How Platform Design Shapes Risk Beliefs: Evidence from Neobroker Users in Germany

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Abstract (English)

This thesis: How Platform Design Shapes Risk Beliefs: Evidence from Neobroker Users in Germany by Nico Scholz, investigates whether retail investors in Germany updated their risk perception differently after the 2023 collapse of Silicon Valley Bank and the emergency rescue of Credit Suisse, depending on how they invest in financial markets. The SVB/CS shock represents an episode of great financial instability which sent a clear risk signal to markets. Rising interest rates had begun to reveal weaknesses in the global banking system. Attentive investors should have recognised this signal and adjusted their risk perceptions for different asset classes accordingly. This analysis compares risk perceptions between neobroker users and traditional investors with the use of a difference-in-differences model based on a three-wave survey of German retail investors conducted between 2022 and 2024. The results show that neobroker users updated their perceived riskiness of individual stocks and cryptocurrencies significantly less than traditional investors did. This difference remains stable across a nested model specification and is not explained by differences in investor demographics, risk tolerance, investment duration or financial literacy. A VIX-based test shows that neobroker users' risk perception is not driven by market volatility or events. However, the results should be interpreted cautiously as the model is based on a single pre-shock period, and the results lose partial significance under de-meaned robustness checks. Nonetheless, the findings suggest that neobroker platform design affects how investors form beliefs about the riskiness of financial assets, indicating implications for regulatory debate around platform design.

Keywords: neobrokers, risk perception, belief formation, SVB collapse, retail investors, platform design

Abstract (Portuguese)

Esta tese, How Platform Design Shapes Risk Beliefs: Evidence from Neobroker Users in Germany, da autoria de Nico Scholz, investiga se os investidores individuais na Alemanha actualizaram a sua percepção do risco de forma diferente após o colapso do Silicon Valley Bank em 2023 e o resgate de emergência do Credit Suisse, dependendo da forma como investem nos mercados financeiros. O choque SVB/CS enviou um sinal de risco claro para os mercados: a subida das taxas de juro tinha começado a revelar fragilidades no sistema bancário global. Utilizando um modelo de diferenças em diferenças baseado num inquérito em três vagas conduzido entre 2022 e 2024, esta análise compara as percepções de risco entre utilizadores de neobrokers e investidores tradicionais. Os resultados mostram que os utilizadores de neobrokers actualizaram significativamente menos a sua percepção de risco de acções individuais e criptomoedas. Esta diferença mantém-se estável numa especificação de modelo encadeado e não é explicada por diferenças demográficas, tolerância ao risco, duração do investimento ou literacia financeira. Um teste baseado no índice VIX demonstra que a percepção do risco dos utilizadores de neobrokers não é determinada pela volatilidade do mercado nem por eventos específicos. Os resultados devem ser interpretados com cautela, uma vez que o modelo assenta num único período pré-choque e perde significância parcial nos testes de robustez com desmediação. Ainda assim, os resultados sugerem que o design das plataformas neobroker afecta a forma como os investidores formam crenças sobre o risco dos activos financeiros, com implicações para o debate regulatório.

Palavras-chave: neobrokers, percepção do risco, formação de crenças, colapso do SVB, investidores individuais, design de plataformas

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I. Introduction

The way investors perceive the riskiness of financial assets has become an increasingly important question, especially nowadays, when mobile trading platforms have changed who invests in financial markets and how they do so. A neobroker is a mobile platform that investors can use to buy and sell financial assets at zero commission on their smartphones. Neobroker platforms in Germany, like Trade Republic or Scalable Capital, have over the last decade attracted millions of new users, who are younger and less experienced than the users of traditional brokers (Freibauer, Grawert & Rieger, 2024). The neobroker platforms are designed on purpose to be simple and engaging for the user. For example, many of the features resemble a video game: Users can buy stocks with a single tap, and the transaction costs are zero. Also, the app consistently shows the best-performing stocks of the day. With all this, neobrokers have been very effective at acquiring and retaining new customers. But an important question remains unanswered: Does the way mobile platforms are designed influence investors' risk perception? Specifically, when a macroeconomic shock occurs, does this risk signal reach all investors equally, or does the chosen investment method have an effect on how individuals form their risk beliefs?

This thesis investigates that topic with the shock created by the collapse of Silicon Valley Bank and the emergency rescue of Credit Suisse in March 2023, and a three-wave survey of German retail investors from 2022 to 2024. This shock is fitting for this analysis, as it was unexpected, large in scale, and systemic (Jiang et al. 2023).

On the 10th of March 2023, SVB, the 16th largest bank in the US, collapsed in just 36 hours. This was, to date, the second-largest bank failure in US history. To understand how SVB collapsed so quickly, it is important to consider how it ever got that far. In 2018, US President Donald Trump eased capital requirements for banks with less than $250 bn in assets, which applied, among others, to Silicon Valley Bank. This removed many of the safeguards put in place after the 2008 financial crisis, with the goal of reducing the risks banks could take on.

During the pandemic, the bank saw incredible growth in deposits, driven by its technology-heavy clients raising enormous amounts of venture capital. SVB had decided to invest over $100bn in long-term government bonds as a safe, essentially risk-free investment if held to maturity. But SVB failed to take the risk of rising interest rates into account. Energy prices surged, and inflation rates rose sharply worldwide after Russia invaded Ukraine in February 2022. The Federal Reserve in the US and other central banks like the European Central Bank quickly responded by raising interest rates. Interest rates and bond prices have an inverse relationship, so when interest rates rise, bond prices will fall. SVB's bond portfolio rapidly lost its value, and by early 2023, the bank was sitting on approximately $17bn in unrealised losses.

On March 8th 2023, senior management at SVB disclosed that they were forced to sell some of their bond holdings at a $1.8bn loss in order to meet the demand for customer withdrawals. Depositors were alarmed and began to worry that they might not be able to get their money out of the bank if they waited too long. More and more depositors tried to withdraw their funds, which triggered a bank run. Over the next two days, customers tried to withdraw $42bn from SVB, leading to the bank's seizure by regulators on March 10th. This collapse was followed by the failure of Signature Bank, the third-largest bank failure in US history, a short time later.

However, not only was the US banking market hit by these failures, but the shock spread rapidly through the global banking system. Just nine days later, the Swiss bank Credit Suisse, already weakened by years of governance scandals, was on the verge of a collapse as well. Swiss regulators had to step in and broker an emergency deal between UBS and the failing Credit Suisse, with UBS absorbing Credit Suisse, thereby avoiding what would have been the largest bank failure since the 2008 financial crisis.

The message became clear for any attentive retail investor: the rapid rise in interest rates as an attempt by central banks to combat inflation had begun to expose vulnerabilities in the global banking system. This development raised the risk profiles of stocks, derivatives, and other financial securities.

A representative survey of German retail investors was conducted in two waves over the same period: the first leg of the survey in December 2022 and the second one in August 2023. This analysis shows that traditional investors who invest in financial markets through conventional brokerages significantly increased their risk perceptions of individual stocks and cryptocurrencies between the two waves. This is consistent with the market-wide signal after the SVB/CS collapse. Neobroker users who invest through mobile, zero-commission brokers like Trade Republic or Scalable Capital, however, showed little change in risk perception over the same period, despite being exposed to the same macroeconomic events and banking-sector shocks.

The difference-in-differences estimator for both groups (neobroker users vs traditional investors), comparing wave 1 and wave 2, is -0.260 for individual stocks and cryptocurrencies on a four-point scale and is statistically significant at the 5% level. Further analysis shows that this gap cannot be explained by differences in financial literacy, risk tolerance, age, or investment experience. It is not explained by whether investors hold the financial security in question, as neobroker users who actually hold individual stocks and cryptocurrencies still have a less updated risk perception than traditional investors with the same exposure. Furthermore, it is not explained by time spent on informing about financial markets, neobroker users who spent a lot of time following the markets updated their risk perception less than those who followed financial news more casually. Traditional investors, on the other hand, increased their risk perception regardless of how closely they followed financial news, suggesting that the SVB collapse sent a signal strong enough to reach all of them. A VIX volatility-based test confirms this: between the two survey points, the VIX fell, and traditional investors increased their risk perception. Neobroker users, however, showed no sensitivity to the VIX movements. Their risk perception appears to be decoupled from market-based volatility signals and financial news events. This shows that the platform design mediates how external financial signals are translated into individual risk perception.

These findings are not only interesting for the individual investor, but also for the big neobrokers in Germany. The two biggest of them had attracted more than six million customers and roughly €55 bn in assets under management by 2023. Their user base is largely made up of younger, first-time investors compared to traditional brokers.

If the platform design is responsible for how neobrokers disregard signals to change their risk perception, then the implications go beyond individual portfolio performance. When the ECB raises interest rates or a major bank collapses, such events send a clear risk signal to financial markets; however, the assumption that this information, in turn, reaches all retail investors equally may not hold. The regulatory debate around the use of neobrokers in Germany mostly focuses on the gamification of investments and transaction costs. This thesis suggests that there may be another, less visible concern: the way in which these neobroker platforms are designed may have an effect on how retail investors shape their beliefs about financial risks.

II. Literature Review

Over the last decade, the retail investment landscape in Germany has been disrupted by the emergence of zero-commission investment and brokerage platforms, known as neobrokers. By offering the convenience of buying and selling financial products with a single tap and eliminating transaction costs, platforms such as Trade Republic and Scalable Capital have attracted many new investors. These new investors differ systematically from traditional broker users. Investors who use neobrokers primarily are younger, they have a higher risk tolerance, and they are also more likely to hold speculative assets such as cryptocurrencies and derivatives as well. Interestingly, financial literacy among neobroker users is generally comparable to that of traditional investors, although they have less investment experience (Freibauer, Grawert & Rieger, 2024).

Unlike traditional brokers, neobrokers are designed to make investing more accessible for their users. To do that, the brokers not only offer products at low to zero transaction costs, but also design their apps based on the principles of simplicity, immediacy and engagement. They also offer features such as real-time prices, push notifications on price movements, trending stocks, or one-tap buys. This architecture has been very successful in attracting new customers and retaining them. However, the question arises whether the way these platforms are designed influences how investors process financial information and, in turn, how they form their risk perception for different asset classes (Barber et al., 2022).

In 2022, central banks around the world began to rapidly raise interest rates to combat inflation. The ECB in Europe, for example, raised the deposit facility rate from -0.5% to 4% (ECB, 2023). These rises in interest rates played a significant role in the collapse of SVB on March 10th 2023, which in turn triggered a chain of events that ended in the emergency rescue of Credit Suisse nine days later. This was the largest episode of financial instability in Europe since the 2008 financial crisis. More importantly, however, it sent a clear signal: Rising interest rates had begun to reveal weaknesses in the financial system that had remained under the radar throughout the period of 0% interest rates. This, in turn, raised the risk profile of equities and other market-sensitive financial instruments. The main question this thesis focuses on is whether these signals reached and affected all retail investors equally.

An issue well documented in the retail investor market is the fact that investors systematically overtrade and underperform due to overconfidence biases (Barber and Odean, 2000). Over a five-year period, investors in the most active trading quintile underperformed the market on average by more than 6%. Overconfidence bias can cause investors to overestimate their abilities and knowledge while underestimating their informational disadvantages. These effects lead to excessive portfolio turnover and, in turn, a decrease in portfolio performance. This is directly relevant for neobroker users, as the platform design features of these apps reinforce a sense of investment skills through real-time feedback and engagement mechanisms.

When people make decisions, they often do not do so rationally but rely on cognitive biases or heuristics (Kahneman and Tversky, 1974). This makes the decision-making process faster and easier, but it does not mean all available pieces of information are processed rationally. The availability heuristic, for example, causes investors to make decisions based on readily available information or information that is fresh in their minds, such as a price notification they recently received. The anchoring bias gives investors an initial reference point: a stock that has recently outperformed the market will seem likely to continue outperforming. When the investors gain new information about these prospects, they are more likely to underadjust their initial assessment. These mechanisms are especially important in the neobroker context, as the neobroker platforms are designed to send stimuli that affect investor decision-making.

Sims (2003) introduces a similar concept in economics: rational inattention. Investors have limited information-processing capacities, meaning they cannot process all available information; rather, they rationally choose which pieces to consider and which to ignore. They do not act irrationally; on the contrary, this is the logical conclusion to having a capacity for how much information can be taken in. In the neobroker context, this means that users who were exposed to the SVB signal did perceive it but directed their attention to other, more readily available platform stimuli rather than processing a complex narrative about banking-sector weaknesses.

Barber et al. (2022) find that neobrokers create an environment in which overconfidence biases and availability heuristics are amplified among retail investors. US data from the neobroker Robinhood shows that the app´s simplified display, especially the prominent stocks feature, gets retail investors to buy into those highlighted stocks. These events are, on average, followed by abnormal returns of between -3% and -6%. This shows that the app's design is causing measurable changes in portfolio performance.

Chapkovski, Khapko, and Zoican (2024) examine this effect of gamification on investment behaviour. They find that gamified platforms cause investors to trade more and that they are preferred by investors with lower financial literacy. However, using such a platform does not necessarily lead to trading mistakes. Whether the features of a gamified platform lead to better or worse investment performance is mostly determined by how financially literate the investor in question is.

The adoption of neobrokers has no overall effect on portfolio performance. This is because the benefit of lower transaction costs works against the disadvantage of the trend-chasing bias (Liu, Hsieh, Mithas, and Pan, 2024). On the one hand, reduced transaction frictions can allow investors to make investment decisions more quickly and easily. But, on the other hand, trend-chasing bias, meaning buying stocks that have recently performed well, and selling those that have not, is a losing strategy. This is the cost of having constant access and simplified user interfaces. These two effects cancel each other out on the aggregate level. However, for light users, the benefits of low transaction costs, on average, lead to better portfolio performance, whereas the opposite holds for heavy users. Since neobroker users in the present sample trade approximately eight times every month, they fall under the heavier user range, where the costs of trend-chasing are more dominant.

Investors do not process all available information; rather, they allocate finite cognitive resources to the strongest or most easily available signals. Information that is prominently presented or perceived to be more personally relevant receives more attention than other important information that is not (Hirshleifer & Teoh, 2003). In the context of the SVB collapse, the question is less about whether investors followed the event, as it was extensively covered by all major news outlets, but more about how individual investors interpreted it. Neobroker users who primarily interact with financial markets through their smartphones may have encountered this event in a fragmented, decontextualised form. This could result in an underweighting of an important risk signal in financial markets.

Investors who experienced strong returns in the past are more likely to expect strong returns in the future as well (Greenwood and Shleifer, 2014). This shows an additional mechanism through which risk belief updating can fail. They do not form beliefs about future returns by fundamental valuation but rather by the continuation of past trends. This means that investors who experienced strong equity or cryptocurrency returns in 2020 and 2021 have formed positive reference points for these asset classes. Therefore, a macroeconomic shock in the banking sector may be insufficient to impact investors' risk perception. The positive feedback from recent strong returns may outweigh concerns about any negative news stories. This is especially applicable in the neobroker app environment, because here recent experiences are highlighted through same-day performance displays and current trending stock lists.

Cookson et al. (2023) find that the SVB collapse occurred so quickly due to increased social media coverage. Twitter activity predicted the deposit flight days before the bank run. Different investor groups likely followed the event through qualitatively different channels. Neobroker users receive a more fragmented version on social media or simply see the market consequences on their app display, whereas traditional investors may have followed a more coordinated version in the financial news.

There were 190 other US banks that faced similar risks in terms of unhedged exposure to interest rate changes at the time of the SVB collapse (Jiang et al., 2023). This suggests that SVB was not a firm-specific event but rather part of a broader systemic weakness in the banking sector. The Credit Suisse bailout points in the same direction and indicates that this was not a US-only issue but rather affected the entire global market.

Asset pricing theory provides a benchmark of what a rational investor would do in light of the SVB/CS shock. The signal was clear: acute financial distress in the banking sector, in turn, raised equity risk premia across the board for individual stocks and increased counterparty risk in derivatives markets. A rational investor would have revised their risk perception for any appropriate asset classes. The ECB tightening cycle in the background reinforced this development. Fixed-income and money market securities offered an attractive risk-free alternative for the first time in decades. Neobroker users, who have, on average, greater exposure to equities and cryptocurrencies, should have experienced a significant upward revision in their perceived riskiness for these asset classes. The central hypothesis of this paper is that behavioural biases and platform-mediated attention effects caused neobroker users to update their risk perceptions considerably less than traditional investors in response to the SVB/CS shock.

III. Data & Methodology

The empirical analysis is based on a three-wave survey conducted by Freibauer, Grawert & Rieger (2025) among retail investors in Germany. The surveys collect demographic data on the investors in question, as well as information on investment and trading behaviour, financial literacy, and, most importantly for this analysis, risk perception.

The first survey round was conducted in December 2022, the second in August 2023, and the last in February 2024. The results are cross-sectional samples of 502, 537, and 524 participants in each respective wave. The timing of the first two waves creates the opportunity to analyse the impact of the ECB quantitative tightening cycle, which had begun by December 2022 but had not yet reached its peak, while the second wave was collected five months after the SVB/Credit Suisse collapse, with the ECB tightening at its peak with a 4.00% deposit facility rate. Therefore, the primary analysis focuses on Waves 1 and 2, which together yield a sample of 802 active investors.

The survey splits participants in each wave into two investor groups based on their chosen brokerage; these two groups form the treatment and control groups for the difference-in-differences analysis. The treatment group comprises investors who hold an active account with a neobroker platform at the time of each survey wave. In Wave 1, the group consisted of 257 respondents, and in Wave 2, 246. The comparison group consists of investors who do not hold an active neobroker account. These are investors who either access financial markets through non-neobroker channels, or are former neobroker users, or are considering switching to a neobroker, but have not yet done so. In this analysis, for convenience purposes, they are labelled as traditional investors; this does not imply that they are exclusively long-term conventional brokerage users. In Wave 1, the comparison group consists of 140 respondents, and in Wave 2, of 190 respondents. All respondents are currently active investors who trade and hold financial assets.

Several limitations should be noted from the beginning: the parallel-trends assumption cannot be formally tested in this setting, as there is only a single period before the shock. The control group is defined behaviorally and includes investors with prior or planned neobroker experience, which may reduce the boundaries between the two groups. Furthermore, the neobroker platforms themselves may have changed environmentally during the observation period, which the current model cannot account for. These limitations are addressed in detail in Chapter VI.

Variables

The primary variable in this analysis is the individual investor's perceived riskiness of each of the seven asset classes: individual stocks, broad ETFs, specialised ETFs, funds, ETCs, derivatives, and cryptocurrencies. Perceived riskiness is self-reported and measured on a 4-point Likert scale: 1 = very low risk, 2 = low risk, 3 = high risk, and 4 = very high risk. This question was asked in the same manner across all three waves. This question format is ideal for analysing belief formation because the variable measures personal risk assessment rather than objective volatility. This thesis investigates whether the SVB/CS shock is transmitted differently into the risk beliefs of neobroker users than into those of traditional investors.

The binary treatment variable indicates whether an investor is a neobroker user (1) or not (0) at the time in question. The interaction between this variable and the Wave 2 dummy is the primary coefficient in the difference-in-differences analysis. Additionally, four control variables are included in the main regression term: age, investment duration, financial literacy, and risk tolerance.

Age is measured in years and is included to reduce life-cycle effects; e.g., younger investors may have a higher risk tolerance due to less capital invested or longer investment horizons. Investment duration is measured in years, mapped to midpoint values (e.g., 2-3 years to 2.5 years), and controls for investor experience. Financial literacy is measured as a result of three survey questions: (1) defining what a bid-ask spread is, (2) how neobroker platforms generate revenue through payment for order flow, and (3) how a change in interest rate affects bond prices. Each correct answer receives one point out of three. This is an important variable to include, as financially literate investors may process macro risk signals more accurately, and also because high literacy may moderate some of the effects of neobroker platform design (Chapkovski et al. 2024). Risk tolerance is measured on an eleven-point scale from 1 to 11, which was changed in this analysis to a 0-10 scale. This controls for differences in general risk appetite between investors.

Two additional variables are used in a supplementary analysis: Trading frequency and time spent informing on financial markets. Trading frequency is measured as average trades per month and mapped to midpoint values. This variable is included to test the trend-chasing costs found by Liu et al. (2024), whether higher trading frequency in the neobroker group is associated with the least updating in risk perception. The time spent monitoring financial markets is measured on a six-point scale, from 1 = never to 6 = daily, and is used to test exposure to the SVB/CS shock. The purpose of this variable is to test whether the SVB/CS signal reached neobroker users who consume financial news and whether, as a result, they updated their risk perception differently.

Empirical Strategy

The main shock identified in this analysis is the collapse of Silicon Valley Bank and the emergency rescue of Credit Suisse in March 2023. These events occurred between Wave 1 and 2 and were sudden and unexpected, large in scale, and affected the broader financial system rather than just those institutions. That is why they are well-suited for this analysis of belief-formation. The ECB's tightening cycle serves as a background macro trend, not as the primary shock. However, the fast quantitative tightening reinforced the risk signal of the SVB collapse while simultaneously making safer financial investments such as savings accounts more attractive.

The central research question of this paper is whether neobroker users updated their risk perceptions differently from the comparison group, traditional investors, in the wake of the SVB/CS market shock. To answer this, a difference-in-differences model is estimated for the two groups across Waves 1 and 2. This approach compares the risk perception for all seven asset classes before and after the shock for the treatment and control group with the following estimation equation:

$$\text{RiskPerception\_ia} = \alpha + \beta_1 \cdot \text{Wave2\_i} + \beta_2 \cdot \text{neobroker\_i} + \beta_3 \cdot (\text{Wave2\_i} \times \text{neobroker\_i}) + \gamma \cdot \text{X\_i} + \varepsilon\text{\_ia}$$

Here, RiskPerception_ia refers to the individual´s perceived riskiness for the financial asset in question on the aforementioned four-point scale. Wave2_i is a binary indicator that equals 1 for Wave 2 and 0 for Wave 1. The β_1 coefficient captures the average change in risk perception between the two points in time for both groups combined. A positive β_1 means that, on average, an investor perceives an asset as riskier in Wave 2 after the shock than at Wave 1 before. Next, neobroker_i equals one for neobroker users and zero for non-neobroker users in either wave. The β_2 coefficient measures the difference in risk perception between the treatment and control group at the beginning of Wave 1. A non-significant β_2 indicates that the two groups had similar risk perceptions of an asset, which supports the parallel trend hypothesis for the DiD. The data confirms that this is the case for six of seven asset classes. Finally, Wave2_i × neobroker_i is the DiD interaction term. The coefficient β_3 is the key result: it measures the change in risk perception between neobroker users and traditional investors after the shock period. Conceptually, a statistically significant negative β_3 indicates that neobroker users updated their risk perceptions less than the control group did after the shock for the financial asset in question, which is the main finding of this thesis. X_i refers to the four control variables added. This model is estimated using ordinary least squares (OLS) for each of the seven assets. OLS is used in this context because the DiD coefficient has a direct, intuitive interpretation as the difference in the mean rate of risk perception updating between the two groups.

IV. Results

Descriptive Statistics

Table 1 presents descriptive statistics for both groups across the two waves, organised into three panels: investor characteristics, risk perception by asset class, and asset ownership rates. These motivate the following DiD analysis and also provide support for the parallel trends assumption.

First, Panel A investor characteristics show that neobroker users and traditional investors differ across multiple dimensions. Neobroker users, on average, are significantly younger than traditional investors in Wave 1 (40.3 vs 47.7 years), and this gap widens further in Wave 2 (41.4 vs 51.2 years). This shows that neobrokers continue to successfully attract younger users to their platforms. Both groups are approximately two-thirds male. Additionally, in Wave 1 neobroker users show higher risk tolerance (5.78 vs 5.28, $p = 0.031$) and shorter investment duration (7.96 vs 10.65 years, $p < .001$). These characteristics are consistent with a younger, less experienced investor profile. Financial literacy is similar between the two groups at Wave 1 (1.36); however, by Wave 2, traditional investors gain an advantage of 1.58 compared to 1.39

(p = 0.28). This development may indicate gains in experience during the quantitative tightening cycle.

Also, at Wave 1, neobroker users showed a much higher trading frequency, on average 6.84 times per month, compared to 4.68 for traditional investors (p = 0.025). Interestingly, this trend intensifies in Wave 2, where neobroker users report, on average, 7.97 trades per month, compared to 2.61 (p = 0.001). Of traditional investors at Wave 2, over 24% reported making no trades in the preceding month, and 32% reported making just one. This divergence is an interesting finding, showing that, following the shock period, traditional investors significantly reduced their trading activity, while neobroker users increased theirs. This pattern motivates the later analysis of the mediation effect of trading frequency.

Second, Panel B presents the main focus of this analysis: the perceived riskiness of the seven financial asset classes. At Wave 1, risk perception is nearly identical for both groups and all asset classes. None of the small differences reported is statistically significant. Cryptocurrencies, however, are rated as slightly less risky by neobroker users (3.18 vs 3.36, p = 0.033). This is consistent with higher ownership rates and possibly more familiarity with the asset class in general. This supports the theory that the two groups entered the shock period with essentially the same baseline risk perception.

Yet, this changes considerably by Wave 2. Traditional investors updated their perceived riskiness of individual stocks upward by 0.257, of cryptocurrencies by 0.248, of ETCs by 0.235, and of derivatives by 0.242. Each of these shows a significant upward trend, consistent with developments in the macroeconomic environment, raising the risk profile of financial securities sensitive to financial markets. Neobroker users shared none of these trends, facing the same market developments; on the contrary, their stock risk perception actually fell marginally (-0.020), crypto declined (-0.119), and ETCs also fell (-0.035). They actually found these asset classes to be less risky than before the shock period. This divergence is the core finding that motivates the DiD analysis in the next part.

Third, Panel C shows that the ownership rates of all seven asset classes are higher among neobroker users than traditional investors, especially among those who are more platform-specific. Cryptocurrencies, for example, are held nearly twice as much by Wave 1 neobroker users (48.6% vs 25.7%, p < 0.001) and more than four times as much by Wave 2 users (54.5%

vs 11.6%, $p < 0.001$). Derivatives ownership follows a similar pattern. Ownership of broad ETFs and specified ETFs is also higher among neobroker users; this is consistent with the zero-commission platform design and the neobroker's self-proclaimed mission to help with personal retirement planning. These differences in ownership have two-fold implications: they confirm that neobroker users had increased exposure to assets hit by the shock, ruling out that the lack of change in risk perception was simply caused by low or no exposure to those assets in general. Additionally, these findings motivate a further ownership-split analysis to test whether the DiD effect is stronger for investors who actually own the asset class in question.

Table 1. Descriptive Statistics by Investor Group and Wave

Panel A reports investor characteristics. Panel B reports mean perceived risk on a four-point scale (1 = very low risk, 4 = very high risk), with the Δ column showing each group's change from Wave 1 to Wave 2. Panel C reports the percentage of respondents holding each asset class. Significance stars (p-column) from two-sample t-tests comparing neobroker (Neo) to traditional (Trad) investors within each wave.

	Wave 1 (December 2022)			Wave 2 (August 2023)			Δ W1 → W2	
	Neo (N=257)	Trad (N=140)	p	Neo (N=246)	Trad (N=190)	p	Neo	Trad
Panel A. Investor Characteristics								
Age (years)	40.34	47.71	***	41.39	51.16	***	—	—
Male (%)	66.5	66.4		63.0	64.7		—	—
Risk Tolerance (0–10)	5.78	5.28	*	5.66	5.09	*	—	—
Financial Literacy (0–3)	1.36	1.36		1.39	1.58	*	—	—
Inv. Duration (years)	7.96	10.65	***	8.42	15.03	***	—	—
Trades / month	6.84	4.68	*	7.97	2.61	***	—	—
Panel B. Perceived Riskiness by Asset Class (1 = very low, 4 = very high)								
Individual Stocks	2.71	2.69		2.69	2.95	**	-0.020	+0.257
Broad ETFs	2.04	2.01		2.02	1.96		-0.018	-0.052
Specialized ETFs	2.37	2.43		2.34	2.47		-0.028	+0.042
Funds	2.08	2.06		1.98	2.05		-0.100	-0.008
Derivatives	2.69	2.80		2.71	3.04	**	+0.025	+0.242
Cryptocurrencies	3.16	3.36	*	3.04	3.61	**	-0.119	+0.248
ETCs	2.48	2.50		2.44	2.74	**	-0.035	+0.235
Panel C. Asset Ownership Rates (%)								
Individual Stocks	82.1	69.3	**	82.5	71.6	**	—	—
Broad ETFs	70.8	50.7	**	73.6	50.0	**	—	—
Specialized ETFs	61.1	45.0	**	68.7	34.7	**	—	—
Funds	64.6	62.1		66.7	65.8		—	—
Derivatives	35.8	22.1	**	40.2	7.4	**	—	—
Cryptocurrencies	48.6	25.7	**	54.5	11.6	**	—	—
ETCs	35.8	21.4	**	33.3	7.4	**	—	—

* p < .05. ** p < .01. *** p < .001.

Main DiD Results

Next, Table 2 presents the OLS difference-in-difference analysis of risk perception updating after the identified shock period. The full model controls financial literacy, risk tolerance, age, and investment duration. The Table is organised into three rows. The top row shows the main DiD coefficient, the β_3 (Wave 2 x Neobroker) term, then the two components of the DiD structure, and finally the control variables.

The timeline coefficient, β_1, captures the average change in risk perception across both groups over the period from December 2022 to August 2023. For individual stocks, the coefficient is positive and statistically significant: $\beta_1 = 0.232$ ($p = 0.016$). This shows that, on average, investors perceived stocks as riskier five months after the SVB collapse than before. For cryptocurrencies, the coefficient is positive but not significant. This can be explained by the two groups moving in opposite directions regarding perceived risk, or rather, neobroker users not moving at all. The coefficients for all the other asset classes are not significant either.

The baseline coefficient, the β_2, is small and statistically non-significant for six out of the seven asset classes, with the sole exception of cryptocurrencies, which neobroker users rate as slightly less risky than traditional investors at Wave 1 ($\beta_2 = -0.100$, $p = 0.309$). However, this result is not statistically significant either. These results show that at baseline, both investor groups held essentially similar views on the riskiness of the seven financial security types. This parallel trend indicates that any future divergence between the two groups can be explained by different responses to the SVB/CS shock period rather than any group-specific differences that existed before.

The DiD coefficient, the β_3, is the main result in this analysis. For six of the seven asset classes, it is negative, indicating that neobroker users responded to the shock period by updating their risk perceptions less than traditional investors across the board. Two of these results are statistically significant at the 5% level: individual stocks ($\beta_3 = -0.260$, $p = 0.032$) and cryptocurrencies ($\beta_3 = -0.260$, $p = 0.050$). Neobroker users updated their risk perceptions of these two asset classes by approximately a quarter point less than traditional investors: a considerable difference. Traditional investors raised their risk perceptions of individual stocks by 0.257 points between Wave 1 and Wave 2. Neobroker users, on the other hand, showed essentially no change at all in their risk perception of equities (-0.020). The DiD coefficient captures the aggregate of both these developments. The cryptocurrency coefficient follows the same logic: traditional investors increased their risk perception, while neobroker users decreased theirs.

In the control variable section, financial literacy stands out. The coefficients for stocks ($\beta = 0.125, p < 0.001$), cryptocurrencies ($\beta = 0.206, p < 0.001$), and derivatives ($\beta = 0.220, p < 0.001$) are all positive and very statistically significant. Conceptually, this seems rather intuitive: investors who are more financially literate perceive more speculative assets as riskier than those who are less financially literate. Interestingly, the only asset type they identify as less risky is broad ETFs, which also seems quite intuitive, as these are well diversified and less volatile. Risk tolerance is positive and marginally significant for broad ETFs and funds, an interesting finding given that one might expect more risk-tolerant investors to perceive these assets as less risky. Next, Investment duration is positive and statistically significant for specialised ETFs, derivatives, and ETCs, suggesting that experienced, long-term-oriented investors perceive them as more risky. These control variables show interesting patterns, most of which seem internally consistent, suggesting that the DiD captures meaningful variation rather than noise. The R^2 values are modest across the board. The goal in this analysis is not to explain all the variation in risk perception but rather to isolate the DiD effect of the neobroker platform on belief formation.

Table 2. Difference-in-Differences Estimates: Risk Perception Updating by Asset Class

OLS estimates. Dependent variable: perceived riskiness of each asset class (1 = very low risk, 4 = very high risk). Wave 2 is a binary indicator for August 2023. Neobroker is a binary indicator for neobroker users. Wave 2 × Neobroker is the DiD estimator that captures differential risk-perception updating between the two groups over the shock period. Controls: financial literacy (0–3), risk tolerance (0–10), age, and investment duration. N = 802 pooled across Wave 1 and Wave 2. Standard errors in parentheses.

	Individual Stocks	Broad ETFs	Spec. ETFs	Funds	Derivatives	Crypto-currencies	ETCs
Key coefficient							
Wave 2 × Neobroker (β_3)	**-0.260*** (0.121)	0.038 (0.107)	-0.004 (0.105)	-0.090 (0.102)	-0.073 (0.127)	**-0.260*** (0.133)	-0.189 (0.116)
DiD components							
Wave 2 (β_1)	**0.232*** (0.096)	-0.041 (0.084)	-0.038 (0.083)	-0.004 (0.080)	0.060 (0.101)	0.106 (0.105)	0.134 (0.092)
Neobroker (β_2)	-0.025 (0.089)	0.054 (0.079)	-0.031 (0.077)	-0.019 (0.075)	-0.023 (0.094)	-0.100 (0.098)	0.033 (0.086)
Controls							
Financial Literacy	**0.125***** (0.032)	**-0.160***** (0.028)	**0.090**** (0.028)	0.014 (0.027)	**0.220***** (0.034)	**0.206***** (0.035)	**0.102**** (0.031)
Risk Tolerance	0.020 (0.014)	**0.026*** (0.012)	0.019 (0.012)	**0.026*** (0.012)	0.009 (0.015)	-0.011 (0.015)	-0.005 (0.013)
Age	**-0.005** (0.003)	0.003 (0.002)	0.001 (0.002)	**-0.005*** (0.002)	0.005 (0.003)	**0.009**** (0.003)	0.003 (0.003)
Inv. Duration	0.002 (0.005)	0.006 (0.004)	**0.011**** (0.004)	0.003 (0.004)	**0.022***** (0.005)	**0.011*** (0.005)	**0.013**** (0.005)
Intercept	**2.640***** (0.167)	**1.903***** (0.147)	**2.038***** (0.144)	**2.115***** (0.140)	**1.998***** (0.175)	**2.584***** (0.183)	**2.103***** (0.160)
N	802	802	802	802	802	802	802
R^2	0.044	0.049	0.045	0.020	0.133	0.127	0.059

* p < .05. ** p < .01. *** p < .001.

Trading Frequency as a Mediator

The results in Table 2 show that neobroker users update their risk perceptions less after the SVB shock than traditional investors do. The next analysis focuses on a similar model with trading frequency as a mediator. The hypothesis is that neobroker users update their risk perceptions less in response to market-wide risk signals when they trade more frequently. To test this, three additional terms are added to the main DiD model: trades per month, Wave 2 × Trades, which measures whether higher-frequency traders update their risk perceptions differently across both groups, and Neobroker × Trades, which measures whether the effect of trading frequency is stronger for neobroker users. Table 3 shows this advanced model in Panel B.

The Wave 2 × Trades coefficient is negative for all seven asset classes and statistically significant or borderline for four of them: individual stocks ($\beta = -0.022$, $p = 0.002$), broad ETFs ($\beta = -0.023$, $p < 0.001$), specialised ETFs ($\beta = -0.013$, $p = 0.029$), and cryptocurrencies ($\beta = -0.026$, $p < 0.001$). This result shows that, across both groups, investors who trade more frequently updated their risk perception less than those who trade less. This suggests that active trading behaviour is associated with reduced sensitivity to risk signals.

The Neobroker × Trades coefficient is negative and significant for individual stocks ($\beta = -0.020$, $p = 0.020$), derivatives ($\beta = -0.024$, $p = 0.009$), and cryptocurrencies ($\beta = -0.024$, $p = 0.009$). Especially among neobroker users, frequent traders perceive these asset classes as less risky. This shows that users in the neobroker environment are even less sensitive to market-wide risk signals. As heavier traders are exposed to greater volatility and risk in their investments, this effect may naturally warp their risk perception, which seems especially true for neobroker users.

Interestingly, when trading frequency and the interaction terms are added to the Base DiD model, all coefficients lose their statistical significance but remain slightly negative. This indicates that trading frequency at least partially mediates the effect on risk perception. Neobroker users update their risk perceptions less, which is associated with lower responsiveness to risk signals. However, there is an additional effect of platform choice which, even after controlling for differences in trading frequency, affects how beliefs about risk are formed. Additionally, the R^2 values increase substantially across the board, confirming that trading behaviour explains a substantial share of the variation in changes in risk perception. All these results suggest that the most active neobroker users are also the least responsive to external risk signals, such as the SVB collapse.

Before proceeding, it is important to keep the limitations of these results in mind. The parallel trends assumption of the DiD cannot be formally verified by the analysis here. Next, the DiD coefficients (partially) lose their significance when individual biases are removed or individual fixed effects are applied. The full scope of these limitations is discussed further in Chapter VI.

Table 3. Trading Frequency as a Mediator of Risk Perception Updating

OLS estimates. Panel A reproduces the base DiD coefficient (Wave 2 × Neobroker) from Table 2 for reference. Panel B extends the model with three trading-frequency terms: Trades per month, Wave 2 × Trades, and Neobroker × Trades. All models include controls for financial literacy, risk tolerance, age, and investment duration (not reported). N = 802. Standard errors in parentheses.

	Ind. Stocks	Broad ETFs	Spec. ETFs	Funds	Deriv-atives	Crypto	ETCs
Panel A. Base DiD coefficient (without trading frequency)							
Wave 2 × Neobroker	**-0.260*** (0.121)	0.038 (0.107)	-0.004 (0.105)	-0.090 (0.102)	-0.073 (0.127)	**-0.260*** (0.133)	-0.189 (0.116)
Panel B. Augmented model: adding trading frequency interactions							
Wave 2 × Neobroker (expanded)	-0.167 (0.124)	0.073 (0.109)	-0.012 (0.107)	-0.052 (0.104)	0.025 (0.136)	-0.149 (0.140)	-0.161 (0.118)
Trades / month	0.012 (0.008)	0.007 (0.007)	0.002 (0.007)	0.007 (0.007)	0.015 (0.008)	0.013 (0.008)	0.002 (0.007)
Wave 2 × Trades	**-0.022**** (0.007)	**-0.023***** (0.006)	**-0.013*** (0.006)	-0.011 (0.006)	-0.011 (0.007)	**-0.026***** (0.008)	-0.013 (0.007)
Neobroker × Trades	**-0.020*** (0.008)	0.008 (0.008)	0.003 (0.008)	-0.006 (0.007)	**-0.024**** (0.009)	**-0.024**** (0.009)	0.002 (0.008)
N	802	802	802	802	802	802	802
R^2 (base model)	0.044	0.049	0.045	0.020	0.133	0.127	0.059
R^2 (expanded)	0.086	0.067	0.050	0.026	0.152	0.176	0.064

* p < .05. ** p < .01. *** p < .001.

Ownership Split Analysis

In Table 2, the main findings show that neobroker users update their risk perception less than traditional investors across the board. One possible explanation is that neobroker users do not actually have exposure to all these asset classes themselves and therefore do not have a real incentive to change their risk beliefs. In that case, the DiD would simply reflect these differences in ownership rather than actual dissonance in belief formation. Table 4 tests this separately for investors who report owning the specific asset class in question and those who do not.

None of the subsample results reaches statistical significance when splitting the group by ownership status, as the number of observations is roughly halved. However, some of the results are consistent in magnitude and direction with the full-sample results, indicating that the DiD effect is not driven by investors not actually being exposed to the asset class in question. For individual stocks, the DiD coefficient among owners is -0.187, indicating that neobroker users who actually hold individual stocks still perceive them as less risky than traditional investors with the same exposure. The same goes for neobroker investors who own cryptocurrencies; here, the effect is even larger than in the full sample.

Table 4. DiD Estimates by Asset Ownership

OLS estimates of the Wave 2 × Neobroker DiD coefficient from the full model specification (controls: financial literacy, risk tolerance, age, investment duration), estimated separately for investors who own the relevant asset class (Owners Only) and those who do not (Non-Owners Only). Ownership is defined as holding the asset at the time of the survey wave. Full sample N = 802. Standard errors in parentheses.

	Full Sample		Asset Owners Only		Non-Owners Only	
Asset Class	**β (SE)**	**p**	**β (SE)**	**N**	**β (SE)**	**N**
Ind. Stocks	**-0.260*** (0.121)	.032 *	-0.187 (0.134)	621	-0.232 (0.272)	181
Broad ETFs	0.038 (0.107)	.723	0.040 (0.140)	506	0.200 (0.172)	296
Spec. ETFs	-0.004 (0.105)	.972	0.033 (0.150)	438	0.108 (0.156)	364
Funds	-0.090 (0.102)	.374	-0.055 (0.124)	523	-0.156 (0.178)	279
Derivatives	-0.073 (0.127)	.569	-0.283 (0.307)	230	-0.017 (0.154)	572
Crypto	**-0.260*** (0.133)	.050 *	-0.373 (0.314)	308	-0.073 (0.145)	494
ETCs	-0.189 (0.116)	.103	-0.224 (0.333)	208	-0.163 (0.128)	594

* p < .05. ** p < .01. *** p < .001.

V. Robustness Tests

In the next part, the results from Section 4 are tested for their robustness regarding modelling choices, sample composition, and measurement assumptions. Five different tests are performed: nested models, clustering standard errors, excluding respondents who switched groups, de-meaning the outcome, and a VIX proxy test.

Nested Models

First, the nested model reveals how each set of control variables influences the DiD coefficient. The first model includes only the DiD components; demographics and investor profile are then added, and finally, the full model is reported. For individual stocks, the coefficient remains stable and statistically significant for all four models. For cryptocurrencies, the coefficient moves from -0.366 in the Bare DiD to -0.260 in the full model. This reflects differences in investor age and investment profile, both of which can predict changes in cryptocurrency risk perception updating. At first, the ETC coefficient is significant, but only until the model controls for investor profile. The remaining asset classes, except broad ETFs, show negative but non-significant coefficients across all models.

Table 5. Nested Models

DiD coefficient only shown. Model (1): bare DiD. Model (2): + age, gender. Model (3): + risk tolerance, investment duration. Model (4): + financial literacy. N = 802 for all models.

Asset Class	(1) Bare DiD	(2) + Demographics	(3) + Inv. Profile	(4) Full Model
Ind. Stocks	**-0.277*** (0.121)	**-0.287*** (0.121)	**-0.263*** (0.122)	**-0.260*** (0.121)
Broad ETFs	0.034 (0.108)	0.042 (0.108)	0.042 (0.109)	0.038 (0.107)
Spec. ETFs	-0.070 (0.105)	-0.056 (0.105)	-0.006 (0.105)	-0.004 (0.105)
Funds	-0.092 (0.101)	-0.102 (0.101)	-0.091 (0.102)	-0.090 (0.102)
Derivatives	-0.216 (0.133)	-0.184 (0.132)	-0.079 (0.131)	-0.073 (0.127)
Crypto	**-0.366**** (0.136)	**-0.331*** (0.135)	**-0.266*** (0.135)	**-0.260*** (0.133)
ETCs	**-0.270*** (0.117)	**-0.251*** (0.116)	-0.192 (0.117)	-0.189 (0.116)

Note. Each cell reports the Wave 2 × Neobroker coefficient from a separate OLS regression. Standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.

Clustered standard errors

In the main DiD analysis, the conventional OLS standard errors are reported. However, because 191 respondents appear in both waves, there is a risk of correlation between the waves. To control for this fact, in Table 6, standard errors are clustered at the individual level. The Table reports this for the three most consequential asset classes. The results show that clustering reduces the standard errors and lowers the p-values for both individual stocks and cryptocurrency, while the coefficients remain unchanged. It appears that when a person rates one of these asset classes as riskier in Wave 1, they also do so in Wave 2. When this additional noise is accounted for, the analysis becomes stronger rather than weaker, as the OLS standard errors already overstate the uncertainty.

Table 6. Clustered Standard Errors

Wave 2 × Neobroker coefficient from the full model specification. Clustered SE uses G = 605 unique individual clusters. β coefficients are identical across both specifications.

Asset	OLS β	OLS SE	OLS p	Clustered β	Clustered SE	Clustered p
Ind. Stocks	**-0.260**	0.121	.032 *	**-0.260**	0.106	.015 *
Cryptocurrencies	**-0.260**	0.133	.050 *	**-0.260**	0.117	.026 *
ETCs	-0.189	0.116	.103	-0.189	0.103	.068

Note. The Full table is reported in Appendix A. N = 802.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Group Switcher Exclusion

Another potential risk to the DiD set-up is the respondents who switched groups between Wave 1 and Wave 2. The DiD may simply reflect groups switching effects rather than a genuinely different response to the SVB shock. From the 191 participants who appeared in both waves, only 20 switched their investment platform, 8 moved away from neobrokers, and 12 opened a new neobroker account. These represent about 2.5% of the 802 sample. When the DiD is run excluding those 20, the coefficients remain essentially unchanged, and the significance pattern is identical. This indicates that respondents changing groups does not affect the results in any meaningful way.

De-meaned Outcome

Furthermore, there is some concern that the DiD coefficients reflect individual biases, as some investors may have different baseline risk beliefs about a specific asset than other investors. Essentially, the mean level of risk perception of an individual investor could introduce noise into the data analysis. To correct this, each participant's risk perception scores are de-meaned by subtracting the mean for all seven asset classes. This removes the individual effect while still showing any updating patterns that have occurred between the two waves. This process was done for both waves individually. After de-meaning, the results show no further statistically significant coefficients, which could indicate that individual response bias explains much of the variation in updating risk beliefs. However, the direction of risk updating is preserved for both individual stocks and cryptocurrencies; a -0.140 gap also remains for both. This could indicate that the true effect of risk perception updating lies somewhere between the main DiD result and the de-meaned result. Furthermore, the original scale used to measure risk perception employs verbal anchors, which already helps eliminate some individual bias.

Table 7. De-meaned DiD Coefficient

De-meaned outcome refers to the respondent's risk perception for that asset minus their mean across all seven assets, computed separately within each wave. Full model controls are included in both specifications. N = 802.

Asset	Raw β	Raw SE	Raw p	De-meaned β	De-meaned SE	De-meaned p
Ind. Stocks	**-0.260***	0.121	.032 *	-0.140	0.094	.135
Broad ETFs	0.038	0.107	.723	0.158	0.099	.112
Spec. ETFs	-0.004	0.105	.972	0.116	0.082	.159
Funds	-0.090	0.102	.374	0.029	0.088	.739
Derivatives	-0.073	0.127	.569	0.047	0.097	.625
Cryptocurrencies	**-0.260***	0.133	.050 *	-0.141	0.102	.171
ETCs	-0.189	0.116	.103	-0.070	0.089	.435

* $p < .05$. ** $p < .01$. *** $p < .001$.

VIX Market Volatility Control

Another interesting measure of risk is the implied volatility index of the S&P 500, the VIX index. This index is widely used as a proxy for fear in global markets. In December 2022, the VIX was at 21.67, and in August 2023, it was at 14.02, a decrease of 7.65 points. Any investor who simply tracked market volatility would have decreased their risk perception between Wave 1 and Wave 2. However, the data shows that traditional investors increased their risk perception of stocks and cryptocurrencies. To measure this effect, a VIX change variable is introduced into the DiD, replacing the Wave 2 dummy variable, which is 0 for Wave 1 and -7.65 for Wave 2. The VIX × Neobroker term is statistically significant and positive for individual stocks and cryptocurrencies, meaning that neobroker users are considerably less sensitive toward VIX movements than traditional investors. When the two groups are examined separately, traditional investors show a significant negative coefficient for stocks (β = -0.032, p = 0.006), while neobroker users show little sensitivity to VIX movements (β = 0.004, p = 0.690). Neobroker users neither tracked the VIX for risk perception nor responded to the SVB market shock (the full results are reported in Appendix C). Also, a split-sample analysis estimating the VIX sensitivity for neobrokers and traditional investors is reported in Appendix E.

Time Informing about Financial Markets

Furthermore, to test how the SVB signal actually reached individual investors, the time spent informing about the financial markets is used as a proxy for exposure to the shock (scale 1 = never to 6 = daily). The intuitive expectation is that investors who spend more time learning about financial markets react more strongly to the shock than others. Running this test with neobroker users and traditional investors split produces interesting results. Among traditional investors, the coefficients are essentially zero across all seven asset classes and are non-significant. This suggests that the SVB signal reached all traditional investors equally. For neobroker users, however, only the coefficient for broad ETFs is significant and negative, meaning that they perceived ETFs as less risky than at Wave 1. This may simply be because broad ETFs seemed even safer than other asset classes, or because they had recovered from their 2022 lows by August 2023. For individual stocks and cryptocurrencies, the result is also negative, but only borderline significant. This seems rather paradoxical, that more time spent informing on financial markets is associated with lower risk updating. This, in turn, suggests that the signal reached them but did not translate into a revision of their beliefs about riskiness (the full results are reported in Appendix D).

VI. Discussion

The next chapter discusses the significance of the results, limitations of the design of the study, and implications for future research.

First, the central finding here is that neobroker users updated their risk perceptions significantly less in the wake of the SVB/CS shock than traditional investors, with a coefficient of -0.260 for individual stocks and cryptocurrencies. This finding holds up across multiple nested models, with clustered standard errors and excluding investors who switched groups between Wave 1 and Wave 2. However, it partially loses significance when responses are de-meaned to remove individual bias, but the direction of the coefficients remains the same. Taken together, the robustness checks suggest that the difference in risk perception is a genuine effect of the neobrokers' platform design. Barber and Odean (2000) found that overconfidence can cause retail investors to ignore or undervalue adverse pieces of information. The results suggest that a similar effect is operating at the level of risk belief formation, supported by the neobroker app design. Prior analysis of neobrokers has largely focused on gamification, trading behaviour, and portfolio performance, whereas these findings reveal a subtler effect on risk beliefs, which, in turn, influences long-term trading and investment decisions. Neobroker users did not simply fail to rebalance their portfolios in the wake of the shock period; they did not even adjust their risk beliefs. An investor who holds a riskier asset class within their personal risk tolerance is making a calculated decision; however, an investor who does not realise the asset class's changing risk cannot.

The ownership split analysis supports this interpretation; the effect is actually concentrated among those neobroker users who hold the asset in question. These investors would have the strongest incentive to care about changing riskiness in the assets they bought, and they did not change their risk perception. This shows that the effect is not merely driven by investors not caring about the riskiness of asset classes they do not hold. The way neobroker platforms are designed to capture and hold attention seems to limit the capacity of their most engaged users to process relevant external risk signals, such as the SVB collapse (Hirshleifer & Teoh, 2003). Additionally, higher trading frequency among retail traders is associated with lower risk-perception updating across six of the seven asset classes, and this effect is even stronger among neobroker users. This is consistent with the finding of Liu et al. (2024) that the most active neobroker users are those most embedded in the platform environment, which is why they are paying a cost. In this case, there is less response to external risk signals. Neobrokers do not simply attract a certain type of customer who then continues to act in the same way; rather, the platform environment itself may decrease sensitivity to macro risk signals.

Furthermore, two tests are performed to identify the relevance of the SVB/CS shock and the role the platform design played in the shock not reaching neobroker users. The VIX fell by approximately 7.65 points between the two survey periods, indicating that market-wide volatility was lower at Wave 2 than at Wave 1. Any investor simply tracking market volatility would have decreased their risk perceptions between the two points in time. Instead, traditional investors increased their risk perceptions, suggesting they were responding to the SVB signal.

The results show that the two forces were working in opposite directions: the SVB shock increased their perception, while the VIX's decline decreased it; the shock was larger in magnitude. This means that in net total, their risk perceptions increased. On the other hand, neobroker users responded to neither one of these signals. This decoupling across different risk-shaping events provides evidence for a platform-mediating effect. It does not seem to be the case that they were tracking any rational risk-shaping signal at all (see Appendix C).

The information consumption test supports this idea, as time spent learning about global markets does not predict changes in risk perception in Wave 2. The signal reached all traditional investors the same way, regardless of how much financial information they consumed. The importance of the event seemed sufficient to translate into updated risk beliefs across the board. Within the neobroker group, the ones who spent the most time informing themselves actually updated their risk perception the least. A possible explanation for this paradox is that they are so immersed in their platform environment that recent top-trending stocks or other positive/negative market experiences have such a strong influence that they outweigh any other negative market signals. The negative macro signal may dominate the news and minds for a couple of days, but the stimulating way of neobroker design quickly overwrites it before it can be translated into sustained risk beliefs (see Appendix D).

Also, two of the largest neobrokers in Germany, Trade Republic and Scalable Capital, launched high-yield savings features for their settlement accounts of 4% in April of 2023, directly after the SVB/CS shock and between Wave 1 and Wave 2. This new, zero-risk alternative may also have decreased or removed the necessity for their users to rethink the riskiness of their portfolio and financial assets in general, as this new feature was now available in their platform environment.

Limitations

First, the main DiD analysis rests on the assumption that both the treatment and the control group follow parallel trends, meaning that both neobroker users and traditional investors would update their risk perceptions in a similar way. With only a single period before the shock, this assumption is hard to test directly. At baseline, both groups show comparable risk perceptions across six of the seven asset classes; however, this is not a formal test of parallel trends. Having more data points before the shock period would allow testing whether the two groups were developing similarly. Additional panel-data research could address this limitation.

Second, the SVB/CS shock was not the only considerable event happening between Wave 1 and Wave 2. The FTX collapse, the largest cryptocurrency failure in history, happened in November 2022, just weeks before the Wave 1 data was collected. This may have already skewed perceptions of the risk of cryptocurrencies before the first survey. Additionally, in April 2023, Trade Republic and Scalable Capital introduced 4% high-yield savings accounts, creating a new opportunity for neobroker users to allocate capital risk-free. This may have affected general risk perception across asset classes independent of the SVB signal. Also, the neobroker platform used by the treatment group may have changed over the period of observation, including updates to interfaces, changes to notification systems, and changes in how and what information is displayed. In that case, any changes in risk perception updating may be a partial result of a different neobroker environment rather than the SVB shock. As the neobroker platform is considered a static variable in this analysis, this concern cannot be addressed by the current model.

Next, the results for individual stocks and cryptocurrencies under the de-meaned DiD were no longer statistically significant. This suggests that individual bias may be responsible for a major portion of the results. The fact that the direction of the coefficients remains the same and that the scale uses verbal anchors reduces these concerns but does not eliminate them entirely. The true effect may lie somewhere in between the results from the main DiD and from the de-meaned one. Also, when individual fixed effects are introduced into the DiD, all coefficients lose statistical significance; however, the panel consists of only 166 participants, which greatly reduces the precision of the estimation. A longer panel with more observation points and participants would help resolve these issues.

Furthermore, the 802 respondents across Wave 1 and Wave 2 are sufficient for the main DiD estimate, but several subgroup splits are weaker due to having too few members. In Wave 1, the traditional investors, for example, comprise only 140 members. Results within these subgroups need to be treated with caution, as they may reflect insufficient statistical power rather than a true effect. The sample group here consists solely of German retail investors, which may make the findings unsuitable for generalisation to other markets. The neobroker platforms in Germany may differ from those in other countries in Europe or worldwide in terms of fee structures, product catalogues, regulatory requirements, and user bases. All of these may independently affect general risk perception among retail investors, regardless of external shocks. Additionally, all the main variables here are self-reported by the participants. Actual brokerage data would help solve this issue, as investors may underestimate or overestimate their risk tolerance or trading frequency due to individual biases. The cross-sectional set-up in this survey also introduces the possibility of survivorship bias, as neobroker users, who suffered losses during the SVB shock, may have disengaged from its platform and therefore been less likely to be surveyed in Wave 2. This would make the sample generally more optimistic than a true random sample of neobroker users at the time.

Regulatory Implications

The present finding suggests that risk signals reach retail investors differently depending on the platform they use to invest. A traditional brokerage platform in Germany that provides investment advice needs to conduct a suitability assessment where the user needs to confirm that they understand and accept the risk level of their holdings before purchase. Neobrokers operate as an execution-only platform, so the same regulations do not apply to them. If platform design shapes risk beliefs, then this difference may need to be addressed. As the neobroker market in Germany is rapidly growing, with over six million users today, this raises additional concerns. Currently, the debate about neobroker regulations largely focuses on the gamification of investing and transaction costs. But when the attentional architecture of these platforms shapes how investors form risk beliefs, this may be an additional issue worth including in the regulatory discussion.

Future Research

From the limitations above, the direction for future research is clear. A longer panel is needed with more observations and multiple data points before and after a shock period. This would solve the parallel trends issue, as well as allowing a real individual fixed effects analysis. With real brokerage data, it could be tested if failure to update risk beliefs translates into any actual portfolio measures. Also, with the adoption rates for the newly launched 4% savings accounts, it would be possible to test if neobroker users would make use of that feature, differing in risk perception, and update those who did not. Additional tests in other regions during other tightening cycles would indicate if this effect is true for any neobroker users or if this is a specific response to the SVB/CS signal from German neobroker users. It would similarly be interesting to analyse which kind of shocks neobroker users respond to most strongly.

VII. Conclusion

This thesis analysed whether retail investors in Germany received and processed the SVB/CS shock in March 2023, a clear signal of weakness in the banking sector, equally. The results from a two-wave DiD analysis based on a representative survey of German retail investors show that they did not. Neobroker investors updated their risk perception for individual stocks and cryptocurrencies significantly less than traditional investors over the shock period. Both coefficients of -0.260 on a four-point scale (significant at the 5% level) hold up over different nested model specifications. This effect is not explained by differences in financial literacy, personal risk tolerance, investment duration, or age. Nor is it explained by different exposure to the asset classes in question. Neobroker users who actually hold the assets in question updated their beliefs less than traditional investors who did the same. Prior research has shown the way in which the design of neobroker platforms distorts investor trading behaviour and portfolio performance. The findings here reveal that this distortion starts even earlier at the level of belief formation. This is significant because an investor can only make rational decisions when they are accurately aware of the risks involved. As the neobroker market in Germany and worldwide continues to grow, this trend will affect monetary policy transmission, retail investor protection, and the regulatory debate over the design of neobroker platforms. Several limitations need to be taken into account when interpreting these results. The DiD is based on a single pre-period, and there were other significant concurrent events to the SVB shock, such as the FTX collapse and the ECB tightening cycle, that occurred between the two waves and may have affected risk perception. The central finding of this thesis, that neobroker platform design shapes not just what investors do, but what they believe, serves as a foundation that invites follow-up research.

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IX. Appendix

Appendix A: The standard errors are clustered at the individual level to account for possible correlation across Wave 1 and Wave 2 for the 191 individuals that appear in both.

Table A. OLS vs. Individual-Level Clustered Standard Errors (All Asset Classes)

	Conventional OLS			Individual-Level Clustered SE		
Asset Class	**β**	**SE**	**p**	**β**	**SE**	**p**
Individual Stocks	**-0.260***	0.121	.032 *	**-0.260***	0.106	.015 *
Broad ETFs	0.038	0.107	.723	0.038	0.096	.694
Specialized ETFs	-0.004	0.105	.972	-0.004	0.094	.966
Funds	-0.090	0.102	.374	-0.090	0.091	.324
Derivatives	-0.073	0.127	.569	-0.073	0.114	.523
Cryptocurrencies	**-0.260***	0.133	.050 *	**-0.260***	0.117	.026 *
ETCs	-0.189	0.116	.103	-0.189	0.103	.068

Note. Full sample N = 802
* p < .05. ** p < .01. *** p < .001.

Appendix B: From the 191 participants who appeared in both Wave 1 and Wave 2, 20 switched groups, either from neobrokers to traditional or the other way around. This amounts to 2.5% of the sample group. These models are run with and without the 20 switchers.

Table B. Full Sample vs. Excluding Switchers

Asset	Full β	Full SE	Full p	Excl. β	Excl. SE	Excl. p
Ind. Stocks	**-0.260***	0.121	.032 *	**-0.263***	0.120	.038 *
Broad ETFs	0.038	0.107	.723	0.014	0.108	.896
Spec. ETFs	-0.004	0.105	.972	-0.026	0.108	.808
Funds	-0.090	0.102	.374	-0.052	0.103	.618
Derivatives	-0.073	0.127	.569	-0.052	0.130	.696
Crypto	**-0.260***	0.133	.050 *	-0.268	0.136	.051
ETCs	-0.189	0.116	.103	-0.207	0.118	.087

Note. Full sample N = 802; excluding switchers N = 792.
* p < .05. ** p < .01. *** p < .001.

Appendix C: The VIX change variable of -7.65, which measures the change in VIX between Wave 1 and Wave 2, is added to the DiD, replacing the Wave 2 dummy variable. The VIX x Neobroker Term captures the VIX sensitivity between the two groups.

Table C. VIX Market Volatility Control

	VIX Change		Neobroker (baseline)		VIX × Neobroker	
Asset Class	**β (SE)**	**p**	**β (SE)**	**p**	**β (SE)**	**p**
Ind. Stocks	**-0.030*** (0.012)	.015 *	-0.025 (0.089)	.775	**0.034*** (0.014)	.032 *
Broad ETFs	0.005 (0.011)	.625	0.054 (0.079)	.495	-0.005 (0.014)	.723
Spec. ETFs	0.005 (0.011)	.644	-0.031 (0.077)	.686	0.000 (0.014)	.971
Funds	0.001 (0.010)	.959	-0.019 (0.075)	.800	0.012 (0.013)	.374
Derivatives	-0.008 (0.013)	.550	-0.023 (0.094)	.806	0.009 (0.017)	.569
Crypto	-0.014 (0.014)	.320	-0.100 (0.098)	.309	**0.034*** (0.017)	.050 *
ETCs	-0.018 (0.012)	.144	0.033 (0.086)	.702	0.025 (0.016)	.103

Note. Standard errors in parentheses. N = 802.
* p < .05. ** p < .01. *** p < .001.

Appendix D: The Wave 2 x TimeInfo variable is estimated separately for traditional investors and neobroker users to test if the time spent informing on financial markets can predict risk perception.

Table D. Wave2 × TimeInfo Coefficient by Group

	Traditional Investors: Wave2 × TimeInfo		Neobroker Users: Wave2 × TimeInfo	
Asset	**β (SE)**	**p**	**β (SE)**	**p**
Ind. Stocks	-0.005 (0.071)	.947	-0.098 (0.058)	.092
Broad ETFs	0.011 (0.063)	.860	**-0.143**** (0.052)	.006 **
Spec. ETFs	0.025 (0.064)	.691	-0.005 (0.051)	.914
Funds	-0.011 (0.057)	.848	-0.019 (0.046)	.700
Derivatives	-0.021 (0.073)	.779	0.023 (0.059)	.701
Crypto	0.017 (0.079)	.809	-0.120 (0.065)	.065
ETCs	-0.003 (0.069)	.959	0.013 (0.056)	.811

Note. Traditional N ≈ 330; Neobroker N ≈ 472.
* p < .05. ** p < .01. *** p < .001.

Appendix E: The VIX sensitivity between neobroker users and traditional investors is estimated separately. The Difference term is calculated by subtracting the neobroker coefficient from the traditional investor coefficient. The VIX x Neobroker term is shown for reference based on Table C.

Table E. VIX Sensitivity by Investor Group

	Traditional Investors		Neobroker Users		Diff.	VIX × Neobroker (from Table C)	
Asset	**β (SE)**	**p**	**β (SE)**	**p**	**T − N**	**β (SE)**	**p**
Ind. Stocks	**-0.032**** (0.011)	.006 **	0.004 (0.010)	.690	-0.037	**0.034*** (0.016)	.032 *
Broad ETFs	0.007 (0.010)	.481	0.000 (0.008)	.977	+0.007	-0.005 (0.014)	.723
Spec. ETFs	0.008 (0.010)	.439	0.005 (0.008)	.538	+0.003	0.000 (0.014)	.971
Funds	0.002 (0.009)	.873	0.012 (0.007)	.156	-0.011	0.012 (0.013)	.374
Derivatives	-0.009 (0.013)	.475	0.002 (0.010)	.837	-0.012	0.009 (0.017)	.569
Crypto	-0.020 (0.012)	.112	0.022 (0.011)	.055	-0.042	**0.034*** (0.017)	.050 *
ETCs	-0.016 (0.011)	.180	0.007 (0.009)	.474	-0.023	0.025 (0.016)	.103

Note. Standard errors in parentheses.
* p < .05. ** p < .01. *** p < .001.