns and realized variance.

37 The empirical evidence regarding the cross-sectional variation of the volatility risk premia for individual portfolios shows that the key determinants of the volatility risk premia are the exposure of these portfolios to the aggregate default premium and to the market volatility risk premium (González-Urteaga and Rubio (2016).

month becomes negative and equal to -0.24%. This is the typical average result reported in previous literature around the world. Investors with long market variance positions experiences an extremely large gain during the initial days of the pandemic that explains the surprising positive average variance risk premium. However, the usual average payoff for long positions in market variance is negative to compensate the positive average gain of sellers of variance who are the providers of the associated insurance for the market.[38]

The Variance Risk Premium (Realized Market Variance minus the VIBEX): Monthly Data from January 2007 to June 2021 FIGURE 15.C



38 Hou Zhou, in his web page https://sites.google.com/site/haozhouspersonalhomepage/, regularly updates the variance risk premium for the U.S. market. The last available data covers the period between January 1990 and December 2020 at monthly frequency. The average premium is negative, even if we do not consider the outbreak of the COVID-19. Both, the positive skewness, and kurtosis are higher for the U.S. market relative to the Spanish market. However, the variance risk premium is Spain shows a higher volatile behavior than the U.S. counterpart.

10 Connectedness Dynamics Across Asset Classes, and Risk-Neutral Volatility and Skewness

The stylized facts of international financial returns and coordinated risk related to expected risk premia across asset classes during the Great Recession and the pandemic have motivated an increasing interest in the formal analysis of connectedness among asset classes in the sense of spillover volatility effects across assets. We employ the methodological econometric framework of Diebold and Yilmaz (2015). These authors have applied this framework to the analysis of volatilities across international markets. In our case, we apply the analysis of connectedness to the IBEX 35 returns, the AIAF General Index of corporate bond returns, the 10-year government bond returns, and two risk-neutral moments, namely the VIBEX and the SKEW.

A detailed description of the statistical approach of this methodology and the presentation of the different connectedness measures can be found in Appendix C. As already mentioned above, we discuss the connected dynamics across asset classes in the sense of volatility spillovers from one asset to the others and to the full system. By spillovers we mean measures of how much future unexpected variation in one asset is explained by current shocks to the other assets. Intuitively, this analysis shows how the arrival of new information contained in one asset class affects or is transmitted to the rest of the assets in the market. Formally, the idea relies on the variance decomposition of the forecasting error using a vector autoregression (VAR) framework. Under this decomposition, the directional connectedness from one variable X_i to another variable X_j in the VAR system is the fraction of the H-step-ahead generalized error variances in forecasting X_j that are due to shocks in X_i.

Connectedness measures based on the variance decomposition are especially appropriate for several reasons. First, they are rigorous in theory and readily implemented in practice and, moreover, they are totally intuitive in the sense that inform about how much of the future unexpected variation of one variable is due to current shocks in another. Second, these connectedness measures present the advantage that the variance decomposition is invariant to the ordering of the variables in the VAR system. Instead of attempting to orthogonalize shocks, Diebold and Yilmaz (2015) propose to use the generalized VAR approach of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) which allows for correlated shocks but accounts appropriately for the correlation. Third this methodology allows not only identifying the dynamics of the connectedness along time, but also expressing these measures as a percentage because they use normalized elements of the variance decomposition matrix (Demirer, Diebold, Liu, and Yilmaz, 2018).

In our case, the VAR dimension (the system) is composed of five elements given by the three asset classes, the VIBEX and the SKEW. In contrast to ex-post volatilities or skewness, we already know that the information content in the VIBEX and the

SKEW reflect expectations about market risk and tail risk, respectively. We already pointed out that the risk-neutral moments adjust for risk by weighting bad states more than good states. Hence, our analysis studies whether the amount investors are willing to pay to hedge equity market and tail risks are connected between them and to other asset classes. To approximate normality in the risk-neutral measures, we take natural logarithms of the original daily series of the VIBEX and the SKEW. Our paper analyzes not only total connectedness, but also the directional (and net) connectedness between each of the asset classes with respect to the others and to the system. To evaluate if this is the case, we estimate dynamic connectedness measures using a 200-day rolling overlapped sample windows. The objective of this analysis is, first, to confirm the potential time varying pattern of connectedness across assets, and how these spillovers react to bad economic times.

We begin by discussing the results for the full sample period from June 21, 2007 to June 30, 2021. In Table 10, we show the unconditional average connectedness across all five assets using all available observations. We choose a forecasting horizon (H) of 12 days following the recommendation of Diebold and Yilmaz (2015). They point out that, although intuitively, there are more chances for connectedness to appear as H lengthens, the conditioning information also becomes progressively less valuable in the variance decompositions of the conditional forecast error.[39] Looking at the "FROM OTHERS" column, on average, the VIBEX is the asset receiving more volatility from the other series, although 83% of this transmission is due to the IBEX, which is the main responsible for the variance of the forecast error of the VIBEX. Conversely, the Spanish long-term government bond is the asset that receive less volatility from the other variables in the system.

Similarly, the "TO OTHERS" row shows that the IBEX and the VIBEX (especially to themselves) are the variables sending more volatility to all other assets. Moreover, the risk-neutral SKEW and the corporate bond returns send less volatility to others, signaling their limited influence on other assets within the Spanish market. Indeed, both assets have a large idiosyncratic volatility connection, as observed from the diagonal entry (i.e., 82.8% and 80.3% of their volatility is generated by their own shocks for the SKEW and corporate bonds, respectively). Interestingly, the 92.6% idiosyncratic volatility of long-term government bond is the highest among asset classes. However, it sends a considerable amount of volatility to the rest of the assets.

The last row of Table 10 presents the net total directional connectedness from each asset to all the others. In this regard, the stock market return is the highest net sender of volatility to the rest of the assets in the system. The government bond return and the VIBEX are also average net senders of volatility, while the SKEW and corporate bonds are net receivers of volatility from other assets in the sample. Finally, the bottom-right entry, which is equal to 22.2%, presents the total connectedness (i.e., the average from or to connectedness) among all the assets in the system.[40]

39 As expected, given the different robustness tests provided by Diebold and Yilmaz (2015), our results are very stable for horizons between 8 and 16 days.

40 This may seem to be an overall low connectedness. González-Urteaga and Rubio (2022) show that, analyzing the Spanish market as part of a full system composed of the Spanish, U.S. and German markets, there is a strong global integration that justifies small overall connections when studying capital markets in isolation. The global connectedness among the stock market returns, the volatilities, and the

Full Sample Connectedness of the Spanish Asset Classes: Daily Data June 21, 2007-June 30, 2021

TABLE 10

	IBEX 35	VIBEX	SKEW	AIAF	10-YEAR GVT. BOND	FROM OTHERS
IBEX 35	70.108	24.755	0.304	2.018	2.815	29.892
VIBEX	30.507	63.369	3.062	1.829	1.233	36.631
SKEW	1.404	15.535	82.881	0.020	0.160	17.119
AIAF	4.888	2.050	0.217	80.265	12.581	19.735
10-YEAR GVT. BOND	4.340	1.072	0.111	1.883	92.595	7.405
TO OTHERS	41.139	43.411	3.694	5.750	16.789	
FROM OTHERS	29.892	36.631	17.119	19.735	7.405	
NET	11.247	6.780	-13.425	-13.985	9.383	22.156

This table shows the full system estimated connectedness with 3580 daily observations from June 21, 2007, through June 30, 2021. The numbers are the percentages of connectedness among stock market returns, risk-neutral volatility, risk-neutral skewness, corporate bond returns, and Government bond returns for the Spanish capital market, and represent the variance of the forecast error of each asset into parts attributable to the system shocks. Entry *i* (row), *j* (column), for example the IBEX 35, VIBEX entry represents the directional connectedness from *j* to *i* means that shocks to the VIBEX are responsible for 24.8% of the 12-day ahead variance of the forecast error in the IBEX 35. The FROM OTHERS column is the row sum excluding the diagonal entries and gives the total directional connectedness from all other series to asset *i*. The TO OTHERS row is the column sum excluding the diagonal entries and gives the total directional connectedness from series *j* to others. NET is the difference between the TO and FROM rows and gives the net total directional connectedness from asset *j* to all others. The bottom-right entry is the total connectedness (the average from connectedness or, equivalently, the average to connectedness) among all assets in the sample. IBEX 35 is the return of the Spanish stock market index; the VIBEX is the log of the risk-neutral volatility of the IBEX 35, SKEW is the log of the risk-neutral skewness of the IBEX 35, AIAF is the return of the global index of corporate bonds with average duration of 4.78 years, and the last column is the return of the10-year Government Bond.

Although the previous unconditional analysis gives an overall picture of connectedness among asset classes and market, from the point of view of our research, it is more appropriate the analysis using connectedness dynamics based on rolling estimation windows. We estimate dynamic connectedness measures using a 200-day rolling overlapped sample windows.[41] This analysis is crucial for understanding how the spillover effects among the five asset classes behave throughout the economic cycle, and how the dynamic spillovers react to a given exogenous shock. Using the five assets, Figure 16 shows that the daily total connectedness dynamics changes significantly over the sample period. As expected, the behavior of total connectedness reflects higher spillovers during financial and economic stressed times. For instance, the maximum total connectedness was 65.0% on March 16, 2020, at the outbreak of the COVID-19, but on April 13, 2012 (a critical period for the stability of the Eurozone), such connectedness was also relatively high at 59.3%. This suggests that the system tends to be more connected during bad economic times. Subsequently, the minimum value of 16.4% occurred on March 24, 2014, while the average connectedness dynamics was 35.5%, with a standard deviation of 7.8% calculated at a daily frequency.

long-term government bonds of the three markets is 58.2%. This result suggests that the Spanish market is strongly influenced by the behavior of other international markets.

41 We check the robustness of our empirical results employing also a 66-day rolling window estimation. Given the similarities between the results, we discuss the findings for the 200-day rolling window case.

Total Connectedness Dynamics (IBEX 35, VIBEX, SKEW, CORPORATE BONDS (AIAF), 10-YEAR GOVERNMENT BONDS): Daily Data from June 21, 2007 to June 30, 2021

FIGURE 16

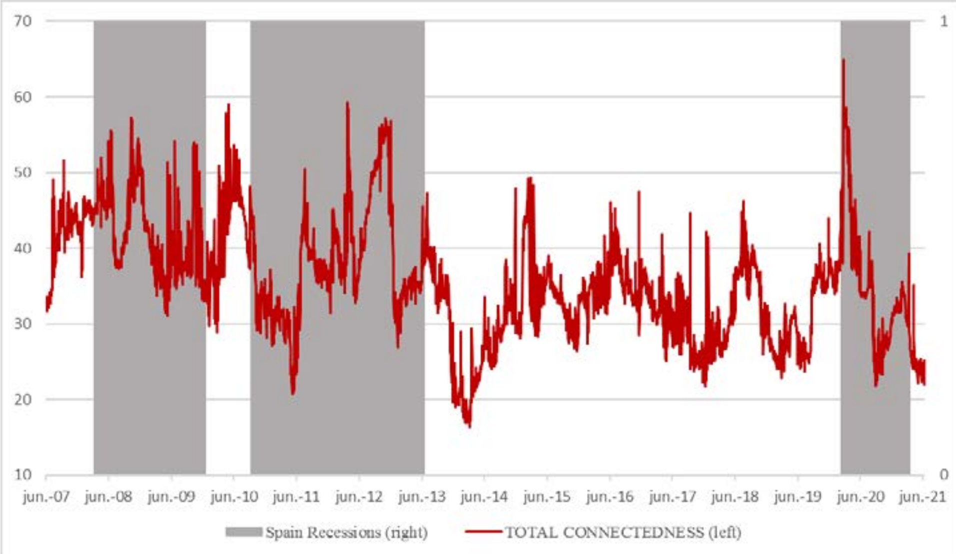


Table 11 reports the average net pairwise volatility connectedness dynamics using daily data from June 21, 2007, to June 30, 2021. These pairwise volatilities are relatively low suggesting the importance of the overall connectedness, which is the main concern of our research. In any case, the average net pairwise directional connectedness dynamics are generally consistent with the net total directional connectedness reported in Table 10. The first column shows that the IBEX is a significantly net sender of volatility to all other asset classes, while the second column confirms that the VIBEX is a net receiver of volatility from the IBEX and the long-term government bond, while it is a significant net sender of volatility shocks to the SKEW. The pairwise net volatility spillover from the VIBEX to corporate bonds is not statistically different from zero. The SKEW index is a net receiver of volatility spillovers from the other assets, and corporate bonds are net senders of volatility to the SKEW. Hence, the tail risk dynamics, as proxied by the SKEW index, is fully dependent on the behavior of the other assets in the system, although it is especially important the net spillovers received from the VIBEX. Finally, although the long-term government bond is a net receiver of volatility from the IBEX, it is a significant net sender of volatility to other assets. It is certainty striking to confirm how important the information contained in the long-term government bond return is for the Spanish risk-neutral moments and corporate bonds.

The dynamic net pairwise spillover effects are shown in Figures D.1 through D.10 in Appendix D. The patterns illustrated by these figures confirms the average net pairwise connectedness of Table 11. We just mention how strong the impact of the IBEX in other assets is, including the VIBEX. We also point out that, for most days during the sample period, the VIBEX is a net sender of volatility to the SKEW. The information embedded in the risk-neutral volatility dominates the information transmitted from the risk-neutral skewness. Finally, once again, for most of the days in the sample, the long-term government bond sends volatility to risk-neutral skewness and corporate bonds, while being a net receiver from the IBEX. Although, on average, the VIBEX is a relatively weak net receiver of volatility from government bond returns, it turns out that during the beginning of the Great Recession and during the most problematic months of the Eurozone crisis, the long-term government bond became a clear net sender of volatility to the VIBEX. This is certainly relevant and provides additional evidence of the extreme weak situation that Spain as a country experienced during those convulsive periods. Note that, given the rapid support from the European Central Bank during the COVID-19, the net pairwise connectedness between the VIBEX and the government bond was precisely the opposite. The long-term bond was a net receiver a volatility during the initial months of the pandemic.

The directional connectedness dynamics from each of the assets analyzed to the full system is displayed in Figures 17.A through 17.E. While the results reported in Table 11 are the average net pairwise spillover effects, these figures show the patterns of the directional connectedness of each class to the rest of the assets taken simultaneously. The results are very robust independently of the way we look at spillover effects. The IBEX sends volatility to the system during 99.5% of the days in the sample, and the maximum directional connectedness occurs during the outbreak of the pandemic and on the Eurozone crisis (Figure 17.A). Although, the VIBEX is a sender of volatility during most part of the Great Recession and the Eurozone crisis, it became a net receiver from the last months of the Eurozone crisis to the beginning of the pandemic. In fact, the VIBEX is a net receiver of volatility during 61.1% of the days in the sample period (Figure 17.B).

Average Net Pairwise (from and to) Volatility Spillover Dynamics for Spanish Asset Classes: Daily Data June 21, 2007-June 30, 2021

TABLE 11

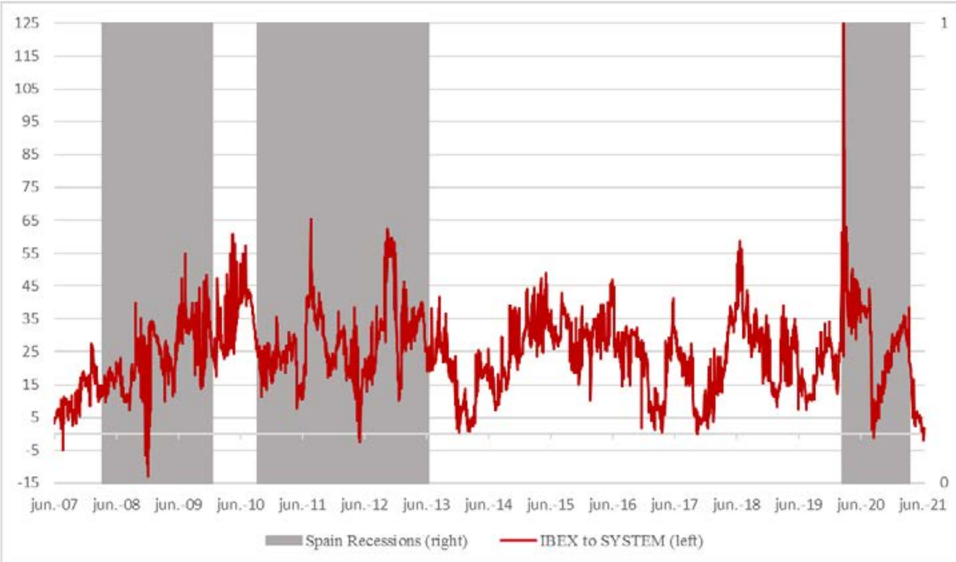
	IBEX 35	VIBEX	SKEW	AIAF	10-YEAR GVT. BOND
IBEX 35	-	-13.643	-5.331	-3.440	-1.941
		(-30.97)	(-19.06)	(-12.68)	(-10.09)
VIBEX	13.643	-	-10.303	-0.175	1.974
	(30.97)		(-21.09)	(-0.69)	(7.92)
SKEW	5.331	10.303	-	2.210	2.202
	(19.06)	(21.09)		(10.42)	(12.61)
AIAF	3.440	0.175	-2.210	-	12.487
	(12.68)	(0.69)	(-10.42)		(20.16)
10-YEAR GVT. BOND	1.941	-1.974	-2.202	-12.487	-
	(10.09)	(-7.92)	(-12.61)	(-20.16)	

This table shows the estimated average net pairwise directional connectedness or spillovers with 3580 daily observations from June 21, 2007, through June 30, 2021. The net pairwise spillovers are estimated over 200-day rolling-sample window during the sample period for a 12-day ahead forecast error variance. Positive (negative) numbers indicate senders (receivers) of volatility. IBEX 35 is the return of the Spanish stock market index; the VIBEX is the log of the risk-neutral volatility of the IBEX 35, SKEW is the log of the risk-neutral skewness of the IBEX 35, AIAF is the return of the global index of corporate bonds with average duration of 4.78 years, and the last column is the return of the10-year Government Bond. HAC-based *t*-statistics for the means are given in parenthesis.

The SKEW is a net receiver of volatility in 94.8% of the days during our sample (Figure 17.C). Corporate bonds are net receivers of volatility during the Great Recession and Eurozone crises, but they become strong net senders of volatility during the outbreak of the COVID.19. Overall, corporate bonds are net receivers of volatility during 86.3% of the days. Finally, the long-term government bond is a net sender of volatility to the system in 89.1% of the days in the sample. This is consistent with our previous comments regarding the significant information contained in the Spanish government bond. It was an especially significant sender of volatility during the Great Recession and Eurozone debt crises, but it became a net receiver of volatility spillovers during the initial months of the pandemic. Once again, this result shows the tremendous importance of the European Central Bank reaction during the health crisis, with completely opposite consequences from the previous financial crises.

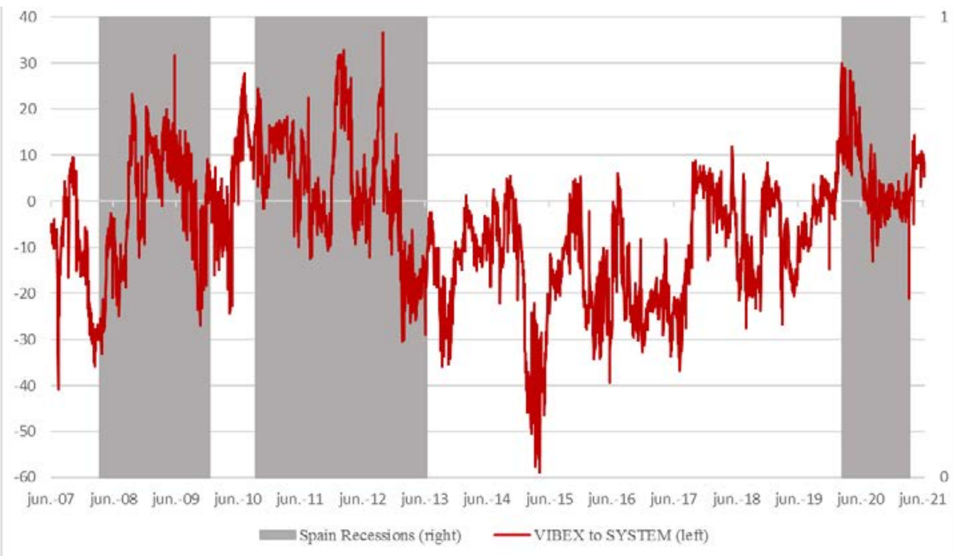
Directional Connectedness Dynamics from the IBEX 35 to the System: June 21, 2007 to June 30, 2021

FIGURE 17.A



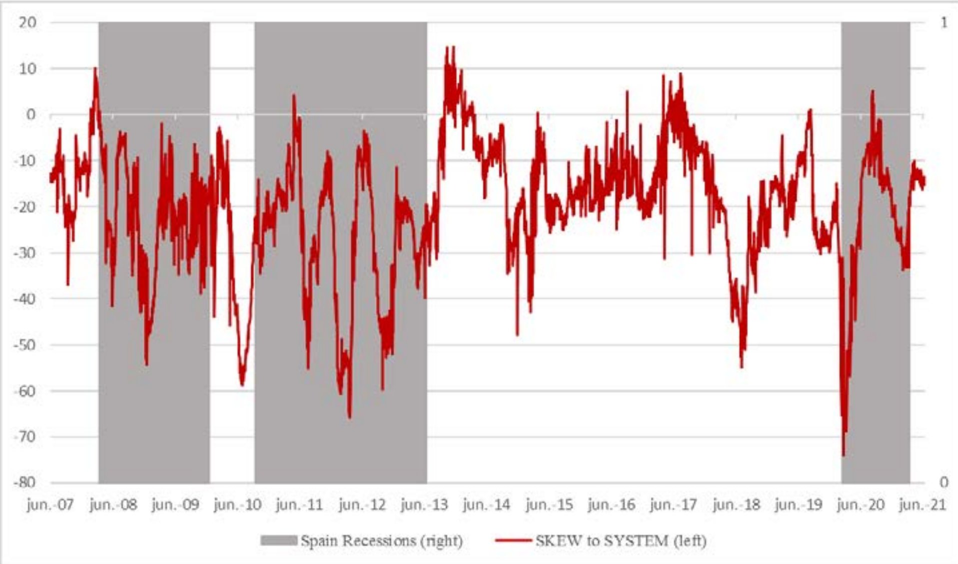
Directional Connectedness Dynamics from the VIBEX to the System: June 21, 2007 to June 30, 2021

FIGURE 17.B



Directional Connectedness Dynamics from the SKEW to the System: June 21, 2007 to June 30, 2021

FIGURE 17.C

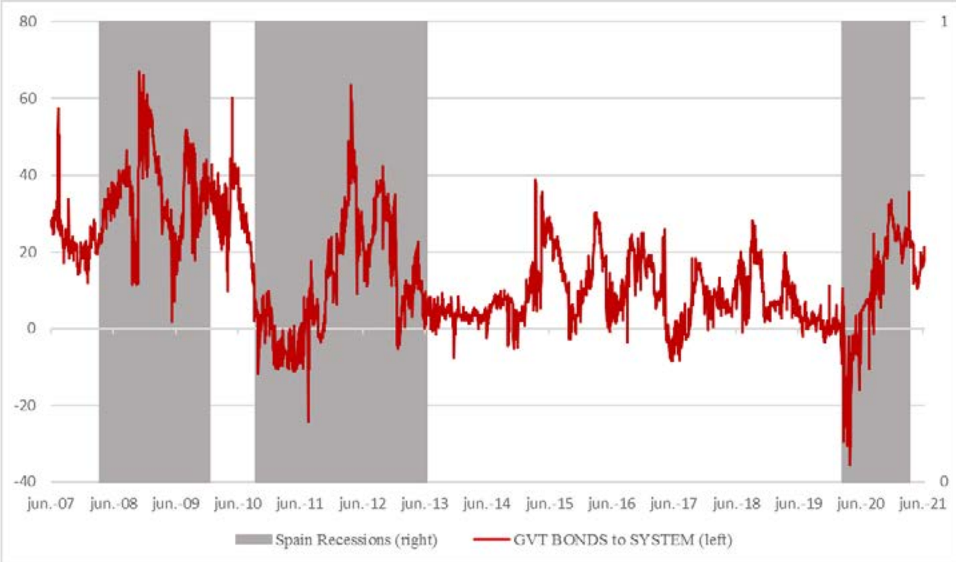


Directional Connectedness Dynamics from CORPORATE BOND RETURNS (AIAF) to the System: June 21, 2007 to June 30, 2021

FIGURE 17.D

Directional Connectedness Dynamics from 10-YEAR GOVERNMENT BOND RETURNS to the System: June 21, 2007 to June 30, 2021

FIGURE 17.E



Our previous analysis, as well as the patterns shown in the figures above, suggest that connectedness increases during bad economic times. The last exercise of this Section formally analyzes this issue by regressing several measures of total and directional connectedness on a dummy variable that equals 1 if there an official recession in the Spanish economy and zero otherwise:

$$C_t = \beta_0 + \beta_1 REC_t + \varepsilon_t, \qquad (17)$$

where C_t is either total or directional connectedness, and *REC* is the dummy variable identifying a day in which there is a recession. HAC-based standard errors are used for statistical inference. The directional connectedness is from each asset class to the system, although we also analyze the effects of recessions on the directional connectedness between risk-neutral moments. Recall that the unconditional correlation between the VIBEX and the SKEW is slightly higher during recessions. Given the importance of volatility and tail risks not only for financial markets, but also for the central clearing counterparties (CCPs) when deciding on initial margins, we analyze with some detail the simultaneous behavior of the VIBEX and the SKEW. Note that we are interested in the slope coefficient of regression (17) that measures the incremental effect in connectedness during recessions.

The empirical results are shown in Panel A of Table 12. Consistent with the behavior of total connectedness dynamics displayed in Figure 16, the slope coefficient is positive and highly significant. Recessions explain around 12% of the variability of total connectedness. We also find positive incremental effects of recessions on the directional connectedness from the IBEX, the VIBEX, and government bonds to the system. These significant results are also consistent with the informal previous evidence shown in the alternative figures above. Interestingly, the directional connectedness from the SKEW and corporate bonds to the system significantly diminishes during recessions. These assets receive volatility from other assets, and this is especially true during recessions. Therefore, it makes sense that both the SKEW and corporate bonds are net receivers of volatility with more intensity precisely during recessions. The relatively high *R*-squared value for corporate bonds suggests that this effect is stronger for corporate bonds than for the SKEW. Finally, the directional connectedness from the VIBEX to the SKEW significantly increases during recessions. This implies that the behavior of the VIBEX is more relevant than the dynamics of the SKEW for the Spanish CCP when taking decisions on the initial margins required when placing itself between two traders becoming a buyer to the seller, and vice versa. The information goes from the VIBEX to the SKEW, but this is even more relevant during recessions.

The final analysis deepens on the simultaneous behavior between the VIBEX and the SKEW using the conditional correlation between them during the COVID-19 health crisis. The idea is to employ a simpler statistical methodology given that data during the pandemic are concentrated in a much smaller sample period. In any case, it is always a good idea to corroborate our previous results during bad economic times using a simple strategy that permits an estimation with daily data withing each month in the sample. Hence, we estimate the conditional correlation between the VIBEX and the SKEW on daily basis, using a rolling window with the previous 22 days in the sample. We perform OLS regressions using a similar strategy than was employed in equation (16) but directed towards the COVID-19 period. For comparison purposes with Panel A of Table 12, we also estimate the regression using a recession dummy:

$$CC_t = \beta_0 + \beta_1 COVID_t + \varepsilon_t, \tag{18}$$

where CC_t is the conditional correlation between the VIBEX and the SKEW at each day *t*, and $COVID_t$ is a dummy variable that equals one if there is a day in which the COVID-19 risk of contagion is extreme (high), more than 250 (150) cases in 14 days per 100,000 people, and zero otherwise. Given the relatively short period, we now use daily data from January 2, 2020, to December 30, 2021.

The results are shown in Panel B of Table 12. As before, we find a positive and significant increment in the conditional correlation between the VIBEX and the SKEW during days in which the contagion become more severe. The effect is particularly strong during days of extreme risk, but it is also statistically significant during times of high risk. Here, we have a simple signal provided by the simultaneous behavior of the VIBEX and the SKEW. Whenever we detect an increase in the conditional correlation between the two risk-neutral moments, it is signal of bad economic times. To confirm the case for recessions and using data from January 2007 until the end of December 2021, the last column of Panel B also shows a positive and significant incremental effect on the conditional correlation during recessions. This result is consistent with the directional connectedness from the VIBEX to the SKEW of Panel A of Table 12.

Incremental Spillover Volatility Dynamics between Asset Classes during Spanish Recessions, and Conditional Correlations between the VIBEX and the SKEW during Days of Extreme and High Risk COVID-19 Contagion, and during Days of Spanish Recessions TABLE 12

Panel A. RECESSIONS	Total Connectedness	IBEX to System	VIBEX to System	SKEW to System	AIAF to System	GVT. BONDS to System	VIBEX to SKEW
Intercept	33.341	22.644	-10.139	-16.681	-7.733	11.909	8.504
	(68.68)	(28.08)	(-10.74)	(-18.82)	(-7.91)	(16.06)	(13.55)
Slope	5.468	4.296	12.551	-8.448	-15.459	7.060	0.266
	(6.61)	(3.44)	(8.84)	(-5.66)	(-8.76)	(4.04)	(3.03)
Adj. R^2	0.119	0.031	0.180	0.091	0.196	0.058	0.120

Panel B. COVID-19	Extreme Risk > 250	High Risk > 150	Recessions
Intercept	-0.094	-0.102	0.010
	(-2.31)	(-2.18)	(3.87)
Slope	0.232	0.189	0.084
	(3.05)	(2.70)	(2.30)
Adj. R^2	0.098	0.071	0.011

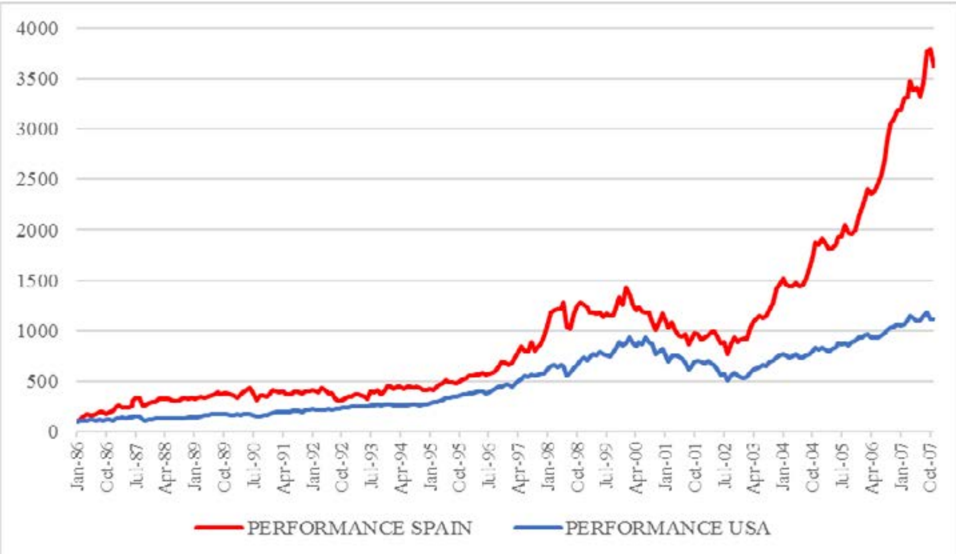
Panel A of this table shows the results of OLS regressions with daily data of several measures of connectedness on dummy variables that are equal one if there is an official recession in the Spanish economy and zero otherwise. Volatility connectedness dynamics is estimated over a 200-day rolling-sample window, and a horizon of 12 days. The sample period is from June 21, 2007, to June 30, 2021. Panel B shows the results of OLS regressions with daily data of the conditional correlation between the VIBEX, and the SKEW estimated with daily data within each month, instead of measures of connectedness, on dummy variables that are equal one if there is a day in which the COVID-19 risk of contagion is extreme (high), more than 250 (150) cases in 14 days per 100,000 people, and zero otherwise. The sample period is from January 2, 2020, through December 30, 2021. The results of the last column in Panel B show a similar regression with conditional correlations using dummy variables that are equal one if there is an official recession in the Spanish economy and zero otherwise. The sample period for these conditional correlations is from March 1, 2007, to December 30, 2021. Volatility connectedness dynamics is estimated over a 200-day rolling-sample window. HAC-based *t*-statistics are given in parenthesis.

11 Concluding Remarks

This paper provides an overall evaluation of the performance of alternative asset classes and risk factors in the Spanish Capital Market. Since the Great Recession, the Spanish stock market has performed relatively worse with respect to other major stock markets around the world. This is an interesting result mainly because the performance of the Spanish Stock Market since the entry of Spain in the European Union until the end of 2007 was extraordinary. As an illustration, in Figure 18.A we show the performance of investing 100 dollars at monthly frequency in the Spanish and U.S. stock markets from January 1986 to December 2007 and, in Figure 18.B, the performance for both markets from January 2008 to June 2021. All figures are in U.S. dollars and represent cumulative total returns in both markets.[42]

Cumulative Total Returns in U.S. Dollars of the Spanish and the U.S. Stock Markets: January 1986 to December 2007

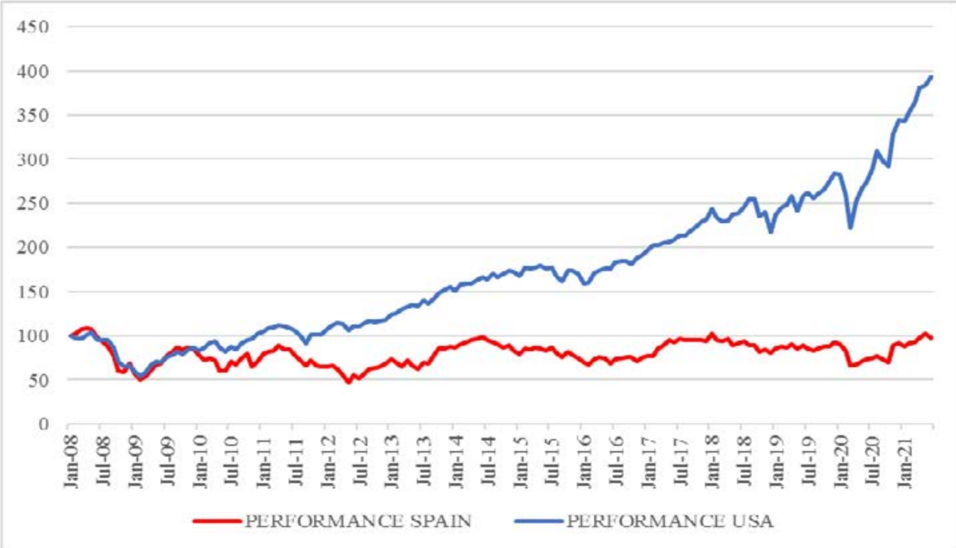
FIGURE 18.A



42 Data are downloaded from AQR Capital Management at www.aqr.com. Results are very similar using local currencies.

Cumulative Total Returns in U.S. Dollars of the Spanish and the U.S. Stock Markets: January 2008 to June 2021

FIGURE 18.B



A relevant research question calls for an understanding of this striking phenomenon. Even accepting that the Spanish stock market may have experienced a bubble between 2002 and 2007, we argue that Spanish macro, micro, and financial economists should try to explain formally these results along the lines of Greenwald et al. (2021). Is the Spanish economy losing competitiveness since the Great Recession? Is this empirical fact a consequence of the continuously decreasing productivity growth in Spain? Is this a consequence of the low levels and business-cycle dependent public and private investments in R&D&I? Is just a consequence of the poor performance of the Spanish banks? Is the explanation related to the quality of institutions, the weak educational system in Spain or is a consequence of labor market regulations and technological advances in the U.S. economy that, as explained in Section 2, increased during the last 25 years the equity wealth attributable to the reallocation of rewards to shareholders at the expense of labor compensation? Is our welfare system counteracting the effects observed in the U.S. economy? Are all these reasons working together? Probably they are a combination of reasons, although it is true that the sectors that have led the growth of the U.S. stock market are very scarce in Spain (and in Europe). Competitive economies are grounded around information technology and information foundation. A very relevant signal of the importance of these sectors for the capital markets is the creation of the S&P Kensho New Economies Composite Index designed to include companies propelling and fostering new industries that will be transformative and will drive the rise of the fourth industrial revolution. This index is currently composed of 569 firms of which 439 are from the U.S., 35 from China, and 14 from Israel. Europe globally has 34 companies, but only 2 are from Spain. Related to this, it would be interesting to know whether the gap between the growth of financial wealth and the output growth is different across the Spanish sectors with special attention to the Consumer Goods, Financial, and Technological sectors.

On top of this, the worrying signs of high inflation and the persistence of negative real interest rates suggest that nominal interest rates may increase substantially relative to the levels of the past twenty years. The Spanish economy needs urgently credible fiscal measures to generate future government budget stability. The increasing maturity of public debt is an appropriate measure, although we should be aware that this will increase the sensitivity of bond prices to changes in interest rates relative to shorter maturity financing.

On the other hand, Spanish corporate bonds perform extraordinary well, although our sample period is characterized by a continuous pattern of decreasing interest rates. It is also important to point out that the lack of liquidity of corporate bonds trading should be urgently incorporated into the calculation of Spanish corporate bonds. Trading in both, the AIAF fixed income market and in the alternative MARF market, would clearly benefit from having bond liquidity measures that would generate much more understandable performance of corporate bonds. It would also be very important to construct corporate bond portfolios by credit rating and not only by maturity. We would strongly recommend following the Trade Reporting and Compliance Engine (TRACE) (https://www.finra.org) that facilitates mandatory reporting in fixed income securities in the U.S. market.

The Spanish equity sectors also show a quite differently performance since the Great Recession. The extraordinary performance of the Consumer Goods sector dramatically contrasts with the results obtained by the Financial Services sector. It would be interesting to study the relation, if any, between the performance of the Consumer Goods sector and its potential financing with corporate bonds. It is also surprising that the Technological and Telecommunication sector shows negative average returns during our sample period. To fully understand the structure of the Spanish Stock Market and the relation between sectors and the industrial structure of the Spanish companies, it would be useful to have a more detailed sector classification. This is an important issue as it has become sadly evident from the asymmetric effects of the pandemic in the alternative sectors of the Spanish economy.

Factor investing is becoming very popular among institutional investors in Spain. Two key results emerge from the performance of risk factors in the Spanish market. First, the momentum factor is the winner with an extraordinary performance since the Great Recession. Data to fully understand the institutional strategies that may explain the performance of the momentum factor would be much appreciated. The new trading platforms, the impact of high-frequency traders in the Spanish market, and a clear understanding of the increasing number of transactions observed in the Spanish stock market together with a simultaneous decline in the effective volume observed approximately since 2012, are research questions that need much more detailed data.[43] Second, the value investment style is the loser showing the worst performance since the Great Recession.[44] As explained in Section 6, quality investing is becoming a very popular strategy with a positive performance record and

43 See Nieto and Rubio (2021) for an initial discussion about the relation between the number of transactions and the effective volume. In addition, the declining number of transactions recently observed in the Spanish market deserves further research to investigate the effects of the introduction of the Tobin tax in Spain. It would also be interesting to check the relation of this phenomenon with the decreasing performance of the MOM factor during the last months in our sample.

44 See Israel, Lauren, and Richardson (2020) for an excellent and insightful discussion about the premature dead of value investing.

well-behaved hedging properties. Value investing seems to be losing popularity relative to quality investing.

We have also argued that extracting the expected market risk premium from option prices on the IBEX 35 index provides a very useful information about the time-varying behavior of the equity cost of capital throughout economic cycles. The market risk premium is strongly counter cyclical. We can extract pure expectations over a precise horizon that do not rely on past data. We have showed that the behavior and the term structure of the Spanish market risk premium is a powerful tool containing information about future real activity. The market risk premium at longer horizons is lower than the near-term market risk premium, and this difference is extremely sensitive to bad economic times. The economic foundation of the expected market risk premium is based on the behavior of risk aversion that is a fundamental variable to understand financial and economic recessions. Indeed, there is a positive and significant relation between the expected market risk premium and the conditional variance estimated form a GARCH model. Related to this, we have also shown that taking long positions in the Spanish stock market variance provides a very reasonable hedging opportunity when the Spanish stock market experiences big declines. The market variance risk premium shows large gains during stressed market periods. The PUTWRITE portfolio is a powerful investment vehicle to take approximate positions on the Spanish market variance.

Finally, we have studied the volatility spillover effects across asset classes in the Spanish market including the risk-neutral volatility and skewness. The idea is to learn about the asset class that contains and more rapidly transmit the arrival of new information to other segments of the markets. We have shown that the IBEX 35 returns are the key transmitter of information to other asset classes. Interestingly, the long-term government bond is also a net sender of volatility spillover to other assets including the VIBEX during the Great Recession and Eurozone debt crisis. However, the VIBEX became a net sender of volatility to the long-term bond at the outbreak of the COVID-19. This suggests that the Spanish economy is very much dependent of the monetary and fiscal policies followed by the monetary and economic authorities from the very beginning of the pandemic. The SKEW, as a proxy for tail risk, and corporate bonds are net receivers of volatility from the stock market, the VIBEX, and the long-term government bonds. The total and directional connectedness dynamics among asset classes and from the IBEX, the VIBEX, and the long-term government bond become higher during bad economic times. Related to these issues, our results suggest that the VIBEX and the SKEW do not reflect the same information contained in the VIX and in the U.S. SKEW index. By construction, our risk-neutral moments are different. It would be useful, if we want to have measures that intrinsically reflect the fears and tail risk perceptions embedded by market participants, to developed additional risk-neutral moments following the methodology employed by the CBOE.

As mentioned in the introduction, the strong counter-cyclical behavior of the expected market risk premium together with the positive stock market exposure of long-term government bond returns, especially during recessions, and the importance of these bonds as net senders of volatility to all assets except for the IBEX-35, signals problematic times for the confidence transmitted by the Spanish economy to international investors. To update the current study on regular basis seems to be useful to keep learning about the Spanish real economy through the lens of the Spanish financial markets.

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APPENDIX A The Fundamental Asset Pricing Equation and the (Lower Bound) Expected Market Risk Premium

The economy is characterized by a representative agent with uncertain future payoffs.[45] We find the value at time t of a payoff X_{t+1}, where this payoff is the stock price next period, P_{t+1}, plus dividend, D_{t+1}:

$$X_{t+1} = P_{t+1} + D_{t+1}. \tag{A.1}$$

The utility function of the representative agent is defined over current and future values of consumption with additive and separable preferences:

$$U\left(C_t, C_{t+1}\right) = U\left(C_t\right) + \rho E_t\left[U\left(C_{t+1}\right)\right], \tag{A.2}$$

where C_t is consumption at time t, and utility is increasing and concave, which means higher marginal utility in bad states or risk aversion. The future expected utility is discounted by the so-called subjective discount factor, ρ, which captures impatience.[46] We denote as e the endowment or original consumption level and denote by z the number of shares chosen by the investor. Then, the optimization problem is given by,

$$\underset{\{z\}}{Max}\, E_t\left[U\left(C_t, C_{t+1}\right)\right]$$

subject to (A.3)

$$C_t = e_t - z_{jt} P_{jt}$$
$$C_{t+1} = e_{t+1} + z_{jt} X_{jt+1}.$$

We substitute the constraints into the objective function,

$$\underset{\{z\}}{Max}\left\{U\left(e_t - z_{jt} P_{jt}\right) + E_t\left[\rho U\left(e_{t+1} + z_{jt} X_{jt+1}\right)\right]\right\}, \tag{A.4}$$

45 The notion of a representative agent is connected to the idea of perfect sharing, which is satisfied in a complete market economy with homogeneous probability beliefs. Perfect sharing requires that the marginal utilities of different investors be perfectly correlated. In addition, with perfect sharing, the consumption allocation in the economy is Pareto optimal, and ensures that all agents have the same ordering of marginal utility across states of nature. With declining marginal utility, this means that they all have the same ordering of consumption across states. This leads to the marginal utility of a composite consumer or representative agent who consumes aggregate consumption and holds the market portfolio. See Campbell (2018) for a detailed analysis.

46 This summary follows closely the detailed presentation by Cochrane (2005).

where $E_t(.)$ denotes conditional expectation on information available as of time t. Solving for z_j:

$$U'\left(e_t - z_{jt}P_{jt}\right)\left(-P_{jt}\right) + E_t\left[\rho U'\left(e_{t+1} + z_{jt}X_{jt+1}\right)X_{jt+1}\right]$$
$$= -P_{jt}U'\left(C_t\right) = E_t\left[\rho U'\left(C_{t+1}\right)\left(P_{jt+1} + D_{jt+1}\right)\right] = 0 \qquad \text{(A.5)}$$
$$\Rightarrow P_{jt}U'\left(C_t\right) = E_t\left[\rho U'\left(C_{t+1}\right)\left(P_{jt+1} + D_{jt+1}\right)\right].$$

The loss in utility when the investor buys the asset must be equal to the increase in discounted expected utility obtained from the payoff of the asset next period. In other word, marginal cost must be equal to (discounted) marginal benefit otherwise the investor will continue trading until equality is obtained.

Solving for the price of asset j we get:

$$P_{jt} = E_t\left[\rho \frac{U'\left(C_{t+1}\right)}{U'\left(C_t\right)} X_{jt+1}\right]. \qquad \text{(A.6)}$$

The aggregate component of the term in brackets in the right-hand side of equation (A.6) is known as the stochastic discount factor (SDF), which is denoted by M_{t+1}:

$$M_{t+1} = \rho \frac{U'\left(C_{t+1}\right)}{U'\left(C_t\right)}. \qquad \text{(A.7)}$$

Therefore, the first order condition of the intertemporal optimization of the representative agent (the Euler equation) can be written in a compact way as:

$$P_{jt} = E_t\left[M_{t+1}X_{jt+1}\right]. \qquad \text{(A.8)}$$

The price of any asset is the conditional expected value of future cash flows where the discount factor, M_{t+1}, is the marginal rate of substitution of aggregate consumption or how much the representative agent values a unit of consumption today relative to consumption in each state of nature in the future. This is the fundamental equation of asset pricing. By dividing both sides by the price of the asset today, we get the expression in terms of gross rates of return:

$$1 = E_t\left[M_{t+1}R_{jt+1}\right]. \qquad \text{(A.9)}$$

The conditional expected return of any asset j scaled by the SDF is equal and constant for all assets. This does not say that expected returns are constant over time. On the contrary, expected returns are time-varying and counter-cyclical. But, once we adjust expected returns by the SDF (by the ratio of marginal utilities) or, in other words, once we adjust asset returns by risk, then all assets offer the same expected return. This is what expression (A.9) implies. It opens the door to predictability of future returns, simply because expected returns are not constant over time. Moreover, note that future returns are especially valuable when marginal utility is high (in bad economic states). In those cases, future returns are highly weighted by the SDF. The opposite occurs when future returns are not that valuable because future states are good states in term of aggregate consumption. Importantly, all asset pricing models amount to alternative specifications of the SDF.

This includes macro-finance models, or factor models like the Capital Asset Pricing Model (CAPM) or multi-factor models like the Fama and French (1993, 2015) models and the like. It also includes intertemporal equilibrium models like the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973), and bond or option pricing models like the Black and Scholes (1973) famous expression. For example, the SDF given by expression (A.7) for the CAPM is a linear function on the market portfolio return, and for the Fama-French factors, the SDF is a linear function on the risk factors. Hence, the use of any of these asset pricing models implies to work under the framework summarized in this Appendix.

To relate the fundamental pricing equation to option pricing note first that the following fact holds for risk-free debt with a riskless rate of return denoted by R_{ft}:

$$1 = E_t\left[M_{t+1}R_{ft}\right] \Rightarrow 1 = R_{ft}E_t\left[M_{t+1}\right] \Rightarrow R_{ft} = \frac{1}{E_t\left[M_{t+1}\right]}. \tag{A.10}$$

We denote risk-neutral and physical probabilities for each state of nature s by π_s^Q and π_s^P, respectively. Then, the relation between both types of probabilities is given by,

$$\pi_s^Q = \frac{M_{t+1}^s}{E_t\left[M_{t+1}\right]}\pi_s^P. \tag{A.11}$$

Therefore, risk-neutral probabilities weight more heavily bad states (high marginal utility) than good states (low marginal utility):

$$\pi_s^Q = \frac{M_{t+1}^s}{E_t\left[M_{t+1}\right]}\pi_s^P \Rightarrow \pi_s^Q > (<)\pi_s^P \Leftrightarrow M_{t+1}^S > (<) E_t\left[M_{t+1}\right]. \tag{A.12}$$

In other words, risk-neutral probabilities adjust for risk. Therefore, the fundamental pricing equation under risk-neutral probabilities is given by:

$$P_{jt} = \frac{1}{R_{ft}}E_t^Q\left[X_{jt+1}\right] \Rightarrow 1 = \frac{1}{R_{ft}}E_t^Q\left[R_{jt+1}\right], \tag{A.13}$$

which is the general expression to value options. Note that assuming a continuous time framework, where prices follow a log-Normal distribution or returns follow a Normal distribution with constant volatility, we get the Black-Scholes formula.

By using the definition of covariances in the fundamental pricing equation (A.9), we get the expected risk premium of any asset:

$$E_t\left(R_{jt+1}\right) - R_{ft} = -\frac{Cov_t\left(M_{t+1}R_{jt+1}\right)}{E_t\left(M_{t+1}\right)} = -\frac{Cov_t\left[U'\left(C_{t+1}\right), R_{jt+1}\right]}{E_t\left[U'\left(C_{t+1}\right)\right]}. \tag{A.14}$$

This is the most general expression we can get of the risk premium of any asset j. Note that if asset j has a negative covariance with the SDF, asset j will pay a low o negative return when marginal utility is high (bad states). The negative covariance with the negative sign in front of the right-hand side of equation (A.14) implies that asset j has a positive expected risk premium, and vice-versa. In other words, risky assets present a negative covariance with the SDF, while hedging assets have a positive covariance with the SDF. Finally, note that we can re-write expression (A.14) in terms of the beta of asset j with respect to the SDF:

$$E_t\left(R_{jt+1}\right)-R_{ft}=-\frac{\sigma_t\left(M_{t+1}\right)}{E_t\left(M_{t+1}\right)}\sigma_t\left(R_{jt+1}\right)correl_t\left(M_{t+1},R_{jt+1}\right)$$

$$E_t\left(R_{jt+1}\right)-R_{ft}=-\frac{\sigma_t\left(M_{t+1}\right)}{E_t\left(M_{t+1}\right)}\ \sigma_t\left(R_{jt+1}\right)\frac{Cov_t\left(M_{t+1},R_{jt+1}\right)}{\sigma_t\ \left(M_{t+1}\right)\sigma_t\left(R_{jt+1}\right)} \tag{A.15}$$

$$E_t\left(R_{jt+1}\right)-R_{ft}=-\frac{\sigma_t^2\left(M_{t+1}\right)}{E_t\left(M_{t+1}\right)}\frac{Cov_t\left(M_{t+1},R_{jt+1}\right)}{\sigma_t^2\left(M_{t+1}\right)}=\lambda_{Mt}*\beta_{jM}.$$

Hence, the expected market risk premium of any asset is the product of the price of risk and the quantity of risk. This general beta expression says that risky assets have negative betas with respect to the SDF or, in other words, with respect to the marginal utility of aggregate consumption. Equivalently, risky assets have positive betas relative to aggregate consumption growth. The price of risk (how the risk of any asset is valued in the market) can be shown to have two market-wide components: risk aversion, denoted by γ, and economic uncertainty.

$$\text{price of risk} \equiv \lambda_{Mt}=\text{risk aversion}\left(\gamma\right)\times\text{economic uncertainty}. \tag{A.16}$$

The fundamental pricing equation (A.9) has two important implications about the characteristics that any potentially valid SDF must have to price assets. First, it must be counter-cyclical, high in bad economic times and low in good times. Recall that the SDF weight heavily the low returns usually observed in bad times. It must therefore be high in those times. The opposite holds in good times. Second, the SDF must be volatile enough to satisfy the Hansen and Jagannathan (1991) volatility bound. By noting that the correlation coefficient is bounded between -1 and +1, it can be shown that expression (A.9) implies the following bound:

$$1=E_t\left[M_{t+1}R_{jt+1}\right]\Leftrightarrow\frac{\sigma_t\left(M_{t+1}\right)}{E_t\left(M_{t+1}\right)}\geq\frac{E_t\left[R^e_{Tt+1}\right]}{\sigma_t\left(R^e_{Tt+1}\right)}, \tag{A.17}$$

where $E_t\left[R^e_{Tt+1}\right]$ is the conditional expected excess return of the tangency portfolio over the risk-free interest rate. The right-hand side of equation (A.17) is the maximum Sharpe ratio reachable for a given universe of asset returns. From equation (A.10), the expected value of the SDF is the inverse of the riskless rate, which is therefore close to one. Consequently, it must be the case that the volatility of the SDF must greater or equal than the maximum Sharpe ratio scaled by a number close to one. In other words, the SDF must be volatile enough to price assets. The lower bound provided by (A.17) is a restriction on the set of SDFs that can price a given set of returns.

Finally, from the previous framework, we can next show how to go from the fundamental pricing equation (A.9) to the lower bound given by equation (8) in the main text of this paper. Using equation (A.8) through (A.13), we can write the fundamental pricing expression either in terms of payoffs or returns for any asset *j* as

$$\text{Payoffs: } P_{jt}=E_t^{\mathrm{P}}\left[M_{t+1}X_{jt+1}\right]=\frac{1}{R_{ft+1}}E_t^{Q}\left[X_{jt+1}\right]. \tag{A.18}$$

$$\text{Rates of return: } 1=E_t^{\mathrm{P}}\left[M_{t+1}R_{jt+1}\right]=\frac{1}{R_{ft+1}}E_t^{Q}\left[R_{jt+1}\right]. \tag{A.19}$$

Then, by the last equation, the risk-free rate is the expected return of any asset under the risk-neutral probability because this probability measure adjusts for risk through the risk-neutral probabilities by its higher weighting of bad states:

$$R_{ft+1} = E_t^Q\left(R_{jt+1}\right) \Rightarrow R_{ft+1}^2 = \left[E_t^Q\left(R_{jt+1}\right)\right]^2. \tag{A.20}$$

Moreover, the expected return under the risk-neutral probability Q can be written as

$$E_t^Q\left[R_{jt+1}\right] = R_{ft+1}E_t^{\mathrm{P}}\left[M_{t+1}R_{jt+1}\right] \Rightarrow E_t^Q\left[R_{jt+1}^2\right] = R_{ft+1}E_t^{\mathrm{P}}\left[M_{t+1}R_{jt+1}^2\right]. \tag{A.21}$$

Using the definition of variance of any random variable, the risk-neutral variance can be written as

$$Var_t^Q\left(R_{jt+1}\right) = E_t^Q\left(R_{jt+1}^2\right) - \left[E_t^Q\left(R_{jt+1}\right)\right]^2. \tag{A.22}$$

Therefore, using (A.20) and (A.21), the risk-neutral variance can be written in terms of the risk-free rate as

$$Var_t^Q\left(R_{jt+1}\right) = R_{ft+1}E_t^P\left(M_{t+1}R_{jt+1}^2\right) - R_{ft+1}^2. \tag{A.23}$$

Next, we write the expected risk premium of asset j as

$$E_t^P\left[R_{jt+1}\right] - R_{ft+1} = \left[E_t^P\left(M_{t+1}R_{jt+1}^2\right) - R_{ft+1}\right] - \left[E_t^P\left(M_{t+1}R_{jt+1}^2\right) - E_t^P\left(R_{jt+1}\right)\right]. \tag{A.24}$$

The first component of the right-hand side of (A.24) is given by,

$$(1) \quad \frac{1}{R_{ft+1}}\left[R_{ft+1}E_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}^2\right) - R_{ft+1}^2\right] = \frac{1}{R_{ft+1}}Var_t^Q\left(R_{jt+1}\right). \tag{A.25}$$

Using (A.9), the second component of the right-hand side of (A.24) is given by,

$$\begin{aligned}(2) \quad & E_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}^2\right) - E_t^{\mathrm{P}}\left(R_{jt+1}\right) = E_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}R_{jt+1}\right) - \\ & E_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}\right)E_t^{\mathrm{P}}\left(R_{jt+1}\right) = Cov_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}, R_{jt+1}\right).\end{aligned} \tag{A.26}$$

Using the expression for (1) and (2), we can now write (A.24) as

$$E_t^{\mathrm{P}}\left[R_{jt+1}\right] - R_{ft+1} = \frac{1}{R_{ft+1}}Var_t^Q\left(R_{jt+1}\right) - Cov_t^{\mathrm{P}}\left(M_{t+1}R_{jt+1}, R_{jt+1}\right). \tag{A.27}$$

By using Martin's (2017) assumption that the negative correlation condition (9) in the main text holds for the market portfolio with return R_m and, therefore, choosing asset j as the market portfolio return, we get the lower bound for the expected market risk premium employed in this paper:

$$Cov_t^{\mathrm{P}}\left(M_{t+1}R_{mt+1}, R_{mt+1}\right) \leq 0 \Rightarrow E_t\left[R_{mt+1}\right] - R_{ft+1} \geq \frac{1}{R_{ft+1}}Var_t^Q\left(R_{mt+1}\right). \tag{A.28}$$

APPENDIX B The Estimation of the Expected Market Risk Premium

The estimation of the lower bound of the expected market risk premia consists of evaluating the risk neutral variance of market returns in equation (10). According to Martin (2017), the model-free risk-neutral market variance can be extracted from an equally weighted set of option prices in the following way:[47]

$$\frac{1}{R_{f,t}} Var_t^{Q}\left(R_{m,T}\right) = \frac{1}{S_t^2}\left[2\int_0^{\infty} call_{t,T}\left(K\right)dK - \frac{F_{t,T}^2}{R_{f,t}}\right], \tag{B.1}$$

where S_t is the underlying price, $F_{t,T}$ is the future price, and K is the strike price. Martin (2017) argues against using deep-in-the-money calls because they are illiquid. Alternatively, he proposes substituting them with out-of-the-money put prices by using put-call parity:

$$\frac{1}{R_{f,t}} Var_t^{Q}\left(R_{m,T}\right) = \frac{2}{S_t^2}\left[\int_0^{F_{t,T}} put_{t,T}\left(K\right)dK + \int_{F_{t,T}}^{\infty} call_{t,T}\left(K\right)dK\right]. \tag{B.2}$$

Our estimation of the lower bound is performed using equation (B.1) with data from put options. Instead of transforming put prices into call prices through put-call parity, we employ the implied volatility surfaces of put options to price the corresponding call options. Therefore, while we calculate call prices to estimate equation (B.1), we are indeed using market information (implied volatilities) from put prices.

Data are obtained from the OptionMetrics IvyDB Global Indices database, which provides daily information on liquid options written on the main international stock indices.

The numerical computation of every point of the term structure of the expected risk premia requires a relatively thin grid of option prices with the same maturity for different levels of moneyness. The volatility surface files contain daily (interpolated) implied volatilities with maturities of 1 to 6, 9, 12, 18 and 24 months. This information is provided for 13 moneyness levels that correspond to a *delta*-δ grid ranging from 0.2 to 0.8 with a step size of 0.05 (for call options). Thus, by using OptionMetrics volatility surfaces we avoid the need to interpolate across maturities

47 This Appendix has been written by Pedro Serrano and Antoni Vaello-Sebastià. This estimation procedure is used by Rubio et al. (2022) to obtain the expected market risk premium of 17 stock markets around the world including the expected market risk premium of the IBEX 35. The cited paper analyzes the term structure of equity returns for the S&P 500, EURO STOXX 50, NIKKEI 225, and FTSE 100 market indices.

in order to get implied volatilities for a constant maturity, reducing the probability of incorporating biases and errors in the manipulation of raw data, thereby easing its replicability.

Some details regarding evaluating the integral in equation (B.1) follow. First, we fit a cubic smoothing spline to the 13 points of the delta/implied volatility smile.[48] Second, the spline is evaluated on a *delta*-δ grid of 1,000 points that are equally spaced. Thus, a thin grid of 1,000 implied volatilities for options is obtained with *deltas* ranging from 0.2 to 0.8. Third, we use a flat implied volatility extrapolation in the tails; we assume the closest implied volatility for those moneyness levels beyond the available data. Fourth, implied volatilities are transformed into call prices, and *delta*-δ*s* are transformed into exercise prices (moneyness). These transformations create a grid with 1,000 points in the moneyness domain that are not equally spaced (e.g., larger grid step length at the tails). Thus, a second interpolation is performed in the moneyness domain to obtain an equally spaced grid. Fifth, we use the zero-coupon curve provided by OptionMetrics to obtain the risk-free rate $R_{f,t}$ for every maturity and currency. The final step of computing the expected market returns involves the evaluation of the integral in equation (B.1) through a trapezoidal rule using the previously obtained grid of call prices and moneyness. This procedure is repeated for each underlying and maturity of our sample of call option prices.

48 Malz (1997) suggests that interpolating/extrapolating implied volatilities in the domain of *deltas* is preferable to the moneyness domain. This procedure ties away-from-the-money options more closely, thereby allowing the data to have a more accurate shape near at-the-money region where the information is more reliable. Moreover, call option delta is bounded between [0; 1], meanwhile the domain of strike prices is theoretically unbounded.

APPENDIX C The Connectedness Estimation Methodology

We consider a covariance stationary *N*-variable VAR(P)

$$X_t = \sum_{p=1}^{\mathrm{P}} \phi_p X_{t-p} + \varepsilon_t , \tag{C.1}$$

where $\varepsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances and X_t denotes an *N*-dimensional vector of variables. In our dynamic analysis, we use the likelihood ratio test to determine the lag *P* of the VAR model for each rolling window.

To estimate the specific variance decomposition, we rewrite the VAR(*P*) model as a moving average representation

$$X_t = \sum_{\tau=0}^{\infty} A_\tau \varepsilon_{t-\tau} \tag{C.2}$$

where the $N \times N$ coefficient matrices are estimated by $A_\tau = \phi_1 A_{\tau-1} + \phi_2 A_{\tau-2} + \ldots + \phi_p A_{\tau-\mathrm{P}}$ with A_O being the identity matrix and $A_{\tau-p} = 0$ for any $p > \tau$.

These moving average coefficients allow for the variance decomposition to parse the *H*-step-forecast error variances of each variable into proportions associated with shocks for the other variables in the total system. The variance proportions defined as the fractions of the *H*-step-ahead generalized error variances in forecasting X_i that are due to shocks to X_j are given by

$$\tilde{C}^G_{j \to i}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i \right)^2}, \tag{C.3}$$

where σ_{jj} is the squared root of the diagonal element j^{th} of the variance-covariance matrix Σ and e_i is a *N*x1 vector with one as the i^{th} element and zeros otherwise.

This generalized variance decomposition eliminates the dependence of the connectedness effects on the ordering of the variables. Nevertheless, as the shocks to each variable are not orthogonalized, the row sum of the variance decomposition is not equal to 1. Thus, each entry of the variance decomposition matrix is normalized by the row sum as

$$C^G_{j \to i}(H) = \frac{\tilde{C}^G_{j \to i}(H)}{\sum_{j=1}^{N} \tilde{C}^G_{j \to i}(H)} \times 100 \cdot \tag{C.4}$$

Hence, the reported results are in percentage terms and note that, by construction, $\sum_{j=1}^{N} C_{j\to i}^{G}\left(H\right)=100$ and $\sum_{i,j=1}^{N} C_{j\to i}^{G}\left(H\right)=N\times 100$. The measure $C_{j\to i}^{G}\left(H\right)$is the pairwise directional connectedness from X_j to X_i at a forecasting horizon *H*. It represents the percentage of variation in X_i that is due to shocks in X_j. It takes high values when the intensity of the directional connectedness or spillover from X_j to X_i is high. When there is no directional connectedness from one series to the others, the indicator equals zero.

In our application, X_t is a five-dimensional vector with the returns of the IBEX 35, the AIAF General Index of Corporate Bonds, the 10-year long-term government bonds, and the natural logarithms of the VIBEX and the SKEW.

Under this pairwise framework, we can also obtain the net directional connectedness from the asset X_j to the asset X_i as the difference between the directional connectedness from X_j to X_i and the directional connectedness from X_i to X_j:

$$Net\left[C_{\mathrm{X}_j,X_i}^{G}\left(H\right)\right] = C_{\mathrm{X}_j\to X_i}^{G}\left(H\right) - C_{\mathrm{X}_i\to X_j}^{G}\left(H\right). \tag{C.7}$$

The net expression indicates the difference between the spillovers transmitted from X_j to the X_i and those transmitted from the X_i to the X_j. Thus, a positive (negative) value implies a higher (lower) impact of the X_j than vice versa.

We can finally obtain a measure of total connectedness between the five variables as the ratio of the sum of the off-diagonal elements of the variance decomposition matrix to the sum of all its elements, which equals five by definition:

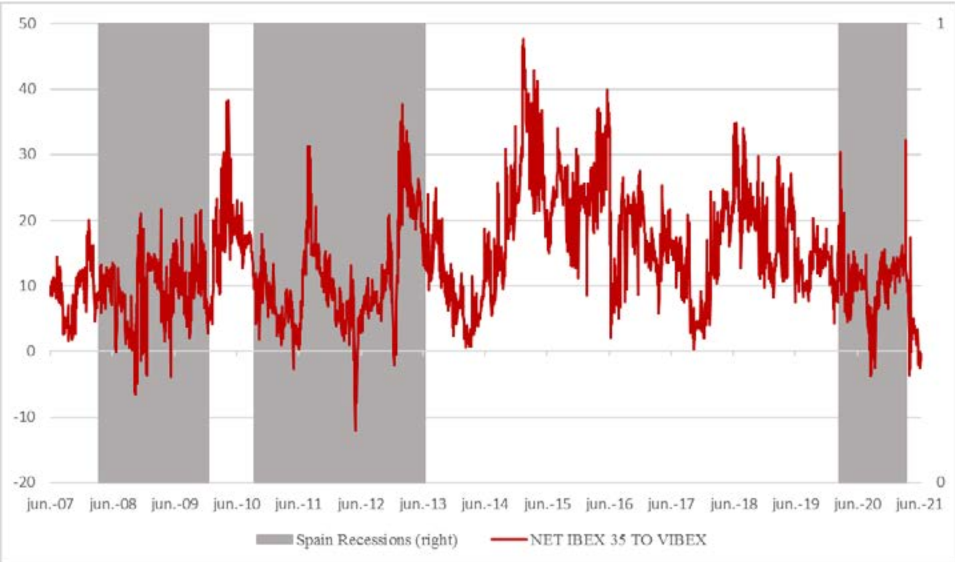
$$C^{G}\left(H\right)=\frac{C_{\mathrm{X}_j\to X_i}^{G}\left(H\right)+C_{\mathrm{X}_i\to X_j}^{G}\left(H\right)}{5}\times 100\cdot \tag{C.8}$$

We choose a forecasting horizon (*H*) of 12 days following the recommendation of Diebold and Yilmaz (2015). They point out that, although intuitively, there are more chances for connectedness to appear as *H* lengthens, the conditioning information also becomes progressively less valuable in the variance decompositions of the conditional forecast error. We check for the sensitivity of the results to the choice of the forecasting horizon, and we see that the dynamic behavior of total connectedness over the rolling windows is robust for forecasting horizons similar as the ones employed by Diebold and Yilmaz (2015). More precisely, they employ either 10 or 12 days in their empirical applications. They also perform several robustness tests for horizons between 6 and 18 days. The results are sensitive for the shortest horizons, but they stabilize in horizons near 10. For longer horizons, the conditioning information losses value. In our robustness tests, the connectedness percentages are very stable for horizons between 6 and 16 days, so that spillovers are practically indistinguishable.

APPENDIX D Net Pairwise Directional Connectedness Dynamics

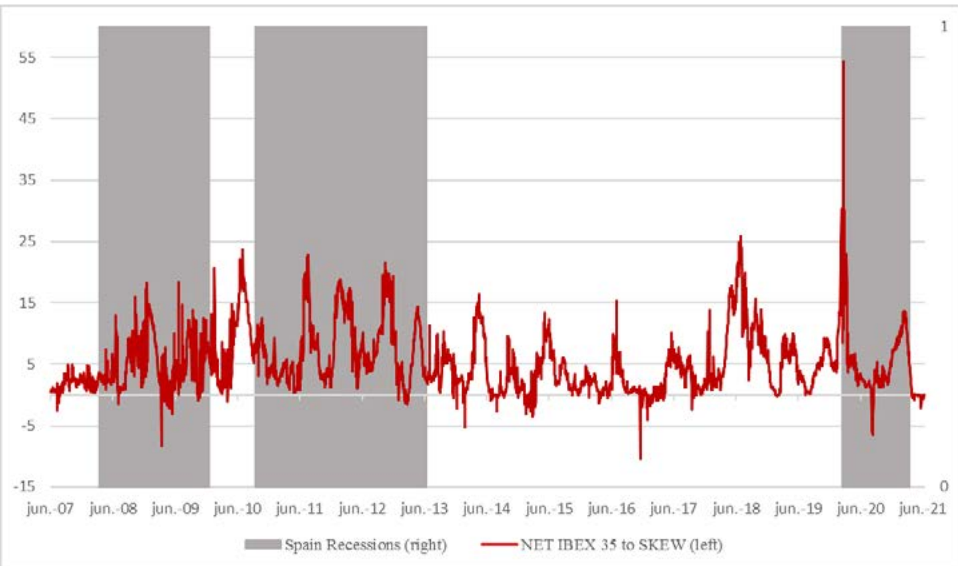
Figure D.1 Net Pairwise Directional Connectedness Dynamics from the IBEX 35 to the VIBEX: June 21, 2007 to June 30, 2021

FIGURE D.1



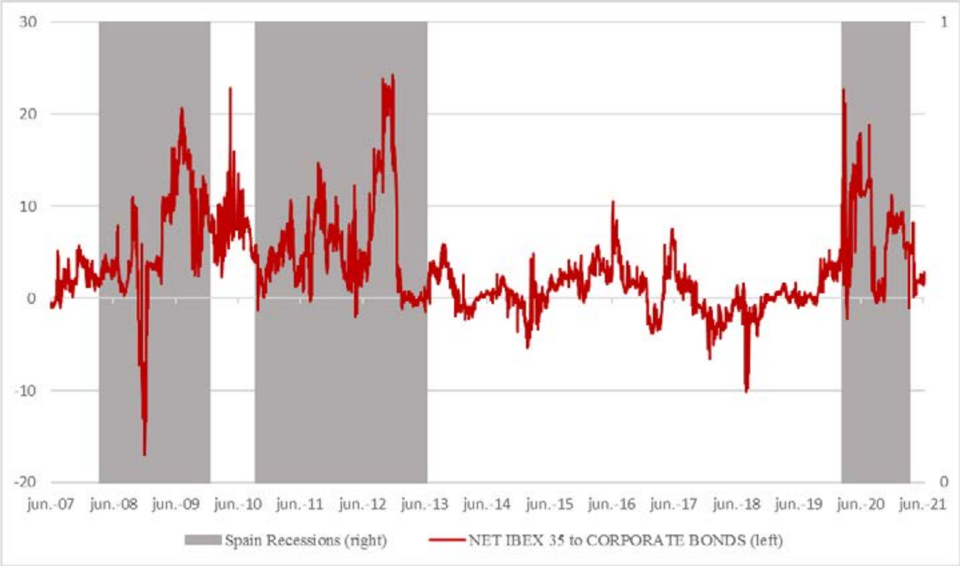
Net Pairwise Directional Connectedness Dynamics from the IBEX 35 to the SKEW: June 21, 2007 to June 30, 2021

FIGURE D.2



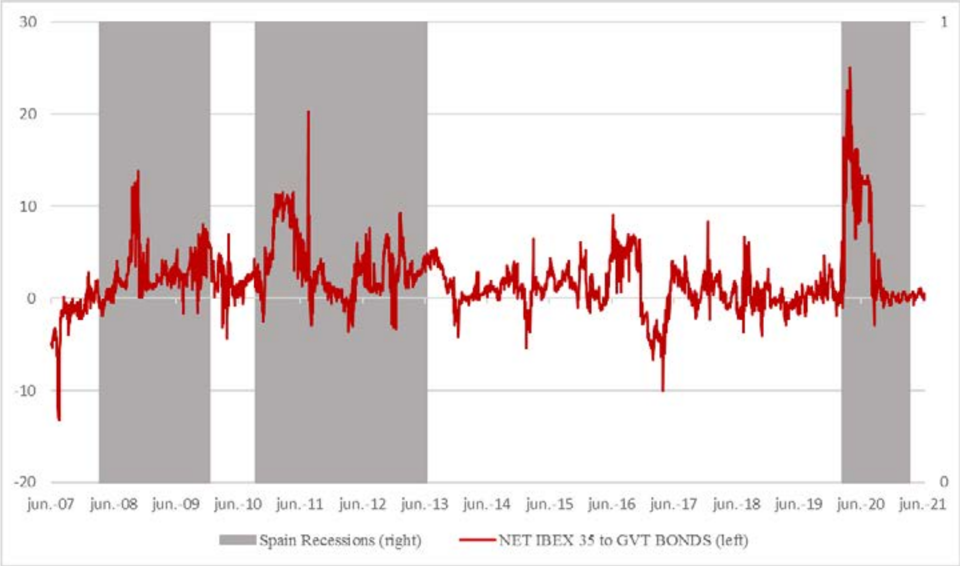
Net Pairwise Directional Connectedness Dynamics from the IBEX 35 to CORPORATE BOND RETURNS (AIAF): June 21, 2007 to June 30, 2021

FIGURE D.3



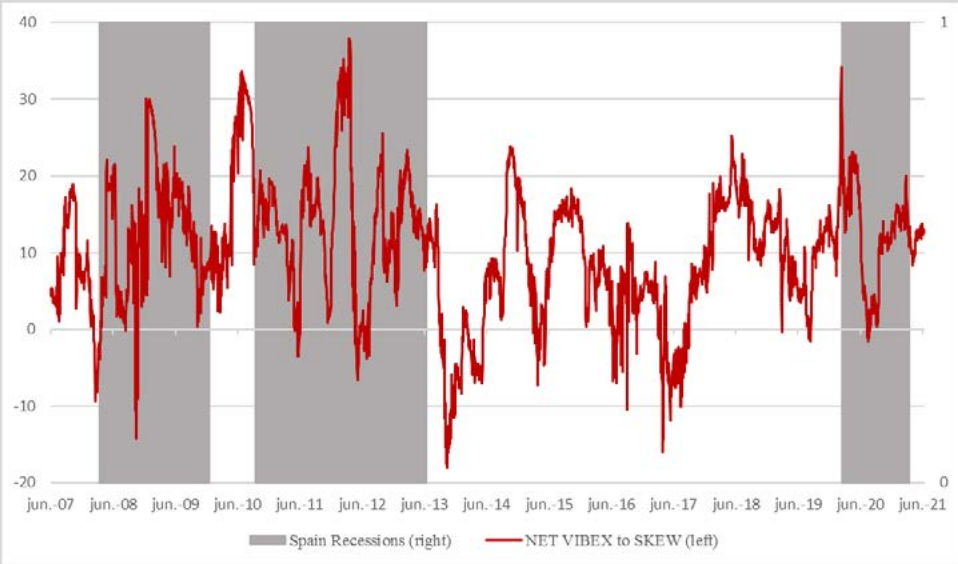
Net Pairwise Directional Connectedness Dynamics from the IBEX 35 to 10-YEAR GOVERNMENT BOND RETURNS: June 21, 2007 to June 30, 2021

FIGURE D.4



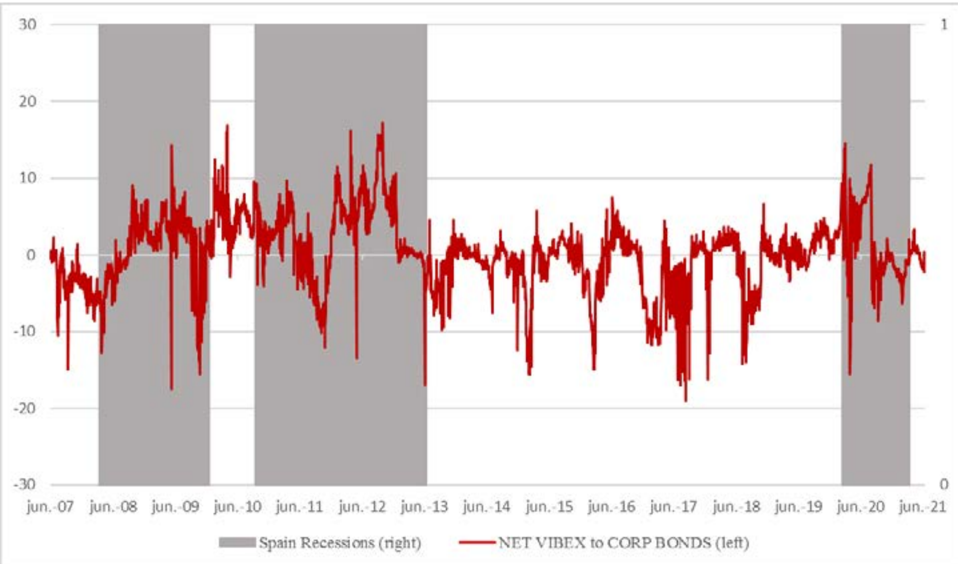
Net Pairwise Directional Connectedness Dynamics from the VIBEX to the SKEW: June 21, 2007 to June 30, 2021

FIGURE D.5



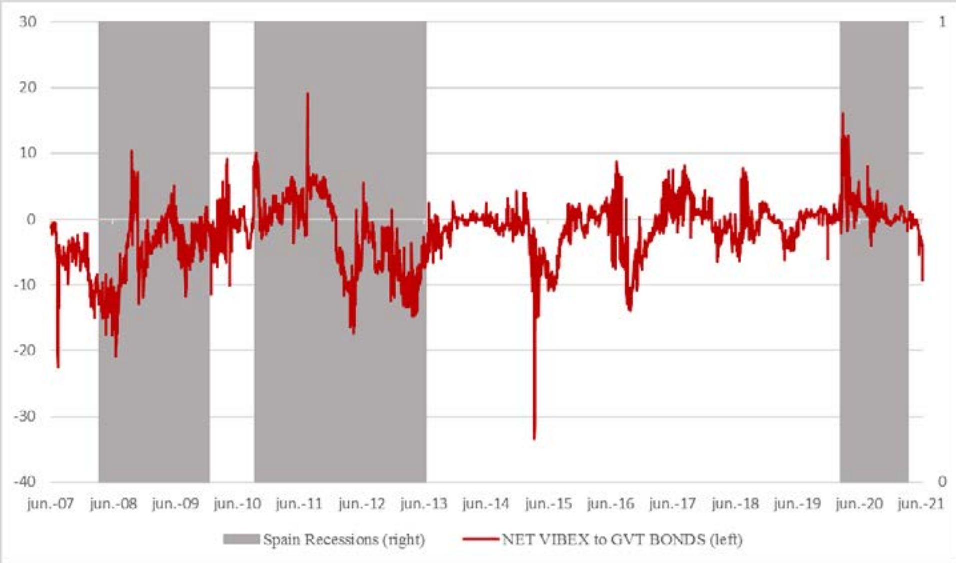
Net Pairwise Directional Connectedness Dynamics from the VIBEX to the CORPORATE BOND RETURNS (AIAF): June 21, 2007 to June 30, 2021

FIGURE D.6



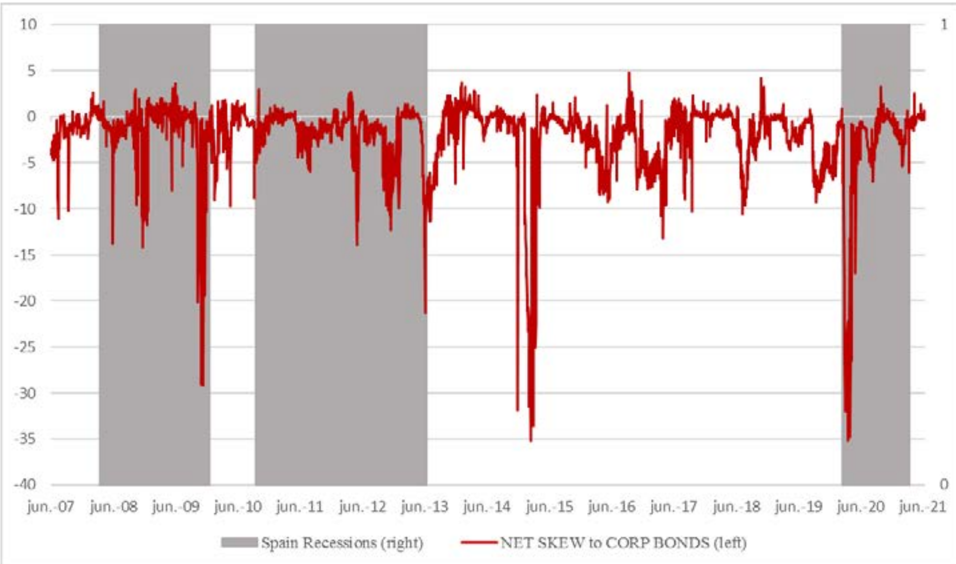
Net Pairwise Directional Connectedness Dynamics from the VIBEX to the GOVERNMENT BOND RETURNS: June 21, 2007 to June 30, 2021

FIGURE D.7



Net Pairwise Directional Connectedness Dynamics from the SKEW to the CORPORATE BOND RETURNS (AIAF): June 21, 2007 to June 30, 2021

FIGURE D.8



Net Pairwise Directional Connectedness Dynamics from the SKEW to the GOVERNMENT BOND RETURNS (AIAF): June 21, 2007 to June 30, 2021

FIGURE D.9

Net Pairwise Directional Connectedness Dynamics from CORPORATE BOND RETURNS (AIAF) to the GOVERNMENT BOND RETURNS: June 21, 2007 to June 30, 2021

FIGURE D.10