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An empirical characterization of volatility dynamics in the DAX

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Abstract

This paper addresses stock market volatility in Germany between 1991 and 2018. Through a GARCH model with leverage term, an estimation of volatility in the DAX is provided. Such estimation is then plugged into a quantile regression model where potential economic determinants are analyzed. The results suggest that stock market volatility in Germany reached its historical peak between 2000 and 2004. Moreover, animal spirits play an important role across different quantiles of the volatility distribution, whereas the relevance of established risk factors proposed in the literature is limited to specific cases. Overall, the findings stress the importance of appropriate distributional assumptions when analyzing extreme financial events.

Keywords: Asset prices, volatility, GARCH, quantile regression, DAX.

JEL codes: G12, G17.

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1. Introduction

Volatility is critical for all financial market participants. It describes the extent to which asset prices fluctuate over a given period, often expressed as the standard deviation of asset prices (Tsay, 2010; McNeil et al., 2015; Ferson, 2019). Financial regulators use volatility to aid the forecasting of potential portfolio losses; central bankers monitor it as a market-based measure of economic uncertainty; risk managers in financial institutions implement volatility estimation methodologies to aid the computation of risk measures and for the pricing of financial derivatives; investors consider it a measure of dispersion around the average return of a financial asset.

The relevance of the concept has resulted into a broad strand literature, where estimation and forecasting has received more attention than outlining potential economic determinants. This is particularly true for the case of Germany, where most volatility studies have focused on forecasting aspects.

I aim to explore the empirical properties of volatility and its determinants in Germany, Europe's largest economy. The econometric workflow starts with a generalized autoregressive conditional heteroskedasticity (GARCH) model which is used to estimate the volatility in DAX returns. Then, a quantile regression model is proposed to explore the influence of risk factors, animal spirits, and inflation on the estimated volatility series over the same period. In both cases, the sample runs from February 1991 to October 2018 at monthly frequency, the longest time span analyzed in volatility studies for Germany. The main findings suggests that stock market volatility reached its historical peak between 2000 and 2004, even when considering the global financial crisis and the multi-year debt crisis in the Eurozone. Further, animal spirits play an important role in determining volatility across different quantiles of its distribution.

The rest of the paper is organized as follows: section two provides a review of the relevant literature within the context of the DAX. Section three addresses the details of the methodologies and sample at hand. Results and conclusions are presented in section four and five, respectively.

2. The study of volatility and the DAX

There are not many studies addressing the empirical properties and determinants of stock market volatility in Germany. This is attributable to both historical causes and the state of the financial economics literature.

On one hand, Germany's financial system remained mostly bank-based until the mid-1980s, when a group of big banks launched the so-called *Finanzplatz Deutschland* initiative

(Detzer et al., 2017) to develop equity markets in Germany and promote Frankfurt as a financial center. The most important regulatory changes leading to a more prominent role of financial markets occurred over the 1990s, propelled by: the start of *Deutsche Börse AG* as the operator of the Frankfurt Stock Exchange[1] in 1990; the abolition of stock market tax in 1991; the legalization of equity buybacks in 1998; the abolition of capital gains taxes for corporations in 2002; and the legalization of hedge funds in 2004 (Hein & Detzer, 2015). Thus, the process of rapid stock market development in Germany is historically recent.

On the other hand, the financial economics literature has made substantial progress in the measurement and forecasting of asset price volatility; following pioneer contributions by Engle (1982) and Bollerslev (1986), the number of studies addressing volatility estimation has increased exponentially and up to the point where it has become difficult to keep track of new contributions[2]. Furthermore, a related body of literature has focused on how volatility can be used for explaining stock market returns, ranging from the work of Fama (1965), Fama & McBeth (1973), and Merton (1980), to influential contributions by Campbell et al. (2001) and Ang et al. (2006). Nevertheless, the study of the determinants of volatility (over time) has received less attention. It is an established empirical fact that volatility tends to appear in *clusters* (Tsay, 2010; McNeil et al, 2015; Ferson, 2019), i.e., a typical financial time series exhibits only some periods of high volatility, but there is not a uniform economic explanation about the determinants of these volatility clusters.

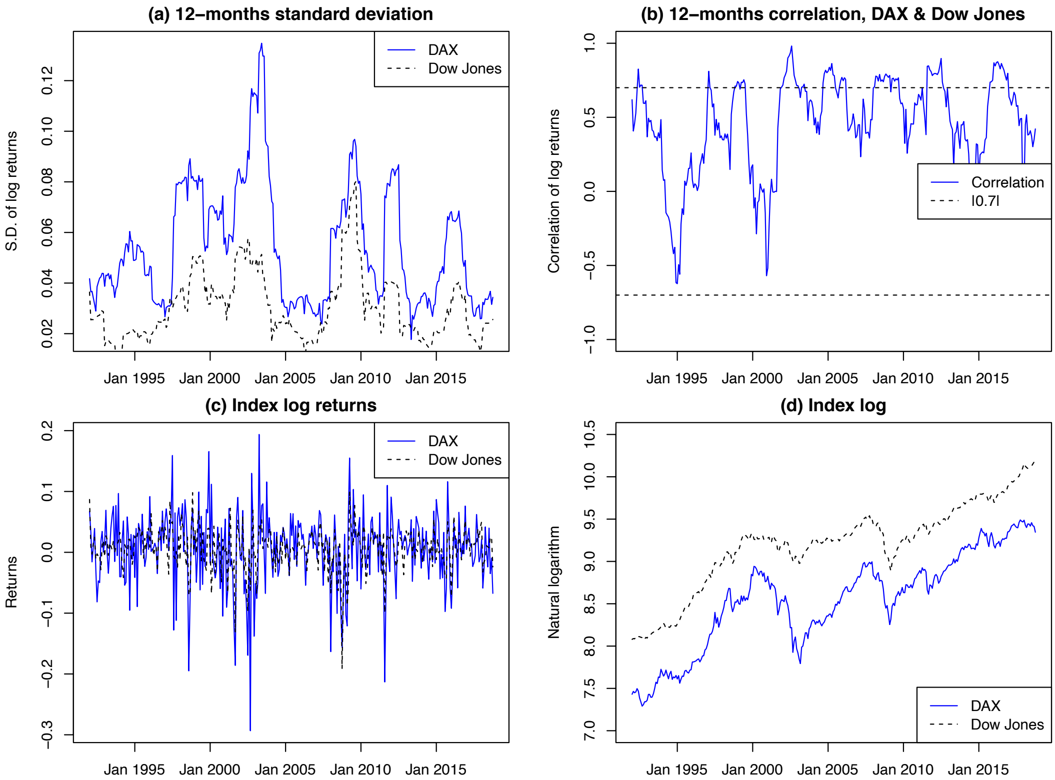
A potential explanation behind volatility could be the fluctuations in the so-called *risk factors* proposed in the literature, such as the market risk factor in the canonical asset pricing model (Sharpe, 1964), the Fama-French (Fama & French 1993, 2015) and momentum (Carhart, 1997) factors, among others. Under the Keynesian tradition, changes in animal spirits[3] could be another explanatory factor behind volatility. In recent literature, Laine (2020) addressed empirically the effect of animal spirits on investment decisions, while Shiller (2021) outlined the importance of popular narratives in shaping economic events.

Some stylized facts are presented in Figure 1. First, the largest decline of the DAX occurred between 2000 and 2004, and not during the global financial crisis or any other episode of distress in the sample. Second, the standard deviation of returns also reached its historical peak

[1] The Frankfurt Stock Exchange was run by the Frankfurt Chamber of Commerce from the 16th century to 1990. The start of *Deutsche Börse* (initially named *Frankfurter Wertpapier*) in 1990 gave birth to a new era that included an electronic trading system called Xetra, and the intention of positioning Frankfurt as a global financial hub.
[2] Chapters 32 and 34 of Ferson (2019), and chapters 4 and 14 of McNeil et al. (2015), provide an extensive list of volatility estimation approaches.
[3] Animal spirits refer to complex political and psychological factors behind investment which describe the "spontaneous urge to action rather than inaction" (Keynes, 1936, p. 161).

between 2000 and 2004. Third, the 12-month standard deviation has been persistently higher in the DAX than in the Dow Jones index[4]. Fourth, the returns of the indices are uncorrelated most of the time, with short periods of positive correlation around periods of financial distress.

Figure 1. Stock market dynamics in Germany and the US



Source: Author's calculations with monthly data from January 1991- December 2020 retrieved from the Bundesbank.

Previous studies have outlined some of the empirical facts outlined before, with the caveat of a shorter sample. Stapf and Werner (2003) found a structural break in 1997, when financial volatility increased and also became *persistent* in statistical terms, i.e., days of high volatility were more likely to be followed by further high volatility days. Since the tails of stock returns distribution became fatter, the likelihood of extreme price movements became greater. The authors link the volatility break to the increase of institutional investors[5] and the increase in the volatility of long-term interest rates.

[4] During the period of analysis, both indices tracked 30 blue-chip companies in Germany and the U.S., respectively.

[5] A similar claim was made for the German bond market in a recent contribution by Barbu et al. (2021).

The Deutsche Bundesbank (2005) also reported that between 1987 and 2005, the number of negative extreme events[6] in the DAX was higher than for the Dow Jones. Later, the institution stated that in periods of high DAX volatility, high frequency trading contributes to amplifying price movements (Deutsche Bundesbank, 2016).

In related research, DAX volatility forecasting has been addressed by Raunig (2006), Claessen & Mitnik (2002), Muzzioli (2011), Tallau (2011), and Weiß (2016), with a focus on forecasting performance. Hanauer (2020) and Dirkx and Peter (2021) estimated risk factors for Germany with the aim of explaining returns. Explaining the economic determinants of volatility has not been the goal of any of these studies.

3. Econometric Strategy

The empirical strategy is based around two methodologies. Initially, I estimate a GARCH model where good and bad news have asymmetric effects on return volatility. Then, I use the conditional variance estimated in the first step to obtain the conditional standard deviation, an estimation of volatility. Finally, I plug the conditional standard deviation series into a quantile regression model, which is used to explain the volatility distribution along relevant regressors. The two methodologies are explained in sections 3.1 and 3.2, respectively.

The sample throughout the analysis (GARCH and quantile regression) runs at monthly frequency through February 1991 to October 2018. Studying financial volatility involves analyzing extreme observations, i.e., the tails of the distribution of returns. Thus, the sample period contains several episodes of economic and political distress: the early aftermath of the German reunification, the inception of the European Central Bank (ECB) and the Euro, the recession of 2003, the global financial crisis of 2008-09, and the multi-year European debt crisis. Consequently, the methods presented here are robust to extreme observations, changing variance (heteroskedasticity), and non-normality.

3.1 GARCH model

The GARCH model class is the academic and industry standard to estimate the volatility of financial asset prices, and several extensions have been proposed in the literature; Tsay (2010), McNeil (2015) and Ferson (2019) provide a full review of the modelling alternatives.

[6] Declines in the DAX index larger than 3% with respect to the previous day's value.

I use a GARCH model *with leverage effect*[7] put forward by Glosten, Jaganathan, and Runkle (1993) to allow for good and bad news to have different effects on volatility; this model is also known in the literature as GJR-GARCH and it is an extension of the original GARCH(1,1) contribution by Bollerslev (1986). Let R_t be the series of the natural logarithm of DAX returns[8], with conditional mean $\mu_t = E(R_t|I_{t-1})$ and conditional variance $\sigma_t^2 = Var(R_t|I_{t-1}) = E[(R_t - \mu_t)^2|I_{t-1}]$. The term I_{t-1} refers to the information set at time $t-1$. The prediction error or innovation is given by $e_t = R_t - \mu_t$. Then, e_t follows a GJR-GARCH process if:

$$e_t = \sigma_t \epsilon_t, \tag{1}$$

$$\sigma_t^2 = \begin{cases} \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2, & e_{t-1} \geq 0, \\ \omega + (\alpha + \gamma) e_{t-1}^2 + \beta \sigma_{t-1}^2, & e_{t-1} < 0, \end{cases} \tag{2}$$

where ω is a constant term, α is the parameter multiplying the previous squared prediction error, β is the parameter multiplying the previous conditional variance prediction, and γ is a leverage parameter only valid for bad news cases (negative e_{t-1}). Additionally, ϵ_t is a sequence of i.i.d. random variables assumed to follow, in this case, a skewed Student-t distribution. In the literature, α is also referred as the *ARCH effect coefficient* and represent the response to a shock to previous news, while β is also referred as the *GARCH coefficient* which represents the time the shock takes to die away. The value of α depicts the sensitivity to new information, the value of β depicts the time for the sensitivity to die out, and the value of $(\alpha + \beta)$ is a measure of the persistence of volatility.

As the long-run variance is equal to $\frac{\omega}{1-\alpha-\beta}$, the long-run volatility can be obtained by the following expression: $\sqrt{\frac{\omega}{1-\alpha-\beta}}$. Moreover, ω, α and β should be > 0 so that the GARCH variance σ_t^2 is always > 0.

Being one of the simplest extensions, the GJR-GARCH by Glosten et al. (1994) seems appropriate for the topic at hand, but it is worth mentioning that there is no agreement in the literature regarding GARCH specifications. The return series R_t used in the GJR-GARCH model was computed using data from the Bundesbank.

[7] Leverage effect refers to the phenomenon where market information has asymmetric effects on volatility. Bad news leading to a fall in the market value of the assets causes an increase in the debt-to-equity ratio and makes the asset price more volatile (McNeil et al., 2015; Tsay, 2010). The effects of bad news are expected to be larger.
[8] The augmented Dickey-Fuller test (Dickey & Fuller, 1979) showed that R_t does not have a unit root.

3.2 Quantile regression

Quantile regression is a semi-parametric technique that is particularly robust to extreme observations, such as episodes of high financial volatility, given that it does not rely on normality, homoscedasticity, or absence of serial correlation. Moreover, it offers a rich characterization of the data as it is suitable for modelling heterogenous conditional distributions.

From the GJR-GARCH model outlined in the previous section, I use the (estimated) conditional variance $\hat{\sigma}_t^2$ to obtain the conditional standard deviation $\hat{\sigma}_t$, which in turn represents the fitted volatilities of the DAX index (returns). $\hat{\sigma}_t$ is used as the dependent variable in a quantile regression framework[9] as specified by Greene (2018):

$$Q[\hat{\sigma}_t|X_t,\theta] = X_t'\mathrm{B}_\theta, \tag{3}$$

such that $Prob[\hat{\sigma}_t \leq X_t'B_\theta|X] = \theta, 0 < \theta < 1$. In this case, X_t is a $K \times 1$ vector of regressors, B_θ is a vector of parameters, and $Q[\hat{\sigma}_t|X_t,\theta]$ is the quantile of $\hat{\sigma}_t$ conditional on the vector of regressors. The distribution of both $\hat{\sigma}_t|X_t$ and model residuals is left unspecified. The estimator b_θ of B_θ, for a specific quantile, is computed by minimizing the function:

$$\begin{aligned} F_n(\mathrm{B}_\theta|\hat{\sigma}_t, X_t) &= \sum_{t:\sigma_t \geq X_t'\mathrm{B}_\theta}^{n} \theta|\hat{\sigma}_t - X_t'B_\theta| + \sum_{t:\sigma_t < X_t'\mathrm{B}_\theta}^{n} (1-\theta)|\hat{\sigma}_t - X_t'B_\theta| \\ &= \sum_{t=1}^{n} g(\hat{\sigma}_t - X_t'B_\theta|\theta), \end{aligned} \tag{4}$$

The minimization problem in equation (4) requires an iterative estimator and can be addressed as a linear programming problem whose details go beyond the scope of this work. Koenker (2005) provides a formal textbook treatment of estimation frameworks for quantile regression.

Initially, I estimate a specification with the following regressors: German firms' assessments of the current business situation $situation_t$, German firm's business expectations for the next six months $expectation_t$, the *market risk factor* (market portfolio return minus a risk free rate) $RMRF_t$, the inflation rate $\Delta \log CPI$, and a dummy variable $ECBdummy_t$ which equals 1 in the years of ECB operations and 0 otherwise. Then the initial specification is

[9] See Koenker & Basset (1978a,b), and Koenker (2005) for a detailed treatment on quantile regression.

augmented by including the *small-minus-big factor* SMB_t, which represents the excess return over a portfolio of stocks with small market capitalization over larger counterparts; the *high-minus-low factor* HML_t, which represents the excess return over a portfolio of stocks with low book-to-market ratio over higher counterparts; and the *momentum factor* MOM_t, representing the performance difference of winners versus losers with respect to the past.

Animal spirits are proxied by $situation_t$ and $expectation_t$, which were retrieved as components from the *Business Climate Index* by IFO Institute[10]. The risk factors for Germany were provided by Hanauer (2020) and account stock market drivers put forward in the literature (Fama & French, 1993, 2015; Ferson, 2019). $ECBdummy_t$ was constructed by the author and the remaining series were retrieved from the Bundesbank. All in all, the length of the sample is dictated by the availability of risk factors data.

I do not discard the possibility that other variables excluded from this analysis could have additional explanatory power, but I assume that they are part of the information set of the business community, captured through $situation_t$ and $expectation_t$.

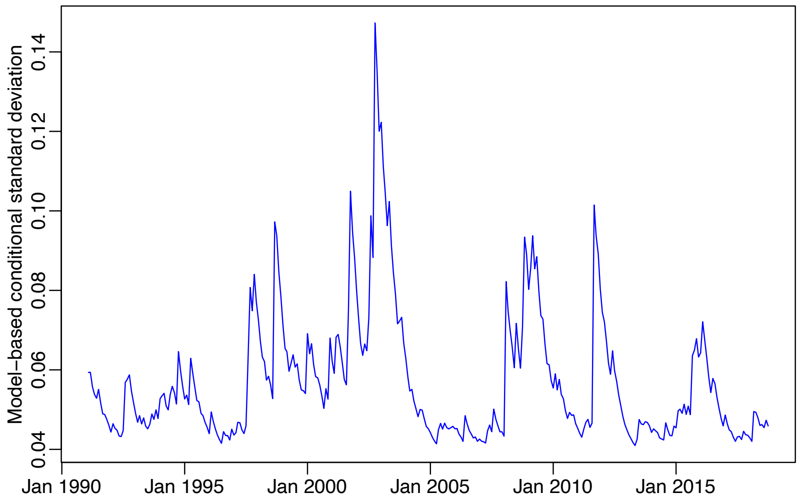
4. Results

4.1 GARCH analysis

Figure 2 shows the estimated monthly volatility of the DAX index from the GJR-GARCH model. Volatility increased to its historical peak between 2000 and 2004. The periods surrounding the global financial crisis (2008-2010) and the midst of the European debt crisis (2012-2013) involved a volatility level substantially lower than the historical peak. Furthermore, the early years following the German reunification (1991-1997) were relatively tranquil for the index.

[10] The Business Climate Index is the leading survey-based economic indicator in Germany. The "industry and trade" version is used here due to data availability. See Sauer & Wohlrabe (2018) for more details.

Figure 2. Estimated monthly volatility of the DAX



Source: Author's estimation. The series in the figure represents $\hat{\sigma}_t$ arising from the GJR-GARCH model.

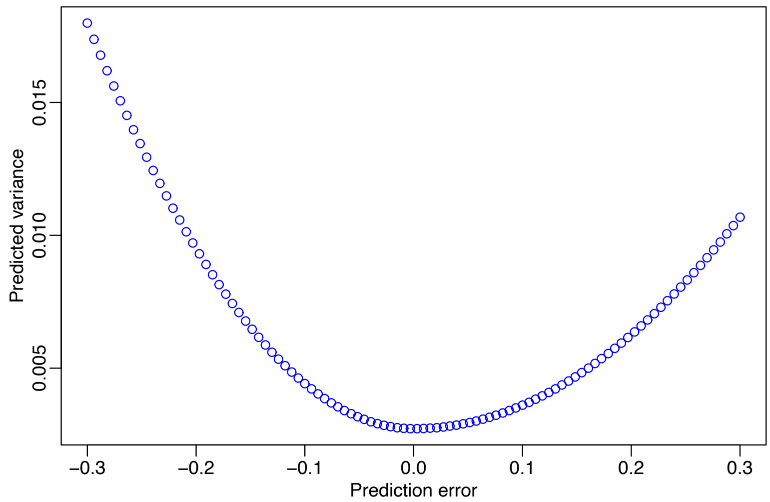
The estimated GJR-GARCH parameters are presented in Table 1. Since the sum of α and β is less than 1, the estimated DAX volatility is mean reverting. Furthermore, γ and Figure 3 show the existence of a leverage effect in the DAX. Therefore, negative return surprises (or negative prediction errors) are associated to larger predicted values in the results of the GJR-GARCH model. The practical implication is that *bad news* tends to have a larger impact than *good news* on the DAX. An asset price decrease resulting from bad news is associated with an increase in the debt-to-equity (leverage) ratio, which then results into higher price volatility. The existence of such leverage effect motivates the selection of a GJR-GARCH over a GARCH(1,1) specification.

Table 1. Estimated parameters of the GJR-GARCH model

Parameter	ω	α	β	γ
Value	0.0003	0.088	0.762	0.081

Source: Author's estimation. See Section 3.1 for model specification details.

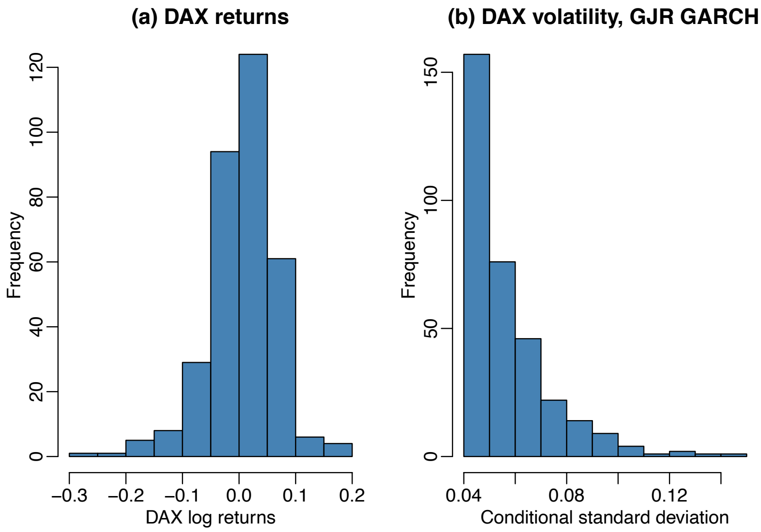
Figure 3. Leverage effect in the DAX



Source: Author's estimation. Effects of positive and negative return surprises in the GJR-GARCH model.

By plugging in the estimated parameters into the long-run variance equation and taking the square root of the result, a long-run volatility of 4% is obtained. Furthermore, the distribution of DAX log returns and estimated volatility clearly deviate from a gaussian case (Figure 4), which in turn motivates the use quantile regression.

Figure 4. Distributional aspects of DAX returns and estimated volatility



Source: Author's estimation. Panel (a) refers to the simple log returns, while (b) refers to $\hat{\sigma}_t$.

4.2 Quantile regression analysis

The first regression specification (Table 2) suggests that the market risk factor is not a relevant regressor at any quantile of the volatility distribution. On the other hand, firms' assessment of business conditions and firms' expectations are significant factors in explaining volatility from the middle quantile (median) onwards. Additionally, the size of such coefficients increases as we move to higher quantiles, implying that animal spirits gain more prominence in contexts of higher volatility. Overall, a positive sentiment across the business community is associated with lower volatility.

Inflation results are significant from the 75th percentile onwards as well, and the sign of the coefficient is negative at the 75th and 90th percentiles, but positive at the 99th percentile. There is no clear theoretical or empirical explanation relationship between volatility and inflation. One could think that higher inflation should be associated with higher volatility, but this has not been the case in distressed periods in the Eurozone.

Table 2. Determinants of volatility across quantiles: Animal spirits and single risk factor

	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.9$	$\theta = 0.99$
Intercept	0.331*** [0.119]	0.585*** [0.073]	0.797*** [0.103]	1.287*** [0.190]	2.309*** [0.262]
$\log Situation_t$	-0.020 [0.013]	-0.046*** [0.010]	-0.048*** [0.010]	0.073*** [0.013]	-0.104*** [0.024]
$\log Expectation_t$	-0.042 [0.028]	-0.071*** [0.018]	-0.113*** [0.024]	-0.192*** [0.042]	-0.380*** [0.045]
$RMRF_t$	-0.0001 [0.0002]	-0.00002 [0.0001]	0.0002 [0.0001]	0.0002 [0.0019]	-0.00009 [0.0002]
$\Delta \log CPI_t$	-0.111 [0.364]	-0.715 [0.436]	-0.691* [0.382]	-0.911** [0.393]	2.152** [1.064]
$ECBdummy_t$	0.007** [0.003]	0.010*** [0.002]	0.004 [0.002]	0.004 [0.003]	0.004 [0.004]
$R^1(\theta)$	0.56	0.16	0.20	0.26	0.37
N	332	332	332	332	332

Source: Author's estimation. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis were computed following Powell (1991). $R^1(\theta)$ is a local measure of goodness of fit in the quantile proposed by Koenker and Machado (1999).

The second regression specification (Table 3) confirms that firms' assessment of business conditions and firms' expectations are significant factors in explaining volatility from the middle quantile (median) onwards. The market risk and momentum factors are only significant at the 99th percentile, i.e., in cases of extreme volatility. The small-minus-big factor is significant from the 75th percentile onwards, while high-minus-low factor is significant only at the 90th percentile. If significant, the relationship between the risk factors and return volatility is always negative. After controlling for risk factors, inflation loses relevance as a predictor and is only significant at the middle quantile. The ECB dummy is associated with higher volatility in some of the quantiles in both specifications.

Table 3. Determinants of volatility across quantiles: Animal spirits and four risk factors

	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.9$	$\theta = 0.99$
Intercept	0.310** [0.131]	0.579*** [0.070]	0.767*** [0.095]	1.324*** [0.199]	1.866*** [0.130]
$\log Situation_t$	-0.023* [0.013]	-0.049*** [0.011]	-0.047*** [0.011]	-0.088*** [0.016]	-0.106*** [0.015]
$\log Expectation_t$	-0.035 [0.035]	-0.067*** [0.018]	-0.107*** [0.022]	-0.186*** [0.044]	-0.283*** [0.033]
$RMRF_t$	-0.0002 [0.0002]	-0.00005 [0.0002]	0.0003 [0.0002]	-0.0001 [0.0002]	-0.0006*** [0.0002]
SMB_t	-0.0002 [0.0004]	-0.000 [0.0003]	0.0006* [0.0003]	-0.001* [0.0006]	-0.001*** [0.0004]
HML_t	0.00003 [0.0003]	-0.0001 [0.0002]	-0.0001 [0.0001]	-0.001*** [0.0004]	-0.0003 [0.0003]
MOM_t	0.0001 [0.0003]	-0.0001 [0.0002]	-0.00005 [0.0001]	-0.0001 [0.0002]	-0.0008*** [0.0002]
$\Delta \log CPI_t$	-0.177 [0.385]	-0.791* [0.446]	-0.459 [0.340]	0.060 [0.631]	1.102 [0.781]
$ECBdummy_t$	0.007** [0.003]	0.010*** [0.002]	0.003 [0.003]	0.008** [0.003]	0.011*** [0.007]
$R^1(\theta)$	0.06	0.16	0.21	0.29	0.50
N	332	332	332	332	332

Source: Author's estimation. *p<0.05, **p<0.01, ***p<0.001. Standard errors in parenthesis were computed following Powell (1991). $R^1(\theta)$ is a local measure of goodness of fit in the quantile proposed by Koenker and Machado (1999).

It is important to place the results into the broader context. On the statistical front, quantile regression offers the advantages of a semi-parametric solution, but it also has drawbacks. For instance, inference can only be made at the quantile level, estimation could become computationally intensive in large sample, and the computation of appropriate standard errors is still under debate. It is useful to stress that the coefficients are specific to the quantile of the dependent variable. Moreover, although GARCH methods are the industry standard to estimate volatility, they are also prone to limitations such as the lack of consensus in the literature regarding model specification.

On the financial front, the economic significance of a coefficient cannot be assessed without further practical context. Beyond the methodology, economic significance lies on the size of the portfolio, e.g., a small market movement could imply big change in the portfolio of an institutional investor. Furthermore, while the sample size was dictated by data availability, the selection of variables was guided by economic reasoning. I assume that other -potentially relevant- variables not included in the model are already incorporated in the information set of the business community, and that this is reflected either in the evaluation of the current business situation or in business expectations[11].

As a matter of fact, stock market volatility is influenced by a plethora of slow- and fast-moving factors, and neither mainstream financial economics nor the heterodox tradition have provided a unified treatment for the determinants of volatility across time. Some studies under Minsky's tradition have attempted to do so (see Nikolaidi & Stockhammer, 2017), but they lack analytical clarity and fall short for practical cases. Additionally, although the *animal spirits* concept has been around for almost a century, the mainstream literature has focused on the so-called risk factors to explain large movements in the stock market.

5. Conclusion

This article provided an estimation of volatility in the returns of the DAX and used the estimation in a quantile regression framework to explore its economic determinants. The main findings indicate that stock market volatility in Germany reached its peaked between 2000 and 2004, and that firms' assessment of the business situation and firms' expectations are important drivers of volatility across different quantiles of its distribution. On the other hand, the so-called risk factors that have been put forward in the financial literature are only relevant in specific cases. A major implication arising from the results is that is that appropriate distributional assumptions are required when analyzing extreme financial events.

Although several studies have provided volatility estimations for Germany, this contribution is not only among the few which have attempted to address the determinants of

[11] Additional regressions were estimated with the ZEW Indicator of Economic Sentiment, which did not add any further explanatory power. Therefore, those estimations are not shown in the paper.

volatility but also the one covering the longest time span. Under the econometric specifications put forward and the sample at hand, the results suggest that monitoring the various dimensions of animal spirits is useful for anticipating and understanding different stages volatility. Conversely, monitoring risk factors becomes a less relevant task when trying to predict volatility, although other studies have suggested their importance for predicting stock returns.

The study of volatility would not only benefit from the use of novel *big data* approaches to capture market uncertainty and the business climate, but also from theoretical contributions to guide the discussion. Future studies should go in that direction.

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