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Alperovych, Yan ; Cumming, Douglas; Czellar, Veronika; Groh, Alexander

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M&A Rumors about Unlisted Firms*

Yan Alperovych†
alperovych@em-lyon.com

Douglas Cumming‡
douglas.cumming@gmail.com

Veronika Czellar§
veronika.czellar@edhec.edu

Alexander Groh†
groh@em-lyon.com

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†EMLYON Business School
‡Florida Atlantic University and Birmingham Business School (University of Birmingham)
§EDHEC Business School

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Abstract

We examine an international sample of 68,044 completed, or envisaged but abandoned, M&A transactions involving unlisted targets to determine the effect of transaction rumors on deal-closing propensity and transaction value. Our focus on unlisted firms eliminates the problem of the groundless M&A rumors that are sometimes spread in public stock markets for trading purposes. Addressing the impact of rumors is challenging because (i) rumors may be spread on purpose or may emerge accidentally; (ii) they may be caused by the same observable and omitted drivers that also effect deal closing and transaction value; and (iii) transaction values are only observable for completed deals and there is no regulatory requirement to disclose this information. We apply indirect inference methodology to overcome these challenges. Our analyses reveal that (1) M&A rumors are deal breakers; (2) rumored deals have higher transaction values if they do actually manage to close; and (3) the combined economic impact of M&A rumors as deal breakers and as value drivers is strongly negative – M&A rumors destroyed 32% of the aggregated transaction value of our sample.

Keywords: Mergers, Acquisitions, Rumors, Unlisted Firms
JEL classification: G12, G14, G18, K22

1 Introduction

Mergers and acquisitions (M&As) are important events in the life cycle of corporations and have the potential to affect a wide range of stakeholders. They can lead, among many other possibilities, to strategic reorganization, product discontinuation, accelerated growth, geographic expansion, layoffs, or increased competition. The transactions are usually initiated by the acquirer or the seller or, alternatively, by the target or outside managers (Fidrmuc & Xia, 2019; Masulis & Simsir, 2018). Deal negotiations eventually start after direct contact between the future partners or following a limited auction process organized by M&A intermediaries. Regardless of the process used to begin "merger talks", the participants regularly bind themselves to strict confidentiality using non-disclosure agreements (NDAs). The purpose of these NDAs is to limit the incidence of deal negotiation information leaks, with their potential knock-on effects on deal consummation and value. These effects are caused by the uncertainty regarding the final merger outcome, as revealed in the transaction rumor.[1] In particular, information leaks can create tension in the respective companies, e.g. among employees, customers, and suppliers, or mistrust among the negotiating parties. Rumors are known to damage employee morale and impede organizational communication (DiFonzo & Bordia, 1998, 2000; DiFonzo et al., 1994). They hamper restructuring and layoffs during periods of corporate change (Burlew et al., 1994; Smeltzer, 1991; Smeltzer & Zener, 1992) and damage sales (Bordia & Rosnow, 2006; DiFonzo & Bordia, 1997). For listed companies, it has been shown that rumors are spread to manipulate stock prices (Putniņš, 2012; Schmidt, 2019; van Bommel, 2003). They adversely affect stock prices (Ahern & Sosyura, 2015; Clarkson et al., 2006; Jia et al., 2020; Leung & Ton, 2015) and thus reduce market efficiency (Han & Yang, 2013; Indjejikian et al., 2014). Merger talks may fail because of rumors, leading deals to collapse or transactions to close at changed deal values.

The value and deal-closing effects of M&A rumors have, to date, been studied ex-

[1] A rumor (or information leak) is defined as "a tall tale of explanations of events circulating from person to person and pertaining to an object, event, or issue in public concern" (Peterson & Gist, 1951).

clusively on public capital markets. Clarkson et al. (2006) and Chou et al. (2015) show that M&A transaction information leakages can affect negotiations, deal value, and the market capitalization of the bidder. Schwert (1996) reveals runups in targets' stock prices prior to the actual merger announcements as part of the deal premium. These runups may stem from toehold acquisitions (Barclay & Holderness, 1991; Choi, 1991; Mikkelson & Ruback, 1985), from insider trades, or from transaction rumors. Betton et al. (2014) show that these runups can create additional costs for the bidder and may thus eliminate the economic viability of the transaction.

Our paper analyzes the impact of M&A rumors on deal completion and deal values, elaborating on a large sample of 68,044 closed, or envisaged but failed, M&A transactions relating to unlisted targets. Our sample spans the period from 1996 to 2017 and includes transactions in a large variety of industries in 88 countries. Approximately 26% of the transactions were rumored prior to their announcement or failure and 34% ultimately failed. Our focus on unlisted companies carries with it special features that are unique and interesting. There are no confounding effects of runups on, or other types of manipulation of, the target price thereby enabling a direct focus on the rumor impact on M&A transaction outcomes. However, the analyses are not straight-forward for several reasons. There are scant disclosure requirements and analyst coverage in private market M&As. In addition, the reported information is not necessarily captured by M&A data providers and deal values are infrequently reported.

We develop a model to accommodate the characteristics of M&A transactions involving non-listed entities. The model first determines the likelihood of an M&A rumor emerging. Second, it allows us to estimate the probability of deal consummation. Third, it traces deal value observability. Fourth, the model controls for the conditional effects on consideration of a rumor emerging, a transaction closing, and a deal value being observed. We apply indirect inference methodology, as proposed in Gouriéroux et al. (1993) and Smith Jr. (1993), to overcome the resulting econometric challenges. Our methodology is based on two requirements. First, it must be possible to simulate the model.

Second, a simple auxiliary model needs to exist, suitable for maximum likelihood, least squares, or moment-based assessment. We determine the structural model by choosing the parameter values that yield auxiliary estimates similar to the auxiliary estimates obtained with empirical data. Indirect inference and similar simulation-based estimation techniques are increasingly common in the economics and finance literature, e.g. in Calzolari et al. (2004), Czellar et al. (2007), Sentana et al. (2008), Gouriéroux et al. (2010), Garcia et al. (2011), Calvet and Czellar (2015), Nikolov et al. (2020), and Terry et al. (2020). The auxiliary model choice in our paper follows the Calvet and Czellar (2015) technique. This means that the auxiliary model corresponds to a constrained version of the structural model with a tractable likelihood. We validate the accuracy of our indirect inference estimator via Monte Carlo simulations and identify the model parameters using empirical data.

Our analyses reveal the following. First, M&A rumors are deal breakers. Information leaks prior to the official announcements diminish the likelihood of deal closing by 26.11%. Second, if a deal does finally manage to close, the premium is 16.0% higher for leaked transactions compared to non-leaked. The effects are robust with respect to the party "who leaks", and after controlling for unobserved deal values. Third, and most importantly, the joint economic impact of M&A rumors as drivers of transaction values and as deal breakers is strongly negative. We estimate that 32.42% of the aggregate transaction value of our sample deals is destroyed. Our paper therefore reveals an important trade-off among M&A deal partners. A seller, for example, may leak confidential information about M&A negotiations, expecting a premium compared with a non-leaked transaction. However, at the same time, the likelihood of consummating the deal decreases, as does the propensity of receiving the premium. The aggregate economic impact is negative, explaining why M&A market participants appreciate confidentiality, bind themselves in NDAs, and dislike transaction rumors.

Shareholders, stakeholders, competitors, individuals involved in the transaction process, or indeed anybody else, may intentionally diffuse information about merger talks to take advantage in some way. In public stock markets, would-be manipulators can deliberately spread M&A rumors to trade on the expected stock price reaction even if the respective companies have no intention of merging (Ahern & Sosyura, 2015; Chou et al., 2015; Indjejikian et al., 2014; Kyle, 1985; Schmidt, 2019; van Bommel, 2003). Betton et al. (2018) find that most of the rumors in public capital markets are indeed inaccurate and probably caused by would-be manipulators. Our focus on non-listed targets leaves only two reasons for the emergence of M&A transaction information leaks. First, a rumor may arise unintentionally due to carelessness in the negotiation process. Second, someone may spread a rumor on purpose to affect the likelihood of transaction closing and deal value. As an extension of the material presented in this paper, the accompanying Online Appendix[2]. shows the impact of unintentional rumors is less pronounced than intentional rumors, and the effects of both are consistent with the evidence presented herein.

The paper is structured as follows. Section 2 describes the model and our estimation technique. Section 3 presents the data and summary statistics. Section 4 discusses the details of our estimations. Section 5 presents the main results. Finally, Section 6 concludes.

2 The econometric model

We assume that confidential information about merger talks either leaks randomly or is leaked on purpose by someone with an interest in the transaction. Examples may include resistance to the merger or, conversely, a desire for it to go ahead. Management ability or carelessness are other factors that may lead to the emergence of M&A rumors. These potential sources of transaction rumor are unmeasurable and unobservable for us. The same factors may also affect the likelihood that the deal is consummated and that the transaction value and consideration are observed. However, a two-step estimation method would still require the observation of deal values (if completed) to be deterministic to allow

[2]The Online Appendix is available at:
http://jfe.rochester.edu/Alperovych_Cumming_Czellar_Groh_app.pdf

inferences. Since this is not the case, we need to derive an ad hoc, multi-part estimator to account for unobserved transaction values. We formally describe our simultaneous model for the emergence of a rumor, its potential impact on deal consummation and deal consideration, and our ability to observe it as follows.

Let n be the number of sampled M&A transactions. For each transaction $i = 1, \ldots, n$, we denote the deal closing state by D_i, with a value of one if the transaction is consummated and zero otherwise. We denote the rumor variable by R_i, with a value of one if D_i was subject to a rumor and zero otherwise. We assume that (R_i, D_i) are generated from the following model:[3]

$$R_i = \begin{cases} 1 & \text{if } X_i b_1 + \varepsilon_{i,1} > 0 \\ 0 & \text{otherwise} \end{cases}, \qquad D_i = \begin{cases} 1 & \text{if } X_i b_2 + \gamma R_i + \varepsilon_{i,2} > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

for $i = 1, \ldots, n$, where $X_i = (1, x_{i1}, \ldots, x_{ik})$ is a matrix with k explanatory variables and:

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]. \tag{2}$$

For each $i \in 1 \ldots, n$, we assume that the transaction multiple P_i at which the deal is closed is generated from:

$$\log P_i = \tilde{X}_i b_3 + \kappa R_i + \varepsilon_{i,3}\,, \quad i = 1, \ldots, n\,, \tag{3}$$

where $\varepsilon_{i,3}$ are i.i.d. normal variables with zero mean and σ^2 variance, independent of $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$. $\tilde{X}_i = (1, x_{i1}, \ldots, x_{il})$ is a matrix with l explanatory variables. Note that this independence does not imply that we can directly estimate the effect of a rumor on the consideration because of a rumor's impact on closing. Only the joint estimation therefore

[3]This formulation corresponds to the standard recursive bivariate probit model with an endogenous binary regressor (see Greene (2018), pp.785-789). It can be estimated directly by the maximum likelihood technique. Recursive bivariate probits are often used to account for endogeneity in the binary variable in single-equation probit models. They follow the endogenous sample selection models in Heckman (1979) and Lee (1978, 1982, 1983).

yields a correct estimate because all three parts are evaluated simultaneously.

There are two additional complexities to consider. First, deal values of unlisted company M&As may or may not be observed. This needs to be accommodated in the joint estimation of deal values conditional on rumor emergence and deal consummation, respectively. Second, the complexity of the processes driving the price observation in the presence of rumors and deal closing may render conventional estimation techniques such as maximum likelihood inappropriate, as we will illustrate.

For each $i = 1, \ldots, n$, the deal value may or may not be available, contingent on a transaction being completed. We denote the availability of the consideration by B_i:

$$B_i = \begin{cases} 1 & \text{if } \tilde{X}_i b_4 + \zeta_1 R_i + \zeta_2 \log P_i + \varepsilon_{i,4} > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{4}$$

where $\varepsilon_{i,4}$ are i.i.d. normal variables with zero mean and unit variance, independent of $\varepsilon_{i,1}$, $\varepsilon_{i,2}$, and $\varepsilon_{i,3}$. For each $i = 1, \ldots, n$, the observed transaction value is:

$$P_i^{obs} = \begin{cases} P_i & \text{if } B_i D_i = 1\,, \\ \text{unavailable} & \text{otherwise} \end{cases}. \tag{5}$$

We denote the $2k + 2l + 10$ parameters as follows:

$$\theta = (b_1, b_2, b_3, b_4, \gamma, \kappa, \sigma, \rho, \zeta_1, \zeta_2)'\,.$$

The density of $\log P_i^{obs}$ conditional on $D_i = 1$ and knowing R_i is:

$$f(\log P_i^{obs} | D_i = 1, R_i) = \left\{ \frac{1}{\sigma} \phi \left(\frac{\log P_i^{obs} - \tilde{X}_i b_3 - \kappa R_i}{\sigma} \right) \cdot \left[1 - \Phi(-\tilde{X}_i b_4 - \zeta_1 R_i - \zeta_2 \log P_i^{obs}) \right] \right\}^{B_i} \times \\ \times \left\{ \int_{-\infty}^{\infty} \frac{1}{\sigma} \phi \left(\frac{p - \tilde{X}_i b_3 - \kappa R_i}{\sigma} \right) \cdot \Phi(-\tilde{X}_i b_4 - \zeta_1 R_i - \zeta_2 p)\, dp \right\}^{1 - B_i} \tag{6}$$

where $\phi(x)$ and $\Phi(x)$ are, respectively, the probability density and cumulative distribution functions of the standard normal distribution. Estimating θ by maximum likelihood is challenging because (6) is not available in closed-form and requires numerical integration, unless $\zeta_2 = 0$. However, θ can be estimated by a simulation-based method such as indirect inference (Gouriéroux et al., 1993; Smith Jr., 1993), which is a two-step estimation procedure. First, a set of auxiliary statistics is chosen and evaluated using the empirical data. Indirect inference estimates are then the parameter values that can generate pseudo-data under equations (1) through (5), providing auxiliary statistics that are similar to the empirical auxiliary statistics. To select the auxiliary statistics, we use Calvet and Czellar (2015)'s method in which the auxiliary statistics are the estimators of a naive model. The naive model corresponds to the case in which some parameters are constrained such that the model becomes tractable. The missing parameters in the auxiliary model are then replaced by sample statistics quantifying the econometric meaning of the missing parameters (see Section 5.2).

3 Data and summary statistics

3.1 Data on M&A transactions and rumors

We examine 68,044 envisaged but failed (34.32%) or completed (65.68%) unlisted firm M&A transactions sourced from Bureau van Dijk's Zephyr data base (Zephyr).[4] The following filters, typical in M&A research, were used to select our sample of transactions. First, the deal must be classified as "Acquisition", "Merger", "Institutional buy-out", "Management buy-out", or "Management buy-in". We further impose a minimum 50%

[4]Bureau van Dijk employs a large number of research staff and AI web scrapers to detect data on transactions and transaction rumors. We cross-checked the data records for a random selection of transactions and found that the rumor dates were remarkably precise. Bollaert and Delanghe (2015) compared the quality of Zephyr with the Securities Data Company M&A database (SDC) and concluded that Zephyr has some disadvantages with respect to consistent information about acquirers and targets, and the systematic representation of several key items, such as the deal type. However, they argue that the database has strong advantages in terms of information about the vendor and about bidder syndicates. They therefore regard Zephyr as an appropriate source for certain types of research questions, including the issues we address in this paper.

stake to be acquired in the transaction. Targets must be unique (multi-target deals are excluded), have a minimum asset size of one million US dollars, and a minimum of 10 employees at the time of the transaction. Finally, we limit our sample to unlisted targets, as explained above.

Zephyr supplies information allowing us to identify whether there was a transaction rumor prior to the official announcement and whether the transaction was completed. Specifically, Zephyr records the date on which a potential transaction was first mentioned in the media (print/radio/TV/internet/etc.). We refer to this date as the rumor date if it is prior to the "official" announcement, which is also provided by Zephyr. The media reference, hence the evidence for an information leak prior to the announcement, may stem from the buyer, the seller, the target company itself, or may be recorded without any proper identification of the source. We define transaction negotiations as being leaked if either of the following two conditions holds:

(i) The rumor date precedes the announcement date by more than three calendar days (thus avoiding over-the-weekend announcements); or

(ii) The announcement never actually took place.

Zephyr collects transaction closing dates and supplies important deal characteristics and additional information on acquirers and targets, which serve as covariates and controls. Our observation period was from 1996 to 2017 and covered 88 countries. Table 1 cross-tabulates our sample of rumored/not-rumored and closed/not-closed transactions. The sample includes 17,440 (25.63%) rumored deals, 23,354 (34.32%) not-closed deals, and 44,690 (65.68%) closed deals. The proportion of leaks in closed transactions amounts to about 14% (=6,063/44,690), which is lower than the proportion of leaks observed in abandoned negotiations of approximately 49% (=11,377/23,354). Alternatively, the proportion of closed deals among the non-leaked transactions is about 76% (38,627/50,604) while only 35% (6,063/17,440) of leaked deals finally consummate.

[Table 1 about here]

Table 2 presents our sample over time. There is no clear trend with respect to the closing likelihood or deal-information leaks. Nevertheless, we accommodate any potential seasonal patterns in our regressions using time fixed effects. Table 3 breaks down the sample according to 18 industry sectors and reveals marked differences in the likelihood of transaction closing, information leaks, and the representation of targets across industries. We address the potential sources of this variation in our analyses using industry descriptives, such as Herfindahl Hirshman indices on concentration and rumor intensity in the industry, or we refer to industry fixed effects.

[Table 2 about here]

[Table 3 about here]

Table 4 presents the emergence of M&A transaction rumors with respect to acquirer types and rumor origin. Following Gorbenko and Malenko (2014), we distinguish transactions by acquirer type. Panel A tabulates leaked transactions according to acquirer type without consideration of the source of the leak.

[Table 4 about here]

Panel B refers to the origin of the rumors and differentiates between acquirers, targets, vendors, others (such as analysts, accountants, or advisors), or unspecified sources. Unfortunately, the originators of the rumors are often unspecified and we therefore do not control for this information in our main model. Nevertheless, we refer to the originators in additional analyses. Of the identified sources of transaction rumors, acquirers leak information most frequently (in about 4.07% of all transactions), while target companies spread rumors least often (in about 1.15% of all transactions).

3.2 Additional independent variables and controls

We gathered additional data to control for target, acquirer, and country characteristics. Here, we comment on the untransformed values, while Table 5 presents the log-transformed descriptive statistics used in the econometric analyses (except for EV/Sales). The definitions of the variables we use in our analyses are provided in Table 6.

[Table 5 about here]

[Table 6 about here]

The median target company was found to be 15 years old (*Age*) with about $15.14 million[5] in total assets (*Assets*) in the year immediately prior to the transaction.

We retrieved data from Worldscope to calculate Herfindahl-Hirshman Indices (*HHI*) as measures for target industry concentration.[6] The M&A target companies operate in relatively concentrated industries. The average (median) level of the concentration index was found to be 0.285 (0.242).[7] The average initial ownership stake of an acquirer in a target (*toehold*) is shown to have a median of 10.3% and a first quartile of 0. This matches the observations in Betton and Eckbo (2000) and Betton et al. (2009) and indicates that acquirers have either no, or rather small, toeholds in the majority of transactions. The median and third quartile of transactions involve a single acquirer, while the average number of acquirers is two (*Number of acquirers*). On average, acquirers completed 0.76 deals in the 20 quarters preceding the focal deal (*Acquirer experience*).

The M&A market volume variable (*M&A market*) captures M&A activity as a proxy for the experience and professionalism of a country's deal-supporting institutions. The time series are sourced from Thomson Reuters. We expect higher activity levels, and hence higher professionalism, to facilitate transaction closing and to lower the propensity of transaction rumors emerging. Nevertheless, the impact of M&A transaction volume

[5]All monetary values in this paper are expressed in constant 2010 US dollars. The monthly US inflation data is sourced from the OECD portal (https://data.oecd.org).

[6]We first downloaded the sales revenues of all listed companies worldwide and aggregated these data at a 2-digit SIC-country-year level to compute the total market sizes for each triad. This allowed us to determine a company's market share. HHIs were then computed as the sum of squared market shares for each country-SIC-year triad. It is clear that this measure depends on the number of listed companies reported in Worldscope for a given country-industry-year. We followed Frésard et al. (2017) and required at least 3 firms in a triad to have a meaningful estimate of industry concentration.

[7]The US Department of Justice considers markets with an HHI of less than 0.15 to be competitive, an HHI of 0.15 to 0.25 to be moderately concentrated, and an HHI of 0.25 or greater to be highly concentrated.

on rumors could also have the opposite effect. Higher volume may yield more financial market noise, which could produce more transaction rumors.

The *Leak-IV* variable can be used to assess the propensity of an M&A rumor emerging. We refer to observations of past transaction rumors in a respective country and industry. The instrument captures the proportion of rumored transactions relative to all transactions in a target's host country and industry in the 12 quarters preceding the focal deal.

We retrieved enterprise value to sales (EV/Sales) transaction multiples for 16,896 transactions (*Price*) from Zephyr. We also observed values for some of the failed transactions in cases where one of the deal partners had announced the consideration prior to the deal negotiations being abandoned. The average target enterprise value was found to be 10.94 times sales, while the median was 1.21 times sales. The right-skewed distribution is caused by outlying transaction multiples and calls for a log-transformation of the measures of deal value as illustrated in Figure 1.

We refer to three dummies as descriptors of additional transaction characteristics. The binary variable *Buyout* flags buyout transactions, which represent 9.0% of the sample deals. The dummy *Local deal* indicates that acquirers and targets are headquartered in the same country and *Same industry* that they are in the same industry, which is the case for 68.5% and 48.8% of our sample transactions, respectively.

[Figure 1 about here]

4 Model parameters

4.1 Transaction rumors

We firstly determined the drivers of M&A transaction rumors and deal consummation using Probit regressions, with these two binary outcomes as dependent variables. Table 7 presents the analyses.

[Table 7 about here]

Specification (1) regresses the flag for rumored transactions on several covariates, industry, year, and country fixed effects. It reveals that the *Leak-IV* instrument, describing the historic emergence of transaction rumors, strongly and statistically significantly affects the current rumor likelihood. The model further shows that the M&A transaction rumor intensity increases with larger targets, the number of bidders, and when the acquirer and the target share the same industry.[8] M&A rumors are less likely if targets are older, with higher toeholds, and if acquirer and target are located in the same country. They are also less likely if bidders are strategic, financial, or individual investors compared to the baseline group, which comprises acquirer types that are not clearly distinguishable and "others". The regression further reveals that acquisitions by government entities encourage the spread of information. All reported effects are significant at the 5% level, at least.

We refer to specification (1) as a model for describing the emergence of transaction rumors when applying our indirect inference estimates as described further below.

4.2 Transaction closing

Along the same lines, we determine the drivers of deal completion by referring to the Probit models presented in Specifications (2) to (5) of Table 7. These specifications regress the binary variable for transaction closing on combinations of the rumor dummy variable, several flags to differentiate the source of the leak, if identifiable, a set of covariates, and industry, year, and country fixed effects. The four different leak sources and the group of unspecified originators are mutually exclusive, with not-leaked transactions being the omitted category. Specifications (2) and (4) exclusively focus on the leak variable and the sources of the leak, respectively, without any further controls. Specification (3) adds the covariates from specification (1) and fixed effects. Specification (5) is analogous to

[8] We refer to horizontal transactions, as in Frésard et al. (2017), or acquisitions by strategic acquirers, as in Gorbenko and Malenko (2014).

(3) but splits the leak dummy into the different leak sources.

Specification (2) reveals the strong negative impact of a transaction rumor on deal completion. The negative coefficient estimate is statistically significant at the 1% level, and robust to the consideration of additional controls as illustrated in Model (3). The analysis in specification (4) differentiates between the transaction leak sources. The coefficient estimates of the "other" (i.e. analysts, accountants, or advisors) and "unspecified" sub-groups show the strongest impact.

The coefficient estimates of the covariates in specifications (3) and (5) reveal that transactions with larger targets, higher toeholds, larger numbers of bidders, in the same industry as the acquirer, and in concentrated industries are less likely to be completed. Conversely, transactions originated by individual investors and buy-outs have a higher likelihood of consummation. The finding that higher toeholds have a negative impact on transaction closing is surprising at first sight. Toeholds reduce the number of shares that need to be acquired at a transaction premium and intuition suggests that the requirement to buy a smaller number of shares facilitates deal-making. Both would improve the likelihood of deal closing. Betton and Eckbo (2000) find that at the time of the initial bid, the probability of a successful single-bid contest increases with the size of the toehold for acquisitions of listed companies. However, Betton et al. (2009) observe that toehold bidding has steadily declined since the '80s, although the toeholds are nevertheless large when they exist (predominantly in hostile transactions).

These papers then argue that toeholds impose a cost on target managers, causing some of them to reject the merger negotiations. Toehold bidding is thus considered aggressive towards the target. Betton et al. (2009) therefore propose a "dual toehold threshold model", which can explain either a successful zero-toehold bidding strategy or a toehold greater than a certain threshold. This threshold is the level at which toehold benefits equal toehold-induced rejection costs.

Taking this to our context we note that, toehold-induced rejection costs are much higher in unquoted markets than in listed capital markets. First of all, building up a toehold is difficult because it is impossible to buy the free floating shares. Second, shares may be restricted from transfer if the other shareholders are not taken along. Third, if it is possible to build up a toehold, or in cases where toeholds stem from the historically gained minority stakes of the bidder, this toehold will be subject to substantial liquidation costs. Illiquidity and share transfer restrictions for holding the shares of unlisted firms thus create a high rejection cost threshold in the sense of Betton et al. (2009). These thresholds may explain the negative impact of toehold bidding on deal consummation.

The average marginal effects (not tabulated) of specification (2) reveal a drop of approximately 40% in terms of the likelihood of a deal being completed compared with a non-leaked transaction. The effect is approximately -30% in Model (3). Both marginal effects are significant at the 1% level, while standard errors are computed using the Delta method. However, as argued above, we do not consider *Leak* to be an exogenous variable because an M&A rumor could be driven by the same unobservable factors that affect deal closing. For example, management ability or a company's internal resistance to a merger may generate a transaction rumor and affect the likelihood of deal closing. Hence, the parameter estimate of *Leak*, i.e. $\hat{\gamma}$ in equation (1), is potentially biased. The extent and direction of the bias in $\hat{\gamma}$ should depend on the correlation structure among the *Leak*, *Closing*, and unobserved variables. If the pairwise correlations are positive (negative), there will be an upward (downward) bias under an OLS specification. However, our models are not linear and the direction and magnitude of the bias is not predictable ex ante. This motivates the joint estimation model that we propose below.

4.3 Deal value obervation

Equation (3) assumes that the enterprise value transaction multiple, P_i is driven by a set of covariates $\tilde{X}_i$ and affected by a rumor via κ, the parameter of interest. However, we unfortunately only observe deal values for a small subset of transactions. First of all, the deal participants need to disclose the consideration. Second, the deal values need to be observed and recorded by the database intelligence team.

We denote disclosed and observed/recorded multiples as P_i^{obs}. There are four possible mutually exclusive cases as defined by Equation (5): (i) the deal is completed and its value is disclosed and recorded; (ii) it is completed but its value is not disclosed; (iii) the transaction ultimately fails to close but a consideration is announced and recorded; (iv) the deal is not closed and no consideration is announced. It seems plausible that the disclosure of a transaction value and its observation by the database intelligence team is contingent on the deal value itself. We might expect higher deal values to be more meaningful and therefore to be more systematically disclosed and recorded. However, controlling for this effect requires P_i. We therefore resort to simulations to bypass this circularity and prove that failing to correct for deal value observability biases κ, the parameter of interest.

5 Results

We follow the model proposed in Section 2 and illustrate the bias that results from naive estimation, i.e. without controlling for deal value observability. We then present unbiased results. We base our analyses on the regressions presented in Table 7, which provide an appropriate set of covariates and controls required for the indirect inference method. We nevertheless add the number of rumor source categories (*Number of sources*) in the specification of price observability and deal value. The *Number of sources* is a count variable that reflects the number of different media sources that have mentioned the M&A rumor. It serves as a proxy for media interest in the deal and, thus, observability of a transaction enterprise multiple.

5.1 A naive joint estimation

By setting $\zeta_2 = 0$, i.e. assuming that the observability of transaction multiples is exogenous, we can estimate the parameter vector $(b_1, b_2, b_3, b_4, \gamma, \rho, \kappa, \zeta_1, \sigma)'$ using various methods. We choose the following naive estimator:

$$(\hat{b}_1, \hat{b}_2, \hat{b}_3, \hat{b}_4, \hat{\gamma}, \hat{\rho}, \hat{\kappa}, \hat{\zeta}_1, \hat{\sigma})'$$

where $(\hat{b}_1, \hat{b}_2, \hat{\gamma}, \hat{\rho})'$ is the ML estimator of equations (1)-(2), $(\hat{b}_4, \hat{\zeta}_1)'$ is the ML estimator of equation (4), and $(\hat{b}_3, \hat{\kappa}, \hat{\sigma})'$ is the LS estimator of equation(3) applied solely to available transaction multiples. We show subsequently that the naive estimator does not correctly estimate the structural parameters θ because it ignores the dependence of the transaction multiple's availability on the multiple itself, among other factors. It is further based solely on observed transaction multiples. Nevertheless, this (incorrect) naive estimator is important because it provides information necessary for the estimation of the structural parameter vector θ described in Section 5.2.

The naive model is simple to assess but underestimates κ and σ. Consider the following Monte Carlo simulation of 100 draws from the model in which deal completion is set to one and $n = 20,000$, $k = 0$, $b_1 = -0.67$, $b_3 = b_4 = 0$, $\kappa = 0.15$, $\zeta_1 = 0.01$, $\zeta_2 = 1$, and $\sigma = 1.5$.[9] The naive estimates of the constrained model are reported in the left-hand side boxplots of each panel of Figure 2.

[Figure 2 about here]

The red dashed lines represent the assumed true values of the parameters, and the bias is, in fact, fairly large. A visual inspection suggests that the naive estimate of κ misses the true value by about 7.5 decimal points, which is approximately equivalent to a 50% downward bias. The average estimate of the variance is downward biased by approximately 75%.

Applying the naive model also leads us to conclude that M&A transaction rumors have a negative impact on deal values, as shown in Table 8. The parameters of interest are the coefficient of the leak dummy and the estimate of the variance (the γ, ζ_1, κ, and σ,

[9] Setting $b_1 = -0.67$ corresponds to simulating rumors from a Bernoulli distribution with a success probability of 0.25. Setting ζ_2 to -1 provides similar results.

respectively). Accordingly, the point estimates of *Leak* are –1.667 (significant at 1%) for closing (γ), 0.214 (significant at 1%) for deal value availability (ζ_1), and –0.066 (significant at 1%) for deal value (κ), respectively. The point estimate of the variance is 1.380 (significant at 1%). Nevertheless, the naive model suggests that enterprise values tend to be observed/recorded more often for larger transactions, as revealed by the positive coefficient estimate of the targets' assets prior to the transaction.

[Table 8 about here]

As discussed above (and presented in Figure 1), the distribution of enterprise value multiples is right-skewed and requires logarithmic transformation. The ζ_2 parameter in (3), missing in the naive model, controls the skewness of the observed log transaction multiples. The presence of a positive (negative) ζ_2 would lead to positively (negatively) skewed observed log-transaction multiples. We reveal this by simulating observable log-transaction multiples from Equation (5) and report the histograms in Figure 3 of the previous simulation on completed deals only with $n = 20,000$, $k = 0$, $b_1 = -0.67$, $b_3 = b_4 = 0$, $\kappa = 0.15$, $\zeta_1 = 0.01$, $\sigma = 1.5$, and $\zeta_2 = -2,\ 0,\ 2$. At the top of each histogram, we also report a robust measure of the sample skewness $\hat{\nu} = \overline{\log P_i^{obs}} - \text{median}\{\log P_i^{obs}\}$.

[Figure 3 about here]

The histograms illustrate that there is a one-to-one relationship between skewness and ζ_2. As a consequence, we cannot simply base our joint estimation model on observable transaction multiples, but instead need to resort to a more refined estimation technique.

5.2 Indirect inference estimation

We collect the auxiliary set of statistics defined in Section 5.1 in a parameter vector of size $2k + 2l + 10$:

$$\hat{\mu} = (\hat{b}_1, \hat{b}_2, \hat{b}_3, \hat{b}_4, \hat{\gamma}, \hat{\kappa}, \hat{\sigma}, \hat{\rho}, \hat{\zeta}_1, \hat{\nu})' \,. \tag{7}$$

Indirect inference (II) requires that for each parameter vector θ in the paramer space, pseudo-data can be simulated from the model described in Section 2. For a given θ, we generate $S = 10$ such pseudo-data samples and denote them by $\{Y_i^{(s)}(\theta)\}_{i=1,\ldots,n}^{s=1,\ldots,S}$ with

$$\{Y_i^{(s)}(\theta)\}_{i=1,\ldots,n} = \{R_i^{(s)}(\theta), D_i^{(s)}(\theta), B_i^{(s)}(\theta), P_i^{obs,(s)}(\theta)\}_{i=1,\ldots,n} ,$$

where $\{(R_i^{(s)}(\theta), D_i^{(s)}(\theta))\}_{i=1,\ldots,n}$ are generated from (1)-(2), $\{B_i^{(s)}(\theta)\}_{i=1,\ldots,n}$ from (3)-(4), and $P_i^{obs,(s)}(\theta)\}_{i=1,\ldots,n}$ from (5). For each pseudo-data sample, we calculate the auxiliary statistic, denoting it by $\hat{\mu}^{(s)}(\theta)$. We define the simulated auxiliary statistic as $\hat{\mu}(\theta) = S^{-1}\sum_{s=1}^{S}\hat{\mu}^{(s)}(\theta)$. A just-identified II estimator is then defined as:

$$\hat{\theta}_{II} = \arg\min_{\theta}[\hat{\mu}(\theta) - \hat{\mu}]'[\hat{\mu}(\theta) - \hat{\mu}] \,. \tag{8}$$

Under the regularity conditions given in Gouriéroux et al. (1993) and Gouriéroux and Monfort (1996), an II estimator is consistent for θ and asymptotically normally distributed. The asymptotic covariance matrix can be efficiently estimated by the estimator given in Gouriéroux et al. (1993). Again, as an illustration, the right-hand side box-plots of Figure 2 report the II estimates of the 100 draws obtained in Section 5.1, which evidently corrects the bias of the naive estimator in this simulation.

[Table 9 about here]

Table 9 displays the result of the II estimation in (8) applied to our empirical data. Referring to Table 9, it is important to emphasize that the coefficient of the leak dummy in this case only controls for the rumor effect and is not biased by any unobserved heterogeneity, which is now captured in the estimate of ρ. The coefficient estimates provide evidence that rumors have a strong negative impact on deal consummation ($\hat{\gamma} = -1.734$), a positive effect on deal value observability ($\hat{\zeta}_1 = 0.270$), and positively drive deal values ($\hat{\kappa} = 0.160$). We determine a larger estimate of $\hat{\gamma}$ compared with Table 7. However, the marginal impact reveals that the reduction in the likelihood of transaction closing is only about 26.11%.[10] The estimate of κ provides evidence that enterprise value to sales multiples for rumored transactions, conditional on the deal being closed and controlled for transaction value observability, are 16.0% greater than for not-leaked and closed transactions.

As hypothesized above, deal value observations depend on the values themselves, with an estimated ζ_2 equal to 0.786 (significant at 1% level). We also calculate the marginal effect of a leak on the observability of deal value and find that the likelihood of observing a transaction multiple is 12.32% higher if there was a transaction rumor.

The positive impact of rumors on M&A transaction values is consistent with the findings in Schwert (1996) and Aktas et al. (2018). However, there is one remaining question, which is the expected deal value given that rumored transactions fail more frequently. The combined effect needs to be negative, otherwise M&A market participants with an interest in high deal values (i.e. vendors or deal-supporting institutions whose fees are related to transaction value) would systematically leak merger talks. In equilibrium, the threat of a deal breaking must at least offset the positive effect from transaction rumors on deal values. Using our previous estimates, we determine the combined effect as follows:

$$\text{Relative rumor price} = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathbb{E}[O_i|R_i=1]-\mathbb{E}[O_i|R_i=0]}{\mathbb{E}[O_i|R_i=0]}\,, \tag{9}$$

where $O_i = D_i P_i$ is the M&A outcome of the i-th deal. The expectation $\mathbb{E}[O_i|R_i = r]$ is calculated by taking the sample mean of $J = 10^4$ simulated outputs of $\{D_i^{(j)} P_i^{(j)}\}_{j=1}^{J}$ using $r = 0$ or 1 and the empirical parameter values in Table 9. Note that this measure is relative.

The intuition is as follows. Assume that there is an unknown potential consideration P_0 at which the transaction can be closed under the best possible conditions. A rumormonger contemplates whether to leak or not, expecting a benefit from spreading a rumor,

[10] As a check, setting ρ to 0 – thus assuming the simple specification for closing from Table 4.2 – provides an estimate of the marginal reduction in likelihood of closing of 33.93%. We therefore conclude that the results are consistent, despite the difference in the estimates between Tables 7 and 9.

but only if the transaction finally goes through. At the same time, there are deal break-up costs. Our model provides us with estimates of the effect of rumors on closed deals as shown in the upper-right boxes in Figure 4. The rumor-monger therefore faces a game, but simply looking at the rumor effect for closed deals, even if unbiased, does not provide an indication of the expected effect of the rumor prior to its emergence. The relative measure allows us to evaluate the expected effect of the rumor before the resolution of the deal and to abstract from P_0. This is necessary because (i) we cannot observe the values of broken deals and (ii) we cannot observe deal values for all closed transactions. In essence, the value effect of an M&A transaction rumor and its computation can be visualized with the two-step binomial tree presented in Figure 4. We also report the more detailed measures of the combined effects in Table 10.

[Table 10 about here]

[Figure 4 about here]

Table 10 reports the total expected damage of M&A rumors taking into account the transaction value forgone as a result of deal-breaking rumors. The positive impact on transaction multiples turns into an overall loss of 32.42% of the aggregate transaction value in our sample. The asymptotic standard errors reported in parentheses reveal that these expectations are significant at the 1% level. This large forgone transaction value is a deterrent for rumor-mongers but also signals the overall economic impact of M&A transaction rumors, highlighting the need for confidentiality among deal participants.

6 Conclusions

M&A transaction rumors are a widespread phenomenon. Deal information can be leaked on purpose or accidentally. If leaked on purpose, then the rationale is to benefit from the leak in some way. The deal makers, their supporting institutions, competitors, employees, suppliers, clients, other stakeholders, politicians, or the media may have an interest in diffusing a rumor to encourage or deter an M&A transaction. If the target is listed, then would-be manipulators may spread M&A rumors to move stock prices in the desired direction. Since public companies are frequently exposed to such stock price manipulations, we cannot use them to assess the effect of M&A rumors on deal closing and value.

We therefore address the impact of M&A transaction rumors on unlisted firms' deal consummation and consideration. This rules out the noise in the public stock market. However, the disadvantage of our identification strategy is that there is no regulatory requirement to disclose deal consideration. Transaction values are therefore frequently not observable for our sample. As a consequence, we need to jointly model the emergence of an M&A transaction rumor, its impact on deal closing, on the disclosure of deal value, and on the deal value itself. We refer to indirect inference methodology to disentangle this complex endogenous process. Our analyses of a sample of 68,044 closed and not-closed, rumored and not-rumored M&A deals reveal the following. First, transaction rumors are deal breakers. The likelihood of a rumored deal being consummated is 26.11% lower than if the merger talks were not leaked. Second, if deals are nevertheless closed, then there is a notable positive difference of 16.0% between the values of leaked compared to not-leaked transactions. Third, and most notably, the overall combined economic impact of M&A rumors as deal breakers and as value boosters is strongly negative. We estimate the transaction value forgone to be 32.42% of our aggregate expected sample transaction value. Information leaks thus need to be considered as being strong drawbacks in the M&A market.

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Tables

Table 1: Tabulation of deal closings and rumors.

Note: The table presents the two-way tabulation of closing and leaks (rumors) observed in the sample. The proportions are the percentages with respect to the total number of observations indicated in bold.

	Not closed	Closed	Totals	Proportion, %
Not leaked	11,977	38,627	50,604	74.37
Leaked	11,377	6,063	17,440	25.63
Totals	23,354	44,690	**68,044**	
Proportion, %	34.32	65.68		

Table 2: Time patterns.

Note: The table presents the time patterns of deal rumors and closings. All proportions are the percentages with respect to the total number of deals in a given year provided in the second column (N).

Year	N	Closed	Proportion of N, %	Not closed	Proportion of N, %	Leaked	Proportion of N, %	Not leaked	Proportion of N, %
1997	82	81	98.78	1	1.22	6	7.32	76	92.68
1998	161	158	98.14	3	1.86	2	1.24	159	98.76
1999	185	181	97.84	4	2.16	2	1.08	183	98.92
2000	321	194	60.44	127	39.56	14	4.36	307	95.64
2001	640	411	64.22	229	35.78	175	27.34	465	72.66
2002	1,257	837	66.59	420	33.41	382	30.39	875	69.61
2003	1,663	1,132	68.07	531	31.93	517	31.09	1,146	68.91
2004	2,152	1,523	70.77	629	29.23	593	27.56	1,559	72.44
2005	2,666	1,822	68.34	844	31.66	687	25.77	1,979	74.23
2006	3,047	2,092	68.66	955	31.34	716	23.50	2,331	76.50
2007	3,942	2,725	69.13	1,217	30.87	746	18.92	3,196	81.08
2008	3,966	2,829	71.33	1,137	28.67	832	20.98	3,134	79.02
2009	4,087	2,657	65.01	1,430	34.99	1,190	29.12	2,897	70.88
2010	4,529	3,158	69.73	1,371	30.27	1,165	25.72	3,364	74.28
2011	5,468	3,361	61.47	2,107	38.53	1,480	27.07	3,988	72.93
2012	5,557	3,583	64.48	1,974	35.52	1,630	29.33	3,927	70.67
2013	5,665	3,822	67.47	1,843	32.53	1,579	27.87	4,086	72.13
2014	6,214	4,096	65.92	2,118	34.08	1,737	27.95	4,477	72.05
2015	5,927	3,896	65.73	2,031	34.27	1,500	25.31	4,427	74.69
2016	5,786	3,612	62.43	2,174	37.57	1,411	24.39	4,375	75.61
2017	4,729	2,520	53.29	2,209	46.71	1,076	22.75	3,653	77.25
Total	68,044	44,690	65.68	23,354	34.32	17,440	25.63	50,604	74.37

Table 3: Industry patterns.

Note: The table presents the industry patterns of deal rumors and closings. All proportions are the percentages with respect to the total number of deals in a given year provided in the second column (N).

Industry	N	Closed	Proportion of N, %	Not closed	Proportion of N, %	Leaked	Proportion of N, %	Not leaked	Proportion of N, %
Chemicals	5,263	3,421	65.00	1,842	35.00	1,268	24.09	3,995	75.91
Construction	3,365	2,222	66.03	1,143	33.97	820	24.37	2,545	75.63
Education & health	1,315	847	64.41	468	35.59	304	23.12	1,011	76.88
Food, beverages, tobacco	3,987	2,635	66.09	1,352	33.91	1,089	27.31	2,898	72.69
Hotels & restaurants	1,416	934	65.96	482	34.04	438	30.93	978	69.07
Machinery & equipment	9,314	6,171	66.26	3,143	33.74	1,852	19.88	7,462	80.12
Metals	3,186	2,160	67.80	1,026	32.20	731	22.94	2,455	77.06
Other	8	3	37.50	5	62.50	1	12.50	7	87.50
Other services	19,074	12,915	67.71	6,159	32.29	4,759	24.95	14,315	75.05
Post & telecom.	1,525	899	58.95	626	41.05	648	42.49	877	57.51
Primary sector	2,181	1,319	60.48	862	39.52	821	37.64	1,360	62.36
Public admin. & defence	121	83	68.60	38	31.40	29	23.97	92	76.03
Publishing, printing	2,171	1,415	65.18	756	34.82	538	24.78	1,633	75.22
Textiles	1,037	700	67.50	337	32.50	258	24.88	779	75.12
Transport	3,021	1,810	59.91	1,211	40.09	1,083	35.85	1,938	64.15
Utilities	1,855	1,028	55.42	827	44.58	757	40.81	1,098	59.19
Wholesale & retail trade	8,203	5,423	66.11	2,780	33.89	1,837	22.39	6,366	77.61
Wood, cork, paper	1,002	705	70.36	297	29.64	207	20.66	795	79.34
Total	68,044	44,690	65.68	23,354	34.32	17,440	25.63	50,604	74.37

Table 4: Several additional statistics.

Note: The table presents a tabulation of rumors, splitting the sample by acquirer type (Panel A) and by source of rumor (Panel B). Note that Panel A provides no information on the source of rumor. It merely states that of the 17,440 leaked deals, 9,434 involved strategic acquirers.

Panel A: Tabulation of leaked deals by acquirer type

	Leaked	Proportion
Strategic	9,434	54.09
Financial	3,332	19.11
Unspecified	3,263	18.71
Other	790	4.53
Individual	457	2.62
Government	164	0.94
Total leaked	17,440	100.00

Panel B: Leaks by information side (i.e. "who leaks?")

	Number	Proportion
Unspecified	10,927	16.06
Acquirer	2,771	4.07
Other	1,637	2.41
Vendor	1,320	1.94
Target	785	1.15
None	50,604	74.37
Total	68,044	100.00

Table 5: Descriptive statistics of main variables.

Note: The table presents descriptive statistics for the main explanatory variables in the form they were entered into the econometric specifications (in log-transformed form). We report the overall number of observations (N) and the number of times each variable is missing in the data (NA's). Q1 and Q3 stand for the first and third quantiles respectively.

Variable	N	NA's	Q1	Mean	Median	Q3	SD
			Continuous variables				
Age	68,044	578	2.303	2.777	2.773	3.258	0.837
Assets	68,044	147	1.764	3.173	2.781	4.185	1.834
HHI	68,044	29,178	0.107	0.285	0.242	0.393	0.222
Toehold	68,044	5,717	0.000	0.103	0.000	0.000	0.239
Number of acquirers	68,044	3,657	0.693	0.731	0.693	0.693	0.160
Acquirer experience	68,044	6,015	0.000	0.761	0.000	0.000	2.931
M&A market	68,044	763	9.723	10.359	10.792	11.464	1.784
Leak-IV	68,044	1,174	0.170	0.282	0.261	0.351	0.170
Price	68,044	51,148	0.518	10.940	1.211	2.952	213.912
Number of sources	68,044	5,584	0.693	0.919	0.693	1.099	0.289
			Dummy variables				
Buyout	68,044	0	0.000	0.090	0.000	0.000	0.287
Local deal	68,044	3,657	0.000	0.685	1.000	1.000	0.465
Same industry	68,044	0	0.000	0.488	0.000	1.000	0.500

Table 6: Definitions of variables.

Name	**Definition**
Leak (D)	Dummy variable indicating whether the deal was rumored as per Zephyr's records. *Source: BvD Zephyr.*
Closing (D)	Dummy variable indicating whether the deal is closed (with the recorded closing date). *Source: BvD Zephyr.*
Price	Deal enterprise value to sales multiple (EV/Sales), defined as the deal enterprise valuation relative to the target's total assets in the pre-transaction year. *Source: BvD Zephyr.*
Leak-IV	Instrumental variable for the rumor (leak), defined as the number of rumored deals within the total number of deals in the same country and industry as the focal deal and over the 12 quarters preceding it. *Source: BvD Zephyr.*
Age	Target age in years at the deal date (log-transformed in the estimations). *Source: BvD Zephyr.*
Assets	Last reported total assets of the target at the deal date (log-transformed in the estimations), in millions of 2010 US dollars. *Source: BvD Zephyr.*
Toehold	Initial equity stake an acquirer has in the target before the transaction. *Source: BvD Zephyr.*
Number of acquirers	Number of acquirers involved in the acquisition (log-transformed in the estimations). *Source: BvD Zephyr.*
Acquirer experience	Number of deals closed by an acquirer in the 20 quarters prior to the focal deal. Averaged across multiple acquirers whenever appropriate. *Source: BvD Zephyr.*
Number of sources	Number of distinct primary sources of information (e.g. newspaper publications, analysts' speculations and/or submissions, press-releases by parties involved in a deal, etc.) that BvD Zephyr uses to identify the deal (log-transformed in the estimations). *Source: BvD Zephyr.*
HHI	Target industry Herfindahl-Hirschman concentration index, defined as the sum of squared market shares of listed firms in the target industry (at SIC 2-digit level) in the pre-transaction year as of the deal date. The computation procedure mirrors Frésard et al. (2017). *Source: Worldscope.*
M&A market	The M&A market volume (in millions of 2010 US dollars) in the pre-transaction year as of the deal date. *Source: Thomson Reuters.*
Acquirer type (D)	Set of dummy variables defining the acquirer types as reported by BvD Zephyr acquirer entities. These include: (i) Individual, when the acquiring entities are individuals and/or families; (ii) Government, when the acquiring entities are governments and their institutions; (iii) Other, when the acquiring entities are classified as such; (iv) Financial acquirers, when the acquiring entities are financial institutions and not classified as any of the above; (v) Strategic acquirers, when the acquiring entities are non-financial institutions and not classified as any of the above.
Buyout (D)	Dummy variable identifying whether the deal is a leveraged buyout. *Source: BvD Zephyr.*
Local deal (D)	Dummy variable identifying whether the acquirers and target companies are from the same country. *Source: BvD Zephyr.*
Same industry (D)	Dummy variable identifying whether the acquirers and target companies operate within the same industry, as defined by the BvD Zephyr's native industry classification. *Source: BvD Zephyr.*

Table 7: Determinants of rumors and deal closings.

Note: The table presents the coefficient estimates of the Probit models of the determinants of M&A rumors and deal closing. The dependent variables are indicated in the top row. Models (2) and (4) use only the reported variables as covariates. The baseline for *Leak* in Models (2) and (3) and its components in Models (4) and (5) is the "no leak" case. Where indicated, models include the control variables as well as country, industry, and time fixed effects (FE). Standard errors are reported in parentheses.

	$Pr(Leak = 1)$	$Pr(Closing = 1)$			
	(1)	(2)	(3)	(4)	(5)
Leak		-1.109^{***}	-0.904^{***}		
		(0.012)	(0.019)		
Leak by acquirer				-0.472^{***}	-0.403^{***}
				(0.025)	(0.034)
Leak by target				-0.574^{***}	-0.398^{***}
				(0.045)	(0.066)
Leak by vendor				-0.889^{***}	-0.387^{***}
				(0.035)	(0.061)
Leak by other				-1.242^{***}	-1.092^{***}
				(0.033)	(0.055)
Leak by unspecified				-1.341^{***}	-1.234^{***}
				(0.014)	(0.025)
Leak-IV	0.670^{***}				
	(0.072)				
Age	-0.041^{***}		0.011		0.011
	(0.010)		(0.010)		(0.010)
Assets	0.193^{***}		-0.016^{***}		-0.014^{***}
	(0.005)		(0.005)		(0.005)
Toehold	-0.468^{***}		-0.111^{***}		-0.153^{***}
	(0.037)		(0.034)		(0.034)
Number of acquirers	0.437^{***}		-0.366^{***}		-0.366^{***}
	(0.065)		(0.065)		(0.066)
Acquirer experience	0.001		0.016^{***}		0.015^{***}
	(0.004)		(0.004)		(0.004)
Financial acquirer	-0.223^{***}		0.052		0.031
	(0.064)		(0.065)		(0.066)
Strategic acquirer	-0.228^{***}		0.090		0.063
	(0.064)		(0.065)		(0.066)
Individual acquirer	-0.444^{***}		0.275^{***}		0.264^{***}
	(0.073)		(0.073)		(0.074)
Government acquirer	0.465^{***}		-0.118		-0.053
	(0.155)		(0.155)		(0.160)
Local deal	-0.046^{**}		-0.008		-0.003
	(0.019)		(0.019)		(0.019)
Same industry	0.055^{***}		-0.033^{*}		-0.034^{**}
	(0.018)		(0.017)		(0.017)
Buyout	0.027		0.334^{***}		0.343^{***}
	(0.035)		(0.037)		(0.037)
HHI	0.069		-0.110^{**}		-0.090^{**}
	(0.046)		(0.045)		(0.045)
M&A market	0.027		-0.014		-0.009
	(0.018)		(0.016)		(0.017)
Industry, year, country FE	Y	N	Y	N	Y
Log-Likelihood	$-15,052.380$	$-38,957.588$	$-16,699.671$	$-38,335.497$	$-16,403.231$
χ^2	3,727.261	9,609.498	5,582.640	10,853.680	6,175.521
χ^2 p-value	0.000	0.000	0.000	0.000	0.000
Adj. Pseudo R-sq.	0.113	0.110	0.146	0.124	0.162
Num. obs.	31,112	68,044	31,363	68,044	31,363

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8: Naive (auxiliary) parameter estimates.

Note: The table presents the results of the naive estimates of the constrained model in which $\zeta_2 = 0$, consisting of four parts, each represented by a column. All models include country, industry, and time fixed effects (FE). Asymptotic standard errors are reported in parentheses.

	Leak	Closing	Price availability	Ln(Price)
Leak (γ, ζ_1, κ)		-1.667^{***}	0.214^{***}	-0.066^{***}
		(0.119)	(0.030)	(0.005)
Log-price (ζ_2)				
Leak-IV	0.777^{***}	-0.053	-0.110	-0.134^{***}
	(0.078)	(0.083)	(0.100)	(0.017)
Number of sources			0.743^{***}	0.345^{***}
			(0.040)	(0.001)
Age	-0.044^{***}	-0.002	-0.031^{**}	-0.099^{***}
	(0.011)	(0.011)	(0.014)	(0.002)
Assets	0.184^{***}	0.035^{***}	0.160^{***}	0.130^{***}
	(0.005)	(0.009)	(0.007)	(0.001)
Toehold	-0.449^{***}	-0.262^{***}	0.678^{***}	0.305^{***}
	(0.034)	(0.039)	(0.047)	(0.008)
Number of acquirers	0.435^{***}	-0.238^{***}	-0.158	0.172^{***}
	(0.076)	(0.084)	(0.097)	(0.010)
Acquirer experience	0.001	0.016^{***}	-0.006	0.014^{***}
	(0.004)	(0.005)	(0.005)	(0.000)
Financial acquirer	-0.233^{***}	-0.008	-0.051	0.199^{***}
	(0.070)	(0.073)	(0.090)	(0.011)
Strategic acquirer	-0.242^{***}	0.035	-0.095	-0.049^{***}
	(0.071)	(0.073)	(0.091)	(0.010)
Individual acquirer	-0.442^{***}	0.189^{**}	-0.070	0.010
	(0.081)	(0.086)	(0.102)	(0.012)
Government acquirer	0.449^{***}	0.005	-0.206	0.003
	(0.161)	(0.153)	(0.270)	(0.017)
Local deal	-0.036^{*}	-0.013	-0.096^{***}	-0.204^{***}
	(0.020)	(0.019)	(0.025)	(0.004)
Same industry	0.055^{***}	-0.017	-0.062^{***}	-0.022^{***}
	(0.019)	(0.018)	(0.023)	(0.004)
Buyout	0.029	0.318^{***}	-0.048	0.112^{***}
	(0.038)	(0.038)	(0.044)	(0.006)
HHI	0.038	-0.081^{*}	-0.246^{***}	-0.083^{***}
	(0.049)	(0.047)	(0.062)	(0.010)
M&A market	0.004	0.017	0.119^{***}	0.055^{***}
	(0.016)	(0.016)	(0.020)	(0.004)
ρ		0.460^{***}		
		(0.079)		
σ				1.380^{***}
				(0.000)
Log-Likelihood				-43868.348
Observations				28,869
Closed deals				19,790
Closed deals with prices				6,007

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: Indirect inference (II) parameter estimates.

Note: The table presents the results of the indirect inference estimates of the full model, consisting of four parts, each represented by a column. All models include country, industry, and time fixed effects (FE). Asymptotic standard errors are reported in parentheses.

	Leak	Closing	Price availability	Ln(Price)
Leak (γ, ζ_1, κ)		-1.734^{***}	0.270^{***}	0.160^{***}
		(0.596)	(0.042)	(0.031)
Log-price (ζ_2)			0.786^{***}	
			(0.039)	
Leak-IV	0.789^{***}	-0.056	-0.069	-0.236^{**}
	(0.011)	(0.194)	(0.099)	(0.120)
Number of sources			0.436^{***}	1.055^{***}
			(0.038)	(0.115)
Age	-0.040^{***}	-0.001	0.048^{***}	-0.124^{***}
	(0.004)	(0.011)	(0.014)	(0.017)
Assets	0.176^{***}	0.039	0.059^{***}	0.279^{***}
	(0.002)	(0.040)	(0.003)	(0.007)
Toehold	-0.419^{***}	-0.268^{***}	0.433^{***}	0.923^{***}
	(0.010)	(0.046)	(0.022)	(0.062)
Number of acquirers	0.408^{***}	-0.218	-0.338^{***}	0.145
	(0.046)	(0.157)	(0.119)	(0.139)
Acquirer experience	0.000	0.015^{***}	-0.014^{***}	0.006^{***}
	(0.002)	(0.001)	(0.004)	(0.001)
Financial acquirer	-0.266^{***}	-0.036	-0.264^{*}	0.218
	(0.059)	(0.036)	(0.147)	(0.194)
Strategic acquirer	-0.265^{***}	0.003	-0.112	-0.102
	(0.069)	(0.017)	(0.156)	(0.216)
Individual acquirer	-0.481^{***}	0.158^{***}	-0.140	-0.055
	(0.059)	(0.012)	(0.177)	(0.205)
Government acquirer	0.354^{***}	-0.035	-0.446^{*}	-0.101
	(0.066)	(0.142)	(0.240)	(0.371)
Local deal	-0.043^{***}	-0.020	0.067^{***}	-0.289^{***}
	(0.007)	(0.015)	(0.020)	(0.007)
Same industry	0.052^{***}	-0.024	-0.040	-0.074^{***}
	(0.011)	(0.019)	(0.025)	(0.020)
Buyout	0.037^{**}	0.296^{***}	-0.136^{***}	0.024
	(0.015)	(0.014)	(0.021)	(0.073)
HHI	0.023	-0.082^{***}	-0.196^{***}	-0.337^{***}
	(0.025)	(0.009)	(0.042)	(0.019)
M&A market	0.004	0.018	0.080^{*}	0.172^{***}
	(0.026)	(0.022)	(0.044)	(0.052)
ρ		0.499		
		(0.391)		
σ				1.816^{***}
				(0.052)
Observations				28,869
Closed deals				19,790
Closed deals with prices				6,007

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Relative price of rumors.

Note: The table reports the back-of-the-envelope, ex-ante calculation of the expected deal price. For a visual representation refer to Figure 4.

	Damage
Mean, %	-32.42^{***}
Standard error, %	(0.12)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Figures

Figure 1: Histogram of the observed log-prices.

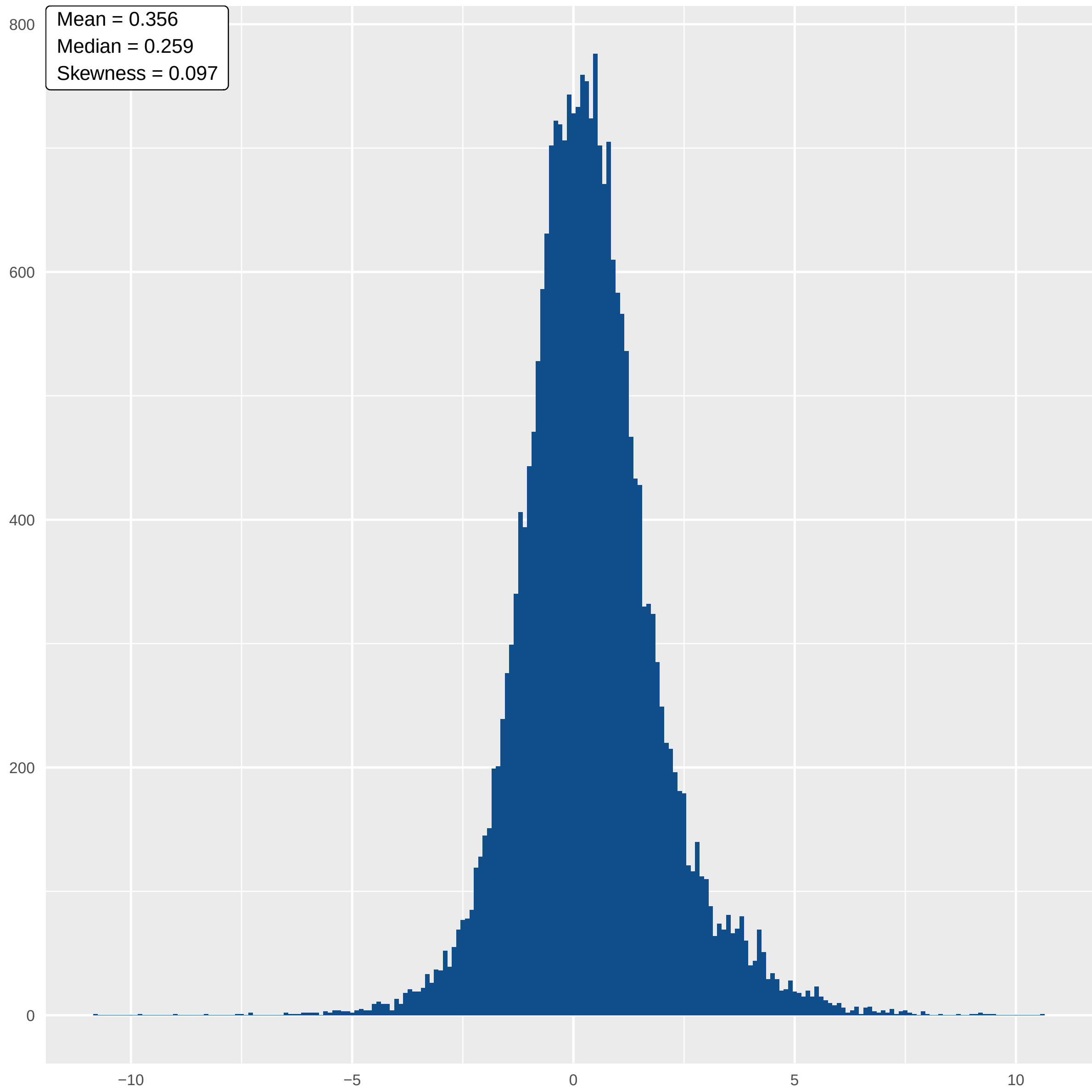

Figure 2: Boxplots of 100 naive estimates (left boxplots) and indirect inference (II) estimates (right boxplots) of κ and σ for the model in Section 2 in which closing is set to one for all M&As and $n = 20000$, $k = 0$, $b_1 = -0.67$, $b_3 = b_4 = 0$, $\kappa = 0.15$, $\zeta_1 = 0.01$, $\zeta_2 = 1$, $\sigma = 1.5$.

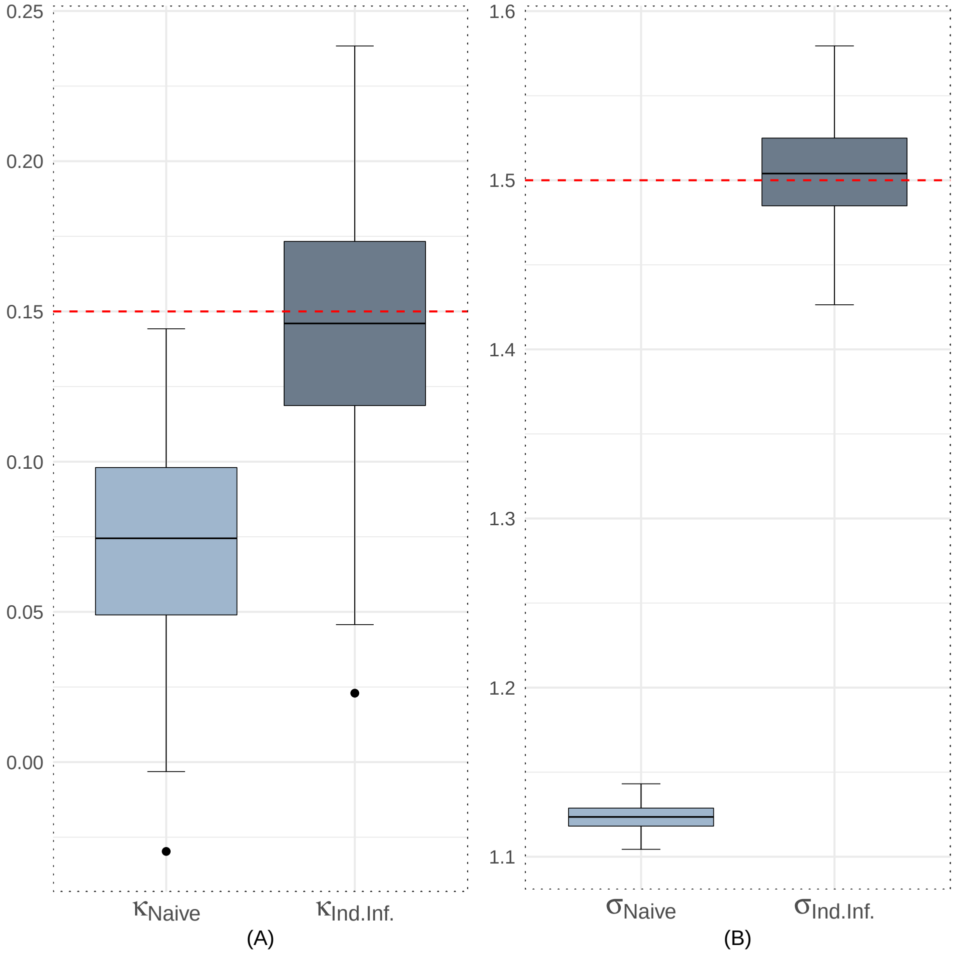

Figure 3: Histograms of observable log-prices $\{\log P_i^{obs}\}$ generated from the model in Section 2 in which closing is set to one for all M&As and $n = 20000$, $k = 0$, $b_1 = -0.67$, $b_3 = b_4 = 0$, $\kappa = 0.15$, $\zeta_1 = 0.01$, $\sigma = 1.5$ and $\zeta_2 = -2, 0, 2$.

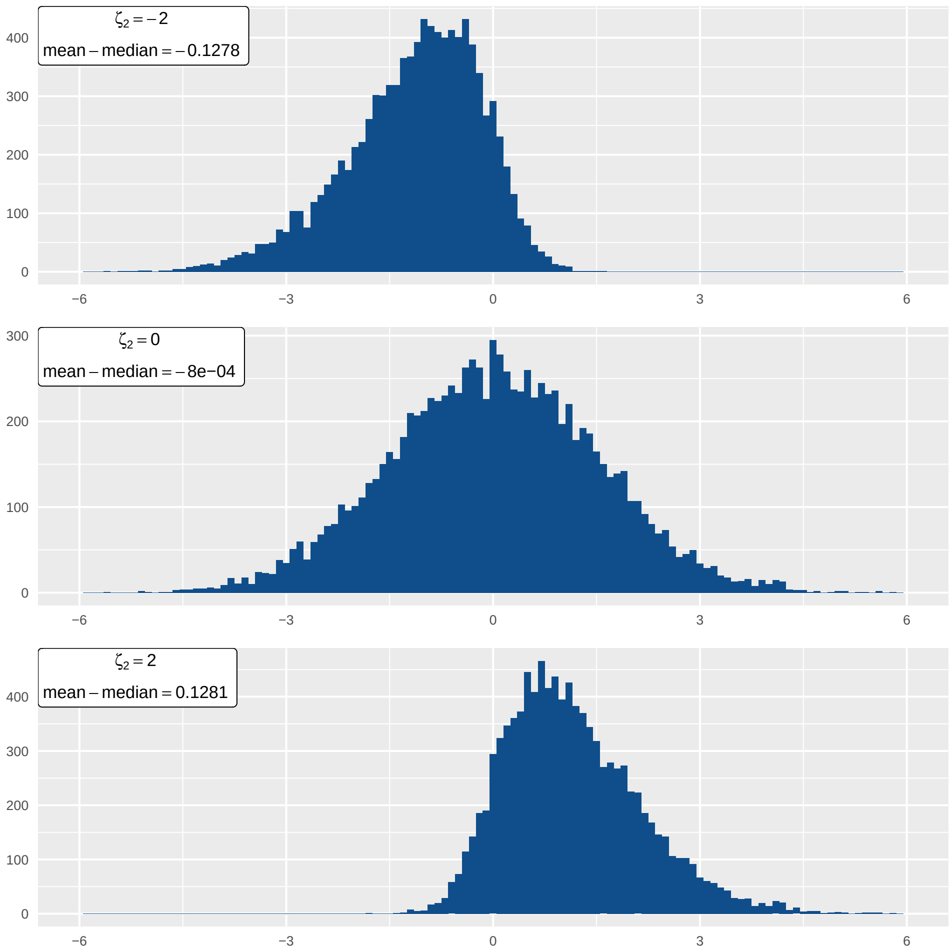

Figure 4: Combined effect of rumors on prices.