



This is a repository copy of *Firm size, market conditions and takeover likelihood*.

White Rose Research Online URL for this paper:
<https://eprints.whiterose.ac.uk/146156/>

Version: Accepted Version

Article:

Tunyi, A. orcid.org/0000-0002-5761-931X (2019) Firm size, market conditions and takeover likelihood. *Review of Accounting and Finance*, 18 (3). pp. 483-507. ISSN 1475-7702

<https://doi.org/10.1108/RAF-07-2018-0145>

This author accepted manuscript is deposited under a Creative Commons Attribution NonCommercial 4.0 International (<http://creativecommons.org/licenses/by-nc/4.0/>) licence. This means that anyone may distribute, adapt, and build upon the work for non-commercial purposes, subject to full attribution. If you wish to use this manuscript for commercial purposes, please contact permissions@emerald.com

Reuse

This article is distributed under the terms of the Creative Commons Attribution-NonCommercial (CC BY-NC) licence. This licence allows you to remix, tweak, and build upon this work non-commercially, and any new works must also acknowledge the authors and be non-commercial. You don't have to license any derivative works on the same terms. More information and the full terms of the licence here:
<https://creativecommons.org/licenses/>

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.



eprints@whiterose.ac.uk
<https://eprints.whiterose.ac.uk/>

Firm size, market conditions and takeover likelihood

Abongeh A Tunyi¹

Accounting and Financial Management
Sheffield University Management School
University of Sheffield

Review of Accounting and Finance, Forthcoming

15 May 2019

DOI (10.1108/RAF-07-2018-0145)

¹ Address for correspondence; Accounting & Financial Management, Sheffield University Management School, University of Sheffield, Conduit Road, Sheffield, S10 1FL, United Kingdom. Email: a.tunyi@sheffield.ac.uk. Tel: +44 (0)114 222 0989.

Firm size, market conditions and takeover likelihood

Abstract

Purpose

The firm size hypothesis—takeover likelihood (*TALI*) decreases with target firm size (*SIZE*)—has enjoyed little traction in the *TALI* modelling literature, hence, this paper seeks to redevelop this hypothesis while taking account of prevailing market conditions—capital liquidity and market performance.

Design

The study uses a logit framework with interaction effects, to model *TALI* and receiver operating characteristic (ROC) curve analyses, to assess model performance. The analysis employs a UK sample of 34,661 firm-year observations drawn from 3,105 firms and 1,396 M&A deals over a 30-year period (1987–2016).

Findings

While acquirers generally seek smaller targets due to transaction cost constraints, we show that the documented negative relation between *SIZE* and *TALI* arises from sampling bias. Over a full sample, mid-sized firms are most at risk of takeovers. Additionally, market conditions moderate the *SIZE*–*TALI* relationship, with acquirers more inclined to pursue comparatively larger targets when financing costs are low and market growth or sentiment is high. The results are generally robust to endogeneity.

Research implications

Sample truncation on the basis of *SIZE*, leads to empirical misspecification of the *TALI*–*SIZE* relation. In an unbiased sample, an inverse U-shaped specification between *TALI* and *SIZE* sufficiently models the underlying relation and leads to improvements in the predictive ability of *TALI* models.

Originality/value

This study advances a new firm size hypothesis which is consistent with classic M&A theories. The study also evidences market conditions as a moderator of the acquirer's choice of target *SIZE*. A new model specification which recognises the non-linear relation between *TALI* and *SIZE* and accounts for the moderating effect of market conditions on the *SIZE*–*TALI* relationship, leads to improvements in the performance of *TALI* prediction models.

Keywords: takeover likelihood, prediction, firm size, capital liquidity, market performance

1.0 Introduction

An assessment of a firm's vulnerability to future takeovers (i.e., takeover likelihood, henceforth *TALI*) is relevant for strategic management, as well as investment purposes (Palepu, 1986; Powell, 2001; Danbolt et al., 2016). Given the high abnormal returns that accrue to such firms (Franks and Harris, 1989; Danbolt, 2004), a potentially lucrative investment strategy can be developed around takeover target prediction (Powell, 2001). Prior research has examined the factors that drive *TALI* and the extent to which these factors can be used to predict future takeover targets (see, for example, Palepu, 1986; Ambrose and Megginson, 1992; Powell, 1997, 2001; Powell and Yawson, 2007; Danbolt et al., 2016; Tunyi and Ntim, 2016). The evidence suggests that takeover targets are inefficiently managed, relatively undervalued, comparatively smaller (than acquirers), suffer from a mismatch between growth opportunities and resources, are young, have substantial tangible property and are likely to hail from "disturbed" industries (see, for, example, Ambrose and Megginson, 1992; Powell and Yawson, 2007 and Cremers et al., 2009). Notwithstanding, these studies concede that further research into the determinants of *TALI* is warranted as current prediction models have low predictive abilities and high levels of misclassification. Powell and Yawson (2007), for example, attribute the low predictive power of current prediction models to their finding that frequently adopted takeover prediction hypotheses explain other restructuring events such as bankruptcies, divestitures and employee layoffs. This study aligns with this literature.

Specifically, this study is motivated by the lack of consistent empirical support for one of the key hypotheses for takeover prediction—the firm size hypothesis. The hypothesis as put forward by Palepu (1986), and widely adopted across the takeover prediction literature (see, for example, Ambrose and Megginson, 1992; Powell, 1997, 2001, 2004; Powell and Yawson, 2007; Gorton et al., 2009; Cremers et al., 2009; Danbolt et al., 2016; Tunyi and Ntim, 2016), argues that *TALI* is decreasing with target firm size (henceforth, *SIZE*) i.e., small (large) firms are more (less) vulnerable to takeover bids. The rationale is that several size-related transaction costs are associated with acquiring a target and, therefore, the number of viable acquirers for a target decreases as its size increases. These costs can include the market price plus a premium for the target, M&A negotiation fees (adviser, consultants and investment banks, amongst others) and the cost of absorbing the target into the acquirer's operating framework (Palepu, 1986; Powell, 2001; Danbolt et al., 2016). In this paper, this is referred to as the "affordability" argument. Several studies, starting with Palepu's seminal study (Palepu, 1986) have tested the firm size hypothesis, with only a few (e.g., Palepu, 1986; Ambrose and Megginson, 1992; Brar et al., 2009) finding any empirical support. Other studies including Barnes (1999), Powell (1997, 2001, 2004), and more recently, Danbolt et al., (2016) and Tunyi and Ntim (2016) have tested this

hypothesis in different settings and found evidence of the contrary, i.e., *TALI* increases with *SIZE*. The present study, therefore, seeks to unpack this conundrum and redevelop a new firm size hypothesis by exploring the possibility of a non-linear *TALI–SIZE* relationship in isolation, as well as exploring how prevailing market conditions inform the acquirer’s choice of a suitable *SIZE*.

We advance three testable hypotheses explaining the relation between target firm size, market condition and *TALI*. These are discussed in detail in section 2.0. In summary, we first hypothesise (*H1*) that *TALI* is an inverse U-shaped function of *SIZE*, with mid-size firms most vulnerable to takeovers (when compared to their small and large counterparts). Our argument is that acquirers prefer comparatively larger targets, subject to transaction costs constraints. *H1* is consistent with several M&A theories including economies of scale, managerial hubris, managerial utility maximisation, empire-building, information asymmetry, and transaction costs. Specifically, we argue that managers seeking to achieve economies of scale, market power or, indeed, personal benefits (empire building, managerial utility maximisation) through M&As will be attracted to larger rather than smaller targets. Nonetheless, anti-trust regulation, high transaction costs and capital requirements will shield the largest firms from takeover activity. Our second (*H2*) and third (*H3*) hypotheses support *H1* by exploring how market conditions, specifically capital liquidity (i.e., the cost of finance or prevailing interest rates) and stock market growth (as a measure of market sentiment), potentially inform the acquirer’s choice of *SIZE*. Acquirers may respond to improvements in market conditions by pursuing growth through organic channels (i.e., internal growth) or inorganic channels (external growth such as through M&As). Contingent on the choice of inorganic growth, the acquirer can achieve growth through the acquisition of (1) several small firms, or alternatively, (2) a single large firm. Drawing from multiple perspectives (e.g., economies of scale, managerial hubris, managerial utility maximisation, empire-building, information asymmetry and transaction costs), we hypothesise (*H2*) that comparatively larger targets will be acquired in periods of high capital liquidity. Our third hypothesis is related to the second (*H2*), but explores the impact of aggregate market growth (a measure of market sentiment, see Danbolt et al., 2016) on the acquirers’ choice of target firm size. We hypothesise (*H3*) that market growth (and hence positive market sentiment) incentivises acquirers to pursue comparatively larger targets.

To our knowledge, *H1* is unique to our study. Prior studies generally argue that takeover likelihood declines with firm size (the firm size hypothesis) but find limited support for this hypothesis (Palepu, 1986; Powell, 1997; Danbolt et al., 2016; Tunyi et al., 2019). *H2* and *H3* build on prior studies (including Maksimovic and Phillips, 2001; Shleifer and Vishny, 2003; Harford, 2005 and Dong et al., 2006) exploring how market conditions drive aggregate levels of M&As (i.e., merger waves). We extend this literature by exploring how market conditions impact on the acquirers’ choice of suitable

targets (with a unique focus on *SIZE*). Finally, we explore whether we can partly address the misclassification problem in *TALI* prediction models (Powell, 1997; 2001; 2004; Powell and Yawson, 2007 and Danbolt et al., 2016), by accounting for the three relationships discussed in *H1-H3*. Our empirical analysis is based on a UK sample of 34,661 firm-year observations drawn from 3,105 unique firms and 1,396 M&A deals over a 30-year period (1987-2016).

Our study makes two main contributions to the literature. First, we develop a new firm size hypothesis which better explains the relationship between a firm's size and exposure to takeovers. To our knowledge, this is the first study to explain the lack of empirical support for the firm size hypothesis (Palepu, 1986, Danbolt et al., 2016). We find that, on average, acquirers tend to pursue comparatively larger targets subject to transaction cost constraints. Hence, mid-size firms tend to have comparatively higher *TALI* compared to their small and large counterparts. The largest firms are shielded from takeovers due to transaction costs constraints. The smallest firms are unattractive as targets as they, perhaps, do not allow the acquirer to address some of the motivations (e.g., economies of scale, managerial hubris, managerial utility maximisation and empire-building) or challenges (e.g., information asymmetry) of M&As. In support of this finding, we provide evidence on the impact of market conditions on the choice of *SIZE*. This part of our study aligns with the literature exploring how market conditions shape acquirers' choices. Particularly, we extend prior studies on merger waves (Mitchell and Mulherin, 1996; Rhodes-Kropf and Viswanathan, 2004; Martynova and Renneboog, 2008 and Gorton et al., 2009)², by showing that, *ceteris paribus*, acquirers tend to acquire comparatively larger targets in periods of high capital liquidity and market growth (or positive market sentiment).

Finally, in response to Powell (1997, 2001, 2004), Powell and Yawson (2007) and Danbolt et al. (2016), we show that the out-of-sample predictive ability of *TALI* models can be improved by re-specifying the *SIZE-TALI* relationship and including other relevant explanatory variables, specifically measures of capital liquidity and market growth, in existing *TALI* prediction models.

The rest of the paper is organised as follows; section 2.0 discusses the hypotheses, section 3.0 discusses the data and methodology, section 4.0 discusses the empirical results and section 5.0 presents concluding remarks.

² This literature suggests that takeovers are most likely to occur in periods of economic recovery, coinciding with rapid credit expansion, burgeoning external capital markets and stock market booms.

2.0 Hypothesis development

The firm size hypothesis (Palepu, 1986; Powell and Yawson, 2007; Danbolt et al., 2016) hinges on an “affordability” argument; *comparatively* smaller firms are easier to acquire due to lower implied acquisition costs. In the context of *TALI* modelling, this implicitly assumes some knowledge of the characteristics of the acquirer. Nonetheless, to mitigate look-ahead bias, a firm’s *TALI* is generally modelled *a priori*, i.e., with no knowledge of the identity or characteristics of the potential acquirer (Palepu, 1986; Powell, 1997, 2001, 2004; Powell and Yawson, 2007, Danbolt et al., 2016; Tunyi et al., 2019). Palepu’s (1986) “affordability” argument (proxied by firm size) is, perhaps, supported if *TALI* of a firm (e.g., firm *i*) increases with γ , the number of firms larger than firm *i*. This will imply that the smallest firms in the population face tremendous takeover threat, and, in time, will be absorbed by larger firms. By extension, over sufficient time, only large firms will continue to exist. Indeed, such a position of “eat or be eaten” is postulated by Gorton et al. (2009) and some empirical evidence on defensive takeovers in the US banking industry is provided in Louis (2004). Nonetheless, if Palepu’s argument is supported, an unbiased proxy for affordability should, perhaps, be γ and not the size of firm *i*. Here, γ should be positively related to *TALI* across the population, as the smallest firms have the largest γ , and vice versa. Considering the universe of potential acquirers, it is empirically challenging to estimate γ for each firm.

Firm size (as a proxy for affordability) is, perhaps, mainly consistent with an antitrust avoidance motive and a variable cost minimisation motive of takeovers but inconsistent with other established theories and motives of takeovers such as economies of scale, managerial hubris, market power, empire-building and transaction costs (Mueller, 1969; Roll, 1986; Hayward and Hambrick, 1997 and Kosnik and Shapiro, 1997). While the smallest firms in the population are the easiest to acquire (due to low capital requirement), their acquisition is unlikely to allow bidding managers to attain typical acquisition motives (e.g., economies of scale, managerial hubris, market power, empire-building). While bidding firms are likely to pursue targets that are comparatively smaller in size for transaction costs reasons (Palepu, 1996; Ambrose and Megginson, 1992; Powell, 1997 and Gorton et al., 2009), the creation of value by the acquirer through increased synergies and economies of scale/scope (Tirole, 1988) is, potentially, dependent on the size of the target. Similarly, acquirers seeking to generate market power, acquire undervalued firms (firm undervaluation hypothesis; Palepu, 1986) or consolidate their “empires” (empire-building theory; Mueller, 1969), are more likely to achieve such motives through the acquisition of larger rather than smaller targets. If managers are overconfident in their managerial ability, as evident by the tendency to overpay for targets (Roll, 1986; Hayward and Hambrick, 1997), given a choice of several targets, they are similarly more likely to pursue larger

rather than smaller targets. These extant M&A theories therefore suggest that comparatively larger targets are more attractive to acquirers.

A counter argument which breaks down the above logic is that acquirers may alternatively achieve these motives of M&As (i.e., economies of scale, managerial hubris, market power, empire-building) by acquiring and consolidating multiple small targets. Clearly, this is not observed in practice, perhaps, due to transaction costs involved in making multiple acquisitions. Specifically, transaction cost savings can be achieved by acquiring a single large firm (subject to resource constraints) rather than multiple small firms, due to fixed costs (e.g., search costs, due diligence, consultants' fees, management time and integration costs etc.) associated with M&A transactions (Kosnik and Shapiro, 1997). Hence, if “bigger is better” to acquirer managers, then a firm's *TALI* should generally increase with *SIZE*. Notwithstanding, high transaction costs, resource constraints and the limited number of comparatively larger firms (i.e., γ) can play an important role in shielding the largest firms from takeover threats. Further, regulatory authorities (e.g., the UK's Competitions and Markets Authority) are more likely to scrutinise deals involving the consolidation of the largest firms on competition grounds. This suggests the existence of an inverse U-shaped relation between a firm's size (*SIZE*) and *TALI*. The hypothesis is stated as follows;

H1: Given a representative sample of firms, takeover likelihood (TALI) increases with target firm size (SIZE) for small firms but declines with SIZE for large firms.

H1, if supported, will explain the results from prior studies—*TALI* is declining in firm size—as several prior studies limit their samples to large firms. For example, the Brar et al. (2009) study, which finds support for the firm size hypothesis, only covers firms with market capitalisation of at least \$100m. This result, while biased towards large firms, is consistent with *H1*, i.e., for large firms, there is a negative relation between *TALI* and *SIZE*.

The new firm size hypothesis is supported by exploring the effect of prevailing market conditions (particularly capital liquidity and stock market performance or market growth) on the acquirer's choice of target size. Capital liquidity—a measure of the availability, ease or cost of obtaining investment capital—appears to play a role in stimulating takeover activity. M&A transactions are generally high capital investments. Prior empirical evidence suggests that a high proportion of M&A transactions involve the use of cash (Danbolt, 2004 and Danbolt and Maciver, 2012). In a UK study, Danbolt (2004), for example, finds that over 95 percent (of 116) foreign acquirers and 30 percent (of 510) domestic acquirers use cash as the preferred method of payment. A high proportion of the remaining acquirers use cash in combination with equity and other alternatives as their preferred method of

payment (Danbolt, 2004). Danbolt and Maciver (2012) also show that UK acquirers have a high preference for cash over other methods of payment, with 44.6 percent of acquirers paying in cash, 45.4 percent using a mixed method and only 10 percent using equity exchange. Even in circumstances where equity is used, acquirers will, perhaps, require substantial cash resources to successfully absorb the target and complete post-merger reorganisation activities (Palepu, 1986; Danbolt et al., 2016).

Most firms are unlikely to have sufficient internally-generated cash resources to complete takeovers without relying on external funding either from equity or debt markets. Hence, the success of M&A activities is, perhaps, contingent on the availability of capital and the ease and costs at which capital can be obtained. This suggests that takeovers are more likely to occur in periods of high capital liquidity i.e., in periods when the cost of capital and prevailing interest rates are lower. Indeed, prior studies in the merger wave literature (e.g., Harford, 2005 and Maksimovic and Phillips, 2001) show that merger waves coincide with periods of high capital availability and high macro-level liquidity. These prior studies are, however, silent on the issue of how capital liquidity informs the size of acquisitions during such merger waves. Clearly, from the acquirer's perspective, the choice of target firm size is contingent on an acquirer's ability to raise finance. Given typical acquisition motives (e.g., economies of scale, managerial hubris, market power, empire-building), we hypothesise that acquirers are likely to pursue relatively larger targets (since they are more affordable) in periods of high capital liquidity. Our second hypothesis is stated as follows;

H2: Relatively larger takeover targets are more likely to be acquired in periods of high capital liquidity.

Our final hypothesis explores another market factor—market growth—and its impact on the *SIZE-TALI* relationship. Danbolt et al. (2016) suggest that market growth captures market sentiment as investor outlook is more positive in periods of market growth. Perhaps market growth or sentiment, as a timing factor, is also critical to the decision to acquire and choice of target size (*SIZE*). Prior research suggests that acquirers' propensity to engage and complete merger deals increases during periods of high stock market valuation and economic expansion (Maksimovic and Phillips, 2001; Shleifer and Vishny, 2003; Harford, 2005 and Dong et al., 2006). Harford (2005), for example, argues that this is because economic growth increases the likelihood of merger success while Rhodes-Kropf and Viswanathan (2004) and Dong et al. (2006) argue that, in the case of stock deals, such mergers are motivated by the acquirers' attempt to take advantage of their overvalued stocks. Again, prior literature is silent on how market growth or sentiment informs the acquirer's selection of a suitable target size. As in the case of market sentiment (*H2*), we similarly extend this literature by considering how market

growth can moderate the acquirer's choice of target size. Specifically, we contend that market growth (i.e., positive market sentiments) will incentivise acquirers to pursue relatively larger targets as this allows them to achieve classic motives of M&As (i.e., economies of scale, managerial hubris, market power, empire-building). Our third hypothesis is stated as follows;

H3: Relatively larger takeover targets are more likely to be acquired in periods of high market growth.

3.0 Data and Methodology

Modelling TALI

The approach to modelling *TALI* is consistent with Palepu et al. (1989), Cremers et al., (2009) and Danbolt et al., (2016). A logit regression framework is adopted, where the probability that a firm (*i*) will be acquired in any period (*t*) is a vector (*Z*) of its characteristics in the previous period (*t-1*). The base model is shown as follows:

$$P_{it} = \frac{1}{1+e^{-Z_{it-1}}} \quad (1)$$

where, P_{it} is the probability that firm *i* will be acquired in the current period (*t*) and Z_{it-1} is a vector of firm *i*'s characteristics in the previous period (*t-1*), given as follows:

$$Z_{it-1} = \beta_0 + \beta_1 X_{1it-1} + \beta_2 X_{2it-1} + \dots + \beta_k X_{kit-1} + \varepsilon_{it-1}, \quad (2)$$

In equation (1), the dependent variable (P_{it}) takes the value of one if a firm (*i*) is the subject of a takeover in a period (*t*), and a value of zero otherwise. In equation (2), β_0 is the intercept term and β_j ($j = 1, \dots, k$) represents the coefficients associated with the corresponding independent variables X_j ($j = 1, \dots, k$) for each firm. The main independent variables in this model are measures of firm size, capital liquidity and market growth, and their interactions (the interaction between firm size and capital liquidity and the interaction between firm size and market growth). These are discussed further below.

Following Soares and Stark (2009), we assume that most (UK) firms will only publish their financial result for the last year (*t-1*) by the end of June this year (*t*). This implies that any bid announcements made between 1st July year (*t*) and 30th June year (*t+1*) is based on financial results for year-end December year (*t-1*). This procedure is fully discussed in Soares and Stark (2009) and adopted in Danbolt et al. (2016). The lags imposed ensures that look-ahead bias in prediction analysis is mitigated, as a firm's *TALI* in period (*t*) is modelled as a function of its publicly available financial information in the last period (*t-1*). Additionally, this addresses one potential source of endogeneity—reverse causality.

Independent variables

Consistent with Powell (1997) and Powell and Yawson (2007), the natural log of total assets is used as a proxy of target firm size (*SIZE*).³ In additional tests, quintiles and quartiles are used to identify different *SIZE* subgroups. For example, mid-size firms are considered as those in quartiles 2 and 3. This is discussed in more detail in section 4.0.

Consistent with Harford (2005)⁴, capital liquidity is first measured as the spread (*iSPRD*) between the London Interbank Offer Rate (*LIBOR*) and the Bank of England Base Rate (*BOEBR*).⁵ A high spread, for example, indicates high cost of capital and, hence, low capital liquidity. Our second measure for capital liquidity is the change in the level of credit (from all sectors) to the non-financial sector (*dCRDT*) as a ratio of gross domestic product (GDP). Higher levels of credit (i.e., a positive change in the level of credit) is consistent with high capital liquidity. Consistent with Bi and Gregory (2011) and Danbolt et al. (2016), the performance of the FTSE All Share index is used to proxy for market growth or sentiment (*dMKT*). *dMKT* in each year is computed as the 12-month (ending June 30th) return on the FTSE All Share index.

Given that we want to explore interaction effects for logit models, as suggested by Ai and Norton (2003), we facilitate interpretation of our results by converting one of our interaction variables to a binary variable. We generate binary variables to capture capital liquidity (i.e., *iSPRDdummy* and *dCRDTdummy*) and market growth (i.e., *dMKTdummy*). Here, *iSPRDdummy* takes a value of 0 if *iSPRD* reduces by at least 5 percent from one year to the next, and a value of 1 otherwise.⁶ Similarly, *dCRDTdummy* and *dMKTdummy* take values of 1 if *dCRDT* and *dMKT*, respectively, increase by at least 5 percent from one year to the next, and values of 0 otherwise. The use of a “5 percent” threshold allows us to ignore small changes (i.e., less than 5 percent) in *iSPRD*, *dCRDT* and *dMKT* as such changes are unlikely to have a material effect on takeover activity.⁷ We use these binary measures of capital liquidity and market growth (*iSPRDdummy*, *dCRDTdummy* and *dMKTdummy*) in place of the continuous variables (*iSPRD*, *dCRDT* and *dMKT*) when exploring interaction effects.

3 In additional analysis (unreported), we find that results are robust to other measures of *SIZE* including market capitalisation and book value of equity.

4 Harford (2005) measures capital liquidity as the spread between the commercial and industrial loan rate and the US Federal Reserve Funds rate.

5 Monthly data is available from the Bank of England webpage. Rate changes from one month to another are slight. We first compute the month spread, then average this over the 12 month period.

6 This definition ensures that, consistent with our *iSPRD* variable, a low (0) *iSPRDdummy* indicates high capital liquidity, and vice versa.

7 Our results are stronger when we use larger thresholds (e.g., 7 and 10 percent) and weaker when we do not impose a threshold. In robustness tests, we have also considered other methods for converting *iSPRD*, *dCRDT* and *dMKT* into binary variables. For example, a binary variable that takes a value of 1 if the variable is above the median (or mean) value and a value of 0, otherwise. In general, the results are qualitatively similar, although their level of significance varies.

Control variables

Our analysis (*HI*) aims to explore the possibility of an inverse U-shaped relationship between *SIZE* and *TALI*. Hence, we need to also rule out the possibility that such a relationship, if it exists, is driven by other firm factors. The relationship between a firm's size, age and lifecycle is well documented outside the *TALI* modelling literature (Cabral and Matta, 2003; Hsieh and Klenow, 2014). Indeed, prior research suggests that new businesses start small but grow over time as they accumulate organisational capital or as the demand for their products rises (Atkeson and Kehoe, 2005). We explicitly control for firm lifecycle by including measures of firm lifecycle (Dickinson, 2011; Hasan and Cheung, 2018) as controls in the model. The derivation of these measures is explained in Table 1.

The remaining control variables in the model include commonly employed predictors of *TALI* (see, for example, Palepu, 1986; Powell, 1997; Brar et al., 2009; Danbolt et al., 2016) including return on capital employed (*ROCE*), average abnormal return (*AAR*), Tobin's Q (*TBQ*), sales growth (*SGW*), liquidity (*LIQ*), leverage (*LEV*), growth-resource mismatch dummy (*GRD*), free cash flow (*FCF*), tangible assets (*TANG*), firm age (*AGE*), the presence of large shareholders (*BLOC*), price momentum (*MOM*) and trading volume (*TVOL*). These variables, their rationale for inclusion and their full definitions are summarised in Table 1.

Finally, to take account of merger waves and industry variations in M&A activity, we also control for year and industry fixed effects using year and (2 digit SIC code) industry dummies.

[Insert Table 1 about here]

Sample and data sources

To empirically test the hypotheses, the sample of all firms (live and dead) listed on the main market of the London Stock Exchange between 1987 and 2016 is identified. Financials (SIC code 60-69) and utilities (SIC code 40-49) are excluded due to their unique reporting standards and regulations. A final sample of 3,105 unique firms is obtained. Accounting and stock returns data are collected from Thomson DataStream and M&A deal information from Thomson One. The focus is on merger deals (involving UK publicly listed targets) which, if completed, will give the acquirer control of the target (Ambrose and Megginson, 1992; Danbolt et al., 2016). The sample consists of 1,396 M&A deals involving non-financial and non-utility firms, announced between 1st June 1987 and 30th June 2018. The two datasets are matched using DataStream codes and time lags are imposed based on the June approach (Soares and Stark, 2009; Danbolt et al., 2016).⁸ Outliers are eliminated from the final dataset by winsorising, *ROCE*, *AAR*, *TBQ*, *SGW*, *LIQ*, *LEV*, *FCF*, *TANG*, *MOM*, *TVOL* at the 1st and 99th percentile. No adjustments are made to dummy variables, as well as *SIZE* and *AGE*. In untabulated

⁸ In general, this approach attributes M&A deals observed in one period/year (t) to firm characteristics in the previous period/year (t-1).

results, alternative outlier treatments are followed (e.g., winsorising at the 5th and 95th percentile), and results remain qualitatively similar. The final dataset is made up of 34,661 firm-year observations drawn from 3,105 firms and 1,396 M&A deals over a 30-year period (1987-2016). About 30 percent of the M&A deals in the dataset are initiated by cross-border acquirers from 48 distinct countries. A majority of cross-border deals (10 percent) involve US acquirers. The results of the hypotheses tests are discussed in the next section.

4.0 Results and Discussion

Acquirers seek comparatively smaller targets

To partly support our argument that transaction cost constraints push acquirers to seek comparatively smaller targets, we first compare the size of acquirers to the size of their corresponding targets using two different measures of size; market capitalisation and total assets. This analysis covers all M&A deals involving UK firms. We present the median of measures of relative (acquirer as a ratio of target) size in Table 2.⁹ Additionally, we explore whether the difference in the sizes of acquirers and targets is robust to deal characteristics (i.e., method of payments, origin of the acquirer, attitude of the acquirer, deal completion and acquirer public status).

[Insert Table 2 about here]

The results support the arguments of Palepu (1986) and Gorton et al. (2009), confirming that targets are, on average, smaller when compared to acquirers. In general, the average (median) acquirer is about 3 (4) times larger than the average (median) target. In terms of relative size of acquirer to target, the median acquirer has about 2.5 times the market capitalisation of its target. This increases significantly for certain deal types such as cash and cross-border deals. Cash and cross-border acquirers are about 6.5 and 5.1 times (respectively) larger than their targets. This relationship is consistent across different subsamples (i.e., public versus private acquirers, friendly versus hostile acquirers and completed versus failed deals), as well as different measures of firm size (i.e., total assets and market capitalisation). Overall, this suggests that ‘affordability’ plays an important role in the acquirer’s choice of a suitable target. This finding, however, does not necessitate a negative relation between *SIZE* and *TALI* as commonly hypothesised (see, Palepu, 1986; Barnes 1999; Powell, 2001; Powell, 2004; Powell and Yawson, 2007; Brar et al., 2009). Indeed, as will be shown (model 1, Table 3), when the full sample of firms is considered, consistent with the results in Powell and Yawson (2007), *TALI* appears to have a positive relation with *SIZE*. This study sheds light on this conundrum.

⁹ In untabulated analysis, we conduct t-tests and median tests to explore statistical significance of the differences in sizes of acquirers and targets. In all cases we find this difference to be statistically significant at the 1 percent level.

Mid-sized firms are more vulnerable to acquisitions

The first hypothesis (*H1*) argues that *TALI* initially increases with target firm size (i.e., *SIZE*) but declines after a certain size threshold is attained. That is, mid-size firms are most at risk of takeovers. A multivariate framework is used to explore the relation between *SIZE* and *TALI* by estimating logistic regressions (i.e., equations 1 and 2). In untabulated analyses, Pearson and Spearman correlations, as well as variance inflation factors, are first estimated to check for multicollinearity issues. The results show that the level of correlations among the independent variables is modest and unlikely to lead to multicollinearity concerns.¹⁰ Next, as in Table 3, different logistic regression models for *TALI* are estimated, with *SIZE* as the main predictor variable, while controlling for other drivers of *TALI* (noted in Table 1). The models also control for (2 digit SIC code) industry and year fixed effects. For brevity, we present marginal effects only.

[Insert Table 3 about here]

Model 1 uses *SIZE* as the main predictor variable and controls for different determinants of *TALI*. The results show that, when the full population of UK firms is considered, *TALI* generally increases with firm size (p-value of 0.002). To put the results into economic perspective, a unit increase in *SIZE* corresponds to a 0.3 percentage points increase in a firm's acquisition likelihood. These results, while counterintuitive, are consistent with Powell and Yawson (2007). They are also consistent with Danbolt et al. (2016) who find that *SIZE* is positively related to *TALI*, although their results are not statistically significant (p-value of 0.181). To shed further light, this relation is explored within different *SIZE* quintiles¹¹.

In models 2 to 6, we run the analysis for firms in different *SIZE* quintiles or subsamples (Q1 to Q5). The results show that *TALI* increases with *SIZE* for firms in Q1 (p-value of 0.000). The relation between *TALI* and *SIZE* is still positive and significant for firms in Q2 (p-value of 0.000). This relation reverts and becomes negative in the case of Q3 (p-value of 0.683). For Q4 and Q5, *TALI* is negatively related to *SIZE*. The relation for Q4 (Q5) is significant at the 10 (1) percent level.¹² In economic terms, a one unit increase in *SIZE* leads to a 2 (2.7) percentage points increase in *TALI* for firms in Q1 (Q2). On the contrary, the same one unit increase in *SIZE* leads to a 1.4 (1.2) percentage points decrease in *TALI* for firms in Q4 (Q5). The marginal effect for Q3 is small (-0.003), suggesting a weak relationship between *SIZE* and *TALI* for firms in Q3. Overall, the results show that *TALI* increases with *SIZE* for small firms (Q1 and Q2) but decreases with *SIZE* for larger firms (Q4 and Q5). (We again confirm this

¹⁰ The variance inflation factors are also under 2 in all cases. These results are available on request.

¹¹ These quintiles are generated by ranking firms by their total assets in each year and creating five (5) equal groups of firms based on their sizes.

¹² In robustness checks, we find that the results are consistent when we use of quartiles in place of quintiles.

directly in models 1 and 2 of Table 4.) By extension, if the above results are robust, we should find that the smallest (Q1) and largest (Q5) firms in the population are least vulnerable to takeovers. We test this directly, by exploring whether membership in Q1 and Q5 (relative to Q3), reduces a firm's vulnerability to takeovers (Table 3, model 7). Indeed, we find that this is the case; as in model 7, membership in Q1 and Q5 reduces *TALI* by 4.5 and 1.1 percentage points respectively. In essence, the results suggest that, within a sample of small firms, the largest firms are most vulnerable to takeovers. On the contrary, within a sample of large firms, the smallest firms are most vulnerable to takeovers. The latter finding is consistent with Brar et al. (2009) who find support for the firm size hypothesis in a sample of large European firms.

[Insert Table 4 about here]

We turn our attention to empirically establishing the nature of the relationship between *SIZE* and *TALI*. Since we hypothesise (*H1*) an inverse U-shaped relationship, we expect that, *ceteris paribus*, mid-size firms should have the highest *TALI*. We define “mid-size firms” as firms in (1) *SIZE* quartiles 2 and 3, (2) *SIZE* quintiles 2, 3, and 4 and (3) *SIZE* quintile 3. We use an indicator variable (*MSDY*) to identify mid-size firms.¹³ Model 3 of Table 4, tests the relation between *MSDY* (membership in *SIZE* quartiles 2 and 3) and *TALI*. The results suggest that mid-size firms have a higher *TALI* than their small (quartile 1) and large (quartile 4) counterparts. Taken together, this suggests an inverse U-shaped relation between *SIZE* and *TALI* with mid-sized firms most at risk of takeovers, when compared to their small and large counterparts. The next analyses (models 4 and 5), focus on modelling this non-linear relation by adding a squared term—firm size squared (*SIZEsq*)—to the model. In model 5, *SIZE* and *SIZEsq* are centred about their means. The results show that *TALI* has a positive (and significant) relation with *SIZE* (p-value of 0.000) and a negative (and significant) relation with *SIZEsq* (p-value of 0.000).

Overall, the results in Tables 3 and 4 are consistent with the first hypothesis. That is, the results show that, given a representative sample of firms, *TALI* initially increases with *SIZE* and later declines as *SIZE* exceeds some threshold. In other words, mid-size firms are more vulnerable to takeovers when compared to their small and large counterparts. Our results do not support Palepu's (1986) argument that *SIZE* and *TALI* are negatively related, at least in a UK sample. The evidence suggests that prior studies such as Brar et al. (2009) achieved empirical results consistent with Palepu's proposition, perhaps, due to sample selection bias, i.e., their sample is biased towards large firms. This issue is further confirmed in subsequent analyses. Finally, this non-linear relation can be easily captured by

¹³ The mid-size dummy (*MSDY*) takes a value of 1 for all firms in (1) *SIZE* quartiles 2 and 3, (2) *SIZE* quintiles 2, 3, and 4 and (3) *SIZE* quintile 3, and a value of 0, otherwise (i.e., for all firms in quartiles 1 and 4). The results are robust to the three definitions [(1) to (3)] of *MSDY*. We present results for (1) in Table 4.

including a squared term for *SIZE* in the model. The performance of this augmented model is also assessed later in this study

Larger firms are acquired in good market conditions

H2 and *H3* suggest that acquisitions targeting larger firms (targets) are more likely to be pursued in periods of good market conditions i.e., high capital liquidity (*H2*) and high market growth (*H3*). We test *H2* by exploring the interaction effect of capital liquidity (*iSPRD*, *dCRDT*) and market growth (*dMKT*) on the *SIZE*–*TALI* relationship. Table 5 presents marginal effects of a logit model with *TALI* as the binary dependent variable, measures of market conditions as the independent variable and a comprehensive set of control variables. As shown in models 1 and 2 of Table 5, we first establish that *TALI* increases with capital liquidity (*iSPRD*, *dCRDT*)¹⁴ and market growth (*dMKT*), after controlling for several firm characteristics (as shown in Table 1) and also for industry and year fixed effects. In economic terms, a unit increase in *iSPRD* (*dCRDT*) is associated with a 0.5 (16.7) percentage points decline (increase) in *TALI*. Similarly, a unit increase in *dMKT* leads to a 4.6 percentage points increase in *TALI*. These results are significant at the 5 percent level. The results complement prior studies on drivers of merger waves (Harford, 2005 and Maksimovic and Phillips, 2001), by showing that increases in capital liquidity and market performance coincide with an increase in firm-level *TALI*. Next, using binary versions of our key variables, we explore whether capital liquidity and market growth moderate the *SIZE*–*TALI* relation using interaction effects.

[Insert Table 5 about here]

In Table 5, models 4 to 6, we explore *H2* and *H3* directly by interacting (1) *iSPRDdummy* and *SIZE*, (2) *dCRDTdummy* and *SIZE*, and (3) *dMKTdummy* and *SIZE*. Consistent with our hypotheses, we find that capital liquidity (model 5) and market growth (model 6) moderate the *SIZE*–*TALI* relationship. In economic terms, a unit increase in *SIZE* leads to an additional 0.3 percentage point increase in *TALI* in periods of good market conditions (i.e., high capital liquidity and market growth) as opposed to poor market conditions. The results are significant at the 5 percent level. The results suggest that, other things being equal, larger targets are selected when cheaper financing is available (high capital liquidity; *iSPRDdummy*=0, *dCRDTdummy*=1) but comparatively smaller targets are selected when financing costs are high (low capital liquidity; *iSPRDdummy*=1 *dCRDTdummy*=0). Similarly, the results suggest that larger firms are more likely to be acquired in periods of high market growth (*dMKTdummy*=1). These results support our second (*H2*) and third (*H3*) hypotheses.

¹⁴ *iSPRD* captures the differences (spread) between LIBOR and the Bank of England Base rate. A lower spread indicates higher capital liquidity or availability of low-cost capital. On the contrary, *dCRDT* captures availability of credit. A higher value indicates higher capital liquidity.

Sample selection bias explains results in prior studies

In this section, we focus on explaining the Palepu (1986) finding—a negative relationship between *SIZE* and *TALI*—which is supported by Brar et al. (2009). Palepu (1986) uses a sample of 163 targets (between 1971 and 1979) and a sample of 256 non-targets (all drawn from 1979). Firm size increases naturally over time, partly driven by inflation. By not accounting for inflation amongst other factors, Palepu (1986) therefore compares “smaller” firms (targets from an earlier period, 1971 to 1979) to “larger” firms (targets from a later period, 1979). Hence, Palepu’s (1986) finding of a negative *SIZE–TALI* relation is partly driven by this sampling bias. We replicate Palepu’s sampling strategy¹⁵ in model 1 of Table 6 and obtain a similar result i.e., a negative relationship between *SIZE* and *TALI*.

[Insert Table 6 about here]

Brar et al. (2009) use a European sample of 294 targets and 722 non-targets. Their sampling is slightly different from Palepu’s (1986), as their targets and non-targets are drawn from different years between 1992 and 2003. Brar et al. (2009) uses the number of targets in each year to derive weights which determine the number of non-targets to match to their sample in each year. We argue that Brar et al. (2009) introduce sampling bias in their analysis by limiting their sample to firms with market capitalisation of at least \$100 million. We replicate the Brar et al. (2009) sampling procedure using our data. In the first instance (model 2 of Table 6), we do not limit our analysis to large firms (market capitalisation of at least \$100 million). In model 3, we impose this *SIZE* restriction. As expected, we find that *SIZE* is positively related to *TALI* in model 2 (p-value of 0.001) and negatively related to *TALI* in model 3 (p-value of 0.000).

The matching procedure does not appear to make a significant difference to our findings. Our main results in Tables 3 and 4 are based on a full sample (panel) of live and dead firms. We find that we can replicate our results using two alternative matching procedures frequently used in the literature. Firstly, we use a random matching procedure where we randomly select an equal number of non-targets to match to the targets in our sample (see models 4 and 5). Secondly, as in models 6 and 7, we apply a propensity score matching (PSM) procedure where we select non-targets that are closest to our targets in terms of firm characteristics including *ROCE*, *SGW*, *LIQ*, *LEV*, *AGE*, *LCIN*, *LCMT*, *LCDC* and *BLOC* (see Table 1).¹⁶

¹⁵ That is, we use targets from the period 1987-2016 and match these with non-targets from 2016.

¹⁶ We exclude other firm characteristics in Table 1 in order to satisfy the balancing property of PSM.

Unlike random matching, PSM allows us to directly control for observable differences in firm characteristics between targets (treated group) and non-targets (control group) prior to assessing the relationship between *SIZE* and *TALI* (Rosenbaum and Rubin, 1983; Rubin, 2001). In our analyses, we find that all treated observations are “on support” with no observations “off support” indicating a significant overlap in (or matching of) propensity scores for the treated and control groups. Our PSM achieves low bias across all variables, with a mean (median) percentage of bias of 2% (2.1%). Our values of Rubin’s B and Rubin’s R are 7.90 and 0.72, respectively, indicating that our samples are sufficiently balanced (Rubin, 2011). We employ pair matching (one-to-one matching without replacement) and nearest-neighbour (30 and 50) matching algorithms to select observations for inclusion in our regression analysis. The results from these different algorithms are qualitatively similar. Hence, for brevity, we only report the results from the former. The results from models 5 and 7 suggest that the inverse U-shape relationship which we hypothesise (*H1*), is robust to the choice of matching procedure.

An augmented prediction model achieves better out-of-sample performance

The analysis is extended here by evaluating whether these new hypotheses can be used to improve the performance of prior prediction models. This is assessed by comparing a null model (which uses only firm size and control variables as inputs) versus a new model (which uses *SIZE*, *SIZE* squared, capital liquidity, market growth, the product of *SIZE* and capital liquidity and control variables). The performance of the null model (M1) versus the new model (M2) is evaluated using standard Receiver Operating Characteristic (ROC) curve analysis. Here, the area under the ROC curve (AUC) for M1 and M2 is computed and the statistical significance of the difference in AUC is assessed using the DeLong et al. (1988) methodology.¹⁷ Several pseudo R-squares for the two models are also computed and analysed. The results are presented in Figure 1.

[Insert Figure 1 about here]

The AUC of the null model (M1) is 59.79 percent while that of the new model (m2) is 65.42 percent. The difference in AUC of 5.63 percentage points is statistically significant (p-value of 0.000). Six (6) different pseudo R-squares for the two different models including McFadden’s, McFadden’s Adjusted, Maximum Likelihood, McKelvey and Zavoina’s, Cragg & Uhler’s and finally, Efron’s R-squares, are computed. In all six (6) cases, the pseudo R square of the new model (M2) is at least

¹⁷ AUC comparisons are based on the non-parametric method discussed in DeLong et al. (1988). A model whose ROC curve equal to the diagonal line in Figure 1 (i.e., AUC = 0.50) has a predictive ability akin to a random guess. The bigger the differential between a model’s ROC curve and the diagonal line (i.e., the larger its AUC), the higher is its predictive ability. A perfect model has an AUC of 1.

double that of the null model (M1). Together this provides evidence that the new hypotheses increase the model's ability to correctly classify targets and non-targets. While these pseudo R-squares appear low, they are generally consistent with the results of prior studies (Powell and Yawson, 2007; Tunyi et al., 2019).

Finally, both models' ability to predict targets in a real-life setting (i.e., out of sample) are directly tested following the procedure in Danbolt et al. (2016). To achieve this, model parameters computed in one period are used to estimate *TALI* in the next period (out-of-sample). That is, data from T_0 (i.e., 1987) to T_n (e.g., 1996) is used to develop model parameters which are then used to estimate firms' *TALI* in T_{n+1} (i.e., 1997). All firms in T_{n+1} (i.e., 1997) are then ranked by their *TALI* and the 20 percent of firms with the highest *TALI* are included in the portfolio of predicted targets. This process is replicated over the 20-year period (1997 to 2016), always using T_0 (1987) as a starting point.¹⁸ Model performance is evaluated as the percentage of actual targets in the portfolio of predicted targets (i.e., target portfolio concentration) in each year and over the 20 years.

The new model achieves an average target concentration of 7.7 percent per year while the null model achieves a lower average target concentration of 6.5 percent per year over the 20-year period. The difference in mean (target concentration) is statistically significant with a p-value of 0.024. The null model only outperforms the new model in 4 (2003, 2011, 2012 and 2016) out of 20 years. This provides further evidence of the relevance of the new hypotheses to *TALI* modelling. It is worth noting that an augmented model that only incorporates *HI* i.e., includes *SIZESq*, also performs considerably better than the null model. It achieves a target concentration of 7.9 percent and similarly outperforms the null model in 16 out of 20 years. The difference in mean (predictions) between this augmented model and the null is statistically significant with a p-value of 0.002. The out-of-sample performance results for the null, augmented and new models are summarised in Figure 2.

[Insert Figure 2 about here]

Additional analyses and robustness checks

Throughout the study, robustness has been ensured by exploring different variable definitions and model specifications. For example, in untabulated results, market capitalisation is used as an alternative measure of firm size with results remaining robust. Also, quartiles are used as an alternative to quintiles when deriving subsamples in Tables 3 and 4, with results remaining robust. We have explored alternative definitions of our control variables, such as the use of ROA (defined as net profit to total asset ratio) in place of ROCE, amongst others, and the main results generally remain robust.

¹⁸ In the next year, for example, data from 1988 to 1997 is used to develop model parameters. These parameters are then used to estimate takeover likelihood for firms in 1998.

We have also explored whether the results are robust across different time periods (i.e., 1987–1996, 1997–2006, and 2007–2016) and found this to be the case.

In this section, we present results for two additional tests we have conducted to strengthen our findings. Our first test considers an alternative measure of market conditions—market intensity—and the second test explores whether our results are robust to endogeneity issues.

Hajbaba and Donnelly (2013) suggest that takeover profitability increases with market (M&A) intensity (*MrktIntensity*) which they measure as the natural log of the number of acquisitions in the 12 months prior to the year of acquisition. They define *HOT* (*COLD*) periods as periods when *MrktIntensity* is greater (less) than the median for the study period. We complement Hajbaba and Donnelly (2013) by exploring whether *MrktIntensity* (as a measure of market conditions) explains *TALI* and moderates the relation between *SIZE* and *TALI*. The correlation between *HOT* (or *MrktIntensity*), *dMKT* and *iSPRD* are low, suggesting that these variables capture different elements of market conditions. The current study has focused on *dMKT* and *iSPRD*, but here, it is shown that the results are broadly consistent with alternative measures of market conditions (i.e., *HOT* or *MrktIntensity*). We find that *TALI* increases with *MrktIntensity* (model 3) and *HOT* (model 4). Consistent with *H2* and *H3*, we also find that comparatively larger firms are acquired during *HOT* periods (model 5). Finally, as shown in models 1 and 2, our main results (*H1*) are robust across *HOT* and *COLD* periods.

[Insert Table 7 about here]

Our main results are also susceptible to endogeneity issues. Our use of the full sample of all live and dead firms reduces exposure to sample selection and self-selection bias. We have also used an extensive set of control variables and have controlled for industry and year fixed effects, partly addressing the issue of omitted variable bias. To partly address reverse causality or simultaneity bias, we have lagged our independent variables by one year (see equation 1). However, *SIZE* and other financial (control) variables are endogenous covariates which may bias the coefficients and standard errors of our regressions. In essence, the relation between *SIZE* and *TALI* may capture the relation between a set of underlying drivers of *SIZE* (i.e., our control variables) and *TALI*. To address this source of endogeneity in our non-linear (i.e., logit model), we follow Hasan and Cheung (2018) and implement a two-stage residual inclusion (2SRI) approach. Using this approach, we purge *SIZE* of its other drivers (i.e., endogenous covariates), and extract the component of *SIZE* which is unrelated to these other variables. Here, we first identify a suitable instrument for firm size.¹⁹ In our case, we use the average size of the other firms in a firm’s (two digit SIC code) industry in each year as an

¹⁹ We conduct a number of tests for relevance and overidentification to confirm this.

instrument for firm size (*SIZE*). We then regress *SIZE* on its instrument and all other control variables in Table 1. We extract the residual from this equation and use it as a “clean” measure of *SIZE*, i.e., the portion of *SIZE* which is unexplained by all other covariates. We term this residual *SIZE* (*rSIZE*). We run all our main analysis again, using *rSIZE*. Our results are presented in the Appendix (Table 1A). Our main results in Tables 3 and 4 remain robust. However, as shown in panel B of Table 1A, when using this more stringent measure of *SIZE*, we find that the interaction effect documented in Table 5 is significant for market growth (*H3*) but not for capital liquidity (*H2*).

5.0 Summary and conclusion

This study explores (1) the relation between target firm size (*SIZE*) and takeover likelihood (*TALI*) and (2) how prevailing market conditions, specifically capital liquidity and market growth, shapes an acquirer’s choice of target firm size. It employs data from a UK panel of 34,661 firm-year observations drawn from 3,105 firms and 1,396 M&A deals over a 30-year period (1987-2016). About 30 percent of the M&A deals involve cross-border acquirers from 48 distinct countries (with 10 percent of deals from US acquirers), making the results potentially generalisable to contexts beyond the UK.

Among other things, the study responds to calls for further research into factors moderating a firm’s acquisition likelihood. The findings confirm assertions that acquirers seek comparatively smaller targets but show that this does not justify the widely held view that *TALI* decreases with target firm size (*SIZE*). The empirical evidence in support of this misconception appears to suffer from sample-selection bias, specifically, the truncation of samples by excluding small firms and the use of non-random sampling strategies. When a representative sample of firms is considered, mid-size firms appear to be more vulnerable to acquisitions. That is, *TALI* increases with *SIZE* until a threshold after which it declines as *SIZE* increases. While small firms are affordable, their acquisition, perhaps, does not allow acquirers to fully realise some of the documented motives or drivers of takeovers such as economies of scale, managerial hubris, market power and empire-building. The largest firms, meanwhile, are shielded from acquisitions due to the prohibitive transaction costs, resource constraints and the limited number of viable acquirers. Our results lend support for potential value-destroying motives in M&As (managerial hubris, manager utility maximisation, and empire building) and the finding that, on average, acquirers experience negative abnormal announcement returns during M&As. Future research might thus directly explore the extent to which *SIZE* captures different value-destroying motives in M&A.

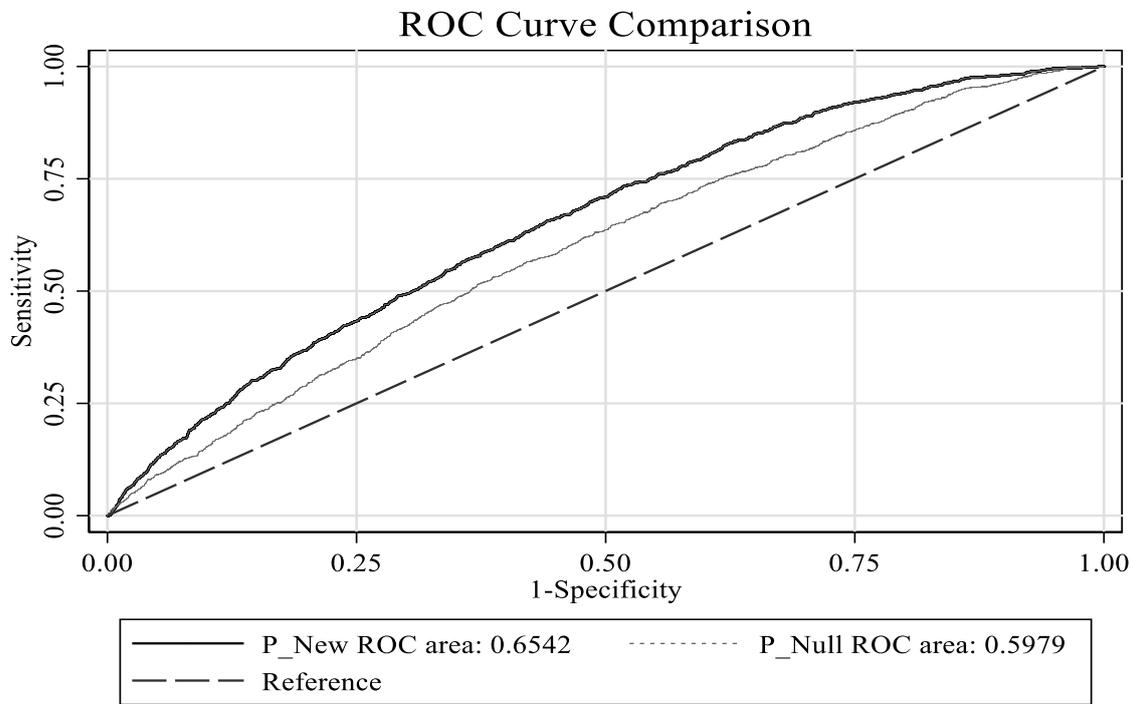
The results reveal that the acquirer’s choice of target firm size appears to be shaped, in part, by prevailing market conditions. That is, comparatively larger targets are more likely to be acquired when

market conditions are good. This highlights the important role of outside market conditions on firm acquisition decisions. This finding has implications for policy-makers, as the evidence suggests that an outcome of monetary policies (i.e., a reduction in interest rates to increase money supply and the availability of credit) shapes firm M&A decisions, specifically, the choice of target firm size. Indeed, positive market conditions (e.g., through improvements in capital liquidity or increased availability of credit) encourages acquirers to pursue larger targets. This may lead to a more active market for corporate control, hence, improved economic outcomes (e.g., efficient allocation of capital, employment and output).

Finally, the study also has implications for takeover prediction modelling (by researchers and practitioners) for investment purposes. Due to the substantial returns to takeover targets, several prior studies seek to explore the extent to which prediction models can form the basis of a profitable investment strategy. The findings reveal that the newly documented relation between target firm size, market conditions and *TALI* can inform the development of an improved *TALI* prediction model in a practical setting. The improvement arises from recognising the non-linear nature of the *SIZE–TALI* relationship, as well as accounting for the interaction effect between *SIZE* and market conditions when modelling *TALI*. Future studies can explore whether these documented improvements in *TALI* models translate to positive abnormal returns net of costs, when these models are used in an investment setting.

Tables and Figures

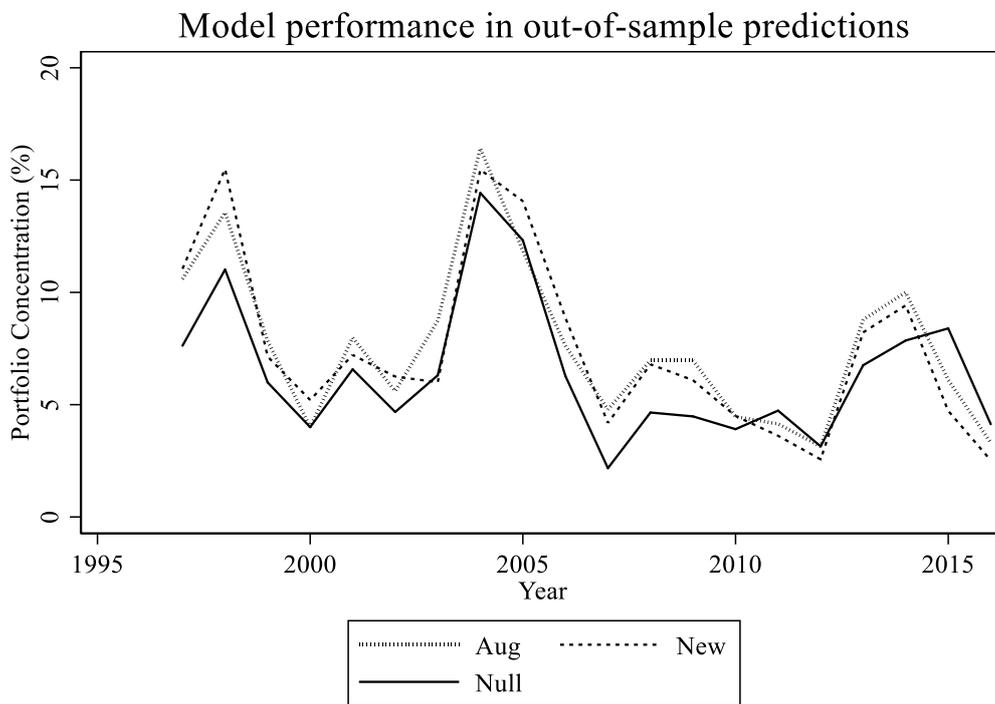
Figure 1: ROC curve analysis and model performance statistics



	<i>M1 (Null)</i>	<i>M2 (New)</i>	<i>Difference (p-value)</i>
<i>Pseudo R-squares</i>			
<i>McFadden's R2</i>	0.017	0.038	
<i>Maximum Likelihood R2</i>	0.007	0.015	
<i>McKelvey and Zavoina's R2</i>	0.079	0.195	
<i>McFadden's Adj R2</i>	0.013	0.033	
<i>Cragg & Uhler's R2</i>	0.020	0.045	
<i>Efron's R2</i>	0.006	0.014	
<i>ROC Area</i>	0.5979	0.6542	0.0563*** (0.000)
<i>OBS.</i>	24308	24308	

Notes: The figure presents ROC curves for New and Null models. The area under the curves (AUC) captures the models' classification ability. Alternative measures of pseudo R-squares are presented for the null and new models. *** indicates statistical significance at the 1 percent level.

Figure 2: Out-of-sample predictive ability of the null versus the new model



Notes: The figure presents results for out-of-sample predictions made by the models (New versus Null) over a 20-year period (1997-2016). Target portfolio concentration measures the number of true-positives as a percentage of total predictions made by the New and Null models.

Table 1: Control variables for modelling takeover likelihood (*TALI*)

Control variable, rationale and reference	Variable definition and computation and expected sign
<p>Life cycle: Firm lifecycle theory explains firm entry and exit from an industry. Shake-out and declining phases are characterised by firms leaving the industry e.g., through takeovers (Dickinson 2011; Hasan and Cheung, 2018).</p>	<ul style="list-style-type: none"> ✓ <i>LCIN</i> (+/-) is an indicator variable which identifies firms in the introductory stage of their lifecycle. It takes a value of 1 if a firm's cash flow from operating activities (CFO) is negative (i.e., CFO<0), its cash flow from investing activities (CFI) is negative (i.e., CFI<0) and its cash flows from financing activities (CFF) is positive (i.e., CFF>0). ✓ <i>LCGR</i> (+/-) identifies firms in the growth stage. It takes a value of 1 if CFO>0, CFI<0 and CFF>0. ✓ <i>LCMT</i> (+/-) identifies firms in the maturity stage. It takes a value of 1 if CFO>0, CFI<0 and CFF>0. ✓ <i>LCDC</i> (+/-) identifies firms in the decline stage. It takes a value of 1 if CFO<0 and CFI>0. ✓ <i>LCSH</i> (+) identifies firms in the shake-out stage. It identifies all observations not classified under the any of the other four stages.
<p>Inefficient management: <i>TALI</i> decreases as a firm's performance increases (Palepu, 1986; Powell 2001).</p>	<ul style="list-style-type: none"> ✓ <i>ROCE</i> (-) is the ratio of EBIT to total capital employed. ✓ <i>ADAR</i> (-) (average daily abnormal returns) is the average daily abnormal return computed using the capital asset pricing model.
<p>Undervaluation: <i>TALI</i> increases with the level of firm undervaluation</p>	<ul style="list-style-type: none"> ✓ <i>TBQ</i> (-) (Tobin's Q) is estimated as the sum of the book value of debt (i.e., the difference between the book value of assets and the book value of equity) and the market value of equity, scaled by the book value of assets.
<p>Growth-resource mismatch: Low-growth-resource-rich firms as well as high-growth-resource-poor firms have a high <i>TALI</i> (Palepu, 1986; Danbolt et al., 2016).</p>	<ul style="list-style-type: none"> ✓ <i>SGR</i> (+/-) (sales growth) is the percentage change in total revenues from the previous period. ✓ <i>LIQ</i> (+/-) (liquidity) is the ratio of cash and short-term investments to total assets. ✓ <i>LEV</i> (+/-) (leverage) is the firm's debt to equity ratio. ✓ <i>GRDY</i> (+/-) (growth-resource dummy) takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources, and a value of 0 otherwise.
<p>Free cash flow: <i>TALI</i> increases with a firm's level of free cash flow (Danbolt et al., 2016).</p>	<ul style="list-style-type: none"> ✓ <i>FCF</i> (+) is the ratio of free cash flow (operating cash flow minus capital investments) to total assets.
<p>Tangible assets: <i>TALI</i> increases with the proportion of tangible assets in a firm's total asset portfolio (Ambrose and Megginson, 1992; Danbolt et al., 2016).</p>	<ul style="list-style-type: none"> ✓ <i>TANG</i> (+) (tangible assets) is the ratio of tangible assets (property, plant and equipment) to total assets.
<p>Firm age: <i>TALI</i> decreases with firm age (Danbolt et al., 2016).</p>	<ul style="list-style-type: none"> ✓ <i>AGE</i> (-) is the natural log number of years since incorporation.
<p>Block holders: <i>TALI</i> increases with the presence of large shareholders (Cremers et al., 2009; Danbolt et al., 2016).</p>	<ul style="list-style-type: none"> ✓ <i>BLOC</i> (+) (block holder's dummy) takes a value of 1 if a firm has a significant shareholder (5 percent or more shareholding) in the 90days to June of each year.

<p>Price Momentum: Active trading potential signals to arrival of takeover bids (Brar et al., 2009; Danbolt et al., 2016).</p>	<p>✓ <i>MOM</i> (+) (momentum) is the t-statistic of a trend line slope fitted to logged daily stock prices over the 90 trading days to June each year.</p>
<p>Trading Volume: High trading volume signals the arrival of potential takeover bids (Brar et al., 2009; Danbolt et al., 2016).</p>	<p>✓ <i>TVOL</i> (+) (trading volume) is the proportion of outstanding shares traded over the 90 days to June each year.</p>

Table 2: Ratio of acquirer to target size (relative size)

		Market Capitalisation	Total Assets
All deals		2.48	1.23
Method of Payment	Cash	6.57	6.65
	Non-cash	2.63	1.72
	Stock	2.39	1.17
	Non-stock	3.87	5.02
Origin of the acquirer	Cross border	5.07	5.63
	Domestic	3.19	2.66
Attitude of the acquirer	Friendly	3.72	4.61
	Hostile	2.41	1.98
Deal status	Completed	3.81	4.61
	Failed	1.85	1.87
Public status of acquirer	Public	3.32	3.01
	Private	-	4.68

Notes: This table presents the median of the relative size of acquirers to targets (size of acquirers divided by size of targets). Market capitalisation and total assets are used as proxies for firm size.

Table 3: Target size and takeover likelihood (TALI) across different size subsamples

	<i>ALL</i>	<i>Q1</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5</i>	<i>ALL</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>SIZE</i>	0.003*** (0.002)	0.020*** (0.000)	0.027*** (0.000)	-0.003 (0.683)	-0.014* (0.062)	-0.012*** (0.000)	
<i>Q1</i>							-0.045*** (0.000)
<i>Q2</i>							-0.013*** (0.002)
<i>Q4</i>							0.005 (0.276)
<i>Q5</i>							-0.011** (0.013)
<i>LCGR</i>	0.027 (0.304)	0.296*** (0.000)	0.058 (0.315)	-0.006 (0.933)	0.068 (0.309)	0.030 (0.596)	0.027 (0.308)
<i>LCMT</i>	0.035** (0.019)	0.299*** (0.000)	0.085** (0.016)	-0.010 (0.751)	0.063 (0.211)	-0.056** (0.043)	0.037** (0.012)
<i>LCSH</i>	0.026* (0.065)	0.283*** (0.000)	0.060* (0.074)	-0.004 (0.893)	0.053 (0.273)	-0.053** (0.037)	0.027** (0.050)
<i>LCDC</i>	0.010 (0.486)	0.265*** (0.000)	0.046 (0.162)	-0.008 (0.777)	0.030 (0.537)	-0.061** (0.046)	0.011 (0.413)
<i>ROCE</i>	0.003 (0.352)	0.002 (0.453)	-0.002 (0.749)	-0.003 (0.743)	0.002 (0.824)	-0.003 (0.758)	0.002 (0.561)
<i>AAR</i>	-1.609*** (0.007)	0.100 (0.878)	-1.108 (0.299)	0.749 (0.596)	-4.666*** (0.006)	-5.380*** (0.002)	-1.431** (0.016)
<i>TBQ</i>	-0.005*** (0.001)	0.002*** (0.003)	-0.003 (0.260)	-0.012*** (0.002)	-0.010*** (0.006)	-0.005 (0.392)	-0.004*** (0.005)
<i>SGW</i>	-0.002 (0.195)	-0.000 (0.935)	-0.008** (0.043)	-0.002 (0.513)	0.000 (0.926)	-0.019 (0.304)	-0.003 (0.166)
<i>LIQ</i>	-0.010 (0.350)	-0.009 (0.419)	0.015 (0.406)	-0.032 (0.231)	0.006 (0.857)	0.001 (0.985)	-0.006 (0.596)
<i>LEV</i>	0.004 (0.683)	-0.009 (0.534)	-0.011 (0.655)	0.019 (0.391)	0.056** (0.014)	-0.019 (0.377)	0.011 (0.215)
<i>GRD</i>	-0.000 (0.943)	0.002 (0.778)	0.011 (0.160)	-0.005 (0.612)	-0.012 (0.298)	0.004 (0.659)	-0.000 (0.913)
<i>FCF</i>	0.037*** (0.003)	0.002 (0.880)	0.014 (0.548)	0.041 (0.322)	0.035 (0.519)	0.037 (0.546)	0.031** (0.019)
<i>TANG</i>	0.019*** (0.003)	-0.015 (0.223)	-0.001 (0.921)	-0.000 (0.984)	0.026 (0.116)	0.043*** (0.008)	0.018*** (0.007)
<i>AGE</i>	-0.010*** (0.000)	-0.004* (0.094)	-0.008** (0.022)	-0.015*** (0.000)	-0.011*** (0.003)	-0.008* (0.052)	-0.009*** (0.000)
<i>BLOC</i>	-0.008 (0.204)	-0.004 (0.604)	-0.023* (0.088)	-0.039*** (0.010)	0.009 (0.577)	0.035** (0.031)	-0.012* (0.063)
<i>MOM</i>	-0.001 (0.694)	0.003* (0.084)	0.001 (0.670)	-0.001 (0.649)	-0.010*** (0.005)	0.005 (0.175)	-0.001 (0.590)
<i>TVOL</i>	-0.002 (0.810)	0.000 (0.701)	0.006** (0.013)	-0.028** (0.014)	-0.016* (0.064)	-0.007 (0.198)	-0.000 (0.985)
<i>Observations</i>	21,991	4,150	4,736	4,776	4,471	3,839	21,991
<i>Industry FE</i>	YES	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES	YES	YES

Notes: The table presents logit regression results (marginal effects) for a takeover likelihood (*TALI*) model (see equations 1 and 2). The dependent variable is a binary variable which takes a value of 1 if a firm receives a takeover bid in period t and a value of 0, otherwise. The main independent variables are the natural log of total assets (*SIZE*) and a dummy which captures membership in the smallest *SIZE* quintile (*Q1*) and a dummy which captures membership in the largest *SIZE* quintile (*Q5*). All control variables are discussed in Table 1. Models control for industry (*Ind*) and year fixed effects (FE). The independent and control variables are lagged by one year. Model 1 uses the full dataset. In models 2 to 6, the dataset is split into 5 quintiles (subsamples) of firm size, with *Q1* representing the smallest 20 percent of firms and *Q5*, the largest 20 percent of firms. The same logit regression as in (1) is run for each subsample. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 4: Target size and takeover likelihood (*TALI*)

	<i>Q1&Q2</i> (1)	<i>Q3,Q4&Q5</i> (2)	<i>Mid-size</i> (3)	<i>Squared</i> (4)	<i>Centred</i> (5)
<i>SIZE</i>	0.023*** (0.000)	-0.005*** (0.000)		0.150*** (0.000)	0.009*** (0.000)
<i>SIZEsq</i>				-0.004*** (0.000)	-0.004*** (0.000)
<i>MSDY</i>			0.024*** (0.000)		
<i>Controls</i>	YES	YES	YES	YES	YES
<i>Observations</i>	8,886	13,105	21,991	21,991	21,991
<i>Industry FE</i>	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES

Notes: The table presents logit regression results (marginal effects) for a takeover likelihood (*TALI*) model (see equations 1 and 2). The dependent variable is a binary variable which takes a value of 1 if a firm receives a takeover bid in period t and a value of 0, otherwise. The main independent variables are the natural log of total assets (*SIZE*), the square of *SIZE* (*SIZEsq*) and a mid-size dummy (*MSDY*) which captures membership in *SIZE* quartiles 2 and 3. The control variables (suppressed for brevity) include all variables in Table 1. Models also control for industry and year fixed effects (FE). The independent and control variables are lagged by one year. Q1 to Q5 represent 5 quintiles of firm size, with Q1 representing the smallest 20 percent of firms and Q5, the largest 20 percent of firms. Model 1 conducts the regression using the smallest 40 percent of firms (Q1 and Q2), while model 2 conducts the regression using the largest 60 percent of firms (Q3 to Q5). In models 4 and 5, the square of firm size (*SIZEsq*) is added to the model. In model 5, *SIZE* and *SIZEsq* are centred about their means. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 5: Target size, market conditions and takeover likelihood (*TALI*)

	(1)	(2)	(3)	(4)	(5)	(6)
<i>iSPRD</i>	-0.005** (0.034)					
<i>dCRDT</i>		0.167*** (0.000)				
<i>dMKT</i>			0.046*** (0.000)			
<i>iSPRDdummy</i>				-0.009*** (0.003)		
<i>iSPRDdummy*SIZE</i>				-0.003** (0.046)		
<i>dCRDTdummy</i>					-0.003 (0.451)	
<i>dCRDTdummy*SIZE</i>					0.003** (0.016)	
<i>dMKTdummy</i>						0.004 (0.186)
<i>dMKTdummy*SIZE</i>						0.003** (0.012)
<i>SIZE</i>	0.003*** (0.003)	0.003*** (0.002)	0.003*** (0.005)	0.003*** (0.002)	0.003*** (0.003)	0.003*** (0.002)
<i>Controls</i>	YES (0.000)	YES (0.000)	YES (0.000)	YES (0.000)	YES (0.000)	YES (0.000)
<i>Observations</i>	21,991	21,991	20,793	21,991	21,991	21,991
<i>Industry FE</i>	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES	YES

Notes: The table presents logit regression (marginal effects) results for a takeover likelihood (*TALI*) model (see equations 1 and 2). The dependent variable is a binary variable which takes a value of 1 if a firm receives a takeover bid in period *t* and a value of 0, otherwise. The main independent variables are measures of capital liquidity (*iSPRD*, *dCRDT*, *iSPRDdummy*, *dCRDTdummy*), market growth (*dMKT*, *dMKTdummy*) and target firm size (*SIZE*). *iSPRD* is the spread between LIBOR and the Bank of England base rate. *dMKT* in each year is computed as the yearly return on the FTSE all share index. *dCRDT* is computed as the percentage change in the level of credit (from all sectors to non-financial sector) to gross domestic product. *iSPRDdummy* takes a value of 0 if *iSPRD* reduces by at least 5 percent from one year to the next, and a value of 1 otherwise. *dCRDTdummy* takes a value of 1 if *dCRDT* increases by at least 5 percent from one year to the next and a value of 0, otherwise. *dMKTdummy* takes a value of 1 if *dMKT* increases by at least 5 percent from one year to the next and value of 0, otherwise. *dCRDTdummy*SIZE*, *dMKTdummy*SIZE* and *iSPRDdummy*SIZE* captures interaction effects between the respective variables. The marginal effects for the interaction are computed based on the difference between the average marginal effects for *SIZE* evaluated in turn for high and low market conditions. The control variables (suppressed for brevity) include all variables in Table 1. Models also control for industry and year fixed effects (FE). The independent and control variables are lagged by one year. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 6: Target size and takeover likelihood under alternative sampling strategies

	<i>Palepu</i>	<i>Brar et al.</i>		<i>Random</i>		<i>PSM</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>SIZE</i>	-0.040*** (0.000)	0.018*** (0.001)	-0.028*** (0.000)	0.012** (0.040)	0.714*** (0.000)	0.016** (0.019)	0.767*** (0.000)
<i>SIZEsq</i>					-0.019*** (0.000)		-0.020*** (0.000)
<i>Controls</i>	YES	YES	YES	YES	YES	YES	YES
<i>Obs</i>	1,707	3,483	1,902	2,931	2,931	2,234	2,234
<i>Industry FE</i>	YES	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	NO	NO	NO	YES	YES	YES	YES

Notes: The table presents logit regression results (marginal effects) for a takeover likelihood (*TALI*) model (see equations 1 and 2) under alternative sampling strategies. The dependent variable is a binary variable which takes a value of 1 if a firm receives a takeover bid in period t and a value of 0, otherwise. The main independent variables are the natural log of total assets (*SIZE*) and the square of *SIZE* (*SIZEsq*). The control variables (suppressed for brevity) include all variables in Table 1. Models also control for industry and year fixed effects (FE). The independent and control variables are lagged by one year. Model 1 presents results when the Palepu (1986) sampling approach is adopted. Model 2 presents results when the Brar et al. (2009) sampling methodology is adopted but the sample is not constraint to firms with a market capitalisation of at least \$100 million. Model 3 is similar to 2, but restricts the sample to firms with market capitalisation of at least \$100 million. Models 4 and 5 show results when a random 1-to-1 (i.e., one target to one non-target) matching approach is adopted. Models 6 and 7 show results under propensity score matching (PSM). Here, propensity scores are derived using the control variables in Table 1. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 7: Target size, takeover likelihood and market intensity

	<i>HOT</i>	<i>COLD</i>	<i>ALL</i>	<i>ALL</i>	<i>ALL</i>
	(1)	(2)	(3)	(4)	(5)
<i>SIZE</i>	0.194*** (0.000)	0.059*** (0.001)	0.004*** (0.000)	0.004*** (0.001)	0.003*** (0.001)
<i>SIZEsq</i>	-0.005*** (0.000)	-0.001*** (0.002)			
<i>MrktIntensity</i>			0.043*** (0.000)		
<i>HOT</i>				0.029*** (0.000)	0.025*** (0.000)
<i>HOT*SIZE</i>					0.004*** (0.006)
<i>Controls</i>	YES	YES	YES	YES	YES
<i>Observations</i>	15,067	6,924	21,991	21,991	21,991
<i>Industry FE</i>	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES

Notes: The table presents logit regression (marginal effects) results for a takeover likelihood (*TALI*) model (see equations 1 and 2). The dependent variable is a binary variable which takes a value of 1 if a firm receives a takeover bid in period t and a value of 0, otherwise. The main independent variables are measures of market intensity (*MrktIntensity*, *HOT*) and target firm size (*SIZE*, *SIZEsq*). *MrktIntensity* is the natural log of the number of acquisitions in the 12 months prior to the year of acquisition. *HOT* (*COLD*) periods as periods when *MrktIntensity* is greater(less) than the median for the study period. *HOT* (*COLD*) periods are years when *MrktIntensity* is greater(less) than the median for the study period. *HOT* is an indicator variable denoting high *MrktIntensity*. *HOT*SIZE* captures the interaction effect between the respective variables. The control variables (suppressed for brevity) include all variables in Table 1. Models also control for industry and year fixed effects (FE). The independent and control variables are lagged by one year. Model 1(2) presents results when the analysis is conducted for a subsample of *HOT* (*COLD*) years only. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Appendix

Table 1A: Takeover likelihood and residual (excess) target firm size

Panel A: A re-estimation of Table 3 results with an alternative measure of firm size

	<i>ALL</i>	<i>Q1</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>rSIZE</i>	0.005*** (0.000)	0.012*** (0.003)	0.027* (0.062)	-0.015 (0.310)	-0.003 (0.818)	-0.007* (0.066)
<i>Controls</i>	YES	YES	YES	YES	YES	YES
<i>Observations</i>	21,965	4,297	4,377	4,395	4,392	4,370
<i>Industry FE</i>	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES	YES

Panel B: A re-estimation of Tables 4 and 5 results with an alternative measure of firm size

	<i>Q1&Q2</i>	<i>Q3-Q5</i>	<i>ALL</i>	<i>ALL</i>	<i>ALL</i>	<i>ALL</i>
	(7)	(8)	(9)	(10)	(11)	(12)
<i>rSIZE</i>	0.019*** (0.000)	-0.003* (0.086)		0.008*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
<i>rSIZEsq</i>				-0.004*** (0.000)		
<i>iSPRDdummy</i>					-0.009*** (0.004)	
<i>iSPRDdummy*rSIZE</i>					0.001 (0.810)	
<i>rMSDY</i>			0.017*** (0.000)			
<i>dMKTdummy</i>						0.004 (0.199)
<i>dMKTdummy *rSIZE</i>						0.004*** (0.004)
<i>Controls</i>	YES	YES	YES	YES	YES	YES
<i>Observations</i>	8,794	13,171	21,991	21,965	21,965	21,965
<i>Industry FE</i>	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES	YES

Notes: The table presents a re-estimation of the results from Tables 3, 4 and 5, using an alternative measure of firm size (residual size, *rSIZE*). *rSIZE* is a component of *SIZE* which is unrelated to these other variables. It is the residual obtained by regressing *SIZE* (natural log of total assets) on its instrument (the average size of firms in a firm's two digit SIC code industry in each year) and all other control variables in Table 1. The dependent variable in all models (panels A and B) is a binary variable which takes a value of 1 if a firm receives a takeover bid in period *t* and a value of 0, otherwise. The main independent variables are measures of firm size (*rSIZE*, *rMSDY*), capital liquidity (*iSPRD*, *iSPRDdummy*), market growth (*dMKT*, *dMKTdummy*) and their interactions. See Tables 3, 4 and 5 for full descriptions. All control variables are discussed in Table 1. Models also control for industry and year fixed effects (FE). The independent and control variables are lagged by one year. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

References

- Ambrose, B. and Megginson, W. L. (1992), "The Role of Asset Structure, Ownership Structure, and Takeover Defenses in Determining Acquisition Likelihood", *Journal of Financial and Quantitative Analysis*, Vol. 27, pp. 575-589.
- Atkeson, A. and Kehoe, P. (2005), "Modeling and Measuring Organization Capital", *Journal of Political Economy*, Vol. 113, pp.1026-1053.
- Barnes, P. (1998), "Can Takeover Targets be Identified by Statistical Techniques?: Some UK Evidence", *Journal of the Royal Statistical Society: Series D (The Statistician)*, Vol. 47, pp. 573-591.
- Barnes, P. (1999), "Predicting UK Takeover Targets: Some Methodological Issues and an Empirical Study", *Review of Quantitative Finance and Accounting*, Vol. 12, pp. 283-302.
- Barnes, P. (2000), "The identification of U.K. takeover targets using published historical cost accounting data Some empirical evidence comparing logit with linear discriminant analysis and raw financial ratios with industry-relative ratios", *International Review of Financial Analysis*, Vol. 9, pp. 147-162.
- Bi, X. G. and Gregory, A. (2011), "Stock Market Driven Acquisitions versus the Q Theory of Takeovers: The UK Evidence", *Journal of Business Finance and Accounting*, Vol. 38, pp. 628-656.
- Brar, G., Giamouridis, D., and Liodakis, M. (2009), "Predicting European Takeover Targets", *European Financial Management*, Vol. 15, pp. 430-450.
- Cabral, L. and Mata, J. (2003), "On the Evolution of the Firm Size Distribution: Facts and Theory", *American Economic Review*, Vol. 93, pp.1075-1090.
- Cremers, K. J. M., Nair, V. B., and John, K. (2009), "Takeovers and the Cross-Section of Returns", *Review of Financial Studies*, 22, pp. 1409-1445.
- Danbolt, J. (2004), "Target Company Cross-border Effects in Acquisitions into the UK", *European Financial Management*, Vol. 10, pp. 83-108.
- Danbolt, J. and Maciver, G. (2012), "Cross-Border versus Domestic Acquisitions and the Impact on Shareholder Wealth", *Journal of Business Finance and Accounting*, Vol. 39, pp. 1028-1067.
- Danbolt, J., Siganos, A., and Tunyi, A. (2016), "Abnormal Returns from Takeover Prediction Modelling: Challenges and Suggested Investment Strategies", *Journal of Business Finance and Accounting*, Vol. 43, pp. 66-97.
- DeLong, E. R., DeLong, D. M., and Clarke-Pearson, D. L. (1988), "Comparing the Areas under Two or More Correlated Receiver Operating Characteristic Curves: A Nonparametric Approach", *Biometrics*, Vol. 44, pp. 837-845.
- Dickinson, V. (2011). Cash Flow Patterns as a Proxy for Firm Life Cycle", *The Accounting Review*, Vol. 86, pp.1969-1994.
- Dong, M., Hirshleifer, D., Richardson, S., and Teoh, S. H. (2006), "Does Investor Misvaluation Drive the Takeover Market?", *The Journal of Finance*, Vol. 61, pp. 725-762.
- Espahbodi, H. and Espahbodi, P. (2003), "Binary choice models and corporate takeover", *Journal of Banking and Finance*, Vol. 27, pp. 549-574.
- Franks, J. R. and Harris, R. S. (1989), "Shareholder wealth effects of corporate takeovers: The U.K. experience 1955-1985", *Journal of Financial Economics*, Vol. 23, pp. 225-249.
- Gorton, G., Kahl, M., and Rosen, R. J. (2009). Eat or Be Eaten: A Theory of Mergers and Firm Size", *The Journal of Finance*, Vol. 64, pp. 1291-1344.
- Hajbaba, A. and Donnelly, R. (2013), "Acquirers' performance in hot and cold merger markets: evidence of mispricing", *Review of Accounting and Finance*, Vol. 12, pp.204-225.
- Harford, J. (2005). What drives merger waves? *Journal of Financial Economics*, Vol. 77, pp. 529-560.
- Hasan, M. and Cheung, A. (2018), "Organization capital and firm life cycle", *Journal of Corporate Finance*, Vol. 48, pp.556-578.
- Hayward, M. A. and Hambrick, D. C. (1997), "Explaining the Premiums Paid for Large Acquisitions: Evidence of CEO Hubris", *Administrative Science Quarterly*, Vol. 42, pp. 103-127.
- Hsieh, C. and Klenow, P. (2014), "The Life Cycle of Plants in India and Mexico", *The Quarterly Journal of Economics*, Vol. 129, pp.1035-1084.
- Jensen, M. (1986), "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers", *American Economic Review*, Vol. 76, pp. 323-329.

- Kosnik, R. and Shapiro, D. (1997), "Agency conflicts between investment banks and corporate clients in merger and acquisition transactions: Causes and remedies", *Academy of Management Perspectives*, Vol. 11, pp.7-20.
- Louis, H. (2004), "The Cost of Using Bank Mergers as Defensive Mechanisms against Takeover Threats", *The Journal of Business*, Vol. 77, pp. 295-310.
- Maksimovic, V. and Phillips, G. (2001), "The Market for Corporate Assets: Who Engages in Mergers and Asset Sales and Are There Efficiency Gains?" *The Journal of Finance*, Vol. 56, pp. 2019-2065.
- Martynova, M. and Renneboog, L. (2008), "A century of corporate takeovers: What have we learned and where do we stand?", *Journal of Banking & Finance*, Vol. 32, pp.2148-2177.
- Mitchell, M. and Mulherin, J. (1996), "The impact of industry shocks on takeover and restructuring activity", *Journal of Financial Economics*, Vol. 41, pp.193-229.
- Mueller, D. C. (1969), "A Theory of Conglomerate Mergers", *The Quarterly Journal of Economics*, Vol. 83, pp. 643-659.
- Palepu, K. G. (1986). Predicting takeover targets: A methodological and empirical analysis", *Journal of Accounting and Economics*, Vol. 8, pp. 3-35.
- Powell, R. and Yawson, A. (2007), "Are Corporate Restructuring Events Driven by Common Factors? Implications for Takeover Prediction", *Journal of Business Finance and Accounting*, Vol. 34, pp. 1169-1192.
- Powell, R. G. (1997), "Modelling Takeover Likelihood", *Journal of Business Finance and Accounting*, Vol. 24, pp. 1009-1030.
- Powell, R. G. (2001), "Takeover Prediction and Portfolio Performance: A Note", *Journal of Business Finance and Accounting*, Vol. 28, pp. 993-1011.
- Powell, R. G. (2004), "Takeover Prediction Models and Portfolio Strategies: A Multinomial Approach", *Multinational Finance Journal*, Vol. 8, pp. 35-72.
- Rhodes-Kropf, M. and Viswanathan, S. (2004), "Market Valuation and Merger Waves", *The Journal of Finance*, Vol. 59, pp. 2685-2718.
- Rubin, D. B. (2001), "Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation", *Health Services & Outcomes Research Methodology*, Vol. 2, pp. 169-188.
- Roll, R. (1986), "The Hubris Hypothesis of Corporate Takeovers", *Journal of Business*, Vol. 59, pp. 197-216.
- Rosenbaum, P. and Rubin, D. (1983). "The central role of the propensity score in observational studies for causal effects", *Biometrika*, Vol. 70, pp. 41-55.
- Shleifer, A. and Vishny, R. W. (2003). Stock market driven acquisitions", *Journal of Financial Economics*, Vol. 70, pp. 295-311.
- Soares, N. and Stark, A. W. (2009), "The accruals anomaly: Can implementable portfolio strategies be developed that are profitable net of transactions costs in the UK?" *Accounting and Business Research*, Vol. 39, pp. 321-345.
- Tirole, J. (1988). *The Theory of Industrial Organization*. (1 ed.) The MIT Press.
- Tunyi, A. A. and Ntim, C. G. (2016), "Location Advantages, Governance Quality, Stock Market Development and Firm Characteristics as Antecedents of African M&As", *Journal of International Management*, Vol. 22, pp. 147-167.
- Tunyi, A. A, Ntim, C. and Danbolt, J. (2019). "Decoupling Management Inefficiency: Myopia, Hyperopia and Takeover Likelihood", *International Review of Financial Analysis*, Vol. 62, pp. 1-20.