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Risk and Reward

The Effect of Executive Stock Options on
Executives' Risk-Taking

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Abstract

Title: Risk and Reward: The Effect of Executive Stock Options on Executives' Risk-Taking

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Key words: Executive Stock Options, Stock Volatility, Risk-taking, Agency Theory, Stewardship Theory

Research Question: What effect do ESOs have on executives' risk-taking?

Purpose: The purpose of this study is to analyze whether Executive Stock Options (ESOs) influence executives' risk-taking behavior, using stock volatility as a proxy. The study aims to address this within the context of European companies.

Methodology: The study adopts a deductive approach, formulating hypotheses based on Agency and Stewardship Theory, and testing them quantitatively through panel data regression analysis. Data was gathered from S&P Capital IQ Pro, encompassing 1,799 observations from 180 firms over a 10-year period (2013–2023).

Theoretical Perspectives: Agency Theory, Stewardship Theory

Result: The results show a statistically insignificant relationship between ESOs and stock volatility.

Conclusions: The findings align with Stewardship Theory, which suggests that CEOs are intrinsically motivated to act as responsible stewards of their firms, prioritizing long-term stability over excessive risk-taking. This diminishes the effectiveness of ESOs as tools to induce risk-taking.

Sammanfattning

Titel: Risk och Belöning: Aktieoptioner till ledningen och dess effekt på deras risktagande

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Handledare: Anamaria Cociorva

Nyckelord: Aktieoptioner till Ledningen, Aktiekursvolatilitet, Risktagande, Agentteorin, Stewardshipteorin

Forskningsfråga: Vilken effekt har aktieoptioner för ledningen på deras risktagande?

Syfte: Syftet med denna studie är att analysera om aktieoptioner till ledningen påverkar deras risktagande, genom att använda aktiekursvolatilitet som ett mått på detta risktagande. Studien syftar till att undersöka detta inom kontexten av europeiska företag.

Metod: Studien utgår från en deduktiv ansats, där hypoteser formuleras baserat på agentteorin och stewardshipteorin och testas kvantitativt genom regressionsanalys av paneldata. Datan är hämtad från S&P Capital IQ Pro och omfattar 1 799 observationer från 180 företag under en 10-årsperiod (2013–2023).

Teoretiskt perspektiv: Agentteorin, stewardshipteorin.

Resultat: Resultaten visar ett statistiskt insignifikant samband mellan aktieoptioner för ledningen och aktiekursvolatilitet.

Slutsats: Resultaten stämmer överens med stewardshipteorin, som föreslår att ledningen är motiverad att agera som ansvarstagande förvaltare av sina företag och prioritera långsiktig stabilitet framför överdrivet risktagande. Detta minskar effektiviteten hos aktieoptioner för ledningen som verktyg för att främja risktagande.

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1. Introduction

1.1 Background

Equity-based compensation programs have become increasingly prevalent in recent years (Lu et al. 2022). Incentive programs, such as equity-based compensation, are long-term incentive programs (LTIP), and work as strategic mechanisms implemented within firms to align the interests of employees and executives with organizational objectives (Nuttall, 2015). One specific type of equity-based compensation is Executive Stock Options (ESOs), which grant executives the right to purchase company stock at a predetermined price, creating financial gains if the stock price exceeds the strike price. This design ties rewards to stock price, aligning executive incentives with firm performance. As an LTIP, ESOs aim to align executives' decisions with the company's long-term interests by promoting sustained value creation (Pass, 2003). However, while the typical vesting period of 3 to 10 years (Gopalan et al. 2013; Berk & DeMarzo, 2023) emphasizes long-term goals, it can also lead to short-term decision-making as executives may prioritize immediate rewards over the program's intended purpose (Dong et al. 2013). By linking performance-based rewards to the attainment of goals, these programs aim to motivate and influence behavior to achieve long-term success.

In Europe, executive compensation historically focused on base salaries and cash bonuses (Lu, 2023; Chen et al. 2024). However, it was not until the late 1990s that European firms began adopting ESOs as a new form of equity-based compensation. ESOs were introduced to align executive and shareholder interests by tying rewards to firm performance and encouraging executives' risk-taking. Risk-taking, in this context, refers to strategic decisions and actions taken by executives that involve higher levels of uncertainty but hold the potential for greater rewards.

By the time ESOs gained traction in Europe, they were already well-established in the United States, where they had sparked public debate. A prominent example of ESO-driven controversy is Elon Musk's compensation package with Tesla. According to the Financial Times (2024), Musk's pay agreement replaced a traditional salary with ESOs, tying his compensation entirely to Tesla's financial performance. This arrangement aligned Tesla's financial performance with Musk's personal wealth. However, in January 2024, a Delaware judge declared Musk's pay package invalid considering its excessively large amount. This

raised legal and ethical concerns about the structure of ESOs (Bloomberg 2024). This case illustrates broader concerns about how ESOs may incentivize excessive risk-taking, potentially increasing stock volatility and jeopardizing firms' long-term stability. These challenges of designing compensation packages that balance motivation, fairness, and governance are particularly relevant as ESOs become a core element of long-term compensation strategies. While extreme cases like Musk's highlight these complexities, they also invite deeper exploration into the impact of ESOs on executive behavior, corporate strategy, and shareholder value.

1.2 Problem Discussion

Lu et al. (2022) presents the payoff structure of ESOs and how the structure can amplify risk-taking among executives. The payoffs generated from ESOs have an unlimited upside potential but a limited downside risk, which indicates an asymmetry. This creates incentives for executives to pursue high-risk strategies. Lu et al. (2022) therefore presents a challenge for firms to motivate performance and risk-taking without encouraging excessive risk-taking at the expense of long-term firm growth. Due to their asymmetric payoff structure, ESOs incentivize executives to prioritize high-risk, high-reward projects, which under certain conditions may undermine long-term corporate stability. These findings underscore the importance of carefully designing ESO-programmes with regards to their intended purpose of driving performance and the potential risk of excessive risk-taking. Huang et al. (2013) provides empirical evidence illustrating how cultural, institutional, and regulatory factors influence the relationship between ESOs and executives' risk-taking behaviour. The research demonstrates that, while ESO mechanisms can encourage executives to take calculated risks for growth, the extent and nature of these behaviors vary depending on market development and governance practices.

Although the relationship between ESOs and executives' risk-taking has been extensively examined, existing literature predominantly centers on markets such as the United States (Lu et al. 2022) or emerging economies like China (Huang et al. 2013). Europe has a unique institutional and economic environment, characterized by harmonized regulations and similarities in market structures (Dobak, 2006). This presents an opportunity to study this region as a homogenous group and necessitates a more nuanced evaluation of ESOs' effects, as research on ESOs within the European context remains limited.

1.3 Purpose

The purpose of this study is to analyze the influence of ESOs on executives' risk-taking within firms in Europe, by using stock volatility as a proxy for executives' risk-taking. The study aims to address this purpose by investigating the following research question:

- What effect do ESOs have on executives' risk-taking?

1.4 Relevancy

This study contributes to the understanding of the effect of ESOs on executives' risk-taking by addressing a critical gap in research in the European context. While previous research focuses on other regions, Europe's unique regulatory and governance diversity remains underexplored. By examining ESOs' impact on executives' risk-taking, this study offers valuable insights for designing compensation structures that balance incentivizing risk-taking with ensuring long-term corporate stability.

1.5 Limitations

The geographical scope of this study is developed countries in Europe due to the availability of extensive data and the harmonization of regulations across European countries (Dobák, 2006). The financial sector is excluded from the analysis, consistent with research by Huang et al. (2013) and Liu et al. (2023). Its distinct regulatory framework, unique risk definitions, and high leverage levels complicate the isolation of ESOs effects and limit generalizability. Excluding this sector ensures greater comparability and a more focused examination of stock volatility in non-financial firms. A 10-year timeframe was chosen to align with the duration of ESO programmes and capture long-term impacts on risk, profitability, and investments. This period minimizes short-term stock volatility, reflects investor interests, and ensures sufficient data for reliable findings (Gopalan et al. 2013). The scope of the limitations will be further explained in section 3.5 *Sample Selection of Data*.

2. Theoretical Framework

2.1 Agency Theory

The Agency Theory addresses the problem that can arise when executives, appointed as agents to make decisions on behalf of shareholders, prioritize personal interests over shareholder interests (Berk & DeMarzo, 2023). The theory stems from the separation of ownership and challenges in monitoring agents' behavior (Zolotoy et al. 2022). This ethical dilemma forces executives to choose between acting in the shareholders' best interests or pursuing personal gain. To address this, the theory suggests the use of ESOs to align executives' incentives with shareholder interests by linking their compensation to corporate performance through stock prices (Martin et al. 2019; Zolotoy et al. 2022).

Zolotoy et al. (2022) presents two aspects of the Agency Theory in relation to ESOs. The first aspect is based on the motive behind ESOs, which is the general observation that executives have a different level of risk aversion compared to shareholders. The other aspect highlights effort aversion by executives which is connected to risk strategy (Alchian & Demsetz, 1972). When it comes to the motive behind ESOs, Jensen and Meckling (1976) found that executives might adopt a more risk-averse approach than what shareholders would ideally prefer. Increased risk-taking creates greater opportunities for growth in stock price. This can incentivize executives to take on higher levels of risk as executives holding ESOs can benefit directly from this growth. The latter aspect explains that executives have control over the allocation of capital towards firm productivity (Eisenhardt, 1989). This means that, in some cases, the efforts of executives towards increasing firm productivity may not be great enough, from the perspective of shareholders. ESOs can motivate executives to enhance these efforts towards improving the firm productivity (Alchian & Demsetz, 1972; Zolotoy et al. 2022).

Furthermore, Martin et al. (2019) explains that executives with significant ESO holdings have a larger personal financial stake in the firm's performance. As a result, the executives may be more aware of the risks that could impact the firm's value. This awareness may drive executives to take actions that protect their wealth (Martin et al. 2019). Executives are likely to account for potential losses in their ESO holdings, resulting in a decline in firm productivity when making strategic decisions (Chadwick et al. 2015). Thus, ESOs can also

have a mitigating effect on executives' risk-taking, which would affect the stock volatility in the other direction (Martin et al. 2019).

Dong et al. (2013) explores moral hazard in Agency Theory, where one party takes risks without fully bearing the consequences. In the context of ESOs, this occurs when executives, driven by their ESO holdings, engage in high-risk strategies for personal gain, potentially harming the firm and its shareholders. ESOs may unintentionally promote a short-term focus, leading executives to pursue high risk investments with high upside but greater potential for financial distress. Since executives are shielded from the full impact of stock price declines, shareholders bear the losses, fostering stock volatility and undermining ESOs' stabilizing goals.

2.2 Stewardship Theory

ESOs have been mainly grounded in the Agency Theory which suggests that they work as mechanisms to align the conflicting interests of executives, such as CEOs, and owners (Zolotoy et al. 2022). In contrast to Agency Theory, Stewardship Theory offers a counter perspective on the effectiveness of ESOs in the context of risk-taking. Stewardship Theory has been introduced to explain relationships based upon other behavioral premises (Donaldson & Davis, 1991). The theory suggests that executives, when acting as stewards, inherently seek to act in the best interest of the organizations, aligning their goals with those of the shareholder. Acting like a steward means that they are more empowered rather than controlled. While the theory posits that executives are intrinsically motivated, extrinsic incentives like ESOs can reinforce behaviors that benefit shareholders but are more likely to be viewed as counterproductive as they could undermine the executive's intrinsic motivation and sense of responsibility. Intrinsic motivators include opportunities for growth achievement and self actualization and the use of power would in this case stem from personal power as opposed to institutional power which is what agents would rely on. Donaldson and Davis (1991) emphasizes that the theory offers a valuable alternative perspective on management relationships, and they highlight that there is some level of interplay between Agency Theory and Stewardship Theory when it comes to the level of risk principles are willing to accept. ESOs incentivize executives to undertake projects that may have higher risk but hold the potential for significant returns. However, under the Stewardship Theory these risks are assumed not to be taken recklessly but are aligned with organisational goals and shareholder

interest, which implies the stock volatility is not as closely tied to ESOs. In general, the theory does not explicitly integrate ESOs roles in executives' decision making, but it could explain the grey zone in the effect of ESOs in some situations.

Tosi et al. (2003) provide critical insights into how stewardship governance frameworks influence executive behavior, focusing on intrinsic motivations and trust-based relationships that prioritize long-term organizational goals. They emphasize that under stewardship frameworks, executives are motivated by intrinsic factors such as organizational loyalty, pride, and the desire to achieve collective goals. The intrinsic alignment between executives' personal values and the organization's strategic goals minimizes the need for external incentives, such as ESOs, to drive behavior. This finding reinforces the idea that stewardship-oriented executives are naturally less inclined to exploit ESOs to engage in risk-taking that increases stock volatility. Stewardship theory advocates for governance structures that empower managers through trust rather than control.

Expanding on this, a way to explain the intrinsic motivations is by understanding the personality traits that play a role in influencing executive risk-taking. For example, Benischke et al. (2019) find that certain personality traits can have a moderating effect on the risk-aversion effect caused by ESOs. This effect, highlighted by Lambert et al. (1999) refers to that CEOs who are undiversified may become more risk-averse as the value of their ESOs increase. Other studies point out overconfidence, age and regulatory focus as other factors which can cause varying risk-taking in response to ESOs (Wowak & Hambrick, 2010; Chen et al. 2024).

2.3 Previous Research

To further understand the effect of ESOs on stock volatility, a review of the previous research within the field is presented. While the selected studies explore the same issue, they have used different proxies. The predominant proxies for executive risk-taking include stock volatility and high risk policy choices. According to the literature, high risk policy choices caused by ESOs are reflected in stock volatility. The most common measures of the incentives provided by ESOs to take risks include the dollar value of ESO holdings as well as Vega, which is the sensitivity of the CEO's ESO portfolio to stock volatility. The chapter will be divided into two sections. The first section presents studies that found evidence of a

significant relationship between ESOs and stock volatility. The second section will present studies that do not find evidence of a significant relationship between ESOs and stock volatility. Furthermore, additional studies related to the selection of variables and the proxies used in this study will be discussed in Section 3.6.1 *Variables and Transformations*.

2.3.1 Evidence for a Significant Relationship Between ESOs and Stock Volatility

A number of studies find a significant and positive relationship between the value of ESO holdings and stock volatility (Chen et al. 2006; Wright et al. 2007). For example, Wright et al. (2007) find a significantly positive relationship between executives' ESO holdings and stock volatility. The author's explanation for their results is that ESOs focus an executive's attention on the upside potential, since they have no downside risk, which induces risk-taking. A strength of this study includes that, unlike the majority of other studies, they control for corporate governance variables such as outside board membership and total blockholder ownership, which they find to be significant and positively related with stock volatility. Their independent variable is the average of the CEO's and the four next highest paid executive's at-the-money ESO holdings in 1996, as valued by the Black–Scholes model. By using the option value in 1996, and including the stock volatility of the following four years, the study attempts to enable a causal interpretation. However, with this method, they do not account for possible changes in ESO values or underlying stock volatility over the years, which can bias results. Moreover, they do not account for in-the-money options, which are expected to have an influence on risk-taking.

Similarly, Chen et al. (2006) demonstrate a significant and positive relationship between the value of the CEO's ESO holdings and stock volatility. Their results are explained by the Agency Theory which states that as the CEO's option-based compensation increases, the executive is induced to take more risks, aligning the interests of the executive and shareholders. Their independent variable is the Black-Scholes value of the accumulated in-the-money stock options held to date by the CEO. A draw-back to their measure is that it does not include at-the-money options which could also incentivize risk-taking. A strength of their study includes that they account for the endogenous relationship between risk-taking and compensation. Using a simultaneous equation model, the authors find that stock volatility and ESOs are jointly determined. The positive and significant relationship shows that firms

with higher risk-taking also give out more ESOs. This two-way relationship is affirmed by Coles et al. (2006), with Vega and stock volatility however, is inconsistent with Garren (1994) who finds insignificant results when regressing ESO incentives on beta. The study by Chen et al. (2006) is based on the US banking sector, with a sample containing 68 banks over the time period 1992 to 2000, resulting in 591 observations. Since the study by Chen et al. (2005) limits itself to the banking sector, the results could potentially not be representative of the effects of ESOs in general, due to the operational and regulatory differences regarding financial firms in comparison to other firms. However, due to their chosen time period and the deregulation of the financial industry, it can be argued that their results are comparable to other industries too.

Several studies find a positive relationship between Vega and stock volatility (Core & Guay, 1999; Coles et al. 2006; Huang et al. 2013). For example, Coles et al. (2006) demonstrate a positive, significant and causal relationship between CEO Vega and stock volatility. Their study is based on 10,687 observations of US firms over the period 1992 to 2002. In their study, the authors also show that risky policy choices such as R&D and leverage are positively and significantly related to stock volatility. They explain that ESOs cause risk-taking in the form of policy choices which are, in turn, reflected in the stock price. They also regress high risk policy choices on Vega, finding that higher Vega causes riskier policy choices such as investment in R&D, less investment in Property, Plant and Equipment (PP&E), greater focus on fewer lines of business and higher leverage. Several other studies confirm a positive relation between Vega and high risk policy choices (Rajgopal & Shevlin, 2002; Coles et al. 2006; Huang et al. 2013). Despite the majority of the literature using high risk policy choices as their dependent variable and as a measure of risk-taking, it can be argued that stock volatility is a more direct measure of the risk implied from ESOs, since it directly reflects the risk implied on shareholders which they will pay for through a more volatile stock. Lu et al. (2022) use a more direct risk-measure, “RiskR”, which is a forward-looking option-implied riskiness measure. They report a positive and significant relationship between Vega as well as the value of CEO Stock Option holdings and “RiskR”. They use a sample of US firms, resulting in 11,930 firm-year observations from 1993 to 2012.

There is also a strand of literature finding a negative relationship between ESOs and stock volatility. A number of studies find that ESO’s can in fact lead to decreased risk when the

executive is risk-averse and undiversified (Lambert et al. 1999; Carpenter, 2000; Ross, 2004; Lewellen, 2006). Unlike the majority of the literature, which states that the convexity of the ESOs payoff incentivises executives to increase stock volatility (Lu et al. 2022), Lambert et al. (1999), using economic models and numerical examples, exemplify the opposite, showing that ESOs may not lead to an increased risk-taking, especially for undiversified and risk averse executives. The authors propose a framework for valuing a compensation contract from the perspective of an executive, which takes into account the executive's levels of outside wealth, personal diversification and risk-aversion. The framework shows that if a risk-averse executive has a significant proportion of other wealth tied to his or her firm's stock price, then the executive may subjectively value the compensation contract as less than its value or cost as regarded by shareholders, and thus may not necessarily be incentivized to take more risk. Hence, the authors argue that market-based valuation methods such as the Black-Scholes model can be subject to measurement error due to not taking into account such parameters. A weakness of the existing studies showing a negative relationship includes that they are primarily based on economic theory rather than empirical studies. Nevertheless, the results from these studies imply that the majority of the literature suffers from endogeneity issues due to factors which are difficult to observe and quantify.

2.3.2 Evidence for No Significant Relationship Between ESOs and Stock Volatility

Some studies do not find a significant relationship between ESOs and stock volatility (Hayes et al, 2012; Armstrong & Vashishtha, 2012). For example, Hayes et al. (2012) use the implementation of FAS 123R as a negative exogenous shock to the accounting treatment of ESOs to examine subsequent changes in firm policies and risk. The findings reveal a substantial decrease in the usage of ESOs following the change in the accounting standards, leading to a decrease in Vega. However, the authors do not find evidence that the decrease in Vega is associated with corresponding reductions in high risk policy choices or stock volatility. Their sample consists of 6,983 observations over the years 2002 to 2008 in the US. Lu et al. (2022) also use the implementation of the accounting standard as a negative exogenous shock, finding no significant relationship between Vega and stock volatility. However, they instead find a significant and positive relationship between Vega and ESO implied risk, showing that the decrease in Vega leads to a decrease in ESO implied risk. The

results are thus somewhat ambiguous. Strengths of these studies include the use of an exogenous shock which mitigates endogeneity and enables a causal interpretation.

Armstrong and Vashishtha (2012), although finding a significant and positive relationship between Vega and the level of both total and systematic risk, do not find Vega and idiosyncratic risk to be significantly related. The authors explain that executive's prefer systematic risk to idiosyncratic risk since, with systematic risk, they can hedge themselves by holding the market portfolio; however, with idiosyncratic risk, they are unable to hedge themselves. Their results provide evidence that ESOs lead to increased total risk through executives increasing systematic rather than idiosyncratic risk. The study is based on a sample of 13,233 firm-year observations from 1992 to 2007, from the US. Only a few studies make a distinction between systematic and idiosyncratic risk. In contrast to Armstrong and Vashishtha (2012), Chen et al. (2006) find a positive and significant relationship between Accumulated Options held by the CEO and idiosyncratic risk. The relationship is thus ambiguous. Both studies account for the endogenous relation of compensation design and firm risk.

In conclusion, there is mixed evidence within the field. Many of the studies find a significant positive relationship between ESOs and stock volatility, highlighting that the convexity of ESOs incentivize risk-taking, which can align the interests of shareholders and executives. However, a portion of the literature instead documents a negative relationship, suggesting that other unobservable factors can influence risk-taking. Insignificant relationships between ESOs and stock volatility have also been found, challenging the notion that ESOs increase risk-taking. Overall, there is ambiguity regarding the effects of ESOs and there is also evidence that the relationship runs in reverse too. Finally, it must be noted that there is significant variation in both the independent and dependent variables across the literature, which could explain certain variation in results. It is evident that policy choices is the most common dependent variable despite stock volatility being a better measure of the direct risk implied on shareholders as a result of ESOs. Lastly, there is a substantial gap in the literature regarding the effects of ESO's in Europe, highlighting the need for further research.

2.4 Hypotheses

This study adopts Agency Theory and Stewardship Theory as well as using previous empirical findings in order to analyze the relationship between ESOs and stock volatility. By doing this, we take contrasting perspectives into account and to address the research question: “What effect do ESOs have on executives’ risk-taking?”

Our choice of using stock volatility as a proxy for executives’ risk-taking is further explained in the section 3.5.1.1 *Dependent Variable: Volatility*.

H₀: ESOs are *not associated* with stock volatility.

Stewardship Theory views executives as stewards who inherently prioritize organizational goals and long-term stability (Donaldson & Davis, 1991). While the theory does not directly address ESOs and their insignificant effect, we see that it might be a way to explain an insignificant relationship. While ESOs may encourage calculated risks aligned with firm strategy, the theory suggests that intrinsic motivators, such as loyalty and achievement, diminish the need for external incentives. Consequently, executives acting as stewards are unlikely to use ESOs in a way that increases stock volatility.

H₁: ESOs are *associated* with stock volatility.

Agency Theory is an established framework in the research area of ESOs, as noted in studies by Jensen and Meckling (1976), Dong et al. (2013), and Zolotoy et al. (2022). The theory highlights the divergence of interests between executives and shareholders (Jensen & Meckling, 1976; Zolotoy et al. 2022). ESOs are designed to align these interests by linking executive compensation to stock performance, encouraging higher effort and risk-taking. However, this alignment may also lead to moral hazard, where executives take excessive risks for short-term gains (Dong et al. 2013). The theory suggests that ESOs are designed to align the interests of executives with shareholders, encouraging executives to take risks that might lead to higher returns (Jensen & Meckling, 1976). This means ESOs incentivize executives to increase firm risk-taking, as their compensation is directly linked to stock price performance. The moral hazard aspect of Agency Theory further supports this hypothesis, suggesting that executives may pursue high-risk investments to maximize personal gains from stock price increases, even if such actions may increase stock volatility (Dong et al. 2013). Therefore, executives’ risk-taking encouraged by ESOs could lead to higher stock

volatility as executives act on incentives that prioritize short-term gains over long-term stability. Furthermore, Martin et al. (2019) suggest that executives with significant ESO holdings can be more aware of risks affecting the firm's value and may take actions to protect it due to their increased accountability. This could reduce risk-taking and mitigate stock volatility. Thus, Agency Theory can be a theoretical tool to understand why ESOs might affect stock volatility by affecting executives' risk-taking.

3. Method

3.1 Scientific Approach

This study adopts a deductive approach, starting with the formulation of hypotheses based on existing theories and previous research. These hypotheses are then tested quantitatively using empirical data by operationalizing theoretical concepts into measurable terms (Bryman et al. 2024). Given the nature of the problem, the study's purpose, and the research question, the hypotheses are tested using regression analysis applied to panel data.

3.2 Data Gathering

This study is based on quantitative secondary data which has been retrieved from S&P Capital IQ Pro (2024). The data utilized for the regressions comprises firm data sourced from the database creating a representative sample of firms in developed Europe. Data of this sort and amount would not be feasible to collect independently, given the time constraints of the study. The use of S&P Capital IQ Pro data allows for a substantial, high quality dataset. As noted by Bryman et al. (2024), a large sample size can enhance the precision of the findings, an aspect the authors consider crucial.

3.3 Data Characteristics

Our research employs a strongly balanced panel, with 1 799 observations collected from 180 firms observed consistently over the period 2013 to 2023. Panel data consist of observations for multiple firms across multiple time periods. This format pools cross-sectional and time-series dimensions, offering increased data points that enhance the degrees of freedom and reduce collinearity among explanatory variables (Wooldridge, 2010; Hsiao, 2021). A balanced panel refers to a dataset where every firm is observed for the same number of time

periods, with no missing observations. This uniform structure offers several methodological advantages in regression analysis. For instance, it simplifies the estimation process and enhances the precision of parameter estimates, as all entities contribute equally across the full time span (Hsiao, 2021). With no missing values, estimation techniques such as fixed-effects or random-effects models can be implemented without additional adjustments for missing data (Wooldridge, 2010).

3.4 Sample Selection of Data

3.4.1 Geography

The selected geography sample is based on the identified gap in research within the scope of the thesis topic. This study aims to expand upon findings from previous research by investigating the effects of ESOs on executives' risk-taking in developed countries in Europe.

While studying a single country could offer interesting contexts due to its specific economic, cultural, or regulatory environment, the availability of data within a single country is limited. Studying developed countries in Europe presents a unique opportunity to investigate ESOs due to its combination of EU harmonized regulatory frameworks and the richness of data available. The S&P Europe 350 and S&P Europe BMI indices in the S&P Capital IQ Pro database include a wide range of firms from Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom (S&P Capital IQ Pro, 2024). Although not all these countries are part of the European Union, the regional dataset allows for meaningful cross-country comparisons while encompassing firms subject to both EU regulations and non-EU regulatory frameworks.

The harmonization of regulations within the European Union significantly reduces the confounding effects of regulatory discrepancies often observed in cross-country analyses involving EU member states. As Dobák (2006) outlines, European corporate governance frameworks within the EU share a foundational alignment due to EU-driven harmonization efforts, creating a relatively uniform regulatory environment. Even though the inclusion of firms from non-EU countries, such as Switzerland, Norway, and the United Kingdom, introduces other regulatory frameworks, they have enough regulatory similarities to be studied as a homogenous group in this study. Within Europe, there are many similarities between countries when it comes to corporate governance (Sautner & Weber, 2011). Sautner

and Weber (2011) emphasize the significance of governance structures in shaping ESO designs. They highlight how factors such as ownership concentration, board composition, and governance mechanisms across developed countries in Europe can contribute to specific designs of ESOs.

Additionally, developed countries also tend to follow standardized accounting principles (Bengtsson & Argento, 2023), which are essential for ensuring data comparability. These accounting standards often impose more detailed reporting requirements, enriching the data collection process. Additionally, Marjerison & Gatto (2024) finds that financial structures and access to capital are more similar among firms in developed countries.

3.4.2 Industry

Similar studies examining the effects of ESOs exclude the financial sector due to its distinct characteristics (Huang et al. 2013; Liu et al. 2023). Adopting their approach in our study allows a higher level of comparisons with existing research.

The decision to exclude the financial sector was made to ensure greater homogeneity in terms of legislation, risk, and corporate structure (Berk & DeMarzo, 2023). Financial institutions are subject to stringent regulations, particularly concerning risk exposure. Consequently, examining the financial sector is less relevant to answering the research question, which focuses on the role of executives' risk-taking decisions. According to Bhullar et al. (2024), the definition and measurement of risk in the financial sector differ significantly from that in the non-financial sector. In financial firms, risk is typically defined through financial losses such as market fluctuations and credit losses. In contrast, risk in the non-financial sector is defined from a more operational standpoint, related to technology and innovation. Additionally, Bhullar et al. (2024) finds that differences between the financial and non-financial sectors can be observed in their capital structure. For example, financial firms, due to their business models, tend to exhibit higher levels of leverage, which influences how risk-taking is realized and complicates the generalizability of findings (Berk & DeMarzo, 2023).

3.4.3 Time Frame

The duration of 10 years has been selected based on several reasons. ESOs are generally structured to span a period of 3–10 years (Huang et al. 2013; Gopalan et al. 2013; Lu et al.

2022; Berk & DeMarzo, 2023). The availability of data and the number of observations required to achieve statistical significance and validity also played a critical role in determining the study's timeframe. A 10-year window ensures an adequate sample size, strengthening the generalizability of the findings. Using a 10-year period also aligns with previous research. Coles et al. (2006) adopted a similar 10-year timeframe to study the relationship between executive compensation and firm risk. Other studies that focused on specific economic or regulatory shifts had shorter observation periods (Huang et al. 2013; Lu et al. 2022). While the studies with a shorter timeframe offer valuable insights into short-term dynamics, using the longer timeframe of 10 years allows for a broader exploration of structural trends in stock volatility and risk-taking across diverse market conditions. This aligns with the study's goals of examining the sustained effects of ESOs on executives' risk-taking and firm performance.

3.4.4 CEO Focus

The study focuses on CEOs, with two of the variables used in the regression being CEO Option Awards and CEO Cash Compensation. The decision to specifically analyze CEO data is based on three key considerations.

Firstly, CEOs hold great power in decision making. CEOs are considered to have the most powerful position in the executive team, and are therefore likely to impact the level of risk-taking. Examining how different firms allocate their ESOs reveals that CEOs are awarded the majority of ESO holdings. However, It should be noted that the theories identified under chapter 2. *Theoretical Framework* refer to executives in general rather than specifically to CEOs. Focusing on CEOs' decision-making offers valuable insights into how individual leadership styles, risk preferences, and ethical considerations shape these dynamics. This approach not only bridges theoretical frameworks with practical applications but also aids in designing stock option structures that effectively align CEO incentives with sustainable shareholder value creation.

Secondly, having a CEO focus allows comparability with previous research. Huang et al. (2013) and Lu et al. (2022) focus on CEOs to examine executives' risk-taking. Drawing on these previous studies, our study uses the CEO as a proxy for executives.

Thirdly, while focusing exclusively on CEOs represents a limitation, it allows more structured and comparable data by maintaining consistency in the examined position across all firms in the sample.

3.5 Data Processing

3.5.1 Variables and Transformations

3.5.1.1 Dependent Variable: Volatility

Our choice of dependent variable is grounded in regression models and methodologies used in similar studies. Lu et al. (2022) use the dependent variable "risk return" to quantify the level of risk implied by executives' ESO holdings. This variable captures the extent to which the value of stock options, often structured to incentivize risk-taking, correlates with the executive's exposure to potential future gains or losses. By examining "risk return," Lu et al. (2022) analyze how executive compensation packages, particularly those involving stock options, influence risk-taking and decision-making, ultimately impacting firm performance.

Similarly, Huang et al. (2013) utilize the dependent variable "return volatility" to measure fluctuations in a company's stock returns. Return volatility, which quantifies deviations from the mean over a specified time period, is employed to assess how equity-based compensation links executives' incentives to company performance and affects their risk-taking. Coles et al. (2006) also employ stock return volatility as a dependent variable, emphasizing its effectiveness as a proxy for firm risk in regression models examining the relationship between executives' incentives, corporate policies, and financial outcomes.

To measure firm risk in our study we chose to use Volatility as a proxy for risk-taking. Stock volatility measures how frequently and to what extent a stock's price fluctuates over time, serving as a way to assess the firm's risk level (Guo et al. 2024). We derive Volatility from the standard deviation of total returns of a rolling 57-week period from 2013 to 2023. The total return, as defined by S&P Capital IQ Pro (2024), combines stock price changes (capital gains) and dividends reinvested, offering a comprehensive view of shareholder value. This metric reflects both price performance and income generation, making it a more accurate measure of overall firm equity performance compared to price returns alone (S&P Capital IQ Pro, 2024). The use of historical returns aligns with the study by Coles et al. (2006), as such

data effectively captures both systematic and idiosyncratic risk factors. By focusing on a rolling period, the calculated Volatility reflects managerial influences and broader structural patterns in firm performance while filtering out short-term market shocks (Coles et al. 2006).

To address issues of skewness and heteroskedasticity common in financial data, Volatility is transformed using $\log(1+x)$. As emphasized by Wooldridge (2010), logarithmic transformations are standard in regression models to stabilize variance and improve the distributional properties of variables. Adding +1 ensures the transformation accommodates zero values, a frequent occurrence in datasets involving financial metrics. This transformation provides a consistent and interpretable measure of firm risk, enabling robust analysis of how managerial incentives affect Volatility.

3.5.1.2 Independent Variable: CEO Option Awards

As noted in section 2.3 *Previous Research*, many studies have been using the measure Vega, referring to the sensitivity of the CEO's ESO portfolio to stock volatility. In this study, we use CEO Option Awards as a proxy for Vega.

Our primary independent variable is CEO Option Awards, which serve as a measure of executives' risk-taking. The use of CEO Option Awards as a measure of executives' risk-taking is supported by studies such as Coles et al. (2006) and Huang et al. (2013), which establish a relationship between equity-based compensation and high risk corporate policies. This variable represents the cost recognized for financial reporting purposes of all equity-based compensation instruments with option-like features, as outlined by S&P Capital IQ Pro. These costs are calculated in accordance with FAS 123R, which mandates that the fair value of such instruments be expensed over their selected period (S&P Capital IQ Pro, 2024).

To prepare the CEO Option Awards variable for regression analysis, $\log(1+x)$ was applied as a transformation. This approach is commonly used in econometric studies to address skewness in the data, a frequent issue with executive compensation variables, and to stabilize variance. By normalizing the distribution of the variable, this transformation ensures compatibility with the assumptions of Ordinary Least Squares (OLS) regression (Wooldridge, 2010). The dataset includes a significant number of zero values for CEO Option Awards, representing firms or periods where no such compensation was granted. The addition of +1 in

the transformation ensures that these zero values are accommodated, allowing the variable to remain continuous and usable for analysis. The transformation facilitates the interpretation of results in a logarithmic scale while maintaining the integrity of the data (Baum, 2021). Additionally, a 1-period lag was subsequently applied to the transformed variable. This addresses potential endogeneity concerns. Lagging variables is a standard econometric approach in panel data analysis to improve causal inference (Wooldridge, 2010).

3.5.1.3 Controlled Variables: Executives' Risk Aversion

3.5.1.3.1 CEO Cash Compensation

CEO Cash Compensation is included as a control variable and serves as a proxy for executive risk aversion. The literature presents mixed views on its relationship with risk-taking. Coles et al. (2006) and Berger et al. (2012) suggest that higher fixed compensation, such as salary and bonuses, may lead to executive entrenchment and increased risk aversion. In contrast, Core and Guay (1999) argues that higher compensation enables CEOs to diversify personal investments, potentially reducing risk aversion. This variable is calculated as the euro amount of the CEO's annual salary and bonus, as reported in company filings and defined by SEC regulations (S&P Capital IQ Pro, 2024). Other forms of compensation, such as equity or long-term incentives, are disregarded to replicate the methodology of studies like Lu et al. (2022) and Coles et al. (2006).

To prepare this variable for analysis, $\log(1+x)$ was applied to address skewness, and a 1-period lag was introduced for the same reasons outlined for the independent variable, CEO Option Awards. These transformations ensure the variable aligns temporally with the dependent variable and is suitable for regression analysis.

3.5.1.4 Control Variables: Firm's Investment Opportunity

3.5.1.4.1 Tangibility

Tangibility is included as a control variable in our study, serving as a proxy for a firm's investment opportunities. It is defined as the ratio of PP&E to total assets, and it reflects a firm's capacity to use tangible assets as collateral for securing financing. The literature shows that firms with abundant investment opportunities often face executive conservatism, leading to the provision of equity-based compensation to encourage risk-taking (Baber et al. 1996; Lu

et al. 2022). Controlling for Tangibility ensures that differences in firms' asset structures and access to financing do not confound the analysis.

Similar to the independent variable, Tangibility was lagged by 1 period to address endogeneity concerns and ensure temporal alignment between explanatory and dependent variables. This lag ensures that tangibility reflects pre-existing conditions and minimizes the risk of reverse causality, as emphasized in econometric literature (Wooldridge, 2010; Baum, 2021). Additionally, the variable was winsorized at the 5th and 95th percentiles to reduce the influence of extreme values, ensuring robustness in the regression analysis.

3.5.1.5 Control Variables: Firm's Financial Health

3.5.1.5.1 Total Assets

The book value of a firm's Total Assets is included to control for firm size, which has been shown to influence executive compensation structures, including the provision of ESOs (Smith & Watts, 1992; Rajgopal & Shevlin, 2002). Larger firms are considered to be less risky due to having more stable incomes and financial situations, which should lower stock volatility. Although, larger firms are also more likely to pay higher compensations, which may impact risk-taking, increasing Volatility. Total assets were transformed using $\log(1+x)$ to address skewness in the data and were lagged by 1 period to ensure temporal alignment with the dependent variable.

3.5.1.5.2 Financial Leverage

Financial leverage, calculated as total debt divided by total assets, is included as a measure of a firm's financial health. The literature demonstrates a positive relationship between leverage and both ESOs and Volatility (Coles et al. 2006; Lu et al. 2022). Leverage was winsorized at the 5th and 95th percentiles to reduce the influence of extreme values and then lagged by 1 period to mitigate endogeneity concerns.

3.5.1.5.3 Cash

Cash, measured as cash and cash equivalents divided by total assets, serves as an additional measure of financial health. Following Lu et al. (2022), cash holdings reflect a firm's liquidity and its ability to manage short-term obligations. The variable was winsorized to limit the impact of outliers and lagged by 1 period to capture pre-existing liquidity conditions relative to the dependent variable.

3.5.1.5.4 Return on Assets (ROA)

ROA, calculated as net income divided by total assets, is used to measure firm performance. Previous research by Mehran (1994) suggests a positive relationship between ROA and equity-based compensation, such as ESOs. Winsorization was applied to address outliers, and a 1-period lag was introduced to ensure that the variable reflects previous firm performance.

3.5.2 Reshaping the Data

To use the collected data for analysis, a structured data processing routine was implemented using Stata, a statistical software package widely used in econometric research (Baum, 2021). The data from the S&P Capital IQ Pro database was first extracted in a wide format and then consolidated by merging separate sheets, ensuring consistency in firm identifiers and time periods. It was subsequently reshaped into a long panel data format, with firm ID and year as unique identifiers. This transformation facilitated the application of econometric techniques such as fixed-effects and random-effects models for panel data analysis (Baum, 2021).

3.6 Regression Model

To analyse the relationships between our dependent variable and explanatory variables, we perform two multiple regressions. The multiple regression models are estimated using ordinary least squares (OLS). The OLS method estimates the unknown parameters by choosing estimates which minimize the sum of squared residuals (Wooldridge, 2010). The Gauss-Markov theorem states that, under the Gauss-Markov assumptions, OLS is the best linear unbiased estimator (BLUE). Assumptions 1 through 5 must be satisfied for the theorem to hold. The assumptions are presented in section *3.7 Assumptions*.

Several other factors, other than our explanatory variables, affect a firm's stock volatility and may be correlated with our explanatory variables. These factors are referred to as unobserved heterogeneity (Bailey, 2019). To deal with unobserved heterogeneity and omitted variable bias, we use an unobserved effects model. As the results from the Hausman test showed us that unobserved heterogeneity is correlated with our explanatory variables, we proceed with a fixed effects estimator. A fixed effects model controls for firm-specific effects, which capture differences in the dependent variable associated with each firm. The unobserved heterogeneity or firm fixed effects are time-constant factors that vary across firms (Bailey, 2019). The unobserved heterogeneity could include corporate culture or the sector in which a

firm operates (Brooks, 2019). The fixed effects estimator uses OLS after a within transformation, eliminating the unobserved heterogeneity (Bailey, 2019; Brooks, 2019). As shown in section 4.1 *Statistical Evaluation of The Model*, the Gauss-Markov assumptions are upheld, thus enabling unbiased and consistent estimates.

We apply a 1-year lag to all our explanatory variables as we do not expect them to affect Volatility immediately in the same time period but rather with a lag. Previous research within the field has also applied lags to their independent variables (Coles et al. 2006).

With the above considerations, our regression model is presented below:

$$\begin{aligned} \log1_Volatility_{i,t} = & \beta_0 + \beta_1 \log1_CEO_Option_Awards_{i,t-1} + \beta_2 \log1_CEO_Cash_Compensation_{i,t-1} \\ & + \beta_3 \log1_Total_Assets_{i,t-1} + \beta_4 ROA_W_{i,t-1} + \beta_5 Leverage_W_{i,t-1} + \beta_6 Cash_W_{i,t-1} \\ & + \beta_7 Tangibility_W_{i,t-1} + \alpha_i + v_{i,t} \end{aligned}$$

3.7 Assumptions

Under the Gauss-Markov assumptions 1 through 4, OLS is unbiased. If assumptions 5 and 6 are added, then OLS is considered the best linear unbiased estimator (Wooldridge, 2010). The assumptions are the following:

Table 1. The OLS Assumptions (Wooldridge, 2010; Brooks, 2019)

OLS	Assumption	Meaning
OLS 1	Linearity	In the population model, the dependent variable, y , is related to the independent variable, x , and the error (or disturbance), u , as: $y = \beta_0 + \beta_1 x + u$
OLS 2	Random Sampling of Observations	The sample is random.
OLS 3	No Multicollinearity	Sample variation in the explanatory variables.
OLS 4	Exogeneity	The error u has an expected value of zero given any value of the explanatory variable. $E(u X) = 0$
OLS 5	Homoscedasticity	The error u has the same variance given any value of the explanatory variable. $Var(u_i X) = \sigma^2$
OLS 6	No Autocorrelation	Conditional on all explanatory variables, the errors are uncorrelated. $Cov(u_i, u_j X) = 0$
OLS 7 (Optional)	Normality	The population error u is independent of the explanatory variables and is normally distributed.

3.7.1 Linearity

A requirement for the use of OLS is a linear model. Specifically, the model's parameters (α and β) must be linear (Brooks, 2019). Models with non-linear variables can often be converted into linear form through transformations such as logarithms. The relationship between the dependent and independent variables should be able to be expressed diagrammatically as a straight line. We test for non-linearity and misspecification of functional form through the Ramsey RESET test.

3.7.2 No Multicollinearity

An assumption that is made when using the OLS estimation method includes that the explanatory variables are not correlated with each other (Brooks, 2019). In practice, explanatory variables are usually correlated with each other to an extent. A small degree of correlation is not an issue, however, a high degree of correlation is problematic and referred to as multicollinearity.

To test for multicollinearity we create a correlation matrix. Solutions to the issue of multicollinearity include dropping one of the collinear variables and transforming highly correlated variables into ratios (Brooks, 2019).

3.7.3 Exogeneity

The assumption of exogeneity refers to the state in which explanatory variables are not correlated with the error term (Wooldridge, 2010). If this assumption does not hold and the explanatory variables are correlated with the error term, there is an endogeneity issue leading to biased estimators. There are a number of ways in which endogeneity can arise.

One source of endogeneity includes omitted variable bias. This occurs when a variable which is correlated with any of the independent variables is omitted (Wooldridge, 2010). To handle this, we include several relevant control variables and use a fixed effects model.

When an explanatory variable is determined simultaneously with the dependent variable, it is generally correlated with the error term (Wooldridge, 2010). This is called simultaneity bias and is another source of endogeneity. Reversed causality is another cause of endogeneity and is where the dependent variable instead causes the independent variable. To reduce the issue

of endogeneity we apply lags. The lagged value of a variable is the value of the variable in a previous period (Brooks, 2019). By applying 1-year lags, the explanatory variables will affect the dependent variable with a 1-year delay, thus outlining a more causal relation and reducing the issue of reverse causality and simultaneity bias.

Measurement errors in the explanatory variables can also lead to endogeneity (Brooks, 2019). Measurement errors can stem from the use of estimations or proxies, which are often used when one cannot observe or obtain data on a required variable. For example, we use stock volatility as a proxy for executives' risk-taking which could potentially be a source of measurement error since stock volatility could also reflect other factors.

One way to test for endogeneity, especially caused by omitted variable bias, is to run a Hausman test. The Hausman test will show us whether to use a fixed or random effects model.

3.7.4 Homoscedasticity

The assumption of homoscedasticity is that the variance of the errors is constant (Brooks, 2019). If the errors do not have a constant variance, heteroscedasticity is present.

Even with heteroscedastic errors, the OLS estimators give unbiased coefficient estimates however they would not be the best linear unbiased estimators (Brooks, 2019). Solutions for heteroscedasticity include the transformation of variables into logarithms and using heteroscedasticity-consistent standard error estimates. It is common in corporate finance to have a heteroscedasticity, therefore we will assume that it exists and use clustered standard errors (Wooldridge, 2010).

3.7.5 No Autocorrelation

The assumption of no autocorrelation refers to the errors being uncorrelated with one another. If that is not the case, they would be "autocorrelated" or "serially correlated" (Brooks, 2019). A solution to autocorrelation is to use appropriately modified standard error estimates. Since it is common in corporate finance to have autocorrelation, we will assume that it exists and use clustered standard errors (Wooldridge, 2010).

3.7.6 Normality

The normality assumption refers to the unobserved error being normally distributed in the population (Wooldridge, 2010). To test for normality we use histograms and the Bera-Jarque test. To address non-normality, variables are log-transformed and winsorized.

3.8 Discussion of Method

3.8.1 Discussion of Data and Regression

In our study, we used the value of the CEO's Option Awards as a proxy of the risk-taking incentives provided to the CEO by the ESOs. An improvement of the study could be to use an alternative proxy for risk-taking incentives provided by ESOs, such as Vega. Another improvement to our study could involve differentiating between salary and bonus, as these components may have differing effects on risk-taking. For instance, salary might be negatively correlated with Volatility, whereas bonuses, often tied to performance, could exhibit a positive correlation. However, this was not implemented due to the significant data reduction that would result from the merging process of the two variables. By combining them into a single sum, we assume that firms not reporting bonuses do not allocate them, allowing us to retain all firms in the sample, rather than limiting the analysis to those that provide bonuses.

Regarding our data, the variables CEO Option Awards and CEO Cash Compensation included a large amount of zero values, and CEO Option Awards also included a few negative values. The inclusion of zero and negative values can be considered a limitation since these values are not expected to have an effect on risk-taking. At the same time, firms do not commonly give out ESOs every year, motivating the inclusion of zero values. The negative values represent accounting adjustments to the value of the CEO Option Awards, which are also not uncommon in practice, thus, they are included. In the literature, there are mixed practices regarding zero values. For example, Lu et al. (2022) exclude zeros for their CEO Option Holdings whereas Chen et al. (2006) include zeros for their CEO Option Holdings. In a robustness check, we exclude the zeros and negative values of the CEO Option Awards.

Additional considerations to improve our model would be to control for year fixed effects, in addition to firm fixed effects, as macroeconomic factors are expected to affect Volatility.

Unfortunately, year fixed effects were not able to be included due to a lack of variation in our data. Another improvement to our model could be to use a simultaneous equation to account for the possibility of a two-way relationship between ESOs and Volatility, which a few studies have documented such as Chen et al. (2006) and Coles et al. (2006). This approach would further handle the issue of endogeneity. In our study, however, we mitigated the possibility of joint causality and reverse causality by applying lags to our explanatory variables.

3.8.2 Use of Artificial Intelligence

We have approached the use of artificial intelligence with great caution, utilizing AI specifically through the ChatGPT service primarily to assist with Stata commands. When uncertainty arose about which command to use for a specific task in Stata, ChatGPT provided suggestions for appropriate commands. This, combined with study materials, has enhanced the efficiency of our use of Stata.

3.8.3 Reliability

Reliability refers to the consistency of results in our study across time and different contexts (Olmsted, 2024). It is a key consideration, especially in the methods, measurements, and observations used, to minimize random errors throughout the research process.

One key aspect of reliability is stability, which assesses whether the results are consistent over time. This can be demonstrated by significant correlations between repeated measurements (Olmsted, 2024). Typically, stability is tested by conducting repeated measurements on the same sample at different time points. Ideally, we would have conducted an additional study with the same sample at a later time, but due to time constraints, this was not possible. Instead, we compared our findings to previous studies that used similar methodologies and focused on the same subject matter at different time intervals. This comparison helps us assess the stability of our results.

Internal reliability refers to the consistency within the study itself (Bryman et al. 2024). To ensure this, we clearly defined the study's purpose, which guarantees coherence and alignment among its components. Each part of the study contributes to the overall objective and measures the same underlying concept (Olmsted, 2024). For instance, we justify the selection of variables for the regression analysis by explaining their relevance to the research

focus. Moreover, we provide precise definitions for the variables to ensure consistency across measurements.

To enhance reliability, we follow standardized methods as suggested by Bryman et al. (2024). By adopting established methodologies from high-quality scientific studies (Olmsted, 2024) and ensuring the quality of data sources, we can strengthen the reliability of our findings. Documenting the methodology thoroughly improves internal consistency and allows for the study to be replicated by other researchers. Furthermore, we increased the sample size to reduce random errors, as a larger sample decreases variability and improves reliability.

Our study uses secondary data, which offers advantages like time and cost efficiency (Bryman et al. 2024). However, the use of secondary data requires careful evaluation of its origin, methodology, and relevance. We ensured the quality of our secondary data by relying on reputable sources. The S&P Capital IQ Pro database was used to gather data for regression analysis, while previous studies were sourced from Lubsearch and Scopus with only peer-reviewed articles included. Additionally, we consulted the Norwegian Register for Scientific Journals, Series, and Publishers (Norwegian Directorate for Higher Education and Skills, 2024) to verify that the journals used met high scholarly standards.

3.8.4 Validity

In this study, validity is crucial for ensuring that our indicators accurately measure the intended constructs in alignment with the research purpose (Olmsted, 2024), specifically the relationship between ESOs and stock prices. Validity is fundamental for minimizing measurement errors that could otherwise distort the results of our analysis.

We differentiate between internal and external validity (Trafimow, 2023). Internal validity in this study focuses on ensuring the correct causal relationship between the dependent variable and the independent variables. To achieve this, the variables are carefully selected and clearly defined, ensuring they measure what they are intended to. Irrelevant variables are excluded to avoid introducing external influences. Control variables are incorporated into the regression models to isolate the effect of ESOs on stock volatility, which helps strengthen the accuracy of our findings by accounting for other potential factors.

To further improve internal validity, our hypotheses are grounded in a robust theoretical framework and supported by existing research, ensuring they are both appropriate and

substantiated (Bryman et al. 2024). This foundation enhances the likelihood that our analysis measures the correct relationships.

This study utilizes quantitative data, which is ideal for analyzing the relationship between ESOs and stock prices across multiple firms (Gruszczyński, 2018). Quantitative research is particularly valuable here, as it allows for large datasets that can be systematically analyzed. Although quantitative research demands significant time and expertise, it offers objectivity, consistency, comparability with other studies, and greater generalizability of results.

External validity, which concerns the generalizability of the findings, is also critical (Trafimow, 2023). In this study, external validity is enhanced by using a diverse sample of firms from the non-financial sector across developed European countries, ensuring that the findings are applicable to firms in various national contexts. While the results are primarily based on European data, they can also be relevant to firms in other developed regions.

To assess the robustness of our findings and ensure they are not driven by outliers or methodological decisions, we perform robustness tests (Bryman et al. 2024). This adds to the strength of internal validity by demonstrating that our results are consistent under varying conditions.

In terms of causality, while regression analysis allows us to identify correlations between ESOs and stock volatility, it does not definitively establish a cause-and-effect relationship (Bryman et al. 2024). Given the absence of definitive causal conclusions, we hypothesize relationships based on theoretical logic, although this introduces potential limitations, as recommended by Bryman et al. (2024).

Additionally, Blumer (1956) finds that while quantitative methods offer a detailed analysis of relationships between measurable variables, they cannot capture intangible factors such as executives' values, emotions, and psychological drivers that may influence stock prices. Blumer (1956) critiqued quantitative methods for offering a static view of reality and excluding subjective aspects, which are particularly important in understanding the role of ESOs in stock price movements. While this study establishes a correlation, it does not measure the psychological factors that may contribute to this relationship. Acknowledging these limitations is essential for a complete understanding of the phenomenon.

4. Results

4.1 Statistical Evaluation of the Model

A statistical evaluation of the model is presented, outlining the results from the tests conducted to ensure compliance with the OLS assumptions along with the corresponding, relevant adjustments.

4.1.1 Test for Linearity

To test the linearity assumption, a Ramsey RESET test was conducted, as presented in *Appendix I*. The null hypothesis(H_0) states that the model is linear. As shown in *Table 2*, the p-value is smaller than the 5% significance level. Thus, the null hypothesis(H_0) is rejected and the assumption of linearity does not hold. To linearise the model, we transform our variables into logarithms.

Table 2. Ramsey RESET Test for Linearity

P-value	0
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4.1.2 Test for Multicollinearity

To test for multicollinearity, we create a correlation matrix, as presented in *Table 3*. The correlation matrix shows that the explanatory variables are not highly correlated with each other, as most Pearson correlation coefficients are close to 0. A few of the variables are moderately correlated with each other such as Total Assets and ROA (0.5098) as well as CEO Option Awards and CEO Cash Compensation (0.4465) but the coefficients are not exceptionally high. Since no coefficient is at or greater than 0.8, which is considered a high degree of correlation, the assumption of no multicollinearity is upheld (Brooks, 2019).

Table 3. Test for Multicollinearity

	Volatility	CEO Option Awards	CEO Cash Compensation	Total Assets	ROA	Leverage	Cash	Tangibility
Volatility	1							
CEO Option Awards	-0,0258	1						
CEO Cash Compensation	-0,0559	0,4465	1					
Total Assets	-0,0243	0,212	0,2009	1				
ROA	-0,0211	0,0547	0,1602	0,5098	1			
Leverage	-0,0164	-0,022	0,0833	0,2784	0,0105	1		
Cash	0,021	0,0409	-0,0505	-0,3759	-0,496	-0,2303	1	
Tangibility	0,0067	-0,003	0,0402	0,1231	0,1006	0,2591	-0,3212	1

4.1.3 Test for Endogeneity

To test if the unobserved effects are correlated with the regressors, a Hausman test is conducted, as presented in *Appendix III*. The null hypothesis(H_0) is that they are not correlated with each other (Wooldridge, 2010). As the p-value is less than the 5% significance level, we reject the null hypothesis(H_0) and choose the fixed effects model.

Table 4. Hausman Test for Endogeneity

P-value	0.0003

4.1.4 Test for Heteroscedasticity

Since it is common in corporate finance to have heteroskedasticity, we assume that it exists and apply clustered standard errors (Wooldridge, 2010).

4.1.5 Test for Autocorrelation

It is also common in corporate finance to have autocorrelation, thus we assume that it exists and apply clustered standard errors (Wooldridge, 2010).

4.1.6 Test for Normality

Lastly, to test for normality we perform the Bera-Jarque test, as presented in *Appendix IV* and create histograms of the residuals before and post transformations, as presented in *Appendix V*, for all of our variables. Since the normality assumption was not satisfied, we transform the variables by winsorizing or applying the natural logarithm.

4.1.7 Descriptive Statistics

Table 5 presents the descriptive statistics of our raw data. Notably, the CEO Option Awards include negative values, which contrasts with findings in other studies. This can occur due to accounting adjustments, often aimed at addressing overconfident CEOs who may overinvest, or as part of a broader effort to rebalance CEO Cash Compensation to align incentives with company objectives (Athanasakou et al. 2017).

Variables that exhibit a high degree of skewness and kurtosis include CEO Option Awards, Total Assets, Leverage and ROA, indicating outliers and non-normal distributions. Some of the variables also exhibit high standard deviations such as Total Assets and CEO Option Awards, driven by outliers.

Table 5. Descriptive Statistics Before Transformations

	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Volatility	98,0614	69,0614	62,7162	39,0622	248,457	1,403618	3,637452
CEO Option Awards	364358,7	0	1818516	-47138	63600000	23,954	776,5068
CEO Cash Compensation	587445,8	331064,8	782216	0	5650704	2,460322	11,065
Total Assets	3465108	266821,8	9980304	386,856	98200000	5,44582	38,3484
Cash	0,217692	0,13135	0,22965	0,00029	0,987121	1,58561	4,68849
Leverage	0,21334	0,21334	0,15929	0	3,869638	3,76348	36,35206
ROA	-0,12074	-0,12074	0,02888	1,59388	-68,1069	-39,4623	1674,775
Tangibility	0,19918	0,19918	0,10637	0,22973	0,00016	1,68512	5,12018

The data post transformations are displayed in Table 6 below. To reduce skewness and normalise the data, appropriate transformations were applied.

Table 6. Descriptive Statistics Post Transformations

	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Volatility	4,437914	4,257531	0,532121	3,690434	5,519287	0,770459	2,574548
CEO Option Awards	4,140147	0	5,984013	0	17,96884	0,828521	1,82246
CEO Cash Compensation	9,489078	12,71007	5,981276	0	15,54729	-0,91592	1,925092
Total Assets	12,64299	12,49434	2,427094	5,960634	18,4	0,107132	2,252624
Cash	-0,05835	0,028881	0,222063	-0,66951	0,181551	-1,47227	4,322047
Leverage	0,198066	0,159292	0,186959	0	0,651511	0,867809	2,902037
ROA	0,213156	0,131347	0,215471	0,015229	0,772619	1,412818	3,919149
Tangibility	0,194329	0,106368	0,21508	0,004694	0,777405	1,492497	4,243433

4.2 Regression Output

Table 7. Regression Output

Variable	Coeff.	P-Value
Dependent variable: Volatility		
CEO Option Awards	0,0033971	0,213
CEO Cash Compensation	-0,0143196	0
Total Assets	-0,0880304	0
ROA	0,02012	0,845
Leverage	0,0300243	0,739
Cash	-0,0674725	0,552
Tangibility	0,308324	0,121
Model Specification		
Firms	180	
Observations	1799	
Entity FE	yes	
Year FE	no	
Clust. Rob. SE.	yes	
Adjusted R ²	0,0256	

4.3 Robustness Test

Table 8. Regression Results: Robustness Test Excluding Zeros From CEO Option Awards

Variable	Coeff.	P-Value
Dependent variable: Volatility		
CEO Option Awards	-0,012942	0,087
CEO Cash Compensation	0,0094832	0,353
Total Assets	-0,0187656	0,666
ROA	-0,0291639	0,888
Leverage	0,712495	0,064
Cash	0,103726	0,996
Tangibility	1,348109	0,0121
Model Specification		
Firms	180	
Observations	1799	
Entity FE	yes	
Year FE	no	
Clust. Rob. SE.	yes	
Adjusted R ²	0,0303	

4.4 Hypothesis: Outcome

Table 7 presents the regression output, providing the necessary statistics to evaluate the hypotheses outlined in section 2.4 *Hypotheses*. The results indicate an insignificant relationship between CEO Option Awards and Volatility, as evidenced by a p-value of 0.213. Consequently, we fail to reject the null hypothesis (H_0) and must reject the alternative hypothesis (H_1). Thus, we conclude that ESOs are *not associated* with stock volatility.

5. Analysis and Discussion

5.1 CEO Option Awards and Volatility

The regression analysis reveals an insignificant relationship between CEO Option Awards and Volatility, with a coefficient of 0.0033971 and a p-value of 0.213. This result suggests that, within the studied sample, CEO Option Awards are not statistically associated with increased Volatility. This means we cannot reject the null hypothesis (H_0), which states that there is no relationship between CEO Option Awards and Volatility. These findings do not support the alternative hypothesis (H_1), challenging the Agency Theory which predicts that equity-based compensation encourages risk-taking, resulting in higher Volatility. Instead, the results may align more closely with Stewardship Theory, which emphasizes intrinsic motivation and long-term stability. Executives acting as stewards may prioritize organizational goals over short-term risk-taking, diminishing the effectiveness of ESOs as risk-inducing tools.

However, these findings must be approached with caution, given the methodological limitations and the model's low explanatory power. The adjusted R^2 of 0.0256 highlights the limited explanatory power of the model. This value is notably lower than in studies like Lu et al. (2022) and Coles et al. (2006), where adjusted R^2 values were higher due to the inclusion of more comprehensive datasets and alternative variables, such as Vega. The low R^2 suggests that a significant portion of the variation in Volatility remains unexplained in this study. This limitation could stem from: data characteristics, transformation effects and our proxy choice. When it comes to datasets, it includes a high proportion of zero values for CEO Option Awards, with a median of 0 in both raw and transformed data. These zero values dilute the potential relationship, as they reflect periods when no CEO Option Awards were granted. The logarithmic transformation's inclusion of the constant 1 ensures that zero values remain in the analysis but alters the interpretation of changes in CEO Option Awards, as a 1% increase now represents a percentage change in the transformed variable. While the transformation done is an effective way to address extreme values, it compresses the variability, reducing the impact of large option awards on Volatility.

The robustness test excluded all zero values for CEO Option Awards, resulting in a negative coefficient of -0.012942 and a p-value of 0.087. While this result is closer to significance, it still fails to conclusively establish a relationship. The adjusted R^2 increased to 0.0303, reflecting a slight improvement in the model's explanatory power. The negative coefficient in the robustness test provides an alternative perspective, suggesting that executives with significant CEO Option Awards may adopt more conservative strategies to protect their personal wealth tied to equity-based compensation. This aligns even more with Stewardship Theory, which emphasizes intrinsic motivation and long-term stability over short-term risk-taking. Under this framework, ESOs may serve as tools for alignment with organizational goals rather than as incentives for excessive risk-taking. The negative coefficient observed in our robustness test can also be explained by the risk-aversion model which highlights that a CEO whose wealth is heavily tied to their firm's stock price tends to be undiversified and risk-averse. This risk aversion may lead to reduced risk-taking, which in turn could lower stock volatility in the context of ESOs (Lambert et al. 1999).

5.2 CEO Cash Compensation and Volatility

The regression analysis of CEO Cash Compensation provides mixed results. In the main regression, the coefficient for CEO Cash Compensation is -0.0143196, with a p-value of 0.000, indicating a statistically significant negative relationship with Volatility. Conversely, in the robustness model, where zero values for CEO Option Awards are excluded, the coefficient shifts to a positive value of 0.0094832, with a p-value of 0.353, suggesting no significant relationship. These contrasting results highlight the sensitivity of CEO Cash Compensation's effect on Volatility to methodological adjustments, such as the exclusion of zero values for other variables.

The negative coefficient in the main regression suggests that higher CEO Cash Compensation which is comprising both fixed salaries and performance-based bonuses may reduce Volatility. This aligns with previous findings in the literature, such as Berger et al. (2012), where fixed compensation was associated with reduced risk-taking due to its stabilizing nature. By providing financial security, fixed salaries diminish the need for executives to take risks in pursuit of higher earnings. However, the shift to a positive coefficient in the regression from the robustness test suggests that the relationship between CEO Cash Compensation and Volatility becomes less consistent in firms where equity-based incentives,

such as CEO Option Awards, are active. This result may reflect the complexity of combining fixed salaries and performance-based bonuses into a single variable. Performance-based bonuses, in particular, are designed to reward short-term results and may incentivize executives to take more risks, leading to increased Volatility (Huang et al. 2013). Separating these components could provide clearer insights, as fixed salaries and bonuses likely influence risk-taking in opposing ways.

The use of the log (1+x) transformation to normalize CEO Cash Compensation was necessary to address skewness and kurtosis, but it likely attenuated the effects of extreme values such as high-value bonuses. This compression of variability could limit the ability to detect stronger relationships between CEO Cash Compensation and Volatility. Additionally, including both fixed salaries and bonuses within the same variable introduces a degree of interaction that complicates interpretation, as their impacts on Volatility may counteract one another.

Finally, it's important to note that while the main regression produces statistically significant results, the small magnitude of the coefficient raises questions about its economic relevance. A 1% increase in CEO Cash Compensation is associated with only a 0.0143% decrease in Volatility. This minimal impact suggests that, although the relationship exists, CEO Cash Compensation likely plays a secondary role in shaping executives' risk-taking, particularly when other incentive structures are in place. In the regression from the robustness test, the positive but statistically insignificant coefficient further underscores the limited practical significance of CEO Cash Compensation when zero values for CEO Option Awards are excluded.

5.3 Tangibility and Volatility

In the main regression, Tangibility demonstrated no statistically significant effect on Volatility, with a coefficient of 0.308 and a p-value of 0.121. However, the robustness test, which excluded zero values from CEO Option Awards, revealed a statistically significant positive relationship, with a coefficient of 1.348 and a p-value of 0.012. These findings suggest that Tangibility might influence Volatility under certain conditions, though the magnitude and direction of this influence vary across model specifications. The robustness test's significant result aligned with the idea that firms with high Tangibility, and thus greater investment opportunities, are characterized by conservatism regarding risk-taking and thus

more commonly utilise ESOs, leading to increased risk-taking and Volatility (Baber et al. 1996; Lu et al. 2022).

Lu et al. (2022) found mixed results regarding Tangibility's influence on "RiskR", with only some models showing significant effects. This inconsistency suggests that the relationship may depend to a large extent on specific sample characteristics. Our regression shows that Tangibility increases Volatility with a great magnitude where a 1 unit increase in Tangibility is associated with a 134.81% increase in Volatility. The high magnitude of the coefficient in the robustness test underscores the importance of understanding the influence of sample selection and data treatment. Excluding zero values might introduce a selection bias, skewing the results toward firms with higher Tangibility and more aggressive risk-taking.

5.4 Total Assets and Volatility

The regression results reveal a statistically significant negative relationship between Total Assets and Volatility in the main regression, with a coefficient of -0.0880304 and a p-value of 0.000. This indicates that a 1% increase in Total Assets is associated with a 0.0880% decrease in Volatility. However, the economic significance of this relationship is minimal due to the small magnitude of the coefficient. In the robustness test, which excludes zero values for CEO Option Awards, the relationship becomes statistically insignificant, with a coefficient of -0.0187656 and a p-value of 0.666. The $\log(1+x)$ transformation effectively reduced skewness (from 5.45 to 0.11) and kurtosis (from 38.35 to 2.25) in the data, making it more suitable for regression analysis. However, the compression of extreme values, particularly at the upper end of the asset distribution, could bias the true extent of the relationship between Total Assets and Volatility. The negative relationship observed in the main regression explained the common idea that larger firms experience lower Volatility due to their more stable revenues. This finding is consistent with previous research, such as Lu et al. (2022), which reported a significant negative relationship between firm size and "RiskR".

5.5 Leverage and Volatility

Our results do not find a statistically significant relationship between Leverage and Volatility in either the main regression or the robustness test. In the main model, the coefficient suggests that a 1-unit increase in Leverage is associated with a 3.00% increase in Volatility ($p=0.739$), while the robustness test shows a much larger coefficient, indicating a 71.25%

increase ($p=0.064$). The significant difference in coefficient magnitude highlights the sensitivity of the results to the exclusion of zero values in CEO Option Awards, suggesting that sample characteristics greatly influence the estimates. Despite the lack of significance, the positive coefficients align with the expectation that higher Leverage increases a firm's financial risk, leading to a greater Volatility.

5.6 Cash and Volatility

Since Cash is calculated as the ratio of cash holdings to Total Assets, its relationship with Volatility shares some similarities with the results observed for Total Assets. The main regression shows a negative coefficient, where a 1-unit increase in cash is associated with a 6.74% decrease in Volatility ($p=0.552$), while the robustness test indicates a positive coefficient of 0.1037 ($p=0.699$). Both results are statistically insignificant, suggesting that cash, as a proportion of Total Assets, does not significantly influence Volatility in this study. However, the positive coefficient in the robustness test hints at a potential alternative narrative: firms with higher cash ratios might engage in riskier investments, particularly in contexts where equity-based compensation, such as CEO Option Awards, is prevalent. Studies show differing perspectives which suggest that Cash's impact on Volatility may depend on contextual factors, such as firm size, industry, or the presence of compensation programmes like ESOs (Hang et al. 2013; Lu et al. 2022). The insignificance of Cash in our model raises questions about whether liquidity truly drives risk mitigation or if its effects are overshadowed by other firm characteristics, such as Leverage or investment opportunities.

5.7 ROA and Volatility

The regression results indicate no statistically significant relationship between ROA and Volatility in both the main regression and robustness test. In the main model, a 1-unit increase in ROA is associated with a 2.01% increase in Volatility ($p=0.845$), while in the robustness test, the coefficient shifts to -0.0292 ($p=0.888$), suggesting a weak and insignificant negative relationship. These findings underscore that ROA, as a measure of profitability, does not play a significant role in explaining variations in Volatility within the context of this model. The lack of statistical significance raises questions about the relevance of profitability metrics, such as ROA, in predicting Volatility. Profitability may reflect operational efficiency, but it might not directly influence Volatility, which is often driven by forward-looking market

expectations, external factors, and firm-specific risk profiles. For instance, Huang et al. (2013) highlight that profitability metrics are less influential when equity-based compensation or market-driven dynamics dominate executive decision-making.

6. Concluding Remarks

6.1 Conclusion

The purpose of this study was to determine whether ESOs have an effect on executives' risk-taking within European companies. As Volatility was used as a proxy for risk-taking, we found that there is no significant effect of ESOs on volatility. This result aligns with Stewardship Theory, which posits that CEOs are intrinsically motivated to act as responsible stewards for their firms, prioritizing long-term goals and stability over short-term or excessive risk-taking. Consequently, ESOs may be less effective as risk-inducing tools than previously assumed. These findings challenge the Agency Theory, which predicts that ESOs align executives' incentives with shareholders' interests by encouraging higher levels of effort and risk-taking to achieve greater returns. Instead, our results suggest that the assumed relationship between ESOs and executives' risk-taking may not hold in the European context. Previous research also supports our findings, highlighting that CEOs commonly hold a significant portion of their wealth tied to the stock price of their firm and that this lack of diversification often leads to risk-averse behavior, minimizing the effectiveness of ESOs in encouraging risk-taking.

Most of the variables were found to be insignificant across both models. Cash Compensation and Total Assets showed a significant relationship with Volatility in only the main model and Tangibility showed a significant relationship with Volatility in only the robustness test. The sensitivity of our results to the exclusion of zero values in CEO Option Awards highlights the importance of methodological considerations when interpreting the findings, as this exclusion notably altered the outcomes.

Our results contribute to the research on ESOs and executives' risk-taking by analysing the effects of ESOs in the significantly unexplored European market in a recent time period, challenging the common notion that ESO's increase risk-taking. Our results underscore the importance of market-specific factors and the need for tailored approaches to the design of

executive incentive programs. The methodological limitations, including the potential for unobserved heterogeneity, invites further research. Nonetheless, this study provides valuable insights into executive compensation design and its implications for risk management.

6.2 Suggestions for Further Research

While there is a considerable amount of research examining the link between ESOs and risk-taking in the US, there is a notable gap in the research investigating the impact of ESOs on risk-taking in Europe. Moreover, the use of ESOs has grown significantly in recent years, particularly in Europe, presenting an opportunity for further exploration.

One interesting suggestion for future research could be to investigate the effects of ESOs on risk-taking in Europe using Vega as a measure of executives' risk-taking incentives. It might also be valuable to examine other forms of compensation, such as restricted stock, using delta, which is a metric reflecting the sensitivity of an executive's restricted stock portfolio to stock price changes. Additionally, exploring the influence of performance-related bonuses on risk-taking or whether firm risk determines executive compensation could give interesting insights. Another area worth investigating might be whether the risk induced by ESOs translates into improved performance and shareholder value.

The role of corporate governance in moderating ESO-induced risk-taking is another interesting aspect. For example, future research could explore whether stronger governance mechanisms, such as a higher proportion of outside directors on the board or reduced CEO duality, have a moderating effect on risk-taking driven by ESOs. Understanding these dynamics could provide a more comprehensive perspective on how ESOs influence executives' risk-taking. In relation to this, a country-specific investigation could also be an intriguing path for future research. By focusing on the unique economic, cultural, and regulatory environments of individual countries, researchers might gain a deeper understanding of how variations in corporate governance structures and national policies shape the relationship between ESOs and stock volatility.

Finally, a methodological consideration that can be suggested for future studies could involve a deeper exploration of the sensitivity of results to zeros and data transformations. Additionally, considering fixed salaries and bonuses as separate variables could also provide

more clarity on their individual contributions and interactions with equity-based compensation structures.

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8. Appendix

Appendix I. Ramsey RESET Test for Linearity

note: fitted_log1 omitted because of collinearity.

Fixed-effects (within) regression
 Group variable: Firm_ID

Number of obs = 1,799
 Number of groups = 180

R-squared:
 Within = 0.0257
 Between = 0.0063
 Overall = 0.0039

Obs per group:
 min = 9
 avg = 10.0
 max = 10

corr(u_i, Xb) = -0.9219
 F(8, 1611) = 5.30
 Prob > F = 0.0000

log1_Volatility	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
log1_options L1.	.0007871	.0127317	0.06	0.951	-.0241852	.0257595
log1_total_comp L1.	-.0038179	.0495251	-0.08	0.939	-.1009583	.0933225
log1_assets L1.	-.0204176	.3188202	-0.06	0.949	-.6457636	.6049284
ROA_w L1.	.0096681	.1324329	0.07	0.942	-.2500909	.269427
Leverage_w L1.	-.0128243	.2413376	-0.05	0.958	-.4861929	.4605443
Cash_w L1.	.0140474	.4080212	0.03	0.973	-.7862607	.8143556
Tangibility_w L1.	.3134197	.2144152	1.46	0.144	-.1071424	.7339818
fitted_log1	0 (omitted)					
c.fitted_log1#c.fitted_log1	.084568	.3976356	0.21	0.832	-.6953694	.8645054
_cons	3.000694	12.37517	0.24	0.808	-21.27242	27.27381
sigma_u	.21203485					
sigma_e	.57874455					
rho	.11834246 (fraction of variance due to u_i)					

F test that all u_i=0: F(179, 1611) = 0.15 Prob > F = 1.0000

Appendix II. Pearson Test for Multicollinearity

	log1_V~y	log1_o~s	log1_t~p	log1_a~s	ROA_w	Levera~w	Cash_w	Tangib~w
log1_Volat~y	1.0000							
log1_options	-0.0258	1.0000						
log1_total~p	-0.0559	0.4465	1.0000					
log1_assets	-0.0243	0.2120	0.2009	1.0000				
ROA_w	-0.0211	0.0547	0.1602	0.5098	1.0000			
Leverage_w	-0.0164	-0.0220	0.0833	0.2784	0.0105	1.0000		
Cash_w	0.0210	0.0409	-0.0505	-0.3759	-0.4960	-0.2303	1.0000	
Tangibilit~w	0.0067	-0.0030	0.0402	0.1231	0.1006	0.2591	-0.3212	1.0000

Appendix III. Hausman Test for Endogeneity

	Coefficients		(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
	(b) fe_model	(B) re_model		
log1_options				
L1.	.0033971	.0015636	.0018336	.0022319
log1_total~p				
L1.	-.0143196	-.0082453	-.0060743	.0029073
log1_assets				
L1.	-.0880304	-.006546	-.0814844	.0230424
ROA_w				
L1.	.02012	.0057784	.0143416	.0965976
Leverage_w				
L1.	.0300243	.0206761	.0093482	.1076059
Cash_w				
L1.	-.0674725	-.0405651	-.0269074	.1182835
Tangibilit~w				
L1.	.308324	.0191678	.2891562	.2027429

b = Consistent under H0 and Ha; obtained from xtreg.
 B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 27.55
 Prob > chi2 = 0.0003

Appendix IV. Normal Distribution Test, Jarque-Bera

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Volatility	1,980	0.0000	0.0000	317.00	0.0000

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
CEO_Option_Awards_	1,980	0.0000	0.0000	.	.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Total_Compensation	1,980	0.0000	0.0000	816.74	0.0000

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Total_Assets	1,980	0.0000	0.0000	.	.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Total_Assets	1,980	0.0000	0.0000	.	.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Cash	1,980	0.0000	0.0000	411.35	0.0000

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Leverage	1,980	0.0000	0.0000	.	.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
ROA	1,980	0.0000	0.0000	.	.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test	
				Adj chi2(2)	Prob>chi2
Tangibility	1,980	0.0000	0.0000	456.11	0.0000

Appendix V. Histogram Residuals

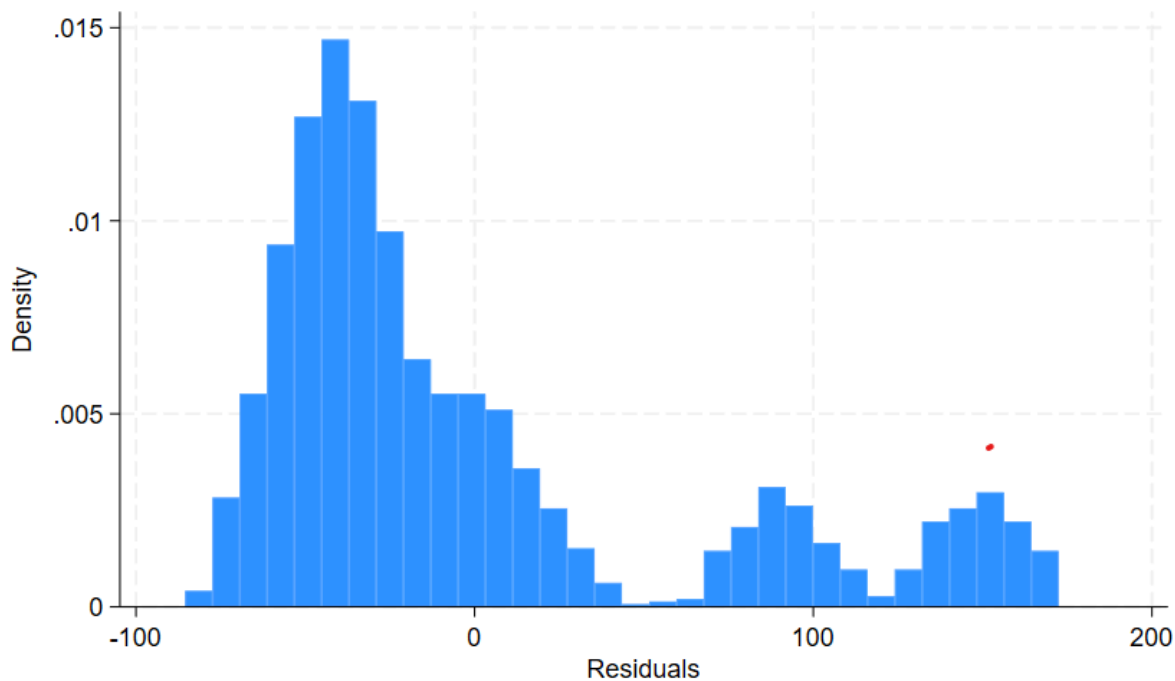


Figure 1. Histogram of Residuals Before Transformations

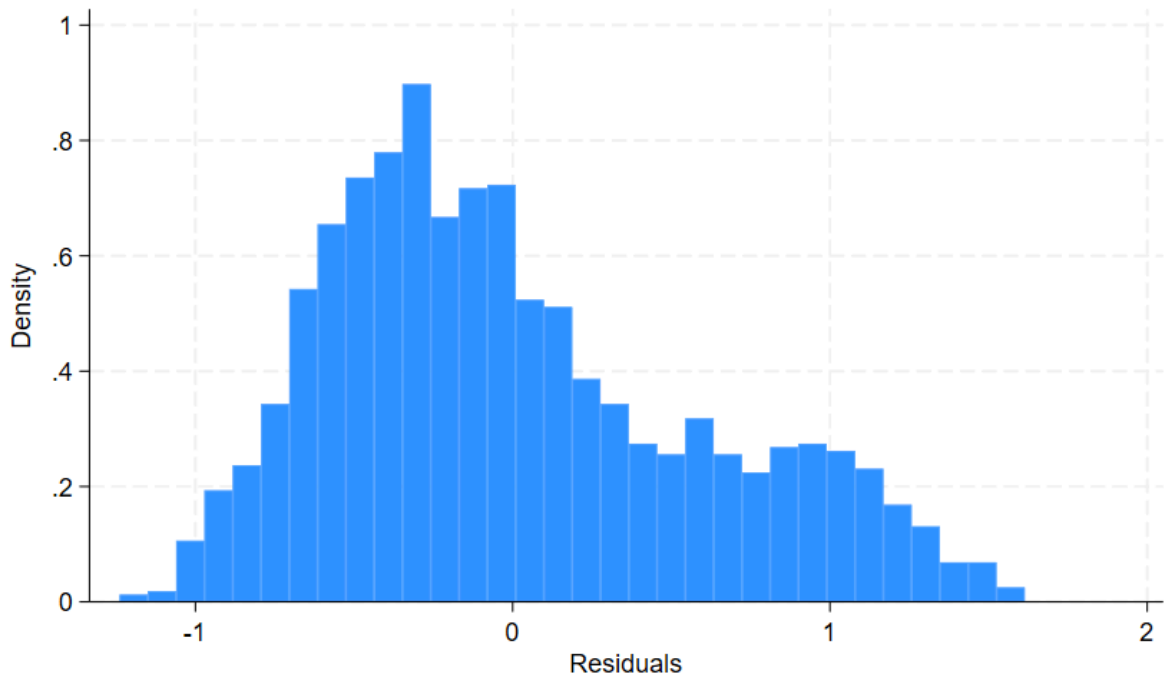


Figure 2. Histogram of Residuals Post Transformations

Appendix VI. Regression Output

Fixed-effects (within) regression
 Group variable: Firm_ID

Number of obs = 1,799
 Number of groups = 180

R-squared:
 Within = 0.0256
 Between = 0.0061
 Overall = 0.0037

Obs per group:
 min = 9
 avg = 10.0
 max = 10

corr(u_i, Xb) = -0.9249

F(7, 179) = 25.22
 Prob > F = 0.0000

(Std. err. adjusted for 180 clusters in Firm_ID)

log1_Volatility	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
log1_options L1.	.0033971	.0027195	1.25	0.213	-.0019693	.0087636
log1_total_comp L1.	-.0143196	.002467	-5.80	0.000	-.0191878	-.0094515
log1_assets L1.	-.0880304	.011747	-7.49	0.000	-.1112108	-.0648501
ROA_w L1.	.02012	.102523	0.20	0.845	-.1821892	.2224292
Leverage_w L1.	.0300243	.0899315	0.33	0.739	-.147438	.2074866
Cash_w L1.	-.0674725	.11313	-0.60	0.552	-.2907126	.1557676
Tangibility_w L1.	.308324	.1977074	1.56	0.121	-.081813	.698461
_cons	5.631844	.1544106	36.47	0.000	5.327145	5.936543
sigma_u	.21657861					
sigma_e	.57857313					
rho	.12290294	(fraction of variance due to u_i)				

Appendix VII. Regression Results: Robustness Test Excluding Zeros From CEO Option Awards

Fixed-effects (within) regression
 Group variable: Firm_ID

Number of obs = 622
 Number of groups = 170

R-squared:
 Within = 0.0303
 Between = 0.0000
 Overall = 0.0008

Obs per group:
 min = 1
 avg = 3.7
 max = 10

corr(u_i, Xb) = -0.8106

F(7, 169) = 2.56
 Prob > F = 0.0156

(Std. err. adjusted for 170 clusters in Firm_ID)

log1_Volatility	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
log1_options L1.	-.012942	.0075177	-1.72	0.087	-.0277828	.0018988
log1_total_comp L1.	.0094832	.0101733	0.93	0.353	-.0106	.0295663
log1_assets L1.	-.0187656	.0434551	-0.43	0.666	-.1045503	.067019
ROA_w L1.	-.0291639	.2073739	-0.14	0.888	-.4385408	.3802129
Leverage_w L1.	.712495	.3816039	1.87	0.064	-.0408293	1.465819
Cash_w L1.	.103726	.2680291	0.39	0.699	-.4253903	.6328424
Tangibility_w L1.	1.348109	.5791513	2.33	0.021	.204806	2.491412
_cons	4.251507	.6313225	6.73	0.000	3.005213	5.497801
sigma_u	.47574914					
sigma_e	.61698616					
rho	.37287286	(fraction of variance due to u_i)				

Appendix VIII. Chat GPT Prompts

You said: linearity test for panel data

ChatGPT said:

Testing for **linearity** in panel data requires adapting methods to account for the structure of the data (e.g., time and entity effects). Here are some common approaches for linearity testing in panel data using **Stata**:

1. Visual Inspection

- A simple approach is to examine the relationship between the dependent and independent variables visually.
- **Steps:**

Generate fitted values from the panel regression model:

stata

CopyEdit

```
xtreg y x1 x2, fe
```

```
predict fitted_values, xb
```

Plot residuals vs. fitted values:

stata

CopyEdit

```
scatter residuals fitted_values
```

Alternatively, plot dependent vs. independent variables for each group or over time:

stata

CopyEdit

```
twoway scatter y x1 || lfit y x1
```

2. Add Polynomial Terms

- Test for non-linear relationships by including polynomial terms in the panel regression model.
- **Steps:**

Generate polynomial terms:

stata

CopyEdit

```
gen x1_sq = x1^2
```

```
gen x1_cu = x1^3
```

Include them in the model:

```
stata
```

```
CopyEdit
```

```
xtreg y x1 x1_sq x1_cu, fe
```

- Check the significance of the higher-order terms (x1_sq, x1_cu).
 - **Interpretation:**
 - If the polynomial terms are significant, the relationship is likely non-linear.
-

3. Ramsey RESET Test (Pooled OLS Approximation)

- While the Ramsey RESET test is not explicitly designed for panel data, you can approximate it using pooled OLS.
- **Steps:**

Run a pooled OLS model:

```
stata
```

```
CopyEdit
```

```
regress y x1 x2
```

Perform the RESET test:

```
stata
```

```
CopyEdit
```

```
estat ovtest
```

- **Limitations:** Ignores the panel structure, so interpret cautiously.
-

4. Use Residual Diagnostics

- Analyze the residuals from the panel model to detect non-linearity.
- **Steps:**

Run a fixed or random effects model:

```
stata
```

```
CopyEdit
```

```
xtreg y x1 x2, fe
```

Predict residuals:

stata

CopyEdit

predict residuals, resid

Check for patterns in residuals using scatterplots or kernel density estimation:

stata

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scatter residuals x1

kdensity residuals

5. Generalized Additive Models (GAMs)

- Fit a semi-parametric model to allow for non-linear relationships.
- **Steps (using xtgee):**

Include spline terms for independent variables:

stata

CopyEdit

mkspline x1_spline=x1, cubic

xtgee y x1_spline*, family(gaussian) link(identity)

Inspect the fitted splines for non-linear patterns.

6. Interaction with Time or Group Effects

- Test for differential linearity across groups or over time.
- **Steps:**

Include interactions:

stata

CopyEdit

gen x1_time = x1 * year

xtreg y x1 x1_time, fe

Check the significance of the interaction term.

7. Linearity Testing via Marginal Effects

- Use the margins command to estimate and plot marginal effects.

- **Steps:**

Fit a model:

stata

CopyEdit

```
xtreg y x1 x2, fe
```

Plot marginal effects:

stata

CopyEdit

```
margins, at(x1=(min(x1)(step_size)max(x1)))
```

```
marginsplot
```

Summary:

- **Direct Tests:** Adding polynomial terms or interaction terms.
- **Visual Inspection:** Scatterplots, residual plots, and fitted curves.
- **Advanced:** Use semi-parametric models (splines or GAMs) or marginal effects analysis.

You said:

jarque bera test

ChatGPT said:

The **Jarque-Bera (JB) test** is used to test whether the residuals of a model (or any dataset) follow a normal distribution. It evaluates skewness and kurtosis, with the null hypothesis that the data is normally distributed.

Steps to Perform the Jarque-Bera Test in Stata

Unfortunately, Stata does not have a built-in command for the Jarque-Bera test. However, you can calculate it manually or use a user-written command.

Option 1: Manual Calculation

Calculate Residuals from Your Model:

stata

CopyEdit

```
regress y x1 x2 x3
```

```
predict residuals, resid
```

Create Variables for Skewness and Kurtosis:

```
stata
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gen residuals_sq = residuals^2
gen skewness = residuals^3 / (sum(residuals_sq)^1.5)
gen kurtosis = residuals^4 / (sum(residuals_sq)^2)
```

Compute the Jarque-Bera Statistic:

1. Use the formula: $JB = n \left(\frac{S^2}{6} + \frac{(K - 3)^2}{24} \right)$ Where:
 - SSS: Skewness
 - KKK: Kurtosis
 - nnn: Sample size

```
stata
CopyEdit
scalar n = _N
scalar jb_stat = n * (skewness^2 / 6 + ((kurtosis - 3)^2) / 24)
display jb_stat
```

2. Compare to Critical Value or Compute p-value:

```
stata
CopyEdit
display chi2tail(2, jb_stat)
```

- A low p-value (e.g., < 0.05) suggests rejecting the null hypothesis of normality.

Option 2: Use User-Written Command

Install the sktest Command:

```
stata
CopyEdit
ssc install sktest
```

Run the Jarque-Bera Test:

```
stata
CopyEdit
sktest residuals
```

- The output includes the skewness and kurtosis components along with the JB statistic and p-value.
-

Interpreting Results:

- **Null Hypothesis (H0H_0H0):** Residuals are normally distributed.
- **Alternative Hypothesis (H1H_1H1):** Residuals are not normally distributed.
 - If p-value < 0.05, reject H0H_0H0; residuals are not normal.
 - If p-value > 0.05, fail to reject H0H_0H0; residuals appear normal.

Variables: log1_Volatility log1_options log1_total_comp log1_assets ROA_w Leverage_w Cash_w Tangibility_w , it is panel data. test/s for hetroscadasdicity

ChatGPT said:

In **panel data**, heteroskedasticity refers to the non-constant variance of residuals across time and entities. For panel data, tests for heteroskedasticity are conducted across the entire model rather than for individual variables. Here's how you can test for heteroskedasticity in your panel data model in **Stata**:

Tests for Heteroskedasticity in Panel Data

1. Breusch-Pagan Test (Using Pooled OLS)

- This tests for heteroskedasticity in the residuals based on the independent variables.

Steps:

Run a pooled OLS regression (ignoring panel structure):

```
stata
```

```
CopyEdit
```

```
regress dependent_variable log1_Volatility log1_options log1_total_comp log1_assets  
ROA_w Leverage_w Cash_w Tangibility_w
```

Perform the Breusch-Pagan test:

```
stata
```

```
CopyEdit
```

```
estat hettest
```

Interpretation:

- **Null Hypothesis (H0H_0H0):** Homoskedasticity (constant variance).
- **Alternative Hypothesis (H1H_1H1):** Heteroskedasticity (non-constant variance).
- If the p-value < 0.05, reject H0H_0H0, indicating heteroskedasticity.

2. Modified Wald Test for Groupwise Heteroskedasticity

- Suitable for fixed-effects models in panel data.

Steps:

Run a fixed-effects regression:

stata

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w
Leverage_w Cash_w Tangibility_w, fe
```

Perform the Modified Wald test:

stata

CopyEdit

xttest3

Interpretation:

- **Null Hypothesis (H0H_0H0):** Homoskedasticity across entities.
 - **Alternative Hypothesis (H1H_1H1):** Heteroskedasticity (variance differs across entities).
 - If the p-value < 0.05, reject H0H_0H0, indicating heteroskedasticity.
-

3. Likelihood Ratio Test (for Random Effects)

- This checks heteroskedasticity for random-effects models.

Steps:

Run a random-effects model:

stata

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w
Leverage_w Cash_w Tangibility_w, re
```

Perform the likelihood ratio test:

stata

CopyEdit

estat hettest

4. Test for Cross-Sectional Dependence (Optional)

If heteroskedasticity is due to cross-sectional dependence, you can perform the **Pesaran test**:

stata

CopyEdit
xtcsd, pesaran abs

- **Null Hypothesis (H0H_0H0):** No cross-sectional dependence.
 - **Alternative Hypothesis (H1H_1H1):** Cross-sectional dependence exists.
-

When to Use Each Test:

- **Breusch-Pagan Test:** If you're starting with a pooled OLS model.
 - **Modified Wald Test:** If you're using a fixed-effects model.
 - **Likelihood Ratio Test:** If you're using a random-effects model.
 - **Pesaran Test:** If cross-sectional dependence is suspected.
-

Addressing Heteroskedasticity:

If heteroskedasticity is detected, consider:

1. **Robust Standard Errors:**

For pooled OLS or fixed-effects:

stata

CopyEdit

```
regress dependent_variable log1_Volatility log1_options log1_total_comp log1_assets  
ROA_w Leverage_w Cash_w Tangibility_w, vce(robust)
```

For random-effects:

stata

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, re vce(robust)
```

2. **Feasible Generalized Least Squares (FGLS):**

Use FGLS to account for panel-specific heteroskedasticity:

stata

CopyEdit

```
xtgls dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, panels(heteroskedastic)
```

You said: Perform the Modified Wald test:

Do I have to install this to work?

ChatGPT said:

No, you **do not need to install anything** to perform the **Modified Wald test** (xttest3) in Stata. It is a built-in command available in Stata, as long as you have run a **fixed-effects model** (xtreg, fe) beforehand.

Steps to Use xttest3:

Run a Fixed-Effects Regression:

stata

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, fe
```

Run the Modified Wald Test:

stata

CopyEdit

```
xttest3
```

Common Issues:

Error Message: If you see an error like "no observations", it might mean there is a problem with your panel data setup. Make sure your dataset is declared as panel data:

stata

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```
xtset panel_variable time_variable
```

- **Data Requirements:** xttest3 requires that you have multiple observations for each panel (cross-sectional unit). If your data is unbalanced (some panels have very few observations), the test might fail.
-

You said:

transform to lag for all the variables

ChatGPT said:

To create lagged variables for all your variables in **Stata**, you need to ensure that your dataset is set up as panel data using the xtset command. Once the data is properly set, you can use Stata's lag operator (L.) to generate lagged variables.

Steps to Create Lagged Variables for All Variables

1. Set Your Data as Panel Data

Before creating lagged variables, you must declare the panel structure:

```
stata
```

```
CopyEdit
```

```
xtset panel_variable time_variable
```

- Replace `panel_variable` with the variable identifying individual entities (e.g., `Firm_ID`).
 - Replace `time_variable` with the variable identifying time (e.g., `year`).
-

2. Generate Lagged Variables

To create lagged variables for all your listed variables, you can use a `foreach` loop.

Example for Your Variables:

```
stata
```

```
CopyEdit
```

```
foreach var in log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w {  
  gen L_`var' = L.`var'
```

- `L_` refers to the first lag of the variable.
 - `L_` is added as a prefix to the new lagged variable (e.g., `L_log1_Volatility`).
-

3. Check the Created Lagged Variables

Verify the newly created lagged variables:

```
stata
```

```
CopyEdit
```

```
list panel_variable time_variable log1_Volatility L_log1_Volatility if _n <= 10
```

Notes:

1. **Missing Values in Lagged Variables:**
 - The first observation for each panel will have missing values in the lagged variables because there is no preceding observation.
2. **Higher-Order Lags:**

To create higher-order lags (e.g., 2-period lag), use L2.:

```
stata
```

```
CopyEdit
```

```
gen L2_log1_Volatility = L2.log1_Volatility
```

3. Lagging Across Panels:

- The xtset declaration ensures that lagged variables are created within panels and do not mix data between entities.

Lag All Variables at Once: If you want to generate lagged variables for all variables in the dataset (except panel and time identifiers), you can loop over all variables:

```
stata
```

```
CopyEdit
```

```
ds panel_variable time_variable, not
```

```
foreach var in `r(varlist)' {
```

```
  gen L_`var' = L.`var' }
```

Breusch-Pagan panel data command

ChatGPT said:

The **Breusch-Pagan test** for heteroskedasticity in panel data is typically adapted through specific tests or commands designed for panel models. Here's how to conduct the **Breusch-Pagan test** for panel data in **Stata**:

Step-by-Step Instructions:

1. Set the Panel Data Structure

First, ensure your data is declared as panel data:

```
stata
```

```
CopyEdit
```

```
xtset panel_variable time_variable
```

- Replace panel_variable with the variable identifying individual entities (e.g., Firm_ID).
- Replace time_variable with the variable identifying time (e.g., year).

2. Run a Breusch-Pagan Test

The **Breusch-Pagan test** for panel data is commonly applied to a pooled OLS model. You can perform the test using the following commands:

Option 1: Basic Breusch-Pagan Test

Fit a pooled OLS regression model:

stata

CopyEdit

```
regress dependent_variable independent_variables
```

Perform the Breusch-Pagan test:

stata

CopyEdit

```
estat hettest
```

- **Interpretation:**

- **Null Hypothesis (H0H_0H0):** Homoskedasticity (constant variance).
 - **Alternative Hypothesis (H1H_1H1):** Heteroskedasticity (non-constant variance).
-

3. Use the Breusch-Pagan LM Test for Random Effects

If you are testing whether a random-effects model is appropriate instead of pooled OLS, you can use the **Breusch-Pagan LM test** for random effects.

Run the random-effects model:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re
```

Perform the Breusch-Pagan LM test:

stata

CopyEdit

```
xttest0
```

- **Interpretation:**

- **Null Hypothesis (H0H_0H0):** No significant differences across entities (pooled OLS is sufficient).
 - **Alternative Hypothesis (H1H_1H1):** Random effects are present.
-

Differences Between the Two Tests

- `estat hettest`: Checks for heteroskedasticity in a pooled OLS model.

- `xttest0`: Checks whether the variance across entities (random effects) is significant.
-

Important Notes:

Heteroskedasticity in Panel Data: If heteroskedasticity is detected, consider using robust standard errors to correct for it:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re vce(robust)
```

Other Tests for Heteroskedasticity: For panel data, you may also use the **Modified Wald Test** (`xttest3`) for groupwise heteroskedasticity (only for fixed-effects models):

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe  
xttest3
```

Summary:

Command for Pooled OLS Heteroskedasticity (Breusch-Pagan):

stata

CopyEdit

```
estat hettest
```

Command for Breusch-Pagan LM Test (Random Effects):

stata

CopyEdit

```
xttest0
```

You said:

White's test, `xtreg` since we have panel data

In **panel data**, White's test for heteroskedasticity is not directly applicable because it is typically designed for cross-sectional models. However, you can adapt it for panel data using a pooled OLS regression approach, or you can address heteroskedasticity in panel data using robust standard errors.

Here's how to perform **White's test** for panel data:

Steps to Perform White's Test in Panel Data

1. Use Pooled OLS for White's Test

White's test can be applied to a pooled OLS model to check for heteroskedasticity.

Run the Pooled OLS Regression:

stata

CopyEdit

```
regress dependent_variable independent_variables
```

Perform White's Test: Use the estat imtest command with the white option:

stata

CopyEdit

```
estat imtest, white
```

- This will compute White's test for heteroskedasticity.
-

2. Panel-Specific Alternatives

If you want to account for the panel structure, White's test is not directly applicable. Instead, you should use robust standard errors or Feasible Generalized Least Squares (FGLS) to account for heteroskedasticity.

Option 1: Use Robust Standard Errors

Run the Fixed-Effects or Random-Effects Model:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe  
or
```

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re
```

Add Robust Standard Errors:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe vce(robust)  
or
```

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re vce(robust)
```

Option 2: Use Feasible Generalized Least Squares (FGLS)

FGLS is another way to handle heteroskedasticity in panel data.

Run the FGLS Model:

stata

CopyEdit

```
xtgls dependent_variable independent_variables, panels(heteroskedastic)
```

- This accounts for heteroskedasticity across panels.
-

3. Modified Wald Test for Groupwise Heteroskedasticity

For fixed-effects models, you can use the **Modified Wald test** as an alternative:

Run the Fixed-Effects Model:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe
```

Perform the Modified Wald Test:

stata

CopyEdit

```
xttest3
```

White's Test vs. Robust Standard Errors

- White's test provides a formal statistical test for heteroskedasticity but is not panel-specific.
 - Robust standard errors (or FGLS) are preferred in panel data because they directly correct for heteroskedasticity, making the model robust to its presence.
-

Summary of Commands:

White's Test for Pooled OLS:

stata

CopyEdit

```
regress dependent_variable independent_variables  
estat imtest, white
```

1. **Robust Standard Errors for Panel Data:**

Fixed Effects:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe vce(robust)
```

Random Effects:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re vce(robust)
```

FGLS for Panel Data:

stata

CopyEdit

```
xtgls dependent_variable independent_variables, panels(heteroskedastic)
```

You said:

command xttest3 is unrecognized, why could that be, and how can I run the modified wald if the command is not working?

ChatGPT said:

The xttest3 command is built into Stata but is specific to fixed-effects models (xtreg, fe). If you're seeing the error "**command xttest3 is unrecognized**", here are some potential reasons and solutions:

Possible Reasons for the Error

1. Panel Data Not Properly Set Up:

- The xttest3 command only works after running a fixed-effects model (xtreg, fe). If you haven't declared your panel data with xtset, the command will not work.

Solution:

stata

CopyEdit

```
xtset panel_variable time_variable  
xtreg dependent_variable independent_variables, fe  
xttest3
```

2. Version of Stata:

- If you are using an older version of Stata (e.g., Stata 11 or earlier), xttest3 might not be available.

- Solution: Update Stata to the latest version or use alternative methods (see below).
3. **Not Running a Fixed-Effects Model:**
- The xttest3 test is specific to **fixed-effects models**. If you ran a random-effects model (xtreg, re) or pooled OLS, the command will not work.
 - Solution: Ensure you use xtreg, fe before calling xttest3.
4. **Installation Issue:**
- If you've recently installed Stata or the installation is incomplete, xttest3 might not be recognized.
 - Solution: Reinstall Stata or check for updates.
-

Alternative to xttest3: Run the Modified Wald Test Manually

If xttest3 does not work, you can calculate the **Modified Wald test** manually using the residuals and a custom variance matrix.

Steps to Run the Modified Wald Test Manually:

Estimate a Fixed-Effects Model:

```
stata
CopyEdit
xtreg dependent_variable independent_variables, fe
```

Predict Residuals:

```
stata
CopyEdit
predict resid, e
```

Group Variance Calculation: Calculate group-specific variances to assess heteroskedasticity.

```
stata
CopyEdit
gen resid2 = resid^2
collapse (mean) resid2, by(panel_variable)
```

1. **Run a Chi-Squared Test:** Compare variances to test for groupwise heteroskedasticity using the chi-squared distribution.
-

Alternative Tests for Heteroskedasticity in Panel Data

If xttest3 is unavailable, consider these alternatives:

1. Use Robust Standard Errors

Bypassing the need for heteroskedasticity testing, robust standard errors address heteroskedasticity directly:

```
stata
CopyEdit
xtreg dependent_variable independent_variables, fe vce(robust)
```

2. Use Feasible Generalized Least Squares (FGLS)

FGLS accounts for heteroskedasticity in panel data:

```
stata
CopyEdit
xtgls dependent_variable independent_variables, panels(heteroskedastic)
```

3. Breusch-Pagan Test

Run a pooled OLS model and test for heteroskedasticity:

```
stata
CopyEdit
regress dependent_variable independent_variables
estat hettest
```

Troubleshooting Steps for xttest3:

Check if you ran xtset to declare panel data:

```
stata
CopyEdit
xtset panel_variable time_variable
```

1. Confirm you ran a fixed-effects model:

```
stata
CopyEdit
xtreg dependent_variable independent_variables, fe
```

2. Ensure your Stata version supports xttest3. If not, use the manual approach or alternatives provided above.

You said:

Do you mean all variables of independent only?

ChatGPT said:

For the **Modified Wald test** (xttest3) or any other heteroskedasticity-related test, the focus is on the **independent variables** and how their relationship with the dependent variable affects the residual variance. Here's a clarification:

Do You Include All Variables or Only Independent Variables?

1. Independent Variables Only:

- The Modified Wald test assesses the heteroskedasticity of residuals, which are derived from the relationship between the **dependent variable** and the **independent variables**.
- Therefore, in the regression model, you include only the independent variables along with the dependent variable to compute the residuals.

2. Exclude the Dependent Variable as an Independent Variable:

- The dependent variable is not included among the predictors; it is the variable being explained by the independent variables.

3. Panel Variable and Time Variable:

- The panel and time variables (e.g., Firm_ID and year) are **not included as independent variables**. These variables are used to set the panel structure with xtset.
-

Summary of Variables to Include in the Regression:

- **Dependent Variable:** The outcome variable you are modeling.
 - **Independent Variables:** All relevant predictors (e.g., log1_Volatility, log1_options, etc.).
 - **Exclude Panel and Time Variables:** These are used for panel setup but are not part of the regression.
-

Example Command:

Step 1: Set Panel Data Structure

stata

CopyEdit

```
xtset panel_variable time_variable
```

- Replace panel_variable (e.g., Firm_ID) and time_variable (e.g., year).

Step 2: Run a Fixed-Effects Model with Independent Variables

```
stata
```

```
CopyEdit
```

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, fe
```

Step 3: Test for Heteroskedasticity (If xttest3 Works)

```
stata
```

```
CopyEdit
```

```
xttest3
```

You said:

```
durbin watson test
```

ChatGPT said:

The **Durbin-Watson (DW) test** is used to detect **autocorrelation** (serial correlation) in the residuals of a regression model. While it is commonly applied to **time-series data**, it can also be used for panel data under certain conditions.

Here's how to conduct the Durbin-Watson test in **Stata**:

Steps to Perform the Durbin-Watson Test

1. For Time-Series or Pooled Data

Run a Regression Model:

```
stata
```

```
CopyEdit
```

```
regress dependent_variable independent_variables
```

Run the Durbin-Watson Test:

```
stata
```

```
CopyEdit
```

```
estat dwatson
```

2. For Panel Data

The standard Durbin-Watson test is not directly applicable to panel data because it does not account for the panel structure. However, you can still use it for pooled OLS or time-series regressions on individual panels.

Options for Panel Data:

1. Use Pooled OLS for the Entire Panel:

If you treat panel data as pooled, run the regression as pooled OLS:

```
stata
CopyEdit
regress dependent_variable independent_variables
estat dwatson
```

2. Run Separate Regressions for Each Panel:

Use the `statsby` command to calculate the Durbin-Watson statistic for each panel individually:

```
stata
CopyEdit
statsby dw = r(dw), by(panel_variable): regress dependent_variable independent_variables
```

Interpreting the Results

- **Durbin-Watson Statistic (ddd):** Ranges between 0 and 4.
 - $d \approx 2$: No autocorrelation.
 - $d < 2$: Positive autocorrelation.
 - $d > 2$: Negative autocorrelation.
- Critical values depend on the sample size and number of predictors. Use a Durbin-Watson table or approximation for precise interpretation.

Alternative Tests for Panel Data

For panel-specific autocorrelation, consider the following tests:

1. Wooldridge Test for Autocorrelation

This test is designed for panel data:

Run the Wooldridge test:

```
stata
CopyEdit
xtset panel_variable time_variable
xtserial dependent_variable independent_variables
```

Interpretation:

- **Null Hypothesis (H0H_0H0):** No first-order autocorrelation.
- **Alternative Hypothesis (H1H_1H1):** First-order autocorrelation exists.

2. Autocorrelation in Fixed or Random Effects Models

For fixed-effects or random-effects models:

Estimate the model:

stata

CopyEdit

xtreg dependent_variable independent_variables, fe

Test for autocorrelation:

stata

CopyEdit

xtserial dependent_variable independent_variables

Addressing Autocorrelation

If autocorrelation is detected:

Clustered Standard Errors: Use robust standard errors to adjust for autocorrelation:

stata

CopyEdit

xtreg dependent_variable independent_variables, fe vce(cluster panel_variable)

Include Lags: Include lagged dependent variables to account for serial dependence:

stata

CopyEdit

xtreg dependent_variable L.dependent_variable independent_variables, fe

Dynamic Panel Models: Use dynamic panel models like **Arellano-Bond (GMM):**

stata

CopyEdit

xtabond dependent_variable L.dependent_variable independent_variables

You said:

it says command xtserial is unrecognised

ChatGPT said:

If the `xtserial` command is unrecognized in your Stata, it likely means the command is not installed, as it is not a default Stata command. You need to install it first, or alternatively use other built-in methods for autocorrelation testing.

Option 1: Install `xtserial`

You can install the `xtserial` command as follows:

```
stata
CopyEdit
ssc install xtserial
```

Once installed, you can run the Wooldridge test for autocorrelation in panel data:

```
stata
CopyEdit
xtserial dependent_variable independent_variables
```

- **Interpretation:**

- **Null Hypothesis (H0H_0H0):** No first-order autocorrelation.
 - **Alternative Hypothesis (H1H_1H1):** First-order autocorrelation exists.
-

Option 2: Use Built-in Commands for Autocorrelation

1. Wooldridge Test Alternative

If you don't want to install `xtserial`, you can manually perform the Wooldridge test for autocorrelation in panel data:

Declare Panel Data:

```
stata
CopyEdit
xtset panel_variable time_variable
```

Run the Test: Use the `xtregar` command, which handles autocorrelation within panels:

```
stata
CopyEdit
xtregar dependent_variable independent_variables
```

2. Durbin-Watson Test for Pooled Data

If your data is treated as pooled (ignoring panel structure), you can use:

```
stata
CopyEdit
regress dependent_variable independent_variables
estat dwatson
```

Option 3: Alternative Tests for Autocorrelation in Panel Data

Breusch-Godfrey Test for Panel Data

You can use the Breusch-Godfrey test for higher-order autocorrelation.

Fit the Fixed-Effects Model:

```
stata
CopyEdit
xtreg dependent_variable independent_variables, fe
```

Include Lagged Residuals:

Predict residuals:

```
stata
CopyEdit
predict residuals, resid
```

- Add lagged residuals as regressors and re-run the model.
-

Fixing Autocorrelation

If autocorrelation exists, you can:

Use robust standard errors:

```
stata
CopyEdit
xtreg dependent_variable independent_variables, fe vce(cluster panel_variable)
```

Include lagged variables to account for serial correlation:

```
stata
CopyEdit
xtreg dependent_variable L.dependent_variable independent_variables, fe
```

You said:

it says command xtserial unrecognised

ChatGPT said:

If the xtserial command is not recognized, it may not be installed. Since xtserial is not a default command in Stata, you must first install it before using it. Here's how you can resolve this issue:

Step 1: Install xtserial

Install the Command:

stata

CopyEdit

```
ssc install xtserial
```

- This downloads and installs the xtserial command from Stata's SSC archive.

Verify the Installation: After installation, confirm that the command works:

stata

CopyEdit

```
xtserial dependent_variable independent_variables
```

Step 2: Alternative if Installation is Not Possible

If you cannot install xtserial (e.g., due to restricted access or network issues), here are other methods for testing autocorrelation in panel data:

1. Wooldridge Test Using xtregar

The xtregar command in Stata allows for autocorrelation testing directly in panel data:

Declare the panel structure:

stata

CopyEdit

```
xtset panel_variable time_variable
```

Run the xtregar model:

stata

CopyEdit

```
xtregar dependent_variable independent_variables
```

- This estimates the model with correction for autocorrelation.

2. Durbin-Watson Test for Pooled OLS

If you treat the data as pooled (ignoring the panel structure):

Run a pooled OLS regression:

stata

CopyEdit
regress dependent_variable independent_variables

Use the estat dwatson command:

stata
CopyEdit
estat dwatson

- This provides the Durbin-Watson statistic for serial correlation.

3. Custom Wooldridge Test

If xtserial cannot be installed, you can manually implement the Wooldridge test by creating lagged variables and running a regression on residuals.

Run the Fixed-Effects Model:

stata
CopyEdit
xtreg dependent_variable independent_variables, fe

Predict Residuals:

stata
CopyEdit
predict resid, resid

Create Lagged Residuals:

stata
CopyEdit
gen lag_resid = L.resid

Test for Autocorrelation: Regress residuals on their lagged values:

stata
CopyEdit
regress resid lag_resid

Fixing Autocorrelation in Panel Data

Use **robust or clustered standard errors:**

stata
CopyEdit
xtreg dependent_variable independent_variables, fe vce(cluster panel_variable)

Include **lagged dependent variables:**

stata

CopyEdit

```
xtreg dependent_variable L.dependent_variable independent_variables, fe
```

You said:

hausman test for my variables

ChatGPT said:

The **Hausman test** is used to determine whether a fixed-effects model or a random-effects model is more appropriate for your panel data. It compares the estimators from both models to test for systematic differences.

Steps to Perform the Hausman Test

1. Set Your Panel Data Structure

First, ensure your panel data is declared with xtset:

```
stata
```

CopyEdit

```
xtset panel_variable time_variable
```

- Replace panel_variable (e.g., Firm_ID) and time_variable (e.g., year) with the respective variables in your dataset.
-

2. Estimate the Fixed-Effects Model

Run the fixed-effects model with your independent variables:

```
stata
```

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, fe
```

3. Estimate the Random-Effects Model

Run the random-effects model with the same independent variables:

```
stata
```

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, re
```

4. Perform the Hausman Test

Run the Hausman test to compare the models:

```
stata  
CopyEdit  
hausman fe re
```

- **Explanation of Commands:**
 - fe: Refers to the fixed-effects estimates.
 - re: Refers to the random-effects estimates.
-

Interpreting the Results

- **Null Hypothesis (H0H_0H0):** The random-effects model is consistent and efficient.
 - **Alternative Hypothesis (H1H_1H1):** The random-effects model is inconsistent; use the fixed-effects model.
 - **Key Outcome:**
 - If **p-value < 0.05**, reject H0H_0H0: Use the fixed-effects model.
 - If **p-value ≥ 0.05**, fail to reject H0H_0H0: Use the random-effects model.
-

Special Cases

1. Error: "Not Positive Semi-Definite"

If you encounter this error, it means the variance-covariance matrix of the test is not invertible. Use the robust version of the Hausman test instead:

```
stata  
CopyEdit  
hausman fe re, sigmamore
```

2. Alternative Method (Manual Hausman Test)

If the hausman command fails, calculate the difference in coefficients and variances manually:

Save the estimates from the fixed-effects model:

```
stata
CopyEdit
estimates store fe_model
```

Save the estimates from the random-effects model:

```
stata
CopyEdit
estimates store re_model
```

Perform the Hausman test:

```
stata
CopyEdit
hausman fe_model re_model
```

Commands for Your Variables

For your dataset, the commands will look like this:

```
stata
CopyEdit
xtset Firm_ID year
```

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w
Leverage_w Cash_w Tangibility_w, fe
```

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w
Leverage_w Cash_w Tangibility_w, re
```

```
hausman fe re
```

You said:

```
estimate fe_model ?
```

ChatGPT said:

To estimate and store the fixed-effects model (fe_model) in Stata, follow these steps:

Steps to Estimate and Store the Fixed-Effects Model

Run the Fixed-Effects Model

```
stata
```

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, fe
```

Store the Fixed-Effects Model Estimates

stata

CopyEdit

```
estimates store fe_model
```

Explanation of Commands:

1. **xtreg ... , fe:** Runs the fixed-effects regression model.
 2. **estimates store fe_model:** Saves the fixed-effects model under the name fe_model for later use in the Hausman test or comparisons.
-

Storing Both Fixed and Random Effects Models for Hausman Test

You will need to store the random-effects model as well:

Run the Random-Effects Model:

stata

CopyEdit

```
xtreg dependent_variable log1_Volatility log1_options log1_total_comp log1_assets ROA_w  
Leverage_w Cash_w Tangibility_w, re
```

Store the Random-Effects Model Estimates:

stata

CopyEdit

```
estimates store re_model
```

Perform the Hausman Test

After storing both models, run the Hausman test:

stata

CopyEdit

```
hausman fe_model re_model
```

Common Issues:

1. **Error: "Not Positive Semi-Definite Matrix"**

If you encounter this error, use the robust version:

stata

CopyEdit

```
hausman fe_model re_model, sigmamore
```

2. Models Must Use the Same Variables:

- Ensure the fixed-effects and random-effects models include the same dependent and independent variables. Any mismatch will cause an error.

You said:

Vif correlation test

ChatGPT said:

The **Variance Inflation Factor (VIF)** and **correlation tests** are used to assess multicollinearity among independent variables in your regression model. Here's how to perform these tests in Stata:

1. Variance Inflation Factor (VIF)

The VIF quantifies the extent of multicollinearity by measuring how much the variance of a regression coefficient is inflated due to collinearity.

Steps to Run VIF Test:

Run the Regression Model:

stata

CopyEdit

```
regress dependent_variable independent_variables
```

Check VIF:

stata

CopyEdit

```
vif
```

Interpreting VIF Values:

- **VIF < 10:** Multicollinearity is not severe.
- **VIF ≥ 10:** High multicollinearity exists; consider addressing it.

2. Correlation Matrix

A correlation matrix shows pairwise correlations among variables to identify potential collinear relationships.

Steps to Generate Correlation Matrix:

Check Pairwise Correlations:

```
stata  
CopyEdit  
corr independent_variables
```

Visualize Correlations (Optional): Create a heatmap or scatterplot matrix for better insights:

```
stata  
CopyEdit  
pwcrr independent_variables, sig
```

Interpreting Correlations:

- **|Correlation| > 0.8:** Strong correlation suggests potential multicollinearity.
-

For Panel Data:

If working with panel data, run VIF after estimating the **pooled OLS model**, as VIF is not designed for xtreg models.

Run a Pooled OLS Model:

```
stata  
CopyEdit  
regress dependent_variable independent_variables
```

Check VIF:

```
stata  
CopyEdit  
vif
```

3. Addressing Multicollinearity

If multicollinearity is detected:

1. **Remove Highly Correlated Variables:** Drop one of the correlated variables or combine them into a composite index.
2. **Center Variables:** Standardize or mean-center the variables to reduce multicollinearity.
3. **Principal Component Analysis (PCA):** Use PCA to create independent components.

Example for Your Variables:

Run Regression and VIF:

```
stata
CopyEdit
regress dependent_variable log1_Volatility log1_options log1_total_comp log1_assets
ROA_w Leverage_w Cash_w Tangibility_w
vif
```

Run Correlation Matrix:

```
stata
CopyEdit
corr log1_Volatility log1_options log1_total_comp log1_assets ROA_w Leverage_w Cash_w
Tangibility_w
```

You said:

Panel data, Ramsey

ChatGPT said:

The **Ramsey RESET test** is primarily designed for cross-sectional or time-series models and does not directly accommodate panel data due to the structure of residuals. However, there are ways to adapt or approximate the test for panel data models:

Options for Ramsey RESET Test in Panel Data

1. Perform Ramsey RESET Test on a Pooled OLS Model

You can ignore the panel structure and treat the data as pooled OLS to run the Ramsey RESET test.

Steps:

Run a pooled OLS regression:

```
stata
CopyEdit
regress dependent_variable independent_variables
```

Perform the Ramsey RESET test:

```
stata
```

CopyEdit
estat ovtest

- **Interpretation:**
 - **Null Hypothesis (H0H_0H0):** The model is correctly specified.
 - **Alternative Hypothesis (H1H_1H1):** The model has functional form misspecification.
 - A low p-value (e.g., < 0.05) suggests misspecification.
-

2. Adapt Ramsey RESET Test for Fixed or Random Effects Models

While there isn't a direct Ramsey RESET test for fixed/random effects models, you can approximate it:

Run a Fixed or Random Effects Model:

stata

CopyEdit

```
xtreg dependent_variable independent_variables, fe
```

or

stata

CopyEdit

```
xtreg dependent_variable independent_variables, re
```

Generate Fitted Values:

stata

CopyEdit

```
predict fitted_values, xb
```

Include Higher-Order Terms of Fitted Values: Add squared or cubic fitted values to the model to check for misspecification.

stata

CopyEdit

```
gen fitted_squared = fitted_values^2
```

```
gen fitted_cubic = fitted_values^3
```

```
xtreg dependent_variable independent_variables fitted_squared fitted_cubic, fe
```

Test for Significance of Higher-Order Terms: If the coefficients of fitted_squared or fitted_cubic are significant, it suggests a functional form issue.

3. Use Dynamic Panel Models

If the suspected misspecification involves omitted dynamics, consider dynamic panel models like **Arellano-Bond GMM**:

Fit the model:

stata

CopyEdit

```
xtabond dependent_variable L.dependent_variable independent_variables
```

When to Use Each Approach

- **Pooled OLS (estat ovtest):** Suitable for an initial functional form check, but ignores the panel structure.
 - **Fitted Value Approach:** More tailored to fixed or random effects models, detecting non-linear relationships.
 - **Dynamic Models (GMM):** Address omitted dynamics in the model specification.
-

Chow test

ChatGPT said:

The **Chow test** is used to determine whether the coefficients in two regressions (e.g., across different groups or time periods) are significantly different. It's often applied in **panel data** to test for structural breaks or whether separate models are needed for subgroups of data.

Steps to Perform the Chow Test in Stata

1. Assumptions:

- The dependent variable is continuous.
 - The two groups (or time periods) are clearly defined.
 - Homoscedasticity (equal variance) across groups is assumed.
-

2. Steps for Implementation

Step 1: Create a Grouping Variable

If you're testing for differences across two groups (e.g., Group 1 and Group 2):

stata

CopyEdit

```
gen group_indicator = (group_variable == "Group 1")
```

Step 2: Run Separate Regressions for Each Group

For Group 1:

stata

CopyEdit

```
regress dependent_variable independent_variables if group_indicator == 1
```

For Group 2:

stata

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```
regress dependent_variable independent_variables if group_indicator == 0
```

Step 3: Run a Combined Regression

Create interaction terms for all independent variables with the group variable to allow for different coefficients across groups:

stata

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```
gen group_independent1 = group_indicator * independent1
```

```
gen group_independent2 = group_indicator * independent2
```

Then run the regression:

stata

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```
regress dependent_variable independent1 independent2 group_independent1
```

```
group_independent2
```

Step 4: Compare the Models

Run the combined regression **without interaction terms** (restricted model):

stata

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```
regress dependent_variable independent1 independent2
```

3. Perform the Chow Test

Use the **manual F-test formula**:

$$F = \frac{(SSR_{restricted} - SSR_{unrestricted}) / k}{SSR_{unrestricted} / (n_1 + n_2 - 2k)}$$
$$F = \frac{SSR_{unrestricted} / (n_1 + n_2 - 2k) - SSR_{restricted} / (n_1 + n_2 - 2k)}{SSR_{unrestricted} / (n_1 + n_2 - 2k)}$$

Where:

- $SSR_{restricted}$: Sum of squared residuals from the restricted (combined) model.
- $SSR_{unrestricted}$: Sum of squared residuals from the unrestricted (group-specific) models.
- kkk : Number of predictors in the model.
- n_1, n_2 : Number of observations in each group.

In Stata:

Retrieve the residual sums of squares (SSR) for each model:

```
stata
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display e(rss)
```

1. Use the formula to compute FFF.

4. Shortcut: Use `suest` for a Built-In Chow Test

Estimate separate regressions for each group:

```
stata
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regress dependent_variable independent_variables if group_indicator == 1
estimates store group1_model
```

```
regress dependent_variable independent_variables if group_indicator == 0
estimates store group2_model
```

Combine the models using `suest`:

```
stata
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suest group1_model group2_model
```

Test for equality of coefficients:

```
stata
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test [group1_model=group2_model]
```

Interpreting Results

- **Null Hypothesis (H_0):** Coefficients for the two groups are the same.
- **Alternative Hypothesis (H_1):** Coefficients for the two groups differ significantly.

- If $p < 0.05$, reject H_0 , indicating a structural break or different models for the groups