# Does hedge disclosure influence cost of capital for European banks?\*

# International Review of Financial Analysis, 78, November 2021, 101942

https://doi.org/10.1016/j.irfa.2021.101942

# **Forthcoming**

# Tamer Elshandidy\*\*

College of Business Administration

Ajman University, UAE

<u>t.elshandidy@ajman.ac.ae</u>

# Albert Acheampong

Bradford School of Management
University of Bradford, UK

a.k.acheampong@bradford.ac.uk

### Cite as:

Elshandidy, T., Acheampong, A. (2021). Does hedge disclosure influence cost of capital for European banks? *International Review of Financial Analysis*, 78, 101942

<sup>\*</sup> We are grateful to Brian M Lucey (the Editor) and the anonymous referees for constructive and helpful comments. This paper has benefited from comments and suggestions from participants at the British Accounting and Finance Association Conference (April 2021).

<sup>\*\*</sup>Correspondence should be addressed to Tamer Elshandidy, Ajman University, College of Business Administration, P. O. Box 346, Ajman, UAE. Email: <u>t.elshandidy@ajman.ac.ae</u>

# Does textual hedge disclosure influence cost of capital for European banks?

#### **Abstract**

Upon extracting and quantifying relevant hedge information from the narrative section of European banks annual reports, this paper examines the impact of such information on cost of capital [as measured by weighted average cost of capital (WACC), cost of equity (COE) and cost of debt (COD)]. Using a sample of 1885 bank-year observations from 19 countries, we find that textual hedge disclosure leads to a significant reduction in WACC, COE, and COD; thus explains a substantial portion of variation in cost of capital. Further, we find that these results are stronger in countries with high corruption and financial openness. Our results are robust to several controls and model specification. Collectively, our findings enrich prior evidence which examines the economic consequences of hedge disclosure.

**JEL Classification**: G20 G21 G32

Keywords: Hedging, Cost of capital, Cost of equity, Cost of debt, Textual analysis, Annual reports

#### 1. Introduction

Practical evidence shows that derivatives have been increasingly used as instruments for active risk management in recent years (e.g., Brewer et al., 2000; Chen & King, 2014). For instance, in Europe, a report by the European Securities and Markets Authority in 2018 reveals an increasing trend in the notional amount of derivatives outstanding from €605 trillion to €660 trillion (ESMA, 2018). This note raises the question of whether users of derivatives experience lower cost of capital than non-users.

Extant studies focus largely on hedging and its association with cost of capital components: cost of equity (e.g., Bartram et al., 2011; Gay et al., 2011), and cost of debt (e.g., Beatty et al., 2012; Deng et al., 2017). The common theme that can be drawn from these studies is that overall hedging position by firms among other benefits results in lower cost of equity or cost of debt. To the best of our knowledge, little research is done to examine extensively the relationship between hedging and overall cost of capital (i.e., equity and debt capital). In many cases, investors' beliefs tend to be diverse; thus their choices of portfolio and proportion of equity and debt in total financing might be determined jointly, so focusing on one component of cost of capital would not present a true reflection of overall capital cost. Put differently, while increase in risk premium will impact cost of equity due to the varying risk exposures, and any uncertainties tend to impact cost of debt through default risk, the overall impact cost of capital depends on the financing mix. Therefore, analysing the association between hedging and overall firm cost of capital is essential because both shareholders and bondholders benefit from hedging by the lowering of risk-based capital requirement and deposit insurance premiums.

Furthermore, most of the above-mentioned studies focus largely on quantitative rather than qualitative (soft) information for capturing hedging. Specifically, they measure hedging activity using a hedging dummy, and/or continuous notional amount of derivatives outstanding (e.g., Bartram et al., 2011; Chang et al., 2018; Deng et al., 2017). The heavy reliance on quantitative information over the years as a proxy for hedging is perhaps because of the difficulties in capturing

and quantifying such information from corporate disclosure (Acheampong & Elshandidy, 2021), as it require rigorous data processing and becomes challenging with regards to data dimensionality. Also, prior studies focus largely on markets outside Europe and less attention is given to financial firms (e.g., Ahmed et al., 2018; Bartram et al., 2011; Carter et al., 2006; Gay et al., 2011). Our paper therefore bridges these gaps by adopting a different analytical lens to examine the association between textual hedge disclosure and cost of capital of European banks over a thirteen-year period. In doing so, our paper utilises a machine learning approach to quantify qualitative information on hedging disclosed in the narrative sections of annual reports of a large-scale sample of European banks to examine its impact on these banks' cost of capital.

Our paper focuses on the European banking industry because of the following. First, the European market over the past decades is reported to have contributed massively to the total global outstanding volume of derivatives. It accounts for 44% of the total outstanding amount and the market appears to be a giant in derivatives trading, which has experienced economic growth both directly and indirectly (BIS, 2008). Second, from a regulatory point of view, banks are distinct from non-financial firms because they are more regulated and highly leveraged than non-financial firms. These distinct features provide a solid ground for drawing fresh inferences on the interconnectedness between hedging, regulation, and bank risk. Finally, there is a high incentive for banks to increase risk in order to exploit the moral hazard frictions entrenched in deposit insurance or government bailouts. Therefore, the derivatives market is more highly populated with banks than non-financial firms because they possess greater access to any relevant information ahead of time and so are able to take immediate action for hedging purposes.

To examine the association between textual hedge disclosure and cost of capital, we gathered annual reports from European banks for the period of 2005 to 2017. Our empirical evidence suggests that textual hedge disclosure significantly reduces overall banks' cost of capital (WACC), cost of equity and cost of debt. This suggests that a significant variation in all cost of

capital measures across countries within and between banks over the chosen period can be explained by our proposed measure of textual hedge disclosure. At the country level, we find that financial stress over time has significantly higher explanatory power over all cost of capital measures. Second, during the IFRS 9 period, the negative association between cost of capital and hedge disclosure remains unchanged, suggesting that the direct association found between these two variables is strengthened by the IFRS 9 period. These results suggest that hedge disclosure contain economically significant information relevant in explaining the cost of capital structure of banks.

Our paper makes the following contributions to the body of literature concerning bank disclosure and cost of capital. First, we add to the limited research on the association between hedge disclosure and cost of capital. While the majority of prior studies focus largely on the association between firm derivative usage and firm value and risk, considering either cost of equity or cost of debt, we provide a different analytical lens by examining the association between textual hedging and cost of capital and its components. We employ a machine learning approach using R to capture all hedge-related statements from the narrative section of annual reports based on our final comprehensive list of keywords. Second, our paper is based on financial firms from the European market, which complements prior literature, which is largely based on non-financial firms from the US, on the impact of hedging on firm risk (e.g., Bartram et al., 2011; Carter et al., 2006; Gay et al., 2011). Given the significant contribution of Europe in the global derivatives market for trading and management purposes and the uniqueness of banks, which differ extensively from non-financial firms, our focus on the banking industry in Europe provides a fresh ground for additional insights. Third, our paper sheds more light on the variations over time in cost of capital, and then associates such variations with changes in textual hedge disclosure captured through machine learning application. We employed repeated measure multilevel analysis (RMMA) to mitigate problems associated with nested effects that are normally ignored in traditional ordinary least square (OLS) regression. Fourth, to the best of our knowledge, our paper is the first to analyse the economic impact of IFRS 9 on hedge disclosure. Given the extant importance of the need for transition from IAS 39 to IFRS 9 in the hope of strengthening the risk management framework of firms, this becomes increasingly important to banks, regulators, and investors. Finally, our paper also answers the call by Elshandidy et al. (2018) for further research on how and why financial firms disclose information about their derivative positions and the extent to which these instruments might help in the assessment of the quality of banks' risk management.

Our findings have implications for regulators and investors. With regard to regulators, our findings strongly support the adherence of banks in disclosing information related to their hedging activities. This has a growing importance to look at the incremental effect of IFRS 9 on hedge accounting and its significant impact on risk management. Therefore, regulators may encourage banking institutions to continue to disclose vital hedging information in order to bridge the information asymmetry with investors and other users of financial information. For users of annual reports, due to the extant stringent regulation, investors now require a large amount of relevant information from firms, including, for example, risk management, and financial review narrations. Such disclosure reveals various risk components. Our findings imply that, under the IFRS 9 regime where banks are obliged to disclose relevant information regarding their hedging position, failure of any bank to disclose this important risk information, which is expected by investors, may be costly through increased cost of capital, because investors are likely to increase their expected rate of return.

The remainder of this paper is organised as follows. The following section introduces the regulatory framework. Section 3 discusses relevant literature and theories while developing hypotheses. Section 4 describes the data collection process, explains the construction of textual hedge disclosure scores, cost of capital measures, and other bank- and country variables, and outline the empirical models. Section 5 discusses the empirical findings while Section 6 introduces further analyses and robustness tests. Finally, Section 7 concludes.

# 2. Regulatory framework

Prior to the wake of the Global Financial Crisis (GFC) in 2007, the fight against various risk exposure was enshrined in the Basel Committee's introduction of credit risk calibration in 2005 such as Basel II. This encouraged banks to forecast and take corrective actions on their risk exposures. In 2006, the Basel Committee required banks to establish and introduce a risk-based credit rating system which was instigated to boost the stability of the banking system and dispel the harmonisation gap (Bitar et al., 2018). However, the GFC pinpointed various shortcomings of regulatory bodies and thus presented an opportunity for Europe to leave a mark on the globe's regulatory response. The EU's response to the GFC reflected a significant shift in the approach adopted towards a transatlantic financial market that was highly seen through their collaboration with international supervisory authorities and global banking standard setters geared towards harmonising capital markets (Bitar et al., 2018). One of the major transitions in the reporting history of Europe is the adoption of the International Financial Reporting Standards (IFRS) which boosted trade among firms within the EU and simplified overseas transactions (Agostino et al., 2011). To protect banks, several stringent regulations were introduced to improve transparency and consolidate many operations that prevents the impact of interconnectedness among banks and most importantly account for financial instruments usage in the capital market.

In Europe, hedge accounting based on the International Accounting Standard Board (IASB) can be traced back to 1999 when IAS 39: "Financial Instruments: Recognition and Measurement", was introduced and became effective on 1 January 2005. IAS 39 aimed to strengthen firms' risk management strategy, the purpose for hedging and the impact of hedging on financial statements, thus ensuring financial stability. Likewise, first, IAS 32: Financial Instruments: Disclosure and presentation and subsequently IFRS 7: Financial Instruments: Disclosures were introduced to accomplish the regulation of financial instruments. These regulations enhanced transparency in derivative usage and general reporting of risk management (Beisland & Frestad, 2013). Notwithstanding the aim of

IAS 39, it is characterised by severe flaws owing to its high controversies and heavily restricted rules (IFRS 9, 2019).

As a remedy to IAS 39, the IASB introduced IFRS 9: "Financial Instruments" to simplify accounting for financial instruments. The final version of IFRS 9 was launched in July 2014 after several modifications and improvements, and it became effective in January 2018. For a firm to qualify for hedge accounting, the hedged item and instrument, together with the hedging relationship, must satisfy certain conditions. Among others, the conditions are: a formal certification and description of firm risk management objective and strategy of the hedging instrument, hedged item, nature of risk being hedged, and the hedge effectiveness. According to IAS 39, firms were to retrospectively and prospectively examine effectiveness testing and also focus on quantitative measurement, while under IFRS 9, firms only require testing prospectively and is to provide for the economic relation between hedging instruments and hedged items.

In summary, the quest of regulators to strengthen the financial system and ensure banking stability has obliged banks to identify, account and communicate their risk exposures to interested parties. A great deal of impact particularly on banks' transparency and risk reporting in general is documented by prior studies. We discuss this further in the next section.

# 3. Relevant literature and hypothesis development.

This paper examines the impact of textual hedge disclosure on cost of capital of banks in the European context. Hedging deals with the issue of underinvestment, especially in the case of high cost of external funding and growth opportunities. As a result, this helps management to raise funds internally and consequently incur lower cost of capital after optimal investment policies. The work of Froot & Stein (1998) shows that risk management policies can be used in place of a strong capital position of banks. Specifically, they argue that it is difficult for banks to raise funds externally at short notice due to market frictions. Therefore, they should curb any risk through hedging to foster external funding. In the banking industry, equity holders and bond holders are

likely to benefit from hedging through deposit insurance premiums and lower risk-based capital requirements. Gay et al. (2011) find that derivatives users reduce their cost of equity. This suggests that firms take derivative positions to reduce their financial distress risk. They add that the reduction in cost of equity is driven by small firms and firms that employ currency and interest rate derivatives. Ahmed et al. (2018) also find that hedgers experience significant decrease in their cost of equity.

On the contrary, Froot & Stein (1998) document that hedging helps banks to pursue more risk by investing more and holding less capital, which subsequently is likely to increase the cost of debt. Brewer et al. (2000) find an increase in industrial and commercial loans for banks that hedge with interest rate derivatives. Deng et al. (2010) conclude that hedging increases banks' desire to pursue additional risk, heightening their overall risk rather than moderating it. Deng et al. (2017) argue that banks may use hedging to increase their exposure to the type of risk in which they have comparative advantage or they may reduce their risk exposure to tradeable risk (e.g., exchange rate risk).

In analysing the impact of derivatives use on cost of capital, prior studies developed various techniques to search for hedge-related keywords from firm disclosure. For instance, Guay (1999) conducted a keywords search on notes in the annual financial statements of firms to identify two classes of sample (i.e., users and non-users of derivatives) and to analyse their impact on risk. Like Guay (1999), Campello et al. (2011) developed hedge-related keywords by employing web-crawler application to search for such keywords in 10-Ks of firms between 1996 and 2002. They hand-coded hedge variables by reading the surrounding text if any keywords were found. Chen & King (2014) also performed a keyword search for derivatives users in 10-K reports. A recent study by Ahmed et al. (2018) also adopts keywords search to identify information on hedging strategies and derivatives use of German firms. Other studies employ wordlists to identify various risk statements within corporate disclosure (e.g., Elshandidy et al., 2015, Elshandidy et al., 2013) to investigate the

informativeness of risk disclosures. In this current paper, we adopt a different analytical lens to identify a comprehensive list of keywords related to hedging (as detailed in Section 4.2.4 and in Appendix A-3) from three different layers: *prior literature*, *professional publications* (i.e., IASB and BCBS), and *annual reports*, to examine whether textual hedge disclosure reduces cost of capital of EU banks, as will be developed in the following section in light of relevant literature (some of key principal papers are summarised in Appendix A-4).

# 3.1 Hypothesis Development

### 3.1.1 Textual hedge disclosure and cost of capital measures

Highly risky debt may result in underinvestment and therefore serve as a hinderance for firms to undertake positive net present value projects if some or all the returns go to bondholders in adverse times. This suggests that hedging resolves the problem associated with underinvestment by reducing the chances of adverse occurrences, which motivates shareholders to invest in value-added projects. Resolving the underinvestment problem through hedging is highly driven by firms with high cost of external funding and high growth opportunities (Froot & Stein, 1998). Thus, managers pursue an optimal investment policy by generating internal funds, which lower the cost of capital.

Arguably managers might increase their equity value by investing in risky projects with negative NPVs in times of high default probabilities. When this happens, any project that performs badly puts bondholders (shareholders) at an advantage (disadvantage). Deng et al. (2010) find that while interest rate and currency hedging lower banks' risk through lower cashflow volatility, they also increase bank risk by shifting risk to the credit market by extending more and riskier loans, thus, increasing banks' desire to pursue additional risk, heightening their overall risk rather than moderating it. Hedging reduces the increase in risk of financial distress and volatility of asset returns. Chang et al. (2018) find a positive relationship between derivatives use and cost of debt. Deng et al. (2017) assert that banks may use hedging to increase their exposure to the type of risk in which they have comparative advantage and from which they accrue high economic rent (e.g.,

credit risk) whiles they simultaneously reduce their risk exposure to tradable risk (e.g., interest rate risk).

Stakeholder theory suggests that banks might disclose risk information geared towards effective interaction and better communication with influential stakeholders. Because managers hold more information about their operations than outsiders, disclosure cost may be high, and managers may distort information for private benefits, thus, leading to disequilibrium in asset prices and expected rate of returns by influencing investors' assessment regarding the distribution of prospective cashflows. The use of derivatives for hedging purposes is associated with lower information asymmetry (Dadalt et al., 2002; Chen & King, 2014). This suggests that through hedging, investors obtain information for more precise assessment of firm value and operational performance and hence this shrinks the "transparency spread". Bravo et al. (2012) assert that information disclosed in corporate reports and cost of capital is of high significance to investors and the capital market as they find that increase in disclosure is an important driver in forecasting and hence lowering cost of capital. This is supported by prior literature (e.g., Francis et al., 2008; Gietzmann & Ireland, 2005; Hail, 2002).

On the other hand, other studies show a positive association between disclosure and cost of capital. Specifically, they report that high disclosure attracts occasional investors, which then increases volatility and consequently cost of equity capital (Bushee & Noe, 2000; Botosan & Plumlee, 2002). Gao (2010) argues that disclosure quality increases with cost of capital. They add that this happens only if the adjustment cost of new investment is sufficiently low and the previous expected profitability of existing investment is sufficiently high. This suggests that less disclosure increases investor uncertainty regarding a firm's marginal profitability, in that investors would like to pay on average a lower price for the firm's share. In a pure exchange economy, lower prices imply high cost of capital, and thus less disclosure monotonically increases cost of capital. Deng et al. (2010) study bank holding companies (BHCs) in the US and their findings show that hedging increases the cost of debt. Their findings suggest that hedging stirs up banks desire to pursue more

risk, therefore piling up their overall risk rather than curbing it. Deng et al. (2017) find a positive relationship between cost of capital and derivative usage by BHCs in the US.

From the discussion above, for banks to be regarded as legitimate owing to compliance with regulation and meeting the expectations of their investors, we argue that they may disclose a high level of hedge information. We therefore formulate the following non-directional hypothesis: H1: European banks are likely to provide information about their hedge activities that reduce their cost of capital (proxied by WACC, COE, and COD).

3.1.2 The interaction between bank-level and country-level factors in explaining variations in cost of capital From a resource dependence perspective, firms depend on the environment in which they operate for resources, and thus are very much concerned about any influence of their operations through the supply of resources. This suggests that the health of banks may be influenced by various country characteristics. Hence, any acquisition of resources imperative to bank's survival, is likely to discipline banks to maintain legitimacy in the eyes of their stakeholders.

In terms of country characteristics, financial openness improves the efficiency and development of the financial institutions, stock market and macroeconomic policies. Chang et al. (2018) find that a country that exhibits more financial openness influences firms to engage in derivatives. Member countries of OECD tend to be developed and as a result, at the bank level, are perceived by investors to be sound avenues for investments. Cheung et al. (2010) assert that the OECD principles are used by investors because they provide guiding framework for the development of corporate governance and practices within a country, in addition to their popularity. Bartram et al. (2009) find that countries that are well developed tend to use derivatives. Therefore, member countries exert more potential to ensure economic growth.

On the other hand, at the bank level, corruption may cause additional cost for business, which retards economic growth as it reduces investment due to operation inefficiencies. Bhattacharya et al. (2020) posit that the interconnectedness of the banking system influence credit risk and stability within the financial system. Thus, increase in financial stress creates tension in

the financial system due to high risk and/or uncertainties and adverse liquidity because of the contraction in economic activities as a result of high procyclicality of leverage in the banking system (Cardarelli et al., 2011). We argue that corruption and financial stress drain investors' confidence and therefore may affect banks' capital structure.

In order for banks to restore investors' confidence in times of corruption and financial stress, and owing to the fact that investors increasingly demand detailed information and advice on their investment, banks tend to voluntarily disclose relevant information regarding their hedging activities to reduce investors' perceived risk and improve market liquidity (Elshandidy et al., 2018). This disclosure is geared towards shareholder monitoring and corporate reputation (Oliverira et al., 2011). In terms of hedging, disclosure because it serves as a tool for investors to make accurate assessment of firm value and operational performance, investors will be less concerned if banks operate in countries that are OECD members and with high financial openness. On the other hand, investors will be much concerned when banks operate in countries which are financially stressed and corrupt.

In line with our expectation of a significant association between hedge disclosure and cost of capital, the question of which country-level variables strengthen such association is of much significance. We therefore conduct cross-level interaction analyses to investigate this question. Elshandidy et al. (2018) call for further research to cover financial institutions in cross-country environments and the use of computer-based assistance to collect risk information. They suggest that multi-level techniques should be used to capture the hierarchical nature of cross-country results, so that researchers can integrate country-level factors with those factors at the bank level. With our nested data, cross-level interaction occurs when bank-level variables on the dependent variable vary with changes in the country-level variables. We therefore to find interaction between bank and country level characteristics and thus formulate our next hypothesis:

H2: Country-level characteristics moderate the relationship existing between text-based hedging and cost of capital.

### 4. Data and empirical method

### 4.1 Sample selection and data sources

We employ a systematic approach in selecting our sample using Datastream Eikon. The criteria and process for our sample selection are summarised in Table 1(Panel A). Our sample covers a thirteen-year period from 2005 to 2017. We begin with 2005 to account for the effect of mandatory IFRS adoption in Europe, thus, accounting for the harmonisation of annual reports quality and enhanced comparability across countries. We end at 2017 because of the transition from IAS 39 to IFRS 9 regarding hedge accounting which started from January 2018, to ensure consistency in our keywords extraction based on IAS 39. For the textual analysis, we rely on annual reports which are obtained from Datastream Eikon, where they are not accessible from banks' websites. We focus on annual reports because these reports remain one of the main sources of information on hedging and hedge policies. They remain the main source of information for investors (Elshandidy et al., 2013; Elshandidy et al., 2015). We obtain all accounting and financial variables from Datastream Eikon. Our initial sample represents 2782 (214 x 13) observations, of which we exclude 897 (69 x 13) due to non-availability of data. Our final sample consists of 145 banks leading to a unique set of 1885 firm-year observations from 19 countries from 2005 to 2017. Table 1 (Panel B) reports the sample distribution of banks across countries.

#### [Insert Table 1]

4.2 Variable construction

4.2.1 Cost of capital

We compute bank's cost of capital (WACC) following Drobetz et al. (2018) which is given as:

$$WACC = COD * LEV(1-t) + (1 - LEV)COE$$
 (1)

where WACC is the weighted average cost of capital, which is the sum of cost of equity and cost of debt. COD is the bank's cost of debt, LEV is the bank's leverage, *t* is bank's corporate tax rate, and COE is the implied cost of equity capital. We estimate COD using interest rate following prior studies (e.g., Minnis, 2011; Pittman & Fortin, 2004). We employ interest rate as a proxy for cost of debt. Interest rate is defined as the finance expense of a bank scaled by its average short-term

and long-term debt. We do not use the actual interest rate; we therefore estimate interest rate by scaling interest expense by the average of beginning and ending debt levels. Pittman & Fortin (2004) and Minnis (2011)note that this approach is associated with significant noise. We therefore truncate the variable at the 5<sup>th</sup> and 95<sup>th</sup> percentiles. After truncating, we notice some banks' interest rates are higher than the prime interest rate for the years by a substantial amount, so we further truncate the variable over the prime interest rate for any observations that exceed 1,000 basis points. In addition to addressing noise, we use the one-year-ahead interest rate to mitigate any stale information. We report this variable in Table 2 (Panel A) and it can be noted that the mean and median cost of debt for our sample are 0.0387 and 0.0384 respectively.

We empirically estimate COE following prior literature (e.g., Dhaliwal et al., 2016; Drobetz et al., 2018) using the average of Claus & Thomas (2001), Gebhardt et al. (2001), Easton (2004), and Ohlson & Juettner-Nauroth (2005) measures, hereafter K<sub>CLS</sub>, K<sub>EST</sub>, K<sub>OHS</sub>, and K<sub>GEB</sub> respectively. This is to mitigate the effect of measurement errors associated with one particular model. The first two models are centred on Ohlson and Juettner-Nauroth's abnormal returns growth model, whereas the latter two are centred on residual income valuation model. We provide detailed explanation of the cost of equity estimations in Appendix A-2.

### 4.2.2 Bank-level variables

Based on the literature, we employ the following bank-level variables: bank size (SIZE), profitability (ROE), deposits (DEPOSITS), leverage (LEVERAGE), and net-interest-margin (NIM). Bank size (SIZE) is measured as the natural logarithm of total assets. There is no concensus reached by prior literature on the association between bank size and cost of capital. Chang et al. (2018) find a positive association between bank size and cost of debt. The intuition behind the positive association is that fixed costs are associated with an initial learning curve in relation to hedging. Large banks accept these fixed costs because they are more capable and likely to use financial instruments for hedging purposes to a greater extent than small banks (Campello et al.,

2011). Also, small banks are sensitive to the disadvantages of not employing the right expertise for hedging in the derivatives market. Prior literature also finds a negative association between size and cost of equity capital (Ahmed et al., 2018; Gay et al., 2011). We therefore anticipate either a positive or negative association between bank size and cost of capital. We proxy bank profitability using return on equity (ROE) which is measured as net income divided by total shareholders' equity. Allayannis & Weston (2001) report that profitable firms trade at a premium compared to less profitable firms. Thus, profitable firms use more derivative instruments for hedging and tend to have higher firm value (Bartram et al., 2011). Chang et al. (2018) find a positive association between bank profitability and cost of debt, suggesting that banks take derivative positions and participate in arbitrage to retain their profits and increase shareholders' wealth. We therefore expect a negative association between bank profitability and cost of capital.

Bank deposits (DEPOSITS) is calculated as total bank deposits assets scaled by total assets. Inflows into transaction deposits increase with borrowers' demands, and therefore form a natural hedge against risk exposure which also cover liquidity needs. Chang et al. (2018) find a positive association between bank deposits and derivatives. On the other hand, bank deposits can spark speculative behaviour by banks. This suggests that deposits cover bank liquidity demands, and therefore banks may take advantage and embark on more risky activities. We therefore anticipate a positive or negative association between deposits and cost of capital. We calculated leverage as the total debt scaled by total assets. Investors are much concerned about the way capital structure changes with respect to risk exposure, as it may be related to its value (Allayannis & Weston, 2001). Firms with higher leverage tend to report higher risk (Bartram et al., 2011; Taylor et al., 2010). Financial distress is reduced by derivative users by widening their debt capacity. This suggests that higher leveraged firms commit to hedging (e.g., Campello et al., 2011; Haushalter, 2000), and hedging leads to higher leverage (Graham & Rogers, 2002). Chen & King (2014) report a positive

relationship between leverage and cost of debt. We therefore anticipate a positive association between leverage and cost of capital.

We capture NIM by dividing net interest income by total assets. Banks trade derivatives to increase their income levels. Chang et al. (2018) find a negative and significant association between NIM and use of derivatives by banks. This suggests that derivative positions are taken by firms to secure their interest margins since banks charge for the services they provide on their interest-rate intermediation for loans, deposit intake, and determining interest-rate risk. We expect a negative association between NIM and cost of capital.

## 4.2.3 Country-level variables

We anticipate that the disclosure of hedge-related information in annual reports by banks will differ significantly across various economic environments. Bartram (2019) argues that, for industrial firms, the likelihood of employing derivatives is essentially higher in well-advanced countries. For this reason, we employ four country-level characteristics to control for the differences across various countries: financial stress (FIN\_STRESS), corruption level (CORRUPTION), financial openness (FIN\_OPENESS), and member countries of the Organisation for Economic Co-operation and Development (OECD). Financial stress reports the exposure of a country's difficulties in cash flows. The index consists mainly of market-based and financial-based measures that account for financial market segments – equity market, bond market, and foreign exchange market. It also considers the co-movement across market segments. The data is reported monthly by European Central Bank. For the purpose of our study, we convert the monthly index into an annual index. We therefore expect a positive relationship between financial stress and cost of capital of banks.

Corruption level (CORRUPTION) is measured using the Corruption Perception Index (CPI) published by Transparency International. Following Park (2012) and to ease interpretation, corruption of a country is calculated as the residual of the maximum score of CPI (10) and a

country's actual CPI, indicating that a lower CPI would reflect lower corruption levels. Chang et al. (2018) find that countries that are members of OECD employ derivatives for hedging purposes. Their work further reveals that a country's financial openness and legal environment are essential drivers in explaining the usage of derivatives. This suggest that banks existing in countries with high financial openness are more capable and likely to enter potentially intricate financial contracts. We measure membership of the OECD as a dichotomous variable which takes the value of 1 when a country is a member and 0 otherwise. Financial openness is measured following Chinn & Ito's (2008) index.<sup>1</sup>

### 4.2.4 Determining textual hedge disclosure measure

The steps employed to measure textual hedge disclosure from the narrative sections of European banks annual reports for the period of thirteen years are described below. We conduct the following steps to identify our final hedge-related keywords. First we rely on prior academic research (e.g., Guay, 1999; Campello et al., 2011; Chen & King, 2014) and professional publications based on the IAS 39 and Basel regulations (e.g., BCBS 2001, 2006, 2011). In order to compile a comprehensive wordlist that reflects the business around hedging, we manually read through 10 annual reports (i.e., year 2017) of the 10 largest banks in our sample based on their assets to identify other related words regarding hedge activities.<sup>2</sup> Next, following Elshandidy et al. (2015) and Elshandidy et al. (2013) we examine the extent to which identified keywords are used by conducting extensive text-search using R for 20 randomly selected annual reports. After the text-search, we eliminate all words that do not appear in the annual reports (e.g., time-period, guarantee, mismatches) to determine our final wordlist, which is further examined for validity and reliability.<sup>3</sup>

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<sup>&</sup>lt;sup>1</sup> Financial Stress variable is obtained from Chinn & Ito (2008), which is accessible via http://web.pdx.edu/~ito/.

<sup>&</sup>lt;sup>2</sup> It is worth mentioning that there are different other methods that might be employed in identifying hedge-related keywords. For example, Google uses Search Volume Index (SVI) to identify keywords which are based on the number of search queries on a keyword, relative to the total queries on different facets of keywords (e.g., Ding & Hou, 2015). Future researchers can employ SVI to identify list of hedge-related keywords.

<sup>&</sup>lt;sup>3</sup> Our final hedge-related keywords comprise the following terms: Future contract, forward contract, forward exchange, forward exchange contract, forward rate agreement, exchange forward, exchange futures, exchange options, exchange contract, currency swaps, currency derivative, currency futures, currency forward contract, currency mismatch, option contract, rate swap, hedging instrument, derivative instrument(s), derivative hedge, derivative trading, trading position, trading volume, derivative gains, derivative loss, financial instruments, financial derivatives,

We design specific coding instructions using R to identify statements in the narrative sections of annual reports based on our final keywords. Next, we use identified statements as a proxy for hedging by counting all statements (texts) containing at least one of the keywords, irrespective of how many times a keyword appears. This is done to mitigate the effect of double counting, commonly occurs with dictionary-based software. Due to the large counts and to reduce the effect of outliers we follow the work of Elshandidy et al. (2013) and Elshandidy et al. (2015) and take the logarithm of all counted statements, which we then label as HEDGE\_TXT, which is the main contribution of this paper. We describe the process for capturing and quantifying textual hedge disclosure in Figure 1.

# 4.2.5 Validity and reliability of hedge disclosure scores

We conduct the validity and reliability analyses of our hedge disclosure scores as follows: first, we examine the extent to which identified keywords portray the business around hedging. This is done by randomly choosing 20 statements from the R output for 10 banks. Our findings indicate that our final hedge-related keywords are successful (73% on average) in identifying statements that reflect hedging activities. Prior research postulates that higher disclosure is associated positively with firm size and leverage (e.g., Taylor et al., 2010). Moreover, strong corporate governance practice would typically expect highly leveraged firms to disclose more information to meet the needs of their investors' internal requirement. Therefore, thirdly, we regress HEDGE\_TXT on bank size and leverage. In an un-tabulated result, we find that there exists a positive association between HEDGE\_TXT and leverage, but not with size. However, the indication that leverage together with size explains 43% of the variation in HEDGE\_TXT validates it as a reliable hedge disclosure measure. This implies that our hedge disclosure score captures significant underlying constructs of hedging and therefore makes it a reliable measure.

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market risk, hedging, hedged, swap agreement, notional amount, risk management, interest rate swap, interest-rate exposure, credit exposure, commodity swap, commodity exposure, cashflow hedges, option swap, options contract, hedge relationship, fair-value hedge, credit default swap, credit derivative, counterparty risk, foreign exchange risk, initial recognition, embedded derivative.

### 4.3 The empirical model

Having data nested at different levels (hierarchical data) violates the assumption (e.g., independence) of traditional modelling techniques such as OLS regression (Luke, 2004). Applying OLS regression to this type of data may overlook important nested effects which may influence estimated variance and covariant effects, resulting in Type 1 error. Specifically, with our data, having banks nested in the same country could result in correlated errors. For this reason, we employed Repeated Measures Multilevel Analysis (RMMA) with a restricted maximum likelihood estimation approach to analyse the relation at the bank level (textual hedge and other bank characteristics) and country level (financial openness, financial stress, corruption, OECD membership) with variations in WACC, COE and COD within each bank (level 1) over the period from 2005 to 2017, and among different banks over these years (level 2) in nineteen countries. We use RMMA because in addition to accounting for effects at different levels across time, from a statistical point of view, it is shown to be conceptually enriching and more precise. By employing RMMA, we assume that bank observations across time are correlated among themselves, once they are nested at a given country, hence, resulting in a strong within-cluster correlation. Similarly, it is reasonable to argue that banks operating in the same country exhibit similar behaviour in line with their risk management, although such patterns differ across countries.

In our analysis, we first develop an empty(null) model, where we do not include any predictors. Through that we focus on random effects and initially ignore fixed effects which in turn provide information relevant for variance decomposition of the dependent variable. We further add predictors at various levels. In doing so we assume the slope of some bank-level variables is random and affected by country characteristics in addition to the random intercept. This is done to examine the indirect effect of bank and country level characteristics on cost of capital. We calculate intra-class correlation (ICC) to assess the proportion of variance in the dependent variables that occurs between banks in comparison with the total variance. We also calculate Adjusted R<sup>2</sup> to assess the proportion of overall variance explained by our predictors at

both levels.<sup>4</sup> -2 Log Likelihood and Chi-square tests are used to assess the relative important of each model relative to the null model. We present the following model at two different levels:

$$COC_{tik} = \beta_{0ik} + \beta_1 T_{tik} + \sum_{n=1}^{Nr} \beta_{rn} Xbl_{nik} + \sum_{n=1}^{Nc} \beta_{cn} Xcl_{nik} + \varepsilon_{tik} + r_{ik}$$
 (2)

where  $COC_{tik}$  represents the cost of capital (i.e., WACC, COE, and COD) of bank i in country k in year t.  $\beta_{0ik}$  is the intercept of bank i in country j.  $\beta_1$  is the slope of the time-varying variables in relation to bank i in country j.  $T_{tik}$  is the linear component of time for bank i in country k at time t and is the main component at level (1), as shown in Model 1, the null model.  $B_{rr}$  denotes the effect of  $Xbl_{nik}$  (a function of bank-level variables) on the linear component of time in the cost of capital measure.  $B_{cn}$  is the effect of  $Xcl_{nik}$  (a function of country-level factors) on the linear component of time in the cost of capital measure.  $\varepsilon_{tik}$  and  $r_{ik}$  are the errors at level 1 and level 2 respectively. Appendix A-1 describes these variables and their sources.

# 5. Results

### 5.1 Descriptive Statistics

Table 2 (Panel A) reports the summary statistics of the variables employed in our analysis. We observe a high sample variability in hedge disclosure (HEDGE\_TXT) and bank size (SIZE). In our sample, hedge disclosure has a mean (standard deviation) of 2.7960 (0.4726) whereas SIZE has a mean (standard deviation) of 20.910 (4.552). The high sample variability in bank size suggests that bank-level characteristics that exist in the banking industry in Europe vary greatly across banks. This reflects the different degrees of disclosure on hedging by the banks. The high variability in bank size is consistent with the work of Beatty et al. (2012) and Chang et al. (2018). WACC has a mean (standard deviation) of 0.0591 (0.0304), cost of debt (COD) has a mean

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<sup>&</sup>lt;sup>4</sup> ICC is calculated differently at each level by dividing the variance at the current level by the total variance. The total variance is the sum of variance at levels 1 and 2. Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n - 1/(n - k - l)]$  where R<sup>2</sup> is computed as  $1 - [(\sigma^2 m 1 + \tau^2 m 0)/(\sigma^2 n u l l + \tau^2 m 0)]$ . Hence, m1 is the current model's variance component, whereas m0 is the null model's variance component. k is the total number of parameters; n is the total sample size.

(standard deviation) of 0.0387 (0.0242), and cost of equity (COE) has a mean (standard deviation) of 0.1399 (0.0893). The profitability indicator (ROE) indicates that on average banks in our sample are profitable. Finally, banks in our sample are more often situated in the larger economies, with fewer difficulties in cashflows and very high financial openness. This suggests some transparency in the market and therefore market access may be very important. Table 2 (Panel B) shows that the K<sub>EST</sub> approach reports the lowest mean (median) of 5.9% (1%) for its estimated cost of equity, whereas K<sub>OHS</sub> reports the highest mean (median) of 21% (19.5%). The highest mean from K<sub>OHS</sub> is consistent with the work of Dhaliwal et al. (2016).

#### [Insert Table 2]

Table 3 reports Pearson and Spearman correlations between the variables employed. Pearson (Spearman) correlations are above (below) the diagonal. We find that HEDGE\_TXT is significant with all cost of capital measures (WACC, COE and COD). WACC and COD exhibit a negative association with HEDGE\_TXT whereas COE exhibits a positive association with HEDGE\_TXT. This provides preliminary evidence that supports our first hypothesis, that hedge disclosure influences cost of capital. HEGDE\_TXT is significant with all bank- and country-level variables except FIN\_OPENESS. WACC and COD are significantly associated with all bank and country variables except FIN\_OPENESS, but COE is significant with only NIM and all country variables except FIN\_STRESS. Consistent with prior literature, hedge disclosure exhibits a positive association with LEVERAGE and SIZE. The positive association between HEDGE\_TXT and LEVERAGE also provides preliminary evidence that banks which are highly leveraged have greater incentives to disclose much information on their hedging activities. This is consistent with the strong corporate governance practices which anticipate more disclosure content to meet investors' requirements from highly leveraged firms. The significant association

between HEDGE\_TXT and SIZE suggests the existence of economies of scale and economies of scope in banks' hedging activities. <sup>5</sup> Overall these correlations are consistent with prior literature.

### [Insert Table 3]

5.2 Impact of bank and country characteristics on cost of capital (WACC) variations

From Table 4 (Model 1), we observe that 33% of cost of capital variation (i.e., 31% in the intercept and 2% in time) is between banks (level 2); these results are significant at p-values 0.000 and 0.026 respectively. The remaining 67% is within banks over time (level 1) which is significant at a p-value of 0.000. This significance indicates the existence of possible variations that could be explained further. We therefore augment bank-level (Model 2-3) and country-level (Model 4) variables in subsequent models.

To examine the variation in WACC explained by our hedge disclosure score, we augment HEDGE\_TXT in Model 2. The result shows that WACC is negative and significantly associated with HEDGE\_TXT, at a p-value of 0.000. The economic impact of this finding indicates that a standard deviation increase in HEDGE\_TXT leads to an approximate decrease of less than one percent in WACC. This result indicates that cost of capital as measured by WACC is significantly influenced by hedge disclosure and therefore reflects the value-relevance of disclosure. This finding is consistent with prior studies (e.g., Gietzmann & Ireland, 2005; Hail, 2002; Francis et al., 2008). Model 2 (Table 4) also shows that HEDGE\_TXT captures 36% (Adjusted R<sup>2</sup>) of all WACC variations between banks across the countries under consideration. This finding suggests that the narrative section of annual reports does contain information that is relevant to cost of capital, a suggestion which complements prior studies (e.g., Gao, 2010; Bravo et al., 2012) and therefore supports H1. As regulators continue to emphasise the need for firm disclosure to exhibit the qualitative features of comparability, reliability, relevance and consistency (FASB, 2007), banks are

<sup>&</sup>lt;sup>5</sup> We examine the potential problem of multicollinearity by calculating the variance inflation factors (VIFs) for each explanatory variable employed. The VIFs show that multicollinearity is not a concern in our study. In addition, from the correlation matrix, the maximum correlation coefficient among variables is observed at 0.59.

compelled to disclose highly relevant information which is of high importance to investors and more relevant to the capital market.

In Model 3 (Table 4), we augment all other bank-level variables. We observe that the significant negative association between WACC and HEDGE\_TXT continue to hold after augmenting variables at the bank-level. This suggests that hedge disclosure score is an important driver in explaining cost of capital. All variables exhibit statistical significance with WACC. SIZE is significant and positively associated with WACC, which suggests that large firms tend to exhibit higher cost of capital, which is in contrast with the work of Nguyen & Faff (2010) who report that large firms are known to be less risky because they tend to exhibit lower variance of cashflows, more tangible assets, and well-established operations. Banks which are more profitable, with high stock of deposits, and income margins tend to experience decrease in cost of capital, whereas banks which are highly leveraged report higher levels of cost of capital. For the effect of profitability, we can explain this association to mean that profitable firms are well placed to trade at a premium compared to non-profitable banks (Bartram et al., 2011; Mahieu & Xu, 2007), and since hedgers are more profitable, they report high firm value (Allayannis & Weston, 2001). The coefficient of leverage contrasts with prior literature (e.g., Campello et al., 2011; Graham & Rogers, 2002; Haushalter, 2000) which finds that banks with high leverage commit to hedging which in turn reduces their risk exposure. We observe that bank variables capture 67% (Adjusted-R<sup>2</sup>) of all WACC variations between banks across the countries under consideration. An incremental significance of the model shows that 31% (67% - 36%) of the variations in Model 3 is not explained by HEDGE\_TXT. In comparison with the null model, these variations increased by 10%, to 41% (Intercept) at the p-value of 0.000. The variations in WACC within banks over the period under study decreased to 59% in comparison with the null model at a p-value of 0.000. This suggests that simply taking into consideration bank level variables improved the model's ability to explain variations in WACC within banks, and more importantly, reduced the unexplained variations

within banks across countries, rather than the unexplained variations between banks over the thirteen years we considered.

Model 4 (Table 4) concerns country-level variables. HEDGE\_TXT continues to hold its negative and significant association. All other bank-level variables are significant drivers in explaining WACC variations. We find that financial stress is the only country variable which is an important driver in explaining variation in WACC. Financial stress exhibits a significant and positive association with WACC, which indicates that banks existing in countries with higher financial difficulties tend to experience deterioration in their capital cost. The economic impact of financial stress based on this finding is less than a one percent increase in WACC upon a one percent increase in standard deviation. We observe that adding country variables improves the model's ability to explain variations in WACC at 68% (Adjusted-R<sup>2</sup>). In addition, the variation between banks increased to 40% compared to the null model at a p-value of 0.000. The variations within banks over 2005 to 2017 decreased to 60% at a p-value of 0.000 when we compare with the null model. Country variables slightly improved the model's ability in explaining variations in WACC compared to bank-level variables (Model 3).

From Model 5, we find that a country's corruption and financial openness strengthens the existing relationship between hedge disclosure and cost of capital. Specifically, corruption suggests a further decrease in cost of capital by less than one percent (0.0013 \* 0.4726 \* 0.0304). Financial openness also suggests a further decrease by less than a percentage (0.0030 \* 0.4726 \* 0.0304). Even though these reduction effects are small, they may be higher for some banks. This suggest that corruption and financial openness strengthen the negative relationship between hedge disclosure and cost of capital. In comparison to the null model, we observe from the ICC that the total WACC variation decreased within banks and increased between banks, suggesting that the interaction terms help improve variation within banks and most importantly reduce the unexplained variation within banks rather than the unexplained variations between banks. The

overall variation explained as indicated by the Adjusted R<sup>2</sup> is 70% which indicates improvement in model fit. Thus, this result supports H2.

#### [Insert Table 4]

5.3 Impact of bank and country characteristics on cost of equity (COE) variations

From Table 5 (Model 1), we observe that 32% of the cost of capital variation (31% in the intercept and 1% in time) is between banks (*level 2*); and these findings are both significant at a p-value of 0.000. This significance indicates the existence of unexplained variations at both levels. We therefore augment bank-level variables (Model 2 - 3) and country-level variables (Model 4).

In Model 2, we examine the amount of cost of equity variation captured by our hedge disclosure score. The result shows that HEDGE\_TXT is significant and negatively associated with cost of equity, which suggests that hedging by banks decreases risk. HEDGE\_TXT captures 5% (i.e., Adjusted-R<sup>2</sup>) of all cost of equity variations between banks across countries. This finding supports H1. While this is consistent with some findings from prior studies (e.g., Gietzmann & Ireland, 2005; Hail, 2002; Francis et al., 2008), it however contrasts with some other research findings (e.g., Bushee & Noe, 2000; Botosan & Plumlee, 2002) which state that as firms disclose more information regarding their hedging activities, they attract more occasional investors, which then increase volatility and consequently cost of equity capital. Gao (2010) asserts that cost of capital increases with disclosure if the adjustment cost of new investment is sufficiently low and previous expected profit margin on investment is sufficiently high. Hedge disclosure by firms does not always discourage unnecessary risk taking by banks but may encourage excessive risk-taking.

In Model 3 (Table 5), all variables exhibit statistical significance with cost of equity, except profitability. HEDGE\_TXT remains negative and significantly associated with COE. SIZE and LEVERAGE exhibit positive coefficients, whereas DEPOSITS and NIM exhibit negative association with cost of equity. The positive association of bank size with cost of equity capital suggests that banks with a large market cap experience higher levels in their capital cost, which

contrasts with the work of Ahmed et al. (2018) and Gay et al. (2011). The positive coefficient of profitability suggests that highly profitable banks possess more financial strength against shocks and are less prone to financial distress because they trade more derivatives in the capital market, which in effect reduces their capital cost (Mahieu & Xu, 2007). Bank level variables explain 41% (Adjusted- R<sup>2</sup>) of the variations in cost of equity, which is a significant incremental effect compared to Model 2. We observe an incremental significance of HEDGE\_TXT and find that 36% (41% - 5%) of the variation in Model 3 is not explained by HEDGE\_TXT.

From Model 4, we find all country variables except OECD membership to be significant in explaining some of the variations in COE. In line with our expectation banks in countries that are financially stressed experience increase in COE. Meanwhile, interestingly, highly corrupt countries experience reduction in cost of equity capital. HEDGE\_TXT also remains negative and significant with cost of equity. All other bank-level variables remain significant, except profitability. We observe that adding country-level variables does not contribute much in explaining variations in cost of equity as indicated by the Adjusted R<sup>2</sup> (42%) compared to Model 3. Considering the variations at both levels, we observe a limited improvement in the model-fit after augmenting bank variables. The ICC reports that approximately 40% (39% in the intercept and 1% in time) of the total variation is captured between banks across countries over the thirteen-year period. These variations are both significant at a p-value of 0.000. The variations within banks decreased by 8% compared to the null model at p-value of 0.000. We observe that adding country variables, brings a slight improvement in the model as indicated by Adjusted R<sup>2</sup> (42%). Here, the within-bank variation remains at 60% at the p-value of 0.000, whereas the between-bank variation increases by 8% to 39% at the p-value of 0.000 compared to the null model. Considering these variations captured at both levels, these results support H1.

We find significant cross-level interaction effects from Model 5. Corruption level, financial openness, and OECD membership exhibit negative and significant moderation effect. Specifically,

the negative association between HEGDE\_TXT and COE is further strengthened by banks operating in countries with high financial openness and that have membership of OECD. The economic impact of financial openness suggests a further reduction in cost of equity capital by less than one percentage point (0.0081 \* 0.4726 \* 0.0581). The ICC here reports that 40% (intercept and time) of the total variation between banks is captured. The within-bank variation decreased by 8% to 60% significant at a p-value of 0.000 compared to the null model and there is no change compared with Model 4. The improvement in model-fit is observed at 45% (Adjusted-R<sup>2</sup>) of all COE variations between banks across countries, higher than models without interaction terms. This suggests that some of the variance is explained by the interaction terms and therefore supports H2.

#### [Insert Table 5]

5.4 Impact of bank and country characteristics on cost of debt (COD) variations

The null model in Table 6 (Model 1) indicates that most of the variation (84%) is accounted for within banks (level 1) whereas level 2 accounts for 16% of the variations in cost of debt. These variations exhibited significance at p-values of 0.000 each, which suggests that there are unexplained variations that could be accounted for at both levels.

In Model 2 (Table 6), HEDGE\_TXT reveals a negative and significant association with cost of debt at the p-value of 0.000. This implies that HEDGE\_TXT captures significant information on cost of debt. The negative association is consistent with prior studies that find a significant reduction in cost of debt by hedge users (e.g., Campello et al., 2011; Chen & King, 2014) This reflects that firms that hedge mitigate the issue of financial distress, which is likely to lead to risk shifting. This significant variation demonstrates the impact of hedge disclosure on the capital structure of banks. It also reflects the impact of accounting reporting standards, which are geared towards meeting the needs of investors. Gietzmann & Ireland (2005) put it this way when accounting policies are more aggressive, disclosure of firms will result in reduction in cost of

capital. Although the economic impact is small, it may have been higher for certain banks. This therefore supports H1.

The addition of bank-level variables in Model 3 (Table 6) shows that HEDGE\_TXT maintained its negative and significant association at the p-value of 0.000. We observed that all other bank-level variables are significant except deposits. The bank variables capture 74% (Adjusted R<sup>2</sup>) of all cost of debt variations between banks across the countries under consideration. When compared to the null model, we observe a one percent increase in the variations captured within banks to 85%, significant at a p-value of 0.000. This indicates that considering bank variables alone improved the model-fit in capturing variations in cost of debt between banks, and more importantly, reduced the unexplained variations between banks over the thirteen-year period.

From Model 4 (Table 6), it appears that HEDGE\_TXT is negative and significantly associated with cost of debt. We observe the economic significance of this finding to be less than one percent decrease in cost of debt upon a 1% standard deviation increase. Banks experience increase in cost of debt capital levels when they operate in countries which are financially stressed and also OECD members. Corruption level and financial openness are not significant drivers in explaining some of the variations in COD. Adding country-level variables presents an incremental explanatory power compared to bank-level variables (Model 2- 3) as indicated by the Adjusted-R<sup>2</sup> at 79%. We observe that adding country variables also contributed much in explaining variations in cost of debt. The total variation captured here is 79% (Adjusted-R<sup>2</sup>) which signifies an incremental effect in capturing variations in cost of debt.

From Table 6 (Model 5), we find that banks operating from countries that are OECD members and are financially stressed moderate the existing relationship between hedge disclosure and cost of debt. Specifically, the negative relationship existing between HEDGE\_TXT and COD is weakened by financial openness and in line with our expectation, these results confirm the notion that a country's financial openness increases the interpretation of the relationship existing between text-based hedging and cost of debt, and thus support H2.

### [Insert Table 6]

## 6. Further analysis and robustness checks

### 6.1 Cross-level interaction using alternative country-level measures

To further test H2, we employ two different measurement effects of our country-level variables. First, we create one hybrid variable for all the country-level variables by aggregation using principal component factor analysis (PCFA). The hybrid variable captures common variation of the five country variables, thus eliminating multicollinearity. We report the results in Table 7. Our results reported in Table 7 (Panel A) show that the principal factor (PCFA) is positively associated with cost of capital measures (WACC, COE, COD) at p-values of 0.000, 0.000, and 0.095 respectively. The interaction term (PCFA \* HEDGE\_TXT) is negative and significant for all models. This suggests that the negative relationship existing between cost of capital and text-based hedging is strengthened more by the principal factor. Therefore, banks that disclose more hedging information operating in countries with the country principal factor have lower levels of cost of capital cost. Total variation explained in WACC is seen at 68% (Adjusted R<sup>2</sup>) and this therefore supports H2.

Second, we form one aggregate measure from all country-level variables to capture the overall country effect based on the equally weighted median summed values of all country variables. Specifically, we convert all continuous country-level variables into categorical variables and then take the sum of all the converted variables, which we label as AGGREGATE. We report the results in Table 7 (Panel B). Results reveal that the country aggregate (AGGREGATE), is significant and positively associated with WACC and COD at p-values of 0.041 and 0.000 respectively. We observe a switch in the coefficient of the interaction term, here, significant, and negative for WACC and COE. This suggests that country characteristics strengthen the negative association between cost of capital and text-based hedging.

## [Insert Table 7]

# 6.2 Pre-IFRS 9 and post-IFRS 9 Analysis

This section investigates whether the introduction of IFRS 9, which replaces IAS 39, has an impact on hedge disclosure and its impact on bank cost of capital. We introduce a dummy variable for IFRS 9 which takes the value of 1 for IFRS 9 years and 0 otherwise. In addition to the IFRS 9 dummy, we include an interaction term between hedge disclosure and the IFRS 9 dummy to capture the change in the association between hedge disclosure and cost of capital in the IFRS 9 period, in comparison to the IAS 39 period. To achieve this, we use two years prior to IFRS 9 (i.e., 2016 – 2017) and two years after IFRS 9 (2018 – 2019). We design the following model using multivariate analyses.

$$COC_{ik} = \alpha + \beta_0 HEDGE\_TXT + \beta_1 IFRS9_{ik} + \beta_2 IFRS9 * HEDGE\_TXT_{ik} + \beta_3 Xbl_{ik} + \beta_4 Xcl_k + \varepsilon_{ik} \ (3)$$

COC<sub>ik</sub> represents the cost of capital measures of bank i in country k. IFRS9 is a dummy variable, IFRS9: HEDGE\_TXT is an interaction variable,  $Xbl_{ik}$  represents bank level variables for bank i in country k,  $Xcl_k$  represents the country variables, and  $\varepsilon_{ik}$  is the error term. All bank- and country-level variables are the same as discussed earlier. HEDGE\_TXT is the hedge disclosure score which is calculated based on the statements from the narrative section of annual reports reflecting hedging, based on our final hedge keywords. The scores for the years 2018 and 2019 are based on keywords in conformity to IFRS 9. We follow the same procedures in compiling the list of keywords as explained in section 4.2.4. All other variables are as described before.

From Table 8 (Panel A), the IFRS9 indicator variable is positive and significant, which suggests that the cost of capital of banks increased after the transition to IFRS 9. Hedge disclosure is significant and positive in explaining cost of capital. The interaction term IFRS9 \* HEDGE\_TXT indicates an increasing effect of hedge disclosure on cost of capital as measured by WACC. In the IFRS 9 period, the coefficient of hedge disclosure shows an increasing effect of -6.7384 (-6.935 + 0.1966) on cost of capital. This indicates that hedge disclosure by banks continued to be higher in the IFRS 9 period than the IAS 39 period. We find all bank-level variables

to be significant except Net Interest Margin. None of the country-level variables shows statistical significance. Overall, the model explains 35% of the total variations in WACC.

From Table 8 (Panel B), we find that IFRS9 is significant and positively associated with COE; its interaction with HEDGE\_TXT remains positive, indicating an incremental effect of -2.766 (-2.417 – 0.3487) on cost of equity This clearly suggests that IFRS 9 has an increasing impact on hedge disclosure but interestingly, in turn, results in an increasing cost of equity. This suggests hedge disclosure increased in the IFRS 9 period, reflecting the goal of IFRS 9 of strengthening the risk management application of banks to be effective and promising. We explain this finding to mean that, because the measurement and classification of hedging under IFRS 9 is concise and loose, banks find it easier and more essential to engage in using derivatives for various hedging purposes, thereby strengthening their risk management approach. All bank-level variables exhibit statistical significance and only financial openness is significant among the country-level variables. Overall, the model explains 47% of the variations in cost of equity. We note from Panel C that hedge disclosure is negative and significant. IFRS 9 here is insignificant, and we report the same for the interaction term. This implies that the introduction of IFRS 9 had no influence on the cost of debt changes of banks. Here all bank-level variables are significant. Corruption and membership of OECD also show no statistical significance.

### 6.3 Robustness checks

### 6.3.1 Alternative cost of capital measures

This section investigates whether our findings in Tables 4 to 6 are robust to alternative model specifications. Our approach of estimating the cost of debt closely follows that of Pittman & Fortin (2004) and Minnis (2011). We therefore check along the time dimension to ensure that our WACC estimate captures the relevant cost of capital faced by firms when complying with disclosure standards. We thus replace cost of debt in the cost of capital measure with the credit ratings from S&P and re-estimate our main model. We rely on S&P ratings over other rating agencies because S&P provides a more timely measure of rating adjustments, which makes it the leading agency in

rating changes before other agencies' adjustments (Kaminsky & Schmukler, 2002). Also S&P rating announcements tend to send greater country-specific stock market effect, which the market seems not to anticipate.

The results in Table 9 (Panel A) shows that all the coefficients of interest are virtually unchanged. Specifically, HEDGE\_TXT is negative and significant in Models 2 and 3, confirming our earlier findings. Profitability and size are the only bank-level variables significant, whereas financial stress is the only country-level variable significant. As can be seen from Table 9 (Panel B), the results confirm the negative statistically significant relationship between HEDGE\_TXT and cost of debt in all models. All bank-level variables are significant except net interest margin. Financial stress remains significant at the p-value of 0.000. Here we also find corruption to be significant at the p-value of 0.046, suggesting that when countries experience highly corrupt economic systems, banks within such countries tend to record high levels of cost of debt.

Next, we address the concern that cost of equity is computed as the arithmetic average of the four implied cost of equity measures (K<sub>GEB</sub>, K<sub>CLS</sub>, K<sub>EST</sub>, K<sub>OHS</sub>). We re-run our model by replacing COE with the individual measures of equity. The results reported in Table 9 (Panel C) show that hedge disclosure is significant and negatively associated with all the implied cost of equity measures except K<sub>GEB</sub>, irrespective of how we measure the cost of equity. This suggests that our main results are not driven by our use of the average of the four cost of equity measures. It is imperative to mention that the estimation of K<sub>EST</sub> and K<sub>GEB</sub> does not require any assumption about long-term growth rate unlike K<sub>OHS</sub> and K<sub>CLS</sub> which entail the assumption of long-term growth rate. This makes K<sub>OHS</sub> and K<sub>CLS</sub> sensitive to the choice of the long-term growth rate assumption. Notwithstanding, this issue does not bias the inferences of our findings since the results reported for K<sub>OHS</sub> and K<sub>CLS</sub> are like those for K<sub>EST</sub> and K<sub>GEB</sub>. Our results still have comparable magnitude for both the cost of debt and cost of equity estimates. All in all, the reported evidence in support

of our hypotheses is robust to using alternative measures of the implied cost of equity capital model.

Following the argument above in respect of cost of capital measures as tantamount to taking oversight of non-deteriorated exposures, it stands to reason that this relationship is expected. This evidence supports our hypothesis that hedge disclosure contains economically significant information relevant in reflecting cost of capital (i.e., WACC, COE, and COD), signifying that our findings are robust to the proxies of cost of capital.

#### [Insert Table 9]

# 6.3.2 Assessing hedge disclosure using risk measures

In section 5, we find that the cost of capital (i.e., WACC, COE and COD) is significantly reduced by hedge disclosure. This significant reduction is attributable to banks that have higher stock of deposits and interest margins and operate in countries that have membership with OECD and have open trade with other economies. Hedging reduces cashflow, interest rate and exchange rate volatility which makes the type of hedge instrument dependent on the type of risk exposure. Ahmed et al. (2018) on the other hand report that firms that are less exposed to risk are those that benefit from cost of capital reduction upon derivative usage. Thus, our empirical finding is connected to the idea that hedging is linked with risk reduction, which in turn results in cost of capital reduction. In contrast, hedging permits banks to expand the size of their lending business and hence pursue a riskier mix of loans. Guay (1999) posits that firms may employ hedging for other purposes rather than risk reduction. For instance, owing to the increase in stock price volatility pertaining to the value of employee stock options, options provide incentives for managers to engage in activities that increase risk. Comparably, managers' compensation bears a resemblance to the payoff of a call option when earnings are at or near the lower bound of a bonus scheme. This incentivises managers to increase volatility of earnings. However, a firm-value maximising compensation package features these risk-taking incentives and will be structured to minimise adverse effects.

Owing to the significant reduction in cost of capital based on hedge disclosure, we further test the informativeness of hedge disclosure on two bank risk measures widely justified in prior literature; Z-score (e.g., Laeven & Levine, 2009; Wu et al., 2020) and total risk (e.g., Cheng et al., 2015; Pathan et al., 2020). Z-score is generally perceived as the inversed probability of bank failure and is measured as the standard deviation upon which bank returns fail to clear all their equity, as indicated below:

$$ZSCORE_{ijt} = \frac{ROA_{ijt} + TETA_{ijt}}{\sigma(ROA)_{ijt}}$$
(4)

where ROA is the return on assets, TETA is total equity to total assets ratio,  $\sigma(ROA)$  is the standard deviation of return on assets. The subscripts i, j, and t denote bank, country and time respectively. Total risk is measured as the standard deviation of daily stock returns measured over a year.

We report the results in Table 10. From Table 10 (Panel A) we find that HEDGE\_TXT is significant and negatively associated with total risk at a p-value of 0.007. This suggests that information content regarding hedging in the narrative section of a bank's annual report contains relevant information which reduces their level of risk. This confirms our previous findings and thus complements prior studies (e.g., Gietzmann & Ireland, 2005; Hail, 2002; Francis et al., 2008). Also, Z-SCORE exhibits a negative association with HEDGE\_TXT, even though not significant. Overall, these findings support the significance of hedge disclosure and its representation of hedging.

#### [Insert Table 10]

6.3.3 Alternative measures of hedge disclosure

6.3.3.1 Notional amount of derivative outstanding and credit derivative

As a further analysis to check the validity of our hedge disclosure scores captured using the textual analysis technique, we employ two alternative measures of hedging, which are highly justified by prior studies: notional amount of outstanding derivatives scaled by total assets (e.g., Allayannis & Weston 2001; Chang et al. 2018; Deng et al. 2017; Purnanandam 2008). and credit derivative (e.g.,

Deng et al., 2017; Purnanandam, 2008) which takes the value of one if a bank uses credit derivative as guarantor, and zero if otherwise. We re-estimate equation 2 by replacing HEDGE\_TXT with these two variables, notional amount of derivative outstanding (NOTIONAL) and credit derivative (CREDIT\_DER) respectively.

We report the results in Table 10 (Panel B). We find a significant and positive association between hedging and cost of capital (WACC). This suggests that a one percent standard deviation increase in the derivatives outstanding tends to increase cost of capital by less than a percentage point (0.1582 \* 0.0304). This, surprisingly, counters our previous findings of a risk-reduction effect, which suggests that hedging as measured by notional amount of derivatives outstanding increases cost of capital. From the credit derivative analysis, we find that credit derivative is negatively associated with cost of capital. This confirms our previous findings and thus reflects the extant significance of hedge disclosure score captured using machine learning approach. All in all, from the evidence above, it is reasonable to conclude that our hedge disclosure score presents itself as a reliable measure of hedging reported in the books of accounts.

# 6.3.3.2 Hedge disclosure score – relative and standardised measure

In light of the large numbers of hedge related statements by some banks, the issue of consistency in modelling may arise. As part of the further analysis, we re-capture the hedge-related statements based on our final keywords using relative and standardised scores. The relative score (RELATIVE) is captured by employing the percentage value of the number of identified statements, whereas the standardised score (STANDARDISED) is captured using z-score approach.<sup>6</sup> We report the results in Table 11.

We find from Panel A (Table 11) that relative score is significant and negative associated with all cost of capital measures at p-values of 0.000. This confirms our initial and thus suggests

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<sup>&</sup>lt;sup>6</sup> We standardise hedge counts as  $(x - \mu)/\sigma$ , where x is the count for bank *i* in year *t*,  $\mu$  is the mean and  $\sigma$  is the standard deviation.

the economic informativeness of hedge disclosure in the capital structure of banks. We note that most of the variables have plausible signs as anticipated and similar to our main analysis. From Panel B (Table 11), we find that standardised score is also negatively associated with cost of capital and cost of debt in Panels A and C, at p-values of 0.000. The economic impact of these findings indicates that a standard deviation increase in STANDARDISED leads to an approximate decrease of less than one percent in WACC and COD. Surprisingly, standardised score is positively associated with cost of equity which suggest increasing risk. Country characteristics also capture a substantial amount of variations in STANDARDISED. For instance, from the WACC analysis in Panel B, we find that all country variables are important drivers in explaining variations in WACC. The overall variation explained as indicated by the Adjusted R<sup>2</sup> is 55%.

All in all, these results indicate that our hedge disclosure score captured using log does not present the issue of inconsistencies in our modelling.

#### [Insert Table 11]

## 6.3.4 Endogeneity problem

We take into consideration that our regression might be biased owing to the impact of unobserved characteristics on hedge disclosure and/or reverse causality, in that banks that disclose more hedge information are likely to have lower cost of capital, although applying RMMA offers a partial remedy as it accounts for bank-specific and time-invariant effects that could have an impact on cost of capital. In addition, we employ fixed-effect estimation in our main analyses to account for omitted variables. Nevertheless, for further robustness checks, we use two main methods from the literature to address these concerns. First, we employ GMM estimation. This estimation is proposed to control for unobserved heterogeneity and reverse causality. It has the advantage of dealing with irregularities in estimates due to unobserved heterogeneity across banking institutions (Nguyen et al. 2010) and is also robust to the distribution of errors. With our nested data, we employ within and between variations of exogeneous variables, with just the within variation of the variables regarded as endogenous. We report the results in Table 12 (Panel A). We find similar

results to this as reported in Tables 4 to 6. Specifically, hedge disclosure exhibits negative statistical association with WACC, COE and COD confirming the extant significance of hedging information to investors. Thus, our results are free from endogeneity issues.

In view of propensity score matching (PSM) being capable of minimising the selection bias and mitigating the "curse of dimensionality" when multiple characteristics are needed for matching (Bartram et al. 2011), we also apply PSM to address potential endogeneity concerns (To et al., 2018). PSM allows us to match banks on the basis of their estimated likelihood of hedge disclosure, instead of matching on a large number of individual bank characteristics. Specifically, we match the treatment group (i.e., high hedge disclosure) to the control group (i.e., low hedge disclosure) by employing a logit model to estimate the propensity score for each observation which is then used to forecast the likelihood of being treated as a function of the bank-level variables. We use nearest neighbour matching to match each observation of high HEGDE\_TXT with banks in the control group which exhibit the closest score in relation to the treated group (Bonaventura et al., 2018). We employ common support to eliminate all extreme boundaries by removing banks in the control group whose scores are higher than the maximum or lower than the minimum propensity score among high HEDGE\_TXT in the treatment group. Results are reported in Table 12 (Panel B). We find that hedge disclosure is significant and negatively associated with cost of capital measures, again confirming our previous findings. This indicates that our results are free from endogeneity problems.

## [Insert Table 12]

## 7. Conclusion

Based on a sample of 145 banks from 19 European countries, this paper investigates the impact of hedge disclosure on cost of capital as measured by WACC, COE and COD. This paper also examines the influence of IFRS 9 transition on hedge disclosure of banks. Our multilevel (RMMA) analysis reveals that hedge disclosure is associated with lower cost of capital. Regarding country characteristics, financial stress exhibits significant explanatory power over all cost of capital

measures. Further, the results imply that country characteristics moderate with hedge disclosure and add to bank value through enhanced reduction in cost of capital, as banks with high interaction of hedge disclosure and country characteristics experience more benefits in relation to lower capital costs. In addition, we find that the transition from IAS 39 to IFRS 9 has motivated banks to disclose more hedge-related information. This impact is evident in the reduction of cost of capital as it strengthens banks' risk management framework. Our findings are robust to several specification of models and specifications that account for potential endogeneity concerns.

As regulators continue to stress the need for firm disclosure to exhibit qualitative features of comparability, reliability, relevance and consistency (FASB, 2007), our findings suggest that policy makers should continue to maintain a good and strong disclosure policy to sustain and increase the capability of banks to cope with potential events that could damage reputation and avoid negative externalities as much as possible, thereby protecting their reputation and ensuring stability. For bank managers, our findings might help them to recognise the importance of their hedge disclosure and thus reduce their capital costs. Understanding that there are cost of capital related benefits in enhancing the reporting of hedging information may motivate banks to commit to improved disclosure of this type of information, supporting the trend in EU regulation that encourages firms to disclose relevant information about their risk exposure rather than waiting for them to do so voluntarily. In this same line, investors would benefit from access to relevant information, reducing the cost of private information gathering. This complements the extant evidence on the significance of the language in corporate disclosure to investors and more importantly to the capital market, which is useful for forecasting (Bravo et al., 2012).

We outline the following limitations of this paper. Notwithstanding the fact that we rely on annual reports as our main source of hedge information because they remain a major source of information for investors (Elshandidy et al., 2013; Elshandidy et al., 2015), there are other potential avenues such as media coverage, earnings releases, and conference calls, that could be employed

to extract and quantify hedge information, to assess its impact on cost of capital. Moreover, with a different theoretical eye, future studies may engage indirect sources such as social media.

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Table 1 Sample extraction and country distribution

Panel A: Sample extraction using Thomson Reuters DataStream Eikon									
Extraction procedures	Firms	Remaining							
Firms must be: (a) public (b) active (c) non-ADR	53,545	53,454							
Firms must be part of the European Union, not only belonging to European community	5,613	5,613							
Firms listed on a country's stock exchange	4,853	4,853							
Firms must be classified under Europe's SIC ("602" and "603")	214	214							
Firms without complete annual reports and data are excluded	(69)	145							
Total number of firm-year observations from 2005 to 2017 (145 x 13)		1885							

# Panel B: Country distribution

Country	N	Firms	0/0
Austria	65	5	3.45
Belgium	78	6	4.13
Croatia	52	4	2.76
Denmark	169	13	8.97
Finland	39	3	2.07
France	234	18	12.41
Germany	104	8	5.52
Greece	78	6	4.14
Ireland	39	3	2.07
Italy	182	14	9.66
Norway	273	21	14.48
Netherlands	26	2	1.38
Poland	104	8	5.52
Portugal	13	1	0.69
Romania	13	1	0.69
Spain	65	5	3.45
Sweden	62	4	2.76
Switzerland	221	17	11.72
United Kingdom	78	6	4.14
Total	1885	145	100

This table reports the country distribution based on a sample of 145 banks from 19 countries within the EU communities from the period of 2005 to 2017.

Table 2 Descriptive statistics

OECD

1885

Panel A: Descriptive Sta	atistics					
	N	Mean	25th	Median	75th	Std. Dev.
Dependent variables						
WACC	1885	0.0591	0.0388	0.0524	0.0727	0.0304
COD	1885	0.0387	0.0204	0.0384	0.0529	0.0242
COE	1885	0.1399	0.0721	0.1044	0.1957	0.0893
Firm-level variables						
HEDGE_TXT	1885	2.7960	2.5660	2.8690	3.1460	0.4726
SIZE	1885	20.910	18.250	20.724	24.436	4.5520
ROE	1885	0.1025	0.0523	0.1052	0.1522	0.1360
DEPOSITS	1885	0.5554	0.3879	0.5566	0.7028	0.2237
LEVERAGE	1885	0.1620	0.1001	0.1452	0.1921	0.0920
NIM	1885	0.0187	0.0127	0.0170	0.0238	0.0094
Country-level variables						
FIN_STRESS	1885	0.1201	0.0720	0.0911	0.1700	0.0823
CORRUPTION	1885	0.5512	0.3201	0.7241	0.8012	0.3441
FIN_OPENESS	1885	2.1293	2.3467	2.3467	2.3467	0.5252

The table presents the descriptive statistics of the variables used in the full sample analysis. It reports the main dependent variables, bank-level variables, and country level variables All continuous variables are winsorised at 1<sup>st</sup> and 99<sup>th</sup> percentiles. The description of all variables is presented in **Appendix A-1**.

1.0000

1.0000

1.0000

0.2534

0.9310

Panel B: Descriptive statistics of cost of equity measures										
	Mean	25%	Median	75%	Std. Dev.					
Ohlson and Juettner (2005) - K <sub>OHS</sub>	0.2135	0.1508	0.1947	0.2203	0.1190					
Easton (2004) - K <sub>EST</sub>	0.0596	0.0000	0.0100	0.0868	0.0967					
Gebhardt et al. (2001) - $K_{GEB}$	0.1307	0.0671	0.1231	0.1864	0.0812					
Claus and Thomas (2001) - K <sub>CLS</sub>	0.0669	0.0000	0.0000	0.0774	0.1491					

Table 3
Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
HEDGE_TXT		-0.61	-0.19	0.10	0.72	-0.02	-0.76	0.80	-0.56	0.06	-0.05	0.12	0.27
WACC	-0.58		0.59	0.12	-0.21	0.09	0.39	-0.56	0.18	-0.06	0.01	-0.04	-0.19
COE	-0.16	0.57		-0.17	-0.04	-0.01	-0.01	-0.05	-0.06	-0.01	0.10	-0.09	-0.10
COD	0.10	0.25	-0.15		0.07	0.09	-0.10	0.25	0.07	0.08	-0.05	-0.06	0.18
SIZE	0.66	-0.18	-0.03	0.09		0.07	-0.42	0.36	-0.30	0.01	0.06	0.04	0.16
ROE	-0.06	0.10	-0.02	0.12	0.11		0.02	-0.04	0.04	-0.14	-0.13	-0.07	0.01
DEPOSITS	-0.83	0.40	-0.02	-0.12	-0.41	0.06		-0.66	0.31	-0.02	-0.02	0.03	-0.21
LEVERAGE	0.80	-0.48	0.01	0.19	0.37	0.04	-0.72		-0.43	0.07	-0.05	-0.05	0.34
NIM	-0.56	0.23	-0.04	0.12	-0.31	0.07	0.36	-0.42		-0.02	0.21	-0.06	-0.13
FIN_STRESS	0.05	-0.02	0.02	0.07	0.01	-0.19	0.00	0.08	-0.04		0.16	0.03	-0.06
CORRUPTION	0.04	-0.02	0.10	-0.02	0.14	-0.18	-0.08	-0.01	0.17	0.13		-0.06	-0.31
FIN_OPENESS	0.03	-0.05	-0.12	0.00	0.05	-0.08	0.02	-0.02	-0.10	0.02	-0.08		0.05
OECD	0.27	-0.14	-0.08	0.18	0.17	-0.01	-0.26	0.27	-0.18	-0.07	-0.30	0.13	

Panel C of Table 2 presents the correlation analysis for all regression variables. The numbers above the diagonal are the linear Pearson coefficients; the numbers below the diagonal are the Spearman coefficients, significant coefficients are highlighted in bold. The description of all variables is presented in **Appendix A-1**.

Table 4 Repeated measure multilevel analysis: Cost of capital (WACC)

Dependent variable: WACC						
	Ex. Sig.	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	(?)	0.0536***	0.0557***	-0.1176***	-0.1267***	-0.1340***
B 11 1 11		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank-level variables	()		0.0127***	0.0202***	0.0202***	0.0220***
HEDGE_TXT	(-)		-0.0127***	-0.0392***	-0.0393***	-0.0330***
CIZE	$\sim$		(0.000)	(0.000)	(0.000)	(0.000)
SIZE	(?)			0.0281***	0.0280***	0.0281***
ROE	()			(0.000) -0.0001**	(0.000) -0.0001*	(0.000) -0.0001*
KOE	(-)			(0.011)	(0.099)	(0.065)
DEPOSITS	(+)			-0.0744***	-0.0745***	-0.0785***
DEI 03113	(1)			(0.000)	(0.000)	(0.000)
LEVERAGE	(+)			0.049***	0.0486***	0.0535***
ELVERGE	(')			(0.000)	(0.000)	(0.000)
NIM	(-)			-1.3548***	-1.3632***	-1.3935***
	()			(0.000)	(0.000)	(0.000)
Country-level variables				(0.000)	(0.000)	(0.000)
FIN_STRESS	(+)				0.0168***	0.0189***
_	<b>、</b> /				(0.005)	(0.000)
CORRUPTION	(+)				0.0010	0.0001
	, ,				(0.425)	(0.869)
FIN_OPENESS	(-)				-0.0002	0.0010
					(0.844)	(0.406)
OECD	(-)				0.0058	0.0114
					(0.506)	(0.222)
Cross-level interactions						
FIN_STRESS*HEDGE_TXT	(+)					0.0038
						(0.167)
CORRUPTION*HEDGE_TXT	(+)					-0.0013***
						(0.000)
FIN_OPENESS*HEDGE_TXT	(-)					-0.0030***
						(0.000)
OCED*HEDGE_TXT	(-)					0.0019
	0)					(0.120)
TIME	(?)	0.0012**	0.0010***	0.0002	0.0003	0.0004
T. 1		(0.026)	(0.003)	(0.341)	(0.212)	(0.167)
Intra-class correlation		770/ YYY	Z 40 / \\	T00/ ***	Z00/ ***	<b>(1</b> 0/ \\\
Repeated Measures		67%***	64%***	59%***	60%***	61%***
Tutanaat		(0.000) 31%***	(0.000) 35%***	(0.000) 41%***	(0.000) 40%***	(0.000) 39%***
Intercept		(0.000)				
Time		2%***	(0.000) 1%***	(0.000) 0%	(0.000) 0%	(0.000) 0%
Time		(0.026)	(0.003)	(0.341)	(0.212)	(0.167)
Model-fit statistics		(0.020)	(0.003)	(0.571)	(0.212)	(0.107)
Adjusted R <sup>2</sup>			36%	67%	68%	70%
AIC		-8190.522	-9024.804	-10195.584	-10160.546	-10209.378
BIC		-8157.278	-8986.023	-10129.135	-10071.981	-10209.576
Δ-2LL		5157.110	836.282	1180.780	27.038	56.833
Δ Chi-square			(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF		1.000	1.000	2.914	2.258	6.337

Observations 1885 1885 1885 1885 1885

This table reports the impact of bank- and country-level characteristics on weighted average cost of capital (WACC) variation. WACC is calculated as LEV \* [COE (1-TAX)] + (1-LEV) COD where LEV is leverage, COE is cost of equity, TAX is annual tax rate, COD is cost of debt. Model 1 is the empty model which does not include any predictors. We augment HEDGE\_TXT in Model 2 and subsequently add bank- and country variables in Model 3 and 4 respectively. Model 5 add interaction terms. The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n - 1/(n - k - l)]$  where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. Year fixed effects are included in Model 2 to 5. Change in -2Log Likelihood ( $\Delta$  -2LL) is used to assess each model's improvement compared with the Model 1 whereas Chi-square ( $\Delta$  Chi-square) is to assess such statistical improvement. See Appendix A-1 for detailed description of all variables. \*\*\*\*, \*\*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 5
Repeated measure multilevel analysis: Cost of Equity (COE)

	Ex. Sig.	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	(?)	0.099***	0.1019***	-0.4534***	-0.4097***	-0.4142***
mercept	(.)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank-level variables		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HEDGE_TXT	(-)		-0.0132***	-0.1127***	-0.1134***	-0.0783***
·	( )		(0.000)	(0.000)	(0.000)	(0.000)
SIZE	(?)		(* * * * *)	0.0713***	0.0719***	0.0723***
	( )			(0.000)	(0.000)	(0.000)
ROE	(-)			-0.0003	-0.0001	-0.0003
	( )			(0.240)	(0.334)	(0.162)
DEPOSITS	(+)			-0.289***	-0.2911***	-0.3096***
221 00110	( ' )			(0.000)	(0.000)	(0.000)
LEVERAGE	(+)			0.3724***	0.3729***	0.3846***
EE (ERTOE	( · )			(0.000)	(0.000)	(0.000)
NIM	(-)			-3.9733***	-3.9989***	-4.1979***
	()			(0.000)	(0.000)	(0.000)
Country-level variables				(0.000)	(0.000)	(0.000)
FIN_STRESS	(+)				0.0452**	0.0557***
111_0114266	(')				(0.020)	(0.004)
CORRUPTION	(+)				-0.0055*	-0.0082**
Coldici Holy	(1)				(0.092)	(0.013)
FIN_OPENESS	()				-0.0054*	-0.0020
TIN_OI ENESS	(-)				(0.095)	(0.532)
OECD	()				-0.0292	-0.0226
OECD	(-)				(0.278)	(0.415)
Cross-level interactions					(0.278)	(0.413)
FIN_STRESS*HEDGE_TXT	(4)					0.0113
FIN_STRESS HEDGE_TAT	(+)					
CORRUPTION*HEDGE_TXT	(1)					(0.308) -0.0059***
CORRUPTION*HEDGE_TXT	(+)					
EIN ODENIESS*HEDGE TVT	()					(0.000) -0.0081***
FIN_OPENESS*HEDGE_TXT	(-)					
OCEDYHEDOE TYT	()					(0.000)
OCED*HEDGE_TXT	(-)					-0.0082*
	(2)	0.0070/bile/	O O O C O Modele		O O C O de le le	(0.092)
TIME	(?)	0.0072***	0.0069***	0.0066***	0.0068***	0.0066***
Today alama a maladan		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intra-class correlation		Z00/ \\	700/***	Z00/ ***	Z00/ ***	<b>(00/ ***</b>
Repeated Measures		68%***	70%***	60%***	60%***	60%***
T		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept		31%***	29%***	39%***	39%***	39%***
res.	•	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time		1%***	1%***	1%***	1%***	1%***
No. 1.1.00		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Model-fit statistics			<b>-</b> 0 :		4.50 /	
Adjusted R <sup>2</sup>		45	5%	41%	42%	45%
AIC		-4085.882	-4163.299	-4987.668	-4959.628	-5010.799
BIC		-4052.638	-4124.518	-4921.218	-4871.064	-4900.136
-2 Log Likelihood			79.417	834.368	20.039	59.171
Chi-square		4.000	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF		1.000	1.000	2.926	2.269	6.433

Observations 1885 1885 1885 1885 1885

This table reports the impact of bank- and country-level characteristics on cost of equity (COE) variation. COE is the estimated implied cost of equity of the average of the four cost of equity measures described in Appendix A-2. Model 1 is the empty model which does not include any predictors. We augment HEDGE\_TXT in Model 2 and subsequently add bank- and country variables in Model 3 and 4 respectively. Model 5 add interaction terms. The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 /  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n-1/(n-k-l)]$  where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. Year fixed effects are included in Model 2 to 5. Change in -2Log Likelihood ( $\Delta$  -2LL) is used to assess each model's improvement compared with the Model 1 whereas Chi-square ( $\Delta$  Chi-square) is to assess such statistical improvement. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 6 Repeated measure multilevel analysis: Cost of Debt (COD)

Dependent variable: COD						
	Ex. Sig.	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	(?)	0.0507***	0.0506***	-0.0505***	-0.0692***	-0.0676***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank-level variables						
HEDGE_TXT	(-)		-0.0010**	-0.0059***	-0.0059***	-0.0115***
			(0.025)	(0.000)	(0.000)	(0.000)
SIZE	(?)			0.0072***	0.0072***	0.0069***
<b>DOE</b>	<b>()</b>			(0.000)	(0.000)	(0.000)
ROE	(-)			-0.0001*	-0.0001 (0.240)	-0.0003
DEPOSITS	(±)			(0.066) 0.0049	(0.240) 0.0050***	(0.335) 0.0074*
DEFOSITS	(+)			(0.200)	(0.191)	(0.057)
LEVERAGE	(+)			0.056***	0.0558***	0.053***
EEVERIGE	( · )			(0.000)	(0.000)	(0.000)
NIM	(-)			0.2158***	0.2106***	0.2367***
	( )			(0.007)	(0.009)	(0.004)
Country-level variables				, ,	,	,
FIN_STRESS	(+)				0.0128**	0.0109*
					(0.038)	(0.077)
CORRUPTION	(+)				0.0013	-0.0014
					(0145)	(0.133)
FIN_OPENESS	(-)				0.0020	-0.0001
OECD	()				(0.869)	(0.907)
OECD	(-)				0.0143** (0.043)	0.0148**
Cross-level interactions					(0.043)	(0.041)
FIN_STRESS*HEDGE_TXT	(+)					0.0038
	( )					(0.293)
CORRUPTION*HEDGE_TXT	(+)					0.0004*
						(0.065)
FIN_OPENESS*HEDGE_TXT	(-)					0.0017***
						(0.005)
OCED*HEDGE_TXT	(-)					0.0011
						(0.496)
TIME	(5)	-0.0023***	-0.0023***	-0.0022***	-0.0021***	-0.0021**
Tatas alam annalation		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intra-class correlation Repeated Measures		84%***	81%***	85%***	75%***	76%***
Repeated Measures		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept		15%***	18%***	14%***	24%***	23%***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time		1%***	1%***	1%***	1%***	1%***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Model-fit statistics			•	. ,		
Adjusted R <sup>2</sup>			3%	74%	79%	84%
AIC		-9243.915	-9232.928	-9307.342	-926.361	-9224.436
BIC		-9210.671	-9194.148	-9240.893	-9179.796	-9113.773
-2 Log Likelihood			(0.003)	84.424	30.981	35.724
Chi-square		4.000	(0.000)	(0.000)	(0.000)	(0.000)
Mean VIF		1.000	1.000	2.946	2.281	6.467

Observations 1885 1885 1885 1885 1885

This table reports the impact of bank- and country-level characteristics on cost of debt (COD) variation. COD is calculated as the interest expense in year t+1 scaled by average debt in year t+1 ( $Debt_{t+1} + Debt_t$ )/2) where debt is measured as (short-term debt + total long-term liabilities). Model 1 is the empty model which does not include any predictors. We augment HEDGE\_TXT in Model 2 and subsequently add bank- and country variables in Model 3 and 4 respectively. Model 5 add interaction terms. The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as 1 – [ $(1 - R^2) * n-1/(n-k-l)$ ] where R<sup>2</sup> is  $(\sigma^2m0 - \sigma^2m1)/\sigma^2m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. Year fixed effects are included in Model 2 to 5. Change in -2Log Likelihood ( $\Delta$  -2LL) is used to assess each model's improvement compared with the Model 1 whereas Chi-square ( $\Delta$  Chi-square) is to assess such statistical improvement. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 7
Alternative country-level effect – cross level interaction

Dependent variable:		Panel A (PC	FA)		Panel B (Ag	Panel B (Aggregate)			
	Ex. Sig.	WACC	ĆOE	COD	WACC	COE	COD		
Intercept	(?)	-0.1173***	-0.4497***	-0.0512***	-0.1198***	-0.4476***	-0.055***		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Firm variables									
HEDGE_TXT	(-)	-0.0396***	-0.1142***	-0.0058***	-0.0386***	-0.1087***	-0.0064***		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
SIZE	(?)	0.0280***	0.0710***	0.0072***	0.0282***	0.0715***	0.0072***		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
ROE	(-)	-0.0001**	-0.0002	-0.0000	-0.0001**	-0.0004*	-0.000		
		(0.046)	(0.315)	(0.241)	(0.018)	(0.091)	(0.323)		
DEPOSITS	(+)	-0.0761***	-0.2963***	0.0057	-0.0754***	-0.2935***	0.0052		
	. ,	(0.000)	(0.000)	(0.139)	(0.000)	(0.000)	(0.175)		
LEVERAGE	(+)	0.0492***	0.3727***	0.0561***	0.0496***	0.3730***	0.0570***		
	` '	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
NIM	(-)	-1.3804***	-4.0584***	0.2123***	-0.0754***	-3.9913***	0.2085***		
	<b>\</b> /	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)		
Country variables		,	,	,	,	,	,		
PCFA	(?)	0.0021***	0.0050**	0.0014**					
		(0.000)	(0.017))	(0.029)					
PCFA * HEDGE_TXT	(?)	-0.0010***	-0.0046***	-0.0010*					
	. ,	(0.000)	(0.000)	(0.095)					
AGGREGATE	(?)	,	,	,	0.0045**	-0.0035	0.0032***		
	``				(0.041)	(0.213)	(0.000)		
AGGREGATE * HEDGE_TXT	(?)				-0.0009***	-0.0051***	0.0005		
_	``				(0.005)	(0.000)	(0.281)		
TIME	(?)	0.0003	0.0068***	-0.0021***	0.0013**	0.0098**	-0.0091**		
	· · ·	(0.196)	(0.000)	(0.000)	(0.025)	(0.038)	(0.015)		
Intra-class correlation		,	,	,	,	,	,		
Repeated Measures		60%***	66%***	80%***	60%***	62%***	79%***		
1		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Intercept		39%***	33%***	19%***	39%***	37%***	20%***		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Time		1%	1%***	1%*	1%	1%***	1%***		
		(0.152)	(0.000)	(0.075)	(0.152)	(0.000)	(0.000)		
Model-fit statistics		(*****)	(01000)	(010.0)	(0110_)	(01000)	(0.000)		
Adjusted R <sup>2</sup>		68%	50%	8%	67%	42%	8%		
AIC		-10194.2	-4987.3	-9284.4	-10175.9	-4978.8	-9292.3		
BIC		-10116.6	-4909.8	-9206.8	-10098.4	-4901.3	-9214.8		
-2 Log Likelihood		2019.6	2507.6	56.436	2001.4	908.96	64.421		
Observations		1885	1885	1885	1885	1885	1885		
This table reports the cross-level intera	ation analysis								

This table reports the cross-level interaction analysis on WACC, COE and COD. WACC is calculated as LEV\* [COE (1-TAX)] + (1-LEV) COD. COE is the estimated implied cost of equity of the average of the four cost of equity measures. COD is calculated as the interest expense in year t+1 scaled by average debt in year t+1 ( $Debt_{t+1} + Debt_t$ )/2) where debt is measured as (short-term debt + total long-term liabilities). Panel A report the results for Principal Component Factor for all country-level variables with the highest loading (PCFA) and Panel B report the result for aggregate country-level variables (AGGREGATE). The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 /  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as 1 - [ $(1 - R^2) * n-1/(n - k - 1)$ ] where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. Year fixed effects are included in Model 2 to 5. Change in -2Log Likelihood ( $\Delta$  -2LL) is used to assess each model's improvement compared with the Model 1 whereas Chi-square ( $\Delta$  Chi-square) is to assess such statistical improvement. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 8
Further analysis: cost of capital for post-IFRS 9

1		Panel A	Panel B	Panel C
	Ex. Sig.	WACC	COE	COD
Intercept	(?)	-6.935**	-2.4170***	0.1812***
1	( )	(0.000)	(0.000)	(0.000)
Firm variables		,	,	,
HEDGE_TXT	(-)	1.3480**	4.6130***	-0.0338***
_	( )	(0.000)	(0.000)	(0.000)
IFRS9	(?)	0.0961***	0.2075**	0.0029
	( )	(0.009)	(0.021)	(0.132)
IFRS9 * HEDGE_TXT	(?)	0.1966***	0.3487***	0.0203
<u> </u>	(*)	(0.000)	(0.007)	(0.466)
SIZE	(?)	0.7701***	2.6130***	-0.0158***
	(•)	(0.000)	(0.000)	(0.000)
ROE	(-)	0.0152***	0.0555***	-0.0006***
~	()	(0.000)	(0.000)	(0.000)
DEPOSITS	(+)	0.0002***	0.0006***	-0.0001**
	( · )	(0.000)	(0.000)	(0.013)
LEVERAGE	(+)	1.5950***	6.0980***	-0.0451***
EE VEREIGE	( ' )	(0.000)	(0.000)	(0.007)
NIM	(-)	-0.0039	-0.0172*	0.0004*
INITY	(-)	(0.337)	(0.082)	(0.085)
Country variables		(0.557)	(0.002)	(0.003)
FIN_STRESS	(+)	-0.6253	-1.6780	0.0456*
111 <b>1_</b> 311 <b>L</b> 233	(')	(0.184)	(0.141)	(0.064)
CORRUPTION	(+)	-1.5110	-0.0276	0.0003
CORROLLION	(1)	(0.905)	(0.370)	(0.700)
FIN_OPENESS	()	0.0619	0.3547***	-0.0056**
TIN_OFENESS	(-)	(0.219)	(0.004)	(0.033)
OECD	()	0.0606	-0.0063	0.0030
OECD	(-)			
TIME	()	(0.423)	(0.974)	(0.472)
TIME	(-)	-0.0047***	-0.0013*** (0.000)	-0.0012*** (0.000)
Intro alors acqualation		(0.000)	(0.000)	(0.000)
Intra class correlation		90%***	87%***	64%***
Repeated Measures				
T., 4., 1., 1., 1.		(0.000) 9%***	(0.000)	(0.000)
Intercept			12%***	35%***
т.		(0.000)	(0.000)	(0.000)
Time		1%***	1%***	1%***
N.C. 1.1.09		(0.000)	(0.000)	(0.000)
Model-fit statistics		250/	450/	2007
Adjusted R <sup>2</sup>		35%	47%	28%
Mean VIF		1.4787	2.4088	1.5470
Observations This table report the impact of		580	580	580

This table report the impact of hedge disclosure on cost of capital for post-IFRS 9 period using repeated multilevel analysis. The sample comprises of 145 EU banks from the period of 2016-2019 where 2016-2017 represents IAS 39 period and 2018-2019 represent IFRS 9 period. WACC is cc is the interest expense in year t+1 scaled by average debt in year t+1 ( $Debt_{t+1} + Debt_t$ )/2) where debt is measured as (short-term debt + total long-term liabilities). The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as ( $\sigma^2$  at level 1 / ( $\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as 1 - [ (1 - R<sup>2</sup>) \* n-1/ (n - k - l)] where R<sup>2</sup> is ( $\sigma^2 m0 - \sigma^2 m1$ )/ $\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. See Appendix A-1 for detailed description of all variables. \*\*\*\*, \*\*Statistical significance at 1, 5 and 10% level, respectively.

Table 9
Robust check: repeated measures multilevel analysis – WACC, COD and COE

_		Panel A			Panel B			Panel C			
Dependent variable:		WACC			COD			COE			
	Ex. Sig.	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	K <sub>CLS</sub>	$K_{GEB}$	K <sub>OHS</sub>	K <sub>EST</sub>
		(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
Intercept	(5)	0.0762***	-0.0458	-0.0339	7.1054***	-2.5743	-1.7955	0.2671***	0.1311***	0.2901***	0.0941**
		(0.000)	(0.330)	(0.582)	(0.000)	(0.222)	(0.534)	(0.000)	(0.000)	(0.000)	(0.0369)
Firm variables											
HEDGE_TXT	(-)	-0.0017	-0.0124**	-0.0119**	-0.1832**	-0.7353***	-0.7065***	-0.1147***	0.0129**	-0.0220**	-0.0374***
		(0.317)	(0.012)	(0.015)	(0.011)	(0.005)	(0.000)	(0.000)	(0.0301)	(0.0137)	(0.000)
SIZE	(?)		0.0141***	0.0141***		0.5380***	0.5349***	-0.0398***	0.0024	-0.0218***	-0.0132***
			(0.003)	(0.004)		(0.009)	(0.009)	(0.000)	(0.4302)	(0.000)	(0.0014)
ROE	(-)		0.0010***	0.0010**		0.0473***	0.0392***	-0.0064***	0.0015***	-0.0051	-0.0039***
D FID C OFFIC			(0.006)	(0.033)		(0.009)	(0.007)	(0.000)	(0.0020)	(0.8510)	(0.000)
DEPOSITS	(+)		-0.0138	-0.0123		1.4375*	1.6812**	-0.1052***	0.0044	-0.0383*	-0.0241
I EVED A CE	(.)		(0.452)	(0.505)		(0.065)	(0.031)	(0.0036)	(0.7235)	(0.0522)	(0.1736)
LEVERAGE	(+)		0.0320	0.0343		5.7462***	5.9554***	0.0622	-0.0120	0.0323	0.0518**
NITS (	()		(0.249)	(0.219)		(0.000)	(0.000)	(1.251)	(0.4434)	(0.1918)	(0.0201)
NIM	(-)		-0.1631	-0.409		-2.7396	-2.9461	1.6218**	-0.1176	1.0260**	-0.0465
T' 11			(0.221)	(0.283)		(0.867)	(0.858)	(0.0102)	(0.6528)	(0.0137)	(0.9025)
Firm variables	(1)			0.0041**			4 F ( 2 + + +	0.6704***	0.0220	0.2215***	0.2754***
FIN_STRESS	(+)			-0.0841**			-4.563***	0.6704***	-0.0328	0.2215***	0.2754***
CORRUPTION	(1)			(0.005)			(0.000)	(0.000)	(0.4179)	(0.0002)	(0.000)
CORRUPTION	(+)			-0.0010			0.3922**	0.0411***	-0.0058**	0.0087**	0.0192***
EIN ODENIECC	()			(0.884)			(0.046)	(0.000)	(0.0207)	(0.0310)	(0.000)
FIN_OPENESS	(-)			0.0041			-0.0341 (0.871)	-0.0191	0.0037	0.0017	-0.0022
OECD	()			(0.412)			` /	(0.1260)	(0.3662)	(0.7626)	(0.6780)
OECD	(-)			-0.0095			-1.5453	-0.0289	-0.0126	-0.0273*	-0.0066
TIME	(2)	0.0041***	0.0043***	(0.818)	0.1272	0.1040**	(0.448)	(0.4525)	(0.1615)	(0.0848)	(0.7685)
TIME	(?)	0.00	0.00.00	0.0039***	0.1362	0.1948**	0.1723*				
		(0.000)	(0.000)	(0.000)	(0.153)	(0.031)	(0.065)				
Intra-class correlation											
Repeated Measures		42%***	42%***	43%***	42%***	41%***	41%***	52%***	60***	57%***	51%***
Repeated Measures		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept		49%***	50%***	50%***	50%***	51%***	51%***	45%***	35%***	39%***	46%***
тистеері		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0010)	(0.000)
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0010)	(0.000)

Time	9%*** (0.000)	8%*** (0.000)	7%*** (0.000)	8% (0.114)	8%** (0.021)	8%* (0.071)	3%*** (0.0054)	5%*** (0.000)	4%** (0.0351)	3%*** (0.000)
Model-fit statistics	()	()	(* * * * * )	( )	( )	( )	()	()	()	(* * * * * )
Adjusted R <sup>2</sup>	18%	30%	34%	28%	41%	50%	39%	37%	41%	35%
AIC	-3423.209	-3399.371	-3372.436	10691.07	10655.95	10645.02	-2326.307	-3952.982	-2662.667	-2458.615
BIC	-3384.428	-3332.922	-3283.872	10729.85	10722.40	10733.58	-2215.611	-3842.287	-2551.972	-2351.018
Observations	1560	1560	1560	1560	1560	1560	1885	1885	1885	1885

This table reports the impact of hedge disclosure and alternative measures of cost of capital. From Panel A, WACC is calculated as LEV \* [COE (1-TAX)] + (1-LEV) COD. COE is the estimated implied cost of equity of the average of the four cost of equity measures. COD is S&P credit ratings. From Panel B, the proxy for COD is S&P credit ratings. In Panel C, the individual cost of equity measures ( $K_{GEB}$ ,  $K_{CLS}$ ,  $K_{EST}$ ,  $K_{OHS}$  are used. The intra-class correlation (ICC) is reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2)$  at level  $(\sigma$ 

Table 10 Further analysis: Assessing the effectiveness of hedge disclosure score

Dependent variable:					
		Panel A		Panel B	
	Ex. Sig.	TOTAL_RISK	Z-SCORE	WACC	WACC
Intercept	(?)	0.9237***	0.3002**	0.1191***	0.1169***
		(0.000)	(0.023)	(0.000)	(0.000)
Firm variables					
SIZE	(?)	-0.0171	0.0106	-0.0003	-0.0011
		(0.347)	(0.344)	(0.745)	(0.818)
ROE	(-)	-0.0011	-0.0010	0.0004***	0.0004***
		(0.491)	(0.340)	(0.000)	(0.000)
DEPOSITS	(+)	-0.0566	-0.1176**	-0.0029	-0.0033
		(0.502)	(0.023)	(0.460)	(0.405)
LEVERAGE	(+)	0.1260	0.0546	-0.1022***	-0.1026***
		(0.367)	(0.518)	(0.000)	(0.000)
NIM	(-)	3.7314**	-0.1040	-0.0792	-0.0688
		(0.031)	(0.915)	(0.3539)	(0.420)
Country variables					
FIN_STRESS	(+)	0.7808***	0.0767	0.0104	0.0102
		(0.000)	(0.378)	(0.149)	(0.155)
CORRUPTION	(+)	0.0416**	-0.0105**	0.0015	0.0015
		(0.010)	(0.028)	(0.141)	(0.151)
FIN_OPENESS	(-)	0.0518**	-0.0029	0.0010	0.0012
		(0.022)	(0.826)	(0.416)	(0.320)
OECD	(-)	-0.5821***	-0.0369	0.023	0.0030
		(0.000)	(0.333)	(0.803)	(0.757)
TIME	(-)	-0.0037	0.0010	0.0010*	0.0010*
		(0.455)	(0.737)	(0.067)	(0.070)
HEDGE_TXT	(-)	-0.0637***	-0.0127		
THE DOE_TAT	()	(0.007)	(0.402)		
NOTIONAL	(-)	(0.007)	(0.102)	0.1582***	
TO HOLLE	()			(0.005)	
CREDIT_DER	(-)			(0.003)	-0.0026*
GREETT_BLIK	()				(0.082)
Intra class correlation					(0.002)
Repeated measures		74%***	63%***	61%***	66%***
		(0.000)	(0.000)	(0.000)	(0.000)
Intercept		25%***	36%***	38%***	33%***
		(0.000)	(0.000)	(0.000)	(0.000)
Time		1%	1%***	1%*	1%*
		(0.692)	(0.003)	(0.050)	(0.074)
Model-fit statistics					
Adjusted R <sup>2</sup>		48%	56%	44%	38%
AIC		2322.11	797.537	-8689.47	-8677.39
BIC		2410.67	886.103	-8600.91	-8588.83
Observations This table was at the investor fleet and in the second seco		1885	1885	1885	1885

This table report the impact of hedge disclosure on bank risk measures using repeated measures multilevel analysis in Panel A. It also the impact of hedging on cost of capital using alternative measures of hedging (i.e., notional amount of derivative outstanding and credit derivative). TOTAL\_RISK is the standard deviation of daily stock returns measured over a year. Z-SCORE is the sum of return on assets and equity to assets ratio divided by the standard deviation of return on assets. NOTIONAL is the notional amount of derivative outstanding scaled by total assets. CREDIT\_DER is a dummy variable which takes the value of one if a bank uses credit derivative and zero if otherwise. The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level  $1 + \sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n-1/(n - k - l)]$  where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. & is total number of parameters; n is total sample size. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 11 Further analysis: Alternative measure of hedge disclosure score

Dependent variable:							
			Panel A			Panel B	
	Ex. Sig.	WACC	COE	COD	WACC	COE	COD
Intercept	(?)	0.2509***	0.3822***	0.1442***	-0.0392***	-0.2752***	0.0177**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
Bank-level variables							
SIZE	(?)	-0.0079***	-0.0161***	-0.0074***	0.0218***	0.0624***	0.0014***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
ROE	(-)	-0.0002	0.0010***	-0.010***	-0.0002***	-0.0003	-0.0002***
		(0.7883)	(0.003)	(0.000)	(0.003)	(0.209)	(0.000)
DEPOSITS	(+)	-0.0154***	-0.0933***	-0.0005	-0.0657***	-0.2980***	0.0252***
		(0.000)	(0.000)	(0.832)	(0.000)	(0.000)	(0.000)
LEVERAGE	(+)	-0.0942***	-0.0566**	0.0438***	0.0011	0.3248***	-0.0081*
		(0.000)	(0.023)	(0.000)	(0.797)	(0.000)	(0.011)
NIM	(-)	-0.3981***	-0.4845*	-0.0501	-1.6827***	-3.9245***	-0.5290***
		(0.000)	(0.098)	(0.324)	(0.000)	(0.000)	(0.000)
Country-level variables							
FIN_STRESS	(+)	-0.0483***	-0.0192	-0.0675***	-0.0433***	0.0660***	-0.1209***
		(0.000)	(0.467)	(0.000)	(0.000)	(0.004)	(0.000)
CORRUPTION	(+)	0.0002	-0.0010	0.0004	-0.0029***	-0.0075**	-0.0044***
		(0.762)	(0.847)	(0.475)	(0.001)	(0.023)	(0.000)
FIN_OPENESS	(-)	-0.0224***	-0.0198***	-0.0316***	0.0129***	0.0002	0.0228***
		(0.000)	(0.005)	(0.000)	(0.000)	(0.954)	(0.000)
OECD	(-)	-0.0013	-0.0284	0.0078	-0.0145*	-0.0610**	-0.0062
		(0.841)	(0.205)	(0.104)	(0.097)	(0.028)	(0.114)
TIME	(?)	0.0011	0.0083***	-0.0015***	0.0010***	0.0009***	-0.0010***
		(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
RELATIVE	(-)	-0.0180***	-0.0142***	-0.0243***			
		(0.000)	(0.000)	(0.000)			
STANDARDISED	(-)				-0.0134***	0.0036	-0.0269***
					(0.000)	(0.878)	(0.000)
Intra-class correlation							
Repeated Measures		69%***	86%***	74%***	87%***	75%***	56%***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept		30%***	13%***	15%***	12%***	24%***	43%***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time		1%***	1%***	1%***	1%***	1%***	1%***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Model-fit statistics							
Adjusted R <sup>2</sup>		42%	37%	49%	55%	14%	50%
AIC		-9127.305	-4075.628	-4075.628	-8384.948	-4011.435	-10601.160
BIC		-9037.74	-3987.063	-3987.063	-8274.285	-3900.772	-10490.497
Observations		1885	1885	1885	1885	1885	1885

This table assess the reliability of hedge disclosure score using relative measure in Panel A and standardised measure in Panel B. RELATIVE is captured as the percentage of hedge related statements whereas STANDARDISED is calculated as the Z-score standardised measure of the total number of hedge-related statements in the bank's narrative section of annual reports for bank *i* in year *t* based on our constructive hedge keywords. The dependent variable is WACC, COE and COD in Panel A, B and C respectively. WACC is calculated as LEV \* [COE (1-TAX)] + (1-LEV) COD where LEV is leverage, COE is cost of equity, TAX is annual tax rate, COD is cost of debt. COE is the estimated implied cost of equity of the average of the four cost of equity measures described in Appendix A-2. COD is calculated as the interest expense in year *t+1* scaled by average debt in year *t+1* (Debt<sub>i+1</sub> + Debt<sub>i</sub>)/2) where debt is measured as (short-term debt + total long-term liabilities). The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 /  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n-1/(n - k - 1)]$  where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, *m*1 is current model's variance component, whereas *m*0 is null model's variance component. *k* is total number of parameters; *n* is total sample size. Year fixed effects are included in Model 2 to 5. Change in -2Log Likelihood ( $\Delta$  -2LL) is used to assess each model's improvement compared with the Model 1 whereas Chi-square ( $\Delta$  Chi-square) is to assess such statistical improvement. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*\*, \*Statistical significance at 1, 5 and 10% level, respectively.

Table 12 Robust check: endogeneity checks

$\begin{array}{ c c c c c c } \hline \text{Dependent variable:} & & & & & & & & & & & & & & & & & & &$	hods (GMM)  COD  -0.0628*** (0.000)  -0.0053*** (0.000) 0.0068*** (0.000) -0.0001* (0.066) 0.0053 (0.168)
Intercept (?) $0.0949^{***}$ $-0.0638$ $-0.0170$ $-0.1180^{***}$ $-0.3793^{***}$ $(0.000)$ $(0.413)$ $(0.348)$ $(0.000)$ $(0.000)$ Bank-level variables HEDGE_TXT (-) $-0.0211^{***}$ $-0.0811^{***}$ $-0.0019$ $-0.0387^{***}$ $-0.1093^{***}$ $(0.000)$ $(0.000)$ $(0.000)$ $(0.238)$ $(0.000)$ $(0.000)$ SIZE (?) $0.0087^{***}$ $0.0275^{***}$ $0.0039^{***}$ $0.0278^{***}$ $0.0278^{***}$ $0.0278^{***}$ $0.0278^{***}$ $0.0000$ $0.000$	-0.0628*** (0.000) -0.0053*** (0.000) 0.0068*** (0.000) -0.0001* (0.066) 0.0053
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	(0.000) -0.0053*** (0.000) 0.0068*** (0.000) -0.0001* (0.066) 0.0053
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	-0.0053*** (0.000) 0.0068*** (0.000) -0.0001* (0.066) 0.0053
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$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	(0.000) 0.0068*** (0.000) -0.0001* (0.066) 0.0053
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0068*** (0.000) -0.0001* (0.066) 0.0053
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	(0.000) -0.0001* (0.066) 0.0053
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.0001* (0.066) 0.0053
(0.901) (0.261) (0.003) (0.032) (0.596) DEPOSITS (+) -0.0184*** -0.196*** 0.0471*** -0.0752*** -0.2884***	(0.066) 0.0053
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0053
	(0.168)
$(0.002) \qquad (0.000) \qquad (0.000) \qquad (0.000) \qquad (0.000)$	(0.100)
LEVERAGE (+) -0.1107*** 0.155*** -0.0221* 0.0430*** 0.3503***	0.0510***
$(0.000) \qquad (0.004) \qquad (0.051) \qquad (0.000) \qquad (0.000)$	(0.000)
NIM (-) -0.0364 0.7871 0.376*** -1.3300*** -3.9857***	0.2580***
$(0.821) \qquad (0.226) \qquad (0.006) \qquad (0.000) \qquad (0.000)$	(0.001)
Country-level variables	` ,
FIN_STRESS (+) 0.0356*** 0.0613* 0.0281*** 0.0147*** 0.0455**	0.0126**
(0.000) $(0.076)$ $(0.000)$ $(0.002)$ $(0.022)$	(0.042)
CORRUPTION (+) -0.0005 -0.0041 0.0031*** 0.0002 -0.0030	0.0012
$(0.717) \qquad (0.343) \qquad (0.007) \qquad (0.830) \qquad (0.323)$	(0.162)
FIN_OPENESS (-) 0.0009 -0.0016 0.0006 -0.0002 -0.0061*	ò.0001
(0.492) $(0.779)$ $(0.634)$ $(0.760)$ $(0.065)$	(0.900)
OECD (-) -0.0072 -0.0880** 0.0254** 0.0078 -0.0218	0.0149**
$(0.552) \qquad (0.027) \qquad (0.028) \qquad (0.385) \qquad (0.386)$	(0.023)
TIME (-) -0.0007* 0.0080*** -0.0028*** 0.0000 0.0062***	-0.0023***
$(0.071) \qquad (0.000) \qquad (0.000) \qquad (0.927) \qquad (0.000)$	(0.000)
Intra-class correlation	,
Repeated Measures 68%*** 71%*** 69%*** 61%*** 65%***	66%***
$(0.000) \qquad (0.000) \qquad (0.000) \qquad (0.000) \qquad (0.000)$	(0.000)
Intercept 32%*** 28%*** 30%*** 39%*** 24%***	34%***
$(0.000) \qquad (0.000) \qquad (0.000) \qquad (0.000) \qquad (0.000)$	(0.000)
Time 0% 1%*** 1%*** 0% 1%***	1%***
$(0.152) \qquad (0.000) \qquad (0.000) \qquad (0.927) \qquad (0.000)$	(0.000)
Model-fit statistics	` /
Adjusted R <sup>2</sup> 26% 16% 19% 21% 19%	23%
AIC -4587.10 -2031.80 -4851.00 -5917.12 -3621.54	-5641.58
BIC -4510.20 -1954.90 -4774.10 -5630.96 -3464.43	-5914.95
Observations 1885 1885 1885 1885 1885	1885

This table report the results for addressing endogeneity concerns Panel A reports the results using Propensity Matching Score (PMS), Panel B reports the results using Generalized Method of Moments (GMM). The dependent variable in Model 1 - 3 are WACC, COE and COD respectively in Panel A, B, and C. WACC is calculated as LEV \* [COE (1-TAX)] + (1-LEV) COD where LEV is leverage, COE is cost of equity, TAX is annual tax rate, COD is cost of debt. The intra-class correlation (ICC) is also reported to show the proportion of variance captured at level 1 (within banks) and level 2 (between banks) overtime. Level 1 variance is calculated as  $(\sigma^2$  at level 1 /  $(\sigma^2$  at level 1 +  $\sigma^2$  at level 2)). The Adjusted R<sup>2</sup> is calculated as  $1 - [(1 - R^2) * n - 1/(n - k - 1)]$  where R<sup>2</sup> is  $(\sigma^2 m0 - \sigma^2 m1)/\sigma^2 m0$ . Hence, m1 is current model's variance component, whereas m0 is null model's variance component. k is total number of parameters; n is total sample size. Year fixed effects are included in all models. See Appendix A-1 for detailed description of all variables. \*\*\*, \*\*, \*Statistical significance at 1, 5 and 10% level, respectively

# Appendix A-1 Variables Definition

Variable	Ex. Sg.	Definition	Sample paper(s)	Source
Dependent variables: C	ost of capi			
WACC		WACC is the weighted average cost of capital, calculated as LEV x COE (1-TAX) + (1-LEV) COD	(Drobetz et al., 2018)	Authors' computation
COD		Average interest rate on debt in year $t+1$ . Interest rate is measured as	(Pittman & Fortin, 2004)	Authors'
		interest expense in year $t+1$ scaled by average debt in year $t+1$ (Debt <sub>t+1</sub> +		computation
		$Debt_t$ )/2); Debt is measured as (short-term debt + total long-term		
		liabilities). Because of the likelihood of estimation problems due to		
		significant changes in Debt, we recode Debt to missing for any observation		
		where <i>Debt</i> is more than doubles or reduces by half.		
COE		The average implied cost of equity from the models of Easton (2004), Gebhardt et al. (2001), Ohlson & Juettner-Nauroth (2005), and Claus & Thomas (2001)	(Dhaliwal et al., 2016; Drobetz et al., 2018)	Authors' computation
Bank-level variables				
HEDGE_TXT		Natural log of the total number of hedge-related statements containing at least one of the final list of keywords in the bank's narrative section of annual reports for bank <i>i</i> in year <i>t</i> based on our constructive hedge keywords.		Authors' computation
SIZE	(?)	Natural log of bank's total assets at the end of the fiscal year in which annual report was prepared	(Ahmed et al., 2018; Bartram et al., 2011; Chang et al., 2018;)	Authors' computation
ROE	(-)	Profit before tax ((if available, otherwise profit after tax)/worth)) x 100	(Nkuyen & Faff, 2010; Chang et al., 2018; Campello et al., 2011)	Authors' computation
DEPOSITS	(+)	Total deposits scaled by total assets	(Chang et al., 2018; Minton et al., 2009)	Authors' computation
LEVERAGE	(+)	Calculated as total debt scaled by total assets, representing change in financial leverage	(Dhaliwal et al., 2016; Drobetz et al., 2018)	DataStream Eikon
NIM	(-)	Net Interest Margin - total interest income less total interest expenses, scaled by total assets	(Chang et al., 2018)	Authors' computation
Country-level variables				
FIN_STRESS	(+)	Country level index of financial stress	(Cardarelli et al., 2011)	ECB
CORRUPTION	(+)	The original score of TI index indicates the perceived level of prevailing corruption on a scale of 0-10. With higher score suggesting a higher economic and political integrity. We use 10 minus this TI index, rendering CI with a higher score indicating more rampant corruption.	(Park, 2012)	Authors' computation
FIN_OPENESS	(-)	Financial Openness captured by Chinn & Ito's (2008) measure of financial openness.	(Chang et al., 2018)	Chinn and Ito's (2008)
OECD	(-)	Organisation for Economic Co-operation and Development – a dichotomous variable = 1 if bank is OECD member, and zero if otherwise	(Chang et al., 2018)	Authors' computation

## Appendix A-2

#### Implied cost of equity estimations

We describe how we capture the various cost of equity measures following Dhaliwal et al. (2016) and Drobetz et al. (2018). First, we estimate four different measures of implied cost of equity. Following Gupta et al. (2018), we only use estimates that are within the range 0 and 1. We winsorised each of the measures at the 1% and 99% percentiles and use the average of these measures as our cost of equity measure. In estimating the four measures of equity, we closely follow the procedure described in Gupta et al. (2018) and Dhaliwal et al. (2016). We define variables that are consistent in three of the four models below:

$P_t =$	Stock price of a bank at time t.
$EPS_{t+1} =$	IBES median forecasted earnings per share or calculated EPS forecasts for next ith year at time t.
$BV_{t+i-1} =$	Book value per equity at time t.
POUT =	Forecasted dividends payout. We use annual dividends and EPS to measure the forecasted payout ratio. If EPS is negative, we assume a return on assets of 6% to aid our computation. We winsorise POUT to be between 0 and 1.

### C.1 Ohlson & Juettner-Nauroth (2005)

$$K_{OHS} = V + \sqrt{V^2 + \left[\frac{\varepsilon_t(EPS_{t+1})}{P_t}\right] * (g_2 - g_{lt})}$$

This model requires both  $EPS_{t+1}$  and  $EPS_{t+2}$  to be greater than 0 where

$$V = 0.5 + (g_{lt} + \frac{DPS_{t+1}}{P_t})$$

 $g_2$  is defined as the average of the forecasted long-term growth rate and EPS<sub>t+1</sub> and EPS<sub>t+2</sub>. The long-term earnings growth rate  $g_{lt}$ , is defined as nominal risk-free rate (10-year Treasury yield on bonds – 3%) following Claus & Thomas (2001) and Dhaliwal et al. (2016).

#### C.2 Gebhardt et al. (2001)

$$P_{t} = BV_{t} + \sum_{i=1}^{T-1} \frac{(FROE_{t+i} - K_{GEB}) * BV_{t+i-1}}{(1 + K_{GEB})^{i}} + \frac{(FROE_{t+T} - K_{GEB}) * BV_{t+T-1}}{K_{GEB} * (1 + K_{GEB})^{T-1}}$$

We use IBES analyst's forecasts to capture expected firm's earnings. In this model, FROE for the first three years (t+1, t+2, and t+3) is defined as FEPS<sub>t+j</sub> divided by BV<sub>t+j-1</sub>. After the third year, FROE is defined by linear interpolation to the ROEs industry median. DPS<sub>t+j</sub> is defined by multiplying FEPS<sub>t+j</sub> by POUT. We estimate future book value of equity assuming a clean surplus relation (i.e., BV<sub>t+1</sub> = B<sub>t</sub> + EPS<sub>t+1</sub> - DPS<sub>t+1</sub>), where we compute DPS<sub>t+i</sub> as the product of EPS<sub>t+1</sub> and POUT. We assume T=12. We use a numerical approximation in excel to derive K<sub>GEB</sub>.

## C.3 Modified PEG ratio by Easton (2004)

$$P_t = \frac{FEPS_{t+2} - FEPS_{t+1} + K_{EST}DPS_{t+1}}{K_{EST}^2}$$

Following Easton (2004), we employ one-year ahead and two-year ahead earnings forecasts from IBES. The model requires  $FEPS_{t+2}$  to be greater than or equal to  $FEPS_{t+1}$ .  $DPS_{t+j}$  is defined by multiplying  $FEPS_{t+j}$  by POUT. We use a numerical approximation in excel VBA to derive  $K_{EASTON}$ .

## C.4 Claus & Thomas (2001)

$$P_{t} = BV_{t} + \sum_{i=1}^{5} \frac{FEPS_{t+i} - (K_{CT} * BV_{t+i-1})}{(1 + K_{CT})^{i}} + \frac{[FEPS_{t+5} - (K_{CT} * BV_{t+4})] * (1 + g_{lt})}{(K_{CT} - g_{lt})(1 + K_{CT})^{5}}$$

Book value is estimated using clean-surplus procedure. Future dividend is estimated as DPS<sub>t+1</sub> = EPS<sub>t+1</sub> x POUT. We estimate abnormal earnings for the next 5 years using IBES earnings forecasts following Dhaliwal et al. (2016) and Gupta et al. (2018). Abnormal earnings for the years t + 4, and t + 5 are estimated from the t + 3 earnings forecast, and long-term earnings growth rate. If the data for long-term growth rate is missing from IBES, we employ implied earnings growth rate using EPS<sub>t+2</sub> and EPS<sub>t+3</sub>. The long-term earnings growth rate  $g_{lt}$ , is defined as nominal risk-free rate (10-year Treasury yield on bonds – 3%) following Claus & Thomas (2001) and Dhaliwal et al. (2016).

**Appendix A-3** Keywords from prior studies

Name	Title	Journal	Keywords
Guay (1999)	The impact of derivatives on firm risk: An empirical examination of new derivative users	JAE	Futures contract(s), option(s) contract (s), rate swap(s), swap agreement (s), hedging instrument (s), derivative instrument(s)
Campello et al. (2011)	The real and financial implications of corporate hedging	JF	Derivative, hedge, financial instrument, swap, market risk, expos, futures, forward contract, forward exchange, notional, option contract, risk management
Chen & King (2014)	Corporate hedging and the cost of debt	JCF	Currency derivative, currency swaps, currency forward contract, currency forwards, currency futures, exchange forward, exchange futures, exchange swap, exchange option, exchange contract, forward exchange contract
Ahmed et al. (2018)	Does derivative use reduce cost of equity?	IRFA	Hedge, derivative, market risk, exposure, foreign, currency, interest-rate, commodity, futures, option, swap, risk management, forward, financial instrument

## Keywords from professional publications

Standard	Title	Keywords
IAS 39	Financial Instruments: Recognition and measurement	Derivative (s), financial, instrument (s), fair value, hedge*, cashflow, foreign, risk (s), management, contract(s), exposure, assets, liabilities, recognition, interest rate, gains, loss
IFRS 9	Financial Instruments	Hedge*, derivative(s), financial, risk(s), instrument(s), relationship, fair-value, cashflow, investment, options, intrinsic, non-derivative, time-value, commodity, transaction, net-investment, recognition, gains, losses
Basel I	The New Basel Capital Accord	Embedded, hedge*, option(s), exposure(s), unhedged, mismatch*, forward, credit, derivative(s), commodities, instruments, financial, contract, position(s), trading, default, swap(s), allowance, volume
Basel II	International Convergence of capital measurement and capital standards	Credit, exposure(s), hedge*, counterparty, derivative(s), recognition, swap(s), protect*, embedded, mismatch(es), risk, instrument(s), trading, position(s), swap, futures,
Basel III	A global regulatory framework for more resilient banks and banking systems	Cashflow, adjustment, hedge*, fair-value, interest-rate, derivative(s), commodity, currency, notional, instrument(s), position, credit

## Aggregate wordlist

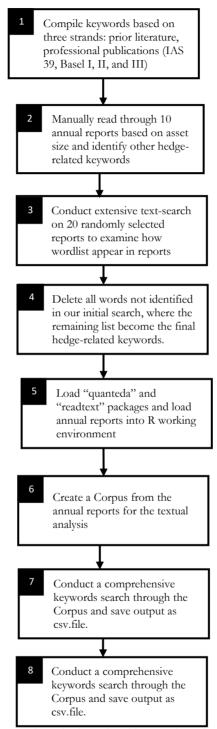
Final wordlist

Future contract, forward contract, forward exchange, forward exchange contract, forward rate agreement, exchange forward, exchange futures, exchange options, exchange contract, currency swaps, currency derivative, currency futures, currency forward contract, currency mismatch, option contract, rate swap, hedging instrument, derivative instrument(s), derivative hedge, derivative trading, trading position, trading volume, derivative gains, derivative loss, financial instruments, financial derivatives, market risk, hedge\*, swap agreement, notional amount, risk management, interest rate swap, interest-rate exposure, credit exposure, commodity swap, commodity exposure, cashflow hedges, option swap, options contract, hedge relationship, fair-value hedge, credit default swap, credit derivative, counterparty risk, foreign exchange risk, initial recognition, embedded derivative

Appendix A-4 Summary of key papers

Name	Theme	Jurisdiction	Journal	Sample	Findings
Ahmed et al. (2018)	Hedge behaviour	Germany	IRFA	357 firms from 1999 – 2009 leading to 1984 firm-year observation	They find that firms that use derivatives experience lower levels of cost of equity and this is predominant with firms that are small in size, and less exposed to risk. First time users of derivatives benefit from significant cost of equity reduction.
Chang et al. (2018)	Hedge behaviour	EU	RQFA	797 banks from 30 countries (2372 observation)	Findings show that banks with low net interest margin, more deposit inflows and high profitability hedge with derivatives. Also, the use of derivatives increases bank risk. In addition, increase in derivative usage is associated with increased bank value (foreign exchange and interest rate derivatives).
Haushalter (2000)	Hedge behaviour	US	JF	100 oil and gas companies from 1992 - 1994	They find a positive and significant association between financial leverage and hedging, suggesting that hedging reduces the cost of financing. Firms that exhibit greater financial leverage tend to hedge more extensively. Also, they find a positive and significant association between total assets and hedging which suggest that firms do firm significant economies of scale when it comes to hedging.
Chen & King (2014)	Hedge disclosure	US	JCF	2612 firms from 1994 to 2009.	Hedging minimises cost of debt. Specifically, on average firms that apply hedging report yield spread of 49.1bp which is lower than firms that do not hedge. They also find that the benefits of hedging are prominent with firms having a high level of financial risk which indicates that hedging reduce the probability of financial stress, leading to lower cost of debt.
Deng et al. (2017)	Hedge disclosure	US	QREF	5076 bank-year observations for 495 issued bonds.	They find a positive association between derivative usage and cost of debt. The positive association is reversed during the financial crisis period (2007 – 2009) which indicate that the existing relationship is driven by sound economic system where banks are financially stable.
Campello et al. (2011)	Hedge disclosure	US	JF	1185 firms based on 2718 loan contracts	They find that hedging reduces cost of debt. Also, their findings reveal that cost of external funding is reduced upon the application of hedging and the process for firm investment becomes easy.
Guay (1999)	Hedge cost of capital	US	JAE	245 non-financial firms	There is a statistical and economically significant reduction in risk (i.e., stock volatility, interest rate exposure, exchange rate exposure) for users of derivatives compared to non-users. They also find that the type of derivative that is employed by firms is dependent of the kind of risk exposure which reflects their hedging behaviour. Additionally, one of the main drivers for a shift in firm risk is the use of derivatives.
Bartram et al. (2011)	Hedge cost of capital	Int'l	JFQA	6888 firm year observations from 47 countries.	Firms that are exposed to commodity prices, interest rate risk and exchange rate risk tend to use more derivatives despite the increase in risk. Findings also show that hedging is used to reduce risk rather than speculate, Specifically, hedge firms experience lower estimated firm value (i.e., both systematic and total risk)
Allayannis & Weston (2001)	Hedge cost of capital	US	RFS	720 large firms from 1990 – 1995.	Foreign currency derivative is positively associated with firm value. Specifically, firms that face currency risk and use foreign currency derivative have 4.87% increased firm value than non-hedgers.
Carter et al. (2006)	Hedge cost of capital	US	FM	259 firm year observation from 1992 - 2003	They find that hedging allows firms to manage future cash flows on account that fuel prices increase after it coincide with financial distress in the airline industry. Also, findings reveal that hedging provides additional source of cash for making acquisitions when such periods prevail.

Figure 1 Textual analysis process using R



This figure presents how we constructed our hedge-related keywords and measured HEDGE\_TXT using R.