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María T. González-Pérez (*)

BANCO DE ESPAÑA

(*) E-mail: mgonzalezperez@bde.es (Banco de España, calle de Alcalá, 48, 28014 Madrid).

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Abstract

This paper estimates the volatility index term structure for the Spanish bank industry (SBVX) using the implied volatility of individual banks and assuming market correlation risk premium. This methodology enables calculating a volatility index for arbitrary (non-traded) portfolios. Using data from 2015 to 2021, we find that SBVX informs about the dynamics of bank returns beyond the standard market volatility index VIBEX, especially when bank returns are negative; and that one-year SBVX beats shorter maturities in explaining bank returns. On the other hand, positive bank returns relate to the dynamics of VIBEX just as much as SBVX, which aligns with the belief that a drop in global volatility (uncertainty) positively affects firm performance and, therefore, bank value projections. We find one-month SBVX better than VIBEX to forecast monthly bank returns volatility, regardless of the tenor we use to compute VIBEX. This paper provides empirical evidence that idiosyncratic implied volatility is just as significant, or even more than global volatility, to monitor current and future banks' share price performance. We advise using SBVX term structure, short-term VIBEX, and market correlation risk premium to monitor uncertainty and returns in the banking sector and foresee periods of stress in this industry. Our results may be of great interest to those seeking to estimate the banking sector's sensitivity to uncertainty, volatility, and risk.

Keywords: volatility term-structure, implied volatility, risk.

JEL classification: G53, G1.

Resumen

Este trabajo presenta la estructura temporal de un índice de volatilidad para la industria bancaria española (SBVX). El índice se calcula a partir de la volatilidad implícita de cada uno de los bancos y de la prima de riesgo de correlación del mercado. Empleando cotizaciones diarias desde 2015 hasta 2021, se muestra una relación significativamente mayor entre el índice de volatilidad SBVX y el rendimiento de las acciones bancarias que entre estas últimas y el VIBEX (índice de volatilidad del mercado), especialmente cuando los rendimientos bancarios son negativos. En concreto, los resultados obtenidos recomiendan utilizar el SBVX a un año como indicador de incertidumbre del sector bancario español, en lugar del VIBEX. Por otro lado, cambios en el VIBEX y el SBVX se relacionan de manera similar con los rendimientos bancarios cuando estos son positivos. Ello se alinea con una hipótesis, ya mencionada en la literatura, que argumenta que una caída en la volatilidad global (incertidumbre) afecta positivamente al desempeño de las empresas y mejora las proyecciones sobre el valor de las entidades bancarias. Adicionalmente, los resultados obtenidos aconsejan usar el índice de volatilidad SBVX a un mes para prever la volatilidad mensual de los retornos bancarios. Este documento proporciona evidencia empírica a favor del uso de medidas idiosincrásicas de volatilidad en combinación con medidas de incertidumbre global (VIBEX) para monitorear y prever el desempeño del precio de las acciones de los bancos. En particular, se aconseja el uso ponderado de tres variables para estudiar la evolución del rendimiento de las acciones bancarias: la estructura temporal del índice SBVX, el VIBEX a corto plazo y la prima de riesgo de correlación de mercado. El uso combinado de estas tres herramientas permitiría, además, prever períodos de estrés en esta industria. Los resultados empíricos aportados en este trabajo contribuyen a las líneas de investigación que estudian la dinámica del precio de las acciones bancarias en el mercado secundario y su sensibilidad a cambios en la incertidumbre, la volatilidad y el riesgo (idiosincrásico y global). Por último, la metodología implementada permite calcular un índice de volatilidad para carteras arbitrarias (no negociadas), lo que supone una contribución al estudio y a la elaboración de medidas de riesgo no estándar.

Palabras clave: estructura temporal de volatilidad, volatilidad implícita, riesgo.

Códigos JEL: G53, G1.

1 Introduction

Measuring uncertainty is essential in economics and finance. Uncertainty affects the decisions of household, business, and policymakers, modifies consumption, investment, and GDP growth,[1] and shapes asset prices.[2] Understanding the heterogenity and spillovers of uncertainty is key to generate a theory around its dymamis and interactions with economic variables. In this regard, the estimation of accurate and informative uncertainty measures becomes essential. There are different sources of uncertainty and there is evidence of interactions among them. For example, there is evidence of interaction between economic and monetary policy uncertainty,[3] and the effect of alternative granular uncertainty sources in financial markets, such as foreign, geopolitical, fiscal, inflation, trading, climate-change, Covid-19, and regulation uncertainty, among others.[4] This paper focuses on measuring average uncertainty associated with the performance of the banking sector.

Previous studies find that uncertainty (primarily economic policy uncertainty) affects the banking industry through different channels. Uncertainty impacts on aggregate bank lending (Danisman et al. 2021, Talavera et al. 2012 among others), with heterogeneous effects across banks (see Buch et al. 2015[5]), what results in evidence of a negative relationship between uncertainty and bank valuation (see He & Niu 2018 and Danisman et al. 2021). On the other hand, Jin et al. 2019 and Christopher et al. 2005 show that lower uncertainty reduces the information asymmetry and bank earnings opacity, providing more visibility of differences among banks' lending and valuation. More recent, Berger et al. 2021 find that banks hoard liquidity in response to higher economic policy uncertainty (EPU), with more pronounced effects for banks with less liquidity, more peer-bank spillover effects, and more EPU exposure. In this framework, Kerry 2020 and Haldane 2012 advise using equity markets, besides accounting ratios, to estimate what they call market-based uncertainty measures that help to identify periods of stress in the banking sector. Our article aligns with this literature and proposes a market-based measure of uncertainty for the banking sector. However, unlike literature, we suggest using prices in the options market, besides the equity market, to reach this goal.

The literature agrees that the options market can price financial uncertainty, see Dew-Becker et al. 2021. However, recent studies find options market suitable to price other uncertainty sources besides financial. Thus, Kelly et al. 2016 find empirical evidence that "political uncertainty is priced in the equity options market as predicted by theory," Stillwagon 2018 confirms that VIX (U.S. volatility index that underlies the S&P 500 returns dynamics) primarily affect the breakeven inflation rate (BEI) on U.S. Treasury Inflation Protected Securities, and Emirhan et al. 2021 conclude that climate policy uncertainty is priced in the options market. This article contributes to this research line and reports empirical evidence in favor of the ability of the options market to price average uncertainty associated with the equity returns dynamics in the Spanish banking sector.

We define a portfolio that includes shares of leading Spanish banks and estimate the expected volatility of such a portfolio or its volatility index. Assume that we label A to our portfolio. If

[1] See Bernanke 1983, Romer 1990, Bloom 2009, Bloom et al. 2007, Jens 2017, Bachmann et al. 2013, Baker et al. 2016, Jurado et al. 2015, Fernandez-Villaverde et al. 2011, Fernandez-Villaverde & Guerron-Quintana 2020, Shin & Zhong 2020, Adrian et al. 2018, Adrian et al. 2019, Fagiolo et al. 2008, Plagborg-Moller & Reichlin 2020, among others.

[2] See Drobetz et al. 2018, Bordo et al. 2016, Gissler et al. 2016, Battalio & Schultz 2011, Aït-Sahalia et al. 2013, Pastor & Veronesi 2012, Pastor & Veronesi 2013, Andersen et al. 2003, among others.

[3] See Greenspan 2004, Bonciani & Roye 2016, Aastveit et al. 2017, Mueller, Tahbaz-Salehi & Vedolin 2017, Husted et al. 2016, Arbatli et al. 2019, among others

[4] See Baker et al. 2020, Caldara et al. 2020, Ahir et al. n.d., Grishchenko et al. 2019, Chan 2017, Londono & Xu 2020, Fernandez-Villaverde et al. 2015, Cascaldi-Garcia & Galvao 2020, Lopez-Salido & Loria 2020, among others.

[5] The authors conclude that lending by banks that are better capitalized and have higher liquidity buffers tends to be affected less.

A options are available, calculating the volatility index of the portfolio is standard.[6] However, the exercise becomes more complex if no options are issued on our portfolio or its liquidity is very low.[7] It is still possible to estimate the portfolio implied volatility; we need individual assets' implied volatility (A_i, $i = 1, ..., n$) and the portfolio correlation matrix under the $\mathbb{Q}$ measure. Notwithstanding, even if individual implied volatilities are available, the literature still struggles in estimating the risk-neutral correlation matrix for the assets included in a portfolio. Buss & Vilkov 2012 relate the portfolio correlation matrices under $\mathbb{Q}$ and $\mathbb{P}$, and the option-implied volatility of the portfolio. However, this means that we need the risk-neutral portfolio variance, precisely the primary goal of this article, to reach the implied correlation matrix, which makes Buss & Vilkov 2012 methodology unsuitable to reach our goal. Related to the frequency of data used, Barndorff-Nielsen & Shephard 2004 and Bibinger et al. 2017 advise using intraday (rather than daily) cross-returns statistics to get a higher estimation accuracy of the correlation matrix under $\mathbb{Q}$, to mitigate the impact of market microstructure on the resulting estimations. On the other hand, [8]. More recently, Bondarenko & Bernard 2020 estimates the risk-neutral correlation matrix from the joint option-implied risk-neutral distribution of portfolio returns. However, this methodology requires liquid options across strikes and maturities for all portfolio constituents, which is uncommon for customized portfolios and not a possibility for the portfolio that includes the Spanish bank shares. This article contributes to research that estimates the risk-neutral volatility for a portfolio and uses individual option-implied volatility of components and a pre-estimation of correlation risk premium to reach it. The researcher can determine the correlation risk premium according to the scenario of interest. This can refer to different assets with the only condition that the risk-neutral volatility of the asset is available (e.g., S&P 500, S&P 100, Euro Stoxx 50, Euro Stoxx Banks, etc.).[9] In this article, we use options on the Ibex-35 future to estimate the term structure of the market volatility index (VIBEX) that we use to assess the IBEX-35 correlation risk premium utilized to estimate SBVX.

It is essential to differentiate between portfolio correlation risk premium and correlation matrix under the $\mathbb{Q}$ measure. The first refers to the compensation the market demands for the uncertainty associated with the portfolio correlation dynamics, while the second informs about expected portfolio correlation. Thus, a high correlation coefficient and low correlation risk premium can coexist if the uncertainty associated with the future correlation dynamics is low. Therefore, we assume equal correlation uncertainty for the market and the banking industry, no similar expected correlation for the portfolios. This way, we estimate SBVX assuming market correlation risk premium and estimated ATM implied volatility for portfolio constituents. Once we get the correlation risk premium, we infer a risk-neutral correlation matrix from the portfolio realized correlation, following Buss & Vilkov 2012, and estimate SBVX per each tenor.

We find SBVX dynamics informing about the banking sector returns dynamics besides the market uncertainty, especially one-year SBVX (less affected by jumps), even if returns are extreme.

[6]For example, assume the market portfolio S&P 500; the implied volatility results from aggregating SPX option quotes (e.g., VIX).

[7]The market provides access to options on the Ibex-35 bank stock index. However, these are no liquid, so we proceed assuming that these are not available.

[8]The correlation index that the Cboe estimates for the S&P500 portfolio is a particular case of the family in Buss & Vilkov 2012, where $\alpha = 0$.

[9]We interpret this as a methodological strength since it provides the researcher an additional degree of freedom in the analysis. A significant advantage of this methodology is that we can define different correlation risk premium frameworks with alternative economic meanings to estimate the portfolio implied volatility and assess its uncertainty at other tenors. Thus, the researcher counts on a flexible toolbox to estimate portfolio uncertainty in different scenarios. For example, we may define a portfolio of assets that quote at the NYSE and use the $S\&P500$, DJI, $Nasdaq$, or any other baseline portfolio to estimate α and the correlation matrix under $\mathbb{Q}$. Conclusions may have different economic readings in each case.

Literature finds jumps an essential channel for generating leverage effect (see Todorov & Tauchen 2011), so our result underscores a significant leverage effect in the banking industry also in the continuous part of the distribution. If negative portfolio returns, the leverage effect is much stronger if SBVX is considered. In contrast, both SBVX and VIBEX report a similar correlation with positive portfolio returns. This result is interesting since the literature finds a robust negative relationship between market uncertainty and bank value due to a reduction in non-performing loans. Thus, our findings support using banking-specific volatility indices in addition to market or economic uncertainty proxies to study the effect of uncertainty in the banking industry return dynamics. Some of the banks included in our portfolio also form part of the Ibex-35 stock index representing around 17% of Ibex-35. Therefore, this percentage does not make us assume both portfolios equal. However, further research would be helpful to understand bank to/from market uncertainty spillovers (and the heterogeneous effects of uncertainty shocks across banks) and deep in the reasons behind the asymmetry in SBVX and VIBEX's role in monitoring bank returns.

To determine volatility indices' forward-looking component, we also explore the ability of VIBEX and SBVX to forecast banks' returns volatility. We observe that short-term SBVX beats market volatility in predicting the monthly volatility of returns in the Spanish banking industry. Therefore, while SBVX and VIBEX form part of the same uncertainty palette to understand current returns dynamics in the banking sector, SBVX seems preferable to forecast the volatility of bank returns.

Overall, this paper proposes and uses a methodology that will be of great use for portfolio managers, policymakers, and researchers who need to assess the implied volatility term structure for arbitrary (non-traded) portfolios, even under several risk scenarios. As a result, we provide a volatility index for the banking sector in Spain and conclude on the significant role of idiosyncratic volatility besides the global volatility, to understand the dynamics of equity prices in this industry. We believe that our results may be of great use for regulators and researchers who seek to monitor, forecast, or evaluate periods of particular stress in this industry.

We divide the analysis into five sections. We start by describing the methodological variant we propose to estimate SBVX. Then, we describe the equations and theories that underlie the variables used in this article. Third, we describe the data, market and bank portfolio composition, and the estimation of the volatility under $\mathbb{P}$ and $\mathbb{Q}$ measure. This section also summarizes the official VIBEX formula and compares it with the formula proposed in this article. Section four studies total and marginal information in the SBVX, not included in the VIBEX. In particular, we study (i) if SBVX can measure leverage effect in the banking sector, (ii) its potential use to forecast volatility, and (ii) its dynamics around the Covid-19 shock. The last section concludes.

2 Methodology

To estimate the portfolio risk-neutral volatility term structure, we need to pay special attention to the time-varying portfolio implied correlation matrix (ICM) since this drives the cross-asset uncertainty relationship in the portfolio. If options on the portfolio of assets are available, we can estimate the portfolio volatility term structure from inverting the option pricing formula. However, this article analyzes those cases with no options issued on the portfolio. In this case, we need to estimate ICM to assess the implied volatility term structure of the portfolio. This section describes the estimation process.

2.1 The Portfolio Implied Volatility Term Structure

The correlation of returns among the assets in a portfolio determines the variance of portfolio returns. Indeed, the variance of a portfolio may be constant while the variance of constituent returns changes. This is possible if portfolio returns correlation modifies appropriately. Suppose a portfolio A that contains N assets $A = \{S_1, S_2, ..., S_N\}$ with weightings ω_i, such that $\omega = [\omega_1, \omega_2, ..., \omega_N]$ and $\sum_{i=1}^{N} \omega_i = 1.0$. The variance of the portfolio returns (σ_A^2) keeps as follows, where $\sigma_{ij} = E(r_i r_j)$ and $\sigma_i^2 = E(r_i^2)$:

$$\sigma_{t,A}^{2,\mathbb{P}} = \omega^T COV_t^{\mathbb{P}}(r_A)\omega = \sum_{i=1}^{N} \omega_i^2 (\sigma_{t,i}^{\mathbb{P}})^2 + 2\sum_{i=1}^{N-1}\sum_{j>i}^{N} \omega_i \omega_{t,j} \sigma_{t,i}^{\mathbb{P}} \sigma_j^{\mathbb{P}} \rho_{t,ij}^{\mathbb{P}} \tag{1}$$

The covariance and correlation matrix of the portfolio returns drives the variance and risk of portfolio assets returns, both under the $\mathbb{P}$ and $\mathbb{Q}$ measures, see (4).[10]

$$\begin{aligned}
\sigma_{t,A}^{2,\mathbb{Q}} &= \omega^T COV_t^{\mathbb{Q}}(r_A)\omega \\
&= \sum_{i=1}^{N}\sum_{j=i}^{N} \omega_i \omega_j \sigma_{t,i}^{\mathbb{Q}} \sigma_{t,j}^{\mathbb{Q}} \rho_{t,ij}^{\mathbb{Q}} = \sum_{i=1}^{N} \omega_i^2 (\sigma_{t,i}^{\mathbb{Q}})^2 + 2\sum_{i=1}^{N-1}\sum_{j>i}^{N} \omega_i \omega_j \sigma_{t,i}^{\mathbb{Q}} \sigma_{t,j}^{\mathbb{Q}} \rho_{t,ij}^{\mathbb{Q}} && (4) \\
&= f(\boldsymbol{\omega}, \boldsymbol{\sigma}^{\mathbb{Q}}, \boldsymbol{\rho}^{\mathbb{Q}}) && (5)
\end{aligned}$$

where,

$$\begin{aligned}
\boldsymbol{\omega} = \{\omega_1, ..., \omega_N\}, \quad \boldsymbol{\sigma}^{\mathbb{Q}} = \{\sigma_1, ..., \sigma_N\}, \\
\boldsymbol{\rho}^{\mathbb{Q}} := N \times N \text{correlation matrix under the } \mathbb{Q} \text{ measure} && (6)
\end{aligned}$$

The implied volatility of the asset can be used to approach $\sigma_{t,i}^{\mathbb{Q}}$ in (4). However, estimating $\rho_{i,j}^{\mathbb{Q}}$ is a nontrivial exercise that recognizes the stochastic character of the individual asset beta.

Given the vital role of correlation determining the variance of portfolio returns, the literature already studies and proposes methodologies to estimate $\rho_{i,j}^{\mathbb{Q}}$. Buss & Vilkov 2012 assume a non-linear relationship between portfolio returns correlation matrices under $\mathbb{Q}$ and $\mathbb{P}$ measures, see (8) and define a parameter α_t ($-1 < \alpha_t \leq 0$) to capture the relationship between these. However, the authors suggest using the implied volatility of the portfolio to reach the implied correlation matrix, and we need to go in the other way. Martin 2020 and Bondarenko & Bernard 2020 propose an alternative method to reach the implied correlation matrix. Still, the process requires a wide range of OTM options on the assets included in the portfolio, which we either do not have or do not trust because these are not liquid.

[10]Consider the following example of a portfolio with two assets and covariance matrix $COV(r_A)$ with assets weights ω_i. The portfolio returns variance is 0.221 and the volatility 47% ($\sqrt{0.221} \times 100$). However, under the assumption of zero correlation among portfolio assets returns, the portfolio returns variance would be 0.214 and volatility 46% so that we would be underestimating the volatility and portfolio risk.

$$\begin{aligned}
\sigma_A^{2,\mathbb{P}} &= \omega^T COV^{\mathbb{P}}(r_A)\omega = \begin{bmatrix}\omega_1 & \omega_2\end{bmatrix} \begin{bmatrix}\sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2\end{bmatrix} \begin{bmatrix}\omega_1 \\ \omega_2\end{bmatrix} = \begin{bmatrix}0.40 & 0.60\end{bmatrix} \begin{bmatrix}0.12 & 0.01 \\ 0.01 & 0.54\end{bmatrix} \begin{bmatrix}0.40 \\ 0.60\end{bmatrix} && (2) \\
&= (0.40^2)(0.12) + (0.60^2)(0.54) + 2(0.40)(0.60)(0.01) = 0.221 && (3)
\end{aligned}$$

$$\rho^{\mathbb{Q}}_{t,i,j} = \rho^{\mathbb{P}}_{t,i,j} - \alpha_t(1-\rho^{\mathbb{P}}_{t,i,j}) \tag{7}$$

$$\alpha_t = -\frac{(\sigma^{\mathbb{Q}}_{t,A})^2 - \sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\sigma^{\mathbb{Q}}_{t,i}\sigma^{\mathbb{Q}}_{t,j}\rho^{\mathbb{P}}_{t,i,j}}{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\sigma^{\mathbb{Q}}_{t,i}\sigma^{\mathbb{Q}}_{t,j}(1-\rho^{\mathbb{P}}_{t,i,j})} \tag{8}$$

Many portfolios of assets lack of options issued on them, or include assets with low-liquid options. Still, we may need to estimate the implied volatility of the portfolio or approach its risk. These portfolios may include assets with a specific characteristics[11] (e.g., size, industry, beta, same fundamental factor, among others). The methodology proposed in this article allows to estimate the implied volatility term structure for a customized portfolio in this framework.

2.2 The estimation process

This paper aims to estimate the implied volatility of a portfolio of assets, and we do it in two stages. First, we estimate the parameter α that controls the portfolio's correlation risk premium using a reference portfolio that the researcher considers suitable for the analysis. The reference portfolio needs to have options issued on it, or we must count on a volatility index that refers to such a portfolio. Second, we include the reference correlation risk premium in the formula that calculates the implied volatility of the banking sector portfolio of assets from the individual ATM IVs. This approach provides the researcher with a feasible tool to assume different compensation risk formulas and scenarios to understand the implied volatility of the portfolio of assets. For example, (e.g., risk compensation discounted at the local market, international market, industry, among others.). We proceed to enumerate all the steps in this two-stage process. For the sake of simplicity, we identify the reference portfolio with *portfolio R* and the portfolio of interest with *portfolio A*.

1. Choose a portfolio of reference R, that contains N assets with known weights ω_i, $\sum_{i=1}^{N}\omega_i = 1.0$. Compute the realized variance and correlation matrix of the portfolio based on historical asset returns $r_{t,i}$.

$$R : \{\omega_i, i = 1, ..., N\}, \quad \text{with: } r_{t,i} = \Delta \ln P_{t,i} \text{ for } i = 1, ..., N, \text{ and } t = 1, ..., n$$

2. Use asset weights, the ATM IV of portfolio R $\sigma^{\mathbb{Q}}_{T,t,R}$ and constituents $\sigma^{\mathbb{Q}}_{T,t,i}$ and portfolio correlation matrix $\rho^{\mathbb{P}}_{T,t}$ under the $\mathbb{P}$ measure to estimate α at solicited tenors (e.g., T_1 = one month, T_2 = two months, T_3 = three months, T_4 = six months, T_5 = one year).

$$\alpha_{T,t,R} = -\frac{(\sigma^{\mathbb{Q}}_{T,t,R})^2 - \sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\sigma^{\mathbb{Q}}_{T,t,i}\sigma^{\mathbb{Q}}_{T,t,j}\rho^{\mathbb{P}}_{T,t,i,j}}{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\sigma^{\mathbb{Q}}_{T,t,i}\sigma^{\mathbb{Q}}_{T,t,j}(1-\rho^{\mathbb{P}}_{T,t,i,j})} \tag{9}$$

3. Use portfolio R estimated α and the portfolio A realized correlation matrix to assess the risk-neutral correlation matrix for portfolio A.

[11] There is a growing need for this in risk-monitoring exercises that seek to study the diverse impacts of global and idiosyncratic uncertainty on a specific sector or country (e.g., Brexit impact in the UK shares vs. EU, Covid-19 impact in banking industry vs. market).

$$A : \{w_i, i = 1, ..., s\}, \qquad \sum_{i=1}^{s} w_i = 1.0 \tag{10}$$

$$\tilde{\rho}^{\mathbb{Q}}_{T,t,i,j,A} = \rho^{\mathbb{P}}_{T,t,i,j,A} - \alpha_{T,t,R}(1 - \rho^{\mathbb{P}}_{T,t,i,j,A}) \tag{11}$$

4. Use the estimated portfolio A correlation matrix under the $\mathbb{Q}$ measure, and individual ATM IVs to estimate the risk-neutral volatility term structure for portfolio A at solicited tenors.

$$(\sigma^{\mathbb{Q}}_{T,t,A})^2 = \sum_{i=1}^{N} \sum_{j=i}^{N} w_i w_j \sigma^{\mathbb{Q}}_{T,t,i} \sigma^{\mathbb{Q}}_{T,t,j} \tilde{\rho}^{\mathbb{Q}}_{T,t,i,j,A}$$

The risk-neutral implied volatility term structure of portfolio A assumes R portfolio correlation risk premium (e.g., the market). In the extreme case of $\alpha_t = 0$, $\forall t$, the investor would not demand any compensation for uncertainty regarding the future correlation of portfolio assets. In the absence of alternatives, authors may assume $\alpha = 0$ to estimate the implied volatility for a portfolio of assets. However, this practice would induce a estimation bias in the resulting volatility index estimation. We estimate the volatility index term structure for the banking sector using market and zero α to illustrate this point.

3 Empirical Exercise

This article intends to estimate the volatility index term structure for a portfolio of assets that replicate the Ibex-35 banking index. The volatility index that results is labeled as the SBVX index (Spanish Banking Volatility Index). The reference portfolio that we select in this exercise is the Ibex-35. It seems natural to use market correlation risk compensation as a baseline approach to the correlation risk premium in the Spanish banking sector.

Bolsa de Madrid (BME) provides daily quotes for (i) assets in the Ibex-35 and Ibex-35 banking portfolios and (ii) both stock indices from May 7, 2015, to April 28, 2021. We start on May 7, 2015, because some Ibex-35 banking portfolio constituents only release options since then. Tables 2 and 1 include the asset weight in each portfolio. On the other hand, MEFF RV provides At-the-money (ATM) implied volatility (IV) data for the abovementioned assets and the Ibex-35 stock index. BME informs that options issued on assets are American and that they use the binomial model and a filter based on a skew factor to estimate the ATM IV in the data set. On the other hand, the ATM IV for Ibex-35 results in inverting the Black Scholes model using European options on Ibex-35 futures. Since ATM IV for American options relates to zero-intrinsic-value options, we assume these comparable to European options ATM IV and proceed accordingly.

Table 1: **Portfolio 1:** *IBEX-35 Banking Sector*

Security Name	Ticker	Weight (%)	Security Name	Ticker	Weight (%)
B. Santander	SAN	36.29	Bankinter	BKT	6.83
BBVA	BBVA	27.48	Bankia	BKIA	4.51
Caixabank	CABK	21.55	B. Sabadell	SAB	3.34

The estimation process for the SBVX term structure is a two-step process. First, we set the Ibex-35 stock index as the reference portfolio and estimate the parameter α that drives the market correlation risk premium. Second, we estimate the SBVX term structure based on (i) the ATM IV and variance of Ibex-35 banking sector constituents and (ii) the market correlation risk premium. We proceed to summarize this process attending to estimations under the $\mathbb{P}$ and $\mathbb{Q}$ measures.

3.1 Measures under the $\mathbb{P}$ measure

We use open (O), close (C), high (H), and low (L) daily prices to estimate the *realized variance per each asset* and the portfolio (see following Parkinson 1980, Garman & Klass 1980 and Rogers & Satchell 1991 and Rogers et al. 1994). We do not find significant differences when we use Parkinson 1980, Garman & Klass 1980, Rogers & Satchell 1991 and Rogers et al. 1994 to estimate the realized variance of the portfolio, so we estimate the variance and correlation matrix applying Garman & Klass 1980.[12] Finally, the correlation coefficients under $\mathbb{P}$ for each pair of assets rely on the historical returns.

Table 2: **Portfolio:** *IBEX-35 Sector*

Security Name	Ticker	Weight (%)	Security Name	Ticker	Weight (%)	Security Name	Ticker	Weight (%)
Iberdrola	IBE	18.09	Endesa	ELE	2.65	Arcel.Mittal	MTS	0.69
Inditex	ITX	12.67	Siemens Gam.	SGRE	2.49	Bankia	BKIA	0.69
B. Santander	SAN	7.68	Red.Ele.Corp.	REE	2.39	Inm. Colonia	COL	0.60
Cellnex	CLNX	7.00	Naturgy Ener.	NTGY	1.83	Pharma Mar	PHM	0.52
Amadeus IT	AMS	6.28	ACS Const.	ACS	1.74	Acerinox	ACX	0.52
Ferrovial	FER	4.51	Int.Airl.Grp	IAG	1.64	B. Sabadell	SAB	0.51
Telefonica	TEF	4.51	Enagas	ENG	1.42	CIE Automot.	CIE	0.41
BBVA	BBVA	4.20	Bankinter	BKT	1.04	Almirall	ALM	0.38
Caixabank	CABK	3.29	Merlin Prop.	MRL	0.91	Indra “A”	IDR	0.32
AENA	AENA	2.92	Acciona	ANA	0.88	Melia Hotels	MEL	0.15
Grifols	GRF	2.81	Mapfre	MAP	0.73			
Repsol	REP	2.80	Viscofan	VIS	0.72			

- Parkinson 1980:

$$(\sigma_{i,t}^{\mathbb{P}})^2 = \frac{1}{4\ln(2)}\left(\ln\frac{H_{i,t}}{L_{i,t}}\right)^2 \tag{12}$$

- Garman & Klass 1980:

$$(\sigma_{i,t}^{\mathbb{P}})^2 = 0.511\left(\ln\frac{H_{i,t}}{L_{i,t}}\right)^2 - 0.019\ln\frac{H_{i,t}}{O_{i,t}}\ln\frac{L_{i,t}}{O_{i,t}}\left[\ln\frac{C_{i,t}}{O_{i,t}} - 2\right] - 0.383\left(\ln\frac{C_{i,t}}{O_{i,t}}\right)^2 \tag{13}$$

- Rogers & Satchell 1991, Rogers et al. 1994:

$$(\sigma_{i,t}^{\mathbb{P}})^2 = \ln\frac{H_{i,t}}{C_{i,t}}\ln\frac{H_{i,t}}{O_{i,t}} + \ln\frac{L_{i,t}}{C_{i,t}}\ln\frac{L_{i,t}}{O_{i,t}} \tag{14}$$

Such that, when t stands for calendar days, then H-days volatility under the $\mathbb{P}$ measure is

$$\sigma_{i,t}^{\mathbb{P}}(H) = \sqrt{\frac{360}{H}\sum_{k=t-H+1}^{t}(\sigma_{i,k}^{\mathbb{P}})^2} \quad H = 30, 60, 90, 180, 360 \tag{15}$$

3.2 Measures under the $\mathbb{Q}$ measure

We call $IV_i(T)^C$ and $IV_i(T)^P$ to the i-th asset ATM IV in call and put options, respectively. T points to the option's maturity and terms the horizon for the volatility expectation. Thus, $IV_{BBVA}(30)$ is the BBVA ATM IV one month ahead. BME provides ATM IV for call and put options on each asset and available maturities. We apply standard interpolation in Whaley 2000 and obtain each asset ATM IV for maturities equal to one, two, three, six, and twelve months ahead.

[12] Quantitative results using estimators alternative to Garman & Klass 1980 are available upon request.

- Given near and far maturities around the maturity of interest T ($T^- \leq T$ and $T^+ \geq T$), we average call and put ATM IVs.

$$IV_{t,i}(T^-) = \frac{IV^C_{t,i}(T^-) + IV^P_{t,i}(T^-)}{2} \quad (16)$$

$$IV_{t,i}(T^+) = \frac{IV^C_{t,i}(T^+) + IV^P_{t,i}(T^+)}{2} \quad (17)$$

- We linear interpolate ATM IV for near and far maturities and assess the ATM IV for maturity T. The literature recommends considering the relative gap between far/near and maturity T to reduce the interpolation bias.

$$IV_{t,i}(T) = IV_{t,i}(T^-)\frac{T^+ - T}{T^+ - T^-} + IV_{t,i}(T^+)\frac{T - T^-}{T^+ - T^-} \quad (18)$$

We use ATM IV to estimate SBVX for different reasons:

1. There is no evidence of high-liquid out-of-the-money (OTM) American options on assets that make it worthy of calculating a model-free volatility index.[13]

2. The current official VIBEX relies on ATM IV. We want to make this analysis as close as possible to existing volatility measures in the Spanish stock market so that the investors can place results included in this article accordingly.

3. The market provides a direct measure of ATM IV for the assets, making it suitable to use as a first approach to the volatility analysis.

3.2.1 VIBEX: the implied volatility of the Ibex-35 portfolio

The portfolio of reference in this paper is the Ibex-35, which includes thirty-five high capitalized stocks in the stock exchange. Bolsas y Mercados Españoles (BME) computes the VIBEX, a volatility index that refers to the expected market volatility in the following month.[14] This article calculates the ATM IV term structure for the Ibex-35, making it available for horizons different than one month for the first time.

BME states that VIBEX is computed following the current VIX formula, although the index only includes "filtered" ATM implied volatility (FIV) from near and far call and put options. Thus, squared VIBEX equals the annualized linear combination of filtered ATM implied variances, rather than two model-free variances, as in VIX (see 19). According to BME, a skew factor (skew- and skew+) alters the original Black Scholes ATM (call and put) implied volatilities (FIV), such that the simple average of call and put FIV results in the VIBEX for near and far maturities (σ_1^2 and σ_2^2, respectively). Ultimately, VIBEX equals a weighted average of the two, with each weigh relating to the fraction of the year that last to maturity per each term (T_1 and T_2) and to fraction of days that separate each term to the next thirty days, this is: $w_1 = (N_2 - N_{30})/(N_2 - N_1)$ and $w_2 = (N_{30} - N_1)/(N_2 - N_1)$ respectively, such that $w_1 + w_2 = 1.00$. Therefore, the BME one-month VIBEX formula is (19).

$$VIBEX_t = 100 \times \sqrt{\frac{365}{30}\left[w_1 T_1 \sigma_1^2 + (1 - w_1) T_2 \sigma_2^2\right]} \quad (19)$$

[13]However, she must also know the limitations and weaknesses of these measures, see Jiang & Tian 2005, Andersen et al. 2015, Griffin & Shams 2018, among others.

[14]See: https://www.bmerv.es/docs/SBolsas/docsSubidos/Indices-volatilidad-IBEX35-SEP17.pdf

The term structure of volatility index series that we estimate in this article uses (i) ATM FIV per each stock and Ibex-35, provided by BME, and (ii) the interpolation methodology in (18). Following Jiang & Tian 2005, the volatility index is sensitive to the interpolation technique. Therefore we decide to estimate VIBEX from (18) instead of (19) because this aligns with previous methodologies that assess volatility index time series using ATM IV as input, see Whaley 2000. The gap between our one-month VIBEX and the official figures sets, on average, between -0.11% and 0.01%, and it is not statistically different than zero, so we assume a zero average gap between the two series[15] (see Figure 1). From now on, we identify VIBEX with the volatility index that results from our methodology.

[Include here Figure 2]

Table 3 reports main descriptive statistics for the resulting VIBEX term structure. The average term structure slope tends to be negative or flat if higher volatility and VIBEX reached the maximum value in our sample for all tenors in 2020, as expected. However, maximum uncertainty usually concentrates on short periods, regardless of the average annual uncertainty reached. 2018 and 2020 exhibit the years with significant average daily increments in the index for all tenors. Movements along the curve usually concentrate on shorten tenors, which exhibit higher daily volatility movements. Finally, 2020 was the year with higher upward and downward market uncertainty movements in the sample. This is, higher volatility of volatility.

In a second step, we estimate the α for the Ibex-35 portfolio in (20) based on (i) realized Ibex-35 portfolio correlation, (ii) daily VIBEX term-structure, and (ii) FIV for constituents. The parameter α_T drives daily Ibex-35 correlation risk premium, which increases (decreases) the closer is α to minus one (zero). Thus, the higher (lower) correlation would reduce (raise) portfolio diversification benefits, increasing (reducing) the portfolio correlation risk premium (investor's uncertainty about future portfolio correlation).

$$\alpha_{T,t}^{Ibex} = -\frac{VIBEX_{T,t}^2 - \sum_{i=1}^{35}\sum_{j=1}^{35}\omega_i\omega_j IV_{T,t,i}^{\mathbb{Q}} IV_{T,t,j}^{\mathbb{Q}} \rho_{T,t,i,j}^{\mathbb{P}}}{s} \quad -1.0 < \alpha \leq 0. \tag{20}$$

Figure 3 includes the estimated Ibex-35 correlation risk-premium for different tenors. Following Buss & Vilkov 2012, we make $\alpha \geq 0$, which makes it possible that α reaches zero values with some

Table 3: **VIBEX term structure**: descriptive statistics (2015-2021)

	Mean				Standard deviation				Minimum				Maximum				
	1m	3m	6m	12m	1m	3m	6m	12m	1m	3m	6m	12m	1m	3m	6m	12m	n
									Daily level								
2015	23.2	22.7	22.4	22.1	4.2	2.3	1.5	1.1	15.8	18.2	19.4	19.9	34.0	28.3	26.2	25.2	256
2016	23.4	23.7	23.7	23.7	5.3	3.4	2.4	1.7	15.2	17.7	19.5	20.8	40.9	35.2	32.2	29.5	257
2017	15.3	16.5	17.4	18.3	2.4	2.0	1.6	1.3	11.9	13.8	14.8	16.2	27.0	22.4	21.1	21.3	255
2018	15.0	15.2	15.6	16.1	2.8	1.9	1.5	1.1	10.3	11.8	13.0	14.3	23.9	21.1	20.3	19.8	255
2019	13.7	14.3	14.8	15.4	2.1	1.7	1.2	1.0	9.5	11.2	12.1	11.9	21.1	20.7	20.0	19.5	255
2020	25.5	24.1	23.0	21.5	11.2	8.5	6.6	4.8	10.1	10.4	11.6	12.5	76.1	59.3	48.9	41.1	257
2021	18.5	19.3	19.8	19.8	2.6	1.9	1.6	1.4	13.6	15.5	16.8	17.4	26.0	24.1	23.7	23.0	83
									Daily returns								
2015	-0.03%	-0.02%	0.01%	0.02%	0.07	0.04	0.03	0.02	-22.55%	-11.06%	-8.16%	-5.83%	27.52%	16.14%	11.30%	8.21%	255
2016	-0.09%	-0.07%	-0.05%	-0.04%	0.06	0.04	0.03	0.02	-20.26%	-10.42%	-7.66%	-5.86%	17.10%	18.38%	14.19%	11.42%	256
2017	-0.11%	-0.10%	-0.09%	-0.08%	0.06	0.04	0.02	0.02	-36.19%	-30.44%	-16.90%	-8.42%	23.53%	16.68%	10.31%	6.34%	254
2018	0.17%	0.12%	0.08%	0.05%	0.06	0.04	0.03	0.02	-17.82%	-14.12%	-9.57%	-8.18%	22.65%	14.81%	11.33%	8.11%	254
2019	-0.20%	-0.19%	-0.15%	-0.12%	0.05	0.03	0.02	0.03	-13.94%	-9.52%	-6.22%	-17.31%	17.86%	12.36%	7.80%	17.65%	254
2020	0.22%	0.20%	0.17%	0.13%	0.09	0.07	0.06	0.05	-21.49%	-19.86%	-24.35%	-20.10%	45.24%	29.89%	27.39%	23.36%	256
2021	-0.37%	-0.27%	-0.20%	-0.15%	0.06	0.04	0.03	0.02	-12.91%	-7.93%	-6.17%	-4.92%	22.69%	11.76%	9.33%	7.03%	82

[15] 95% confidence interval for the mean gap.

frequency. If $\alpha = 0$, we assume an equal correlation matrix under the $\mathbb{Q}$ and $\mathbb{P}$ measures. Positive α implies a positive risk premium. In contrast, negative values for the parameter would imply a negative correlation risk premium, which turns counterintuitive since it implies the investor is willing to pay for future correlation risk. Although it is possible considering this scenario, we decide to proceed following the standard approach by Buss & Vilkov 2012 and assume $\alpha = 0$, such that if we get $\alpha < 0$, we make it zero.

Figure 3 exhibits a time-varying series for α, which highlights the different but significant role of correlation and volatility risk in explaining the dynamics of future market returns (see Driessen et al. 209, Buss et al. 2019, Mueller, Stathopoulos & Vedolin 2017, Hollstein et al. 2019, among others), in particular, in the Spanish financial market. If portfolio correlation increases, feasible portfolio diversification strategies reduce (no-place-to-hide state). Consider a recent stress episode, the Covid-19 shock. All prices moved down during the Covid-19 crisis, implied and realized correlation increased, and variance risk premium raised. However, correlation risk premium does not have to be maximum, particularly if the portfolio is low-diversified. Additionally, this article also brings light to the non-flat term structure of correlation risk premium. There is valuable information in the term structure of correlation risk premium. The Ibex-35 portfolio correlation risk compensation reaches values more extreme at shorter horizons when correlation risk premium concentrates after Covid-19. This result offers an exciting reflection on how volatility and correlation risk premium relates.

[Include here Figure 3]

3.2.2 The SBVX: the implied volatility of the Ibex-35 banking portfolio

This section estimates the SBVX term structure, assuming market α (correlation risk premium). The banking equity portfolio is less diversified than Ibex-35, so does equity return correlation. However, a higher correlation between returns does not necessarily imply a higher correlation risk premium. Indeed, the average idiosyncratic component of equity returns in the banking portfolio is low, which may help forecast the portfolio correlation matrix and reduce the correlation risk

Table 4: **SBVX term structure**: descriptive statistics (2015-2021)

	Mean				Standard deviation				Minimum				Maximum				
Daily level																	
	1m	3m	6m	12m	1m	3m	6m	12m	1m	3m	6m	12m	1m	3m	6m	12m	n
2015	28.7	27.6	27.1	27.1	4.4	2.8	2.0	1.4	21.5	22.0	22.8	24.2	39.2	35.9	32.6	31.0	256
2016	36.5	35.4	34.9	33.7	6.8	4.6	3.5	2.7	26.1	27.6	29.4	29.2	58.2	50.1	44.9	41.1	257
2017	24.8	25.5	25.7	26.2	3.8	3.2	2.4	1.8	17.8	20.8	21.8	23.0	41.7	34.2	31.6	30.0	255
2018	22.3	21.7	21.9	22.1	3.4	2.5	2.0	1.4	14.3	15.4	17.0	18.6	32.1	30.0	28.9	27.2	255
2019	25.4	24.8	24.4	24.1	2.5	1.8	1.5	1.0	20.5	21.5	21.9	22.1	32.3	29.6	28.4	26.9	255
2020	43.8	40.4	37.8	34.8	12.2	9.4	7.5	5.8	21.0	21.0	21.9	21.7	88.7	68.6	58.0	48.2	257
2021	34.9	33.6	33.2	32.2	3.8	3.3	2.6	1.9	27.9	26.9	27.4	27.5	43.5	39.2	37.8	35.4	83
Daily returns																	
2015	-0.02%	0.01%	0.02%	0.01%	0.06	0.03	0.03	0.02	-16.83%	-8.35%	-5.82%	-4.54%	19.77%	11.66%	8.61%	5.78%	255
2016	0.01%	0.01%	0.02%	0.02%	0.04	0.03	0.03	0.02	-9.93%	-7.43%	-6.96%	-4.65%	17.25%	18.61%	14.04%	12.12%	256
2017	-0.14%	-0.11%	-0.11%	-0.10%	0.04	0.02	0.02	0.01	-17.90%	-13.12%	-10.43%	-5.11%	12.57%	9.79%	6.11%	3.54%	254
2018	0.16%	0.10%	0.09%	0.06%	0.05	0.03	0.02	0.02	-13.30%	-9.44%	-7.16%	-4.68%	18.72%	13.97%	11.47%	7.71%	254
2019	-0.11%	-0.07%	-0.07%	-0.06%	0.03	0.02	0.02	0.01	-7.80%	-6.35%	-4.11%	-4.36%	10.69%	6.78%	4.56%	3.58%	254
2020	0.22%	0.17%	0.16%	0.15%	0.05	0.04	0.03	0.03	-10.71%	-12.07%	-11.90%	-10.60%	29.86%	24.87%	20.37%	16.05%	256
2021	-0.46%	-0.40%	-0.33%	-0.26%	0.03	0.02	0.01	0.01	-5.27%	-5.90%	-3.66%	-3.84%	7.63%	5.63%	4.63%	2.60%	82

premium. Therefore, we may see the SBVX under market α as a conservative estimator of the actual SBVX[16] On the other side of the spectrum, some authors take zero correlation risk premium; if so, we may be underestimating SBVX. Overall, we consider the market correlation risk premium SBVX more plausible to approach actual SBVX. However, to study potential estimation bias, we estimate zero-α SBVX series and find estimation bias around 2-3%, see Figure 4.[17] The bias is time-varying and seems challenging to forecast, which helps justify an economic criterion to estimate the correlation risk premium when this is unavailable, like our case. From now on, we focus on the SBVX assuming market correlation risk premium.

[Include here Figure 4]

Figure 5 introduces the daily SBVX term structure, and Table 4 includes main descriptive statistics for the series. The uncertainty around the future returns of the banking equity portfolio drives parallel to the market returns uncertainty. However, it usually overcomes the market, see figure 6. The covered sample includes the Sovereign debt crisis and Covid-19 periods, two significant experiences that shaped the uncertainty around future banking sector returns. The banking equity portfolio is less diversified than the Ibex-35, contributing to increasing the portfolio volatility relative to the market. However, uncertainty around future banking sector return varies less than uncertainty around the market. This makes the volatility index of the banking sector less challenging to forecast.

[Include here Figures 5 and 6]

4 The information contained in the SBVX

This section studies the importance of using SBVX measures to analyze the equity portfolio returns dynamics in the banking sector.

In finance, we claim that the investor usually demands higher returns to reward a higher risk. However, the financial literature also recognizes a “leverage effect,” a stylized fact describing the negative relationship between (asset or portfolio) returns and volatility. This relationship associates with the theory that negative returns imply a fall in prices and an increase in the debt-to-equity ratio (leverage) value, which relates to the higher asset risk (volatility). This relationship also fulfills between returns and expected (or anticipated) volatility. As Campbell & Hentschel 1992 explain, “volatility is typically higher after the stock market falls than after it rises, so stock returns are negatively correlated with future volatility.” Thus, the main selling point for official volatility indices is their negative correlation with the underlying returns transforming this into a suitable volatility measure to measure the leverage effect.

We construct Table 5 to explore the distribution of jumps in the volatility indices. Similar to Andersen et al. 2015, we relate volatility stock index returns attending to extreme return values and sign. The table classifies volatility jumps according to size. We observe SBVX daily returns above two standard deviations in 10.8%, and this frequency reduces with the tenor reaching 0.9% when

[16]Notwithstanding the above, it is fair to say that the Covid-19 shock affected all shares and sectors equally in this period, so the correlation risk premium in the banking portfolio may have been very similar to the market. Therefore, in that period, the estimated market α series may be closer to the actual banking sector portfolio α. When this is not the case, we would expect a lower correlation risk premium for a portfolio in which constituents share fundamental value since the investor would be more accurate about the future correlation of this portfolio than for the Ibex-35 portfolio. In this case, we may see the resulting volatility term structure for the banking sector that assumes market correlation risk premium as an upward threshold of the average.

[17]Note that if the equity portfolio correlation is negative, the estimation bias can vary sign.

SBVX reflects one-year expectations. A similar reduction is observed for alternative definitions of jumps (higher than three and four standard deviations). VIBEX reports identical results, although the probability of jumps is higher for this index than for the SBVX for all tenors. This is a relevant observation since the literature relates volatility and stock return distribution to the leverage effect. Near to each column with the number of jumps within each sigma-bucket, we register the average Ibex-35 bank equity return on those days. Extreme upward (downward) movements in both volatility indices relate to bank equity returns of the opposite sign. However, SBVX's extreme values usually relate more to the banking sector's jump returns than the VIBEX. Although further analysis is required to confirm the volatility index that better informs about extreme return dynamics in the banking sector, this exercise provides a first insight suggesting that extreme values of SBVX relate to excessive equity returns in the banking sector beyond the VIBEX.

A natural way to measure the leverage effect (in the banking industry) is by studying the linear correlation between stock index returns and volatility index dynamics, see Aït-Sahalia et al. 2013. Therefore, we estimate the linear correlation coefficients that relate VIBEX and SBVX with stock index returns and provide results in Figure 7. The top panel includes the correlation coefficient and confidence intervals when comparing bank index returns with volatility indices at different tenors. We observe no significant differences at short maturities but a significantly higher relationship between one-year SBVX and bank equity return dynamics. This result highlights the goodness of estimating a volatility index specific to the banking sector and the whole term structure to understand and monitor the bank sector return dynamics. The bottom panel includes correlation coefficient and confidence intervals for VIBEX (left) and SBVX (right) when we differ between negative and positive bank equity returns. The strength of the relationship is asymmetric, varying with the equity return sign. We find a more robust connection when bank equity return is negative. The correlation coefficient may reach up to -0.7 if we use one-year SBVX (red line in the bottom-right panel), a

Table 5: Distribution of extreme volatility "returns" (jumps). This table classifies daily log-returns of the SBVX and VIBEX term structure, according to size in terms of "sigma," computed as the median standard deviation of series across tenors. We also provide the number of jumps lying on each jump bucket (#J), the average stock index return at each volatility jump size (I.R.), and the probability of jumps for different sigmas (two, three, and four). Sample size: $n = 1,386$.

SBVX	1m		2m		3m		6m		1y	
Jum size	#J	I.R.	#J	I.R.	#J	I.R.	#J	I.R.	#J	I.R.
$(-\infty, -9)$	0	–	0	–	0	–	0	–	0	–
$(-9, -6)$	0	–	0	–	0	–	0	–	0	–
$(-6, -4)$	2	3.0%	1	5.6%	1	5.6%	0	–	0	–
$(-4, -3)$	13	1.5%	4	3.0%	4	2.7%	2	7.5%	1	9.5%
$(-3, -2)$	48	1.6%	34	1.8%	17	2.3%	7	4.0%	2	11.2%
$(-2, 2)$	1,237	0.1%	1,291	0.1%	1,322	0.1%	1,356	0.0%	1,373	0.0%
$(2, 3)$	48	-2.1%	31	-2.3%	23	-3.0%	11	-3.5%	6	-4.4%
$(3, 4)$	21	-2.6%	16	-4.0%	11	-4.3%	7	-5.5%	2	-16.2%
$(4, 6)$	15	-6.3%	8	-7.3%	7	-8.2%	2	-18.6%	2	-15.0%
$(6, 9)$	1	-3.7%	1	-12.6%	1	-12.6%	1	-12.6%	0	–
$(9, +\infty)$	1	-12.6%	0	–	0	–	0	–	0	–
$\lvert Jump \rvert > 2\sigma$	10.8%		6.9%		4.6%		2.2%		0.9%	
$\lvert Jump \rvert > 3\sigma$	3.8%		2.2%		1.7%		0.9%		0.4%	
$\lvert Jump \rvert > 4\sigma$	1.4%		0.7%		0.6%		0.2%		0.1%	

VIBEX	1m		2m		3m		6m		1y	
Jum size	#J	I.R.	#J	I.R.	#J	I.R.	#J	I.R.	#J	I.R.
$(-\infty,-9)$	0	–	0	–	0	–	0	–	0	–
$(-9,-6)$	1	5.6%	1	5.6%	1	5.6%	0	–	0	–
$(-6,-4)$	6	0.7%	1	0.4%	1	9.5%	1	9.5%	1	9.5%
$(-4,-3)$	12	1.3%	8	4.9%	6	4.4%	2	5.9%	2	0.2%
$(-3,-2)$	59	1.2%	28	1.3%	11	-0.1%	9	2.5%	4	6.8%
$(-2,2)$	1,209	0.1%	1,288	0.1%	1,324	0.1%	1,354	0.0%	1,366	0.0%
$(2,3)$	59	-2.1%	39	-2.4%	28	-2.6%	12	-4.2%	7	-4.9%
$(3,4)$	22	-2.6%	12	-3.4%	9	-4.1%	4	-8.7%	2	-1.0%
$(4,6)$	13	-2.6%	6	-5.3%	4	-7.4%	3	-8.0%	4	-11.3%
$(6,9)$	4	-9.6%	3	-11.3%	2	-15.0%	1	-12.6%	0	–
$(9,+\infty)$	1	-3.9%	0	–	0	–	0	–	0	–
$\|Jump\| > 2\sigma$	12.8%		7.1%		4.5%		2.3%		1.4%	
$\|Jump\| > 3\sigma$	4.3%		2.2%		1.7%		0.8%		0.6%	
$\|Jump\| > 4\sigma$	1.8%		0.8%		0.6%		0.4%		0.4%	

Table 6: Estimation results. Sample: daily volatility returns from May 8, 2015 to April 29, 2021. Model: $\Delta \ln VIBEX_t = C + \beta \Delta \ln SBVX_t + \epsilon_t$

	1m		2m		3m		6m		1y	
$\Delta \ln VIBEX$	(+)	(−)	(+)	(−)	(+)	(−)	(+)	(−)	(+)	(−)
C	0.03	−0.03	0.02	−0.02	0.02	−0.02	0.01	−0.01	0.01	−0.01
	(16.60)	(−20.14)	(15.20)	(−17.53)	(14.11)	(−16.34)	(11.29)	(−15.23)	(11.19)	(−14.14)
$\Delta \ln SBVX$	0.93	0.78	0.99	0.85	0.95	0.83	1.00	0.83	1.05	0.87
	(28.58)	(22.54)	(34.31)	(25.83)	(31.72)	(24.62)	(32.54)	(25.27)	(29.12)	(21.49)
n	713	817	724	806	715	815	704	826	716	814
R^2	0.54	0.38	0.62	0.45	0.59	0.43	0.60	0.44	0.54	0.36

volatility index not only specific to the sector but less affected by jumps. This index can explain positive bank equity returns as well as the market. However, suppose the researcher uses one-month volatility indices. In that case, it is better to use VIBEX to understand positive returns in the banking sector and SBVX to explain negative returns.

[Include here Figure 7]

Therefore, we get that higher bank equity value relates to lower VIBEX (less uncertainty on firms' performance) while negative bank returns relate to higher SBVX. This result suggests that SBVX can capture the effect of "bad news" on future banks' performance. At the same time, VIBEX is a more suitable volatility proxy to understand how "good news" affects the banking sector fostering a rise in bank equity returns. Consequently, we advise the joint estimation of portfolio and market uncertainty to understand and monitor returns' dynamics in the Spanish banking sector.

Given the different strengths of both indices to explain returns in the bank sector, we consider it essential to understand how VIBEX and SBVX return dynamics relate. Is there additional information in SBVX beyond the VIBEX dynamics? We answer this question by estimating a linear model that relates both indices over the term structure (see Table 6) and confirm the positive correlation between the two indices, as expected. However, VIBEX is much more volatile than SBVX, regardless of the volatility return sign. Thus, a 1% increase (decrease) in one-month SBVX associates to a raise (decline) of +3.9% (-3.8%) of one-month VIBEX.[18] The sensitivity reduces to +3.0% (-2.8%) if three-month volatility indices, and to +2.1% (-1.9%) for the one-year indices. This result emphasizes that VIBEX is a much more noisy measure of uncertainty than SBVX by four (one-month) to two times (one year). This result helps to explain the lower rate of outliers we find in SBVX and the better performance of this index to explain bank equity returns dynamics, especially one-year SBVX.

Thus, we use VIBEX and SBVX alternatively to understand the marginal gain of using SBVX in the study of banking portfolio return dynamics. We find VIBEX and SBVX related to equity returns in the banking sector. However, a reduction in VIBEX matches much more with positive portfolio returns than a drop in SBVX. At the same time, a raise in SBVX relates to negative portfolio returns more strongly than a VIBEX fall. Finally, we find one-year VIBEX and SBVX more capable of explaining return dynamics in the banking sector than short tenors similar volatility indices. We document the existence of a fewer jump size and frequency in long-term SBVX, which explains this result, see Aït-Sahalia et al. 2013.

4.1 Bank-to-market volatility gap and contemporary bank returns

Since, in some scenarios, SBVX and VIBEX may contain essential information to monitor bank returns, we decide to study the information in the bank-to-market volatility gap. Moreover, we will use this gap as an instrumental variable to capture the marginal contribution of each to explain bank returns. We define the bank-to-market volatility gap as the log ratio of both volatility indices. The literature describes two causality relations between returns and volatility; see Bekaert & Wu 2000. The first claims that return shocks lead to changes in conditional volatility, and the time-varying risk premium theory concludes that changes in conditional volatility cause return shocks. Assuming the time-varying risk premium theory, we use model (21) to relate volatility and returns. The model includes daily variation in the SBVX and the banking-market volatility indices as explanatory variables for daily stock returns in the banking industry. Reformulating the model, we may estimate the aggregated contribution of both volatility measures to returns. Estimated correlation coefficients in the previous subsection suggest a negative relationship between returns and volatility, so that we would expect $\beta_1+\beta_2<0$ and $\beta_2>0$. Therefore, a raise in SBVX will reduce baking portfolio value, and this reduction is more substantial if SBVX increases much more than VIBEX on that day.

Table 7 includes estimation results considering one-month and one-year volatility proxies. The results confirm our hypothesis. Suppose VIBEX represents global firms' volatility and SBVX, the idiosyncratic volatility component of the banking sector. In that case, we find empirical evidence in favor of the significant role of both in explaining banking sector returns. We confirm $\beta_1+\beta_2<0$ and $\beta_2>0$, thus the relevance of one-year idiosyncratic volatility to explain banking portfolio returns. On average, one percent drop (raise) in SBVX relates with a raise (drop) of 0.74% in the banking portfolio returns, with one-month VIBEX dynamics contributing an additional 0.03%.

$$\begin{aligned}\Delta\ln P_t &= \alpha+\beta_1\Delta\ln SBVX_t+\beta_2\Delta\ln\left(\frac{SBVX_t}{VIBEX_t}\right)+\epsilon_t \\ &= \alpha+(\beta_1+\beta_2)\Delta\ln SBVX_t-\beta_2\Delta\ln VIBEX_t+\epsilon_t\end{aligned} \tag{21}$$

[18]Assume that SBVX grows 1%, then VIBEX increases by (0.03) + (0.93)(0.01) = 3.9%. If SBVX declines by 1%, VIBEX decreases by (-0.03) + (-0.01)(0.78) = -3.8%.

4.2 Using SBVX to forecast the volatility of bank returns

There is evidence in favor of using implied volatility index to forecast volatility, see Noh et al. 1994, Poon & Granger 2003, Wang et al. 2017, among many others. This section studies if SBVX can provide useful information regarding future monthly volatility of bank index returns. We use non-overlapping volatility series and estimate the model (22), where V^T equals to SBVX and VIBEX volatility index, respectively, for tenors T, $T = 1, 2, 3, 6, 12$ months. We apply natural logarithm to

Table 7: Estimation results: banking industry returns versus volatility indices (leverage effect). Sample: 2015 to 2021.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
C	−0.00 (−0.77)	−0.00 (−0.85)	−0.00 (−0.82)	−0.00 (−0.84)	−0.00 (−0.92)	−0.00 (−0.85)	−0.00 (−0.86)
$\Delta\ln$ SBVX(1M)	−0.27 (−22.17)	–	−0.25 (−20.45)	–	–	–	–
$\Delta\ln$ VIBEX(1M)	–	−0.16 (−20.97)	–	–	–	–	–
$\Delta\ln$ SBVX(1M)/VIBEX(1M)	–	–	0.08 (6.26)	–	–	–	0.03 (2.99)
$\Delta\ln$ SBVX(1Y)	–	–	–	−0.80 (−32.15)	–	−0.79 (−30.75)	−0.77 (−29.82)
$\Delta\ln$ VIBEX(1Y)	–	–	–	–	−0.40 (−23.38)	–	–
$\Delta\ln$ SBVX(1Y)/VIBEX(1Y)	–	–	–	–	–	0.04 (1.57)	–
R^2	0.26	0.24	0.28	0.43	0.28	0.43	0.43
n	1,386	1,386	1,386	1,386	1,386	1,386	1,386

the variables to estimate elasticities and because the relationship can be reached in volatility units and translate to variance units if needed ($\ln V^2 = 2\ln V$). It is relevant comparing the capacity of SBVX and VIBEX to forecast RLZ. Still, it is also essential to understand the marginal contribution of VIBEX if we decide to use SBVX to forecast realized volatility. We propose a framework similar to previous section and define equation (23). However, volatility indices are now at levels since we assume they are cointegrated, and the bank-to-volatility gap is stationary. Note that if we rearrange (23), we obtain (24), where $\beta_1 - \beta_2$ describes the marginal VIBEX contribution to forecast bank returns volatility that is not contained in the SBVX series. Table 8 exhibits model coefficients obtained by regressing future realized volatility on volatility indices and bank-to-market volatility gap. The analysis reveals in-sample predictability (high R-squared and reasonable RMSE, MSE and MAPE) and positive volatility risk premium (constant), as expected.Results suggest that SBVX provides a more accurate prediction of future bank returns volatility than the VIBEX. Moreover, we cannot reject that $\beta_1 - \beta_2 = 0$, which means that VIBEX does not contain additional information that helps forecast bank returns volatility beyond the SBVX.

Therefore, while the previous section provides evidence in favor of one-year SBVX to study the dynamics of current bank returns, one-month SBVX emerges as the volatility index that better informs about future volatility dynamics. The change in the tenor would result naturally since short-term volatility indices are more sensitive to the arrival of new information that may affect future bank returns and volatility. Hence, obtained results confirm the significant role of SBVX in monitoring bank share returns and volatility in the equity market and that SBVX would overcome the VIBEX in this task.

$$\ln RLZ_{t+1} = C+\beta_1 \ln V_t^T + e_t \tag{22}$$

$$\ln RLZ_{t+1} = C+\beta_1 \ln VIBEX_t^T + \beta_2 \ln\left(\frac{SBVX_t^T}{VIBEX^T t}\right) e_t \tag{23}$$

$$= C+(\beta_1-\beta_2)\ln VIBEX_t^T + \beta_2 \ln SBVX_t^T + e_t \tag{24}$$

4.3 The Covid-19 shock

The Covid-19 event is one recent uncertainty-driven episode of interest included in our sample. This section aims to summarize the dynamics of volatility indices and bank returns in this period.

Attending to series in Figure 3 we see market correlation risk premium peaking around the Covid-19 shock, which confirms the investor's demand for the correlation risk premium in addition to the volatility risk premium. This is because the size and strength of the impact affected all assets, regardless of the industry, so most asset prices drop. In this scenario, the investor will generate expectations about future joint and marginal movements in the market prices. The magnitude of the correlation risk premium relates to how confident the investor is about her expectation. The less sure the investor is about her anticipation, the higher the correlation risk premium. It is common to believe that the portfolio that includes the share of larger banks suffered from similar uncertainty. The uncertainty that emerged was so high that it affected all banks and made it difficult to differentiate between them. On the other hand, however, banks are heterogeneous, so that a shock may affect them differently. Although the provision of liquidity programs helped reduce uncertainty (see Figure 8), the market still worried about economic growth recovery timing and continues demanding correlation risk premium in the short term. However, economic recovery forecasts seem to be more optimistic in a one-year horizon and the SBVX aligned with no correlation risk premium required for this tenor. A high correlation risk premium in a highly diversified portfolio will probably emerge at times of global shocks. Therefore, we advise using correlation risk premium series and term structure to monitor uncertainty scenarios considered by the investors at any moment in time and horizon.

[Include here Figure 8]

Regarding the volatility indices dynamics, Figure 8 provides a closer look at around Covid-19 shock. The figure confirms that SBVX responded to significant events affecting the banking sector in this period, such as announcing different liquidity provisions and fiscal programs. There is also a Pfizer announcement effect on November 10, 2020, and a GameStop effect. Interestingly, the term structure did not move equally as a result of the events. The SBVX is more sensitive at short tenors, as expected. However, there is an additional piece of information that we may consider. The SBVX term structure inverted before the shock and continues inverted since then, although flatter. This evidence informs about higher uncertainty concentrated in shorter tenors. Literature relates negative slope in the volatility term structure with extreme unexpected uncertainty concentrated at short tenors, as was in the Covid-19 period. Thus, attending to international volatility indices of reference, VIX term structure inverted 31% of days from January 2020 to February 2021,[19]

Table 8: In-sample forecasting exercise. Estimation results (n=61 months). We provide R-squared and estimations for parameters for the models that consider individual volatility indices and those including the bank-to-market volatility gap.

$$\ln RLZ_{t+1} = C+\beta \ln V_t^T + \beta_2 \underbrace{\ln\left(\frac{SBVX_t^T}{VIBEX_t^T}\right)}_{\text{Vol.gap}} + \varepsilon_t$$

[19]We define slope as one-year to one-month volatility indices.

V

T	R^2 (%)	C	VIBEX		MSE	RMSE	MAPE
1m	44.7	-6.97**	1.46**		0.29	0.54	0.17
2m	45.1	-7.44**	1.61**		0.28	0.53	0.17
3m	44.6	-7.74**	1.71**		0.29	0.54	0.17
6m	43.7	-8.56**	1.97**		0.29	0.54	0.18
12m	40.2	-9.71**	2.36**		0.31	0.56	0.19
T	R^2 (%)	C	SBVX		MSE	RMSE	MAPE
1m	55.0	-8.67**	1.74**		0.23	0.48	0.15
2m	54.8	-9.08**	1.87**		0.23	0.48	0.16
3m	53.7	-9.37**	1.96**		0.24	0.49	0.16
6m	54.2	-10.25**	2.23**		0.24	0.49	0.17
12m	49.9	-11.13**	2.50**		0.26	0.51	0.18
T	R^2 (%)	C	VIBEX	Vol.gap	MSE	RMSE	MAPE
1m	55.0	-8.38**	1.67**	1.54**	0.23	0.48	0.15
2m	54.1	-9.06**	1.87**	1.82**	0.22	0.47	0.15
3m	53.7	-9.34**	1.96**	1.87**	0.24	0.49	0.16
6m	53.5	-10.28**	2.22**	2.38**	0.24	0.49	0.17
12m	49.1	-11.13**	2.49**	2.61**	0.26	0.51	0.18

the VSTOXX 42% of times and the VIBEX 83% of days. A possible interpretation of this result will advise that short-term uncertainty dominated the market on those days. Indeed, the term structure of volatility indices incorporates useful information (level, slope, and curvature) about market performance (see Hasler & Jeanneret 2021, Kamal & Gatheral 2010, H. et al. 2021, among others). This article contributes to this literature and provides the ATM volatility term-structure for the Spanish market and bank sector, such that further empirical research in this direction is possible. Such research will help build on risk-returns channels in the Spanish financial industry, attending to the level, slope, and curvature of global and idiosyncratic volatility surfaces. However, this study deserves a separate paper that treats this topic in the detail that it deserves.

5 Conclusion

This paper uses individual implied volatilities from 2015 to 2021 and the market correlation risk premium to estimate a volatility index for the Spanish banking sector (SBVX) from one month to one year tenors. The modified methodology proposed will make it possible to calculate a volatility index for a non-tradable portfolio, which constitutes the first empirical contribution of this paper to the literature. We apply this methodology to obtain the term structure for the Spanish market volatility index, VIBEX, currently available for one month. We use these series to reach the market correlation risk premium (term structure) term structure and the SBVX daily series for tenors that varies from one month to one year. The primary goal of this paper is not the estimation of VIBEX term structure, but we consider this an intermediate empirical contribution to literature.

We analyze the information content of the Spanish bank volatility index and find this significantly related to the dynamics of current and future bank sector share returns. First, we find one-year SBVX strongly related to bank sector returns, especially if returns are negative and VIBEX dynamics contributing mainly if bank returns are positive. However, we advise using one-month SBVX to forecast the monthly variance of bank returns. Reported results align with existing literature and also provide new insights, specifics to the Spanish bank sector. First, in line with the literature, we provide evidence of lower market uncertainty (e.g., lower uncertainty about firms' performance) related to higher bank share returns (lower non-performing loans, less uncertainty about future bank performance, etc.). Macro-finance literature suggests that lower market uncertainty affects aggregate demand and firms' perspectives (future demand, prices, leverage, etc.), reducing firm performance forecast error and increasing bank market value. Second, we find SBVX and bank returns strongly related in the continuous part of the distribution and the tails. The literature claims that a tail-risk solid correlation may overfit market leverage evidence. However, we find indications of a significant correlation in and out the tails for the Spanish bank sector. SBVX is less volatile than VIBEX at all tenors, which may contribute to explain this result. Our outcome also contributes to empirical research that provides evidence of leverage effect attending to the returns distribution. Finally, we provide evidence of the rich uncertainty-driven information in the term structure of correlation risk premium and encourage the estimation of these series to enhance the uncertainty scenarios definitions.

Finally, we find one-month SBVX a better predictor of monthly bank return volatility than VIBEX (regardless of the tenor of the former). We study whether VIBEX may contribute marginally to forecast volatility beyond SBVX and provide statistical evidence against it. We consider this result empirical evidence of the significant importance of idiosyncratic volatility measures such as SBVX to monitor bank returns in the equity market and foresee periods of stress in this industry.

We pay special attention to the uncertainty priced during the Covid-19 event and provide evidence of the sensitivity of quantitative uncertainty measures to the correlation risk premium. We find a graphical relationship between unexpected events of different nature in this period and SBVX and market correlation risk premium. This outcome aligns, once again, with one of the previous findings, volatility indices will be biased if we assume zero correlation risk premium with no economic or financial reason that supports it. We report different sensitivity of the SBVX curve to monetary, economic, fiscal, and even operational risk events, which justifies the whole term structure's estimation and not just the one-month volatility index. Our paper opens the possibility to build up volatility indices for non-tradable portfolios under certain assumptions, even for different tenors. Thus, we open the race for research on the information contained in the term structure of several volatility indices, particularly in the Spanish financial market. This paper contributes to monitoring and forecasting volatility and returns and will help design different uncertainty scenarios following the researcher's needs.

To summarize, this paper contributes to the literature that studies portfolio uncertainty and the correlation risk premium dynamics in financial markets. It also contributes to research lines that estimate the volatility of a portfolio under the $\mathbb{Q}$ measure and risk factors, especially in the Spanish financial market. This paper also provides empirical insights into recent literature that focuses on the market's sensitivity to uncertainty around the Covid-19 shock. Future research lines of interest using daily SBVX include, but no restrict, to study bank-to-market spillover effects and the impact of uncertainty shocks in bank returns during the European Sovereign Debt Crisis. Accessing a reliable measure of uncertainty covering the Spanish bank sector is key to reaching these goals; this paper makes it achievable.

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Appendix A. Tables

Appendix B. Figures

Figure 1: Daily VIBEX: official volatility index (orange) vs. our own calculation (blue). Sample: 2008-2021

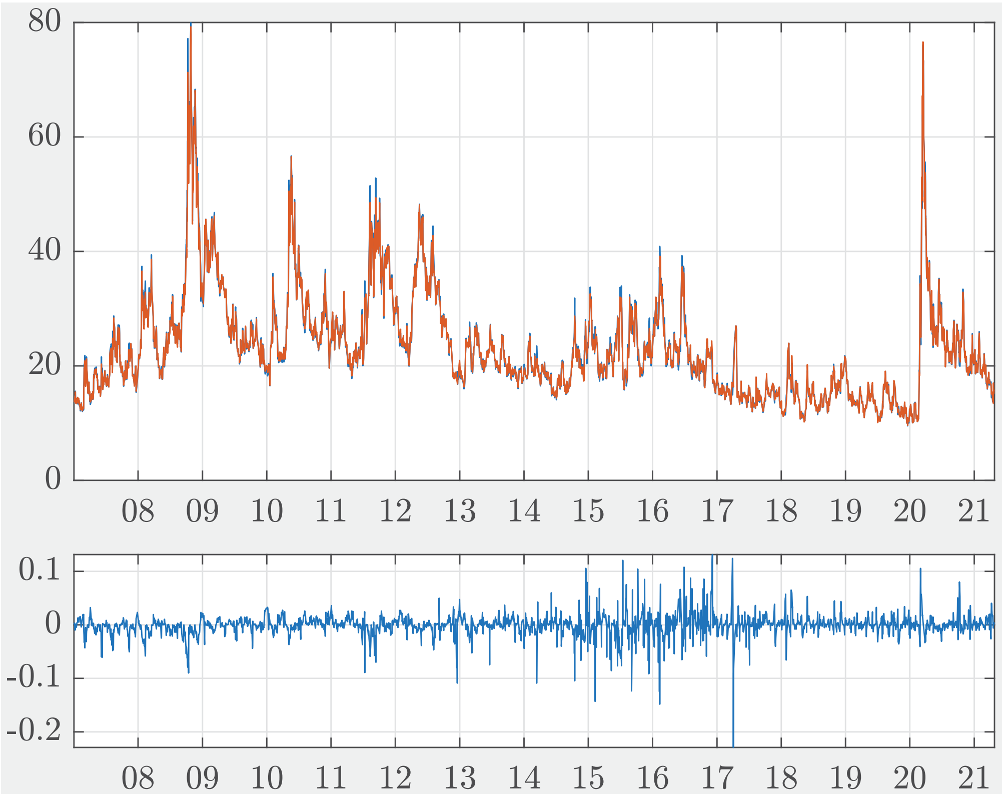


Figure 2: Daily VIBEX Term-structure - top panel - (one month to one year) and the term-structure slope - bottom pabnel - $\left(\ln \frac{V_{1Y}}{V_{1M}}\right)$, with V = VIBEX. Expected volatility contango (ln > 0) usually relates to downward expected volatility trends, while backwardation usually holds in maximum expected volatility levels (e.g., GFC and Covid-19). Sample: November 21, 2005 to April 26, 2021 (n = 3,937 trading days).

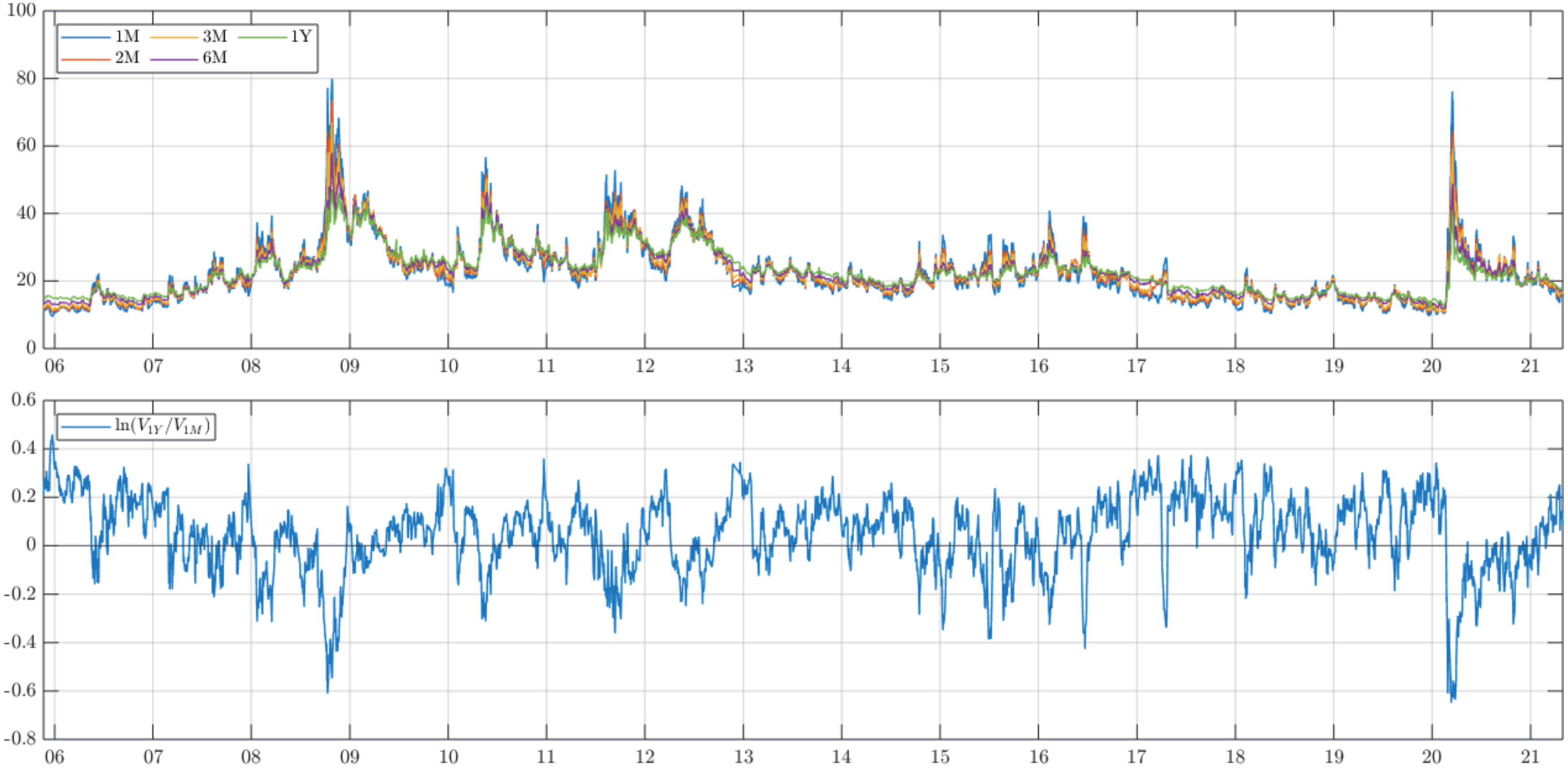


Figure 3: Daily implied (grey) and realized (black) correlation parameters for the Ibex-35 stock index (left axis). The correlation risk premium is defined as the log-ratio of implied to realized correlations (pink, right axes). Sample: November 21, 2015 to April 28, 2021 (n =3,936 trading days).

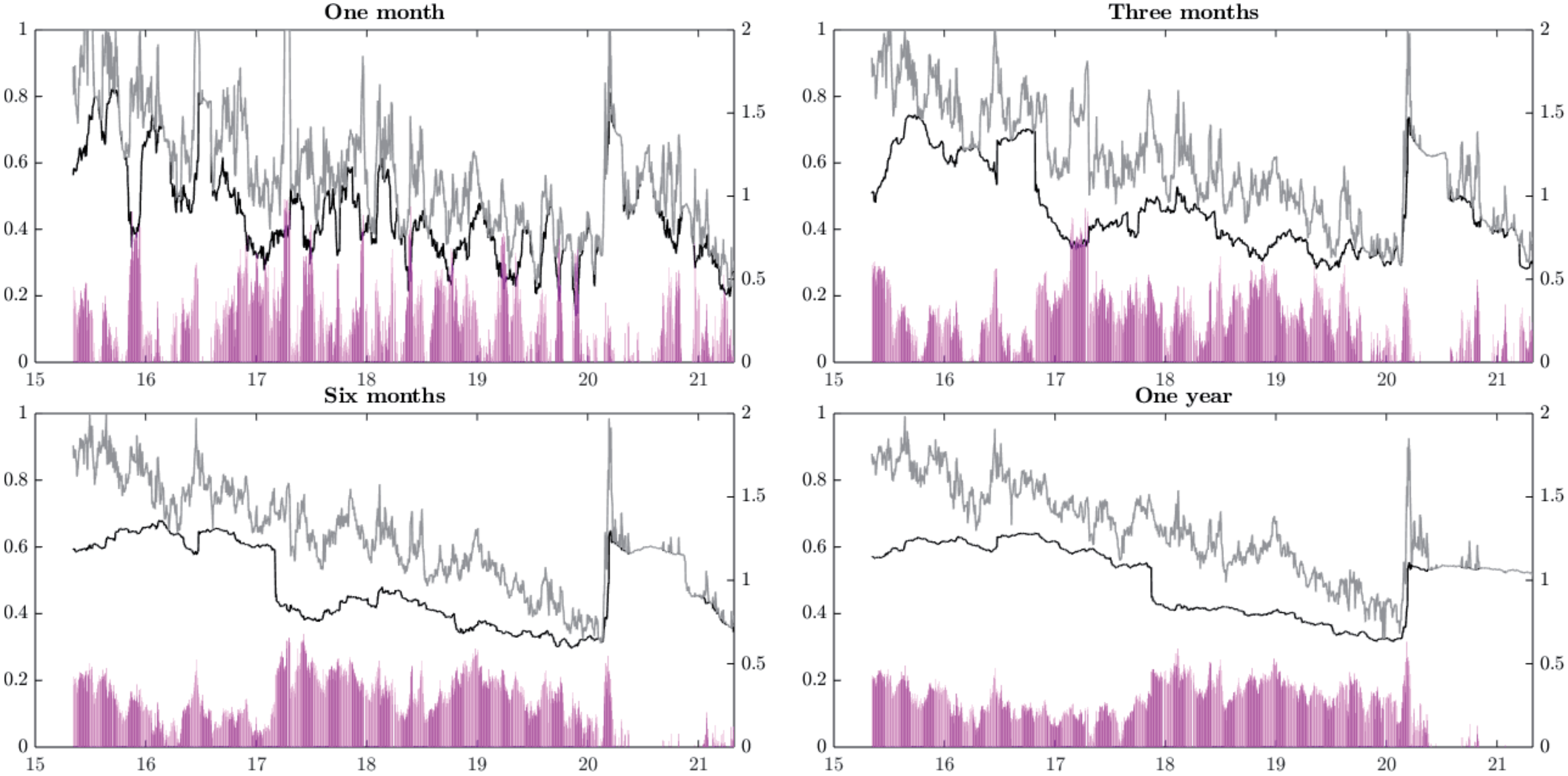


Figure 4: Log-ratio of SBVX assuming market and zero correlation risk premium for different tenors (top panel) and the log-ratio distribution (bottom panel). Sample: November 21, 2015 to April 28, 2021 (n =3,936 trading days).

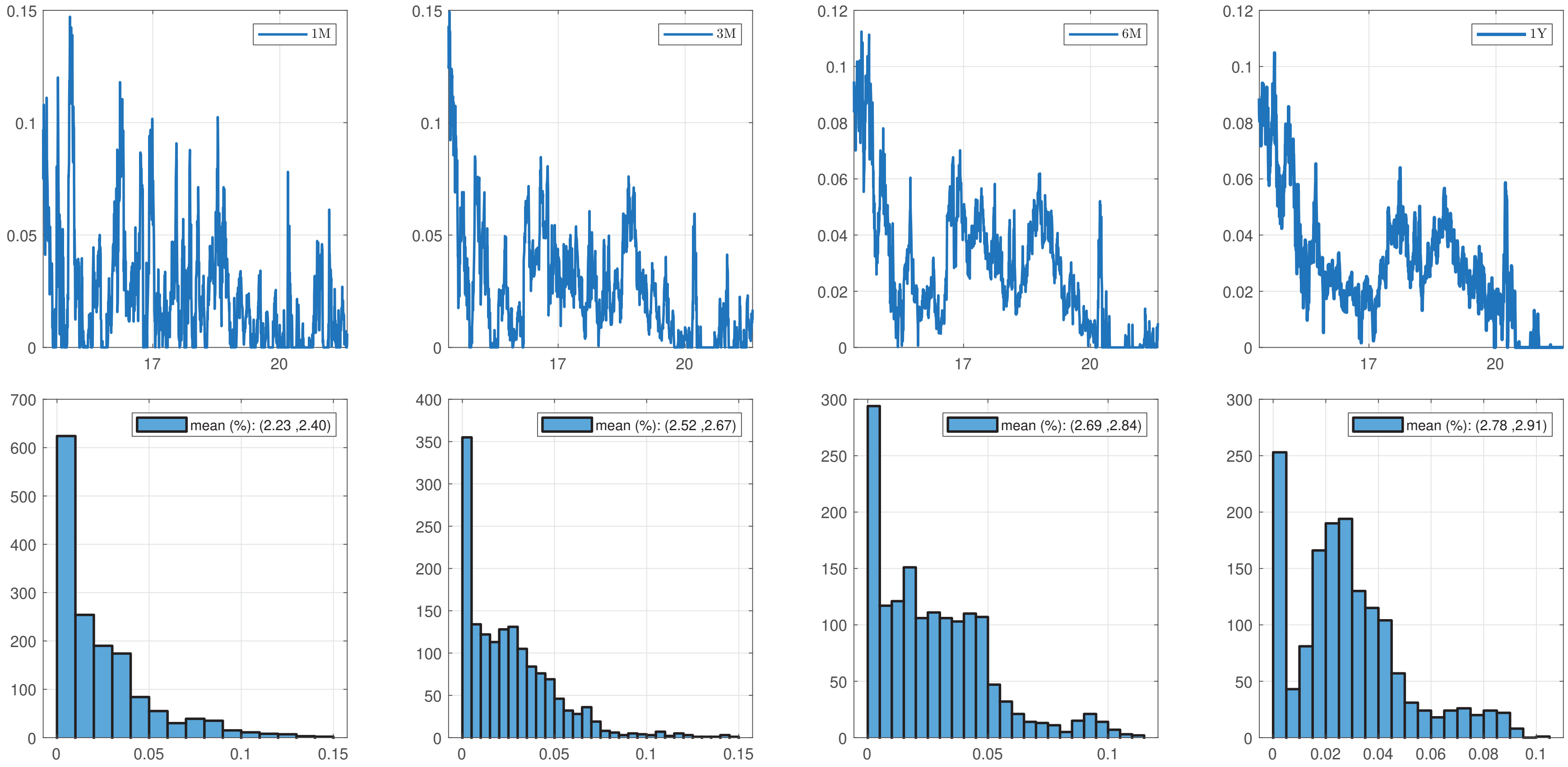


Figure 5: Daily SBVX term structure. Sample: November 21, 2015 to April 28, 2021 (n =3,936 trading days)

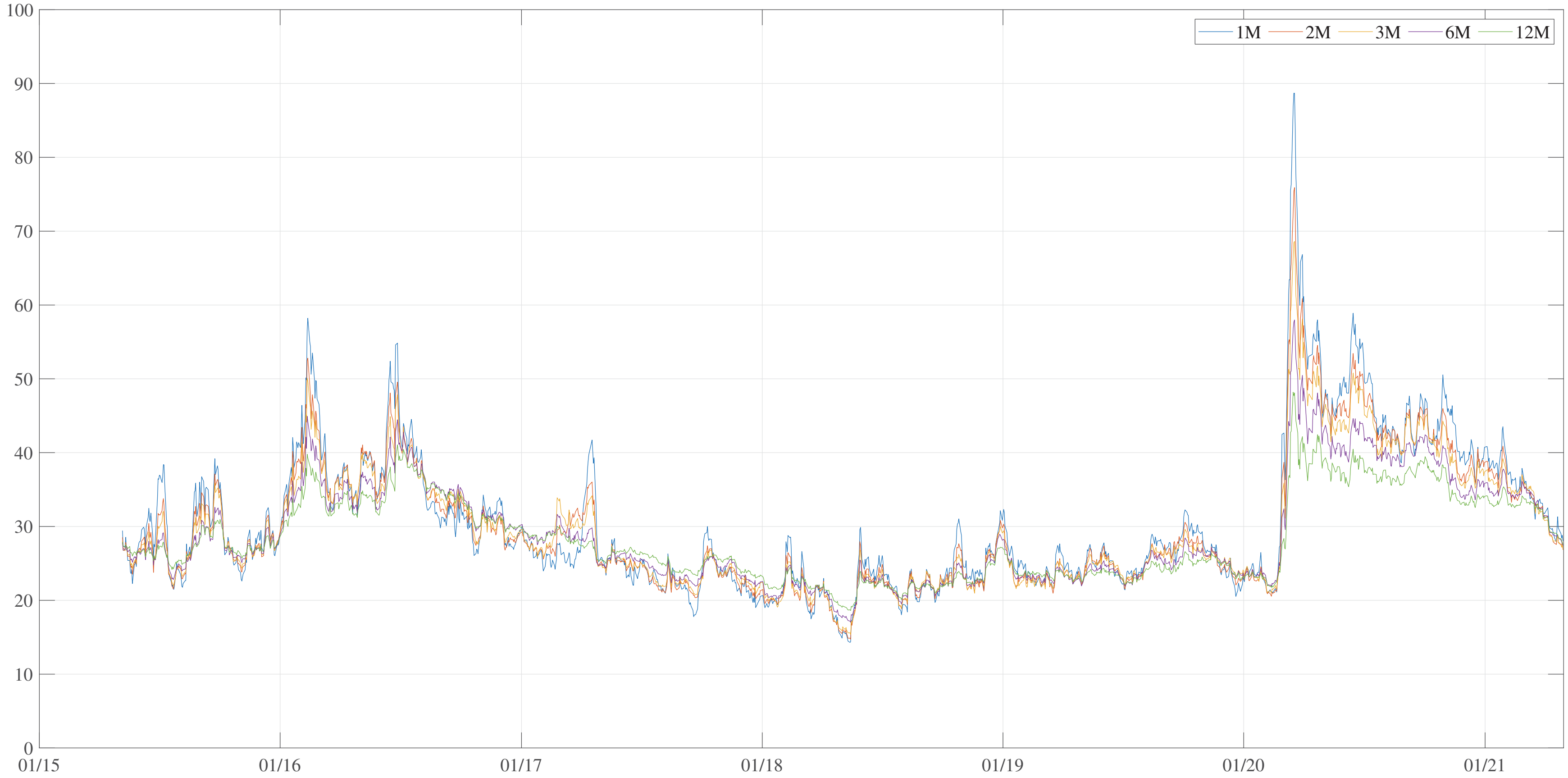


Figure 6: Daily SBVX term structure to VIBEX -top panel- and daily SBVX term-structure slope (1 year vs. 1 month). Sample: November 21, 2015 to April 28, 2021 (n =3,936 trading days)

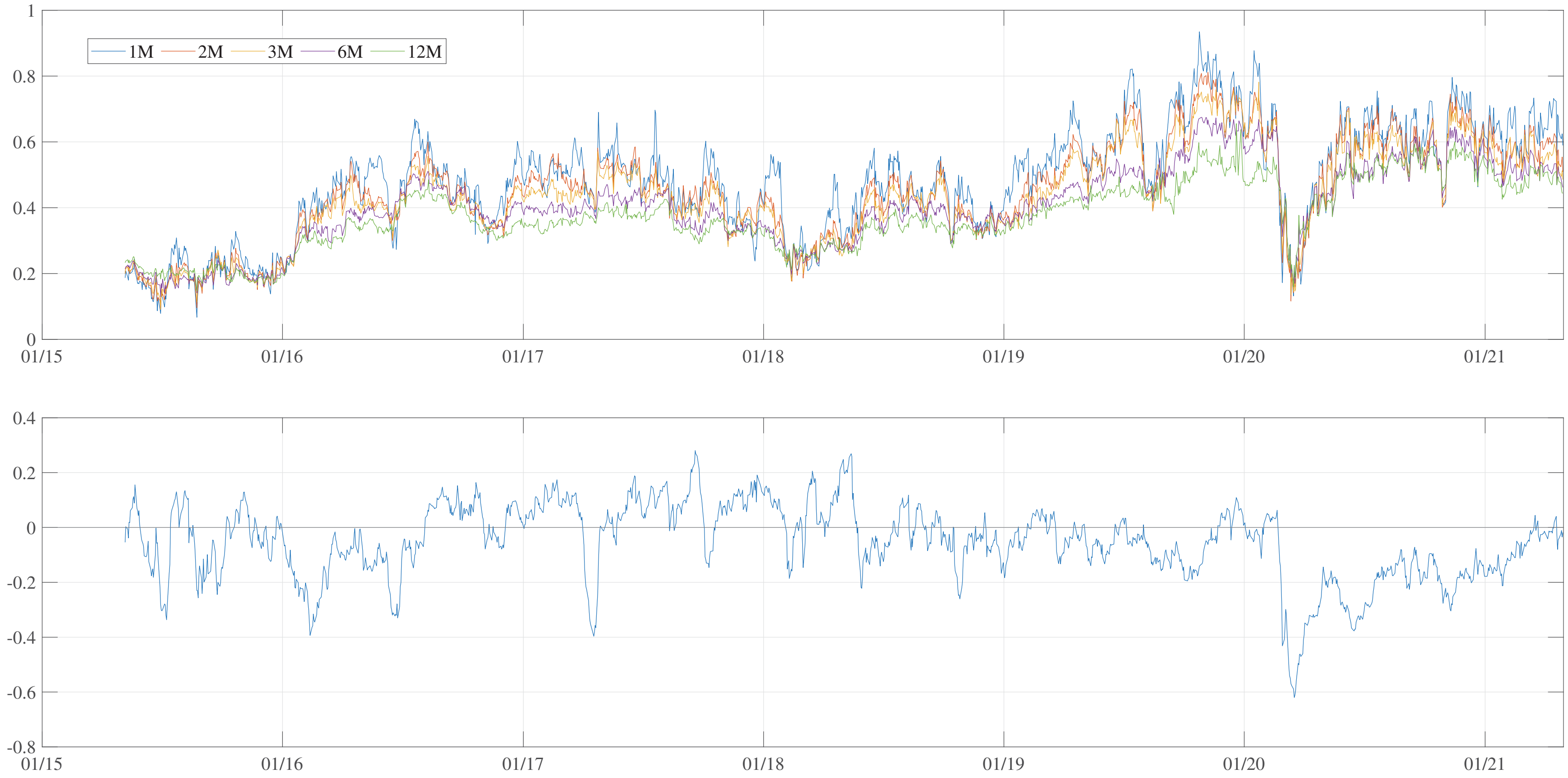
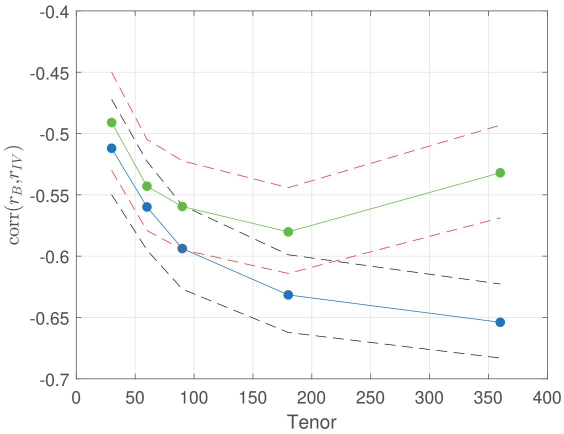


Figure 7: Leverage effect: banking portfolio returns vs. market and banking portfolio volatility (term-structure) returns. 95% CI bands.

Banking portfolio returns vs. VIBEX (green) and SBVX (blue) returns



Banking portfolio returns vs. VIBEX and SBVX returns if we differ between negative (red) and positive (blue) banking portfolio returns.

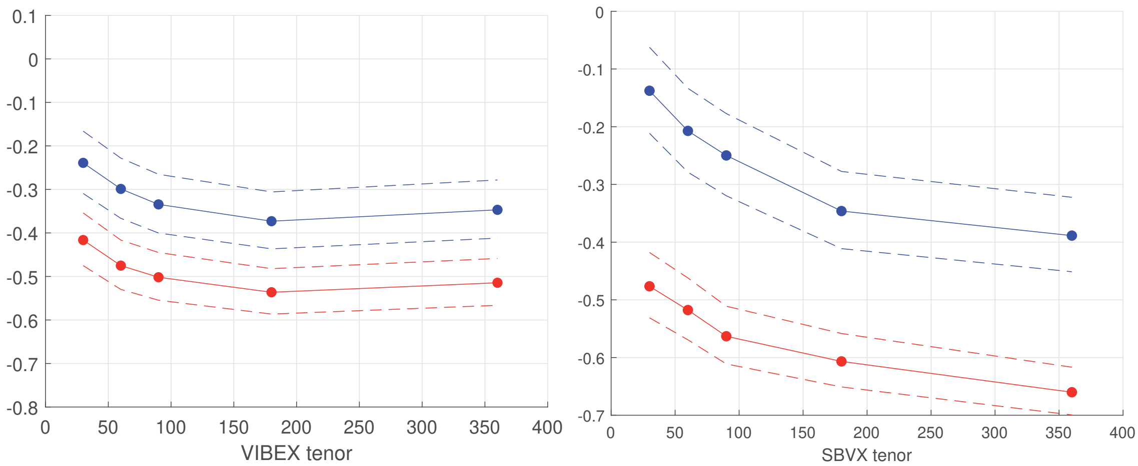
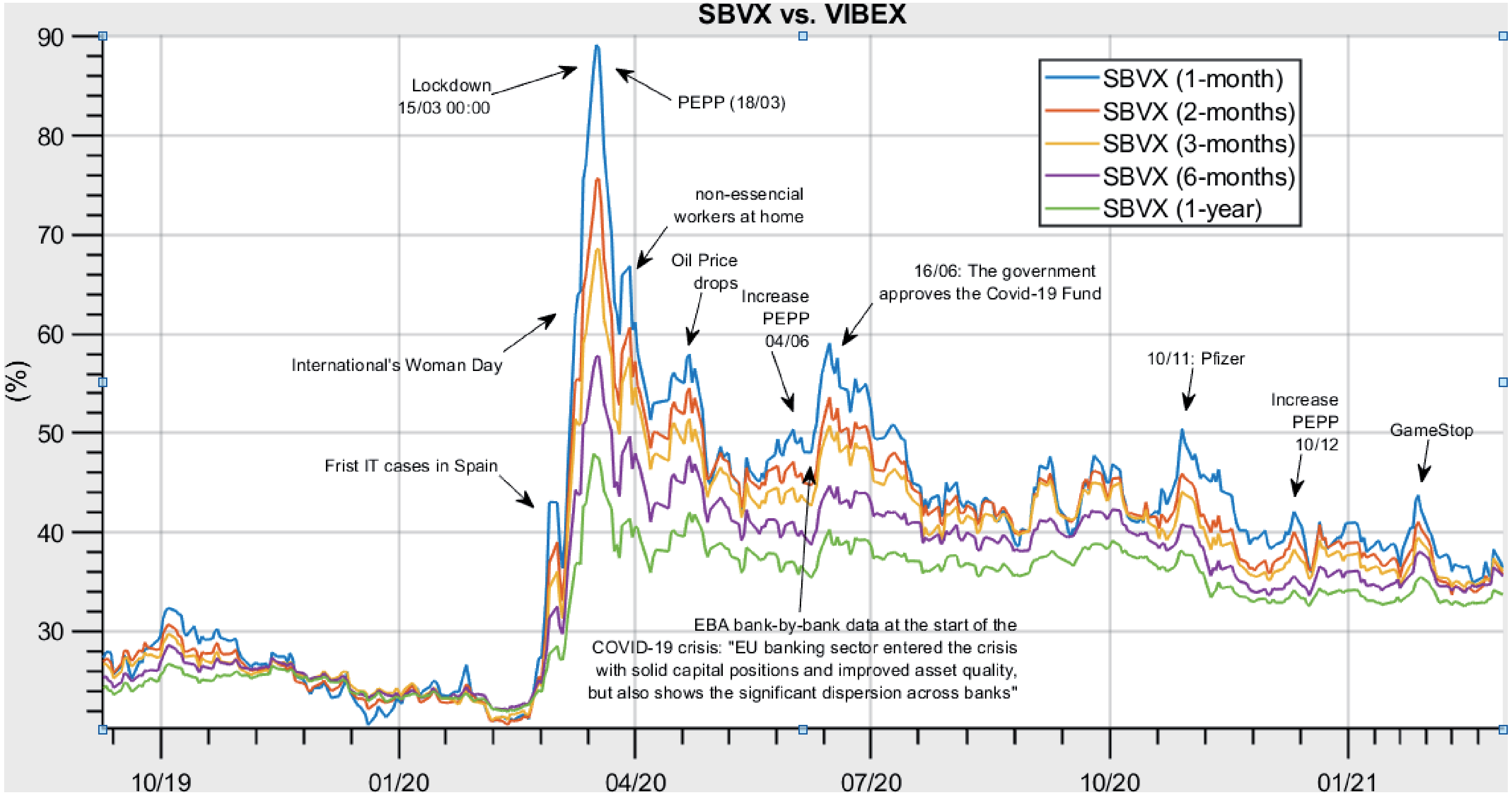


Figure 8: Covid-19: volatility term-structure for the Spanish banking sector. An event study first approach.



Appendix C. Notes

Current empirical approaches to estimate the Implied Correlation Index of a portfolio

Related but different from our approach, industry, and academia have proposed various methods to assess the portfolio's "implied correlation index". Although this exercise differs from ours, since we look for a portfolio's implied correlation matrix rather than an implied correlation index for a specific portfolio, there is a relationship between the two concepts and we proceed to briefly describe the main proposals to date. See that the implied correlation index is a function of the portfolio's IVTS.

The Cboe implied correlation index

Starting July 2009, the Chicago board options exchange (Cboe) disseminates a CBOE S&P 500 Implied Correlation Index dating back to 2007 for different maturities.[20] This index measures "the expected average correlation of price returns of S&P 500 Index components, implied through SPX option prices and prices of single-stock options on the 50 largest components of the SPX." The market defines an SPX "tracking basket" with the 50 largest components measured by market capitalization and compute the index for the former. The index estimation process starts by calculating the 50 normalized market capitalization weights as in (25), so that $\sum_{i=1}^{N}\omega_i = 1.00$. Second, the tracking basket implied variance is computed as a function of weighted individual option implied volatility indices following (26). Finally, the "market-capitalization weighted average correlation of the Index" $\rho_{Average}$ in (27) depends on σ^2_{Index}, the at-the-money implied variance for the SPX, σ_i, the at-the-money implied volatility per each i-th component of the SPX "tracking basket," and the cross-correlation coefficient ρ_{ij} per each pair of assets in the portfolio.[21]

$$\omega_i = \frac{P_i S_i}{\sum_{i=1}^{50} P_i S_i} \tag{25}$$

$$\sigma^2_{Index} = \sum_{i=1}^{N}\omega_i^2\sigma_i^2 + 2\sum_{i=1}^{N-1}\sum_{j>1}^{N}\omega_i\omega_j\sigma_i\sigma_j\rho_{ij} \tag{26}$$

$$\rho_{Average} = \frac{\sigma^2_{Index} - \sum_{i=1}^{N}\omega_i^2\sigma_i^2}{2\sum_{i=1}^{N-1}\sum_{j>i}^{N}\omega_i\omega_j\sigma_i\sigma_j} = \frac{\sum_{i=1}^{N-1}\sum_{j>i}^{N}\omega_i\omega_j\sigma_i\sigma_j\rho_{ij}}{\sum_{i=1}^{N-1}\sum_{j>i}^{N}\omega_i\omega_j\sigma_i\sigma_j} \tag{27}$$

A model-free approach to the implied correlation index

Driessen et al. 2013 derive the IC (implied correlation) coefficient as a function of model-free implied variances for index and individual options and provide the IC (implied correlation) index for a portfolio in (28). In essence, expressions (27) and (28) are equivalent. However, the Cboe uses ATM SPX individual implied volatilities, while Driessen et al. 2013 suggest using model-free volatility measures to estimate the portfolio implied correlation.

$$IC_t = \frac{\sigma^2_{MF} - \sum_{i=1}^{N}\omega_i^2\sigma^2_{MF,i}}{\sum_{i=1}^{N}\sum_{j\neq i}\omega_i\omega_j\sqrt{\sigma^2_{MF,i}}\sqrt{\sigma^2_{MF,j}}} \tag{28}$$

[20]See White Paper for the CBOE S&P 500 Implied Correlation Index at the Cboe URL webpage.

[21]Cboe computes the average implied correlation coefficients for three maturities (January 2021, January 2022, and January 2023).

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