

# Does financial market volatility influence the real economy ?

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## Introduction

After a quiet period on the financial markets in 2017, there was eventually a resurgence of volatility in February and again more recently in October 2018. Many financial analysts say that these sudden surges could be connected with changing expectations about the pace of normalisation of American monetary policy, and typically coincide with the publication of inflation and employment figures. The financial markets react to the publication of macroeconomic data, and that is particularly true in the present context of international trade tensions. In all probability, there could therefore be further spikes in volatility due to specific events or announcements.

In general, and often rightly, high financial market volatility is associated with stock market crashes, or even economic recessions. Various episodes come to mind, such as the latest financial crisis, the bursting of the dot.com bubble, the Great Depression triggered in 1929, and many others. In principle, high market volatility reflects an increased risk for investment, thus hampering decisions by market players. It could also have repercussions beyond the financial sector, for example if a volatility risk premium adds to the cost of issuing company shares. High or increasing volatility is therefore generally seen as a negative signal from the financial markets regarding the outlook for the real economy.

Conversely, we might ask whether periods of low market volatility presage a favourable economic future. In that respect, it is striking that market volatility was particularly low between 2003 and 2007, but that did not stop the eruption of the latest financial crisis. That observation again drew attention to a hypothesis formulated in 1977 by Hyman P. Minsky: the financial instability hypothesis, which states that economic agents tend to be too optimistic and take more risks if they perceive the environment as presenting little risk, for example if financial market volatility is low. The accumulation of risks resulting from that process could ultimately trigger economic crises.

The article comprises three sections. The first presents the various measures of financial market volatility and sets out their main characteristics. Section 2 examines the historical empirical regularities which reveal the effects of high or low market volatility on the real economy. Section 3 examines market volatility in greater depth in the current context.

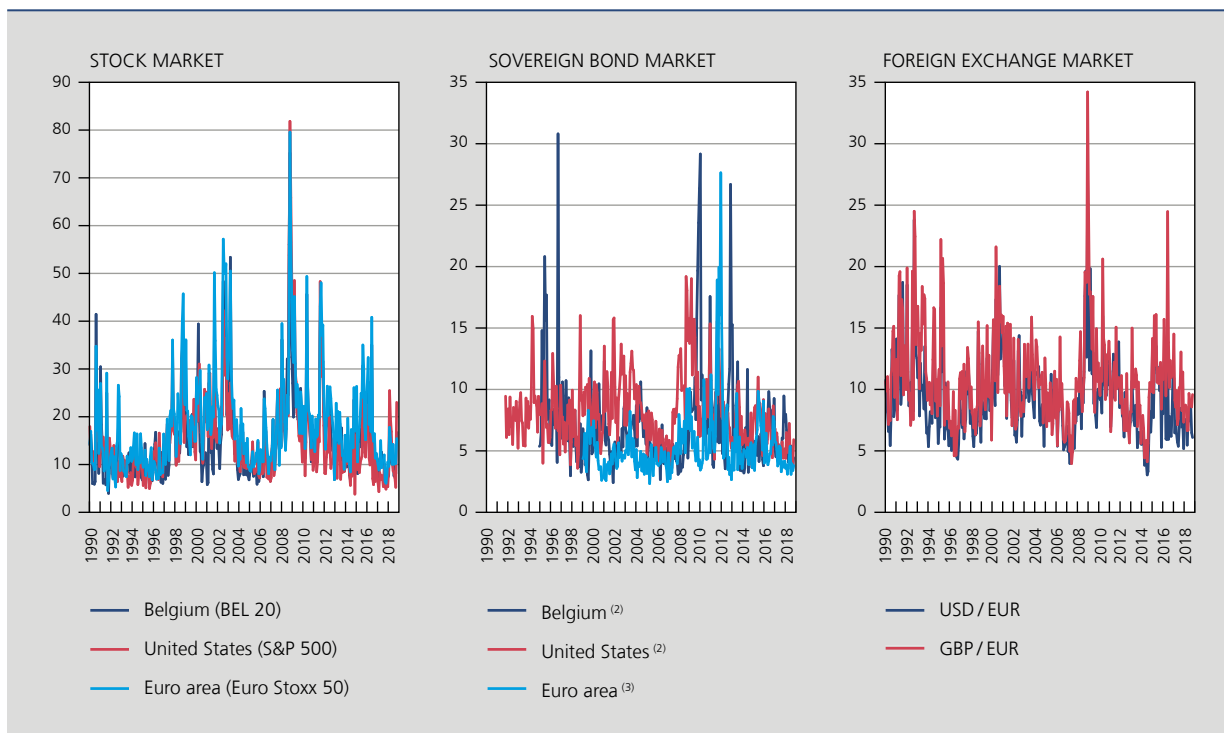
(\*) The author is grateful to J. Hilgers, P. Ilbas and Ch. Van Nieuwenhuyze for their valuable comments and suggestions.

# 1. What is financial market volatility?

## 1.1 Measuring market volatility

Financial market volatility is often assessed by measuring “realised volatility”. That measurement is taken retrospectively for a given period. For example, imagine that we want to calculate the volatility of a stock market index over a given month, recording the value of the index each day when the market closes. The volatility during that month is calculated simply as the standard deviation of the daily returns. A similar calculation can be carried out for bond market and foreign exchange market returns.

**CHART 1** FINANCIAL MARKET VOLATILITY IS OFTEN ASSESSED BY MEASURING “REALISED VOLATILITY” <sup>(1)</sup>  
(in %, annualised monthly volatility)



Sources: Thomson Reuters, NBB.

(1) Realised volatility over one month is calculated in much the same way as a standard deviation: it is the square root of the sum of the squared centred daily returns.

(2) Realised volatility based on prices of ten-year zero coupon sovereign bonds.

(3) Realised volatility based on prices of ten-year zero coupon sovereign bonds with at least an AA rating (S&P) in the euro area.

According to this measure, American and European financial markets have experienced several periods of volatility since 1990 (see chart 1). In the early 1990s, the European exchange rate mechanism crisis generated some volatility on the foreign exchange market. In the late 1990s, there was increased volatility on stock markets and foreign exchange markets against the backdrop of the Asian/Russian financial crisis and the LTCM crisis, and volatility remained fairly high until the dot.com bubble burst at the beginning of the 2000s. During the latest financial crisis, volatility increased rapidly and peaked, either in October 2008 just after the collapse of Lehman Brothers (stock markets and foreign exchange markets), or during the sovereign debt crisis (European sovereign bond market). More recently, stock market volatility was relatively high in 2015 – when the slump in Chinese stock market indices spread to the United States and Europe – and at the time of the Brexit vote in mid-2016. Thereafter, volatility declined sharply up to 2018, when it was rekindled by two corrections, NBB on the American and European stock markets in February and October.

The main advantage of this realised volatility measure is that it does not depend on any model. Moreover, the measurement can be refined by observing returns more frequently. Intra-day data are often used to calculate realised volatility day by day (for example, the value of stock market indices is recorded every five or ten minutes).

There are two other volatility measures: “implicit” volatility and “conditional” volatility. It is important to understand these concepts, because this article uses various measures of volatility mainly according to the available data. That said, from a macroeconomic point of view, there is little harm in switching from one volatility measure to another because the same general tendencies are often apparent in the different series.

Implicit volatility is deduced indirectly from a formula using the prices of financial derivatives. In the case of the stock markets, that is often the Black and Scholes formula in which the price of a call and put option depends on the volatility of the underlying asset. Once the financial derivative’s price is known, the volatility of the underlying asset can be deduced by inverting the formula. The best-known example of an implicit volatility measure is the one-month VIX index which measures the implicit volatility of the S&P 500 index over the next 30 days, sometimes known as the “fear index”.

Conditional volatility measures the estimated volatility on a given date according to the information available up to that date. Conditional volatility measures necessarily depend on models that filter the information. Robert F. Engle was the first to develop this type of model (from 1982), commonly known by the acronym “GARCH” (generalised auto-regressive conditional heteroskedasticity). There are numerous models for conditional volatility.

## 1.2 Main characteristics of market volatility

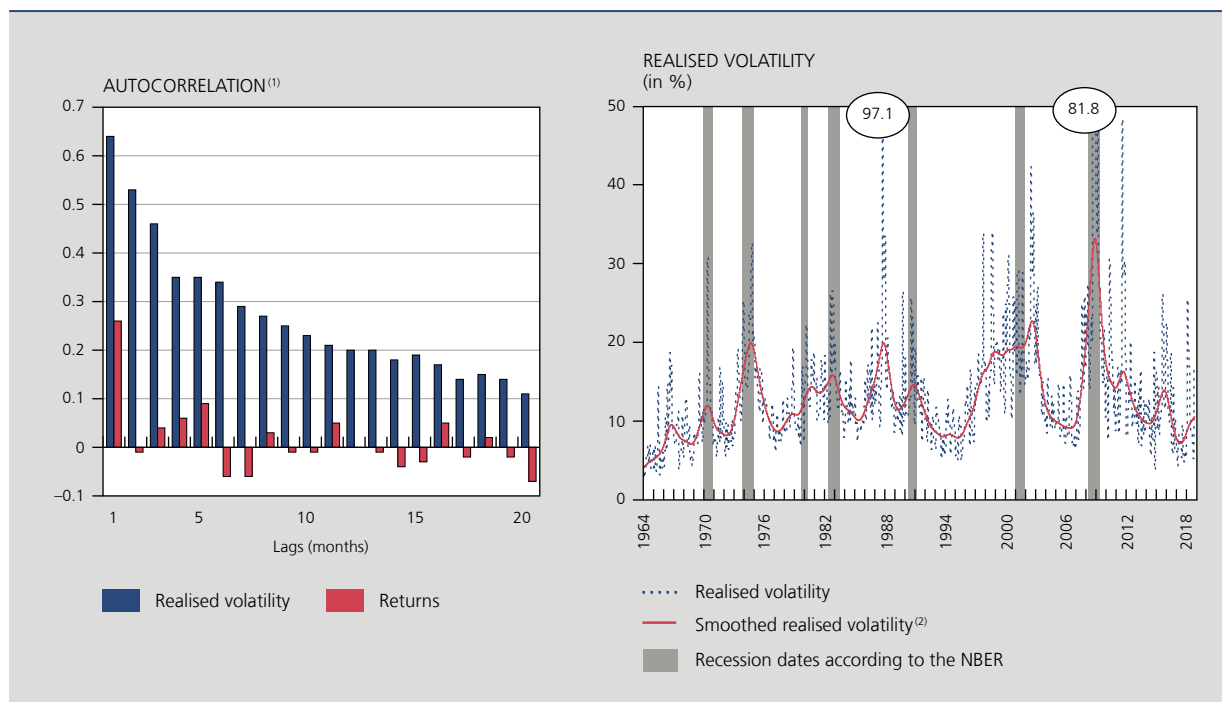
A great deal of research is still needed to gain a better understanding of financial market volatility and thus improve the volatility models. In particular, in the academic world there is no agreement as yet on what precisely determines volatility. However, the existing research provides useful insight into at least three characteristics of market volatility. This section illustrates those three characteristics by focusing on the American stock market, since this is the market on which most analysis has been done, and sufficient data are available to conduct historical empirical analysis. The volatility of the American stock market is assessed via the monthly realised volatility of the S&P 500 index, a measure which does not depend on any model and is based on a broad American index for which daily data are available going back several decades.

The first characteristic is that volatility displays a “long memory”, i.e. it is closely correlated over time (strong autocorrelation; see left-hand panel of chart 2). In the sample considered, the volatility of the S&P 500 index during a given month has a correlation of 0.64 with the previous month’s volatility (one-month lag). Year on year (12-month lag), the autocorrelation is still significant (0.20). This autocorrelation diminishes as the lag increases, but the decline is gradual and slow. For comparison, the autocorrelation of stock market returns is low. The correlation between the return in a given month and that in the previous month is only 0.26. The correlation is (not statistically different from) zero for lags of more than one month. In addition, a regression of realised volatility and the returns over their first 20 lags accounts for 45 % of the realised volatility and barely 11 % of the returns ( $R^2$  of regressions with a constant).

The “long memory” characteristic implies that volatility can be forecast solely on the basis of past volatility measurements. These forecasts are usually smoothed (with no sudden fluctuations) because they generally represent a weighted average of numerous estimates of volatility in the past.

The second characteristic is that volatility can be divided into a low-frequency and a high-frequency component (see the right-hand panel in chart 2). The low-frequency component varies relatively little over time; it indicates the general trend in volatility. The volatility’s long memory is attributable mainly to that component. The high-frequency component is more erratic, often varying as a result of specific events such as the publication of macroeconomic data, (unexpected) economic or monetary policy announcements, or incidents specific to the financial markets. For example, the high-frequency component captures the Black Monday crash of 19 October 1987, when the S&P 500 lost 20 % of its value in a single day.

**CHART 2** THE VOLATILITY OF THE S&P 500 FOLLOWS A “LONG MEMORY” PROCESS, BUT SUDDEN SPIKES MAY OCCUR



Sources: Thomson Reuters, NBB.

(1) Estimate based on data from 1 January 1964 to 31 October 2018.

(2) The low-frequency component of the realised volatility of the S&P 500 is estimated using a Hodrick-Prescott filter with a smoothing parameter equal to 500.

This second characteristic indicates that sudden surges in volatility are unpredictable. Fortunately, they are often only temporary, as was the case in February 2018. Generally speaking, sudden increases in the high-frequency component are much more common than recessions as defined by the National Bureau of Economic Research (NBER) in the United States, which suggests that these erratic increases have little connection with major economic developments.

The third characteristic is that the low-frequency component of volatility is potentially subject to occasional regime changes, as it is possible to identify periods in which volatility has been persistently higher. Those periods can be clearly linked to significant events or crises. For example, the low-frequency component increased in 1973 at the time of the oil shock, in the late 1990s at the time of the Asian/Russian crisis and the LTCM crisis, and at the time of the dot.com bubble. The component went up again during the latest financial crisis.

To sum up, these characteristics indicate that, if there is no change of regime – in other words, if no crisis erupts – market volatility is likely to develop relatively smoothly, though temporary spikes due to specific events cannot be ruled out. The fundamental question is whether a rise in the low-frequency component of volatility – i.e. a gradual, sustained rise – could have adverse consequences for the real economy or whether, from the opposite angle, persistently low volatility is risk-free. A number of important lessons can be derived from the historical empirical regularities discussed in the next section.

## 2. Lessons of the past

Research into the influence of financial market volatility on the real economy is hampered by a potential reverse causality dilemma: could it be that real activity influences volatility? The influence is likely to operate in both directions. Moreover, in some cases fluctuations in volatility and real activity are due to a third factor which affects both variables simultaneously. For example, that is probably what happened in the early 1980s when the US Federal Reserve (the Fed) began to tighten its monetary policy in order to combat runaway inflation. In doing so, the Fed simultaneously curbed real economic activity and created a degree of financial market volatility by influencing asset prices.

These endogeneity and simultaneity issues show how difficult it is to establish the links between market volatility and the real economy. This section therefore begins with a (brief) review of the literature on the subject before presenting the empirical results obtained on the basis of a historical database.

## 2.1 Review of the literature and stylised facts

### *Influence of the real economy on financial market volatility*

In theory, financial market volatility is influenced by the real economy. That connection is derived from traditional financial theory – the market efficiency theory – whereby the price of a financial asset “at any time fully reflects all available information” (Fama, 1970). Under certain conditions, this assumption implies that a share price is equal to the discounted value of the expected future dividends. Consequently, share price volatility depends on: (1) changes in the economic activity generating dividends, and (2) fluctuations in the discount rate.

Some of the academic literature from the 1980s criticised traditional financial theory and supported the idea that the volatility of stock market indices (especially the S&P 500) was too high compared to dividend volatility. This “excess volatility” was said to indicate the presence of “animal spirits” creating waves of optimism and pessimism on the financial markets without any link to the fundamentals (LeRoy and Porter, 1981; Shiller, 1981a, 1981b, 1981c, 1987 and 1990). The criticism is based on the “general theory” of John M. Keynes (1936) who argued that dealers are bound to have a “preference for immediacy”, whereby they devote their intelligence to anticipating what average opinion expects the average opinion to be, hence facilitating self-fulfilling price fluctuations.

This literature was largely rejected by supporters of traditional theory, pointing out that the excess volatility of stock market indices compared to that of dividends can be explained by the volatility of the discount rate (Fama, 1991; Cochrane, 2011). They also protested against the excess volatility tests which can only be conducted with underlying models: if stock market index volatility is considered excessive compared to predicted dividends or consumption trends, it is possible that incorrect or over-simplistic models are used to produce the dividend forecasts or to link the price of financial assets to consumption.

Whether financial market volatility is too high to be attributed to the fundamentals is a question still being debated today. Recently, researchers found that the business cycle had a considerable influence on the low-frequency component of volatility, while sudden spikes in volatility might be due partly to reversals of market sentiment (Adrian and Rosenberg, 2008; Engle and Rangel, 2008; Engle *et al.*, 2013; Corradi *et al.*, 2013; Chiu *et al.*, 2018).

### *Influence of financial market volatility on the real economy*

As regards the opposite connection, i.e. the influence of market volatility on the real economy, there are two different types of study: those that analyse the effects of an increase in volatility and those which examine the effects of a prolonged period of low volatility.

Three transmission channels for increases in market volatility are often mentioned in the literature (Fornari and Mele, 2013; Bekeart and Hoerova, 2014). First, heightened volatility can drive up firms’ funding costs. More specifically, investors will be inclined to demand a higher return (a reduction in the share purchase price) if they are unsure whether they can recoup their investment or sell their shares in the future at the desired price. Second, an increase in volatility may lead to postponement of investment projects. According to the “irreversible investment theory” (Bernanke, 1983), there is a trade-off between initiating a project (and making a quick return) and postponing it in order to gather information, e.g. on how the economic environment is changing, so as to arrive at a more accurate estimate of the project’s chances of success. Third, an increase in volatility can cause a loss of confidence and the accumulation of precautionary savings. In a risk-averse world, heightened uncertainty over (future) financial assets curbs (current) consumption.

In regard to the effects of a prolonged period of low volatility, there is some relatively old literature that may be relevant if low market volatility is considered equivalent to financial stability (or tranquillity) in general. As long ago as 1977, Hyman P. Minsky described how, in his view, a capitalist economy endogenously generates a financial structure subject to financial crises. In his own words, “stability is destabilising”. The basic idea is that long periods of financial stability foster

general optimism and encourage risk-taking. During such periods, profits net of taxes and interest charges are often positive, causing dividends to rise. If optimism prevails regarding the economy's future ability to generate profits, share prices may go up substantially. In addition, the debt level deemed acceptable rises, and growing numbers of market players engage in "speculative" financial activities (which requires constant renewal of the debt), or even Ponzi schemes, while financial intermediaries increase their leverage. According to this scenario, economic agents exhibit procyclical behaviour by increasing their debt burden during calm periods, so that they become more vulnerable in the event of a financial shock.

Minsky's idea has attracted renewed interest since the latest financial crisis, as the period of economic growth and financial stability from 2003 to 2007 seems to have been accompanied by excesses, particularly on the property market in the United States, thus paving the way to the ensuing financial crisis. Brunnermeier and Sannikov (2014) and Bhattacharya *et al.* (2015), among others, updated Minsky's original idea and renamed it the "volatility paradox". In their theoretical models, an environment in which the idiosyncratic risks are (perceived as) low – i.e. a low volatility environment – paradoxically exacerbates the risk of a systemic crisis since the market players are endogenously encouraged to take more risks, thus leading to an accumulation of systemic risks. Those mechanisms were confirmed empirically by Danielsson *et al.* (2018), who built up a historical database to show that periods of low volatility are often associated with abnormally strong credit expansion and increased leverage in the banking sector.

In addition, some recent analyses demonstrated modern mechanisms for risk-taking by financial intermediaries (ECB, 2017; OFR, 2017). For example, as well as taking more risks via the leverage effect and searching for yield, financial intermediaries may reduce the hedging of their positions. But other mechanisms are activated endogenously. For example, the widespread use of value-at-risk (VaR) models may give out the wrong signals in a period of low volatility because a reduction in volatility lowers a portfolio's VaR, thus enabling investors to expand their risky positions without exceeding a pre-set VaR limit. Furthermore, the financial innovations that proliferated before the last crisis (securitisation, credit default swaps, etc.) made it possible to hedge certain idiosyncratic risks, creating an impression of stability from the point of view of individual financial intermediaries without any reduction in the macrofinancial risks.

### ***Stylised facts***

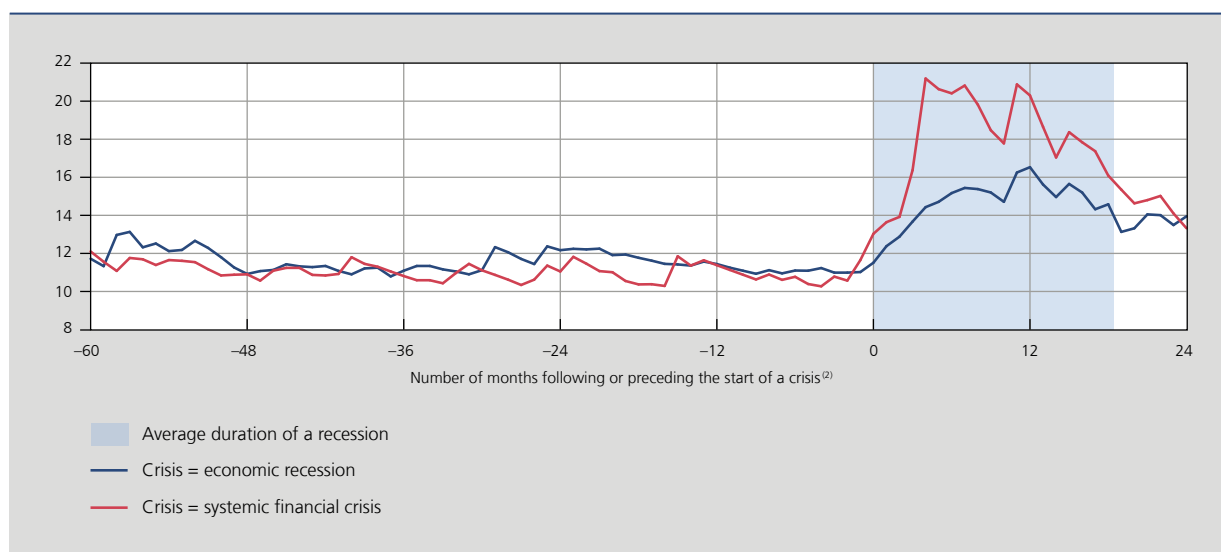
The dynamic of volatility during major economic and financial crises shows that various theories summarised above are relevant. For the moment, the analysis is confined to the United States because that country offers the longest series of asset prices. Robert Shiller supplies the S&P 500 index on a monthly basis since 1871, making it possible to estimate a monthly measure of conditional volatility. The period covers 29 American recessions identified by the NBER and defined as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales". The period also covers 6 systemic financial crises identified by Jordà *et al.* (2012) and defined as "events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions".

These data clearly indicate that the S&P 500 becomes more volatile during crises (see chart 3). The level of volatility is generally higher in the case of a systemic financial crisis than in an economic recession. However, it should be noted that volatility generally increases *after* the start of a crisis. It therefore seems that increased volatility is not usually the source of economic recessions or systemic financial crises, but seems to coincide with the crises and potentially accentuate them.

Conversely, it is clear that crises are typically preceded by lengthy periods of low volatility. That finding tallies with the hypothesis that prolonged periods of low volatility encourage risk-taking and lead to crises. The rest of this section examines in particular how long periods of low volatility influence the emergence of crises, by means of a more refined analysis based on econometric models.

**CHART 3** THE VOLATILITY OF THE S&P 500 TENDS TO INCREASE DURING CRISES AND TO BE LOW FOR A LONG PERIOD BEFORE THEY BEGIN <sup>(1)</sup>

(in %, annualised monthly volatility)



Sources: NBER, Robert Shiller, NBB.

(1) The conditional volatility of the S&P 500 is estimated on the basis of the GJR-GARCH(1,1,1) model with Student distribution. The NBER identifies 29 economic recessions in the United States since 1871. Jordà *et al.* (2017) also identified the dates of 6 systemic financial crises.

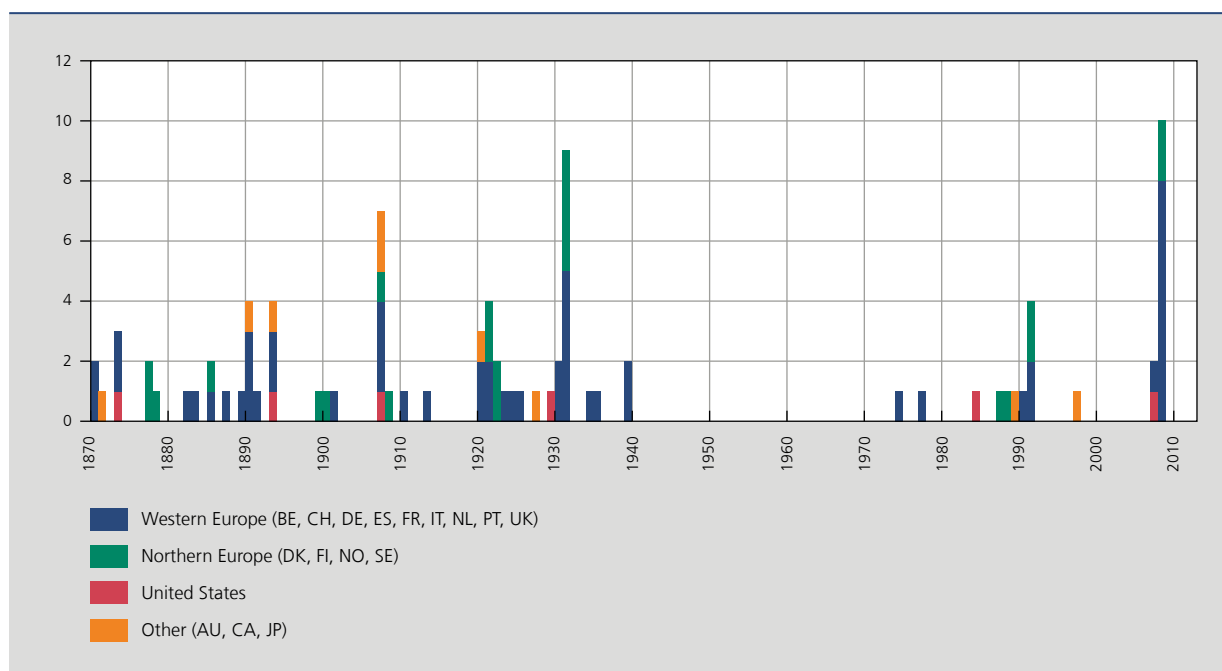
(2) The number of months after (before) the start of an economic recession is confined to the end of the (previous) recession. For the recession beginning in May 1937, only 29 months are taken into account (from January 1935), in order to exclude the volatility due to the Great Depression. For the recession that began in February 1945, only 13 months are taken into account (from January 1944), in order to exclude the volatility due to the war. For the recession starting in July 1990, the volatility due to Black Monday (19 October 1987) is disregarded. For the recession that began in October 1873, only 32 months are taken into account (start of the sample). According to the NBER, the average duration of a recession is 17.2 months.

## 2.2 Study based on a historical database

Systemic financial crises are the main focus of attention because they are generally more severe than classic economic recessions, and volatility seems to react more strongly to those crises. The historical database of Jordà *et al.* (2017) is an ideal information source since it covers a large number of countries over a long period. More specifically, it contains data on the financial systemic crises affecting 17 advanced economies since 1870, giving a total of 90 crises. The crisis dates used are similar to those reported by Bordo *et al.* (2001), Laeven and Valencia (2008), and Reinhart and Rogoff (2009). The database ensures that the results do not suffer from any lack of observations (on systemic financial crises in particular), or from any bias in favour of certain countries. However, it should be noted that the macrofinancial series in this database are only available on an annual basis.

The time profile of the systemic financial crises identified by Jordà *et al.* (2017) clearly captures the most serious financial crises (see chart 4). The most recent crisis affected 12 economies (out of 17): the United States and the United Kingdom from 2007 plus two economies in Northern Europe and eight in Western Europe from 2008. The database also covers the Great American Depression which began in 1929 (and affected the European economies from 1930 or 1931), the American bank run of 1907 which rapidly spread to the other advanced economies, the chaos of European reconstruction following the First World War, the Nordic banking crisis and the European exchange rate mechanism crisis in the early 1990s, etc.

**CHART 4** HISTORICAL PROFILE OF SYSTEMIC FINANCIAL CRISES



Source: Jordà *et al.* (2017).

### Predicting the emergence of systemic financial crises on the basis of financial market volatility

First, estimates of realised financial market volatility have to be derived from stock market indices. Since those are only available annually in the database of Jordà *et al.* (2017), it is not possible to estimate the realised volatility for a given year as the standard deviation of the (e.g. monthly) returns. The method used is therefore that of Schwert (1989), whose approach was to regress annual stock market returns on their own lags, to extract the residuals from that regression and to estimate the realised annual volatility as the absolute value of the residuals.

Since the data are only available on an annual basis, the volatility estimates are smoothed (using a three-year moving average) in order to avoid abnormal values. The volatility estimates are then broken down into a long-term trend and a cyclical component using the method of Hamilton (2017), which entails calculating the trend as the projection of volatility on its own lags (while the cyclical component is obtained as the difference)<sup>(1)</sup>.

The following logit model is estimated in a panel:

$$\text{logit}(I_{i,t}^{SFC}) = \alpha I_{i,t-1 \text{ to } t-5}^{SFC} + \beta \Gamma_{i,t-1 \text{ to } t-5} + \gamma X_{i,t-1 \text{ to } t-5} + \nu_t + \eta_i + \epsilon_{i,t}$$

where the dependent variable  $I_{i,t}^{SFC}$  takes the value "1" to indicate the starting date of a systemic financial crisis in country  $i$  at time  $t$ , and the value "0" in other cases. Among the explanatory variables, three measures of volatility are considered in turn in the term  $\Gamma$ . The first is simply realised volatility, denoted by  $\sigma$ . The second is the absolute value of the cyclical component:  $|c|$ . The third distinguishes between the positive cyclical component ( $c^+$ ), i.e. where volatility exceeds its trend or takes the value 0, and the negative component ( $c^-$ ), where volatility is below its trend or takes the value 0. The time indices " $t - 1$  to  $t - 5$ " indicate that the variables are introduced in the form of retrospective moving averages over five years (to capture prolonged periods of low volatility). Introducing the explanatory variables with a lag eliminates the endogeneity problem if it is assumed that the explanatory variables are predetermined. In addition, various control variables are included in the model (vector  $X$ ) in an attempt to take account of the macroeconomic environment.

(1) For both the Schwert and the Hamilton method, a second-order autoregressive model is recommended by t-tests.



These control variables are the (logarithm of) real per capita GDP, inflation, the change in the public debt/GDP ratio, the current account as a ratio of GDP, and the real short-term interest rate. The elements  $\nu_t$  and  $\eta_i$  respectively represent fixed effects per decade and per country;  $\epsilon_{i,t}$  corresponds to the error term.

The estimation of the first model indicates that the realised stock market index volatility cannot, in itself, explain the emergence of systemic financial crises (see table 1). The effect of a change in the level of volatility is not statistically significant (for a confidence interval of 90%), regardless of whether the control variables are taken into account. In contrast, the absolute value of the cyclical component of volatility does seem to have predictive power. It therefore seems that if volatility deviates from its trend in either direction, that implies a greater risk of a systemic financial crisis.

The distinction between the positive and negative cyclical components reveals that the direction in which volatility deviates from its trend is significant. On the one hand, the results show that the positive cyclical component of volatility is not particularly good at predicting the emergence of systemic crises, since the 90% confidence interval of the coefficient includes 0 if we control for the macroeconomic environment. On the other hand, the negative cyclical

**TABLE 1** LOGIT MODEL <sup>(1)</sup>: PROLONGED PERIODS OF LOW VOLATILITY PRESAGE SYSTEMIC FINANCIAL CRISES

Dependent variable: $I_{i,t}^{SFC}$	1	2	3	4	5	6
$\sigma_{i,t-1 \text{ to } t-5}$ .....	0.78 (1.69)	1.22 (1.78)				
$ c _{i,t-1 \text{ to } t-5}$ .....			9.38** (4.55)	10.47* (6.27)		
$c_{i,t-1 \text{ to } t-5}^+$ .....					8.53* (4.67)	8.52 (6.03)
$c_{i,t-1 \text{ to } t-5}^-$ .....					-12.07* (6.88)	-16.20** (7.52)
$I_{i,t-1 \text{ to } t-5}^{SFC}$ .....	-10.57*** (2.00)	-11.34*** (2.24)	-10.47*** (1.98)	-11.24*** (2.25)	-10.51*** (1.98)	-11.24*** (2.27)
$\ln(GDP)_{i,t-1 \text{ to } t-5}$ .....		0.43 (0.75)		0.48 (0.86)		0.39 (0.85)
$inflation_{i,t-1 \text{ to } t-5}$ .....		9.30*** (3.57)		9.21*** (3.88)		9.80*** (3.81)
$\Delta \frac{\text{public debt}}{GDP}_{i,t-1 \text{ to } t-5}$ .....		-9.89** (4.05)		-9.48** (4.23)		-9.65** (4.17)
$\frac{\text{current account}}{GDP}_{i,t-1 \text{ to } t-5}$ .....		-5.96 (3.84)		-5.24 (4.30)		-4.88 (4.38)
$interest\ rate_{i,t-1 \text{ to } t-5}$ .....		0.03 (0.05)		0.05 (0.05)		0.05 (0.05)
Number of observations .....	1 734	1 510	1 683	1 480	1 683	1 480
Pseudo R <sup>2</sup> .....	0.24	0.37	0.26	0.38	0.26	0.39
<b>Marginal effects</b>						
$\sigma_{i,t-1 \text{ to } t-5}$ .....	0.03 (0.07)	0.05 (0.07)				
$ c _{i,t-1 \text{ to } t-5}$ .....			0.41** (0.19)	0.43* (0.26)		
$c_{i,t-1 \text{ to } t-5}^+$ .....					0.37* (0.20)	0.35 (0.25)
$c_{i,t-1 \text{ to } t-5}^-$ .....					-0.52* (0.30)	-0.66** (0.31)

Sources: Jordà et al. (2017), NBB.

(1) Logit model estimated in a panel over the period 1870-2013. The explanatory variables are included in the form of a retrospective moving average over five years.

The robust standard errors are shown in brackets. Fixed effects are included per decade and per country. The confidence intervals of 90, 95 and 99% which do not include 0 are indicated respectively by one, two or three asterisks.

component is clearly significant, even if the control variables are included in the model. That result is precisely the main conclusion of Danielsson *et al.* (2018)<sup>(1)</sup>. Depending on the estimated marginal effect, a 1 percentage point fall in the negative cyclical component of volatility increases the probability of a systemic financial crisis by 0.66 percentage point, all other things being equal.

The historical database of Jordà *et al.* (2017) provides an opportunity for testing the Minsky hypothesis in more detail. First, it is demonstrated that periods of low volatility associated with stock market bubbles presage more serious and prolonged economic recessions. Next, periods of low volatility are linked to credit boom periods.

### *Profile of economic recessions at various levels of market volatility*

According to the scheme described by Minsky (1977), financial asset prices may rise steeply during periods of financial stability. If that is so, the higher prices could reflect excessive optimism and increased risk-taking, which could turn against the economy in the long term.

To test this hypothesis, it is necessary to be able to identify stock market bubbles. The strategy used in this article is comparable to the methodology of Jordà *et al.* (2015). Two signals are needed. The first signal is overvaluation that occurs when a stock market index significantly exceeds its long-term trend, estimated with the aid of the Hodrick-Prescott filter<sup>(2)</sup>. The second is a correction signal: the index has to fall by at least 15 % in three years. A bubble is identified on a given date if: (1) an overvaluation signal is given on that date, and (2) a correction signal is given on that date or in the three preceding years.

The model shows the impact of periods of low volatility on real GDP growth per capita during economic recessions. It is similar to a local projection as described by Jordà (2005). Economic recession years are identified simply as years in which GDP declined<sup>(3)</sup>. The estimated model is as follows:

$$\Delta_h \mathcal{Y}_{i,t(p)} = \left( \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} \right) + \mu_h + \beta_h^{low} \delta_{i,t(p)}^{low} + \beta_h^{high} \delta_{i,t(p)}^{high} + \gamma_h^{low} d_{i,t(p)} \delta_{i,t(p)}^{low} + \gamma_h^{normal} d_{i,t(p)} \delta_{i,t(p)}^{normal} + \gamma_h^{high} d_{i,t(p)} \delta_{i,t(p)}^{high} + \Phi X_{i,t(p)} + \epsilon_{i,t(p)},$$

in which  $\mathcal{Y}_{i,t(p)}$  is the logarithm of the GDP of country  $i$  in year  $t$  corresponding to peak  $p$ , or the moment when GDP reaches a maximum before declining for at least one year. The term  $\Delta_h \mathcal{Y}_{i,t(p)}$  corresponds to the cumulative (percentage) change in GDP during  $h = 1, 2, \dots, 5$  years after the start of a recession. The  $D_i$  represent the fixed effects of 16 (of the  $I = 17$ ) advanced economies, and  $\mu_h$  the fixed effect of the United States, used as the benchmark to estimate the typical path of GDP in a recession. The terms  $\delta^{low}$ ,  $\delta^{normal}$  and  $\delta^{high}$  are dummy variables which indicate when volatility is low, normal or high. The variable  $\delta^{low}$  takes the value 1 when the (five-year average of the) negative cyclical component of volatility is less than its average. Conversely, the variable  $\delta^{high}$  takes the value 1 when the positive and negative cyclical components exceed their average. The variable  $\delta^{normal}$  takes the value 1 whenever neither  $\delta^{low}$  nor  $\delta^{high}$  is equal to 1. Owing to their colinearity, these three variables therefore cannot be included simultaneously in the model. Consequently, only  $\delta^{low}$  and  $\delta^{high}$  are present. However, they can be used simultaneously if they are combined with the dummy variable indicating a stock market bubble. The term  $d_{i,t(p)}$  indicates whether or not the year  $t(p)$  in country  $i$  is associated with a bubble. The vector  $X$  contains the same control variables as before (with the exception of GDP which is now the dependent variable).

The results show that a typical economic recession leads to a decline in GDP of around 2 % in the first year (see the line with the term  $\mu_h$  in table 2). In the second year, GDP expands again but without entirely making good the first year's losses (note nonetheless that  $\mu_h$  is not statistically different from 0 in the second year). GDP exceeds its previous peak in the third year and continues to rise thereafter.

(1) This result stands up to numerous robustness tests (Danielsson *et al.*, 2018).

(2) The cyclical component of the index must exceed once times its standard deviation. Smoothing parameter is 100 (annual data).

(3) Since the data are annual, this strategy for identifying economic recessions corresponds to the algorithm of Bry and Boschan (1971). Also, a series of years in which GDP declines continuously is considered as a single recession. The same applies if the series is only interrupted for one year.

**TABLE 2** LOCAL PROJECTIONS <sup>(1)</sup>: PERIODS OF LOW VOLATILITY LINKED TO FINANCIAL BUBBLES PRESAGE MORE SEVERE AND PROLONGED ECONOMIC RECESSIONS

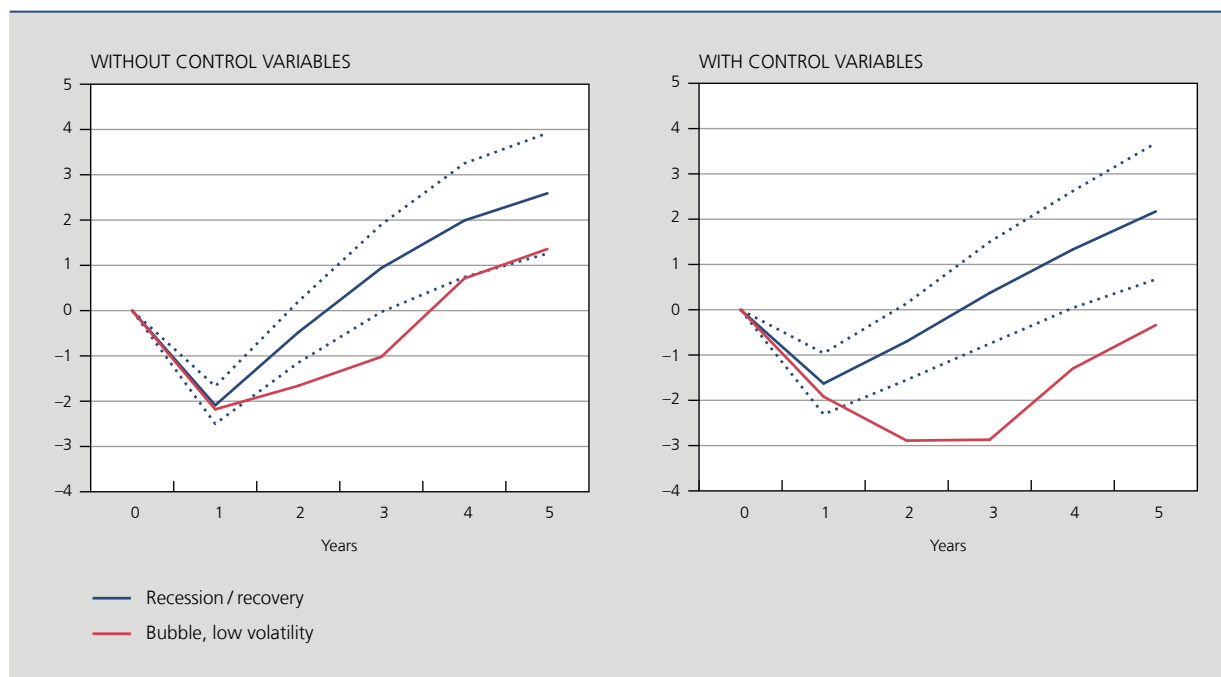
Dependent variable: $\Delta_h \mathcal{Y}_{i,t(p)}$	Year					Year				
	1	2	3	4	5	1	2	3	4	5
$\mu_h$ .....	-2.09*** (0.40)	-0.48 (0.66)	0.94 (0.94)	1.99* (1.22)	2.59** (1.30)	-1.63*** (0.66)	-0.70 (0.82)	0.37 (1.09)	1.32* (1.26)	2.17* (1.47)
$\delta_{i,t(p)}^{low}$ .....	-0.60 (0.64)	-1.42* (0.10)	-0.67 (1.59)	-0.60 (1.99)	-0.08 (1.95)	-0.37 (0.65)	0.03 (0.84)	0.95 (1.24)	0.58 (1.64)	0.32 (1.94)
$\delta_{i,t(p)}^{high}$ .....	-0.60* (0.56)	-1.65* (1.20)	-1.52 (1.73)	-2.08 (2.25)	-0.64 (2.44)	-0.80* (0.66)	-1.52* (1.47)	-0.33 (1.40)	-2.97 (3.21)	-0.41 (3.72)
$d_{i,t(p)} \delta_{i,t(p)}^{low}$ .....	-0.09 (0.94)	-1.18* (1.02)	-1.96* (1.67)	-1.28 (2.30)	-1.23 (2.41)	-0.29 (0.85)	-2.19*** (0.84)	-3.24*** (1.40)	-2.63* (1.93)	-2.51* (2.21)
$d_{i,t(p)} \delta_{i,t(p)}^{normal}$ .....	-0.29 (1.14)	-0.84 (1.78)	-1.05 (2.50)	0.17 (2.93)	0.70 (3.23)	-0.51 (1.50)	-1.24 (1.74)	-1.68 (2.38)	-0.80 (2.73)	-1.40 (2.91)
$d_{i,t(p)} \delta_{i,t(p)}^{high}$ .....	-0.43 (0.56)	-0.21 (1.19)	0.00 (1.99)	0.83 (3.09)	2.08 (3.35)	-0.07 (0.65)	0.13 (1.64)	-1.20 (2.86)	0.86 (4.38)	1.02 (4.93)
Control variables .....	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Number of observations ..	288	280	269	265	264	230	227	216	212	211

Sources: Jordà *et al.* (2017), NBB.

(1) Model estimated in a panel over the period 1870-2013. The robust standard errors are shown in brackets. The confidence intervals of 90, 95 and 99% which do not include 0 are indicated respectively by one, two or three asterisks.

**CHART 5** LOCAL PROJECTIONS: CUMULATIVE GDP GROWTH IN AN ECONOMIC RECESSION

(in %, confidence intervals of 68%)



Sources: Jordà *et al.* (2017), NBB.

Periods of low volatility as such, designated by the term  $\delta_{i,t(p)}^{low}$ , do not appear to exacerbate or prolong economic recessions: the coefficient of the variable is (negative and) significant only in the second year, and the significance vanishes if the control variables are included in the model. However, periods of low volatility linked to financial bubbles presage more severe and prolonged recessions: the coefficients of the interaction term  $d_{i,t(p)}\delta_{i,t(p)}^{low}$  are often significant, even if the macroeconomic variables are included in the model. These results may be due to the fact that a low volatility environment does not have any major negative impact on the real economy unless it gives rise to greater optimism or increased risk-taking which may be reflected, for example, in a substantial rise in share prices<sup>(1)</sup>.

The typical path of GDP in a recession with low volatility and a financial bubble is illustrated in chart 5. The blue lines represent the coefficient  $\mu_h$  and the confidence interval of 68 % around that coefficient (a standard confidence interval for local projections). The red lines represent the sum of coefficient  $\mu_h$  and the coefficient of the variable  $d_{i,t(p)}\delta_{i,t(p)}^{low}$  which indicates low volatility linked to a financial bubble. GDP does not decline noticeably more sharply in the first year, but takes longer to make good the losses. If we consider only the results that take account of the control variables, GDP actually continues to fall in the second year until it is about 3 % below the previous peak. GDP then stabilises in the third year, and only begins to increase from the fourth year.

In view of the lack of significance of the variable  $\delta_{i,t(p)}^{high}$ , high volatility preceding a recession does not appear to make the recession particularly more acute. Nonetheless, above-normal volatility does seem to predict a sharper fall in GDP at the beginning of a recession. That result could be due to the use of annual data, which implies that increases in volatility generally start a bit earlier than recessions because the increase in volatility may be sudden and substantial<sup>(2)</sup>. In addition, the interaction variables  $d_{i,t(p)}\delta_{i,t(p)}^{high}$  and  $d_{i,t(p)}\delta_{i,t(p)}^{normal}$  are not significant, indicating that only financial bubbles accompanied by low volatility are a reliable sign of excessive risk-taking which could ultimately be detrimental to the real economy.

To sum up, periods of low volatility may be harmful to the real economy if they lead to widespread optimism and/or increased risk-taking, generating a financial bubble, for example. But widespread optimism and increased risk-taking may also arise in other ways, such as via excessive credit expansion and debt, as Minsky proposes. In fact, Jordà *et al.* (2015) have already shown in a similar exercise that strong credit growth combined with a stock market bubble and (especially) a property market bubble exacerbates and prolongs economic recessions. These findings therefore suggest a link between periods of low volatility and a credit boom (see next sub-section).

### ***The link between periods of low volatility and a credit boom***

The database of Jordà *et al.* (2017) includes the outstanding bank loans to the non-financial private sector. Those series can be used to estimate a model similar to that of Danielsson *et al.* (2018) who link the credit-to-GDP gap to a number of macroeconomic variables. The credit-to-GDP gap is the difference between the credit-to-GDP ratio and its long-term trend<sup>(3)</sup>. More specifically, the model of Danielsson *et al.* (2018) regresses the positive component of the credit-to-GDP gap on the cyclical components of volatility and on a number of control variables.

The model is estimated four times, for different periods and countries (see table 3). The first two estimates – with and without control variables – consider the longest credit series, namely the series starting in 1880, for 10 of the 17 advanced economies in the sample (Canada, Denmark, Finland, Italy, Japan, Norway, Sweden, Switzerland, the United Kingdom and the United States). The other two estimates consider the credit series from 1950 for all the advanced economies (including Australia, Belgium, France, Germany, the Netherlands, Portugal and Spain). The four estimates produce similar results: the effect of a prolonged period of low volatility is statistically significant, whereas the impact of a prolonged period of high volatility is not. When the credit-to-GDP gap is positive, all other things being equal, a 1 percentage point fall in the low market volatility component increases the credit-to-GDP gap by between 15 and 21 basis points of GDP (depending on the country and period considered). According to these findings, periods of low volatility therefore stimulate lending.

(1) The results stand up to numerous robustness tests, including for the historical periods taken into account. Those tests are not described in detail for reasons of conciseness. Just as in the case of Jordà *et al.* (2015), the results presented are rationalised taking account of specific economic developments observed in certain countries during the two world wars.

(2) For example, an increase in volatility and a decline in GDP may occur at the end of year *t*. If the increase in volatility is sufficiently sudden, year *t* will be considered a high volatility year. Conversely, if the decline in GDP is relatively gradual, year *t* might not be seen as a recession year whereas year *t*+1 could be.

(3) The long-term trend in the credit-to-GDP ratio is estimated with the aid of a Hodrick-Prescott filter with a smoothing parameter equal to 100 (annual data).

These results are important because credit variables such as the credit-to-GDP gap are in practice widely used as early warning indicators of future financial crises. These credit variables generally obtain the best scores in terms of the “area under the curve” (AUC). This is a statistic measuring the reliability of the signals given by one or more variables by combining correct predictions with incorrect signals. This statistic can also be calculated for low volatility indicators. If the AUC is equal to (i.e. not statistically different from) 50 %, that means that the signals given by the low volatility indicators are just as random as those obtained by tossing a coin. If the AUC were to be 100 %, the signals would be perfect at predicting crises (and the absence of crises).

**TABLE 3** PERIODS OF LOW VOLATILITY STIMULATE LENDING<sup>(1)</sup>

Dependent variable: $credit\text{-}to\text{-}GDP\ gap_{i,t}^+$	Data since 1880 for 10 countries	Data since 1880 for 10 countries	Data since 1950 for 17 countries	Data since 1950 for 17 countries
$c_{i,t-1\ to\ t-5}^+$ .....	0.19 (4.62)	11.11 (6.35)	6.53 (6.35)	10.46 (6.71)
$c_{i,t-1\ to\ t-5}^-$ .....	-15.06** (6.27)	-18.02* (9.29)	-16.00* (8.59)	-21.20** (8.95)
$credit\text{-}to\text{-}GDP\ gap_{i,t-1\ to\ t-5}^+$ .....	0.27*** (0.07)	0.22** (0.07)	0.38*** (0.08)	0.34*** (0.06)
$\ln(GDP)_{i,t-1\ to\ t-5}$ .....		1.43 (0.87)		2.29** (1.00)
$inflation_{i,t-1\ to\ t-5}$ .....		-4.82* (2.06)		-14.00** (5.10)
$\Delta \frac{public\ debt}{GDP}_{i,t-1\ to\ t-5}$ .....		-7.34 (4.82)		-22.69** (9.52)
$\frac{current\ account}{GDP}_{i,t-1\ to\ t-5}$ .....		-11.88** (4.00)		-15.20* (7.73)
$interest\ rate_{i,t-1\ to\ t-5}$ .....		0.04 (0.02)		0.08 (0.07)
Number of observations .....	956	815	986	963
R <sup>2</sup> .....	0.13	0.16	0.12	0.14

Sources: Jordà *et al.* (2017), NBB.

(1) Model estimated in a panel over the period 1870-2013. The robust standard errors are shown in brackets. The credit-to-GDP gap is the difference between the credit-to-GDP ratio and its long-term trend, which is estimated with the aid of a Hodrick-Prescott filter with a smoothing parameter equal to 100 (annual data). The confidence intervals of 90, 95 and 99 % which do not include 0 are indicated respectively by one, two or three asterisks.

The logit model introduced above serves as the benchmark. The AUC value of the model that only includes the control variables and the fixed effects is equal to 75.83 %. If we also take account of the positive component of the credit-to-GDP gap, calculated using the method of Hamilton (2017) for a (virtually) real-time estimate similar to that of the cyclical component of volatility<sup>(1)</sup>, the AUC increases significantly to 79.69 %. That result proves that the credit-to-GDP gap is reliable as an early warning indicator and is consistent with the estimates of Jordà *et al.* (2012). If we add the negative cyclical component of volatility to the model which already includes the credit variable, the AUC value goes up slightly to 80.02 %<sup>(2)</sup>. In the light of that result, it does not appear clearly that monitoring financial market volatility as well as credit developments is a better way of anticipating systemic financial crises. That finding is logical to some extent since it was demonstrated that prolonged periods of low volatility tend to lead to a widening of the credit gap. Also, it seems that a crisis is less likely after a period of low volatility if there is no accompanying excessive credit expansion. However, more analysis is needed on that finding (in a future research project). Danielsson *et al.* (2018) consider, for example, that the addition of their measure of low volatility to the credit gap significantly increases the AUC of their logit model. It is also possible that the signals given by the low volatility indicators precede the ones given by the credit variables, so that they could supplement them.

(1) As recommended by Hamilton (2017), a fourth order autoregressive model is used to predict the credit-to-GDP ratio for the next five years. The whole sample is taken into account in estimating the coefficients.

(2) A similar result is obtained if the credit gap is replaced by the financial bubble indicator. In principle, a real-time financial bubble indicator ought to be developed, but for the sake of brevity, we keep the indicator presented in the previous sub-section of the article (which is not calculated in real time). The simple logit model with the financial bubble indicator gives an AUC of 77.92 %, and if the negative cyclical component of volatility is added the AUC only rises to 78.11 %.

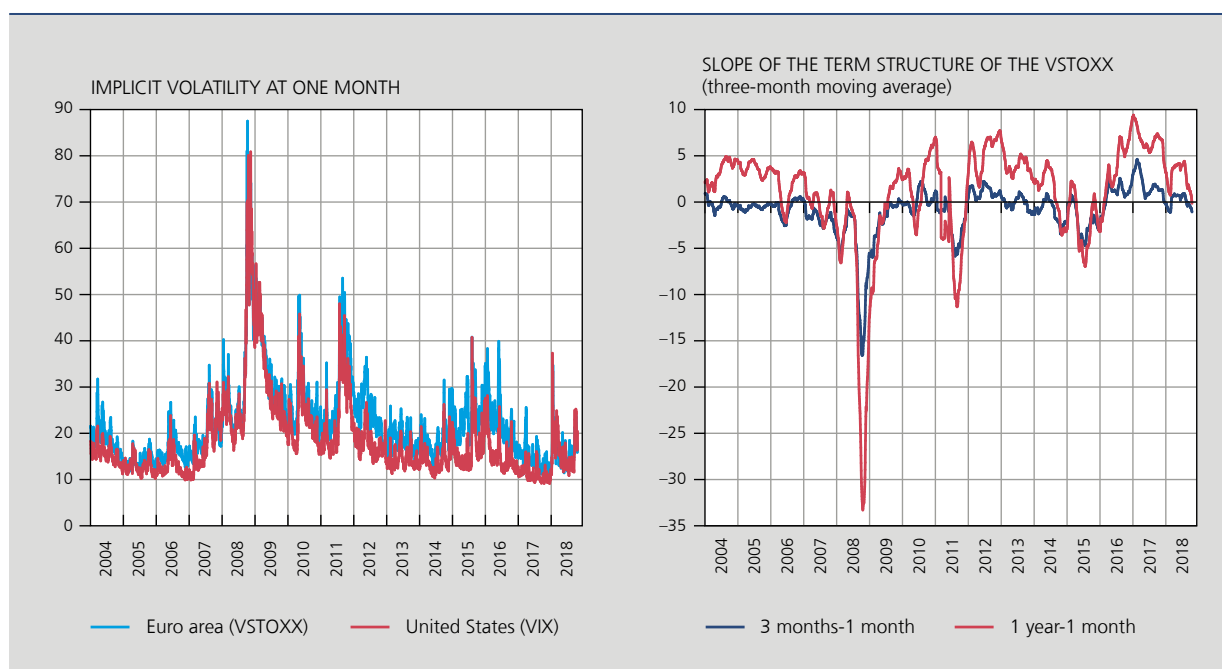
### 3. The current situation in the euro area

The current situation is analysed from three angles: financial market volatility, the potential materialisation of excessive risk-taking – in terms of financial asset prices and credit developments – and the effects of monetary policy.

#### *Financial market volatility*

Mirroring the American volatility measures, the volatility of stock markets in the euro area began to decline after the Brexit vote in mid-2016 (see chart 6). At the end of 2017, the one-month VSTOXX index – which measures the implicit volatility of the Euro Stoxx 50 over the next 30 days – stood at 10%, a level comparable to the pre-crisis figure. This decline in volatility was probably due in part to the favourable economic situation at that time, and the resolutely accommodative monetary policy stance (see also ECB, 2017).

**CHART 6** STOCK MARKET VOLATILITY: CHANGE OF DYNAMIC IN 2018?  
(in %, annualised volatility)



Source: Thomson Reuters.

However, in February 2018, market volatility suddenly increased following the publication of inflation and employment figures in the United States. Those figures suggested that the Fed might normalise its monetary policy more quickly than expected, triggering a sharp fall in stock market indices. The one-month VIX and VSTOXX indices jumped to 40% and 30% respectively. In the ensuing weeks, the indices gradually declined, dropping to 12% in May. This episode therefore seems to form part of the high-frequency component of volatility, i.e. an (almost) unforeseeable increase in volatility with no significant impact on the real economy.

In October 2018, there was another stock market correction and a further spike in volatility – the one-month VIX and VSTOXX went up to 25% and 21%. This indicates that the markets are still very responsive to specific announcements related to, for instance, monetary policy, trade disputes, political tensions (Brexit, Italy), and the publication of slightly disappointing macroeconomic data. When this article was written, it was too soon to judge the duration of this period of volatility. Consequently, there is a possibility that the year 2018 may mark the transition from relatively calm stock markets to a more turbulent climate.

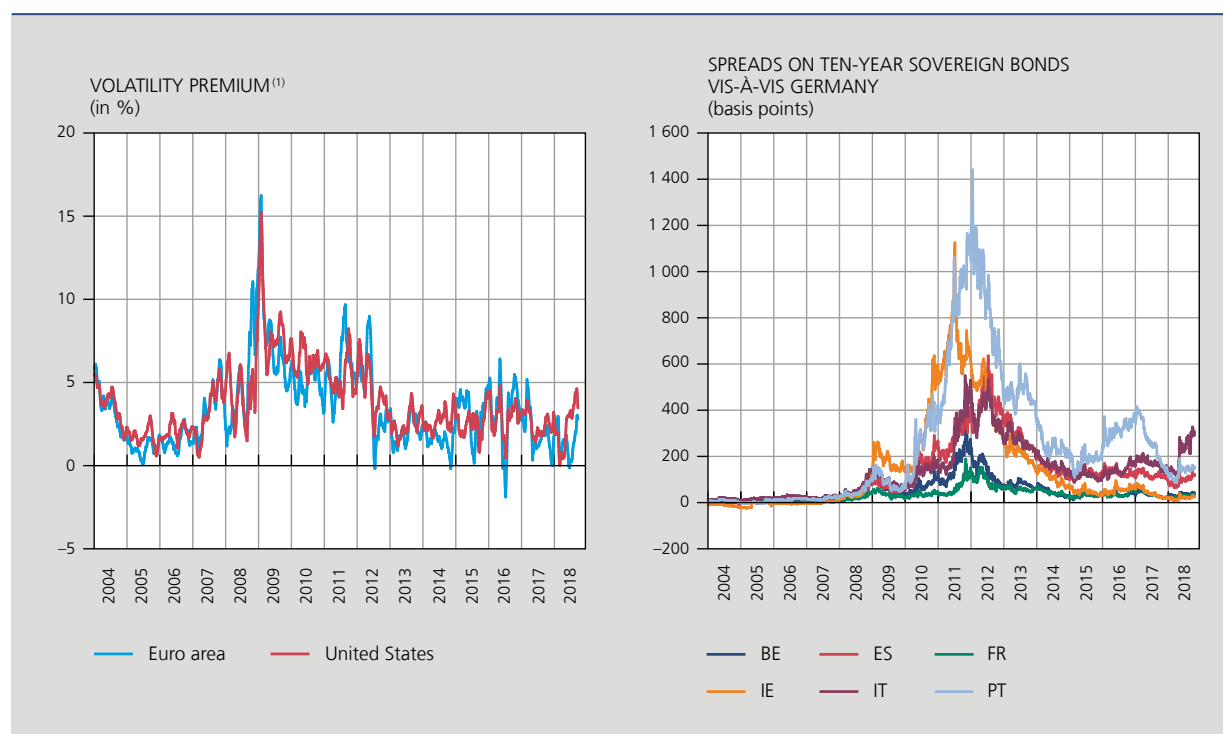
The market volatility dynamics described above are reflected in the term structure of the VSTOXX indices. While market volatility and risk premiums were generally low at the end of 2017, the positive slope of the term structure of the VSTOXX indices probably reflected expectations of increased volatility. In 2018, following the stock market correction in October, the term structure levelled out in view of the sudden rise in the VSTOXX indices for short maturities and the relative stability of the indices for longer maturities. That levelling out indicates that the markets probably do not expect the VSTOXX indices for short maturities to continue rising in the months ahead.

In 2018, the risk premiums for volatility – or volatility premiums – appeared to be heading towards higher values (see chart 7). These premiums are calculated as the difference between the implicit volatility and a forecast of realised volatility. They have to be estimated on the basis of a forecasting model, and the chosen model may affect the estimates, making it more difficult to interpret the movements in volatility premiums. In general, volatility premiums are positive since investors usually assume that volatility will be higher than forecast when pricing a derivative, in order to avoid the risk that their forecast underestimates the realised volatility (risk aversion). Nonetheless, the volatility premiums according to the model used in this article were practically zero at the end of 2017. However, in 2018, the volatility premiums seem to have reverted to more positive values. Higher volatility premiums could be a sign of increased wariness on the part of investors.

Other measures of risk premiums – not based on models – tended to rise in 2018. For example, sovereign spreads in relation to Germany widened slightly in peripheral euro area countries in February 2018 as a result of financial market turbulence. In May 2018, Italian interest rate differentials widened more significantly following the formation of the new government, and that had partial repercussions on some other spreads. Similarly, the premiums on credit default swaps on bank and sovereign bonds and the spreads on corporate bonds also increased in 2018.

Although volatility premiums and certain other risk premiums seemed to be rising in 2018, it is prudent to consider that the low volatility environment may still exist so that risks are still being accumulated. The implicit volatility was

**CHART 7** INCREASE IN RISK PREMIUMS IN 2018



Sources: Thomson Reuters, NBB.

(1) The volatility forecasts of the S&P 500 and Euro Stoxx 50 indices recorded over 22 days are based on a model similar to model 8 of Bekaert and Hoerova (2014). That model predicts the realised volatility on the basis of three variables with a 1-month lag: realised volatility, the average realised volatility over one week, and the average over one month. The premiums are obtained as the difference between the one-month VIX/VSTOXX and the predicted realised volatility, and are smoothed by means of a 45-day centred moving average.

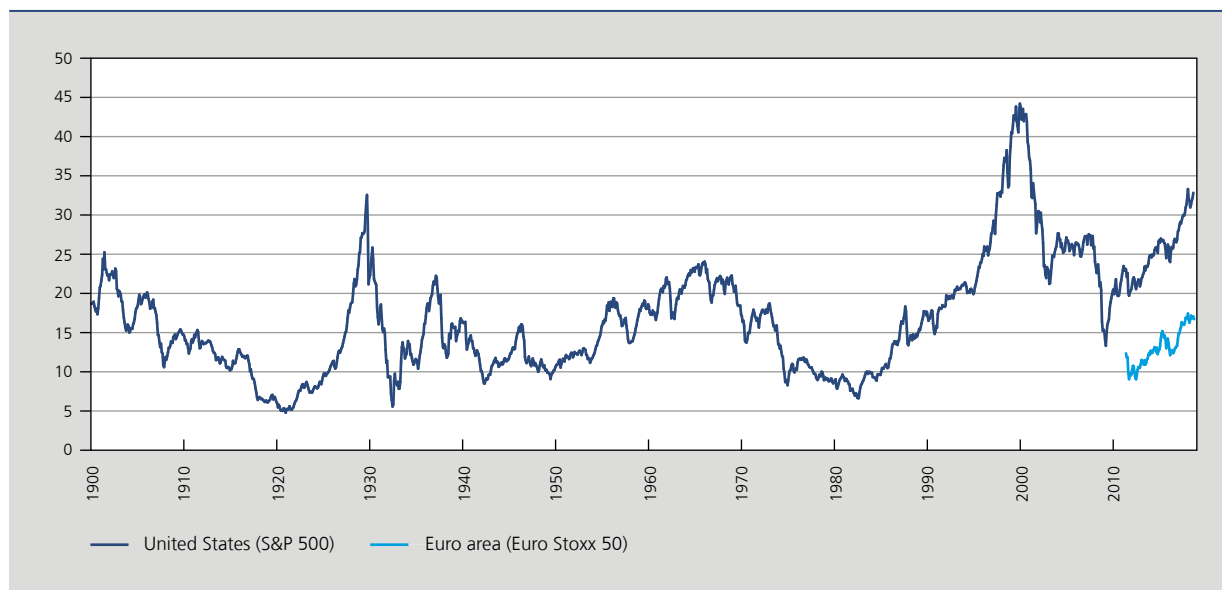
still particularly low prior to the sudden rise in October 2018, an increase which might not be sustained. It is therefore desirable to examine indicators that reveal the existence of optimism and excessive risk-taking.

### Asset prices and credit developments

It is not possible to calculate the financial bubble indicator used in the previous chapter because it is not available in real time, as there is no way of predicting whether the stock market indices will fall by at least 15% over the next three years. Conversely, other indicators which are often used to assess asset prices are easy to calculate. For example, in the United States there has been a noticeable divergence in recent years between share prices and corporate earnings. The S&P 500 price/earnings ratio increased from 15 in 2012 to 24 in 2018 owing to the relatively slow growth of corporate earnings. According to Robert Shiller, the cyclically adjusted price/earnings ratio reached 33 in 2018 (see chart 8). In judging the (fairly high) level of this ratio, it is necessary to be aware that it is comparable to the ratio in 1929, immediately before the Great Depression. In the euro area, the divergence between share prices and earnings in the post-crisis recovery period was not as great. The Euro Stoxx 50 price/earnings ratio has even declined slightly in recent years, dropping to 15 in 2018, while the cyclically adjusted ratio stands at 16.

Apart from share prices, sovereign and corporate bond prices were generally high in 2018. That is largely due to the fall in monetary policy interest rates and the asset purchases made by central banks to support inflation and economic activity following the financial crisis. The banking channel usually passes on this general decline in interest rates in its loans to households and non-financial corporations, stimulating demand for credit and helping to reinvigorate the economy.

**CHART 8** CYCLICALLY ADJUSTED PRICE/EARNINGS RATIOS HAVE RISEN IN THE UNITED STATES AND THE EURO AREA SINCE THE LAST FINANCIAL CRISIS <sup>(1)</sup>



Sources: Robert Shiller, Thomson Reuters, NBB.

(1) Cyclically adjusted price/earnings ratios are calculated as real share prices divided by the 10-year average of real earnings.

In regard to bank credit, it is noticeable that the pre-crisis period featured relatively strong credit expansion in the euro area (see chart 9). In 2007, the annual average growth rate was about 10% for households and reached 13% for non-financial corporations. There were also some clear excesses in certain countries. For example, at the end of 2005, the growth rates for lending to households in Estonia, Ireland and Slovenia stood at 69%, 27% and 25% respectively. The picture was similar in the case of lending to non-financial corporations.

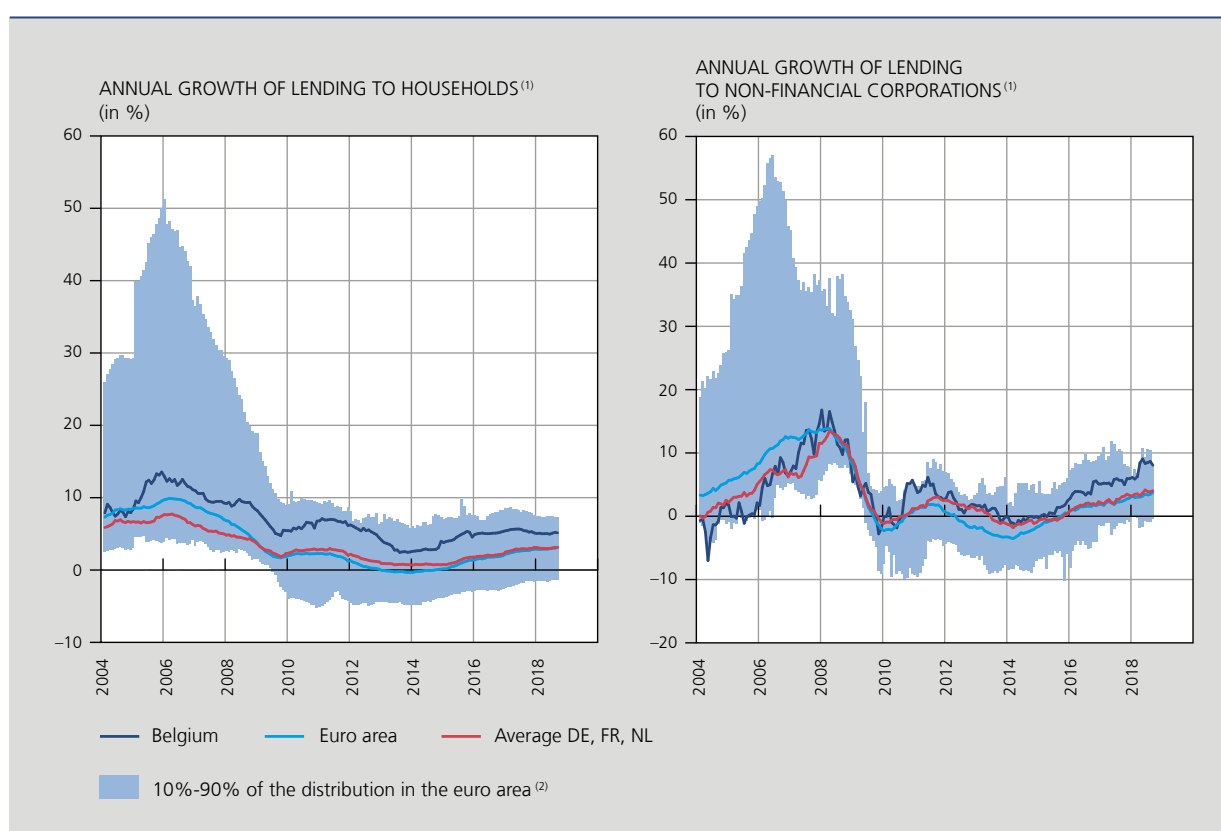
Since the crisis, lending has regained momentum in the euro area, although the expansion is much more reasonable than in the period preceding the crisis. The growth of lending to households increased in the euro area from a slightly



negative figure at the beginning of 2014 (−0.3% in January) to +3.1% in September 2018. Over the same period, the growth of lending to businesses increased from −3.3% to +3.7%. A similar upward trend can be seen in the statistics on credit-to-GDP gaps.

Although this revival is partly due to the successful transmission of monetary policy, the strengthening of the credit cycle in the euro area still needs to be monitored closely in order to avoid excessive lending in certain Member States. In that connection, some Member States decided to activate a countercyclical capital buffer as part of their macroprudential policy. That buffer is meant to be increased gradually if credit developments tend to indicate an accumulation of systemic risks. The primary intention here is that, in the event of a crisis, the buffer can be reduced in order to release part of the banks' capital. But the buffer may also have the (desirable) secondary effect of slowing credit expansion. The national flexibility of macroprudential policy accorded to the Member States may therefore prove valuable if the credit cycle accelerates in one country while an accommodative monetary policy remains necessary for the euro area as a whole.

**CHART 9** CREDIT DEVELOPMENTS IN THE EURO AREA ARE INTENSIFYING



Sources: ECB, NBB.

(1) Lending by resident banks to the resident non-financial private sector. Securitised loans are taken into account. For Belgium, account is also taken of otherwise transferred mortgage loans. The annual growth rates are calculated as the sum of the net credit flows over twelve months divided by the initial outstanding amount of loans.

(2) The growth figures for lending to households in Lithuania are not taken into account before 2009.

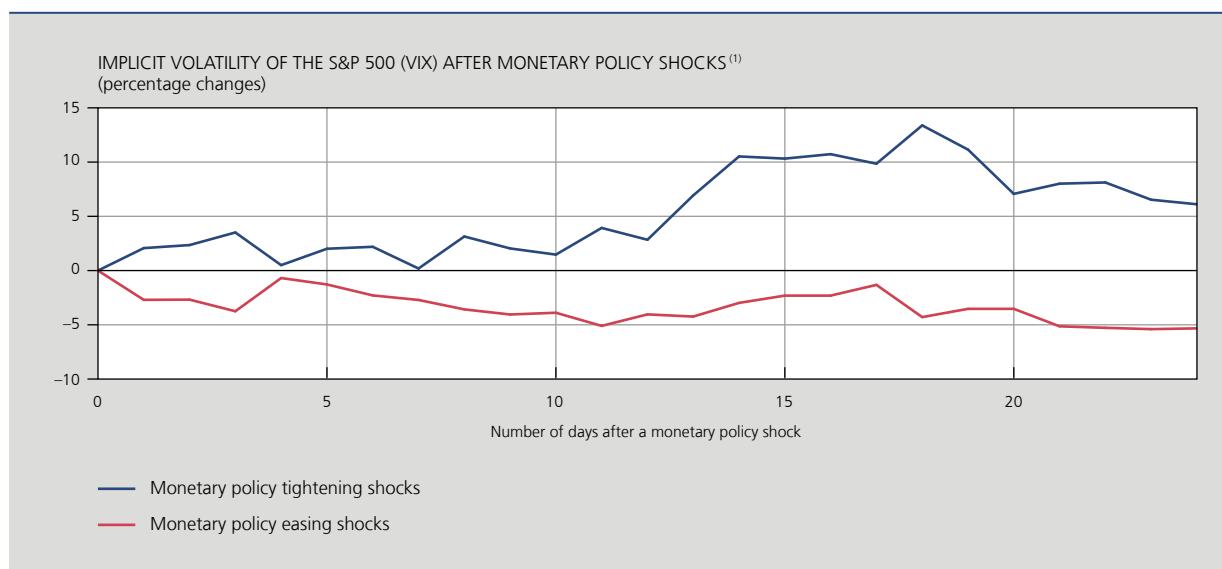
The new Basel III rules which have come into force since the last financial crisis comprise more measures than just the countercyclical capital buffer. They primarily incorporate other capital ratios aimed at improving the banking sector's solvency. Consequently, in the past ten years, there has been a general decline in leverage in the banking sector of the euro area. That is significant, since the procyclicality of leverage effects in the banking sector was named as one of the factors behind the worsening of the latest crisis, if not one of its causes. Adrian and Shin (2014) show that leverage in the banking sector varies with the business cycle and that these fluctuations constitute a means for banks to step up their lending to the economy. Danielsson *et al.* (2018) demonstrate that a prolonged period of low volatility may not only stimulate an increase in lending to the real economy, but may also trigger a rise in the banking sector's leverage ratio.

A decline in leverage in the banking sector is therefore an encouraging sign for macroprudential policy in Europe. However, it must be borne in mind that the downward trend cannot continue indefinitely, and is liable to weaken towards the end of the period for phasing in the new Basel III rules. Moreover, some of the risks could switch from the banking sector to a shadow banking sector which is subject to lower prudential requirements and which could therefore exhibit more procyclical behaviour. According to the limited definition of the Financial Stability Board, the shadow banking sector grew by 14% between 2010 and 2016 in terms of total assets<sup>(1)</sup>.

### Market volatility generally increases following monetary policy tightening shocks

One of the characteristics of the current situation concerns the dynamics of monetary policy. In the United States, the Fed began normalising its monetary policy several years ago and is now about to embark on monetary tightening. It halted its net asset purchases in October 2014 and began raising the target range for the federal funds rate in December 2015. In the euro area, the ECB Governing Council decided in December 2018 to end its net asset purchases. The Governing Council announced that the ECB expects to keep the key interest rates at their current level at least until the summer of 2019; after that, it will raise the key rates if inflation in the euro area continues to converge on a level lower than, but close to, 2%.

**CHART 10** MARKET VOLATILITY GENERALLY INCREASES FOLLOWING MONETARY POLICY TIGHTENING SHOCKS



Source: NBB.

(1) The shocks are derived in the same way as in Rogers *et al.* (2014) and ECB (2017). A shock due to tightening (easing) is assumed to occur if, on the day of an FOMC meeting, the yield to maturity of a one-year American government bond increases (falls) by more than twice the standard deviation of the daily change. Data from January 1990 to October 2018.

In such an environment featuring the gradual withdrawal of the monetary stimulus, or even monetary tightening in the United States, past experience suggests that a (modest) increase in volatility is likely. That prediction is based on analysis of the effects that meetings of the Federal Open Market Committee (FOMC) have had on the financial markets since 1990 (see chart 10). Following a monetary tightening shock, the implicit volatility of the S&P 500 tends to increase by slightly more than 10% in the two weeks after the meeting. Conversely, following a monetary easing shock, the volatility of the S&P 500 tends to decline slightly.

In view of this finding, it seems that the accommodative monetary policy after the crisis helped to restore calm on the financial markets. During the current normalisation, if greater market volatility is undesirable, any adjustment to monetary policy should be gradual and the market should be able to anticipate it as far as possible.

(1) Sum of the total assets in Belgium, France, Germany, Ireland, Italy, Luxembourg, the Netherlands and Spain.

## Conclusion

As regards the historical link between financial market volatility and economic crises, the econometric findings show that prolonged periods of low volatility presage systemic financial crises. Periods of low volatility seem to nurture a degree of optimism among economic agents and encourage them to take more risks. Among other things, that optimism and increased risk-taking may result in a financial bubble and a credit surplus in the economy. The empirical study revealed that: (1) recessions preceded by a period of low volatility associated with a stock market bubble are more serious and prolonged than others; and (2) long periods of low volatility stimulate lending to households and non-financial corporations.

In the event of excessive risk-taking, e.g. if the debt burden of households and firms becomes too large, a classic financial shock such as an interest rate hike could have a serious impact on the economy, for instance if it casts doubt on the sustainability of the debt. If volatility has already been low for a number of months/years, a small and lasting increase in market volatility would therefore be desirable if it enables the economic agents to gain a better understanding of the macroeconomic risks.

In the current situation, it seems prudent to consider that the low volatility environment may still be relevant, since the sudden rise in volatility in October might not persist. If that is the case, then it is necessary to keep a close eye on financial asset prices and credit developments to the extent that they indicate a potential accumulation of systemic risks.

More generally, macroprudential policy has a role to play where the optimism prevailing during periods of low volatility reflects a “this-time-is-different” syndrome. According to Reinhart and Rogoff (2009), “financial professionals and, all too often, government leaders explain that we are doing things better than before, we are smarter, and we have learned from past mistakes. Each time, society convinces itself that the current boom, unlike the many booms that preceded catastrophic collapses in the past, is built on sound fundamentals, structural reforms, technological innovation, and good policy.” (p. xxxiv). The trap due to this way of thinking seems perfectly applicable to periods of low volatility. During these periods, the financial markets appear calm, while credit expands steadily and facilitates the funding of investment that promotes economic growth. However, the systemic risks may accumulate and ultimately lead to a crisis. It is therefore during these periods of apparent calm that countercyclical macroprudential policy can take action. Its aim may be twofold: to build up reserves that can be used during crises, and possibly to slow the build-up of risks if they can be identified sufficiently clearly. If macroprudential policy were to succeed in doing that, it could limit the chances of a systemic financial crisis or mitigate its impact.

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