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Investor Relations' Quality and Mispricing

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Abstract

We investigate the role of corporate investor relations (IR) in the correction process of mispricing. We provide robust evidence of accruals' mispricing for the sub-sample of firms with lower-rated IR. However, mispricing is more pronounced among firms with higher valuation uncertainty. Further analyses show that firms with higher-rated IR on average earn higher returns, and this relation is resilient to known risk/mispricing factors. More important, IR likely has countervailing effects on mispricing. IR may widen the information asymmetry among investors and concomitantly reduce future analyst forecast errors. Overall, high-quality IR appears to facilitate the market's ability to establish efficient stock prices.

Keywords: Investor relations; Mispricing; Mishkin test; Information asymmetry; Information uncertainty.

JEL classification: G12, G14, D82

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1 Introduction

Stock prices play an important economic role because they convey information that facilitates the efficient allocation of resources (e.g. Goldstein and Guembel, 2008; Chung *et al.*, 2012). However, mispricing might constrain this beneficial role of stock prices by distorting corporate investment and financing decisions (e.g. Warr *et al.*, 2012; Chang *et al.*, 2013), and creating incentives for corporate misconduct (Chi and Gupta, 2009; Sawicki and Shrestha, 2014). The costs associated with mispricing are potentially large (Hau and Lai, 2013) given that investor activists, rating agencies, and regulators often take corrective actions based on information inferred from stock prices (Bond *et al.*, 2010). In this vein, Chang *et al.* (2013) find that a faster correction of mispricing is associated with more efficient resource allocation in the real economy. Relatedly, Lev (1992, p. 18) argues that "managers have an implicit responsibility to investors to continually maintain market values as close as feasible to intrinsic ones."

Our objective in this study is to examine the role of investor relations (IR) quality in affecting stock mispricing. Following Chang *et al.* (2013), we define mispricing as the deviation of a stock price from its predicted intrinsic value. In turn, we construe IR as the functional area dedicated to communications between the firm and the investment community. The IR function thus plays a major role in determining a firm's disclosure policies, and in addressing visibility and investor following concerns (Bushee and Miller, 2012). In line with this, the U.S. National Investor Relations Institute (NIRI, 2014) states that IR practitioners can be thought of as "chief disclosure officers" who make sure that their firms and board members understand and respond to investors' concerns. By enabling direct access to senior management and providing market participants with more timely, accurate, and complete firm-specific information, the IR function "ultimately contributes to a company's securities achieving fair valuation" (NIRI, 2013, p. 1).

We hypothesize that shares of firms with higher-rated IR would be priced more efficiently than their counterparts with lower-rated IR. A body of literature (biased toward equity undervaluation) provides indirect evidence that mispricing is inversely related to IR quality (heareafter, IRQ; e.g. Kennedy and Wilson, 1980; Byrd *et al.*, 1993; Kirk and Vincent, 2014; Karolyi and Liao, 2015). The existing literature also shows that information asymmetry/uncertainty (hereafter, IA/IU) and mispricing are positively associated. While Lev (1992, p. 17) posits that "by definition, the source of misvaluations is information asymmetry", Thomas (2000) and Drake *et al.* (2009) contend that low-quality disclosures cause investors to misprice earnings information. Moreover, Jiang *et al.* (2005) show that the correction process of mispricing is more likely to be protracted when the fundamental value is uncertain. Similarly, Zhang (2006a) argues that mispricing effects should be strongest among firms about which there is high uncertainty and poor information. Overall, IRQ seems to be primarily related to mispricing through its impact on IA/IU (Agarwal *et al.*, 2016).

To test the impact of IRQ on mispricing, we rely on proprietary analysts' and institutional investors' evaluations of 252 European non-financial firms' IR over the 2002-2011 period, and make two complementary research design choices. These choices help elucidate (i) what type of mispricing IRQ affects, and (ii) how this influence works. Specifically, following existing research (e.g. Sloan, 1996; Kraft *et al.*, 2007; Drake *et al.*, 2009), we first use the Mishkin (1983) two-stage rational expectations framework to assess whether the earnings expectations embedded in stock prices accurately reflect the differential persistence of accruals and cash flows. We ask: (i) Do stock prices reflect the asymmetric persistence of accruals and cash flows resulting from conditional conservatism? (ii) Does IRQ affect investor mispricing of either component of earnings? Second, we employ the pricing deviation-based approach introduced by Rhodes-Kropf *et al.* (2005, hereafter, RKRV) to test the channels through which IRQ is related to mispricing.

We argue that a high-quality IR function provides an effective way for investor preferences to be communicated to corporate managers and to reduce IA/IU, which ultimately mitigates investor mispricing of firms' stocks. Indeed, high-quality IR programs induce firms to create useful disclosures, and attract more analyst and media coverage (e.g., Bushee and Miller, 2012; Chen *et al.*, 2013; Kirk and Vincent, 2014), thereby resolving equivocality of communication (Weick, 1995; Roberts *et al.*, 2006; Barker *et al.*, 2012), and allowing more precise information to be incorporated into stock prices (Bailey *et al.*, 2006).

However, IA/IU may simultaneously affect IRQ and mispricing. A firm may respond to perceived increases in IA/IU by devoting more effort to improving its IR. Related to this, Anantharaman and Zhang (2011) show that managers increase public financial guidance after exogenous decreases in analyst coverage. Similarly, Green *et al.* (2014a) find that greater client demand for management access among hard-to-value firms leads younger, illiquid firms and prospective equity issuers to attend more broker-hosted investor conferences.[1] Thus, firms may strategically choose IRQ levels based on the necessity to reduce IA/IU, and mitigate stock mispricing. The existence of implicit managerial incentives inherent in mispricing supports the view that IRQ and mispricing are endogenously determined. We consider two complementary approaches to tackle this endogeneity concern (see sections 3.2 and 5.3): a linear instrumental variable model (heareafter, two stage least squares or 2SLS) and a piecewise linear Heckman's sample selection model (heareafter, Heckit).

Mishkin tests provide robust evidence of accruals' mispricing for the sub-sample of firms with lower-rated IR. In line with Zhang (2006a), we find that mispricing is more pronounced among firms with high valuation uncertainty. Surprisingly enough, the differential persistence of accruals and cash flows is widest in gain states, not in loss states, which refutes the earnings fixation hypothesis (EFH) documented in, e.g., Shi and Zhang (2012). Besides, portfolio analyses reveal that firms with higher-rated IR on average earn higher stock returns, and this relation is resilient to known risk and mispricing factors. More important, IR appears to play two countervailing roles in its relation with mispricing. Specifically, IR quality may widen the information asymmetry among investors (potentially stemming from private meetings with a select group of investors) and concomitantly reduce any future analyst forecast errors. Together, our results suggest that high-quality IR programs are instrumental in facilitating the market's ability to efficiently impound accounting information into stock prices. These results are robust to the endogenous nature of IR quality.

Our study makes three main contributions. First, we further the debate on the economic value of IR by showing that IR quality reduces mispricing primarily through its adverse impact on future analyst forecast errors. This attests to the primacy of the accuracy over just the depth of analyst coverage when establishing stock prices (Chang and Hong, 2016). Second, the Heckit results suggest that IR quality has no direct effect on mispricing when we control for the probability of underpricing in the next period. Indeed, firms appear to endogenously respond to mispricing in an asymmetric manner; they are more concerned about underpricing than about overpricing although either kind of mispricing is harmful for the economy (e.g., Jensen, 2005). Third, unlike Peasnell *et al.* (2011), we find robust returns to IR even in periods of declining market confidence, thereby supporting the view that IR can add value (e.g., Laskin, 2011; Karolyi and Liao, 2015) by reducing mispricing.

[1] Chung *et al.* (2012) document that absent plans to issue new securities, exercise or grant stock options in the near future, managers would have no strong incentives to correct the mispricing of their stocks in advance of the subsequent release of mandatory disclosures.

The remainder of the paper is organized as follows. Section 2 presents the background and develops testable hypotheses. Section 3 discusses the econometric framework. Section 4 introduces the data. Section 5 shows the empirical results and Section 6 concludes.

2 Background and Hypothesis Development

2.1 Investor Relations

IR specialists view their work as managing market expectations and the disclosure process, altering stakeholders' perceptions, institutionalizing shareholder relations, and diversifying the investor base (Kennedy and Wilson, 1980; Rao and Sivakumar, 1999). Although IR departments use various channels for investor outreach non-deal roadshows, broker-hosted investor conferences, and investor visits to firm headquarters are considered as the most significant ones (Gedvila, 2010).

Research relates successful IR, inter alia, to reduced costs of acquiring and processing firm-specific information, greater investor recognition, enhanced stock liquidity, and ultimately to improved market valuations (Lang and Lundholm, 1996; Brennan and Tamarowski, 2000; Kirk and Vincent, 2014). The general tenor of that research is that IR activities improve the information environment of the firm, thereby improving the reliability of investors' valuation models and building corporate reputation (Metzker, 2002; de Jong *et al.*, 2007). More importantly, these benefits seem to derive primarily from direct access to senior management (Barker *et al.*, 2012; Bushee and Miller, 2012; Solomon and Soltes, 2015).

A large body of the literature points to the idea that the desired goal of IR is to increase stock market valuations. In line with this, IR professionals often regard IR events as opportunities for stock promotions (Chugh and Meador, 1984; Solomon, 2012) or occasions for firms to "negotiate favorable identities" (Rao and Sivakumar, 1999, p. 36). There is evidence that firms have often used aggressive IR strategies to "hype" their stocks in the short run (e.g., de Jong *et al.*, 2007; Lang and Lundholm, 2000). Doukas *et al.* (2005, p. 99) note that "there is growing suspicion that the wedge between stock prices and fundamental values is likely associated with excessive analyst coverage." Similarly, Chen *et al.* (2013) find that abnormal media coverage of firm-generated news creates sentiment among investors, thereby exacerbating stock mispricing. Indeed, increasing sentiment adds to speculative demands, which may contribute to maintaining stock mispricing.

Because overvaluation might induce the illusion of growth and engender managerial malfeasance (Jensen, 2005), it appears as harmful to shareholders' wealth as undervaluation which might cause losses from potential underinvestment. This is also in the spirit of Lu *et al.* (2014), who find that large short-term price shocks of either sign are followed by negative abnormal returns over the subsequent year. We therefore contend that the ultimate goal of successful IR should be to establish and/or maintain the pricing efficiency of a firm's securities. More importantly, firms may attain pricing efficiency of their shares by reducing information risk (Farragher *et al.*, 1994). Information risk arises when there are information asymmetries between the firm and outside investors or when investors are uncertain about the quality of information relative to the firm's prospects. Aslan *et al.* (2011) find that the size of such risk depends on the quality of a firm's information environment.

High-quality IR programs involve direct investor-management interactions that go beyond just providing data; they should additionally deliver information, knowledge, and insight. The benefits associated with these interactions consist in gathering information that is, on its own, non-material to complement the potentially ambiguous signals already in the public domain. Drake *et al.* (2014) find that the business press broadcasts more broadly firm-generated news and adds an editorial content, thus helping mitigate cash flow mispricing. However, neither the information dissemination role of the press nor its information creation role significantly reduces the accruals' mispricing. We anticipate that, through its impact on IA/IU, IR can aid in mitigating the accruals' mispricing as its major audience, the analyst community, presumably possesses the expertise necessary to fully appreciate the implications of accruals than the press.

2.2 IR Quality and Information Asymmetry (IA)

IA exists when players have unequal information sets. Prior studies show that high-quality IR programs attract more information intermediaries (e.g., analysts and the business press). Beyond increasing the visibility of corporate news, these intermediaries might create private firm-specific information, thus increasing the amount and quality of information available to market participants (Lang and Lundholm, 2000; Drake *et al.*, 2014; Green *et al.*, 2014a). The result is a reduction in the information acquisition costs borne by traders and a decrease in the adverse selection component of bid-ask spreads, which fosters a more complete capitalization of the news into stock prices (Brennan and Subrahmanyam, 1995).

In the context of Merton's (1987) model of incomplete information high-quality IR "will induce more trading in the firm's stock by uninformed investors" (Brown and Hillegeist, 2007, p. 446). However, intensified trading by the uninformed proportionately attracts more informed trading (Kyle, 1985). Yet, to the extent that informed traders are risk-averse and/or capital constrained, one would observe a relative decrease in these agents' propensity to trade as uninformed trading increases. In sum, IRQ reduces the level of IA through the investor recognition channel, thereby lowering stock mispricing (e.g., Lev, 1992; Collins *et al.*, 2003; Brown *et al.*, 2004; Brown and Hillegeist, 2007). Increased analyst and media coverage could additionally mitigate stock mispricing by providing investors with credible and timely editorial content that improves their understanding of the implication of the news for future performance (Drake *et al.*, 2014).

Alternatively, IRQ might affect IA by altering the incentives to search for private information. High-quality IR programs in form of more timely, consistent, accurate, and complete public disclosures (e.g., Byrd *et al.*, 1993; Kirk and Vincent, 2014; Karolyi and Liao, 2015) might reduce private information search incentives (Verrecchia, 1982). By "bringing the future forward" (Lundholm and Myers, 2002, p. 818), IR reduce the frequency of private information events, i.e. the rate at which informed traders discover and trade on private information (Lundholm and Myers, 2002).[2]

It follows that IRQ reduces IA because (i) it adversely affects the relative amount of informed trading, and/or (ii) it is inversely related to the frequency of private information events. This conclusion is in line with the empirical evidence in Brown *et al.* (2004) that firms holding more frequent conference calls exhibit lower degrees of IA than their non-holding counterparts (see also Agarwal *et al.*, 2016).

2.3 IR Quality and Information Uncertainty (IU)

Jiang *et al.* (2005, p. 185) define IU in terms of "value ambiguity, or the precision with which a firm's value can be estimated by knowledgeable investors at reasonable cost." Similarly, Zhang (2006a, p. 105) notes that IU potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information.

A central result in Jiang *et al.* (2005) is that market pricing dynamics vary systematically, depending on the degree of IU. Relatedly, Zhang (2006a) finds that uncertainty delays

[2] As Verrecchia (2001) points out, this conclusion relies on the assumption that investors' private information is exogenously endowed. It is possible that more frequent disclosures increase the incentives of sophisticated investors to acquire and trade on private information (Fu *et al.*, 2012). Moreover, increasing the frequency of mandatory disclosures may reduce firms' voluntary disclosures (Gigler and Hemmer, 2001), and encourage or discourage the production of information by information intermediaries.

the flow of ambiguous information into stock prices. In turn, Jiang *et al.* (2005) provide empirical evidence that high IU exacerbates investor psychological biases (Hirshleifer, 2001) and limits rational arbitrage.[3] Furthermore, Boyarchenko (2012) finds that ambiguity-averse investors assign higher probabilities to lower utility states and charge an ambiguity premium, leading to lower stock prices, when they are faced with doubts about the quality of information and uncertainty about the data-generating process (see also Epstein and Schneider, 2008).

IU-induced mispricing may result from two types of sensemaking occasions: ambiguity and uncertainty. Investors engage in sensemaking in the case of ambiguity because they are confused by too many interpretations; in the case of uncertainty, investors do so because they are ignorant of any interpretations (Weick, 1995). Indeed, under uncertainty, investors suffer from "imprecision in estimates of future consequences conditional on present actions" (March, 1994, p. 174). In turn, investors face ambiguity when information lacks clarity, is highly complex, or when a paradox makes multiple explanations plausible (Martin, 1992).

Firms can remove ignorance by providing a greater quantity of information to investors. In contrast, Weick (1995, p. 99) argues that the resolution of confusion requires that a different kind of information be conveyed to the marketplace, "namely, the information that is constructed in face-to-face interaction that provides multiple cues." That is, resolving confusion requires debate, clarifications, and enactment more than merely increasing the amount of data (Daft and Lengel, 1986).

To the extent that the IR function manages the firm's disclosure process and institutionalizes firm/investor relationships, high-quality IR can aid in resolving both ignorance (uncertainty) and confusion (ambiguity). Bushee and Miller (2012) and Kirk and Vincent (2014), among others, show that U.S. firms initiating professional IR experience increases in public disclosure and in investor awareness. Furthermore, Bushee *et al.* (2011) demonstrate in a U.S. context that firm/investor private meetings affect the degree to which information intermediaries can update their priors about the firms through direct interactions with senior management and other informed participants. For Roberts *et al.* (2006), because of the rich sensory data of the shared physical context, IR meetings clearly offer the greatest potential for building reciprocal understanding, thereby reducing mispricing.

Besides, the financial community also relies heavily on public information, properties of which may be clarified during IR private meetings (Green *et al.*, 2014b; Solomon and Soltes, 2015). Notwithstanding the absence of private communication of price-sensitive information, Barker *et al.* (2012)) find that U.K. fund managers paradoxically consider IR meetings as the primary source of information, especially on long-term strategy and prospects, and management capabilities and orientation (see also Marston, 2008; Lok, 2010; Hobson *et al.*, 2012). In turn, Roberts *et al.* (2006, p. 282) report that firms also attach considerable value to IR meetings; this is because such meetings enable firms to alter the "the complex and mobile gestalt of company identity that is the basis of investor decision-making".

By expediting the resolution of uncertainty (Lang and Lundholm, 1996) and resolving equivocality of communication (Roberts *et al.*, 2006), high-quality IR should fasten the correct capitalization of otherwise ambiguous information into stock prices (Zhang, 2006a).

So far, we have constrained IRQ to affect mispricing through its impact on IA/IU. However, while a direct effect of IR on mispricing is theoretically unclear, we lean on Kirk and Vincent (2014) to hypothesize a direct negative link between IRQ and mispricing. This direct link helps test partial mediation through IA/IU, or test whether IR meetings are organized for

[3] While our focus in this study is on IA/IU, we acknowledge that investor cognitive processing biases are another source of mispricing (e.g., Lev *et al.*, 2005; Warr *et al.*, 2012). However, the effects of such biases are found to be strongest in settings characterized by high uncertainty and poor information. Therefore, our tests do, albeit weakly, embody the effect of cognitive biases on mispricing.

reasons other than firm-specific news (Soltes, 2014), but that affect mispricing. On a view of the above, we form and test three main hypotheses:

Hypothesis 1a. The adverse effect of high-quality IR on mispricing runs through its impact on information asymmetry

Hypothesis 1b. High-quality IR deters information uncertainty, thereby mitigating mispricing

Hypothesis 2. High-quality IR adversely affects mispricing beyond its impact on information asymmetry/uncertainty.

Despite the preceding expectations, there are credible reasons that may weaken the ability of IR to mitigate mispricing. In spite of its importance, credibility may sometimes be sacrificed by both IR departments and information intermediaries. IR teams may strategically choose to cater to investors' sentiment by just reporting news that confirms investor beliefs while discounting others, thus 'catching up' investor intermediaries in the 'hype' (e.g., Lang and Lundholm, 2000; Hong and Huang, 2005; de Jong *et al.*, 2007; Solomon, 2012). Also, there seems to be an implicit quid pro quo arrangement between information intermediaries and firms' management with respect to favorable coverage and access to senior management (e.g., Ke and Yu, 2006; Chen *et al.*, 2013). These implicit incentives are likely to momentarily and artificially boost stock prices, and cause return reversals around earnings announcements (Solomon, 2012). In addition, private access to management via IR meetings can exacerbate IA among investors, which runs counter to the notion of level playing field with regard to information that regulators seek to create (Solomon and Soltes, 2015). Whether IRQ mitigates or contributes to mispricing is, therefore, an empirical issue.

3 Econometric Framework

Drake *et al.* (2014) argue that accruals and cash flows provide an ideal setting to explore the role of an investor intermediary in market pricing dynamics. Therefore, we first investigate the extent to which IR quality aids in correctly pricing these two primary components of earnings before exploring the possible channels through which this effect can work.

3.1 Tests of Efficient Pricing of Accruals and Cash Flows: The Mishkin (1983) Test

The Mishkin test (MT) aims at assessing the extent to which investors correctly account for the implication of current earnings' components for future earnings. This procedure can be used to test whether the accruals and cash flow components of earnings are correctly priced by investors. The MT relies on two equations of the following type:

$$EAR_{i,t+1} = \gamma_0 + \gamma_1 ACC_{i,t} + \gamma_2 CF_{i,t} + u_{i,t+1} \tag{1}$$

$$RET_{i,t+1} = \delta \left(EAR_{i,t+1} - \gamma_0^* - \gamma_1^* ACC_{i,t} - \gamma_2^* CF_{i,t} \right) + v_{i,t+1} \tag{2}$$

where $EAR_{i,t}$, $ACC_{i,t}$, $CF_{i,t}$ and $RET_{i,t}$ are respectively the earnings, accruals, cash flows and returns on the stock of firm i during year t. In the system above, (1) is a forecasting equation while (2) is a pricing equation. To ease interpretation, it is customary in this literature to convert the variables into terms of their fractional ranks within sectors before proceeding with model estimation (Larcker and Rusticus, 2010). For instance, $EAR_{i,t}$ is the fractional rank of firm i's earnings within its sector during year t. This transformation is applied to all variables.

Substituting the expression of $EAR_{i,t+1}$ into the right hand side of Equation (2) yields a reduced-form representation of returns:

$$RET_{i,t+1} = \delta\left(\gamma_0 - \gamma_0^*\right) + \delta\left(\gamma_1 - \gamma_1^*\right)ACC_{i,t} + \delta\left(\gamma_2 - \gamma_2^*\right)CF_{i,t} + \delta u_{i,t+1} + v_{i,t+1} \quad (3)$$

Assuming that the forecasting equation is correctly specified, the accruals and cash flows are correctly priced by the market if $\gamma_1 - \gamma_1^* = 0$ and $\gamma_2 - \gamma_2^* = 0$. See Kraft *et al.* (2007) for details. The MT of market efficiency is, therefore, equivalent to a likelihood ratio (LR) test that compares the full model given by (1)-(2) to a constrained model that imposes $\gamma_1 - \gamma_1^* = 0$ and $\gamma_2 - \gamma_2^* = 0$. This LR test is performed within a nonlinear seemingly unrelated regression (NL-SUR) procedure.

Equation (3) suggests that the MT of market efficiency may also be conducted via an OLS regression of returns on accruals and cash flows. The theoretical expressions of this regression's coefficients are given by $\beta_k = \delta\left(\gamma_k - \gamma_k^*\right)$, $k = 0, 1, 2$. In principle, this allows us to conduct the MT as simple significance tests on the coefficients β_1 and β_2. However, the simulations conducted by Kraft *et al.* (2007) suggest that a large sample is needed for the OLS regression-based MT to be as powerful as the LR test. This is not surprising given that a test of the null hypothesis $\beta_k = 0$ tends to be more conservative than a direct test of $\gamma_k - \gamma_k^* = 0$. For that reason, the OLS regression-based MT is not used in this paper.

Kraft *et al.* (2007) show that excluding relevant earnings' components that are not rationally priced from the model creates an omitted variable bias that can lead to invalid inferences. In an attempt to avoid this kind of bias, we expand Equation (1) as follows:

$$\begin{aligned} EAR_{i,t+1} \quad = \quad & \gamma_0 + \gamma_1 ACC_{i,t} + \gamma_2 CF_{i,t} + \gamma_3 SALGR_{i,t} \\ & + \gamma_4 TRVOL_{i,t} + \gamma_5 MCAP_{i,t} + \gamma_6 P2B_{i,t} + u_{i,t+1} \end{aligned} \quad (4)$$

where $SALGR_{i,t}$, $TRVOL_{i,t}$, $MCAP_{i,t}$ and $P2B_{i,t}$ are respectively the sales growth, trade volume, market capitalization, and price-to-book ratio of firm i during year t. The pricing equation is modified accordingly:

$$\begin{aligned} RET_{i,t+1} \quad = \quad & \delta(EAR_{i,t+1} - \gamma_0^* - \gamma_1^* ACC_{i,t} - \gamma_2^* CF_{i,t} - \gamma_3^* SALGR_{i,t} \\ & - \gamma_4^* TRVOL_{i,t} - \gamma_5^* MCAP_{i,t} - \gamma_6^* P2B_{i,t}) + v_{i,t+1} \end{aligned} \quad (5)$$

As previously, a given component of earnings is correctly priced by the market if and only if its coefficient satisfies $\gamma_k - \gamma_k^* = 0$, for $k = 1, ..., 6$.

With this improved model specification, we can investigate the possible associations between IRQ and the patterns of mispricing. First, we define a binary variable $IRQM_{i,t}$ that takes the value 1 if firm i's IRQ index is above the median of its industry, and 0 otherwise. Next, we estimate the system (4)-(5) and perform the MT separately for the sub-samples identified by $IRQM_{i,t} = 1$ and $IRQM_{i,t} = 0$. By considering these sub-samples separately, we will be able to identify the components of earnings that are likely mispriced for each sub-group.

Recent research (e.g., Konstantinidi *et al.*, 2016) suggests that MT should be modified to incorporate both the asymmetric persistence of accruals and the differential pricing of accruals and cash flows. Failing to account for the effect of timely loss recognition will bias expectations' models, which makes inferences about market efficiency sensitive to such bias. Moreover, while prior research has imposed identical pricing for accruals and cash flows, theory suggests that the pricing of these earnings' components would differ depending on their persistence and ability to predict earnings (Barth *et al.*, 1999; Pope and Wang, 2005). Indeed, Konstantinidi *et al.* (2016) provide empirical evidence that investors price these components differently, thereby rejecting rational pricing and the EFH.

To examine the robustness of our inferences based on the system (4)-(5), we first investigate whether investors anticipate the lower persistence of accruals in loss years due to timely loss recognition (conditional conservatism). To this end, we determine economic gain states (years) and economic loss states following Ball and Shivakumar (2006). Our proxy for gain and loss states is an indicator variable (D_t) that takes the value 1 if the industry-adjusted cash flows for a firm in year t are negative, and 0 otherwise. Incorporating this indicator permits us to identify the state of the world under which mispricing is found. Under timely loss recognition, one would expect higher mean reversion of accruals in loss states relative to gain states.

In a second step, we relax the restriction, usually imposed in MT, that accruals and cash flows are identically priced (as suggested, e.g., by the coefficient δ in the system (4)-(5)). Doing so requires estimating a three-equation system, including two predictive regressions for future earnings (one for accruals and one for cash flows) and a regression that articulates how unexpected earnings' components map into future stock returns. Accounting for asymmetry across states and differential pricing of cash flows and accruals surprises allows more direct tests of the naive EFH. Under conditional conservatism, EFH would require that the accruals anomaly be more pronounced among loss firms relative to profit firms (Patatoukas, 2016). For expository purposes, we rely on a parsimonious model that allows a valid test for market efficiency (see also Konstantinidi *et al.*, 2016).

$$ACC_{i,t+1} = \gamma_0 + \gamma_{01}D_t + \gamma_1 ACC_{i,t} + \gamma_2 CF_{i,t} + \gamma_3 ACC_{i,t}D_t + \gamma_4 CF_{i,t}D_t + u_{1i,t+1} \quad (6)$$

$$CF_{i,t+1} = \omega_0 + \omega_{01}D_t + \omega_1 ACC_{i,t} + \omega_2 CF_{i,t} + \omega_3 ACC_{i,t}D_t + \omega_4 CF_{i,t}D_t + u_{2i,t+1} \quad (7)$$

$$\begin{aligned} RET_{i,t+1} = {} & \delta_1 \left(ACC_{i,t+1} - \gamma_0^* - \gamma_{01}^* D_t - \gamma_1^* ACC_{i,t} - \gamma_2^* CF_{i,t} - \gamma_3^* ACC_{i,t}D_t - \gamma_4^* CF_{i,t}D_t\right) \\ & + \delta_2 \left(CF_{i,t+1} - \omega_0^* - \omega_{01}^* D_t - \omega_1^* ACC_{i,t} - \omega_2^* CF_{i,t} - \omega_3^* ACC_{i,t}D_t - \omega_4^* CF_{i,t}D_t\right) \\ & + v_{i,t+1} \end{aligned} \quad (8)$$

where the parameters γ_3, γ_4, ω_3, and ω_4 are incremental coefficients pertaining to loss states in the predictive equations. In contrast to the parameters in the predictive equations, the pricing parameters (γ_k^* and ω_k^*) are collectively underidentified, which prompts us to rewrite Equation (8) for the purpose of our empirical tests of rationality conditions:

$$\begin{aligned} RET_{i,t+1} = {} & \delta_1 ACC_{i,t+1} + \delta_2 CF_{i,t+1} \\ & - \left(\kappa_0^* - \kappa_{01}^* D_t - \kappa_1^* ACC_{i,t} - \kappa_2^* CF_{i,t} - \kappa_3^* ACC_{i,t}D_t - \kappa_4^* CF_{i,t}D_t\right) \\ & + v_{i,t+1} \end{aligned} \quad (9)$$

where $\kappa_k^* = \delta_1\gamma_k^* + \delta_2\omega_k^*$, with $k = 0, 1, 2, 3, 4$.

3.2 Investigating the Causal Links between IR Quality and Mispricing

In Section 2, we have suggested that IR quality ($IRQ_{i,t}$) may have a direct effect on mispricing (MSV). However, IRQ may also affect MSV via the channels of IA and IU. We have also argued that firms may select IRQ strategically in response to undesirable levels of IU, IA, and MSV. Therefore, the latter variables potentially have a causal effect on IRQ as well.

Our main objective is to investigate the causal effects of IRQ, IU, and IA on MSV. To this end, we operationalize the IU and IA using six variables (see Section 4.2): the bid-ask spread ($BASP_{i,t}$), Amihud's (2002) illiquidity ratio ($AMIH_{i,t}$), the trading volume ($TRVOL_{i,t}$), analyst forecast errors ($ERR_{i,t}$), the number of analysts following a firm ($NOEST_{i,t}$) and the dispersion of analyst forecasts ($DISP_{i,t}$). Six other variables that potentially reflect various aspects of IU and IA are also considered for control purposes. These are the relative systematic risk as measured by the realized beta ($RBETA_{i,t}$), the realized idiosyncratic volatility ($RIVOL_{i,t}$), the realized idiosyncratic skewness ($RSKEW_{i,t}$), the use of public capital markets ($UPCM_{i,t}$), the cross-listing on either the NYSE or the LSE ($CLIST_{i,t}$) and the leverage ratio ($LEV_{i,t}$). Our regressions control for three other firm characteristics used in the MT, namely the price-to-book ratio ($P2B_{i,t}$), the market capitalization ($MCAP_{i,t}$) and sales growth ($SALGR_{i,t}$).

First, we seek to understand whether MSV can be predicted using lagged information. For that purpose, we specify the following regression model:

$$\begin{aligned} MSV_{i,t} \;=\;& \beta_{0,0} + \beta_{0,1}IRQ_{i,t-1} + \beta_{0,2}AMIH_{i,t-1} + \beta_{0,3}BASP_{i,t-1} + \beta_{0,4}TRVOL_{i,t-1} \\ &+\beta_{0,5}ERR_{i,t-1} + \beta_{0,6}DISP_{i,t-1} + \beta_{0,7}NOEST_{i,t-1} + \beta_{0,8}MSV_{i,t-1} \\ &+\beta_{0,9}RBETA_{i,t-1} + \beta_{0,10}RIVOL_{i,t-1} + \beta_{0,11}RSKEW_{i,t-1} + \beta_{0,12}UPCM_{i,t-1} \\ &+\beta_{0,13}CLIST_{i,t-1} + \beta_{0,14}LEV_{i,t-1} + \beta_{0,15}P2B_{i,t-1} + \beta_{0,16}MCAP_{i,t-1} \\ &+\beta_{0,17}SALGR_{i,t-1} + \varepsilon_{0,i,t} \end{aligned} \tag{10}$$

The inclusion of the lagged value of MSV in the RHS of the regression above allows us to control for the persistence of misvaluation so that the coefficients of the other regressors basically capture their effects on the increments of MSV over time.

Second, we perform a regression of MSV onto contemporaneous information controlling for lagged MSV in order to explore the directions in which the coefficients of IRQ, IA and IU would change. The model estimated is:

$$\begin{aligned} MSV_{i,t} \;=\;& \beta_{1,0} + \beta_{1,1}IRQ_{i,t} + \beta_{1,2}AMIH_{i,t} + \beta_{1,3}BASP_{i,t} + \beta_{1,4}TRVOL_{i,t} \\ &+\beta_{1,5}ERR_{i,t} + \beta_{1,6}DISP_{i,t} + \beta_{1,7}NOEST_{i,t} + \beta_{1,8}MSV_{i,t-1} \\ &+\beta_{1,9}RBETA_{i,t} + \beta_{1,10}RIVOL_{i,t} + \beta_{1,11}RSKEW_{i,t} + \beta_{1,12}UPCM_{i,t} \\ &+\beta_{1,13}CLIST_{i,t} + \beta_{1,14}LEV_{i,t} + \beta_{1,15}P2B_{i,t} + \beta_{1,16}MCAP_{i,t} \\ &+\beta_{1,17}SALGR_{i,t} + \varepsilon_{1,i,t} \end{aligned} \tag{11}$$

It can be shown that the differences between the coefficients of the regressors across both models is mainly driven by the increments of the regressors between periods $t-1$ and t and their correlations with the error term $\varepsilon_{1,i,t}$. For instance, if the coefficient of IRQ in the second regression ($\theta_{1,1}$) is very different from its coefficient in the first ($\theta_{0,1}$), this would suggest that the incremental effort devoted by firms to attaining or maintaining a certain level of IRQ between periods $t-1$ and t is non-random (endogenous). In this context, endogeneity means that firms strategically choose their IRQ level in order to control the magnitude of mispricing.

As we shall see in the sequel, the empirical results support the intuition that the increments of IRQ are endogenous. This suggests that the other regressors operationalizing IA and IU are possibly endogenous as well. We consider two complementary approaches to tackle this endogeneity problem: a linear instrumental variable model (heareafter, 2SLS) and a piecewise linear Heckman's sample selection model (heareafter, Heckit). In both approaches, lagged regressors are used as instruments.

In the first-step of the 2SLS procedure, we regress each of the variables $IRQ_{i,t}$, $BASP_{i,t}$, $AMIH_{i,t}$, $TRVOL_{i,t}$, $ERR_{i,t}$, $NOEST_{i,t}$, and $DISP_{i,t}$ onto past information. For instance, our first instrumental regression is given by:

$$\begin{aligned} IRQ_{i,t} \;=\;& \theta_0 + \theta_1 IRQ_{i,t-1} + \theta_2 AMIH_{i,t-1} + \theta_3 BASP_{i,t-1} + \theta_4 TRVOL_{i,t-1} \\ &+\theta_5 ERR_{i,t-1} + \theta_6 DISP_{i,t-1} + \theta_7 NOEST_{i,t-1} + \theta_8 MSV_{i,t-1} \\ &+\theta_9 RBETA_{i,t-1} + \theta_{10} RIVOL_{i,t-1} + \theta_{11} RSKEW_{i,t-1} + \theta_{12} UPCM_{i,t-1} \\ &+\theta_{13} CLIST_{i,t-1} + \theta_{14} LEV_{i,t-1} + \theta_{15} P2B_{i,t-1} + \theta_{16} MCAP_{i,t-1} \\ &+\theta_{17} SALGR_{i,t-1} + \varepsilon_{2,i,t}. \end{aligned} \tag{12}$$

Likewise, each of the variables $BASP_{i,t}$, $AMIH_{i,t}$, $TRVOL_{i,t}$, $ERR_{i,t}$, $NOEST_{i,t}$, and $DISP_{i,t}$ is regressed onto the same set of regressors as on the RHS above. The results of these seven instrumental regressions will shed light on the complexity of the interactions that may exist between IR quality and mispricing. For instance, if θ_8 turns out to be positive and significant in Equation (12), this would lead us to infer that higher past misvaluation is associated with higher future IRQ.

The second-step estimating equation of the 2SLS procedure is given by:

$$\begin{aligned} MSV_{i,t} \;=\;& \beta_{1,0} + \beta_{1,1}\widehat{IRQ}_{i,t} + \beta_{1,2}\widehat{AMIH}_{i,t} + \beta_{1,3}\widehat{BASP}_{i,t} + \beta_{1,4}\widehat{TRVOL}_{i,t} \\ &+\beta_{1,5}\widehat{ERR}_{i,t} + \beta_{1,6}\widehat{DISP}_{i,t} + \beta_{1,7}\widehat{NOEST}_{i,t} + \beta_{1,8} MSV_{i,t-1} \\ &+\beta_{1,9} RBETA_{i,t} + \beta_{1,10} RIVOL_{i,t} + \beta_{1,11} RSKEW_{i,t} + \beta_{1,12} UPCM_{i,t} \\ &+\beta_{1,13} CLIST_{i,t} + \beta_{1,14} LEV_{i,t} + \beta_{1,15} P2B_{i,t} + \beta_{1,16} MCAP_{i,t} \\ &+\beta_{1,17} SALGR_{i,t} + \tilde{\varepsilon}_{1,i,t} \end{aligned} \tag{13}$$

where the regressors with a "hat" symbol denote their fitted values obtained from the first-step instrumental regressions. Note that we are advocating that the regressors without a "hat" symbol are exogenous.

Considering the Heckit approach, we split our original sample into two sub-samples: a sub-sample where pricing errors are negative and another sub-sample with positive pricing errors. A negative pricing error means that the underlying company's stock is undervalued, and vice versa (RKRV, 2005). Also, recall that observations consist of firm-years such that a given firm may migrate across both sub-samples over time.

We first ask: Can past information be used to predict the probability of a firm being overvalued or undervalued in the next period? To answer this question, we define a binary variable $UNDER_{i,t}$ that takes the value 1 if firm i is undervalued at period t, and 0 otherwise. Next, we estimate a Probit model where past information conditions the probability of $UNDER_{i,t} = 1$. This amounts to assuming the existence of a lead indicator $Z_{i,t}$ taking the form:

$$\begin{aligned} Z_{i,t} \;=\;& \gamma_0 + \gamma_1 IRQ_{i,t-1} + \gamma_2 AMIH_{i,t-1} + \gamma_3 BASP_{i,t-1} + \gamma_4 TRVOL_{i,t-1} \\ &+\gamma_5 ERR_{i,t-1} + \gamma_6 DISP_{i,t-1} + \gamma_7 NOEST_{i,t-1} + \gamma_8 MSV_{i,t-1} \\ &+\gamma_9 RBETA_{i,t-1} + \gamma_{10} RIVOL_{i,t-1} + \gamma_{11} RSKEW_{i,t-1} + \gamma_{12} UPCM_{i,t-1} \\ &+\gamma_{13} CLIST_{i,t-1} + \gamma_{14} LEV_{i,t-1} + \gamma_{15} P2B_{i,t-1} + \gamma_{16} MCAP_{i,t-1} \\ &+\gamma_{17} SALGR_{i,t-1} + \varepsilon_{3,i,t} \end{aligned} \tag{14}$$

where $\varepsilon_{3,i,t} \sim N(0,1)$ and $UNDER_{i,t} = 1$ if and only if $Z_{i,t}>0$. Hence,

$$Prob\left(UNDER_{i,t}=1|X_{i,t-1}\right)=\Phi\left(\hat{Z}_{i,t}\right)$$

where $X_{i,t-1}$ is the vector of lagged regressors and $\hat{Z}_{i,t}$ is the fitted value of $Z_{i,t}$.

Next, we ask whether the determinants of mispricing are the same when $UNDER_{i,t}=1$ and when $UNDER_{i,t}=0$. A naive approach to answer this question would be to estimate Equation (11) separately for the sub-samples identified by $UNDER_{i,t}=1$ and $UNDER_{i,t}=0$. However, we need to control for biases stemming from the correlation between the error term of the equation governing the truncation ($\varepsilon_{3,i,t}$) and the error term of the equation of MSV ($\varepsilon_{1,i,t}$). Therefore, the equations that we consider are:

$$\begin{aligned} MSV_{i,t} = {} & \beta_{2,0}+\beta_{2,1}IRQ_{i,t}+\beta_{2,2}AMIH_{i,t}+\beta_{2,3}BASP_{i,t}+\beta_{2,4}TRVOL_{i,t} \\ & +\beta_{2,5}ERR_{i,t}+\beta_{2,6}DISP_{i,t}+\beta_{2,7}NOEST_{i,t}+\beta_{2,8}MSV_{i,t-1} \\ & +\beta_{2,9}RBETA_{i,t}+\beta_{2,10}RIVOL_{i,t}+\beta_{2,11}RSKEW_{i,t}+\beta_{2,12}UPCM_{i,t} \\ & +\beta_{2,13}CLIST_{i,t}+\beta_{2,14}LEV_{i,t}+\beta_{2,15}P2B_{i,t}+\beta_{2,16}MCAP_{i,t} \\ & +\beta_{2,17}SALGR_{i,t}+\lambda_1 IMR_{1,i,t}+\eta_{1,i,t} \end{aligned} \tag{15}$$

and

$$\begin{aligned} MSV_{i,t} = {} & \beta_{3,0}+\beta_{3,1}IRQ_{i,t}+\beta_{3,2}AMIH_{i,t}+\beta_{3,3}BASP_{i,t}+\beta_{3,4}TRVOL_{i,t} \\ & +\beta_{3,5}ERR_{i,t}+\beta_{3,6}DISP_{i,t}+\beta_{3,7}NOEST_{i,t}+\beta_{3,8}MSV_{i,t-1} \\ & +\beta_{3,9}RBETA_{i,t}+\beta_{3,10}RIVOL_{i,t}+\beta_{3,11}RSKEW_{i,t}+\beta_{3,12}UPCM_{i,t} \\ & +\beta_{3,13}CLIST_{i,t}+\beta_{3,14}LEV_{i,t}+\beta_{3,15}P2B_{i,t}+\beta_{3,16}MCAP_{i,t} \\ & +\beta_{3,17}SALGR_{i,t}+\lambda_0 IMR_{0,i,t}+\eta_{0,i,t} \end{aligned} \tag{16}$$

where $IMR_{1,i,t}=\frac{\phi\left(\hat{Z}_{i,t}\right)}{\Phi\left(\hat{Z}_{i,t}\right)}$ is proportional to the expectation of $\varepsilon_{1,i,t}$ conditional on $UNDER_{i,t}=1$ and $IMR_{0,i,t}=-\frac{\phi\left(\hat{Z}_{i,t}\right)}{1-\Phi\left(\hat{Z}_{i,t}\right)}$ is proportional to the expectation of $\varepsilon_{1,i,t}$ conditional on $UNDER_{i,t}=0$. Accordingly, Equation (15) is restricted to the sub-sample $UNDER_{i,t}=1$ while Equation (16) is restricted to the sub-sample $UNDER_{i,t}=0$.

If either of the coefficients λ_1 or λ_0 in Equations (15) and (16) is significant, this would imply that the truncation biases matter. Moreover, the signs of these coefficients coincide with the sign of the linear correlation coefficient of $\varepsilon_{0,i,t}$ (in Equation (10)) and $\varepsilon_{3,i,t}$ on each sub-sample. If λ_1 is negative, for instance, this would suggest that a perceived higher probability of undervaluation ex ante is associated with a lower magnitude of undervaluation ex post.

4 The Data

4.1 Sample

The sample consists of stocks included in the European index EURO STOXX 50, and in the German indices DAX (large-caps), MDAX (mid-caps in classical sectors), TecDAX (technology mid- and small-caps) and SDAX (small-caps in classical sectors).[4] We require observations to have non-negative values on the total assets, sales, leverage, and book value of equity. The final sample includes 252 non-financial European firms, and spans the period from 2002 to 2011. Our measure of IR quality is derived from the proprietary ratings of firm IR programs by analysts and institutional investors compiled by the Society of Investment Professionals in Germany (DVFA) on behalf of the magazine *Capital*. Capital market and accounting data are obtained from Datastream, while the data on analyst forecasts are collected from I/B/E/S.

[4] See Online Appendix Part A for more details about the sample.

4.2 Main Variables

We discuss the construction of the main variables and relegate the definition of all variables used in the empirical analysis to Appendix 1.

Earnings' components. EAR is income before extraordinary items and dividends; CF is cash flows from operations; ACC is accruals defined as EAR minus CF. These variables are then deflated by one-year lagged total assets.

Stock returns. RET is the log buy and hold return on a given stock over a 12-month period beginning three months after the fiscal year-end (see Drake *et al.*, 2009). An alternative measure used in the MT is $SIZERET$ which denotes the difference between a firm's buy and hold return and a return on a corresponding size decile-matched portfolio.

Mispricing. Our measure of mispricing, MSV, is widely used in finance and is derived from the RKRV (2005) model that decomposes the market-to-book ratio (MBR) into mispricing effects and growth options. Indeed, the non-fundamental component of the MBR, MSV, is assumed to be positively related to investor sentiment in the stock market and involves a firm-specific component and a sector-wide component. For brevity, we have relegated the extraction of MSV to Online Appendix Part B.[5]

IR quality (IRQ). IRQ consists of four components and relies on the 'DVFA principles for effective capital market communication'.[6] The "target group orientation" component measures how well IR departments provide information to the investment community on a proactive basis. This component likely measures private disclosure activities and access to management. The "transparency" component probably tracks management credibility and the quality of corporate governance. The "track record" component pertains to the accuracy and precision of a firm's communications over time. Finally, the "sustainability reporting" component measures the extent to which firms disclose non-financial information; this component helps gauge a firm's commitment to social and environmental issues. Although these four components capture different aspects of IR, they are highly correlated. Therefore, subsequent analyses use only the aggregate measure.

Information Asymmetry (IA). We use three proxies for IA: bid-ask spreads, trading volume and price impact. The bid-ask spread ($BASP$) is commonly thought to measure information asymmetry explicitly (Leuz and Verrecchia, 2000). This pertains to the adverse selection arising from having asymmetrically informed investors trading in the same security. The more severe the IA, the wider the spread necessary for market makers to recoup losses from trading with potentially informed traders. We calculate $BASP$ as: (ask-bid)/((ask+bid)/2). The trading volume ($TRVOL$) captures investors' willingness to transact in a stock which, in turn, is inversely related to the existence of IA (Leuz and Verrecchia, 2000). Yet, $TRVOL$ is noisy as it might reflect such factors unrelated to IA as portfolio rebalancing needs. The Amihud (2002) illiquidity ratio ($AMIH$), computed as the ratio of daily absolute returns over euro trading volume is intended to capture the ability of an investor to trade in a stock without moving its price. As in Daske *et al.* (2008), we use the annual median of $AMIH$ in our empirical analyses.

Information Uncertainty (IU). We rely on three proxies for IU. The first proxy is the number of analysts who cover a firm ($NOEST$). A firm with deeper analyst following is theoretically more transparent in its future prospects and intended actions, and is therefore

[5]To obtain reliable estimates, we use a much larger sample of 30,446 observations for 2,312 European firms (except for financials and utilities) collected from Datastream from 1991 to 2011.

[6]URL: www.dvfa.de/verband/publikationen/effektive-finanzkommunikation/(accessed 7 July 2015). On behalf of the Magazine *Capital*, the DVFA administers annual web-based questionnaires to over 400 institutional investors and analysts, and commissions an independent researcher to compute normalized overall realizations of IRQ, ranging from 0 to 500. The list is published in Capital magazine each year and thus highly visible to investors. The publication date was typically in mid-June. These realizations form the basis of IRQ.

less uncertain in its valuation (Zhang, 2006a; Lu *et al.*, 2010). The second proxy for IU is the dispersion in analyst earnings forecasts ($DISP$). Widely used in the literature (e.g. Barron and Stuerke, 1998; Bissessur and Veenman, 2016), $DISP$ reflects the uncertainty about the future prospects of a firm by capturing the degree of consensus among analysts. We measure $DISP$ as the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity. Our last measure for IU is analyst forecast error (hereafter ERR; Farragher *et al.*, 1994; Gu and Hackbarth, 2013). We calculate ERR as the natural log of one plus the difference between analysts' earnings per share (EPS) forecasts and actual EPS scaled by the absolute value of median. ERR can thus be considered a measure for the accuracy of analyst forecasts.

4.3 Summary Statistics

Table 1 provides descriptive statistics for the full sample and for sub-samples of firms with higher-rated IR (H_IRQ) and those with lower-rated IR (L_IRQ). The mean (median) firm has a market value of €12.3 billion (€1.7 billion) and the standard deviation is €22.1 billion. In turn, the average firm reports total earnings, cash flows, and accruals (each in percent of lagged total assets) of 4.8%, 10%, and -5.2%, respectively. MSV is statistically significant (t = 3.46), suggesting that market participants and firm managers rely on different sets of information about the prospects of the firms in our sample.[7]

We find that both groups of firms are relatively overpriced; however, higher-rated firms tend to be more overvalued. More importantly, the differences in mispricing turn out to stem from the firm-specific component of MSV, which shows that lower-rated firms are generally underpriced while higher-rated firms on average are overvalued. The average firms in the two sub-samples are of similar size. Interestingly, our proxies for IA are collectively higher for the sub-sample of firms with lower-rated IR. By contrast, IU measures provide no clear picture. Indeed, we find no difference in analyst forecast errors; at the same time, better-rated firms have deeper analyst following and less dispersed analyst forecasts. Finally, we observe that lower-rated firms exhibit higher idiosyncratic risk and leverage, while they are associated with lower values of EAR, CF, ACC, and returns.

[Table 1 about here]

5 Results

5.1 Mishkin Tests

5.1.1 *Primary results*

In Table 2, we use the system (4)-(5) to perform the MT via a NL-SUR. Column 1 corroborates the findings in Sloan (1996) that accruals are significantly less persistent than cash flows ($\gamma_1 - \gamma_2 = -0.174$). However, these results do not support the null hypothesis that investors rationally anticipate and price the differential persistence of accruals and cash flows with respect to their implications for future earnings. The LR test for the null hypothesis of market efficiency recommends rejection at the 1% level. We, therefore, explore potential sources of the apparent market inefficiencies. Parameter tests based on column 1 of Table 2 reveal that investors appear to systematically overweight accruals' surprises ($\gamma_1^* > \gamma_1$)

[7]Because mispricing is rather transient in nature (Baker *et al.*, 2009), we examine the adequacy of MSV by testing whether high MSV firms earn subsequently lower returns. Our results are consistent with this prediction (Online Appendix Part B). Therefore, mispricing persists long enough to allow managers to respond.

while they tend to correctly price information conveyed in cash flows' surprises ($\gamma_2^* \approx \gamma_2$). Our data do not support the EFH, which would require that both accruals and cash flows be jointly mispriced (Konstantinidi *et al.*, 2016). Indeed, in unreported analyses we find that the average persistence parameter obtained from regressing one-year ahead earnings on current earnings is 0.63, clearly indicating that $\gamma_1 < \gamma_2 < 0.63$. In this setting, for investors to naively fixate on reported total earnings both accruals and cash flows would have to be overweighted in the pricing equation such that $\gamma_1^* = \gamma_2^* = 0.63$.[8]

[Table 2 about here]

The rejection of rational pricing for accruals surprises suggests that accruals are a far too more complex accounting disclosure than cash flows, the interpretation of which requires high levels of sophistication. Recall that the most important audience of IR departments is composed of sophisticated delegated information intermediaries of investors (Collins *et al.*, 2003; Karolyi and Liao, 2015): sell-side analysts. This constituency is reportedly more sophisticated than individual investors and the business press (Drake *et al.*, 2014), and, as with institutional investors (especially hedge funds), continues to hold private meetings with companies' senior management even after Reg FD in the U.S. (Solomon and Soltes, 2015). In spite of the absence of privately communicating material information, IR meetings do increase the accessibility and clarity of information provided to investors (Kalay, 2015), thereby reducing IA/IU (Agarwal *et al.*, 2016; see also Section 2).

Therefore, we anticipate that high-quality IR programs would aid in reducing the documented mispricing of the accruals component of earnings. To explore this conjecture, we first group firms into two sub-samples on a year-by-year basis using the industry-specific median of IRQ: higher-quality IR firms (see column 2 of Table 2) vs. lower-quality IR firms (column 3 of Table 2). As our proxy of IRQ might systematically vary across industries and years, this procedure ensures that the median firm in each industry gets a ranking of 0.5.

As expected, we could not reject the null hypothesis of rational pricing of both components of earnings on the sub-sample of higher-quality IR firms ($\chi_2^2 = 0.19$, $p = 0.91$). In contrast, we find that pricing inefficiency is restricted to the sub-sample of firms with lower-quality IR programs. There, the LR test of rational pricing of both components of earnings is rejected at the 1% level ($\chi_2^2 = 10.88$, $p = 0.0043$). What is more, cash flows continue to be rationally priced even in this latter sub-sample ($p = 0.42$). As in column 1 of Table 2, accruals remain the mispriced component of total earnings ($p = 0.003$). Together, the evidence in columns 1–3 indicates that IRQ is instrumental in providing guidance on the valuation implications of a harder-to-value component of earnings (accruals).[9] In Section 5.3, we elaborate on the possible channels through which this effect might operate.

Notwithstanding, prior research suggests that financial analysts can influence the information content of stock prices. By translating a mixture of public and private information (gleaned from private meetings with senior management and applying the mosaic approach) into earnings forecasts, sell-side analysts likely facilitate the process of valuing firms. For example, Lee *et al.* (2014) document a significant reduction in return continuation following analyst forecast revisions and earnings announcements. In a similar vein, Karolyi

[8] The results remain qualitatively unaltered when we cluster standard errors by year to account for cross-sectional correlations of residuals in different years in the MT. We refrain from clustering standard errors on two dimensions (by firm and by year), relying on Petersen (2009) and Konstantinidi et al. (2016), who provide evidence that firm effects are likely negligible when returns are the dependent variable.

[9] Although the results discussed here use raw returns calculated in the interval starting at the beginning of April t and ending at the end of March $t+1$ (similar to Drake *et al.*, 2009), the inferences hitherto are resilient to the use of alternative measures of returns. Specifically, we employ size-adjusted returns (i.e. the difference between a firm's raw returns and the contemporaneous returns on a size-matched portfolio). The conclusions remain qualitatively unaltered. Details are available upon request from the authors.

and Liao (2015) show that the positive impact of IR on firm market value runs essentially through greater analyst following, improved analyst forecast accuracy, and lower forecast dispersion. Consistent with this, we find, in unreported tests, that firms with higher-quality IR exhibit subsequently deeper coverage by sell-side analysts ($t = 9.42$, $p < 0.001$), more accurate analyst forecasts ($t = 3.04$, $p = 0.002$), and lower forecast dispersion ($t = 3.86$, $p < 0.001$) than their counterparts with lower-rated IR. While not definitive, these univariate results are in line with Bushee *et al.* (2011), who argue that IR meetings in a "well-defined physical and social milieu" affect the degree to which the audience can update their priors about the firm through direct interactions with management and other informed participants.

Debate is ongoing about what causes the accruals anomaly (Shi and Zhang, 2012).[10] To provide exploratory evidence, we find (see columns 4–7 of Table 2), however, that the irrational pricing of accruals tends to be concentrated in firms with high realized idiosyncratic risk, high trading volume, low quoted bid-ask spreads, and low realized market beta. This evidence partially supports the notion that risk-averse arbitrageurs might shy away from fully exploiting the accruals anomaly in the presence of excessive idiosyncratic risk. At the same time, it runs counter to the transaction costs argument advanced by Mashruwala *et al.* (2006), because investors appear to correctly price the two earnings' components of firms for which they are more likely to bear higher transaction costs – that is, firms with low trading volume and high quoted bid-ask spreads. However, while puzzling at first sight, Hirshleifer *et al.* (2013) interpret firms with higher turnover (i.e. ratio of trading volume over outstanding shares) as having higher valuation uncertainty. Firms with lower trading volume can thus be seen as firms with lower valuation uncertainty, hence the ability of investors to rationally price such stocks. Unlike Shi and Zhang (2012), who dismiss the arbitrage explanation of the accruals anomaly, we tentatively conclude that the apparent mispricing of accruals is driven, not necessarily by prohibitive transaction costs, but by arbitrage risk potentially due to the absence of close substitutes (Mashruwala *et al.*, 2006).

5.1.2 *Accounting for Asymmetry in Persistence and Differential Pricing of Earnings' Components*

[Table 3 about here]

Table 3 summarizes the results from our three-equation MT conditional on loss and gain states. It contains the coefficient estimates of four specifications. Columns 1–2 show the results relative to the specification that uses raw stock returns as the dependent variable in Equation (8) while columns 3–4 pertain to specifications in which size-adjusted differential returns are the dependent variable. Standard errors in columns 2 and 4 are clustered by year. The sample size in each panel remains the same for each specification.

The results suggest that accruals and cash flows show differential persistence in gain and loss states when forecasting future cash flows. The earnings response coefficients for accruals and cash flows range from 0.18 to 0.20 and from 0.51 to 0.54, respectively (see Table 3). Therefore, one would expect rational investors to price these two earnings' components as well as their surprises differently. It turns out that investors value cash flow surprises much higher than accruals surprises. Indeed, the differential earnings response coefficient ($\delta_1 - \delta_2$) is significantly negative and amounts to -0.33. As a result, investors tend to distinguish between news related to cash flows and that related to accruals. This is strong evidence against the naive earnings fixation explanation for the accruals anomaly (see also Konstantinidi *et al.*, 2016).

[10] Providing a comprehensive review of this debate goes beyond the scope of this study; please, refer to, e.g., Richardson *et al.* (2010), for an excellent review.

In the predictive equation for future accruals, current accruals and cash flows exhibit similar persistence. The picture is reversed when forecasting future cash flows, where we note a differential persistence in both gain states ($\chi^2_2 = 48.15$, $p < 0.001$) and loss years ($\chi^2_2 = 64.95$, $p < 0.001$). However, unlike Konstantinidi *et al.* (2016), our results indicate that the related differential persistence between accruals and cash flows is seemingly greatest, not in loss states, but in gain years. Also, the differential persistence resides in the magnitude, not in the sign. Specifically, the incremental coefficient on cash flows during loss states (-0.168) is significantly lower than that on accruals (-0.063) when predicting cash flows ($\chi^2_2 = 11.09$, $p = 0.004$). The significant negative incremental coefficient on accruals is suggestive of the transitory nature of accruals in loss years under timely loss recognition. Thus, our finding is not supportive of the evidence by Konstantinidi *et al.* (2016) that cash flows are more persistent in loss states when forecasting cash flows and using industry-adjusted cash flows as the conditioning variable to identify the economic states.

We next use Equation (9) to test rational pricing conditions in different economic states via non-linear combinations of estimators. In gain states, the null hypothesis of rational pricing of both accruals and cash flows surprises is rejected at the 1% level. However, investors appear to rationally price cash flows in loss years. Opposed to this evidence, we provide that investors irrationally process information related to accruals surprises in loss years. We further test whether accruals and cash flows surprises are indeed differently priced in gain years and loss years. The aim is to identify potential sources of apparent mispricing by revealing the mispriced component of earnings and the economic states under which mispricing is observed. To this end, we test the restrictions $\kappa_3^* = \delta_1\gamma_3 + \delta_2\omega_3$ for accruals, and $\kappa_4^* = \delta_1\gamma_4 + \delta_2\omega_4$ for cash flows. Results from these tests reveal that (see column 2 of Table 3) the differential coefficient on cash flows surprises in gain and loss states is negative but statistically insignificant ($p = 0.39$). The corresponding differential coefficient for accruals is insignificant ($p = 0.73$).

In sum, we find evidence of asymmetric persistence of both accruals and cash flows only when forecasting future cash flows. Surprisingly enough, the differential persistence of accruals and cash flows is widest in gain states, not in loss states. Moreover, our parsimonious specifications indicate that the accruals anomaly in gain states is significant at the 5% level or better (see columns 1–4 of Table 3) while it is significant only at the 10% level in loss states; it even becomes insignificant in loss states when we use size-adjusted returns as the dependent variable in the pricing equation and standard errors are clustered by year. Despite these contrasts, we find no evidence conducive to asymmetric persistence of accruals across gain and loss years (the related p-values range from 0.39 to 0.73, see Table 3). Finally, there is limited, if any, evidence that investors tend to misprice cash flows only in gain years (see the bottom lines in Table 3). Similarly to accruals, we find no evidence that investors are more likely to misprice the cash flows of loss firms relative to gain firms. These results thus refute the naive EFH.

5.1.3 *Does the role of IR in mitigating mispricing vary across economic states?*

Table 3 uses parsimonious specifications and does not account for the role of IR in mitigating the market inefficiencies observed in pricing accruals in gain and loss states, and to a lesser extent, in pricing cash flows in gain states. We re-run the system (6)–(8) above while re-writing (8) as shown in (9) and including all the controls used in Table 2 in order to avoid the omitted variable bias and strengthen our ability to make clear inferences about the sources of inefficiencies. The standard errors are clustered by year, and the results are summarized in Table 4. Column 1 shows the full sample, which is contrasted in column 2 with the estimates from column 2 of Table 3. Columns 3 and 4 contain the results relative to firms with higher-quality IR and firms with lower-quality IR, respectively.

[Table 4 about here]

On the one hand, using the full sample in column 1 of Table 4, we find strong evidence of accruals' mispricing in both gain and loss states. In addition, we find no evidence that the mispricing of accruals systematically differs in loss and gain states. On the other hand, if anything, we can reject the null hypothesis of rational pricing of cash flows only in gain years at the 10% level ($p = 0.06$). Together, the evidence in column 1 of Table 4 suggests that investor mispricing of earnings' components is more likely for accruals and less so for the cash flow component and, if anything, it should be limited to gain years. These results contradict partly the conclusions attained from Table ,2 where we reported that cash flows are generally rationally priced but accruals are not. To that extent, one may conclude that allowing for asymmetric persistence, differential pricing and standard errors clustered by year may matter for inferences drawn from the MT. However, using size-adjusted returns as the dependent variable in the pricing equation (untabulated), cash flows appear to be rationally priced in both gain and loss years. What is more, the mispricing of accruals is now restricted to gain years.

Firms with higher-rated IR exhibit a rather interesting picture, in that investors tend to systematically overvalue their cash flows in gain states ($p = 0.003$) while this item is fairly rationally priced in loss states. Remarkably though, investors seem to correctly understand the valuation implications conveyed in the accruals' disclosures of these firms. This seems at first sight to contradict the ability of IR to improve the accessibility and clarity of information provided to investors. For the sub-sample of firms with lower-rated IR, accruals are consistently mispriced in gain and loss states, and the incremental mispricing in loss years (-0.07) is insignificant ($p = 0.66$). We interpret this result to mean that there is no asymmetry across states in the mispricing of accruals for firms with lower-rated IR. In rebuttal, the null hypothesis of rational pricing of cash flows in gain years is rejected only at the 10% level ($p = 0.076$).[11]

If investor mispricing is driven by the naive earnings fixation, IR may have no explanatory power or could exacerbate the mispricing (Drake *et al.*, 2014). At odds with this prediction, the results hitherto suggest that higher-quality IR improve investors' ability to efficiently impound accounting information into stock prices. If anything, cash flows tend to be mispriced only in gain states, but the evidence is not resilient to alternative measures for returns in the pricing equation.

Barone and Magilke (2009) find that cash flow mispricing is reduced by the trading activity of sophisticated investors. In a similar vein, Call (2008) shows that analysts' cash flow forecasts correct underpricing of operating cash flows while Mohanram (2014) reports that analysts' cash flow forecasts mitigate accruals' mispricing because earnings forecasts and cash flow forecasts jointly provide investors with implicit accrual forecasts (Drake *et al.*, 2014). These studies suggest potential channels through which IR may affect (mis)pricing of earnings' components: the analyst forecasts and trading activity of sophisticated investors.

A subtle but remarkable outcome of superior IR programs is the subsequent shift of the investor base away from more sophisticated investors toward more concentration of less sophisticated investors. This conjecture relies on Merton's (1987) investor recognition hypothesis (hereafter, IRH), which predicts decreasing information acquisition and processing costs as a result of heightened investor cognizance of a company's brand. Consistent with this prediction, Kalay (2015) finds that there is a higher concentration of less sophisticated investors in firms with superior IR (top decile). In contrast, Karolyi and Liao

[11] When we use size-adjusted stock returns in lieu of raw returns in the pricing equation (14), higher-quality IR appear pivotal in facilitating the market's ability to efficiently impound accruals and cash flows information into stock prices irrespective of the economic state. In contrast, investors tend to misprice the accruals of firms with lower-rated IR indifferently in gain and loss states; only is the mispricing in gain years significantly larger in magnitude than in loss states ($0.33 > 0.20$).

(2015) report that firms with more active IR are associated with higher institutional and hedge fund ownership; they, however, add that the economic magnitude of these relations are smaller relative to analyst variables. Therefore, the relationship between superior IR and subsequent concentration of sophisticated investors is an empirical issue.

To address this empirical issue, we investigate whether our data support the widening investor base argument for firms with superior IR programs. We crudely project our one-year-ahead measure of institutional ownership onto current-period levels of IR fractional ranks and control for year and sector fixed effects. We find that firms with higher-quality IR exhibit a decrease in institutional ownership in magnitude of up to 5.1%[12] (t = -2.68, p = 0.007) relative to firms with lower-quality IR in the subsequent year. While we have no fine-grained data to distinguish between the different types of institutional investors, it seems likely that IR benefits more individual investors.

The observed decrease in relative institutional holdings in firms with higher-quality IR is potentially consistent with Merton's (1987) investor recognition hypothesis. It attests to high-quality IR inducing more trading in the firm's stock by uninformed investors (Collins *et al.*, 2003). To the extent that more uninformed trading would prompt proportionate informed trading (Kyle, 1985), the significant relative decrease in institutional holdings for the sub-sample of firms with higher-rated IR is strong evidence that IR likely affects the investor mispricing of accounting information through its adverse impact on IA. In addition, the documented dwindling institutional ownership is potentially attributable to perceived decreased incentives to search for private information as more assertive IR programs are associated with more forthcoming disclosures (Lundholm and Myers, 2002) and thus lower frequency of private information events. Our results corroborate the finding in Brown and Hillegeist (2007) that IA is negatively associated with IR activities (see Section 2.2). It is, however, unclear whether our weak evidence of cash flow mispricing in gain states for firms with higher-rated IR can be associated with the significant reduction in institutional ownership (Barone and Magilke, 2009).

This evidence interests managers, investors, and market regulators as well. Companies' senior management should recognize the potential for the existence of disclosure clientele (Kalay, 2015); that is, there is possibly heterogeneity in the demand for information across investors, which is a function of an investor's ability to parse information. IR can bring about changes in the shareholder mix (Brennan and Tamarowski, 2000). Thus, IR programs appear as a device of choice to effectively "get rid of" cumbrous investor types and achieve fair valuation. However, there has to be a warning of caveat emptor for managers here. Basse Mama and Bassen (2016) show that higher-quality IR programs subtly instill managerial discipline in the form of reduced agency costs. Indeed, heightened visibility improves firm transparency, making possible processes of managerial subjection to investor rights. To that extent, market regulators motivated by investor protection and efficient allocation of capital should pursue measures to improve IR. Using a sample of publicly listed firms in China, Firth *et al.* (2015) observe that corporate accessibility, as measured by the amount and the quality of private communications between firms and investors, complements public information sources in reducing future stock price crash risk.

5.2 Portfolio Analysis on the Role of IR

The MT provide robust evidence of accruals' mispricing for the sub-sample of firms with lower-rated IR. Therefore, we focus on the accruals' mispricing to validate the results from the MT. We investigate whether, conditionally on the level of accruals and the quality of a firm's IR, the stock is systematically mispriced. We first independently classify the sample firms into deciles based on their accruals and IRQ in each year. For either conditioning

[12] This estimate is similar to the subsequent decrease of institutional ownership by 4% reported by Kalay (2015) in a U.S. context. He uses IR scores published by *IR Magazine* from 2002 to 2007.

variable (accruals and IRQ), we define firms in the top 30% (bottom 30%) as high (low), and consider the middle 40% as neutral. As a result, we pursue our analyses only with firms in the top 30% and bottom 30% of the distribution of accruals. We then re-sort the two accruals-based portfolio stocks by the quality of their IR programs to obtain 4 double-sorted long-only accruals/IR portfolios: [1] low accruals/low IR, [2] high accruals/low IR, [3] low accruals/high IR, and [4] high accruals/high IR.[13]

Next, we compute yearly value-weighted average one-year-ahead returns on each portfolio. The holding period spans from 1 July 2002 to 30 June 2012. We construct the portfolios at the end of June of year t because the IR awards forming the basis of our proxy for IR quality are typically bestowed in mid-June of each year (see Section 4.2). The awards' ceremony and the results are largely publicized by the business press.

Theory suggests that high accruals are associated with overvaluation, thus leading to lower future returns. If high-quality IR programs play a major role in mitigating accruals' mispricing, [4] would outperform [2], and [1] would under-perform [3]. We, therefore, construct two hedge portfolios that we refer to as *Hedge_high* (HH, a portfolio that is long in high accruals/high IR firms [4] and short in high accruals/low IR firms [2]) and *Hedge_low* (HL, a portfolio that is long in low accruals/high IR firms [3] and short in low accruals/low IR firms [1]). The idea is to explore the role of IR quality for each level of accruals (low vs. high). Toward this end, we obtain the widely used Fama and French (1993) monthly factors (MKTRF, SMB, HML) and the monthly series of Carhart (1997) WML factor from Wharton Research Data Services.[14] Finally, to capture potential commonality in the mispricing of IR quality we augment the Carhart (1997) model by the mispricing factor Undervalued Minus Overvalued (UMO; Hirshleifer and Jiang, 2010)[15]. Because the returns on these pricing factors are collectively dollar-denominated, we first convert them into euro terms (see Solnik and McLeavey (2009)) before using them in the regressions.

We subsequently regress the monthly returns pertaining to each of the long-only portfolios from [1] through [4] and the two hedge portfolios on euro denominated Fama-French factors augmented by the factors WML and UMO over the period from 1 July 2002 through 30 June 2012 in a SUR framework.

[Table 5 about here]

A general result from Table 5 is that risk-adjusted returns increase monotonically in IR quality. Indeed, a portfolio that is long in firms with high accruals levels and higher-rated IR [4] outperforms a portfolio of firms with comparable accruals levels but which have lower-rated IR programs [2] when we use the augmented Carhart model as benchmark return-generating process. Similarly, in the sub-group of firms with lower levels of accruals ([1] and [3]), we find that the portfolio comprising of firms with lower-rated IR [1] is dominated by the portfolio of firms with higher-rated IR [3]. Specifically, the annualized differential risk-adjusted return between [4] and [2], HH, levels out at 8.2% and is statistically significant and economically meaningful. Correspondingly, the annualized differential risk-adjusted return between [3] and [1], HL, amounts to 8.9% and is both statistically and substantively significant.[16] To appreciate the economic meaning of the documented differential return

[13]This mode of portfolio construction is widely used in the finance literature. Also, we do not distinguish between gain and loss states because we find no asymmetry in the mispricing of accruals.

[14]MKTRF: market risk premium; SMB: small minus big; HML: high minus low; WML: winners minus losers. SMB, HML, and WML are hedge portfolios and are widely used in finance.

[15]We collected data relative to this factor from Danling Jiang's website: https://sites.google.com/site/danlingjiang/data-library. We adjusted the series the same way as with the factors in the Carhart (1997) model. In a slight abuse of language, we refer to the resulting model as the augmented Carhart model.

[16]The alphas estimated from the Fama and French three-factor models and Fama and French five-factor models are qualitatively similar to the ones shown in this section (available upon request).

estimates, suffice it to observe that the average annualized returns on the various pricing factors used in our augmented Carhart model range from 0.36% (HML) to 4.62% (UMO) over the sample period; the corresponding market risk premium is 2.39%.[17]

Table 5 shows that high-quality IR firms have, on average, smaller loadings than low-quality IR firms on the market factor, suggesting that high-quality IR firms are less risky than low-quality IR firms. In addition, we evaluate the weights allocated to the two hedge portfolios (HH and HL) and the four factors used in the Carhart (1997) model in the ex post tangency portfolio. The weights level out at 52.82% (HH), 37.4% (HL), 19.72% (MKTRF), 8.31% (SMB), -58.7% (HML), -56.74% (WML), and 97.2% (UMO), respectively. By according high weights to portfolios of firms with higher-rated IR, the stock market recognizes the value of high-quality IR. At the same time, the market does not seem to fully reflect the effect of high-quality IR. Consistent with Karolyi and Liao (2015), our results indicate that firms with higher-rated IR do not merely manipulate IR-induced media coverage (Solomon, 2012), or choreograph earnings conference calls (Cohen *et al.*, 2013). Instead, our results suggest that high-quality IR programs can be used as value-relevant signals by investors.

At the same time, these results seem to cast doubt on the rational factor risk explanation of the accruals anomaly (see Hirshleifer *et al.*, 2012). We hark back to the results from the MT in Section 5.1 to recall that the accruals anomaly tends to be limited to firms with high realized idiosyncratic risk, low realized market beta, and high trading volume. Such firm-level attributes can be considered as capturing a higher valuation uncertainty that places a greater burden on investor attention (e.g. Hirshleifer *et al.*, 2013). Taking this evidence from the MT and controlling for well-known risk-based or mispricing factors in our portfolio analysis, we conclude that the IR effect on future returns potentially comes from mispricing (see Hirshleifer *et al.*, 2013, for similar conclusions).

Inconsistent with findings in recent studies (e.g. Green *et al.*, 2011; Shi and Zhang, 2012; Konstantinidi *et al.*, 2016) it seems that the accruals anomaly is still alive but is less pronounced in firms with stronger information environments. The results in this study provide valuable insights to investors interested in trading on the accruals anomaly. We propose that investors might be better off when they take long positions in firms with higher-rated IR programs or alternatively design long/short positions conditional on the quality of the underlying firms. Managers and regulators may also be interested in our results because we find no evidence that firms assertively engage in IR to choreograph earnings conference calls or to manipulate media coverage, all actions that are associated with subsequent lower returns.

5.3 Causal Links between MSV, IRQ, IA and IU

This section presents the results of the investigations on the potential channels through which IR quality and mispricing (as per RKRV, 2005) influence each other. Below, the first subsection presents preliminary results which suggest that IRQ is endogenously determined. The second subsection presents the results of the 2SLS estimation and the third subsection presents the Heckit regressions. In all regressions, standard errors are clustered by year and by firm (Petersen, 2009).

5.3.1 Preliminary results

Column 1 of Table 6 contains the regression of MSV onto lagged information. Surprisingly enough, the results suggest that the past IRQ is positively associated with current pricing

[17] The German stock market, as measured by the Composite DAX index, earns an annual average raw return of only 4.43% with a standard deviation of 25.34% over the holding period. We use the German stock market as a potential benchmark as the sample is dominated by German firms (see Online Appendix Part A).

errors while the past bid-ask spread is negatively associated with current pricing errors. A plausible explanation of the sign of the coefficient of lagged IRQ in this regression is that pricing errors respond in real time to firms' effort to improve their IRQ. Also, the sign of the coefficient of the lagged bid-ask spread suggest that firms facing large IA in the past devote more effort to mitigating it, thereby reducing their current pricing errors. The coefficient of lagged MSV is positive and significant as well, which suggests that pricing errors are quite persistent over time. Past realized idiosyncratic volatility increases current pricing errors while prior cross-listing of the firm on either the NYSE or the LSE decreases them.

Column 2 of Table 6 shows the regression of MSV onto contemporaneous information. Interestingly, the results suggest that IRQ is negatively associated with contemporaneous mispricing. Amihud's illiquidity ratio, analysts' forecast errors, and market capitalization are all positively related to contemporaneous pricing errors. The realized idiosyncratic volatility has a positive and significant effect on contemporaneous MSV while contemporaneous cross-listing has no significant effect. The signs of the coefficient of IRQ, Amihud's illiquidity ratio and the analysts' forecast errors are rather intuitive. Indeed, pricing errors are expected to be higher when IRQ is lower and when investors face greater IA/IU (e.g. Lev, 1992; Zhang, 2006a, 2006b). The fact that IRQ is negatively associated with contemporaneous pricing errors but positively associated with future pricing errors confirms that MSV responds in real time to the effort devoted by firms to maintaining good IRQ (Anantharaman and Zhang, 2011). Moreover, the changes in the effects of the variables operationalizing IA and IU, depending on whether they are lagged or not suggest that these regressors are endogenous in the second regression (Table 6).

[Table 6 about here]

In order to test the robustness of the results above, we consider a third regression where MSV is regressed onto an information set containing contemporaneous and lagged regressors. More precisely, we take the second regression and add the first lags of the seven variables operationalizing IRQ, IU, and IA. Column 3 of Table 6 presents the results of this regression which are largely consistent with the two previous ones. Indeed, the effects of lagged and contemporaneous IRQ are more pronounced than in the separate regressions (shown in Columns 1 and 2 of Table 6). The effect of market capitalization is not significant here, while cross-listing appears to reduce mispricing again. Otherwise, the other coefficients that were found significant in the separate regressions are significant here as well.

Given our claim that some contemporaneous regressors are endogenous, the last two regressions may be providing biased coefficients. We therefore address this endogeneity issue in the ensuing subsections.

5.3.2 The Two-Stage Least Square Approach

First-stage instrumental regression

The seven regressors suspected of endogeneity are IR quality ($IRQ_{i,t}$), bid-ask spread ($BASP_{i,t}$), Amihud's illiquidity ratio ($AMIH_{i,t}$), trading volume ($TRVOL_{i,t}$), analyst forecast errors ($ERR_{i,t}$), the number of analysts following a firm ($NOEST_{i,t}$) and dispersion of analysts' forecast ($DISP_{i,t}$). Each of these variables is regressed onto their own first lags and the first lags of the other control variables.

The first regression is of particular interest as it allows us to identify the determinants of IRQ and assessing its predictability. First, we note that IRQ is quite persistent as the coefficient of the lagged IRQ is approximately equal to 0.43. Second, past MSV has no significant effect on current IRQ. Third, we note that IRQ is quite predictable. The variables that positively affect current IRQ are the lagged bid-ask spread, number of analysts, realized idiosyncratic skewness, market capitalization and sales growth. Hence, a large bid-ask spread in the past compels firms to take actions directed at increasing current IRQ and reducing current MSV (cf. the previous subsection). On the contrary, current IRQ is negatively associated with lagged Amihud's illiquidity ratio, trading volume and analysts' forecast errors. The sign of the effect of trading volume on IRQ possibly mirrors the one of the bid-ask spread. Indeed, larger bid-ask spreads are associated with lower trading volume and higher illiquidity levels, ceteris paribus.

This relation is confirmed by the second instrumental regression, where a high trading volume and market capitalization at the previous period predict a lower level for the current Amihud's illiquidity ratio. The illiquidity ratio is quite persistent, as shown by the sign and significance of the coefficient of its lag. More important, past MSV is positively associated with current illiquidity ratio, indicating that perceived mispricing in the previous period deters investors from transacting in a stock.

The third instrumental regression suggests that higher past IRQ, illiquidity ratio, bid-ask spread, and analyst forecast errors all predict a higher bid-ask spread for the current period. In contrast, the lagged number of analysts, the lagged realized idiosyncratic skewness, the lagged market capitalization and the use of public capital markets at the previous period are all negatively associated with current bid-ask spreads. The results also suggest that past pricing errors are unrelated to current bid-ask spreads.

The fourth instrumental regression documents that the current trading volume is positively related to the lagged trading volume (high persistence), lagged dispersion of analyst forecasts, lagged cross-listing and lagged leverage. However, current trading volume is negatively associated with lagged Amihud's illiquidity ratio and lagged realized idiosyncratic skewness. The positive association of trading volume with the dispersion of analyst forecasts supports the view that the trading volume is an appropriate measure of IA. Indeed, IA contributes to divergence of opinions among investors, which in turn is necessary for (information-based) trades to take place. In another vein, Polk and Sapienza (2009) hold that firms with higher share turnover are firms with shorter shareholder horizons. Finally, we note that current trading volume is unrelated to past pricing errors.

Our fifth instrumental regression shows that analyst forecast errors are persistent over time, but less so than the remaining endogenous regressors. In addition, current analysts forecast errors respond positively to the lagged dispersion of analyst forecasts, lagged realized idiosyncratic volatility and lagged use of public capital markets. This evidence corroborates the finding by Bissessur and Veenman (2016) that greater forecast uncertainty is associated with larger absolute forecast errors. On the contrary, current analyst forecast errors are negatively related to lagged IRQ, lagged number of analysts, and lagged sales growth. Because analysts collect, process, and distribute information about the prospects of the firm they cover, the activity of financial analysts contributes to increasing the amount of information available about the firm, thereby reducing uncertainty. Markedly, however, past pricing errors have no effect on current analyst forecast errors.

The sixth instrumental regression suggests that the dispersion of analyst forecasts is quite persistent over time. In addition, the dispersion of analyst forecasts responds positively to the lagged analyst forecast errors, the lagged number of analyst estimates and the realized idiosyncratic volatility. On the contrary, it responds negatively to the price to book ratio. Past pricing errors have no effect on the current dispersion of analyst forecasts.

The seventh and last instrumental regression concerns the number of analysts following a firm, which is found to be quite persistent over time. Moreover, the number of analysts following a firm is positively associated with the lagged market capitalization, lagged sales growth, and lagged cross-listing. In rebuttal, the depth of analyst coverage is negatively associated with lagged analyst forecast errors and lagged pricing errors.

These instrumental regressions shed light on the complexity of the relations between MSV, IRQ, IU, and IA. From the last instrumental regression, for instance, one could imagine that large pricing errors at year $t-1$ leads firms to take actions that draw more attention from analysts as a means to reducing future pricing errors. Besides, all the variables used to operationalize IRQ, IU, IA, and MSV are persistent over time.

Our third and fifth instrumental regressions suggest that lagged IRQ potentially plays two countervailing roles in that it is positively associated with BASP (a measure for IA) while it is inversely related to analyst forecast errors (a measure of IU). The induced increase in IA potentially stems from corporate selective disclosure. This evidence points to the possibility that firms either provide material information to a select group of investors during private meetings (in violation of the EU Market Abuse Directive) or that such private meetings exacerbate IA among investors due to heterogenous abilities to process information. In turn, the negative relation between IRQ and IU is reminiscent of the finding by Solomon and Soltes (2015) that investors who have access to management exhibit better timing ability when they meet with the firm; however, the increase in timing ability is restricted to the group of hedge funds that are reportedly more sophisticated than pension or mutual funds. In line with the evidence in this subsection, Bissessur and Veenman (2016) find that private access to management enhances the precision of analysts' estimates and thereby reduces expected forecast errors. Because investors systematically overweight analyst forecasts when they face poor information environments (So, 2013), IRQ might mitigate mispricing through its adverse impact on IU. However, our findings are inconsistent with the evidence in Farragher *et al.* (1994) who report a significant inverse relation between IR quality and the dispersion of analyst forecasts while they fail to document a significant impact of IR quality on the accuracy of analyst forecasts.

[Table 7 about here]

Second-stage regression

We now consider the estimating Equation (13) for MSV, where all the regressors suspected of endogeneity are replaced by their fitted values obtained from the previous first-step regressions. Table 8 presents the estimation results. Counter-intuitively, the estimated effect of IRQ is positive, and more pronounced than in the preliminary regression of MSV onto lagged information (see previous sub-subsection). Equally surprising is the effect of the bid-ask spread, which is negative, significant and more pronounced than previously. The coefficient of Amihud's illiquidity ratio is positive but not significant. The other regressors with significant coefficients are the lagged MSV (which indicates a positive persistence), the realized idiosyncratic volatility (positive effect) and cross-listing on either the NYSE or the LSE (negative effect). Overall, the results of the 2SLS estimation are qualitatively similar to those obtained by regressing MSV onto lagged information. However, the coefficients stemming from the 2SLS have the interpretation of contemporaneous effects that are corrected for endogeneity.

The fact that the 2SLS yields similar results as the regression of MSV onto lagged information is not completely absurd, since our instruments consist of lagged regressors. If we decide to trust these instruments, then we shall interpret the regression of MSV onto lagged information as "predictive" and the 2SLS regression as "causal". Both models predict that the IRQ (lagged in the predictive model and contemporaneous in the 2SLS) is positively associated with mispricing while the bid-ask spread is negatively associated with mispricing. The signs of these coefficients are rationalized by noting that the pricing errors of year t can be affected by the actions taken by firms between year $t-1$ and year t. Such actions are not reflected in the lagged regressors used as instruments. This explains why the contemporaneous association of IRQ and MSV is negative as expected (see Table 6) while the effect of IRQ measured by 2SLS is counter-intuitively positive. In order to reconcile the two approaches, we need to construct instruments that are forward-looking, that is, instruments that can be measured at time $t-1$ while incorporating firms' anticipations about time t. This is what we attempt to do in the next sub-subsection.

[Table 8 about here]

5.3.3 The Heckit Approach

Unlike in the 2SLS, where linear relationships are assumed between MSV and the instruments, we now consider constructing instruments that capture firms' anticipation on the level of their future pricing errors. For simplicity, we ask whether firms can predict the probability that their stocks will be underpriced at the next period. To answer this question, we fit a Probit model to the binary variable $UNDER_{i,t}$ which takes 1 when firm i is underpriced at year t, and 0 otherwise. The latent variable underlying this Probit model is given by Equation (14), which contains lagged regressors on the RHS. Panel A of Table 9 shows the estimation results.

The results suggest that only four variables have an effect on the probability of underpricing at the next period. The number of analysts following a firm has a positive effect on undervaluation, which suggests that analyst coverage does not always contribute to reducing IA and IU as one would expect. This evidence attests to the importance of the accuracy of stock coverage as opposed to just the depth of coverage for determining stock prices (Chang and Hong, 2016). Indeed, analysts produce public signals about firm earnings of heterogenous precision, and prior research provides evidence consistent with what Chang and Hong (2016) label the positive "assortative matching" in the labor market for analysts. That is, more talented analysts are paid significantly more than their peers with lower ability, and are assigned to cover larger firms (Hong and Kubik, 2003). In turn, market capitalization and price-to-book ratio are negatively related to the probability of underpricing at the next period, while a high leverage at the current period predicts a higher probability of underpricing at the next period.

[Table 9 about here]

Next, we generate the inverse Mills ratios $IMR_{0,i,t}$ and $IMR_{1,i,t}$ and estimate the models described by Equations (15) and (16). Equation (15) is the regression of MSV onto contemporaneous information and $IMR_{1,i,t}$ using the sub-sample $UNDER_{i,t} = 1$ (underpriced sub-sample). Equation (16) is the regression of MSV onto contemporaneous information and $IMR_{0,i,t}$ using the sub-sample $UNDER_{i,t} = 0$ (overpriced sub-sample). Panel B of Table 9 presents the estimation results. First, we note that the coefficient of IRQ is not significant in either regression. This suggests that IRQ has no direct effect on MSV once we control for the probability of underpricing at the next period.

Second, the truncation bias captured by the coefficients of the inverse Mills ratios is significant only in the undervalued sub-sample. Indeed, the coefficients of $IMR_{0,i,t}$ and $IMR_{1,i,t}$ are both negative, but only that of $IMR_{1,i,t}$ is significant. This indicates that the error term on the latent variable underlying the Probit model is negatively correlated with the error term of Equation (15). Concretely, this means that in the set of underpriced firms, a higher ex-ante probability of underpricing at the next period is associated with a lower level of ex-post mispricing. Undervalued firms that perceive ex-ante that they have a high probability of being undervalued again at the next period take specific actions to reduce IA/IU and improve their IRQ so that their ex-post mispricing is mitigated. In the subset of overvalued firms, there is no visible correlation between the ex-ante probability of underpricing and the ex-post mispricing. Note that the non-linear mechanism that links past information to future mispricing through the anticipations of the probability of undervaluation cannot be detected within a linear instrumental variable framework. Overall, firms are averse to underpricing but not to overpricing.

Some asymmetries can also be noted in the effects of the regressors. Indeed, the bid-ask spread is negatively associated with mispricing in the set of undervalued firms but has no effect in the set of overvalued firms. The dispersion of analysts' forecasts is positively associated with mispricing in the set of undervalued firms but has no effect in the set of overvalued firm. The idiosyncratic realized volatility, the price-to-book ratio, and the market capitalization are positively associated with mispricing in the set of overvalued firms but have no effect in the set of undervalued firms. Analysts forecast errors are positively associated with mispricing in both sub-samples. Recall that column 5 of Table 7 suggests that IRQ is negatively related to ERR, but not to DISP. Combining this evidence with the results in Panel B of Table 9, we argue that IRQ might affect mispricing through its adverse impact on analyst forecast errors. Finally, mispricing is significantly persistent on both sub-samples.

6 Conclusion

Despite the diffusion of IR departments among public firms, we know remarkably little about the contribution of IR to shareholder value (Laskin, 2011; Karolyi and Liao, 2015). That the IR function plays an information role in determining security prices is better known. What is less clear relates to the channels through which IR activity is related to mispricing. This question is important because shareholder value and resource allocation could be substantially enhanced due to reduced pricing errors (Lu *et al.*, 2014).

Our paper combines the Mishkin (1983) two-stage rational expectations framework with the RKRV (2005) pricing deviation-based approach to test whether and what type of mispricing IRQ affects, and examine specific mechanisms through which IRQ is related to mispricing. To capture the quality of IR investments and actions, we rely on the proprietary ratings of firm IR programs by analysts and institutional investors compiled by the Society of Investment Professionals in Germany (DVFA) on behalf of the magazine *Capital*. Our sample includes 252 non-financial European firms, and spans the period from 2002 to 2011.

Allowing for asymmetric persistence and differential pricing of accruals and cash flows surprises, our Mishkin tests suggest that there is robust evidence of accruals' mispricing for the sub-sample of firms with lower-rated IR. However, accruals' mispricing tends to be concentrated among firms with high realized idiosyncratic risk, high trading volume, low quoted bid-ask spreads, and low realized market beta. By contrast, evidence of cash flows mispricing is weak. Surprisingly enough, the differential persistence of accruals and cash flows is widest in gain states, not in loss states, thereby refuting the EFH. High-quality IR thus foster the market's ability to efficiently impound accounting information into stock prices.

Further, portfolio analyses reveal that firms with higher-rated IR on average earn higher risk-adjusted stock returns. We show that the positive relationship between IRQ with subsequent stock returns cannot be fully explained by known risk and mispricing factors. Because accruals' mispricing tends to be more pronounced in firms with greater valuation uncertainty, our evidence of a positive IRQ-return relation is, therefore, likely driven by psychological biases or constraints (Hirshleifer *et al.*, 2013).

We find that IR potentially plays two countervailing roles in its relation with mispricing. IRQ may widen IA among investors (potentially stemming from private meetings with a select group of investors), while it is inversely related to future analyst forecast errors. This result is important on three grounds. First, although analyst forecast errors may differentially affect the welfare of retail and institutional investors, a matter of greater concern is the impact on the efficient allocation of capital in the economy. So (2013) shows that investors systematically overweight analyst forecasts when facing IA/IU. It results that over-reliance on analyst forecasts (of poor precision) could result in substantial valuation errors. Thus, So (2013) recommends that regulators pursue measures to improve analyst forecasts. We contribute to this debate by documenting that high-quality IR can reduce mispricing through their adverse impact on analyst forecast errors.

Second, the empirical literature on stock coverage has largely focused on the number of analysts following a firm. However, the evidence in this paper highlights the importance of the accuracy of analyst coverage as opposed to just the depth of coverage for determining stock prices (Chang and Hong, 2016). Karolyi and Liao (2015) find that greater IR activity is associated with higher Tobin's q valuations. The latter authors add that this effect runs substantially via increased analyst following and forecast accuracy, and reduced analyst forecast dispersion. Indeed, analysts and managers of firms with more active IR programs consume a significant amount of time interacting privately and offer the investing community a unique window into a firm's operations (Soltes, 2014; Solomon and Soltes, 2015). Third, our results indicate that firms do not engage in IR activity to manipulate media coverage (Solomon, 2012), or choreograph earnings conference calls (Cohen *et al.*, 2013). In contrast, our results suggest that high-quality IR programs may be used as value-relevant signals by investors. Therefore, inconsistent with the reasoning in Karolyi and Liao (2015), our results suggest that externally-observable proxies such as IR Magazine ratings are not the root cause of some studies relating IR to negative outcomes.

Finally, we find that firms exhibit a preference for overvaluation and abhor undervaluation. Indeed, in the set of underpriced firms, a higher ex-ante probability of underpricing at the next period is associated with a lower level of ex-post mispricing. Undervalued firms that perceive ex-ante that they have a high probability of being undervalued again at the next period take specific actions to reduce IA/IU and improve their IRQ such that their ex-post mispricing is mitigated. In contrast, there is no visible correlation between the ex-ante probability of underpricing and the ex-post mispricing in the subset of overvalued firms. Such asymmetric behavior toward either type of mispricing unveils potential implicit managerial incentives – that is, managers may exploit IR as a launching pad for offensive operations directed at securing their own interests via short-lived overvaluations.

Appendix 1: Variables Definitions[18]

A.1.1 Variables

IRQ Aggregate measure for IR quality measure (This measure aggregates the components target group orientation, transparency, track record and sustainability reporting using the average ex post weights allocated by survey respondents. IRQ is used in its industry-year fractional rank version which is defined as: (rank - 1)/(number of firms in the industry - 1), with values ranging from 0 (the lowest-rated IR) to 1 (the highest-rated IR).) [DVFA]

MSV Aggregate non-fundamental component of the market-to-book ratio obtained from the Rhodes-Kropf et al. (RKRV, 2005) decomposition technique. This item is used to proxy for stock mispricing in this study. [Datastream]

MSVS Measure for sector-wide mispricing derived from the RKRV (2005) model. See Online Appendix Part B. [Datastream]

MSVF Measure for firm-specific mispricing derived from the RKRV (2005) model. See Online Appendix Part B. [Datastream]

BASP Bid-ask spread calculated as the ratio of the difference between the Ask and the Bid quote over the midpoint. [Datastream]

[18][...] is the data source.

AMIH	Annual median of the Amihud (2002) illiquidity ratio calculated as the ratio of daily absolute returns over euro trading volume. See Online Appendix 2. [Datastream]
TRVOL	Median of weekly trading volume. [Datastream]
ERR	Analyst forecast errors, calculated as the natural log of one plus the difference between analysts' earnings per share (EPS) forecasts and actual EPS, scaled by the absolute value of median. [I/B/E/S]
NOEST	Number of analysts covering a firm over the year. [I/B/E/S]
INST	Percentage of outstanding shares owned by institutional investors such as investment banks and pension funds. [Datastream]
DISP	Dispersion in analyst earnings forecasts calculated as the standard deviation of analyst forecasts, scaled by the prior year-end stock price. [I/B/E/S]
EAR	Income before extraordinary items and dividends, deflated by one-year lagged total assets. This item is used as our proxy for net income. [Datastream]
CF	Cash flows from operations, deflated by one-year lagged total assets. [Datastream]
ACC	Accruals calculated as EAR minus CF, deflated by one-year lagged total assets. [Datastream]
RET	Log buy and hold return on a given stock over a 12-month period beginning three months after the fiscal year-end (see Drake *et al.*, 2009). [Datastream]
MCAP	Market capitalization (as of end of March of year t) used as a proxy for firm size. [Datastream]
P2B	Price-to-book ratio. [Datastream]
SALGR	Annual sales growth. [Datastream]
TA	Total assets. [Datastream]
BE	Book value of equity. [Datastream]
LEV	Leverage computed as the ratio of total debt over total assets. [Datastream]
UPCM	Use of public capital markets in subsequent periods; it as construed as an indicator variable that takes a value of 1 if the firm issues public debt or equity in the next two fiscal years, and 0 otherwise. [Datastream]
CLIST	Cross-listing on either the New York Stock Exchange (NYSE) or on the London Stock Exchange (LSE). [Datastream]

A.1.2 Realized Measures

Let $r_{i,n,t}$ be the log-return on the stock of firm i on week n of year t, and $r_{M,n,t}$ the corresponding market log-return. The realized beta, $RBETA$, of firm i is:

$$\hat{\beta}_{i,t} = \frac{\sum_{n=1}^{N} r_{M,n,t} r_{i,n,t}}{\sum_{n=1}^{N} r_{M,n,t}^2},$$

where N is the number of opening weeks during year t. The numerator of $\hat{\beta}$ is the realized covariance and the denominator is the realized market volatility.

The weekly residuals of the regression are $r_{i,n,t} - \hat{\beta}_{i,t} r_{M,n,t}$. The realized idiosyncratic volatility, $RIVOL$, of firm i's stock is:

$\hat{\sigma}_{i,t} = \sqrt{\sum_{n=1}^{N} (r_{i,n,t} - \hat{\beta}_{i,t} r_{M,n,t})^2}$.

Finally, the realized idiosyncratic skewness, $RSKEW$, is:

$\hat{S}_{i,t} = \frac{N^{1/2}}{\hat{\sigma}_{i,t}^3} \sum_{n=1}^{N} \left(r_{i,n,t} - \hat{\beta}_{i,t} r_{M,n,t} \right)^3$.

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Table 1: Summary statistics

	mean	SD	Q1	median	Q3	H_IRQ	L_IRQ	t-test
IRQ	0.4994	0.3079	0.2300	0.5000	0.7670	0.7746	0.2414	-66.58***
MSV	0.0703	0.7105	-0.3496	0.0793	0.4908	0.1300	0.0113	-2.94***
MSVF	-0.0046	0.8665	-0.3583	0.0367	0.4077	0.0837	-0.0913	-3.57***
MSVS	0.0480	0.6333	-0.2297	0.0781	0.3019	0.0409	0.0550	0.39
SALGR	0.0759	0.2516	-0.0160	0.0609	0.1436	0.0855	0.0666	-1.42
MCAP	12300	22100	440	1700	14000	13000	11600	-1.17
P2B	2.4531	1.9248	1.2781	1.9078	2.8865	2.6369	2.2753	-3.50***
BASP	0.0088	0.0082	0.0025	0.007	0.0125	0.0077	0.0098	5.10***
AMIH	0.0643	0.2183	0.0022	0.0185	0.0577	0.0460	0.0814	3.20***
TRVOL	11233	46698	16	59	309	7088	15164	3.34***
ERR	-0.0138	0.6666	-0.0566	0.0751	0.2516	-0.0361	0.0091	1.23
DISP	0.0566	0.1326	0.0119	0.0240	0.0482	0.0416	0.0710	4.28***
NOEST	17.5565	10.9603	9	16	26	19.8069	15.4200	-7.71***
INST	0.3435	0.2611	0.1	0.31	0.55	0.3301	0.3560	1.89*
UPCM	0.5031	0.5002	0	1	1	0.4972	0.5086	0.44
CLIST	0.1653	0.3716	0	0	0	0.1597	0.1706	0.57
RBETA	0.1438	0.3657	-0.0700	0.1242	0.3229	0.1419	0.1455	0.19
RIVOL	0.3838	0.2144	0.2493	0.3279	0.4564	0.3562	0.4097	4.85***
RSKEW	-0.0039	0.1246	-0.0739	0.0003	0.0711	-0.0058	-0.0021	0.58
LEV	0.2331	0.1634	0.1081	0.2177	0.3329	0.2109	0.2543	5.06***
EAR	0.0476	0.1043	0.0171	0.0432	0.0833	0.0652	0.0308	-6.33***
CF	0.0998	0.0987	0.0559	0.0909	0.1345	0.1111	0.0889	-4.24***
ACC	-0.0519	0.1038	-0.0834	-0.0489	-0.0155	-0.0455	-0.0580	-2.27**
RET	0.0330	0.5373	-0.2140	0.1022	0.3400	0.1026	-0.0354	-4.76***
SIZERET	0.0075	0.3969	-0.1784	0.0010	0.1727	0.0756	-0.0595	-6.35***

Note. Table 1 reports the summary statistics of the sample characteristics. The sample covers 252 non-financial European firms and spans the period 2002–2011. All variables are defined in Appendix 1 above.Variables of primary interest are the measure for IR quality (*IRQ*) and the aggregate measure of mispricing (*MSV*). *MCAP* is in millions of €. Except for the last three columns, the summary statistics in this table refer to the full sample of 252 firms. In contrast, the columns headed H_IRQ and L_IRQ relate to sub-samples of firms with higher-rated IR programs and those with lower-rated IR programs, respectively. The last column compares the means of these two sub-samples. *MSVF* and *MSVS*, in turn, stand for the firm-specific component and the sector-wide component of mispricing, respectively (Please, refer to Online Appendix Part B, for more details on these two variables.) ***, **, * denote significance at the 1%, 5%, and 5% level, respectively.

Table 2: Primary results of the Mishkin tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ_0	-0.1590***	-0.1837***	-0.1184**	-0.1596***	-0.1117***	-0.2594***	-0.1343**
	(0.0000)	(0.0000)	(0.0349)	(0.0010)	(0.0002)	(0.0000)	(0.0197)
γ_1	0.3411***	0.3962***	0.2762***	0.3534***	0.3145***	0.3251***	0.3307***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_2	0.5153***	0.5234***	0.4893***	0.5181***	0.4916***	0.5265***	0.4524***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_3	0.1755***	0.1779***	0.1650***	0.1994***	0.1625***	0.1401***	0.2289***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_4	-0.0443**	0.0166	-0.0592*	-0.0638*	-0.0272	0.0919	-0.0232
	(0.0237)	(0.5199)	(0.0502)	(0.0588)	(0.4755)	(0.1493)	(0.7637)
γ_5	0.0466***	-0.0175	0.0710**	0.0048	0.0355	0.0835***	-0.0234
	(0.0065)	(0.5762)	(0.0387)	(0.8910)	(0.4678)	(0.0081)	(0.4551)
γ_6	0.2744***	0.3074***	0.2425***	0.2543***	0.2719***	0.2450***	0.3207***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	0.3242***	0.2489***	0.3178***	0.3666***	0.2927***	0.2964***	0.3844***
	(0.0000)	(0.0052)	(0.0000)	(0.0000)	(0.0012)	(0.0000)	(0.0000)
γ_0^*	-1.9307***	-2.6909***	-1.9290***	-1.7916***	-2.0276***	-2.1922***	-1.5183***
	(0.0000)	(0.0058)	(0.0001)	(0.0000)	(0.0027)	(0.0030)	(0.0000)
γ_1^*	0.6143***	0.3247*	0.9392***	0.6384***	0.5443***	0.7617***	0.4350***
	(0.0000)	(0.0694)	(0.0000)	(0.0000)	(0.0020)	(0.0001)	(0.0022)
γ_2^*	0.5484***	0.5188**	0.6669***	0.5127***	0.5577***	0.7499***	0.2910
	(0.0000)	(0.0213)	(0.0002)	(0.0054)	(0.0020)	(0.0000)	(0.1950)
γ_3^*	-0.2345	-0.2460	-0.2605	-0.3055***	-0.1207	-0.5112***	0.0957
	(0.1188)	(0.3425)	(0.2538)	(0.0068)	(0.5635)	(0.0058)	(0.5044)
γ_4^*	0.4032***	0.1709	0.3996*	0.3868*	0.4682***	0.7673**	-0.1684
	(0.0099)	(0.4698)	(0.0749)	(0.0846)	(0.0061)	(0.0257)	(0.3527)
γ_5^*	-0.1048	0.3575	-0.2217	-0.0084	-0.2713	-0.3236	0.0035
	(0.6032)	(0.2251)	(0.4092)	(0.9635)	(0.2881)	(0.2482)	(0.9803)
γ_6^*	0.4186**	0.6099**	0.3483*	0.4537**	0.4170***	0.3658	0.4754***
	(0.0106)	(0.0314)	(0.0631)	(0.0257)	(0.0006)	(0.1770)	(0.0024)
N	1096	561	535	467	629	580	516

Note. Table 2 reports the results obtained from estimating the system (4)-(5). The dependent variable in the forecasting equation is EAR as defined above, while the pricing equation uses RET as the dependent variable. In all specifications shown in this table, we follow Konstantinidi et al. (2016) and adjust standard errors for clusters in year. Coefficients without a star as superscript stem from the forecasting equation while estimates with a star derive from the pricing equation. δ is the earnings response coefficient and N is the number of observations used in a given estimation. Column 1 shows the results of the MT using the full the full sample of 252 non-financial firms; columns 2 and 3 show the MT for the sub-samples of firms with higher-rated IR and firms with lower-rated IR programs, respectively. Columns 4-5, exhibit MT results for firms with high idiosyncratic volatility and firms with low idiosyncratic volatility, respectively. Finally, columns 6-7 contain MT results pertaining to firms with high trading volume and those with low trading volume, respectively. p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 3: Mishkin tests under asymmetry and differential pricing of earnings' components

	(1)	(2)	(3)	(4)
	Forecasting cash flows [Equation (7)]			
D_t	-0.3102***	-0.3102***	-0.3102***	-0.3102***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CF	0.2939***	0.2939***	0.2939***	0.2939***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ACC	0.0815***	0.0815***	0.0815***	0.0815***
	(0.0002)	(0.0021)	(0.0002)	(0.0021)
$CF.D_t$	-0.1678***	-0.1678***	-0.1678***	-0.1678***
	(0.0000)	(0.0012)	(0.0000)	(0.0012)
$ACC.D_t$	-0.0635**	-0.0635*	-0.0635**	-0.0635*
	(0.0485)	(0.0774)	(0.0485)	(0.0774)
	Forecasting accruals [Equation (6)]			
D_t	0.2221***	0.2221***	0.2221***	0.2221***
	(0.0000)	(0.0040)	(0.0000)	(0.0040)
CF	0.2965***	0.2965***	0.2965***	0.2965***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ACC	0.3734***	0.3734***	0.3734***	0.3734***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$CF.D_t$	0.0883	0.0883	0.0883	0.0883
	(0.1592)	(0.2304)	(0.1592)	(0.2304)
$ACC.D_t$	0.0299	0.0299	0.0299	0.0299
	(0.5933)	(0.7367)	(0.5933)	(0.7367)
	Pricing Equation [Equation (9)]			
δ_1	0.1765***	0.1765***	0.2047***	0.2047***
	(0.0000)	(0.0079)	(0.0000)	(0.0005)
δ_2	0.5100***	0.5100***	0.5424***	0.5424***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D_t	0.0318	0.0318	-0.0005	-0.0005
	(0.7423)	(0.8364)	(0.9953)	(0.9968)
CF	0.4507***	0.4507***	0.4043***	0.4043***
	(0.0000)	(0.0001)	(0.0000)	(0.0002)
ACC	0.3098***	0.3098***	0.3231***	0.3231***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$CF.D_t$	-0.2244**	-0.2244	-0.1174	-0.1174
	(0.0397)	(0.1588)	(0.2410)	(0.4035)
$ACC.D_t$	-0.0667	-0.0667	-0.1072	-0.1072
	(0.4870)	(0.5467)	(0.2307)	(0.2789)

Note. Table 3 reports the results obtained from estimating the parsimonious three-equation system (6)-(8), whereby Equation (8) is re-written as in Equation (9). The dependent variable in the forecasting equations are CF and ACC, respectively. In this table, columns 1 and 2 use in the pricing equation RET as the dependent variable while the dependent variable in columns 3 and 4 is a size-decile adjusted return, $SIZERET$. In turn, only in columns 2 and 4 do we adjust standard errors for cluster in year as proposed in Konstantinidi et al. (2016). δ_1 is the response coefficient relative to accruals while δ_2 denotes the response coefficient of cash flows. N is the number of observations used in the estimation and equals 1,105 for each of the four estimations shown in this table. The estimations therefore pertain to the full sample of 252 non-financial firms. D_t is an indicator that captures an economic loss state. p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 4: Role of IR in the correction process of mispricing across economic gain/loss states

	(1)	(2)	(3)	(4)
		Forecasting cash flows		
D_t	-0.3150***	-0.3102***	-0.2835***	-0.3439***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CF	0.2413***	0.2939***	0.2709***	0.2001***
	(0.0000)	(0.0000)	(0.0000)	(0.0015)
ACC	0.0436**	0.0815***	0.0671***	0.0124
	(0.0282)	(0.0021)	(0.0071)	(0.7402)
$CF.D_t$	-0.1572***	-0.1678***	-0.2122***	-0.1043
	(0.0018)	(0.0012)	(0.0001)	(0.2470)
$ACC.D_t$	-0.0494	-0.0635*	-0.0687***	-0.0292
	(0.1187)	(0.0774)	(0.0048)	(0.5365)
		Forecasting accruals		
D_t	0.2269**	0.2221***	0.2883***	0.1852
	(0.0109)	(0.0040)	(0.0007)	(0.1389)
CF	0.2012***	0.2965***	0.2104**	0.1934*
	(0.0026)	(0.0000)	(0.0114)	(0.0524)
ACC	0.3291***	0.3734***	0.3714***	0.2797***
	(0.0000)	(0.0000)	(0.0000)	(0.0078)
$CF.D_t$	0.1066	0.0883	0.0892	0.0900
	(0.2268)	(0.2304)	(0.3394)	(0.4093)
$ACC.D_t$	0.0316	0.0299	-0.0149	0.0694
	(0.7399)	(0.7367)	(0.8906)	(0.6228)
		Pricing Equation		
δ_1	0.2000***	0.1765***	0.1154**	0.2169***
	(0.0003)	(0.0079)	(0.0430)	(0.0013)
δ_2	0.5259***	0.5100***	0.3616***	0.5512***
	(0.0000)	(0.0000)	(0.0091)	(0.0000)
D_t	0.0219	0.0318	0.0107	0.0683
	(0.8804)	(0.8364)	(0.9341)	(0.7229)
CF	0.3893***	0.4507***	0.3897***	0.4754***
	(0.0000)	(0.0001)	(0.0003)	(0.0006)
ACC	0.2669***	0.3098***	0.1395	0.4061***
	(0.0002)	(0.0000)	(0.2499)	(0.0003)
$CF.D_t$	-0.1969	-0.2244	-0.0096	-0.3446*
	(0.1801)	(0.1588)	(0.9641)	(0.0660)
$ACC.D_t$	-0.0395	-0.0667	-0.0227	-0.0714
	(0.7257)	(0.5467)	(0.8243)	(0.6640)
N	1096	1105	561	535

Note. Table 4 reports the results obtained from estimating the three-equation system (6)-(8), whereby Equation (8) is re-written as in Equation (9). Unlike Table 3, this table controls for *SALGR*, *TRVOL*, *MCAP*, and *P2B*, thereby allowing us not only to test rational pricing but also to explore sources of potential inefficiency (Konstantinidi et al., 2016). The dependent variable in the forecasting equations are CF and ACC, respectively. In this table, RET is the dependent variable in the pricing equation. Standard errors are adjusted for clusters in year as proposed in Konstantinidi et al. (2016). δ_1 is the response coefficient relative to accruals while δ_2 denotes the response coefficient of cash flows. N is the number of observations used in a given estimation Column 1 shows the full sample results that are contrasted with those reported in column 2 of Table 3. Columns 3 and 4 contain the corresponding results for the sub-samples of firms with higher-rated and lower-rated IR, respectively. D_t is an indicator that captures an economic loss state. p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 5: Portfolio analysis on the role of IR

Panel A: Summary statistics of the different portfolios

Portfolio	[1]	[2]	[3]	[4]	HH	HL
mean	0.0112	0.0629	0.0831	0.0819	0.0190	0.0719
median	0.1094	0.0415	0.1068	0.1304	0.0617	0.0316
SD	0.3379	0.3227	0.2635	0.2972	0.1676	0.1225

Panel B: Estimating the alphas using monthly returns

	[1]	[2]	[3]	[4]	HH	HL
MKTRF	1.4146***	1.2629***	1.1503***	1.1085***	-0.1545***	-0.2644***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SMB	-1.5068***	-0.6754***	-1.0870***	-1.1655***	-0.4902***	0.4198***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
HML	-0.5192**	-0.7720***	0.1910	-0.1997	0.5723***	0.7101***
	(0.041)	(0.0000)	(0.414)	(0.380)	(0.0000)	(0.0000)
WML	-0.2104**	-0.5721***	-0.0623	0.3478***	0.9199***	0.1481***
	(0.020)	(0.0000)	(0.454)	(0.0000)	(0.0000)	(0.0065)
UMO	0.3440***	0.6571***	-0.0384	-0.7766***	-1.4337***	-0.3825***
	(0.006)	(0.0000)	(0.737)	(0.0000)	(0.0000)	(0.0000)
Intercept	-0.0020*	0.0012	0.0052***	0.0077***	0.0066***	0.0071***
	(0.053)	(0.1216)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	120	120	120	120	120	120
Adj. R-sq	87%	91%	81%	86%	89%	64%

Note. Panel A reports the summary statistics relative to four two-sorted portfolios based on annualized excess returns over the period from 1 July 2002 to 30 June 2012. [1] low accruals/low IR, [2] high accruals/low IR, [3] low accruals/high IR, and [4] high accruals/high IR. HH is a portfolio that is long in high accruals/high IR firms [4] and short in high accruals/low IR firms [2]); HL is a portfolio that is long in low accruals/high IR firms [3] and short in low accruals/low IR firms [1]. In contrast, Panel B reports the results from estimating the alphas using the augmented Carhart (1997) model. The pricing factors MKTRF, SMB, HML, and WML are taken from Wharton Research Data Services (WRDS) while we download the factor UMO from Jiang's website (https://sites.google.com/site/danlingjiang/data-library). All estimations are in euro terms. p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 6: Preliminary results of the causal link between IRQ, IA/IU, and MSV

	(1)	(2)	(3)
IRQ_{t-1}	0.0560*		0.0851**
	(0.0579)		(0.0299)
$AMIH_{t-1}$	0.0619		-0.1119
	(0.5259)		(0.3664)
$BASP_{t-1}$	-0.1090*		-0.1398***
	(0.0655)		(0.0003)
$TRVOL_{t-1}$	-0.0484		-0.0194
	(0.5168)		(0.8347)
$\lvert ERR_{t-1}\rvert$	-0.0074		-0.0517
	(0.8789)		(0.3184)
$DISP_{t-1}$	-0.0010		-0.0059
	(0.9763)		(0.8584)
$NOEST_{t-1}$	-0.0756		0.0224
	(0.3077)		(0.7864)
$\lvert MSV_{t-1}\rvert$	0.3969***	0.3568***	0.4022***
	(0.0000)	(0.0000)	(0.0000)
$RIVOL_{t-1}$	0.0995**		
	(0.0416)		
$CLIST_{t-1}$	-0.0528**		
	(0.0421)		
IRQ		-0.0731***	-0.1034***
		(0.0001)	(0.0000)
$AMIH$		0.2026***	0.2157**
		(0.0079)	(0.0132)
$BASP$		-0.0566	0.1297
		(0.3691)	(0.2535)
$TRVOL$		0.0093	-0.0121
		(0.8230)	(0.8633)
$\lvert ERR\rvert$		0.0781***	0.1197***
		(0.0006)	(0.0000)
$DISP$		-0.0049	0.0230
		(0.9083)	(0.5701)
$NOEST$		-0.0910	-0.0325
		(0.2309)	(0.7278)
$RIVOL$		0.0907***	0.0844**
		(0.0021)	(0.0185)
$MCAP$		0.2106*	0.1186
		(0.0514)	(0.4113)
$CRSLIST$		-0.0286	-0.0441***
		(0.1228)	(0.0056)
LEV		0.0383	0.0435
		(0.2347)	(0.2592)
N	899	1020	802
$R-sq$	0.19	0.20	0.24

Note. The sample in Table 6 includes 252 European non-financial firms and spans the period from 2002 to 2011. The dependent variable is the absoluted value of our mispricing measure, MSV. Column 1 contains the regression of MSV onto lagged information. Colum 2 shows the regression of MSV onto contemporaneous information, and column 3 regresses MSV onto an information set containing contemporaneous and lagged regressors. While not shown here for expository purposes, the full set of controls inlcude RBETA, RIVOL, RSKEW, MCAP, P2B, SALGR, UPCM, CLIST, and LEV. Standard errors are clustered by firm and year (Petersen, 2009). p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 7: First-stage regressions under the 2SLS approach

	IRQ	$AMIH$	$BASP$	$TRVOL$	$\|ERR\|$	$DISP$	$NOEST$
IRQ_{t-1}	0.4288***	0.0024	0.0387***	-0.0194	-0.0515*	-0.0051	0.0198
	(0.0000)	(0.8495)	(0.0000)	(0.1736)	(0.0637)	(0.7418)	(0.1452)
$AMIH_{t-1}$	-0.1891*	0.6291***	0.1706***	-0.0522*	-0.0321	-0.0634	-0.0050
	(0.0755)	(0.0000)	(0.0013)	(0.0736)	(0.7985)	(0.4547)	(0.8713)
$BASP_{t-1}$	0.2814***	0.0344	0.4770***	0.0028	0.0260	-0.0286	0.0100
	(0.0009)	(0.4488)	(0.0000)	(0.9044)	(0.7521)	(0.7981)	(0.7104)
$TRVOL_{t-1}$	-0.1936**	-0.1599***	-0.0073	0.8937***	0.0925	-0.0207	0.0413
	(0.0369)	(0.0000)	(0.8266)	(0.0000)	(0.3114)	(0.6189)	(0.1729)
$\|ERR_{t-1}\|$	-0.0279*	0.0128	0.0312***	-0.0014	0.1758***	0.0722***	-0.0342**
	(0.0852)	(0.1847)	(0.0043)	(0.8955)	(0.0000)	(0.0031)	(0.0114)
$DISP_{t-1}$	-0.0262	0.0076	0.0156	0.0341**	0.2107***	0.4667***	0.0049
	(0.5381)	(0.4369)	(0.1916)	(0.0208)	(0.0000)	(0.0000)	(0.8122)
$NOEST_{t-1}$	0.1449*	-0.0203	-0.0823***	0.0123	-0.0836**	0.1889***	0.7044***
	(0.0581)	(0.1364)	(0.0000)	(0.3722)	(0.0346)	(0.0000)	(0.0000)
$\|MSV_{t-1}\|$	-0.0381	0.0232**	0.0112	-0.0064	0.0141	0.0092	-0.0249*
	(0.2798)	(0.0148)	(0.3458)	(0.3928)	(0.5882)	(0.6397)	(0.0518)
$RBETA_{t-1}$	-0.0429	-0.0049	-0.0067	0.0079	-0.0068	-0.0080	-0.0075
	(0.1392)	(0.6543)	(0.5951)	(0.6695)	(0.8882)	(0.7265)	(0.6637)
$RIVOL_{t-1}$	-0.0264	-0.0015	0.0100	0.0026	0.1388***	0.1517***	-0.0075
	(0.5432)	(0.9218)	(0.5710)	(0.8441)	(0.0001)	(0.0000)	(0.6365)
$RSKEW_{t-1}$	0.0980***	-0.0071	-0.0215*	-0.0324***	-0.0145	-0.0320	-0.0215
	(0.0001)	(0.5166)	(0.0890)	(0.0047)	(0.7145)	(0.2876)	(0.1909)
$MCAP_{t-1}$	0.1972**	-0.1553***	-0.2526***	0.0009	-0.0108	-0.0887	0.1733***
	(0.0131)	(0.0000)	(0.0000)	(0.9556)	(0.9092)	(0.1717)	(0.0000)
$P2B_{t-1}$	-0.0315	-0.0002	-0.0001	-0.0033	-0.0442	-0.1051***	-0.0118
	(0.2918)	(0.9712)	(0.9932)	(0.8247)	(0.3873)	(0.0000)	(0.3464)
$SALGR_{t-1}$	0.0612*	-0.0151	0.0056	0.0022	-0.0788**	0.0149	0.0408***
	(0.0783)	(0.1542)	(0.6025)	(0.7652)	(0.0186)	(0.6422)	(0.0009)
$UPCM_{t-1}$	-0.0170	-0.0019	-0.0195***	0.0051	0.0350	-0.0069	-0.0035
	(0.3254)	(0.6131)	(0.0020)	(0.2174)	(0.1084)	(0.6706)	(0.7430)
$CLIST_{t-1}$	0.0148	-0.0050	-0.0011	0.0131	-0.0205	0.0099	0.0153*
	(0.7825)	(0.5344)	(0.8724)	(0.1114)	(0.5087)	(0.4818)	(0.0882)
LEV_{t-1}	-0.0353	-0.0135	-0.0113	0.0247***	-0.0190	0.0344	-0.0030
	(0.1817)	(0.2237)	(0.4786)	(0.0018)	(0.4842)	(0.2700)	(0.8171)
$Intercept$	0.2053**	0.3333***	0.3155***	0.0530	0.3310**	0.2161***	0.0781
	(0.0121)	(0.0000)	(0.0000)	(0.1025)	(0.0190)	(0.0001)	(0.1148)
N	861	1023	1023	1023	949	1018	1023
$R-sq$	0.33	0.88	0.84	0.91	0.18	0.40	0.77

Note. The sample in Table 7 includes 252 European non-financial firms and spans the period from 2002 to 2011. In this table, we regress seven regressors suspected of endogeneity onto their own first lags and the first lags of the other control variables including the proxy for mispricing, MSV. The variables are as defined in Appendix 1. Standard errors are clustered by firm and year (Petersen, 2009). p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 8: Second-step regression of the linear instrumental variable model (2SLS)

	(1)
IRQ	0.1258**
	(0.0363)
$AMIH$	0.2166
	(0.3390)
$BASP$	-0.2797*
	(0.0928)
$TRVOL$	0.0384
	(0.7934)
$\|ERR\|$	-0.0618
	(0.8175)
$DISP$	0.1347
	(0.4631)
$NOEST$	-0.1708
	(0.1475)
$\|MSV_{t-1}\|$	0.3931***
	(0.0000)
$RBETA$	-0.0251
	(0.2134)
$RIVOL$	0.0803*
	(0.0879)
$RSKEW$	-0.0086
	(0.7551)
$MCAP$	0.0202
	(0.8802)
$P2B$	0.0648
	(0.2969)
$SALGR$	-0.0043
	(0.8826)
$UPCM$	0.0040
	(0.7801)
$CLIST$	-0.0487**
	(0.0179)
LEV	0.0264
	(0.5030)
$Intercept$	0.2174*
	(0.0797)
N	899
$R-sq$	0.19

Note. Table 8 reports the results from the second-stage of our linear instrumental variable model. The sample includes 252 European non-financial firms and spans the period from 2002 to 2011. In this table, the seven regressors suspected of endogeneity are replaced by their fitted values obtained from Table 7. The variables are as defined in Appendix 1. Standard errors are clustered by firm and year (Petersen, 2009). p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.

Table 9: Results of the Heckit model

Panel A: First-stage		Panel B: Second-stage		
	$UNDER$		(1)	(2)
IRQ_{t-1}	-0.0919	IRQ	-0.0322	-0.0513
	(0.5485)		(0.4305)	(0.2226)
$AMIH_{t-1}$	0.1135	$AMIH$	0.1504	0.1402
	(0.8038)		(0.2245)	(0.3526)
$BASP_{t-1}$	-0.1710	$BASP$	-0.2291***	0.0955
	(0.6373)		(0.0013)	(0.4239)
$TRVOL_{t-1}$	-0.0579	$TRVOL$	-0.0869	0.0159
	(0.8463)		(0.3471)	(0.8639)
$\|ERR_{t-1}\|$	0.0724	$\|ERR\|$	0.0885***	0.1018***
	(0.6413)		(0.0094)	(0.0000)
$DISP_{t-1}$	0.2231	$DISP$	0.0981*	-0.0477
	(0.2320)		(0.0983)	(0.3623)
$NOEST_{t-1}$	0.5549**	$NOEST$	0.1519	-0.1087
	(0.0482)		(0.2669)	(0.2817)
$\|MSV_{t-1}\|$	0.0425	$\|MSV\|$	0.2580*	0.3444***
	(0.7804)		(0.0980)	(0.0000)
$RBETA_{t-1}$	0.1536	$RBETA$	-0.0265	-0.0212
	(0.3036)		(0.6048)	(0.5911)
$RIVOL_{t-1}$	0.2486	$RIVOL$	0.0843	0.0933*
	(0.1824)		(0.3424)	(0.0609)
$RSKEW_{t-1}$	0.0226	$RSKEW$	-0.0218	0.0228
	(0.8836)		(0.7054)	(0.4462)
$MCAP_{t-1}$	-0.8914***	$MCAP$	-0.2021	0.4231***
	(0.0088)		(0.1897)	(0.0002)
$P2B_{t-1}$	-1.3563***	$P2B$	-0.0520	0.2934***
	(0.0000)		(0.4732)	(0.0010)
$SALGR_{t-1}$	-0.0009	$SALGR$	0.0330	-0.0231
	(0.9955)		(0.4045)	(0.4471)
$UPCM_{t-1}$	0.1186	$UPCM$	-0.0135	0.0180
	(0.1848)		(0.6690)	(0.2768)
$CLIST_{t-1}$	0.0408	$CLIST$	-0.0177	-0.0542***
	(0.7562)		(0.6070)	(0.0024)
LEV_{t-1}	0.4400***	LEV	0.0116	0.0327
	(0.0038)		(0.8452)	(0.5324)
		IMR_1	-0.2512***	
			(0.0059)	
		IMR_0		-0.0403
				(0.6423)
$Intercept$	-0.0350	$Intercept$	0.5525***	-0.2010
	(0.9424)		(0.0000)	(0.1735)
N	1023	N	333	463
$Pseudo-R-sq$	0.1020	$R-sq$	0.30	0.34

Note. Table 9 reports the results of the piecewise linear Heckman's sample selection model (Heckit). The sample includes 252 European non-financial firms and spans the period from 2002 to 2011. Panel A of Table 9 fits a Probit model to the binary variable $UNDER_{i,t}$ which takes 1 when firm i is underpriced at year t, and 0 otherwise; the latent variable governing this Probit regression is given in Equation (14). In turn, Column (1) of Panel B is the regression of MSV onto contemporaneous information and $IMR_{1,i,t}$ using the subsample $UNDER_{i,t} = 1$ (underpriced subsample). The second equation is the regression of MSV onto contemporaneous information and $IMR_{0,i,t}$ using the subsample $UNDER_{i,t} = 0$ (overpriced subsample). The variables are as defined in Appendix 1. Standard errors are clustered by firm and year (Petersen, 2009). p-values are in parentheses. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively.