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The certification role of the EU-wide stress testing exercises in the stock market. What can we learn from the stress tests (2014-2021)?

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#### Abstract

What is the impact of stress tests on bank stock prices? To answer this question we study the impact of the publication of the EU-wide stress tests in 2014, 2016, 2018, and 2021 on the first $(\lambda)$ and second $(\delta)$ moment of equity returns. First, we study the effect of the disclosure of stress tests on (cumulative) excess/abnormal returns through a one-factor market model. Second, we study whether both returns and volatility of bank stock prices changes upon the disclosure of stress tests through a structural GARCH model, developed by Engle and Siriwardane (2018). Our results suggest that the publication of stress tests provides new information to markets. Banks performing poorly in stress tests experience, on average, a reduction in returns and an increase in volatility, while the reverse holds true for banks performing well. Banks performing moderately have rather a small effect on both mean and variance process. Our findings are corroborated by the observed rank correlation between bank abnormal returns or equity volatility and stress test performance, which experiences a steady increase after each publication event. These results suggest that the publication of stress tests improves price discrimination between 'good' and 'bad' banks, which can be interpreted as a certification role of the stress tests in the stock market.


Keywords: Stress tests, Financial stability, Stock markets, Excess return, Volatility
JEL Codes: G11, G14, G21, G28

## Non-Technical Summary

After the Global Financial Crisis, the European Union (EU) banking system moved to a centralised Banking Union, with the establishment of the Single Supervisory Mechanism (SSM). This crisis led to a higher scrutiny from banking supervisors on the banking system, where the stress tests became an important assessment tool, ensuring a banking system robust and resilient to adverse macro-financial shocks.

This paper studies whether the publication of the EU-wide stress tests of 2014, 2016, 2018, and 2021 affect market behaviour. We study whether both returns and volatility of bank equity prices are affected by the disclosure of stress tests, i.e., the first and second moments of bank equity returns. First, we study the effect of the publication of stress tests on cumulative abnormal returns through a one-factor market model. Second, we study whether both return mean and volatility of bank stock prices changes upon the disclosure of stress tests through a structural generalized autoregressive conditional heteroskedasticity (GARCH) model. Our empirical strategy relies on daily and 5 -minute intraday frequencies of the equity prices.

Our contribution to the literature is twofold. First, we study the effect of stress tests in the stock market for European banks and provide new evidence to policy makers regarding the potential certification role of the stress tests, i.e. we assess if the information provided by the stress tests on bank robustness (good and bad banks) is used by investors. Second, we focus whether the disclosure of stress tests had a significant effect on the first and second moment equity returns. So far the literature has focused mainly on the relationship between stress test publications and the first moment, while limited attention has been paid to higher moments. As a robustness check, we also investigate the correlation between stress test results and bank abnormal returns or equity volatility changes around the disclosure period for each exercise.

Our results suggest that the publication of stress tests provides new information to markets. Banks performing poorly in stress tests experience, on average, a reduction in returns and an increase in volatility, while the reverse holds true for banks performing well. Banks performing moderately have a rather small effect on both the mean and variance process. Our findings are confirmed by the observed rank correlation coefficient, which experiences a steady increase after each publication event, enforcing the idea that markets incorporate the new information provided by stress tests. These results support the hypothesis that the publication of the EU-wide stress tests improves price discrimination between 'good' and 'bad' banks, which can be interpreted as a certification role of the stress tests in the stock market, which follows and complements the literature (Peristian et al. (2010), Tarullo (2010, 2016), Hirtle et al. (2011), Bernanke (2013), Petrella and Resti (2013), Goldstein and Sapra (2014), Alves et al. (2015), Flannery et al. (2017), Georgescu et al. (2017), Sahin et al. (2020), etc.).

## 1 Introduction

The Global Financial Crisis revealed the constraints of the supervisory framework in safeguarding the resilience of the banking system to adverse shocks. The crisis led to higher scrutiny from banking supervisors and regulators on the banking system. To restore market confidence, the European Union (EU) banking system moved to a centralised Banking Union, with the establishment of the Single Supervisory Mechanism (SSM) and the corresponding joint approach to micro- and macroprudential policies. Henceforth, stress testing exercises became an important assessment tool for supervisors and regulators to ensure a banking system that is robust and resilient to adverse macro-financial shocks.

The EU-wide stress testing exercises are led by the European Banking Authority (EBA) in cooperation with the European Systemic Risk Board (ESRB), the European Central Bank (ECB) and the national authorities to assess bank capital positions under both a baseline and adverse scenario. ${ }^{1}$ The stress tests aim to enhance market discipline through the publication of the results in conjunction with transparency reports, which are disclosed at bank level for significant institutions in the EU. The criteria chosen by the EBA to select the participating banks in stress tests was designed to keep the focus on a broad coverage of EU banking assets and to capture largest banks. In general, the EBA sample of banks accounts for a share of over 70 percent of bank assets in Europe. ${ }^{2}$ These tests are run at the highest level of consolidation (i.e., at the banking group level), as defined by the Capital Requirements Directive (CRD). The impact of stress tests is reported in terms of Common Equity Tier 1 (CET1) depletion over a three-year horizon. ${ }^{3}$ The stress tests are subject to a solid quality assurance process, covering the design, development and execution, which imply a standardised methodology applied to all participant banks in a hybrid setting of bank projections challenged by the ECB top-down models. Since 2016, European stress tests are no longer a "pass or fail" exercise, yet results influence capital requirements of banks, which is determined in "Supervisory Review and Evaluation Process" (SREP) decisions. ${ }^{4}$ The stress test results of banks that form part of the EBA sample are published, while results of banks that are part of the SREP sample were not published at individual

[^0]level until the 2021 stress tests. ${ }^{5}$ The EU-wide stress tests included 124, 51, 48, and 50 banks, respectively, of which $49,34,34$, and 33 were listed banks. The respective exercises were launched at the end of January or beginning of February ${ }^{6}$ and results were published on 26 October 2014, 29 July 2016, 2 November 2018 and 30 July 2021, respectively.

There is a consensus in the literature that the stress tests are effective in reducing bank incentives to take risks and therefore in enhancing financial stability (Borio et al., 2014; Gick and Pausch, 2012; Goldstein and Sapra, 2014; Pierret and Steri, 2019; Cortés et al., 2020; Kok et al., 2021; Konietschke et al., 2022; among others). This paper aims to investigate whether the publication of stress tests provides new information to market participants by increasing transparency on the resilience of individual banks.

This paper contributes to the literature in two ways. First, we contribute to the existing literature on the impact of the stress testing exercises on European bank stocks. More specifically, our study aims to investigate the presence of a certification role of the EU-wide stress test exercises in the capital markets through the assessment of stock market reactions. The certification role in this context intends to assess if the information provided by stress tests on bank robustness (good and bad banks) is used by investors. Second, we analyse whether the disclosure of stress tests had a significant effect on the first and second moment of bank equity returns. We study the effect of the publication of stress tests on cumulative abnormal returns through a one-factor market model, as well as the effect on the mean and volatility processes of bank stock return series through a structural GARCH model, developed by Engle and Siriwardane (2018). Our empirical strategy relies on daily and 5 -minute intraday frequencies of equity prices. As a robustness check, we also investigate whether the (Spearman's) rank correlation changes around the disclosure period of the stress test results. This paper contributes to the ongoing discussion about the strategy for stress testing in the European context by investigating market reactions after the disclosure of the EU-wide stress test results of 2014, 2016, 2018, and 2021.

Our results show evidence that stress tests provide new information to market participants and improve the ability of markets to distinguish between banks. Results reveal that banks that perform poorly in stress tests experience, on average, a reduction in the first moment (of mean returns) but an increase in the second moment, while the reverse holds true for banks that perform well. More specifically, we find that banks that perform well during stress tests experience, on average, an increase in equity returns of 0.18 percentage points and a reduction in the variance process of 28 percent upon the disclosure of the results. While banks that perform poorly experience, on average, a decrease in equity returns of 0.80 percentage points and an increase in the variance process of 19 percent. These results are corroborated by the observed

[^1]rank correlation between abnormal returns or equity volatility and stress tests bank performance, where the correlation steadily increases after the publication of each stress test. This confirms a certification role of stress tests in stock markets, which complements the findings of other authors (Peristian et al. (2010), Tarullo (2010, 2016), Hirtle et al. (2011), Bernanke (2013), Petrella and Resti (2013), Goldstein and Sapra (2014), Alves et al. (2015), Flannery et al. (2017), Georgescu et al. (2017), Sahin et al. (2020), etc.).

These findings could be related with the fact that the publication of stress tests are of special interest to bank shareholders since it provides deeper insights in the financial strength of banks, as well as the quality of its risk management and capital planning. Market investors may consider that higher capital ratios are consistent with a "precautionary" view of bank capital, although this behaviour is evident only since the financial crisis (Hirtle et al. (2011)). Also, bad (good) performance during the stress tests may increase (decrease) the probability for mandatory equity issuance, which sets shareholders at a disadvantage if stock dilution takes place (Georgescu et al., 2017). Another related explanation could be that the fundamentals of good (bad) performing banks were better (worse) than anticipated by shareholders, which was therefore priced in by markets during the days after the publication of the stress tests (Ellahie, 2012). Therefore, even if the bank risk profile is to a certain extent already reflected in the behaviour of stock markets, our results suggest that the publication of stress tests provide new information to the markets, thus changing the informational environment in a tangible way such that both the first and second moment in bank equity returns were impacted.

The paper is structured as follows. The next subsection describes the literature review. Section 2 describes our empirical strategy and demonstrates the robustness of the analysis. Section 3 presents the data, while Section 4 summarises the results. Section 5 concludes.

### 1.1 Literature review

The stress tests are used to assess how well banks are able to cope with financial and economic shocks. The rational is that having better capitalised banks, as a result of the stress tests, enhances financial stability by increasing bank capital against losses and at the same time reducing bank risk-taking incentives. The literature on the impact of capital based regulation and stress tests show that better capitalised banks, as a result of higher capital requirements (e.g. from stress tests), enhances financial stability by reducing bank risk-taking incentives and increasing bank capital buffers to withstand losses. Borio (2011) outlines how financial stability and macroprudential policy became more important after the 2007-09 financial crisis. Regulation and supervision changed from the stability of individual banks to the stability of the financial system as a whole. Borio et al. (2014) mention the additional side benefits, stemming largely from the stress
tests that can discipline thinking about financial stability risks. In a theoretical model, Gick and Pausch (2012) show that announcing the disclosure of the stress test methodology and the results can increase welfare. Similarly, the theoretical model in Goldstein and Sapra (2014) concludes that disclosure of stress tests at the aggregate level promotes financial stability and is thus beneficial. Pierret and Steri (2019) indicate that stress tests improve financial stability because banks are better capitalised and engage in safer lending. Cortés et al. (2020) show the movement of credit supply from large, non-local lenders toward smaller banks with more local knowledge which may help enhance both financial stability and the efficiency of credit allocation. Kok et al. (2021) show evidence on the disciplining effect of the stress tests. Konietschke et al. (2022) show that the publication of bank capital requirements, from both stress tests and Pillar 2 requirements, can have a disciplinary effect since banks publishing their requirements tend to have more robust capital ratios, which improves financial stability. Authors suggest that the EBA sample of banks (sample publishing stress test results) are more robust to absorb scenario shocks resulting in less additional capital required by the supervisor. In terms of policy implications, as mentioned by Repullo (2004), Gersbach and Rochet (2017), Gropp et al. (2019), Cappelletti et al. (2019, 2020) and Hirtle et al. (2019), higher capital requirements have potentially a positive disciplining effect by reducing risk-taking which enhances financial stability.

The empirical literature related to the effects of stress tests on market reactions is scarce, in particular for the European context. So far, only few empirical studies estimate the short-term effects of stress testing exercises and most of them are related with exercises led by the Federal Reserve System in the United States (U.S.). The consensus however is that the disclosure of stress test results generally reveals new information to markets (e.g., Peristian et al. (2010), Hirtle et al. (2011), Tarullo (2010, 2016), Bernanke (2013), Goldstein and Sapra (2014), Flannery et al. (2017) and Sahin et al. (2020)). However, some authors argue that while promoting market discipline, such disclosures may exacerbate bank-specific inefficiencies (e.g. Goldstein and Sapra (2014)). A more detailed description on studies led by the U.S. is available in the Appendix, Table 10.

For stress tests conducted in Europe, several authors found similar results. Ellahie (2012) investigates the market impact of bank stress tests in the euro area during the Global Financial Crisis of 2007-2012. The author finds evidence, through a difference-in-difference approach, that stress test announcements do not significantly affect measures of information asymmetry or uncertainty for tested banks. This author also suggests a role for transparent stress tests to improve the information environment in capital markets during crises. Petrella and Resti (2013) and Georgescu et al. (2017) detect significant capital market reactions after the publication of the EU stress tests by employing an event study to estimate cumulative abnormal returns. Moreover, Georgescu et al. (2017) find that the publication of stress test results enhanced price discrimination as the impact on bank credit default swap (CDS) spreads and equity prices were stronger
for the weaker performing banks in stress tests. Finally, authors provide some evidence that also sovereign funding costs were affected in the aftermath of the stress test publications. Alves et al. (2015) compare the CDS and stock market performance after the disclosure of the EBA stress tests and argue that the ability of both markets to anticipate and incorporate information is different. Authors show that stress tests provided new information that were not anticipated by stock markets but were partially anticipated by the CDS market. Barucci et al. (2016) consider the capital deficit of a bank, identified in the comprehensive assessment, is positively related to its market-based risk measure, such as the historical volatility, where the post-adjustment leverage ratio is related to this measure. These results show that the comprehensive assessment captures bank riskiness, where the leverage ratio is a better indicator than the risk-weighted capital ratio. Barucci et al. (2018) analyse the results of both the 2014 asset quality review (AQR) and the stress tests and find that risk-adjusted capital ratios are negatively related with the AQR shortfall, but not with the stress tests shortfall, whereas the leverage ratio plays a significant role in both cases. ${ }^{7}$ Ahnert et al. (2018) incorporate both U.S. and European stress tests between 2010 and 2017 and find different market reactions for passing and failing banks. More specifically, they find that passing banks experience positive abnormal equity returns and smaller CDS spreads, while failing banks experience negative abnormal equity returns and widening of CDS spreads.

While these studies, among others, have shed considerable light on the relationship between stress test publications and returns of bank CDS spreads and stock prices, little attention has been devoted to higher return moments. More specifically, most studies implicitly assume that the second moment of these returns remains constant. This is surprising since the concept of volatility pervades almost every facet in finance. ${ }^{8}$ In this paper, our focus includes the relationship between both returns and volatility and the projected endCommon Equity Tier 1 (CET1) ratio under the adverse scenario. Thus, a relevant contribution of this paper is the impact of stress tests disclosure on the second moment of equity returns (or volatility). This extended analysis suggests that the disclosure of stress test results allowed price discrimination between 'good' and 'bad' banks.

[^2]
## 2 Empirical strategy

This section details the empirical strategy of our study. It is divided in three subsections. Subsection 2.1 details our empirical strategy to study the effect of the publication of stress tests on the first moment of equity returns (abnormal returns). Subsection 2.2 presents our econometric specification to study the impact of stress test disclosures on the first and second moments of equity prices jointly. Subsection 2.3 presents our model validation using realised variance and Subsection 2.4 details the rank correlation between abnormal returns, equity volatility and stress test results.

### 2.1 Effect of the publication of the stress tests on the first moment of equity returns: abnormal returns through a one-factor market model

To measure whether the publication of stress test results was priced in stock markets, w.r.t. the first moment in equity returns, our study relies on abnormal returns (or excess returns) around the event date of interest, i.e., stress test publication date. Abnormal returns can be described as the difference between the actual ex-post return of the security and the expected return (MacKinlay, 1997). More formally, this can be expressed as follows:

$$
\begin{equation*}
A R_{i, \tau}=r_{i, \tau}-E\left(r_{i, \tau} \mid X_{\tau}\right) \tag{1}
\end{equation*}
$$

Where $A R_{i, \tau}, r_{i, \tau}$ and $E\left(r_{i, \tau} \mid X_{\tau}\right)$ are the abnormal, actual and normal returns, respectively, for the time period $\tau . X_{\tau}$ is the conditioning information for the normal returns model. To model normal returns, King (2009) and Petrella and Resti (2013) is followed, which models bank stock returns through a one-factor market model:

$$
\begin{equation*}
r_{i, t}=a+b_{i} r_{m, t}+e_{i, t} \tag{2}
\end{equation*}
$$

Where $r_{i, t}, r_{m, t}$ denote (daily) returns on equity $i$ and the market portfolio, respectively, and $e_{i, t}$ is the zero mean disturbance term. We follow Petrella and Resti (2013) by relying on national stock-market indices, which corresponds to the bank jurisdiction to proxy the market portfolio. When taking into account cross-country heterogeneity in the stock markets, it is ensured that residuals will only include idiosyncratic effects. In the second stage, expected returns over the relevant window around the event date are computed in order to derive (cumulative) excess/abnormal returns. In line with other event study papers, a 2 days event window is considered, with an estimation window of 250 days. Finally, $a$ and $b$ are estimated via an iteratively re-weighted least squares (IRLS) method to reduce the effect of extreme data points.

Lastly, in the third stage, cross-sectional insights are inferred by examining the link between the cumula-
tive abnormal returns (CARs) and the projected end-CET1 ratio under the adverse scenario while controlling for bank level characteristics. The panel regression model can be described as:

$$
\begin{equation*}
C A R_{j, t}=\alpha+\beta_{1} Y_{j, t}+\beta_{2} X_{j, t}+\eta_{j, t} \tag{3}
\end{equation*}
$$

Where $Y_{j, t}$ denotes the projected end-capital ratio under the adverse scenario after a stress tests, and $X_{j, t}$ a vector of control variables containing the bank assets and the leverage ratio. ${ }^{9}$

### 2.2 Effect of the publication of the stress tests on the first and second moments of equity returns: GARCH model

The econometric setup in the previous section is suitable in analysing whether the first moment of stock price returns change in any tangible way. To infer whether both returns and volatility of bank stock returns changes upon the disclosure of stress test returns, we use the structural generalized autoregressive conditional heteroskedasticity (GARCH) model developed by Engle and Siriwardane (2018). For the mean specification, our study relies on the specification used in (1), and model the return process of bank stocks through national stock-market indices. In addition, the dummy variable $S_{t}$ is introduced to control for abnormal returns during the event window.

$$
\begin{equation*}
r_{E, t}=a+b r_{m, t}+\lambda S_{t} \tag{4}
\end{equation*}
$$

To estimate the innovation process, the demeaned return process is used to model volatility through the structural GARCH model.

$$
\begin{equation*}
\widehat{r}_{E, t}=r_{E, t}-\left(a+b r_{m, t}+\lambda S_{t}\right) \tag{5}
\end{equation*}
$$

Engle and Siriwardane (2018) show that if a firm's equity is treated as a call option on its assets, daily equity returns, and its variance process can be approximated as follows:

$$
\begin{align*}
& \widehat{r}_{E, t}=L M_{t-1} r_{A, t}  \tag{6}\\
& h_{E, t}=L M_{t-1}^{2} h_{A, t} \tag{7}
\end{align*}
$$

In more simple terms, the structural GARCH model supposes that equity returns are a result of the product of (latent) asset returns and the leverage multiplier. In the next step, we take the assumption that the variance of asset returns evolves according to the conditional volatility model introduced by Glosten,

[^3]Janagannathan and Runkle (1993), which can be expressed as follows:

$$
\begin{gather*}
\left.r_{A, t}=\sqrt{h_{A, t}} \epsilon_{A, t}, \quad \epsilon_{( } A, t\right) \sim N(0,1)  \tag{8}\\
h_{A, t}=\omega+\alpha\left(\frac{\widehat{r}_{E, t-1}}{L M_{t-2}}\right)^{2}+D_{t} \gamma\left(\frac{\widehat{r}_{E, t-1}}{L M_{t-2}}\right)^{2}+\beta h_{A, t-1} \tag{9}
\end{gather*}
$$

Where $\omega, \alpha$ and $\beta$ are constants and $D$ a dummy variable that takes the value of 1 if $\widehat{r}_{E, t-1}<0$, and 0 otherwise.

To quantify how leverage amplifies asset volatility into equity volatility, transformation functions from the Black-Scholes-Merton model (BSM) are imposed:

$$
\begin{equation*}
L M_{t-1}=\left[L M^{B S M}\left(\frac{D_{t-1}}{E_{t-1}}, \sigma_{A, t-1}^{\tau}, \tau_{t-1}, r_{E, t-1}\right)\right]^{\phi} \tag{10}
\end{equation*}
$$

In general, the leverage multiplier can be interpreted as follows: higher leverage leads to an increased level of equity volatility because higher leverage corresponds to a smaller likelihood that equity expires "in the money". To appreciate this idea more clearly, below it is presented how $L M^{B S M}$ can be decomposed:

$$
\begin{equation*}
L M^{B S M}=\Delta_{t}^{B S M}\left(g_{t}^{B S M}, 1, \sigma_{A}, \tau_{t}, r_{E, t}\right) \cdot g_{t}^{B S M}\left(\frac{E_{t}}{D_{t}}, 1, \sigma_{A}, \tau_{t}, r_{E, t}\right) \cdot \frac{D_{t}}{E_{t}} \tag{11}
\end{equation*}
$$

Where $g_{t}^{B S M}$ denotes the inverse BSM-call pricing function evaluated at strike 1 and call price $\frac{E_{t}}{D_{t}}$, and $\Delta_{t}^{B S M}$ denotes the delta of the BSM call option pricing formula, evaluated at $g_{t}^{B S M}$ and strike price 1 . Lastly, $\phi$ is employed to capture the concave relationship between the leverage multiplier and debt-to-equity ratio. If $\phi$ is estimated to be equal to zero, then the structural GARCH model falls back to the Glosten-Jagannathan-Runkle (GJR)-GARCH model, suggesting that leverage has no direct effect on equity volatility. Alternatively, if $\phi$ is statistically different from zero, then there is a reason to believe that leverage plays a role in driving equity volatility. The estimation process takes the following steps recursively for each point in time: 1) compute asset returns as $\left.r_{A, t}=\frac{\widehat{r}_{E, t}}{L M_{t-1}} ; 2\right)$ derive implied $\frac{\text { asset }_{t}}{d e b t_{t}}$ value through the BSM equation; and 3) compute $L M_{t}$ as described in (10).

Finally, to measure directly the effect of stress test announcements on stock price volatility in the short-run on a individual bank level, the approach by Bomfim (2003) is followed. The previously employed structural GARCH model is extended as follows:

$$
\begin{equation*}
E\left(\widehat{r}_{E, t}^{2} \mid F_{t-1}\right)=k_{t} h_{E, t} \tag{12}
\end{equation*}
$$

$$
\begin{equation*}
k_{t}=1+\delta S_{t} \tag{13}
\end{equation*}
$$

Where $F_{t-1}$ denotes the information set and $S_{t}$ a dummy variable set to 1 during the event window and zero elsewhere. If empirical results show that $\delta$ is significantly greater (lower) than zero, then this indicates that volatility is higher (lower) than average on the days after the disclosure of the results. To be consistent with the previous section, an event window of two days is also considered in this specification.

### 2.3 Model validation using realised variance

Return volatility is a frequently used measure of risk by both academics and investors. However, in contrast to raw returns, a complicating aspect in modelling return volatility is that actual realizations are not directly observable (Andersen and Benzoni, 2008). A common strategy to overcome this is to conduct inference through complex econometric procedures. A breakaway from this approach is to instead rely on realised variance. Given continuously quoted data, realised variance provides a solution for deriving stock market volatility in a "model free" manner. Therefore, to ensure that the findings from our GARCH specification are robust, we also explore if realised volatility is significantly higher or lower during the event window. First, a daily measure of realised variance is computed using 5 -minute intraday returns ${ }^{10}$ by following the steps suggested by Andersen et al. (2003). Second, we explore whether realised variance is significantly higher or lower during the event window.

### 2.4 Cross sectional correlation between abnormal returns, equity volatility and stress tests results

To investigate the ordinal association between abnormal returns/equity volatility and stress test results, the rank correlation is computed. More specifically, for each point in time, banks are ranked based on abnormal returns/equity volatility, which enables the computation of the rank correlation with the projected CET1 ratio under the adverse scenario. To calculate the rank correlation, the Spearman's formula is used, which can be expressed as follows:

$$
\begin{equation*}
\rho_{s}=1-\frac{\sum_{i=1}^{n} 6 d_{i}^{2}}{n\left(n^{2}-1\right)} \tag{14}
\end{equation*}
$$

Where, $n$ is the number of banks in our sample and

$$
\begin{equation*}
d_{i}=r a n k_{\text {abnormal returns or equity volatility }}-r a n k_{\text {projected }} C E T 1 \tag{15}
\end{equation*}
$$

[^4]
## 3 Data

In this section, the background information of our primary data sources is described.

### 3.1 Equity returns and market

Table 1: Cross-sectional summary statistics

|  | D/E | Market value | Equity |
| :---: | :---: | :---: | :---: |
|  |  | of equity capital (million Euros) | volatility (\%, annualised) |
| Mean | 24.29 | 24,042 | 37.91 |
| Standard deviation | 13.75 | 23,696 | 7.67 |
| Min | 3.86 | 2,733 | 26.50 |
| 25 th percentile | 14.52 | 7,567 | 32.61 |
| 50 th percentile | 19.10 | 17,288 | 36.35 |
| 75th percentile | 30.26 | 32,273 | 41.58 |
| Max | 60.24 | 133,480 | 63.46 |

Notes: This table displays cross-sectional summary statistics for the sample of banks being studied. The values in this table are calculated by first computing the mean for each bank series. Based on these means, cross-sectional summary statistics are calculated. $\mathrm{D} / \mathrm{E}$ denotes the book value of debt (smoothed) divided by the market value of equity capital. Market value of equity capital is expressed in million of euros and equity volatility in percentage is annualised.

The information on daily stock prices and the market value of equity capital is obtained from Bloomberg for banks that participated in the EU-wide stress tests of 2014, 2016, 2018 and 2021. The number of banks included in our analysis is constrained by the fact that stock prices are not available for all banks participating in stress tests. Also, the sample of banks used in each stress test varies since the list of participating banks is slightly different in each exercise. As an example, banks from the United Kingdom were part of the 2014, 2016 and 2018 stress tests but did not participate in the 2021 exercise due to Brexit. The set of banks included in our study, for each stress test exercise, is detailed in the Appendix, Table 7. ${ }^{11}$ As illustrated in the Appendix, Figure 9, the sample of banks included in our study is representative of the entire set of tested institutions in each stress test, where the kernel distribution of the projected end-CET1 ratio under the adverse scenario is similar between our sub-sample and the full set of tested banks, i.e., our sample is representative of the full universe of tested banks in terms of stress test impact. Cross-sectional summary statistics on the market value of equity capital are provided in Table 1, while summary statistics on individual bank equity return series are provided in the Appendix, Table 8. In addition, to ensure the robustness of our analysis, our study includes intraday frequency from Reuters.

[^5]
### 3.2 Debt

To derive the leverage multiplier, the face value of debt for each bank throughout time is used. Data on deposits, short-term debt, long-term debt, and other liabilities is retrieved at a quarterly frequency from Bloomberg. However, since the structural GARCH model relies on daily data of debt series, the same approach as Engle and Siriwardane (2018) is followed where the exponential smoothing method is applied to convert quarterly reported debt values into daily frequency.

$$
\begin{equation*}
D_{t}=\eta D_{t}^{A}+(1-\eta) D_{t-1}, \quad D_{0}=D_{0}^{A} \tag{16}
\end{equation*}
$$

Where $D_{t}$ is the smoothed time-series of debt, and $D_{t}^{A}$ is the actual observed debt series. $\eta$ is fixed to 0.01 which implies a half-life of around 70 days. In addition, in line with the option pricing literature, it is relevant to consider the maturity of the total debt that each bank holds throughout time. This is done by designating a maturity to each type of liability that makes sense from an economic perspective: Deposits: 1 year; Short-term debt: 2 years; Long-term debt: 8 years and Other liabilities: 3 years. Finally, the maturity of the debt series is calculated for each point in time by computing the maturity as a weighted average, where the weight is defined as the debt value for each maturity divided by the total face value of debt. Cross-sectional summary statistics on debt to market equity ratio are provided in Table 1.

### 3.3 Risk-free rate

A third input used to compute the leverage multiplier is the risk-free rate, which is linked to the maturity of the debt series for each bank. These rates are retrieved through zero-curves provided by the statistical data warehouse maintained by the ECB. ${ }^{12}$ In addition, a linear interpolation is employed to build out a broader term structure to overcome the fact that zero-curve data is only reported for a restricted number of maturities. This allows us to attain a higher precision in mapping maturities derived in Subsection 3.2 to risk-free rates.

[^6]
### 3.4 Asset volatility $\sigma_{A, t}^{\tau}$

As in the conventional Black-Scholes-Model (BSM), an estimation of the volatility of the underlying security throughout the life of the option is required to compute the option value. This application can be roughly translated as the volatility of the value of assets that a bank holds until the maturity of the debt is reached. To estimate this, the unconditional asset volatility is used, which can be easily obtained from the GJR-GARCH model:

$$
\begin{equation*}
\sigma_{A, t}^{\tau}=\frac{\omega}{1-\alpha-0.5 \gamma-\beta} \tag{17}
\end{equation*}
$$

### 3.5 Initial conditions

To estimate the parameters of the model, a quasi-maximum likelihood estimation is conducted as outlined by Bollerslev and Wooldridge (1992). However, due to the iterative nature of the structural GARCH model, starting values for $h_{A, 1}$ and $L M_{0}$ need to be chosen. Thus, $h_{A, 1}$ is initialized by setting it equal to the unconditional equity volatility obtained from the GJR-GARCH model and $L M_{0}$ is initialised with 1 .

## 4 Results

This section presents the main results of our study. It is divided in three subsections. Subsection 4.1 details the results for the effect of the publication of the stress tests on the first moment of equity returns (abnormal returns). Subsection 4.2 presents the results for the stress test disclosures on the first and second moments of equity prices. Subsection 4.3 presents the estimates for the realised variance and Subsection 4.4 details the outcomes for the rank correlation between abnormal returns, equity volatility and stress test results.

### 4.1 Estimates from the one-factor market model

There is some difficulty in evaluating banks given the informational asymmetry between banks and market participants. This may undermine the ability of external parties to distinguish between 'good' and 'bad' banks. Disclosing stress test results are thus an attempt to effectively reduce this information gap (Goldstein and Sapra, 2012). Table 2 provides summary statistics of abnormal equity returns on tested banks around the publication date of stress tests. ${ }^{13}$ First, in aggregated terms for the full set of banks of our sample, results show that on average negative abnormal returns were reported on the day after of each stress test

[^7]publication event. Second, apart from 2018, our findings reveal that the dispersion among abnormal returns increased on the day after the publication in comparison with abnormal returns reported on the day before the publication, as measured by both the standard deviation and the interquartile range.

Table 2: Summary statistics

|  | 2014 |  | $\mathbf{2 0 1 6}$ |  | $\mathbf{2 0 1 8}$ |  | $\mathbf{2 0 2 1}$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | day -1 | day +1 | day -1 | day +1 | day -1 | day +1 | day -1 | day +1 |
|  |  |  |  |  |  |  |  |  |
| Mean | 0.50 | -0.81 | -0.62 | -1.33 | 0.70 | -0.06 | 0.57 | -0.47 |
| Standard deviation | 1.67 | 3.96 | 1.47 | 2.00 | 1.93 | 0.70 | 0.93 | 1.08 |
| 25th percentile | -0.27 | -1.36 | -1.03 | -2.14 | -0.17 | -0.57 | 0.08 | -1.19 |
| 50th percentile | 0.14 | -0.43 | -0.77 | -1.02 | 0.59 | -0.16 | 0.81 | -0.54 |
| 75th percentile | 0.68 | 0.64 | 0.68 | 0.64 | 1.58 | 0.42 | 1.14 | -0.12 |

Notes: This table denotes the summary statistics on abnormal returns on the day before and after the disclosure of the 2014, 2016, 2018 and 2021 stress test results. Abnormal returns are computed as the difference between realised returns and expected returns, estimated through the one-factor market model.

To explore whether the publication of stress tests helped to improve bank price discrimination, scatter plots are displayed in Figure 1 for the relation between abnormal returns and projected end-CET1 ratio on the day before and after the stress test publication. Ordinary least squares (OLS)-fitted trend lines and correlation coefficients indicate that on the day before stress test publication events, the relationship is rather weak and statistically insignificant. However, the correlation coefficient on the day after the publication reveals a much stronger relationship and is statistically significant across all stress test events. More specifically, the right panel of Figure 1 shows that banks performing better during stress tests tend to report higher excess returns than banks that perform worse (i.e., banks with larger capital gaps in stress tests experienced higher negative abnormal returns). This comparison confirms that stress tests provide new information to market participants, leading to stock return changes that follow the risk profile of the bank (in this case in terms of stress tests performance).

Figure 1: Relationship between abnormal returns and stress tests performance (in terms of end-CET1 ratio)


Notes: This figure plots the relationship between abnormal returns and projected end-CET1 ratios (from the stress tests) on the day before (left) and after (right) the publication of the 2014, 2016, 2018 and 2021 stress test results. The OLS-fitted trend line (red) has been added for reference. The x-axis presents the projected end-CET1 ratios and the y-axis presents the abnormal returns expressed as percentages. The data sources are obtained from Bloomberg and authors' calculations.

To formally test this hypothesis, the panel regression model defined in (3) is estimated. Our results displayed in Table 3 confirm the hypothesis that the projected end-CET1 ratio has a significant effect on the CARs after the disclosure of stress tests. Results indicate that on average, a 1 percentage point increase in the projected end-CET1 ratio generates on average 0.34 percentage points higher CARs. ${ }^{14}$ This suggests that a higher projected end-CET1 ratio after a stress tests serves as a signal to the markets of greater bank resilience to an adverse shock, and therefore decreases the risk of holding the bank stock. In sum, by solely focusing on the first moment of equity returns, our findings show that the disclosure of stress test results generates new information to market participants and aids in improving price discrimination.

[^8]Table 3: Effect of stress tests performance (in terms of end-CET1 ratio) on cumulative abnormal returns

| Variables | (1) <br> Model 1 | (2) <br> Model 2 |
| :---: | :---: | :---: |
| end-CET1 Ratio | $\begin{aligned} & 0.35^{* *} \\ & (0.14) \end{aligned}$ | $\begin{aligned} & 0.34^{* *} \\ & (0.16) \end{aligned}$ |
| Constant | $\begin{aligned} & -3.89^{* * *} \\ & (1.20) \end{aligned}$ | $\begin{aligned} & 24.58 \\ & (33.99) \end{aligned}$ |
| R-squared Number of banks controls | $\begin{aligned} & 0.21 \\ & 53 \\ & \text { NO } \end{aligned}$ | $\begin{aligned} & 0.25 \\ & 53 \\ & \text { YES } \end{aligned}$ |

Notes: This table presents the estimates for the average effect of the bank projected end-CET1 ratio of the stress tests on cumulative abnormal returns (in percentage points change), through a panel regression with bank and time fixed-effects. The dependent variable is the bank projected end-CET1 capital ratio under the adverse scenario in a stress test. Model 1 reports the results without controlling for covariates. Model 2 presents the results conditional on the logarithm of total assets and on the leverage ratio to control for bank heterogeneity. The leverage ratio is defined as the bank Tier 1 capital (numerator) divided by its total exposure (denominator). Standard errors in parentheses are clustered by bank. ***, ** and * denote significance at the 1,5 and 10 percent level respectively.

### 4.2 Estimates from the structural GARCH model

Table 4 presents the point estimates and t-statistics of all parameters related with the GARCH model, for the 25 th, 50 th and 75 th percentiles respectively, while in the Appendix, Figure 6 presents a financial sector index for equity volatility for the entire sample of banks in our study. First, in line with the literature, our results find evidence for the presence of some stylized facts commonly found in financial time-series data. For instance, both volatility clustering and volatility asymmetry is present across all three quartiles, as indicated by the values of $\beta$ and $\gamma$. Second, when looking at the value of $\phi$, we find that the point estimates are significantly different from zero for all three quartiles, suggesting that leverage has a significant effect on equity volatility. Finally, point estimates of $b$ reveal a strong relationship between national stock-market indices and bank stock returns.

Table 4: Estimates from the structural GARCH model

|  |  | $a$ | $b$ | $\omega$ | $\alpha$ | $\gamma$ | $\beta$ | $\phi$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 25th percentile | Point estimate | -0.02 | 1.89 | $6.03 \mathrm{e}-08$ | 0.03 | 0.04 | 0.87 | 0.70 |
|  | t-statistic | -0.04 | 2.79 | 3.79 | 3.38 | 2.25 | 6.06 | 1.99 |
|  |  |  |  |  |  |  |  |  |
| 50th percentile | Point estimate | 0.02 | 1.27 | $9.07 \mathrm{e}-08$ | 0.04 | 0.08 | 0.90 | 0.90 |
|  | t-statistic | 0.06 | 6.52 | 1.01 | 3.56 | 3.80 | 7.28 | 8.21 |
|  |  |  |  |  |  |  |  |  |
| 75th percentile | Point estimate | 0.07 | 1.44 | $5.86 \mathrm{e}-07$ | 0.05 | 0.09 | 0.91 | 0.98 |
|  | t-statistic | 0.14 | 12.47 | 2.18 | 2.90 | 3.56 | 8.48 | 9.30 |

Notes: This table contains point estimates from the structural GARCH model (Engle and Siriwardane, 2018) computed through daily return data. Estimation results are presented for the 25 th, 50 th, and 75 th percentile to reflect the heterogeneity across banks in our sample. The t-stats included in this table are robust and computed as described in Bollerslev-Wooldridge (1992). Parameters $a$ and $b$ denote the estimated coefficients of the mean process described in (4), while parameters $\omega, \alpha, \gamma, \beta$ and $\phi$ denote the estimated coefficients of the variance process described in (6) to (11).

As a result of our econometric setup, it is possible to study whether the disclosure of stress test results had a significant effect on the first $(\lambda)$ and second $(\delta)$ moments of equity returns. Table 5 reports the estimates of $\lambda$ and $\delta$ for each quartile. By aggregating the results across the four stress test exercises (Table 5 last row), our results indicate that on average 58 percent of tested banks in our sample exhibit a significant change in the conditional mean of daily returns, and 54 percent in the conditional variance of daily returns upon the publication of the stress test results. As evidenced by the point estimates of the variables $\lambda$ and $\delta$, there is a high degree of heterogeneity on the change in the first and second moments of equity returns. Concerning the change in the first moment, it is observed that on average, the median value (50th percentile) for $\lambda$ amounts to -0.25 , whilst the average interquartile range is $1.13 .^{15}$ Put differently, when controlling for the dynamics in the market index, our results reveal that the median bank experiences on average a change of -0.25 percentage points in returns during the event window. Regarding the second moment of returns, results reveal that on average the median value ( 50 th percentile) of $\delta$ equals -0.06 , i.e., the median bank experiences on average a 6 percent reduction in the variance process of its equity, while on average the interquartile range amounts to 62 percent. ${ }^{16}$

[^9]Table 5: Summary statistics on abnormal returns

|  |  | $\lambda_{2014}$ | $\delta_{2014}$ | $\lambda_{2016}$ | $\delta_{2016}$ | $\lambda_{2018}$ | $\delta_{2018}$ | $\lambda_{2021}$ | $\delta_{2021}$ | $\lambda_{\mu}$ | $\delta_{\mu}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 25th pctl | point estimate | -1.13 | -0.14 | -0.51 | -0.59 | -0.20 | -0.38 | -0.96 | -0.39 | -0.70 | -0.38 |
|  | t-statistic | -3.84 | -2.21 | -4.55 | -2.76 | -3.20 | -2.55 | -4.57 | -2.83 | -4.04 | -2.59 |
| 50th petl | point estimate | -0.46 | 0.15 | -0.14 | -0.15 | 0.08 | -0.08 | -0.48 | -0.15 | -0.25 | -0.06 |
|  | t-statistic | -1.94 | 1.65 | -1.10 | -1.57 | -1.27 | -0.63 | -1.26 | -1.71 | -1.39 | -0.57 |
| 75th petl | point estimate | 0.17 | 0.33 | 0.27 | 0.27 | 0.58 | 0.21 | 0.71 | 0.18 | 0.43 | 0.25 |
|  | t-statistic | 1.12 | 2.20 | 3.44 | 1.81 | 3.85 | 2.96 | 3.44 | 1.81 | 2.96 | 2.20 |
| \% with $\mathrm{t}>\|1.64\|$ |  | 0.57 | 0.54 | 0.68 | 0.59 | 0.50 | 0.47 | 0.59 | 0.56 | 0.59 | 0.54 |

Notes: This table contains point estimates from regressions (4) and (13), where $\lambda$ denotes the percentage points change in the first moment of equity returns and $\delta$ denotes the percentage change in the second moment of equity returns during the event window computed through daily return data. Estimation results are presented for the 25 th, 50 th and 75 th percentiles (pctl) for each stress test event in the sample to reflect the heterogeneity across banks in our sample while columns $\lambda_{\mu}$ and $\delta_{\mu}$ represent the average values across all stress test events. The t-stats included in this table are robust and computed as described in Bollerslev-Wooldridge (1992).

To explore whether the variation in $\delta$ and $\lambda$ is tied to the performance of banks in stress tests, the following steps are performed: i) the sample of banks for each stress test is divided in 3 groups: good, moderate and bad by classifying banks which complete the stress tests with a projected end-CET1 ratio above the 67 th percentile of the distribution of banks as good performers; and banks with a projected end-CET1 ratio below the 33 rd percentile as bad performers; ii) the average estimated $\delta$ and $\lambda$ for banks in each group is computed. Our findings are displayed in Figure 2.

Figure 2 shows that even though the magnitude of the coefficients vary for each stress test, the pattern remains consistent. More specifically, results reveal that banks performing poorly in the stress test exercises experience on average, keeping all else constant, a reduction in the first moment of equity returns but an increase in the second moment, while the reverse holds true for banks that perform well. Concerning banks performing moderately in stress tests, our findings indicate that the disclosure of stress test results has a rather small effect on both the mean and the variance process. Aggregating our estimated coefficients across the four stress test exercises, shows that on average banks performing well during the stress test exercises experience an increase in equity returns of 0.18 percentage points and a reduction in the variance process of 28 percent. While banks that perform poorly, experience on average a decrease in equity returns of 0.80 percentage points and an increase in the variance process of 19 percent. This is similar with the results of Table 3 , while also bringing volatility into the picture. ${ }^{17}$

A possible explanation behind our results may lie in the fact that stress test results are of special interest to shareholders. Bad (good) performance during the stress test exercises may increase (decrease)

[^10]Figure 2: Average change in the first (blue, returns) and second (yellow, volatility) moments


Notes: This figure presents the average change in the first (blue, returns) and second (yellow, volatility) moment as estimated by the structural GARCH model for each category of banks (good, moderate, bad) after the 2014, 2016, 2018 and 2021 stress test publication. Banks are categorised as good if they complete the stress tests with a projected end-CET1 ratio above the 67 th percentile of the distribution of banks, and as bad if banks complete the stress tests with a projected end-CET1 ratio below the 33 rd percentile of the distribution. The x -axis represents the stress test performance per bank category (in terms of projected end-CET1 ratios), and the y-axis represents the average values for estimated coefficients $\lambda_{\mu}$ (blue) and $\delta_{\mu}$ (yellow) in percentage point changes. The data sources are obtained from Bloomberg and Refinitiv.
the probability for mandatory equity issuance, which sets shareholders at a disadvantage if stock dilution takes place (Georgescu et al., 2017). Another explanation, may be that the fundamentals of good (bad) performing banks were better (worse) than anticipated by shareholders, which was therefore priced in by markets during the days after the disclosure of the stress test results (Ellahie, 2012). Therefore, even if the bank risk profile is already reflected in the behaviour of stock markets, our results suggest that the new information provided by the publication of stress tests have changed the informational environment in a tangible way such that both the first and second moment in banks equity return series were impacted.

### 4.3 Estimates from the realised variance

As described in Section 2.3, the latent property of return volatility remains a challenge while modelling the second moment of equity returns. A large part of literature attempts to conduct inference on the volatility process of equity return series through the means of complex mathematical models, such as GARCH models.

Figure 3: Average change in realised variance


Notes: This figure presents the average change in realised variance (RV) computed through 5-minute intraday quoted data for each category of banks (good, moderate, bad) after the 2014, 2016, 2018 and 2021 stress test publications. Banks are categorised as good if they complete the stress tests with a projected end-CET1 ratio above the 67 th percentile of the distribution of banks, and as bad if banks complete the stress tests with a projected end-CET1 ratio below the 33rd percentile of the distribution. The x -axis represents the stress test performance per bank category (in terms of projected end-CET1 ratios) and the y-axis presents the average percentage changes in realised variance (RV). The data sources are obtained from Bloomberg and Refinitiv.

To validate our results, and to ensure that our findings are "model independent", realised variance is computed by using 5 -minute intraday returns. In Figure 7 a financial sector index is displayed for the entire sample of banks in our study. Similar as in Section 4.2, the sample of banks for each stress test is divided in 3 groups: good, moderate and bad by classifying banks based on the projected end-CET1 ratio after the stress tests. Afterwards, the average change in realised variance is computed for each group. Our findings are displayed in Figure 3 and confirm our earlier results with respect to the second moments of equity returns obtained from the GARCH specification. Our results are therefore robust and confirm that on average the
variance during the event window increases for bad performing banks, while the reverse holds true for banks performing well during the stress tests.

### 4.4 Rank correlation: abnormal returns, equity volatility and stress test results

To delve deeper into the cross-sectional relationship between the behaviour of stock markets and stress tests performance, we also investigate whether the (Spearman's) rank correlation changes around the disclosure period of stress test results. To come up with the rank correlation for abnormal returns (equity volatility), banks are ranked in descending (ascending) order based on the projected end-CET1 ratio under the adverse scenario. Figures 4 and 5, present the outcomes of this exercise. Figure 4 denotes the rank correlation between abnormal returns and the projected end-CET1 ratio in stress tests, whereas Figure 5 presents the rank correlation between equity volatility and the projected end-CET1 ratio in stress tests.

Results reveal that the rank correlation experiences a steady increase for both measures after each publication event, which enforces the idea that markets incorporate new information provided by the stress tests. However, a key difference between both variables, is that the change in rank correlation is rather short-lived and relatively large for abnormal returns, whereas the change in rank correlation for equity volatility appears to be smaller in size but more persistent on the days following the disclosure of the stress test results. To quantify the increase in rank correlation (Table 6), the difference between the rank correlation on the day before and the day after the disclosure of the stress test results is calculated. Results, aggregated across the four stress tests, show that for abnormal returns and return volatility the increase amounts, on average, to 62 and 10 percentage points, respectively. The observed trend in the rank correlation corroborates the findings in previous sections. Banks with a higher (lower) projected end-CET1 ratio in the stress test display on average higher (lower) abnormal returns and lower (higher) volatility, which is shown by the increase in the rank correlation on the days after the publication of stress test results.

Table 6: Delta rank correlation: bank abnormal returns and equity volatility in relation to the projected end-CET1 ratio of the stress tests

|  | 2014 | 2016 | 2018 | 2021 |
| :--- | ---: | ---: | ---: | ---: |
| Delta rank correlation: end-CET1 ratio and equity volatility | 0.12 | 0.09 | 0.07 | 0.10 |
| Delta rank correlation: end-CET1 ratio and abnormal returns | 0.38 | 0.77 | 0.68 | 0.66 |

Notes: This table displays the increase in the Spearman's rank correlation for bank abnormal returns and equity volatility in relation to the projected end-CET1 ratio for the 2014, 2016, 2018 and 2021 stress tests. This is calculated as the difference in the rank correlation on days $[\mathrm{t}-1, \mathrm{t}+1]$, where t denotes the disclosure date of the stress tests.

Figure 4: Rank correlation: abnormal returns


Notes: This figure denotes the Spearman's rank correlation between bank abnormal returns and the projected end-CET1 ratio under the adverse scenario, computed through the Spearman's rank correlation formula (14). The time-window spans [ $\mathrm{t}-5, \mathrm{t}+5$ ], where $t$ stands for the disclosure date of stress test results. The publication date is represented by the red dashed line.

Figure 5: Rank correlation: equity return volatility


Notes: This figure denotes the Spearman's rank correlation between equity volatility of banks' stocks and the projected endCET1 ratio under the adverse scenario, computed through the Spearman's rank correlation formula (14). The time-window spans $[t-5, t+5]$, where $t$ stands for the disclosure date of stress test results. The publication date is represented by the red dashed line.

## 5 Conclusions

The Global Financial Crisis revealed strong limitations of the supervisory framework in safeguarding the resilience of the banking system to adverse shocks. To restore market confidence, the EU banking system moved to a centralised Banking Union, with the establishment of the Single Supervisory Mechanism (SSM). This centralisation was primarily set up to ensure financial stability, reduce systemic risk build-up and to make financial institutions equipped to withstand adverse shocks. Therefore, the centralised stress testing exercises have become an important assessment tool for supervisors and regulators ensuring a banking system resilient to adverse macro-financial shocks. The stress tests mitigate bank opaqueness among market participants and, at the same time, build up confidence in the banking system.

In this paper we investigate whether the publication of the EU-wide stress tests of 2014, 2016, 2018 and 2021 affect the short-term behaviour of the stock market. In detail, by exploiting the EU-wide stress tests we examine how markets react to the new information provided by these exercises. We study whether the disclosure of stress test results had a significant effect on the first and second moments of equity returns. First, we study the effect of the publication of stress tests on bank cumulative abnormal returns through a one-factor market model. Second, we study whether both returns and volatility of bank stock prices changes upon the disclosure of stress tests through a structural GARCH model developed by Engle and Siriwardane (2018). Our empirical strategy relies on daily and 5-minute intraday frequency of equity prices.

Our contribution to the literature is twofold. First, we study the effect of the publication of stress tests on the market behaviour of European banks and provide new evidence to policy makers regarding the potential certification role of the stress tests, i.e. we examine whether the information provided by the stress tests on bank individual robustness (good and bad banks) is used by investors. Second, we focus whether the disclosure of stress tests had a significant effect on the first and second moment equity returns. So far the literature has focused mainly on the relationship between stress test publications on the first moment of equity returns, while limited attention has been paid to higher moments.

Our results show that banks performing poorly in stress tests face a reduction in the first moment of equity returns but an increase in volatility, while the reverse holds true for banks that perform well. Stock returns of banks that perform moderately in stress tests have a rather small effect on both the mean and variance process. These findings are corroborated by the rank correlation coefficient, which experiences a steady increase after each publication event, suggesting a short-term reaction from the markets incorporating the new information from stress tests. Our findings suggest that stress tests expand the information available to market participants and enhance price discrimination given that abnormal price behaviour in bank stocks was highly correlated with stress test performance in the days following the disclosure of the results, suggesting
that individual bank resilience was priced by the market.
A possible explanation behind our results may lie in the fact that stress test results are of special interest to shareholders since it provides deeper insights to market participants on the the financial strength of individual banks, as well as the quality of its risk management and capital planning. Market investors may consider that higher capital ratios are consistent with a "precautionary" view of bank capital, although this behaviour is evident only since the financial crisis (Hirtle et al. (2011)). In addition, banks with bad (good) performance during the stress tests may increase (decrease) the probability for mandatory equity issuance, which sets shareholders at a disadvantage if stock dilution takes place (Georgescu et al., 2017). Another explanation may be that the fundamentals of good (bad) performing banks were better (worse) than anticipated by shareholders, which was therefore priced in by markets during the days after the disclosure of the stress tests (Ellahie, 2012). Therefore, even if the bank risk profile is already reflected in the behaviour of stock markets, our results suggest that the new information provided by the publication of stress tests have changed the informational environment in a tangible way such that both the first and second moment in bank equity return series were impacted.

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## A Additional Tables and Figures

Figure 6: Financial sector: equity volatility


Notes: This figure displays the equity volatility of banks that participated in the EU-wide stress test exercises. For each bank, daily estimates of equity volatility are obtained through the structural GARCH model (Engle and Siriwardane, 2018), which are converted into weekly frequency by averaging within each week. Next, an aggregate index is created at each point in time by taking an asset weighted-average across banks, where assets are proxied by the market value of equity plus the face value of outstanding debt.

Figure 7: Financial sector: realised volatility


Notes: This figure displays the realised volatility of banks that participated in the EU-wide stress test exercises. For each bank, daily estimates of realised volatility are obtained from 5-minute intraday returns, which are converted into weekly frequency by averaging within each week. Next, an aggregate index is created at each point in time by taking an asset weighted-average across banks, where assets are proxied by the market value of equity plus the face value of outstanding debt.

Table 7: Tested banks

| Bank name | Tested 2014 | Tested 2016 | Tested 2018 | Tested 2021 |
| :---: | :---: | :---: | :---: | :---: |
| Aareal Bank | yes | no | no | no |
| ABN AMRO Bank N.V. | yes | yes | yes | yes |
| AIB Group plc | yes | yes | yes | yes |
| Alpha Bank | yes | no | no | no |
| Banca Carige | yes | no | no | no |
| Banca Monte dei Paschi di Siena S.p.A. | yes | yes | no | yes |
| Banca Piccolo Credito Valtellinese | yes | no | no | no |
| Banca Popolare dell'Emilia Rom. | yes | no | no | no |
| Banca Popolare di Sondrio | yes | no | no | no |
| Banco Bilbao Vizcaya Argentaria S.A. | yes | yes | yes | yes |
| Banco BPI | yes | no | no | no |
| Banco BPM | yes | no | yes | yes |
| Banco Comercial Português, SA | yes | no | no | yes |
| Banco de Sabadell S.A. | yes | yes | yes | yes |
| Banco Popular Español S.A. | yes | yes | no | no |
| Banco Santander, S.A. | yes | yes | yes | yes |
| Bank of Ireland Group plc | yes | yes | yes | yes |
| Bank of Valletta | yes | no | no | no |
| Bank Polska Kasa Opieki SA | no | no | yes | yes |
| Bankinter | yes | no | no | yes |
| Barclays Plc | yes | yes | yes | no |
| BNP Paribas | yes | yes | yes | yes |
| CaixaBank, S.A. | no | yes | yes | no |
| Commerzbank Aktiengesellschaft | yes | yes | yes | yes |
| Credito Emiliano | yes | no | no | no |
| Danske Bank | yes | yes | yes | yes |
| Deutsche Bank AG | yes | yes | yes | yes |
| DNB Bank Group | yes | yes | yes | yes |
| Erste Group Bank AG | yes | yes | yes | yes |
| Eurobank Ergasias | yes | no | no | no |

Table 7: Tested banks

| Bank name | Tested 2014 | Tested 2016 | Tested 2018 | Tested 2021 |
| :--- | :---: | :---: | :---: | :---: |
| Groupe Crédit Agricole | yes | yes | yes | yes |
| Hellenic Bank Public Co. | yes | no | no | no |
| HSBC Holdings Plc | yes | yes | yes | no |
| ING Groep N.V. | yes | yes | yes | yes |
| Intesa Sanpaolo S.p.A. | yes | yes | yes | yes |
| Jyske Bank | yes | yes | yes | yes |
| KBC Group NV | yes | yes | yes | yes |
| Lloyds Banking Group Plc | yes | yes | yes | no |
| Mediobanca | yes | no | no | yes |
| National Bank of Greece | yes | no | no | no |
| Nordea Bank - group | yes | yes | yes | no |
| Nordea Bank Abp | no | no | no | yes |
| OTP Bank Nyrt. | yes | yes | yes | yes |
| Piraeus Bank | yes | no | no | no |
| Powszechna Kasa Oszczednosci Bank Polski SA | yes | yes | yes | yes |
| Raiffeisen Bank International AG | no | yes | yes | yes |
| Skandinaviska Enskilda Banken - group | yes | yes | yes | yes |
| Société générale S.A. | yes | yes | yes | yes |
| Svenska Handelsbanken - group | yes | yes | yes | yes |
| Swedbank - group | yes | yes | yes |  |
| The Royal Bank of Scotland Group Plc | yes | yes | no |  |
| UniCredit S.p.A. | yes | yes | yes | yes |
| Unione di Banche Italiane Società Per Azioni | yes | yes | no |  |

Table 8: Summary statistics: stock returns (2005-2021)

| Bank name | mean | std | 25 th pet. | 50th pet. | 75th pct. | autocorr |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Aareal Bank | -0.17 | 11.80 | -1.17 | 0.03 | 0.90 | 0.00 |
| ABN AMRO Bank N.V. | -0.02 | 2.28 | -0.94 | 0.04 | 0.79 | 0.04 |
| AIB Group plc | -0.19 | 5.16 | -2.20 | -0.18 | 1.29 | 0.09 |
| Alpha Bank | -0.14 | 4.71 | -2.18 | -0.16 | 1.48 | 0.08 |
| Banca Carige | -0.31 | 5.88 | -1.50 | -0.17 | 0.78 | -0.04 |
| Banca Monte dei Paschi di Siena S.p.A. | -0.21 | 3.89 | -1.57 | -0.18 | 0.85 | 0.06 |
| Banca Piccolo Credito Valtellinese | -0.20 | 6.67 | -1.30 | -0.13 | 0.78 | 0.01 |
| Banca Popolare dell'Emilia Rom. | -0.24 | 13.75 | -1.36 | -0.05 | 0.89 | 0.00 |
| Banca Popolare di Sondrio | -0.23 | 14.09 | -1.12 | -0.08 | 0.77 | 0.00 |
| Banco Bilbao Vizcaya Argentaria S.A. | -0.02 | 2.20 | -1.08 | -0.05 | 0.82 | 0.06 |
| Banco BPI | -0.02 | 2.46 | -1.11 | -0.09 | 0.74 | 0.05 |
| Banco BPM | -0.10 | 3.24 | -1.87 | -0.13 | 1.17 | 0.07 |
| Banco Comercial Português, SA | -0.10 | 2.92 | -1.53 | -0.24 | 0.97 | 0.07 |
| Banco de Sabadell S.A. | -0.04 | 2.34 | -1.10 | 0.04 | 0.71 | 0.07 |
| Banco Popular Español S.A. | -0.14 | 2.65 | -1.32 | -0.10 | 0.72 | 0.13 |
| Banco Santander, S.A. | -0.02 | 2.24 | -1.09 | 0.04 | 0.80 | 0.03 |
| Bank of Ireland Group plc | -0.10 | 4.59 | -1.89 | -0.17 | 1.16 | 0.06 |
| Bank of Valletta | -0.36 | 19.07 | -0.80 | -0.05 | 0.55 | 0.00 |
| Bank Polska Kasa Opieki SA | -0.01 | 2.42 | -1.25 | 0.02 | 0.98 | 0.04 |
| Bankinter, S.A. | 0.01 | 2.20 | -1.11 | -0.04 | 0.78 | 0.02 |
| Barclays Plc | -0.03 | 3.09 | -1.28 | -0.04 | 0.86 | 0.06 |
| BNP Paribas | -0.01 | 2.61 | -1.20 | -0.02 | 0.90 | 0.02 |
| CaixaBank, S.A. | -0.02 | 2.18 | -1.19 | -0.03 | 0.89 | -0.01 |
| Commerzbank Aktiengesellschaft | -0.07 | 2.93 | -1.41 | -0.09 | 0.94 | 0.04 |
| Credito Emiliano | -0.21 | 13.38 | -1.14 | -0.05 | 0.85 | 0.00 |
| Danske Bank | -0.01 | 2.05 | -0.97 | 0.00 | 0.73 | 0.07 |
| Deutsche Bank AG | -0.04 | 2.55 | -1.26 | -0.01 | 0.90 | 0.04 |
| DNB Bank Group | 0.02 | 2.46 | -1.01 | 0.04 | 0.84 | 0.02 |
| Erste Group Bank AG | 0.00 | 2.76 | -1.27 | 0.03 | 1.02 | 0.06 |
| Eurobank Ergasias | -0.24 | 7.11 | -2.31 | -0.16 | 1.39 | -0.19 |

Table 8: Summary statistics: stock returns (2005-2021)

| Bank name | mean | std | 25 th pct. | 50 th pct. | 75 th pct. | autocorr |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Groupe Crédit Agricole | -0.02 | 2.77 | -1.35 | -0.04 | 0.96 | 0.04 |
| Hellenic Bank Public Co. | -0.32 | 13.03 | -1.74 | -0.30 | 1.16 | 0.00 |
| HSBC Holdings Plc | -0.02 | 1.76 | -0.77 | -0.01 | 0.57 | -0.02 |
| ING Groep N.V. | -0.01 | 2.89 | -1.12 | 0.03 | 0.84 | 0.04 |
| Intesa Sanpaolo S.p.A. | -0.01 | 2.52 | -1.13 | 0.05 | 0.90 | 0.01 |
| Jyske Bank | -0.01 | 1.99 | -0.94 | 0.00 | 0.71 | 0.09 |
| KBC Group NV | 0.00 | 3.12 | -1.16 | 0.05 | 0.90 | 0.11 |
| Lloyds Banking Group Plc | -0.04 | 3.07 | -1.11 | -0.05 | 0.77 | 0.09 |
| Mediobanca | 0.00 | 2.17 | -1.05 | -0.02 | 0.84 | 0.04 |
| National Bank of Greece | -0.23 | 6.60 | -2.25 | -0.10 | 1.47 | -0.18 |
| Nordea Bank - group | 0.01 | 2.13 | -0.95 | 0.02 | 0.77 | -0.02 |
| Nordea Bank Abp | 0.01 | 2.13 | -0.98 | 0.07 | 0.79 | -0.02 |
| OTP Bank Nyrt. | 0.02 | 2.69 | -1.24 | 0.07 | 1.05 | 0.09 |
| Piraeus Bank | -0.35 | 7.80 | -2.43 | -0.16 | 1.42 | -0.15 |
| Powszechna Kasa Oszczednosci Bank Polski SA | 0.01 | 2.27 | -1.21 | 0.00 | 0.97 | 0.04 |
| Raiffeisen Bank International AG | -0.01 | 2.97 | -1.44 | 0.02 | 1.11 | 0.03 |
| Skandinaviska Enskilda Banken - group | 0.01 | 2.49 | -0.99 | 0.04 | 0.80 | 0.03 |
| Société générale S.A. | -0.04 | 2.96 | -1.40 | -0.03 | 1.01 | 0.06 |
| Svenska Handelsbanken - group | 0.01 | 1.99 | -0.84 | 0.04 | 0.70 | -0.05 |
| Swedbank - group | 0.00 | 2.35 | -0.92 | 0.11 | 0.80 | -0.01 |
| The Royal Bank of Scotland Group Plc | -0.08 | 3.57 | -1.31 | -0.06 | 0.92 | 0.13 |
| UniCredit S.p.A. | -0.06 | 2.92 | -1.43 | -0.02 | 0.99 | 0.03 |
| Unione di Banche Italiane Società Per Azioni | -0.03 | 2.64 | -1.29 | -0.05 | 0.95 | -0.02 |
| AVERAGE | -0.09 | 4.80 | -1.31 | -0.04 | $\mathbf{0 . 9 2}$ | $\mathbf{0 . 0 2}$ |

Figure 8: Kernel density plot of abnormal returns


Notes: This figure displays the kernel distribution of abnormal returns on the day before (blue) and after (green) the publication of stress test results. Abnormal returns are computed as the residual of the one-factor market model.

Figure 9: Kernel density plot of the projected end-CET1 ratio under the adverse scenario


Notes: This figure displays the kernel distribution of the projected end-CET1 ratio under the adverse scenario for the participating banks in the stress tests (blue) and the sample of banks that are listed in the stock market (green).

Table 9: Robustness check: Effect of stress tests performance (in terms of end-CET1 ratio) on cumulative abnormal returns

|  | $(2)$ |  |
| :--- | :--- | :--- |
| Variables | $(2)$ <br> Model 3 | Model 4 |
| end-CET1 Ratio | $0.30^{* *}$ <br> $(0.15)$ | $0.29^{* *}$ <br> $(0.14)$ |
| Constant | $59.73^{*}$ | $61.01^{*}$ |
|  | $(30.65)$ | $(30.00)$ |
| R-squared | 0.24 | 0.24 |
| Number of banks <br> controls | 53 | 53 |
|  | YES | YES |

Notes: This table presents the estimates for the average effect of the bank projected end-CET1 ratio of the stress tests on cumulative abnormal returns, through a panel regression with bank and time fixed-effects. The dependent variable is the bank projected end-CET1 ratio under the adverse scenario in a stress tests. Model 3 presents the results conditional on the logarithm of total risk-weighted assets and on the leverage ratio to control for bank heterogeneity. The leverage ratio is defined as the bank Tier 1 capital (numerator) divided by its total exposure (denominator). Model 4 includes the covariates of Model 3, as well as the return-on-assets. Standard errors in parentheses are clustered by bank. ${ }^{* * *}$, ${ }^{* *}$, and ${ }^{*}$ denote significance at the 1 , 5 and 10 percent level, respectively.

Table 10: Empirical studies estimating the effects of disclosing stress test results in the U.S.

| Author | Title | Findings |
| :---: | :---: | :---: |
| Peristian et <br> al. (2010) | The information value of the stress test and bank opacity | Authors find that the U.S. stress test aided in suppressing financial panic by providing meaningful information to the markets. Results suggest that banks with larger capital gaps experienced more negative abnormal returns. |
| Spargoli (2012) | Bank recapitalization and the information value of a stress test in a crisis | Author shows that the market reaction to stress tests was favourable in the U.S. and negligible in Europe for the 2010 and 2011 stress tests, mentioning that recapitalizing banks through the European Stability Mechanism would make bank stress tests more effective in Europe. |
| Morgan et al. (2014) | The information value of the stress test | Authors find that the 2009 stress test organized by the U.S. generated significant reactions in the stock market, especially for banks with larger capital gaps. |
| Goldstein and Sapra (2014) | Should Banks' Stress Test Results be Disclosed? An Analysis of the Costs and Benefits | Authors argue that supervisory stress tests are valuable since information on banks' resilience to adverse shocks helps to avert negative spillover effects to the real economy when financial markets are under distress. However, they highlight various potential endogenous costs that are accompanied with disclosing stress test results. |
| Flannery et al. (2017) | Evaluating the information in the federal reserve stress tests | Authors find that the publication of U.S. stress tests generated higher absolute returns and higher trading volume and that riskier banks were more affected by the stress test information. |
| Ahnert et al. (2018) | The Impact of Regulatory Stress Testing on Bank's Equity and CDS Performance | Authors show that both European and U.S. stress tests have impacted equity and credit markets. They find that stress tests enhanced price discrimination as passing banks experienced positive abnormal returns and smaller CDS spreads, while the reverse was true for failing banks. |
| Fernandes et <br> al. (2020) | March madness in Wall Street: (What) does the market learn from stress tests? | Authors argue that U.S. Stress tests contain important information, especially during times of turmoil and does not scale down private incentives to generate information. |
| Sahin et al. (2020) | Banking stress test effects on returns and risks | Authors document that the disclosure of U.S. stress tests had a significant effect on stock and credit markets and decreased both bank systematic risk and systemic risk. |
| Guerrieri and Modugno (2021) | The information content of stress test announcements | Authors find evidence by computing overnight returns that market participants value stress test announcements to gauge both future capital distributions and bank resilience. |

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[^0]:    ${ }^{1}$ The ECB and the ESRB, in close cooperation with national authorities, provide a common macroeconomic baseline and adverse scenarios, which includes risk-type specific shocks. Regulation No 1093/2010 of the European Parliament and of the Council of 24 November 2010 establishes a European Supervisory Authority (European Banking Authority) to "initiate and coordinate Union-wide assessments of the resilience of financial institutions to adverse market developments.
    ${ }^{2}$ Banks must have a minimum of EUR 30 bn in assets. This minimum is consistent with the criteria used for inclusion in the sample of banks reporting supervisory data to the EBA, as well as with the SSM definition of a significant institution. Competent authorities could also, at their discretion, request to include additional institutions in their jurisdiction if they have a minimum of EUR 100 bn in assets. The ECB performs stress tests for the remaining significant institutions not included in the EBA sample, i.e., additional "Supervisory Review and Evaluation Process" (SREP) banks which are also SSM significant institutions but are below the EBA threshold for asset size.
    ${ }^{3}$ The implementation of the Basel III capital rules was designed to be phased-in. The process of implementation for the rules began to take effect in 2013, but the full suite of changes only came into effect later. Because of this phased-in implementation, bank capital ratios are often reported on both transitional and fully loaded basis to allow regulators and other stakeholders to better understand the current capital position of a bank, as well as what the capital position of a bank will be when the full suite of new capital rules apply.
    ${ }^{4}$ Results of the stress tests are incorporated into the definition of supervisory measures and can even have an impact on Pillar 2 (requirements or guidance).

[^1]:    ${ }^{5}$ This was the first time the ECB published more individual data on ECB-supervised banks not part of the EBA sample.
    ${ }^{6}$ The stress tests were launched on 31 January 2014, 24 February 2016, 31 January 2018 and 29 January 2021, respectively.

[^2]:    ${ }^{7}$ However there is some controversy regarding these exercises. Acharya et al. (2014), Acharya and Steffen (2014a) and Acharya and Steffen (2014b) benchmark the ECB's comprehensive assessment results in 2014 through a market-based measure of systemic risk (SRISK) and find that the ECB underestimated the projected capital shortfall of eurozone banks due to the reliance on regulatory risk-weights in determining required levels of capital. Homar et al. (2016) argue however that SRISK may be a poor benchmark due to deeply rooted differences between SRISK and supervisory stress tests.
    ${ }^{8}$ Volatility is a frequently used risk measure that has numerous applications in risk management, option pricing models, asset pricing models, portfolio optimization, etc.

[^3]:    ${ }^{9}$ In accordance with the Capital Requirements Regulation (CRR) Regulation (EU) No $575 / 2013$, the leverage ratio is the bank supervisory Tier 1 capital (numerator) divided by its total exposure (denominator).

[^4]:    ${ }^{10}$ More specifically, realised variance is estimated as the sum of squared 5 -minute intraday returns.

[^5]:    ${ }^{11}$ In total, 53 banks are analysed over a period that starts in January 2005 and ends in August 2021. The average sample in each stress test consists of 37 banks.

[^6]:    ${ }^{12}$ For more information on how these euro area zero-curves are constructed, please refer to: https://www.ecb.europa.eu/ stats/financial_markets_and_interest_rates/euro_area_yield_curves/html/index.en.html.

[^7]:    ${ }^{13}$ For a more broad overview on the distribution of abnormal returns around the publication date of stress test results, kernel plots are included in the Appendix, Figure 8.

[^8]:    ${ }^{14}$ A table with alternative specifications is included, in the Appendix, Table A, and results reveal that the effect of the projected end-CET1 ratio on CARs remains the same.

[^9]:    ${ }^{15}$ The average interquartile range for $\lambda$ is computed as the average difference between the 75 th percentile and 25 th percentile across the four stress test publication events: $\frac{1.30}{4}+\frac{0.78}{4}+\frac{0.78}{4}+\frac{1.67}{4}=1.13$.
    ${ }^{16}$ Analogous to $\lambda$, the average interquartile range for $\delta$ is calculated as $\frac{0.47}{4}+\frac{0.86}{4}+\frac{0.59}{4}+\frac{0.57}{4}=0.62$.

[^10]:    ${ }^{17}$ As a crude computation, from Table 3 and for an end-CET1 ratio of 6.5 percent (as an average of bad performers banks) we have: $(-3.89+(0.35) \times 6.5) / 2=0.81$ (for daily).

