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Earnings Management by Classification Shifting and IPO Survival

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Abstract

The study examines the effect of earnings management by classification shifting on firm success, focusing on the survival of newly listed firms. We argue that shifting income-decreasing expenses from core to special items should negatively associate with future operating performance because of improper signaling of actual repeatable core profitability. We find that classification shifting strongly and negatively affects future Initial Public Offering (IPO) success and survival. We further identify the economic mechanisms that drive this finding and observe that our results are mitigated when the quality of external corporate governance alleviating agency concerns is stronger, also for IPO firms operating within stronger business contexts. Therefore, in an environment that facilitates firm survivability, the existence of weaker than reported sustainable performance may not end up materializing in the form of lower firm survivability as these factors aid firms' continuing operations from a business perspective. Our findings provide evidence of the longer-term implications of a method of earnings management that has long been considered "soft" and without any longer-term reversing consequences.

JEL Classification: M41; M48; G14; G30; G32

Keywords: classification shifting; investor protection; initial public offering.

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Abstract

The study examines the effect of earnings management by classification shifting on firm success, focusing on the survival of newly listed firms. We argue that shifting income-decreasing expenses from core to special items should negatively associate with future operating performance because of improper signaling of actual repeatable core profitability. We find that classification shifting strongly and negatively affects future Initial Public Offering (IPO) success and survival. We further identify the economic mechanisms that drive this finding and observe that our results are mitigated when the quality of external corporate governance alleviating agency concerns is stronger, also for IPO firms operating within stronger business contexts. Therefore, in an environment that facilitates firm survivability, the existence of weaker than reported sustainable performance may not end up materializing in the form of lower firm survivability as these factors aid firms' continuing operations from a business perspective. Our findings provide evidence of the longer-term implications of a method of earnings management that has long been considered "soft" and without any longer-term reversing consequences.

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1. Introduction

This study examines the effect of earnings management by classification shifting (hereafter, CS) on firm success, focusing on the survival of Initial Public Offering (IPO) firms. Further, in relation to accrual-based and real earnings management, which focus on altering bottom-line profits, the CS of income-decreasing expenses from core to special items (hereafter, SIs) represents a form of non-bottom-line profit manipulation that has received increasing attention since the milestone study of McVay (2006) (Fan, Barua, Cready, and Thomas 2010; Haw, Ho, and Li 2011; Joo and Chamberlain 2017; Fan, Thomas, and Yu 2019). CS does not flow through the accounting system (Athanasakou, Strong, and Walker 2009), but rather increases core earnings by deliberately misclassifying core expenses as noncore SIs within the income statement, without affecting bottom-line income (McVay 2006; Haw et al. 2011). CS is attractive because core earnings are more informative for predicting future profitability, giving managers relevant incentives to shift core expenses to SIs (Haw et al. 2011). More importantly, the vertical movement of expenses within the income statement should be less easily traceable than the other bottom-line profit-fixating forms of earnings manipulation, and without any negative net profit consequences, CS should be less costly than the use of accrual-based earnings management or the manipulation of real activities (Haw et al. 2011). Therefore, CS is considered a method of manipulating the presentation of the income statement that is not expected to lead to any reversal or "settling up" of net profit in the future (McVay 2006) nor to any adverse consequences in terms of future cash flows, unlike the other two, more traditional, methods of earnings management.

Conceptually, we expect that because CS represents a form of earnings management without identified negative and reversing consequences for future bottom-line performance, the practice should have no effect on future firm failure. In our study, we challenge the latter assertion and examine whether CS influences future firm success or failure by focusing on the mortality rates for recent IPO firms. We argue that because IPO survival is typically considered a consequence of good firm operating performance (Espenlaub, Khurshed, Mohamed, and Saadouni 2016), or even a proxy for IPO performance (Espenlaub, Khurshed, and Mohamed 2012), the context of IPO survival provides an ideal framework for our examination. Existing research has identified a number of factors that aggravate or enhance IPO survivability, such as underpricing, firm age, offer size (Hensler, Rutherford, and Springer 1997), venture-capital backing (Jain and Kini 2000), underwriter prestige (Schultz 1993), high-quality auditing (Jain and Martin 2005), and leverage (Demers and Joos 2007).

We expect that engagement in earnings management by CS around the time of the IPO should also put the survivability of newly listed firms at risk. This is because strong business performance in its core form should be a fundamental factor in supporting future IPO survival. When a firm provides a false signal about core (non-transitory) – and thus potentially repeatable – profitability and the ability to generate future cash flows, this misleading signal does not permit realistic expectations of consistently positive core performance in the future. The different components of the income statement should provide information about underlying firm economics for firms' core, i.e. repeatable in the future, vs. transitory performance. Therefore, CS around the IPO may not negatively reflect in future operating performance measured in terms of net profit in a more mechanically reversing way, as would be the case for accrual-based or real profit manipulation (Li and Zhou 2006; Alhadab, Clacher, and Keasey 2015); however, if CS causes a firm to appear more operationally robust than it actually is, a firm engaging in CS should end up performing according to its true (and more negative) potential in the future, leading to lower chances of survivability and success. Indeed, CS may not reverse on the basis of the GAAP net profit reported in future periods; however, it is naturally expected to reverse in terms of future reported operating profit (Cain, Kolev and McVay 2020) and negatively associate with future reported core earnings, with evidence that investors are negatively surprised when misclassified core expenses recur in future periods (Cain, Kolev and McVay 2020; Liu and Wu 2020). This is because, for example, in the case that cash expenses, such as marketing costs, which have been misclassified within special items recur, they should negatively associate with future operating income. At the same time, CS involves inflating reported core earnings, and so it makes the current year reported performance provide invalid information for the prediction of the future cash flow generation ability of firms. Therefore, even if CS does not mechanically offset net profit in the future, in the same way as other bottom-line profit-manipulating forms of earnings management, we expect a negative association between this form of earnings management and future IPO success. This expectation is based on the assumption that the presentation of distorted operating profits does not provide a realistic indication of an IPO firm's future operating performance and ability to generate operating profits and cash flows in a repeatable and sustainable way.

To explore this issue, we use a dataset of 1,969 non-financial US firms during 1990–2018, measuring CS via income-decreasing SIs in accordance with previous research (e.g., McVay 2006; Joo and Chamberlain 2017). Computationally, we follow Joo and Chamberlain (2017) and measure CS through the use of income-decreasing SIs, assuming that SIs should be positively and significantly associated with unexpected core earnings, based on the intuition of McVay (2006). Our results indicate that CS undertaken using income-decreasing SIs during the year of the IPO is significantly and negatively associated with IPO survival over the five years following IPO as well as with the long-term probability of post-IPO survival. This evidence is robust to the application of all mainstream controls employed in IPO survival analysis, including industry and year fixed effects.

We then attempt to identify the underlying economic channels that explain our result. On the one hand, strong external corporate governance mitigates agency problems and can also preclude CEOs from harming shareholder value by holding them accountable for firm performance (Kim and Lu 2011). For example, a CEO may face little leeway when it comes to avoiding a high risk but value-enhancing project in the presence of substantial external pressure, so undertaking such a project might be the only option (Kim and Lu 2011). At the same time, other research has shown that strong institutional pressure on corporate governance plays an important role in reducing the incentives to engage in CS (Haw et al. 2011). Therefore, we examine whether the external corporate governance mechanisms that induce managerial discipline mitigate the negative association between CS and future IPO survival. We use the external threat of takeover index developed by Cain, McKeon, and Solomon (2017) as well as the Herfindahl-Hirschman index of institutional ownership concentration as proxies for the strength of external governance. This is because a limited number of takeover defenses, or high takeover susceptibility, as measured by the Cain et al. (2017) index, makes firms uninsulated, at least in part, from the market of corporate control, and this market can play a managerial discipline role for the firms in question (Blanco and Wehrheim 2017). Moreover, high institutional investor concentration implies a less dispersed institutional shareholder base, indicating more intense pressure and monitoring from these financial stakeholders. Our evidence indicates that the negative effect of CS on IPO success is mitigated in the presence of stronger external corporate governance. We conjecture that despite the fact that CS-engaging IPO firm performance can be worse than reported thanks to CS, and thus provide weak indications about the ability of such firms to sustain robust performance in the future, the existence of strong external pressure forcing managers to take value-maximizing operating decisions may curb this effect.

On the other hand, stronger business factors may also work as protective mechanisms against the negative effect of CS on firm survival. This is because CS indicates that the repeatability of firm core performance is lower than reported; however, the existence of firm-specific characteristics that make the firm better able to perform in a sustainable way could mitigate the negative effect of CS on IPO survival. Recent research has indicated that business dispersion across multiple states within the US significantly influences corporate performance (Gao, Ng, and Wang 2008; García and Norli 2012; Giroud 2013; Platikanova and Mattei 2016). A similar expectation can be formulated about firm complexity, measured through the number of segments in which a firm operates (Duchin, Matsusaka, and Ozbas 2010). This is because a firm's engagement in several segments has been associated with inefficient capital allocation (Stein 1997), while higher industry diversification has been associated with lower firm value (Denis, Denis, and Yost 2002; Lamont and Polk 2002). Moreover, the degree of product market competition decreases the chances of success and increases the threat of firm bankruptcy (Blanco and Wehrheim 2017). Our evidence indicates that the negative effect of CS on IPO survival is mitigated for firms operating in a single business segment, for more geographically concentrated firms, and for firms operating in less competitive industries. In this way, firms that keep their business interests geographically concentrated, focus on one business segment, and operate in a less competitive environment have a greater chance of survival, to the extent that the significant effect of CS on firm mortality is mitigated for these firms.

Therefore, we conclude that the existence of either a) external governance mechanisms that force a firm's leadership to refrain from potentially sub-optimal decisions when managing the firm, or b) important business factors that work in favor of firms' operating sustainability act as protective mechanisms and mitigate the negative effect of any CS undertaken around the time of the IPO on future survival. Put differently, in the presence of strong external governance and business factors that should facilitate firm survivability, the existence of weaker than reported sustainable performance may not end up materializing in terms of lower firm survivability as such business and managerial disciplining factors aid the firm in surviving nevertheless.

Furthermore, Cain et al. (2020) report that the frequency of reporting special or nonrecurring items observed in more recent years has offered a convenient conduit for the inappropriate classification of past, present, and future recurring expenses as "nonrecurring". Cain et al. (2020) construct a method for identifying the predicted or "normal" level of SIs by attributing any excess to opportunism, and they provide evidence that the opportunistic portion of SIs is actually associated with lower future earnings, cash flows, and returns.[2]

[2] Evidence from Cain et al. (2020) is conceptually consistent with older evidence from Doyle, Lundholm, and Soliman (2003), which suggests that the items firms exclude from Street, or pro forma, earnings are negatively associated with future operating performance. The approach employed by Cain et al. (2020) to isolate the

Therefore, the existence of higher vs. lower opportunistic SIs may provide the technical opportunity for a more intensive window-dressing type of CS, through which operating profit is overstated. We follow a lightly modified methodology of Cain et al. (2020) to decompose income-decreasing SIs into a normal and an opportunistic component, given the lack of lagged and market data necessary with which to estimate their model because of the unavailability of back data for our IPO sample. We find that opportunistic SIs are negatively and significantly associated with the future performance of IPO firms in terms of both profitability and cash flows. In this way, we consider that our evidence on SIs, especially opportunistic ones, negatively reflecting into future IPO operating performance provides additional indications about how CS around the time of the IPO negatively and significantly relates to the likelihood of firm success.

In our tests, in addition to controlling for the non-classification-shifted portion of income-decreasing SIs, we purposely implement controls for the other two bottom-line profit-enhancing forms of earnings management, that is, accrual-based and real activities manipulation, to ensure that our results are incrementally obtained in relation to the forms of profit manipulation that have already been negatively associated with future IPO survival (Alhadab et al. 2015). We consider these controls to be necessary in the context of arguments and evidence from past research that CS is a low-cost mechanism for manipulating performance that may be used when other options for earnings management are more costly (Fan et al. 2010; Joo and Chamberlain 2017). Importantly, our findings hold after controlling for an alternative explanation for our evidence. This involves explicitly accounting for the restructuring events that led to the generation of corresponding SIs – in the year before the IPO or in the year of the issue – to alleviate concerns that a negative signal arising from an eventual underlying corporate event could have driven the negative SIs, rather than CS *per se*. Finally, our findings remain unchanged upon imposing controls for the potential endogeneity of the decision to engage in CS around the time of the IPO by propensity score-matching classification-shifter to non-shifter IPOs.

In a recent study, Liu and Wu (2020) provided evidence on significant CS taking place around IPO issues, with CS negatively affecting one year-ahead stock returns following the IPO. Our study is fundamentally different from Liu and Wu (2020) because their focus was on short-term initial and imminent investor reaction to CS taking place around IPOs, while

opportunistic component of SIs considers the inappropriate classification of past, present, and future recurring expenses within current year special or nonrecurring items, but nevertheless indicates that the tool used to apply CS (that is, opportunistic SIs) is negatively associated with future performance.

we focus on IPO survival. The examination of short-term investor reaction to CS undertaken around IPO issues does not answer the question of whether this practice has any longer-term effects on the future success or failure of these firms; at the same time, CS has traditionally been considered as a method of earnings management without long-term negative effects. Correspondingly, the arguments justifiably used by their study to formulate expectations about immediate investor reactions to CS around IPOs relate to the timing of revelation of any CS occurring around such events and the corresponding investor reactions to such revelation. However, the argumentation used by our study develops along the lines of theoretical expectations about why the occurrence of CS around IPOs should more fundamentally associate with the long-term success of firms. In this way, our study positions itself among IPO survival, rather than the IPO short-term investor reaction research. At the same time, we consider that the examination of IPO survival provides a useful context for empirically testing whether earnings management by CS associates with any longer-term consequences for firm success, while existing research has often considered the opposite.

Our study provides a number of contributions to existing research. Our results have implications for the seriousness of a seemingly harmless tactic for earnings management, as CS has traditionally been perceived, in terms of the future performance of firms operating in a context of great information asymmetry, as is the case for IPOs. We examine, for the first time, the longer-term implications of an earnings-management method, CS, that has generally been considered as innocuous or, according to a stream of recent research (Lattanzio and Thomas 2019; Ha and Thomas 2020), has even been seen as having a positive signaling role. We provide indications about the underlying economic mechanism that justifies this result when reported sustainable performance is overstated while external monitoring and underlying business factors that could make firms better able to survive are not present. This examination is performed for a context, namely that of newly listed firms, in which corporate survival is crucial, and this survival has generally been regarded as the proof of the success or failure of an IPO (Espenlaub et al. 2012). We explore whether, for newly listed firms, their engagement in CS results in such practice actually not representing an earnings-management method as harmless to future performance, as it has long been perceived. Furthermore, we foreground the role that strong business prospects and the efficiency of external governance mechanisms may play in corporate survival in the presence of managerial opportunism, as manifested by the profit-manipulation practices involving the reclassification of core expenses as transitory SIs. Finally, our research context provides the opportunity, within the IPO setting, to empirically validate the predictions as to the negative performance effects of opportunistic SIs, as identified by Cain et al. (2020). Specifically, we show that such items, representing the tool for CS, negatively reflect into the future performance of IPO firms, given that the higher vs. lower SIs, particularly opportunistic ones, used in the course of CS are found to adversely affect future performance and are, thus, consistent with lower IPO survival.

The rest of the paper is organized as follows: In Section 2, we review the literature and present our central research hypothesis. Section 3 describes the research design, including the measurement of CS, and the methodology used to investigate the association between CS and IPO survival. The empirical findings are reported and discussed in Section 4, and Section 5 reports on the analysis about the underlying economic mechanisms that could explain the association between CS and future IPO survival. We conduct supplementary analyses and report a number of robustness checks in Section 6. Section 7 provides concluding remarks.

2. Literature review and hypothesis development

2.1 Earnings management by classification shifting

Past research has identified three possible ways to manage earnings: accrual-based and real earnings management, both of which affect bottom-line reported profitability; while more recently, the pervasiveness of CS has been underlined (McVay 2006; Fan et al. 2010; Skaife, Swenson, and Wangerin 2013; Joo and Chamberlain 2017; Fan et al. 2019), representing a method that produces vertical movements within the income statement in order to overstate operating profit by reclassifying recurring operating expenses as nonrecurring SIs (McVay 2006). Thus, CS manipulates the presentation of the income statement in order to affect perceptions of performance for outsiders (McVay 2006).

SIs are nonrecurring or transitory in nature (Haw et al. 2011), and have a lower degree of information content than regular and recurring items (Bradshaw and Sloan 2002; Kaplan, Kenchington, and Wenzel 2020). Investors attach different values to different line items in the income statement (Haw et al. 2011), and this is because it is expected that the closer a line item is to sales, the more permanent this item tends to be (Lipe 1986; Elliott and Hanna 1996; Fairfield, Sweeney, and Yohn 1996; Francis, Hanna, and Vincent 1996; McVay 2006). Negative SIs for a given firm are generated when economic circumstances create the need for write-offs or reserves (Joo and Chamberlain 2017). In order to inflate core earnings, managers can misclassify regular core expenses, normally included within the cost of goods sold, or within selling, general and administrative expenses, as e.g. restructuring or M&A-related charges, which are considered transitory and non-recurring (McVay 2006).[3]

Although CS represents the method of earnings management that has received least research attention over recent years, research into the determinants of this method has been on the increase (McVay 2006; Athanasakou et al. 2009; Fan et al. 2010; Haw et al. 2011; Joo and Chamberlain 2017). Overall, this research indicates that managers regularly misclassify income-decreasing core expenses as nonrecurring SIs, particularly in order to achieve earnings benchmarks (McVay 2006; Fan et al. 2010; Haw et al. 2011) or to avoid operating-performance-related covenant violations (Fan et al. 2019). At the same time, solid corporate governance at the national (Haw et al. 2011) and corporate levels (Zalata and Roberts 2016) has been shown to decrease the severity of this phenomenon. Interestingly, the number of firms that report SIs has been on the increase in recent years (Collins, Maydew, and Weiss 1997; Donelson, Jennings, and McInnis 2011; Cain et al. 2020), with 50 percent of publicly traded US firms reporting income-decreasing SIs by 2016 (Cain et al. 2020).

The rationale for the misclassification of core expenses as income-decreasing SIs has mainly been attributed to managerial opportunism (McVay 2006; Haw et al. 2011), despite some recent claims that this practice actually reflects efficient signaling by managers about profitability that is expected to persist, with CS being representing a practice with a positive effect on firm value, as opposed to being a tool for operating-income misstatement (Lattanzio and Thomas 2019; Ha and Thomas 2020). This latter stream of research has been motivated by evidence that pro forma or Street earnings prepared by managers themselves, as opposed to official reporting or GAAP earnings, are more value-relevant for market participants (Lipe 1986; Kinney and Trezevant 1997; Bradshaw and Sloan 2002; Gu and Chen 2004; Jiang, Ma, and Wang 2020).

All three methods of earnings management raise expectations about future performance. However, while accrual-based and real earnings management should result in earnings reduction in the future (McVay 2006), there is no “settling up” when using CS; in other words, in the absence of any additional profit manipulation, next-period bottom-line earnings are equal to actual earnings, as opposed to earnings minus the cost of earnings

[3] It should be mentioned at this point that we focus on core income-increasing earnings manipulation via CS of negative SIs, in line with previous research (e.g., McVay 2006; Cain et al. 2020). The inflation of core performance can also occur via the misclassification of non-core or transitory revenues within operating income, as documented by other recent research (Malikov, Manson, and Coakley 2018). The examination of this latter is beyond the scope of our present study.

management in the current period (McVay 2006). In this case, CS does not result in any income-decreasing discretionary accruals that reverse for net income formulation in the following periods, or any opportunities of missed investment resulting from managing profits (Haw et al. 2011). Moreover, as net income does not change with the application of CS, the practice does not attract scrutiny from auditors and regulators (McVay 2006; Nelson and Skinner 2013). This is because the appropriate categorization of an item is the result of judgment applied by managers, and external monitoring may have a limited ability to identify this kind of behavior, resulting in lower costs for misclassification as an earnings manipulation method (Haw et al. 2011). In this way, CS is expected to be less costly than other bottom-line-affecting methods of earnings management, because of reduced outside scrutiny for this method that does not positively affect reported net profit (Athanasakou et al. 2009) and it being naturally more difficult to detect (Haw et al. 2011).

2.2 Earnings management around IPOs

IPOs inherently constitute corporate events with very high levels of information asymmetry between insiders and outsiders (Gounopoulos and Pham 2018), in terms of knowledge about corporate operations prior to the IPO, and insiders having information advantages compared to outsiders. Upward profit manipulation in the context of IPOs involves incentives as well as constraints and costs due to significant outsider scrutiny, and has been extensively examined in past research, in relation to both accrual-based and real earnings management (e.g., Aharony, Lin, and Loeb 1993; Friedlan 1994; Teoh, Wong, and Rao 1998; Teoh, Welch, and Wong 1998; Ball and Shivakumar 2008; Lo 2008). This research has shown that IPO firms engage in financial misreporting around the IPO in order to alter investor perceptions about the true financial picture of the firm (Aharony et al. 1993; Friedlan 1994; Teoh, Wong, et al. 1998; Teoh, Welch, et al. 1998). Such income manipulation tactics have been theoretically justified on the basis of agency (Jensen and Meckling 1976) and incomplete contracting (Warfield, Wild, and Wild 1995; Darrough and Rangan 2005; Wongsunwai 2013) theories, as well as being attributed to violations of the so-called "revelation principle" (Walker 2013; Alhadab et al. 2015).

More recently, Liu and Wu (2020) produced evidence of earnings management by CS taking place around the IPO year, with this practice favorably affecting investor perceptions at the time of its realization, but ultimately negatively affecting one-year ahead stock returns after the IPO. The explanation offered is that investor perceptions are initially clouded by CS around the IPO, but when CS is revealed after the event and investors realize that firms involved in pre-IPO CS have been overvalued, they adjust their valuation downward accordingly.

IPO survival is important for both firms themselves and policy makers, because as long as a company remains listed, it can raise funding from public markets (Espenlaub et al. 2012). IPO survival has been considered a measure of firm performance (Welbourne and Andrews 1996; Caves 1998; Espenlaub et al. 2012), to the point of considering IPO survival to be an adequate benchmark against which the success of an IPO should be measured. A series of firm-specific attributes have been identified as significantly affecting IPO survival, including underwriter reputation (Schultz 1993), firm age, offer size, underpricing (Hensler et al. 1997), auditor quality (Jain and Martin 2005), venture backing (Jain and Kini 2000), leverage (Demers and Joos 2007) and real/accrual-based earnings management (Alhadab et al. 2015).

Regarding earnings manipulation around the time of the IPO, and the repercussions of this practice for IPO survival, Li and Zhou (2006) were the first to examine the effect of accrual-based earnings management on IPO survival. Their evidence indicates that the degree of accruals manipulation is a strong predictor of future IPO failure, based on the argument that well-performing firms with solid earnings streams and prospects have low incentives to manipulate earnings; in this way, the level of earnings management associated with the IPO should decrease as the quality of the IPO increases. More importantly, Alhadab et al. (2015), using a UK sample, test for the effect of accrual-based and real activities manipulation around the IPO on future IPO survival. They argue that firms that engage in these forms of earnings management around the IPO fail more frequently, because both types of income manipulation have negative consequences for future operating and market performance. Their evidence indicates that both accrual-based and real earnings management are harmful to post-IPO survival, with real activities management exhibiting the more severe consequences of the two.

2.3 Development of research hypothesis

CS differs from the other two bottom-line profit-enhancing forms of earnings management, i.e. accrual-based and real, because it does not involve mechanical reversals of future bottom-line performance. Rather, CS involves changing the classification of core expenses within the income statement in order to artificially inflate reported core profitability; for this reason, it has long been considered the most innocuous and least costly form of profit manipulation. Nevertheless, we expect that CS should negatively affect IPO survival as it distorts both the true picture of operating results for a firm and the corresponding perceptions of financial statements by users and investors. Operating performance has long been considered, and has been empirically documented, to be the most predictable and value-relevant part of the income statement, offering the strongest indications about the ability to generate future cash flows. In this way, misleadingly high reported operating profitability should not provide correct indications of the resilience of future operating profit and cash-generation ability, with corresponding repercussions for firm failure. Properly identified and defined SIs should be transitory in nature, and so can be justifiably excluded from core earnings (Lougee and Marquardt 2004), while also possessing a lower degree of information content than regular and recurring items (Bradshaw and Sloan 2002). A distortion of the actual strength of core earnings, which are more informative in the prediction of future earnings (Haw et al. 2011), constitutes a misleading signal about the financial health of a firm and, thus, the anticipated persistence of its economic performance.

CS will not reverse in terms of future net profit, as would be the case for real and accrual-based earnings management, but it should reverse in terms of future reported operating profit, given that the misclassification of core items as non-recurring may not be possibly sustained on a continuous basis without raising any scrutiny. In the case that cash-based core expenses (e.g., marketing or other operating costs) which have been misclassified within special items recur, they should be negatively associated with future operating income, resulting in any CS undertaken in a year being negatively reflected in future core reported performance (Liu and Wu 2020). Furthermore, misrepresented core performance attributable to CS will not provide valid indications about the ability of firms to actually generate cash flows in a sustainable manner. Therefore, we expect a negative association between this form of earnings management and future IPO success, based on the assumption that the presentation of inflated core profitability, representing an income-generation ability that should be expected to persist, does not provide a realistic indication of an IPO firm's ability to sustainably perform and generate cash flows in a repeatable manner, leading to our central hypothesis:

Hypothesis 1. *IPO firms that opportunistically engage in classification shifting using income-decreasing special items during the issue year will,* ceteris paribus, *have a higher probability of failure and lower survival rates in the post-IPO period.*

We formulate Hypothesis 1 with reference to both a higher probability of failure, and a lower survival rate, on the grounds that the underlying mechanisms that drive lower success for IPOs relate to both higher chances of failure and lower survivability. Our empirical analysis tests for both of these outcomes separately. Particularly, the analysis of failure probability is complemented by the survival analysis, as the latter permits the consideration of more than just binary information as to whether or not a firm survives for a specified period, by incorporating the length of time for which the firm survives (Espenlaub et al. 2012).

At this point, we should reiterate that another stream of research has considered CS to be a value-enhancing practice (Lattanzio and Thomas 2019) that permits efficient signaling by management (Ha and Thomas 2020) in order to justifiably guide the perceptions of investors about the recurrent vs. transitory components of performance. This research has deemed the classification of core expenses as nonrecurring costs to be representative of correct managerial signaling, as opposed to representing a method of income manipulation meant to mislead outsiders about the true performance of the firm. This viewpoint is conceptually close to the distinction of profit into GAAP-calculated vs. Street earnings, with the latter being treated as more value-relevant for investors (Lipe 1986; Kinney and Trezevant 1997; Bradshaw and Sloan 2002; Gu and Chen 2004). Despite the identification of such justifiable or "correct" economic motives for undertaking CS, we consider that the misrepresentation of firm performance via CS of non-transitory income-decreasing SIs, along with evidence of opportunistic SIs being negatively associated with future performance, justifies our expectation that opportunistic CS should negatively reflect into the future success of the IPO.

3. Research design

3.1 Measuring classification shifting

We follow Joo and Chamberlain (2017) in measuring CS. Their methodology is suitable for our research context, as it allows us to employ a stand-alone independent variable as the proxy for CS, which can be easily interpreted when examining how this particular form of earnings management affects firm survival. In many CS studies, CS has been frequently captured through a focus on the dependent variable, which takes the form of unexpected core earnings, and regressing this variable on income-decreasing SIs. The CS measurement methodology of Joo and Chamberlain (2017) explicitly includes the portion of SIs which are not classification-shifted, in addition to the income-decreasing SIs that are so. We consider that imposing a control for the proportion of non-classification-shifted SIs is necessary for our particular research context, as these items could contain information about transitory business events. The latter may associate with firm survival, but do not indicate earnings management. Consequently, in the spirit of Joo and Chamberlain (2017), CS is measured as follows.

We first estimate unexpected core earnings using the following model developed by McVay (2006)[4]:

$$CE_{i,t} = \beta_0 + \beta_1 CE_{i,t-1} + \beta_2 ATO_{i,t} + \beta_3 ACCRUALS_{i,t-1} + \beta_4 ACCRUALS_{i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 NEG\_\Delta SALES_{i,t} + \mu_{i,t} \tag{1}$$

where $CE_{i,t}$ is core earnings for firm i in year t, defined as operating income before depreciation divided by sales; $ATO_{i,t}$ is asset turnover ratio, defined as $Sales_{i,t}$ /(($NOA_{i,t}$ + $NOA_{i,t-1}$)/2), where *NOA* (net operating assets) are calculated as the difference between operating assets and operating liabilities; $ACCRUALS_{i,t-1}$ is total accruals, defined as net income before extraordinary items, minus cash from operations scaled by sales; $\Delta SALES_{i,t}$ is the percentage change in sales; and $NEG\_\Delta SALES_{i,t}$ is the percentage change in sales if the latter is negative, and zero otherwise. Model (1) is estimated cross-sectionally for each industry-year where industry classifications are based on two-digit Standard Industrial Classification (SIC) codes.[5] Unexpected core earnings are calculated as the difference between reported and expected core earnings, where the latter are estimated using the predicted coefficients from model (1).

We then measure CS as unexpected core earnings if their number is positive and the SIs are income-decreasing, and zero otherwise. Thus, our CS measure can have either a positive or a zero value. Positive values of CS imply the use of CS, because they capture the amount of core expenses that are misclassified as income-decreasing SIs (Joo and Chamberlain 2017). The proportion of income-decreasing SIs that are not classification-shifted is measured by subtracting our CS measure from the total amount of negative SIs.

3.2 Classification shifting and IPO failure risks - Logit regression

Hypothesis 1 predicts that IPO firms that engage in CS during their issue year tend to have a higher probability of failure in the subsequent period. To test this hypothesis, we focus on the occurrence of involuntary delisting events within the first five years post-IPO, in

[4] Unexpected core earnings can also be estimated using the model in Fan et al. (2010) which includes lagged stock returns. We are unable to employ their model as data on lagged stock returns is not available for pre-IPO years.

[5] Expected core earnings are calculated for each industry-year using all firms included in Compustat. To ensure that there are sufficient data for the estimation of expected core earnings, we require, following McVay (2006), at least 15 observations per industry-year group. Furthermore, we use data for up to one year before the IPO has taken place for variable calculations, in accordance with previous studies in the field (e.g., Teoh, Welch, et al. 1998; DuCharme, Malatesta, and Sefcik 2004; Liu and Wu 2020), given the limited data availability from Compustat for newly listed firms for more pre-IPO years.

accordance with prior studies (e.g., Jain and Kini 2000; Demers and Joos 2007; Espenlaub et al. 2016) and estimate the following logit model regression:

$$\begin{aligned} FAILURE\_5_{i,t} = {} & \alpha_0 + \alpha_1 CS_{i,t} + \alpha_2 A\_CFO_{i,t} + \alpha_3 A\_DISX_{i,t} + \alpha_4 A\_TA_{i,t} \\ & + \alpha_5 NCS_{i,t} + \alpha_6 ROA_{i,t} + \alpha_7 MTB_{i,t} + \alpha_8 LEV_{i,t} + \alpha_9 VC_{i,t} \\ & + \alpha_{10} BIG\_4_{i,t} + \alpha_{11} UND\_WRIT_{i,t} + \alpha_{12} PROCEEDS_{i,t} \\ & + \alpha_{13} FIRM\_AGE_{i,t} + \beta_{14} INITIAL\_RET_{i,t} + INDUSTRY \\ & + YEAR + \varepsilon_{i,t} \end{aligned} \tag{2}$$

In model (2), $FAILURE\_5$ is equal to one if the firm is involuntarily delisted within five years of the offering, and zero otherwise. CS is our main variable of interest, which refers to the measure of CS. Hypothesis 1 predicts that the coefficient for CS will be positive.

We control for several firm and offering characteristics that may affect the probability of IPO failure, as suggested by existing literature. Cohen and Zarowin (2010), Wongsunwai (2013), and Alhadab et al. (2015) document that accrual-based and real earnings management tend to significantly increase the chances of failure for IPO firms. Therefore, we include abnormal accruals (A_TA) as a proxy for accrual-based earnings management, and abnormal cash flows from operations (A_CFO) and abnormal discretionary expenses (A_DISX) as proxies for real earnings management.[6] The proportion of negative SIs that are not classification-shifted (NCS) is also included as a regressor, to control for any effect on IPO survival by transitory items which can naturally occur and do not reflect earnings management by CS. We also control for firm performance and growth opportunities, proxied by the return on-assets ratio (ROA) and market-to-book ratio (MTB), respectively (Gounopoulos and Pham 2018). Furthermore, leveraged firms appear to have a higher probability of failure (Demers and Joos 2007); thus, we add a control for leverage (LEV) to the model. In addition, investment banks, venture capitalists and auditing firms play substantial roles during the IPO process. The quality and reputation of these key financial intermediaries are highly significant in ensuring the success of IPOs (Schultz 1993; Jain and Kini 2000; Jain and Martin 2005; Masulis and Nahata 2009; Lee and Masulis 2011; Krishnan, Ivanov, Masulis, and Singh 2011; Gompers, Gornall, Kaplan, and Strebulaev

[6] We do not include the real earnings management method of production cost manipulation, given that this practice is mainly employed by manufacturing firms (Roychowdhury 2006; Alhadab et al. 2015) and only 4% of our IPO sample comes from the manufacturing industry. Moreover, the measurement of abnormal production costs requires two years of lagged data; including abnormal production costs in the model reduces our sample size from 1,969 to 752 IPOs. For robustness purposes, we include *A_PROD* as a measure of abnormal production costs in the regression and our main results (reported in Table 10) remain intact.

2020). We, therefore, account for venture capitalists (VC), Big Four accountancy firms (BIG_4) and the involvement of reputable underwriters (UND_WRIT) in the IPO process. Furthermore, we include the following IPO issue-specific variables – offering proceeds ($PROCEEDS$), firm age ($FIRM\_AGE$) and initial returns ($INITIAL\_RET$) – to control for the positive effects of these factors on IPO survival, as documented by Hensler et al. (1997). Finally, we incorporate industry and year fixed effects in the model to account for any remaining eventual unmodeled macro and industry-specific factors. Complete variable definitions are provided in Appendix A.

3.3 Classification shifting and IPO failure risks - Survival analysis

Hypothesis 1 also predicts that IPO firms that employ CS during the IPO year are likely to have lower survival rates in the post-IPO period. Survival analysis is widely used in the existing literature (e.g., Jain and Kini 2008; Alhadab et al. 2015; Espenlaub et al. 2016; Gounopoulos and Pham 2018) to examine the probability of failure and survival time of IPO firms. The primary advantage of survival analysis over logistic regression is that it considers both the incident and the time until the incident takes place. Moreover, survival analysis is beneficial when handling censored data and time-series data with different time horizons (Jain and Kini 2000). This is because IPO data is right-censored, given that many firms have not been delisted as of the end of the sample period, and each firm has a different time window of existence depending upon its listing date. To examine the impact of CS on the survivability of IPO firms, we estimate the Cox proportional hazards model that allows the baseline hazard function to take any functional form. The Cox model is expressed as follows:[7]

$$\begin{aligned} h(t) = h_0(t)\exp[&\beta_1 CS_{i,t} + \beta_2 A\_CFO_{i,t} + \beta_3 A\_DISX_{i,t} + \beta_4 A\_TA_{i,t} \\ &+ \beta_5 NCS_{i,t} + \beta_6 ROA_{i,t} + \beta_7 MTB_{i,t} + \beta_8 LEV_{i,t} + \beta_9 VC_{i,t} \\ &+ \beta_{10} BIG\_4_{i,t} + \beta_{11} UND\_WRIT_{i,t} + \beta_{12} PROCEEDS_{i,t} \\ &+ \beta_{13} FIRM\_AGE_{i,t} + \beta_{14} INITIAL\_RET_{i,t} + INDUSTRY \\ &+ YEAR] \end{aligned} \quad (3)$$

where $h_0(t)$ is the baseline hazard function, and *t* is the time to failure (i.e., the duration until the delisting date). The dependent variable indicates the risk of failure. The independent variables are the same as in model (2) and include our main variable of interest, *CS*, as well

[7] In the form of a robustness check, we employ the accelerated failure time (AFT) model, which is also widely used in the literature (e.g., Hensler et al. 1997; Jain and Kini 2000; Espenlaub et al. 2012, 2016). The results of the AFT model (untabulated) are consistent with those obtained using the Cox proportional hazards model.

as controls for firm and offering characteristics. Hypothesis 1 predicts that the coefficient for *CS* will be positive.

4. Empirical results

4.1 Sample description

We obtain a sample of US common share IPOs from January 1, 1990 to December 31, 2013 (tracking their post-IPO survival until year 2018) from the Securities Data Company (SDC) New Issues database.[8] Consistent with prior IPO literature, we exclude IPOs with an offer price below US $5 per share, leveraged buyouts (LBOs), American depositary receipts (ADRs), real-estate investment trusts (REITs), closed-end funds, spin-offs and privatizations, unit offerings, limited partnerships, rights issues and financial institutions. Financial statement data is collected from Compustat, and stock prices and delisting information from the Center for Research in Security Prices (CRSP). We require availability of all main data items for all IPO firms in our sample. Consequently, our final IPO sample consists of 1,969 firms.[9]

Each firm is tracked from its listing date to whichever is earlier of its delisting date or the end of 2018. Following previous studies on IPO survival (e.g., Demers and Joos 2007; Jain and Kini 2008; Espenlaub et al. 2012; Alhadab et al. 2015), we consider surviving firms as the ones that are still trading, and failed firms as those that are involuntarily delisted for negative reasons, such as failure to meet listing requirements, bankruptcy, liquidation, corporate governance violation, and so on.[10] We use the CRSP delisting codes to classify IPO firms into those that survived and those that failed. In particular, surviving firms hold a delisting code of 100, and failed firms have delisting codes of 300 and above. The failed IPO sample consists of 381 firms that have been delisted for negative reasons by the end of the sample period; among them, 218 firms are delisted within five years of their issue. The surviving IPO sample consists of 377 firms that are still trading at the end of the sample period.

Insert Table 1 about here.

[8] We require up to two years of lagged data and five years of future data to compute variables for our empirical tests. Therefore, we collect data for all IPO firms from 1988 to 2018 for hypothesis testing of the period 1990–2013.

[9] Our sample for applying logit analysis (model (2)) consists of a smaller total of 1,828 IPOs, because we experience some information loss due to firms that have not delisted five years after their issue, but have delisted by the final year in which their performance is tracked, which is 2018.

[10] As a sensitivity check, we include in the group of failed firms those that are acquired via mergers, to account for the possibility that firms may be acquired due to financial distress. Our results (untabulated) remain robust.

Table 1 presents the distribution of IPO firms by year and industry. Panel A shows the IPO distribution by issue year. The upturn in the US economy after the 1990 recession led to a surge in the number of firms going public in the 1990s. IPO activity slowed down in the early 2000s, coinciding with the crash of the stock market following the burst of the Dot-com bubble. The IPO market improved slightly during 2004–2007, before witnessing a slump following the 2008 financial crisis. Nevertheless, there is an uptick in IPOs toward the end of the sample period.[11] The proportion of IPO firms failing within five years of their listing is highest for issues made during 1996–2001 (with nearly 20% of firms listed in these years failing), and in 2003 and 2008 (with 14% of firms listed in these years failing). Panel B shows the IPO distribution by two-digit SIC industry codes. IPO firms are more heavily concentrated in the industries of computer equipment and services, electronic equipment, scientific instruments, and wholesale and retail trade. Not surprisingly, these industries also show the highest percentages of failing IPOs in the sample. In particular, the computer equipment and services industries have the lowest survival rates (with approximately 13% of firms in these industries surviving, compared to around 20–25% in other industries).

Insert Table 2 about here.

Table 2 illustrates descriptive statistics for the overall IPO sample, as well as for the subsamples of failed and surviving IPOs. Panel A presents summary statistics for the entire IPO sample. The mean *UE_CE* (unexpected core earnings) is -0.029, while the mean *SI* (income-decreasing SIs scaled by sales, multiplied by negative one) is 0.022, and the mean *CS* (unexpected core earnings if their number is positive and SIs are negative, and zero otherwise) is 0.016. Thus, values for all of these CS-specific variables are close to zero for the full IPO sample, which is consistent with previous research (Joo and Chamberlain 2017). Corresponding mean and median values for the non-shifted portion of SIs are also marginally positive or close to zero, respectively. The mean *A_TA* (abnormal accruals) and mean *A_CFO* (abnormal cash flow from operations) in the issue year are marginally positive (0.021 and 0.041, respectively), while *A_DISX* (abnormal discretionary expenses) is negative (-0.367). This is consistent with previous studies on earnings management of IPO firms (e.g., DuCharme et al. 2001; Lo 2008; Alhadab et al. 2015; Gounopoulos and Pham 2017),

[11] We further observe from Table 1 that many IPO issues took place between years 1992-1997, a fact that justifies the selection of 1990 as the starting year of our sample period. One could counter-argue that non-GAAP earnings have gained importance in the more recent years, however, we weighted this argument against using a sample period that incorporates a significantly higher number of IPOs, with corresponding effects for the power of our tests. Nevertheless, we repeat our analyses for a shorter time period beginning in the late 1990's, and observe that our results are insensitive to using a shorter time period excluding most of the companies listed during the 90's.

suggesting that issuers tend to engage in earnings management around the IPO through manipulation of accruals and real activities. In terms of corporate characteristics, IPO firms are observed to be in operation for an average of 17 years before they go public. They show a mean ratio of return-on-assets of 8%, and an average leverage ratio of 17%. More than one third (36%) of the firms are underwritten by a top-tier investment bank, half (47%) are backed by a venture capitalist, and the great majority (92%) are audited by a Big Four accountancy company. IPO firms raise an average amount of 98 million dollars of proceeds through their offerings, receive an average return of 23% on their first day of trading (slightly higher than the first-day returns observed by Loughran, Ritter, and Rydqvist (2020) for the full 1960–2019 period in the US), and have an average market-to-book ratio of 3.13 in the year of issue.

Panel B provides the means and differences in means for the two groups of IPO firms, those that are delisted for negative reasons within five years post-IPO, and those that survive during the sample period. Mean *CS* is significantly higher for the group of failed firms than for the group of surviving ones (0.026 and 0.012, respectively). This univariate result indicates that failed firms tend to have a significantly higher level of CS in the issue year. Earnings-management measures are also significantly higher for failed firms. In particular, while *A_TA* and *A_CFO* are negative for the surviving group (-0.004 and -0.007, respectively), they are both positive for the failed group (0.091 and 0.244, respectively). The result is consistent with previous research (e.g., Alhadab et al. 2015) that reports a positive association between IPO failure and abnormal accruals and abnormal cash flows from operations. In terms of firm characteristics, at the time of the IPO issue, the average age of subsequently failed firms is about 11 years, while the mean age of subsequently survived ones is about 24 years. While survivors show a positive mean *ROA* (12.6%), failed firms experience negative average performance, with a mean *ROA* of -4.5%. The mean leverage ratio is also significantly lower for surviving firms (0.172) than for failed ones (0.205). A smaller proportion of IPOs in the failed sample are audited by a Big Four firm (84% vs. 89%) and underwritten by a reputable investment bank (28% vs. 42%). The surviving group also raises significantly more IPO proceeds, and experiences less underpricing in comparison to the failed group (213 million dollars vs. 52 million dollars in proceeds, and 18% vs. 26% in initial returns). Finally, there are no significant differences in market-to-book ratios and venture-capital financing rates between the two groups of failed and surviving IPOs.

4.2 The effects of classification shifting on IPO failure risks

We perform two preliminary analyses before proceeding with our baseline investigation of the effect of CS on IPO failure risks. First, we examine whether IPO firms employ CS in the year of the offer. To do this, we regress *UE_CE* (unexpected core earnings) on *SI* (income-decreasing SIs scaled by sales, multiplied by negative one), controlling for several firm characteristics that may influence unexpected core earnings, including *ROA* (return-on-assets ratio), *MTB* (market-to-book ratio), *LEV* (leverage ratio), *SIZE* (natural log of total assets), *CFO* (cash flows from operations), and industry and year fixed effects. The results of the regression results are reported in column (1) of Table 3. *SI* is positively and significantly associated with *UE_CE*, indicating that IPO firms misclassify core expenses as income-decreasing SIs during the issue year. This result is in accordance with Liu and Wu (2020). Second, we investigate whether failed firms that are involuntarily delisted after going public employ CS more pervasively than their surviving counterparts. To perform this investigation, we add the variable *FAILURE_5* (indicator variable equal to one if the IPO firm is delisted for negative reasons within five years of the offering, and zero otherwise) or *FAILURE* (indicator variable equal to one if the IPO firm is delisted for negative reasons by the end of the sample period, and zero otherwise), as well as an interaction term between *SI* and *FAILURE_5* (or *FAILURE*). Our findings are presented in columns (2) and (3) of Table 3. The coefficients for *SI* × *FAILURE_5* and *SI* × *FAILURE* are positive and significant. This suggests that failed firms, in comparison to surviving ones, significantly misclassify core expenses as income-decreasing SIs to a greater extent to boost declared core earnings in the issue year.

Insert Table 3 about here.

We now proceed with our main analyses. The results from the base-case logit model (2) employed to test whether CS significantly affects the probability of IPO failure are reported in Table 4. Column (1) of the table shows results for the model without controlling for accrual-based or real earnings management; columns (2) and (3) present findings for the model when controlling for only one of the two earnings-management methods, either real or accrual-based, respectively. Column (4) reports results for the full model when controlling for both bottom-line earnings-management methods. The results obtained are consistent in all four model specifications. Specifically, the coefficients for *CS* are positive and significant at the 1% level each time. This suggests that the use of CS in the issue year significantly increases the probability of being delisted within five years of the offering. Thus, Hypothesis 1 is supported. In terms of the behavior of the control variables, this is generally in line with previous literature. The coefficient for *A_CFO* is consistently positive and significant, indicating that IPO firms that engage in real activities management via sales manipulation carry a significantly higher probability of IPO failure. The coefficient for *A_TA* is positive and significant only when the model does not control for real earnings management. This suggests that real activities manipulation has more severe consequences on the long-term performance of IPO firms than does accrual-based earnings management, which is consistent with the relevant results reported by Alhadab et al. (2015). Moreover, profitability (*ROA*), growth opportunities (*MTB*), high-quality audit (*BIG_4*), offer size (*PROCEEDS*), and firm age (*FIRM_AGE*) are all negatively associated with the probability of failure, while leverage (*LEV*) shows the opposite relationship. The behavior of these variables is consistent with existing research (e.g., Hensler et al. 1997; Jain and Martin 2005; Demers and Joos 2007; Gounopoulos and Pham 2018).

Insert Table 4 about here.

The results from the Cox proportional hazards model (3) are illustrated in Table 5. The findings confirm those of the logit regressions reported in Table 4. Specifically, we find positive and statistically significant coefficients for *CS*, suggesting that IPO firms that misclassify core expenses as income-decreasing SIs during the issue year have higher failure risks in the period following their IPO. In particular, the hazard ratio for *CS* in column (4) of Table 5, which is the model specification with controls for both real and accrual-based earnings management, is 6.50. This indicates that for each unit increase in the use of CS, the firm's failure risk increases approximately 5.5-fold. Thus, these findings provide support for our Hypothesis 1. Turning to control variables, we clearly observe again that the negative impact of earnings management on IPO survivability is more evident for real earnings management (particularly if this takes the form of sales manipulation) than for accrual-based manipulation. In addition, firms that are older, larger, more profitable, audited by a Big Four auditor, or have more growth opportunities are found to be less likely to fail in the long run, while firms with more leverage tend to have a higher probability of failure.

Insert Table 5 about here.

Overall, the results from both the logit regression and the Cox proportional hazards models reported in Tables 4 and 5 support our hypothesis. They suggest that IPO issuers that misclassify core expenses as income-decreasing SIs in order to inflate their core earnings in the IPO year have a significantly higher probability of post-IPO failure, and a shorter survival time in periods subsequent to the offering year.

5. Possible mechanisms

In this section, we investigate the economic mechanisms that may drive our results regarding a negative association between CS and IPO survival. We suggest two possible explanations for our findings. Both suggested channels provide indications in the direction of the underlying factors, either business-related or the external drivers of managerial discipline, which may mitigate the observed negative association between CS and IPO survival. The underlying argument used by our research is that CS makes firms appear more operationally robust than they really are; therefore, in the case that this robustness does not persist in the future as is indicated by the core profits reported under CS, firms engaging in CS should be more prone to experiencing IPO failure. For this reason, the existence of factors such as the ones identified by our research could help firms survive during the years post-IPO, even if their actual repeatable performance is lower than indicated thanks to CS around the time of the IPO. Therefore, any factor that can aid survival from a business or managerial disciplining perspective should be able to alleviate this effect, by supporting IPO survival, thus constituting a mechanism which confirms that in the absence thereof, lower than reported core firm performance should revert and associate with decreased chances for IPO survival. As underlined by Blanco and Wehrheim (2017), while such investigated channels do not provide definitive proof about such conjectures, the relevant argumentation and evidence are suggestive of the explanation provided.

5.1 External corporate governance

As is also the case for other manifestations of earnings management, the existence of strong external governance mechanisms appears to associate with a lower degree of misclassifying core expenses as special (Haw et al. 2011). The existence of efficient and strong external corporate governance should mitigate agency problems, hold firm managers accountable for achieved performance, and prevent them from deviating from optimal business decisions that enhance value-creation (Kim and Lu 2011). The first economic mechanism we consider is external corporate governance, reflecting managerial disciplining factors and their effect on the association between CS and IPO survival. CS makes firms' reported performance that is expected to be repeatable look better than it actually is; therefore, externally imposed discipline should make corporate leadership work in the best interests of the firm and manage the firm in an efficient way that actually advances survivability. We use two proxies for the strength of external governance. The first one is the index developed by Cain et al. (2017) measuring the external threat of takeovers, which represents an important corporate governance mechanism. This index constitutes a reliable measure of external pressure on firms' corporate governance (Cain et al. 2017). This is because as hostile takeovers normally involve replacing a firm's management, by making it easier to remove managers who engage in value-destroying activities, active markets for corporate control play an important role in corporate governance (Jensen and Meckling 1976; Scharfstein 1988; Gormley and Matsa 2016), decreasing the scope for managerial agency conflicts (Gormley and Matsa 2016). Cain et al. (2017) construct a firm-level takeover index that expresses the probability of hostile takeover taking place for a firm. Thus, a higher (lower) value for the index indicates a higher (lower) chance of takeover susceptibility, and hence, greater (lower) market discipline and lower (higher) takeover protection. In this way, we define firms with better (worse) external corporate governance as those with values above (below) the sample median for Cain et al.'s (2017) index.

The second proxy we use is the degree of concentration of institutional investor holdings, as measured by the Herfindahl-Hirschman index of ownership concentration, under the assumption that a more concentrated institutional shareholder base is indicative of stronger pressure and monitoring from their side, and should, therefore, provide indications about the quality of external governance. A higher value for the Herfindahl-Hirschman index of institutional ownership concentration indicates a less dispersed institutional shareholder base, consistent with the possibility of more efficient monitoring and disciplining power by these financial stakeholders. Again, we define firms with better (worse) external corporate governance as those with values above (below) the sample median of the Herfindahl-Hirschman index of institutional ownership concentration.

Insert Table 6 about here.

The relevant findings on the role of external governance mechanisms in explaining the negative effect of CS on firm survival are presented in Table 6. Column (1) reports the results for our baseline model (3) after including a binary high takeover susceptibility indicator variable, *HIGH_TOIND*, that is equal to one if the takeover index is greater than the sample median, and zero otherwise. The coefficient on our main variable of interest, *CS*, remains positive and statistically significant, suggesting that our primary results are robust to controlling for the strength of external governance expressed in terms of susceptibility to takeovers. Column (2) shows the results for our baseline model (3) when including the interaction between CS and the high takeover index indicator variable. In this specification, the coefficient on *CS* × *HIGH_TOIND* is significantly negative, while the coefficient on *CS* is significantly positive. This implies that high takeover susceptibility, or high market discipline, significantly decreases the negative effect of CS on firm survival. Column (3) shows the results for our baseline model (3) after adding a high institutional ownership concentration binary indicator variable, *HIGH_OCONC*, that is equal to one if the concentration of institutional ownership as measured by Herfindahl-Hirschman index is greater than the sample median, and zero otherwise. The coefficient on *CS* continues to be positive and statistically significant, demonstrating that the primary results are robust to controlling for ownership concentration. Column (4) presents the results for the baseline model (3) when including the interaction between CS and the high concentration of the institutional ownership indicator variable. We observe that the coefficient on *CS* × *HIGH_OCONC* is significantly negative, while the coefficient on *CS* is significantly positive. This implies that a high concentration of institutional ownership, which is again consistent with stronger than average external corporate governance for firms in question, also mitigates the negative effect of CS on firm survival.[12]

5.2 Business factors

We further consider stronger business factors as possible protective mechanisms from the negative association between CS and firm survival. IPO firm engagement in CS indicates that the persistence and ability to sustain core operating performance should be lower than reported by the firms themselves. Therefore, important business factors that aid firms to sustainably perform and address competitive challenges could potentially reinforce their chances for survival from a business perspective, and thereby alleviate the negative effect of CS on IPO survival. We consider possible business factors that could perform this role.

First, we use the degree of firm complexity, measured by the number of segments in which firms operate (Doyle, Ge, and McVay 2007; Duchin et al. 2010), as a proxy for the strength of business factors that could aid IPO survival. Competing in multiple industries makes firms engage in more complex operational and informational environments (Bushman, Chen, Engel, and Smith 2004). Multi-segment engagement has been empirically associated with capital allocation inefficiency and lower firm value (Stein 1997; Lamont and Polk 2002; Denis et al. 2002), making such firms more prone to benefit from costly monitoring activities

[12] Our baseline results reported in Table 5 are also robust to the inclusion of controls for the quality of internal corporate governance, as proxied by the quality of the CEO, expressed in terms of CEO duality, founder CEO and CEO stock ownership, in the context of previous research indicating that this quality mitigates firms' tendency towards profit manipulation, as well as future firm performance (e.g., Xie, Davidson, and Dadalt 2003; Bhagat and Bolton 2008).

and managerial talent compared to firms with a tighter industry focus (Bushman et al. 2004). In this way, we expect that higher, rather than lower, firm complexity should contribute to creating adverse business prospects for firms with weaker than indicated reported operating performance that should be expected to persist. Thus, we construct a binary indicator taking the value of one if a firm operates in only one business segment in a year, and zero for multi-segment firms, where operating in only one (multiple) business segment(s) is interpreted as being indicative of lower (higher) firm complexity.

Second, recent studies report that the geographic location of corporate activities is an imperative in corporate decision-making. Local firms with concentrated businesses are strongly favored because of substantial benefits, such as area awareness, social networks, investor recognition, and in particular, information quality (Garcia and Norli 2012; Grullon, Larki, and Michaely 2019). The geographic dispersion of business activities hinders information flows within the organization, and thus intensifies information asymmetry (Landier, Nair, and Wulf 2009). Moreover, both external and internal monitoring costs might be inflated by geographic business expansion (Gao et al. 2008). Giroud (2013) showed that proximity to manufacturing plants facilitates the acquisition of information and improves oversight of the production process. In addition, increased internal information asymmetry, as a result of geographic dispersion, creates greater incentives for dishonest managers to engage in opportunistic accounting activities (Shi, Sun, and Luo 2015). The negative future consequences of opportunistic financial reporting behaviors might be more severe when coupled with deteriorating operating performance, caused by inefficient investment and financial decisions. Therefore, it is possible that the impact of CS on post-IPO longevity is heterogeneous among issuers with different levels of business concentration. We consider the degree of the geographical business concentration of firms as a factor that should favor firms' chances for survivability, and construct a variable that measures the degree of geographic dispersion of a firm across different states in the US in a year (e.g. Platikanova and Mattei 2016). Higher values for this variable indicate that a firm has more concentrated business interests, and so is less dispersed, and vice versa. A detailed variable definition is reported in Appendix A.

Finally, we consider the degree of product market competition as a factor that should negatively affect firms' opportunity for survivability. The ability to exercise market power and avoid competition decreases the uncertainty about the future performance of firms (Gaspar and Massa 2006). The degree of product market competition increases the threat of bankruptcy, and thus, puts firm success at risk (Blanco and Wehrheim 2017). For this reason, we expect that stronger competition in product markets should make IPO firms more prone to failure if they have misleadingly inflated their core or repeatable profitability in financial statements. We define product market competition using the median value of a firm's Lerner index in an industry-year (Blanco and Wehrheim 2017), whereby larger (smaller) values for this index indicate a less (more) intense competitive environment.[13]

Insert Table 7 about here.

The relevant findings on the role of business factors in explaining the negative effect of CS on firm survival are presented in Table 7. Column (1) shows the results for our baseline model (3) after adding the single business segment indicator variable (*S_BSEG*). The key coefficient on *CS* is positive and statistically significant, suggesting that our primary results are robust to controlling for business segments. Column (2) reports the results for the baseline model (3) when including the interaction between CS and the single business segment indicator variable. In this specification, the coefficient on *CS* × *S_BSEG* is significantly negative, while the coefficient on *CS* is significantly positive. The implication is that the negative effect of CS on firm survival significantly decreases when a firm operates in a single business segment. Column (3) shows the results for our baseline model (3) after adding our proxy for business concentration (*BCONC*). The coefficient on *CS* continues to be positive and statistically significant, demonstrating that our baseline results are robust to controlling for business concentration. Column (4) presents the results for our baseline model (3) when including the interaction between CS and the business concentration variable. We find that the coefficient on *CS* × *BCONC* is significantly negative, while the coefficient on *CS* is significantly positive. This suggests that the existence of CS in the IPO year becomes significantly less aggravating for firm survival when firms' geographical concentration is higher. Finally, column (5) shows the results for the baseline model (3) after incorporating our proxy for product market competition (*MCOMP*). The coefficient on *CS* is positive and statistically significant, indicating that our primary results are robust to controlling for product market competition. Column (6) reports the results for the baseline model (3) when including the interaction between CS and the product market competition variable. In this specification, the coefficient on *CS* × *MCOMP* is significantly negative, while the coefficient

[13] It should be noted at this point that other research has considered the degree of product market competition as an external governance enhancing factor, as firms should exert more effort in order to survive in the presence of competitive product markets (Kim and Lu 2011). However, in addition to this role, product market competition has also been expected to increase a firm's chances for failure. Thus, it is under this anticipated function that we consider the intensity of competition in product markets to be working as a factor that should make the survival of newly listed firms less, rather than more, probable.

on *CS* is significantly positive. The implication is that the negative effect of CS on firm survival is again less pronounced when the degree of product market competition is lower.

Overall, the findings from Table 7 indicate that business factors that could make survival easier for IPO firms; in other words, operating in a single business segment, keeping the business geographically concentrated, and facing less product market competition significantly mitigate the negative effect of any CS undertaken in the year of the IPO on firm survival. Even though CS involves misreporting the level of profitability – a fact that raises questions about the ability of firms to repeat the level of performance actually reported and perform accordingly in the future – business factors that aid survival can work as mechanisms that protect from IPO failure. The same type of effect is observed from the findings in Table 6 in the presence of factors that improve corporate governance with a disciplining effect on managers. The underlying assumption behind this interpretation of our results is that firms which misreport their core or repeatable profitability should not be able to sustain this practice for longer time windows, so these firms should eventually perform according to the actual – and lower than reported and thus less sustainable – performance levels.

6. Additional analyses and robustness controls

6.1 Opportunistic special items

In our baseline analysis, we demonstrate that the level of CS in the offering year negatively influences the longevity and success of IPO firms. The existence and availability of SIs create inherent and mechanical opportunities for managers to inappropriately reclassify past, present, and future recurring core expenses into current-period income-decreasing SIs in order to inflate reported core earnings (McVay 2006). Cain et al. (2020) propose a methodology for partitioning income-decreasing SIs into two components, namely economically driven and opportunistic ones, and report evidence to indicate that the opportunistic portion of income-decreasing SIs is associated with lower future earnings and cash flows. In this context, we additionally examine, in the form of supplementary analysis, whether opportunistic SIs, constituting the tool or conduit for engaging in CS, negatively affect IPO firms' future profitability and ability to generate cash flows.

We employ the model developed by Cain et al. (2020) to estimate opportunistic SIs, and examine whether the magnitude of opportunistic SIs for our sample of IPO firms is associated with poorer post-issue performance. We replicate Cain et al. (2020) by regressing reported income-decreasing SIs on key economic factors that may determine the propensity for, and magnitude of, income-decreasing SIs using a Tobit regression, estimated according to industry-years, although we make a few small modifications to their model to account for the limitations present in an IPO setting, specifically, constraints for lagged information and market data. Details of the methodology used to measure opportunistic SIs are provided in Appendix B. In Appendix C, we validate our modified version of the model of Cain et al. (2020) for the entire population of Compustat by obtaining similar results to theirs: the fitted value from the model indicates the economically driven component, or predicted SIs (*PredSI*), and the residual value reflects the opportunistic SIs (*OppSI*).

Insert Table 8 about here.

Table 8 Panel A reports the mean values for opportunistic and predicted SIs and the differences in these means for failed vs. surviving IPO firms. IPO firms delisted for negative reasons have significantly higher average *OppSI* than survivor firms (0.087 vs. 0.053, respectively). However, the value for *PredSI* is not significantly different when comparing failed to surviving firms (0.003 vs. 0.004, respectively). These results suggest that opportunistic SIs, but not the predicted ones, are significantly more pronounced among involuntarily delisted firms.

Next, we directly examine the association between opportunistic SIs and future performance defined in terms of future earnings and operating cash flows for our IPO sample. Panel B of Table 8 reports the estimation results when regressing net income before taxes and SIs (*NIBTSI*) accumulated over years *t*+2 and *t*+3 on opportunistic SIs (*OppSI*), controlling for predicted levels of SIs (*PredSI*), current-year *NIBTSI*, and change in sales (Δ*SALES*) as well as industry and year fixed effects. The regression is estimated for three separate samples: the full sample (including all IPO firms with available data for this analysis), the so-called *SI* sample (consisting of IPO firms that report income-decreasing SIs in the issue year), and the *OppSI* sample (consisting of IPO firms with identified opportunistic SIs in the issue year). Similar to Cain et al. (2020), we focus on the latter two samples to analyze the effects of opportunistic SIs on future performance. The results show that the coefficients for *OppSI* are negative and significant for both the *SI* and *OppSI* samples. We further investigate whether opportunistic SIs exert a similar impact on future cash flows. We regress cash flows from operations (*CFO*) accumulated over years *t*+2 and *t*+3 on *OppSI*, *PredSI*, current-year *CFO*, *ΔSALES*, *A_ACCRUALS* (total accruals adjusted for income-decreasing SIs), and industry and year fixed effects. Our results from Table 8 Panel C corroborate those observed for future earnings in Panel B because we find that the coefficients for *OppSI* are negative and significant for both the *SI* and *OppSI* samples. Overall, these results suggest that for IPO firms that report income-decreasing SIs, the opportunistic component of these SIs negatively and significantly affects future corporate earnings and cash flows. This applies in the periods following the offering and corroborates our previous analyses on why CS (or the method of profit manipulation that makes use of SIs) is found to be negatively associated with firm success.

One could argue that the validity of the results reported in Table 8 is affected by the modifications made in the estimation of the model of Cain et al. (2020) due to data limitations in our IPO sample. To tackle this concern, we extend our analysis of the effect of income-decreasing SIs on future earnings and cash flows, but this time for IPO firms suspected of having engaged in the window-dressing form of CS. Table 9 shows the relevant results estimated for the following four groups: all IPO firms; IPO firms that report SIs; IPO firms that report SIs and also exhibit positive unexpected core earnings (*UE_CE*); and IPO firms with SIs and negative *UE_CE*. The SI-reporting sample with positive *UE_CE* is representative of firms that tend to engage in image-enhancing CS, while the SI-reporting sample with negative *UE_CE* includes firms that are less likely to classification-shift within this scope. The underlying expectation is that the negative association of SIs with future operating performance should be stronger for firms engaging in image-improving CS than for firms that do not, if it is the case that SIs represent the mechanism that drives future poor performance and increased failure rates for IPO firms. We observe from Panel A of Table 9 that *SI* is positively related to future profit (*NIBTSI*) for the full sample, and is negatively and significantly related to *NIBTSI* for the overall SIs sample as well as for the SIs subsample with positive *UE_CE*, but it is *not* significantly associated with future profits for the SIs subsample with negative *UE_CE*. The results from Panel B of Table 9, for cash flows, show that *SI* is not significantly associated with future cash flows for the full sample, the overall SIs sample, and the SIs subsample with negative *UE_CE*, but is so for the SIs subsample with positive *UE_CE*.

Insert Table 9 about here.

Overall, the results from Table 9 complement the findings from Table 8 by confirming the expectation that income-decreasing SIs exert a negative influence on future earnings and cash flows for classification shifters, but not for IPO firms with no evidence of using CS for image-enhancement purposes.

6.2 Robustness controls

6.2.1 Possibility for alternative explanations

In this study, we present evidence on the influence of CS on firm success, when simultaneously controlling for the non-classification-shifted portion of negative SIs, in addition to their classification-shifted portion. However, one could argue at this point that our results might be affected by eventual negative signals arising from underlying negative events that occurred in firms going public before or around the time of their issue. Such events, which could relate, for example, to firm restructuring, could be driving the generation of income-decreasing SIs, rather than CS. The occurrence of negative events that could trigger the generation of SIs, as opposed to CS representing the triggering factor for SIs, could lead to measurement errors when identifying the classification-shifted vs. non-classification-shifted components of SIs. In case such events negatively affect firm survival, and our CS methodology captures the classification-shifted portion of SIs with a significant degree of noise, by incorporating, for example, important amounts of restructuring charges undertaken because of challenging business conditions, then our main findings could be attributable to the occurrence of restructuring around the IPO time, as opposed to earnings management in the form of CS. Thus, our results would be reflective of the negative signal of such events, rather than CS.

Insert Table 10 about here.

The possibility for this alternative explanation for our findings is addressed in two ways. First, we estimate our baseline model (3) by excluding firms that engage in restructuring either in the year before the IPO, or in the issue year. We observe from our data that only 80 IPOs out of 1,962 in our sample actually reported restructuring charges around their IPO years. Results in column (1) of Table 10 show that the coefficient on *CS* remains positive and statistically significant, suggesting that our findings are not sensitive to the exclusion of restructuring firms. Second, we control for firm restructuring activities around the time of issue by adding a relevant regressor (*REST*) to our baseline model (3), estimated for the full sample. Results reported in column (2) of Table 10 reveal that *REST* is positively associated with IPO failure risk, while we document that the coefficient on *CS* still remains positive and statistically significant, suggesting that the results are robust to imposing an explicit control for restructuring activities. Therefore, this evidence does not point towards the direction of eventual negative underlying events around the time of the IPO to be working as drivers of the observed significant association between CS and IPO survivability.

6.2.2 High-tech-industry participation

High-technology (high-tech) firms are increasingly important in the IPO market. They tend to rely more heavily on equity financing, possess more intangible assets, and incur greater research and development expenditures than non-technology (non-tech) firms (Demers and Joos 2007). In addition, high-tech firms are often regarded as high-growth firms with more upside opportunities. However, these firms face intense competition because of continuous demand for technological advancements, which may challenge their prosperity and longevity (Gounopoulos and Pham 2018). Given such economic differences between high-tech and non-tech sectors, CS may be an important determinant of failure risk in each of these sectors. Therefore, in the form of a robustness check, we control for the possible effects of high-tech-industry participation on the association between CS and IPO firms' survivability. We add an indicator variable, *HIGH-TECH*, to our baseline model (3), in which high-tech industries are identified according to their SIC codes. The findings in column (3) of Table 10 show that the *HIGH-TECH* indicator is not significantly related to the IPO failure risk, while we document that the coefficient for CS remains positive and statistically significant, suggesting that our main results are robust to the control for high-tech-industry participation.

6.2.3 Real earnings management through production-cost manipulation

In the baseline analysis, we control for the potential effects of earnings management via accrual-based and real earnings management through the manipulation of sales and discretionary expenses on IPO failure risks, but do not control for the effect of real earnings management undertaken through production-cost manipulation. For robustness purposes, despite the reduction in the number of usable observations that this control brings because of data requirements for two year pre-issue figures, we include *A_PROD*[14] in our baseline model (3) as a proxy for abnormal production costs, following Roychowdhury (2006). The results reported in column (4) of Table 10 reveal that the coefficient on *CS* remains positive and statistically significant. This indicates that the use of CS in the issue year increases future failure risks even when controlling for real earnings manipulation via overproduction.

6.2.4 Endogeneity of the decision to engage in CS around the time of the IPO

Although we include several control variables consistent with prior research, and further examine the robustness of our results using a number of additional controls, we

[14] A detailed description of the calculation of this proxy for real earnings management is provided in Appendix A.

cannot exclude the possibility for the existence of other omitted or correlated variables. At the same time, we cannot preclude the possibility for firms with underlying performance problems, thereby more likely to fail, to decide to engage in CS opportunistically so as to reap short-term benefits. To mitigate such potential endogeneity concerns related to the decision to engage in CS, we apply a propensity score matching approach following Espenlaub et al. (2016). In specific, we match classification shifter IPO firms to non-classification shifter IPOs, by making use of several firm-level characteristics which might drive the CS decision. These include firm age, total sales and return on assets for the year before the issue, and initial stock returns on the first day of trading of the IPO. Because our CS measure can be either positive or zero, we define classification shifters as those firm-year observations that have positive values for this variable (and non-classifications shifters as having a zero value) in the year of the IPO. Column (5) of Table 10 shows the Cox model results estimated using the propensity score matched sample. Results indicate that inferences are unaffected upon controlling for potential endogeneity of the CS decision. Specifically, *CS* remains positive and statistically significant, while the impact of other control variables is also observed to be similar to the main findings reported in Table 5. Results from column (5) of Table 10 indicate that CS represents a factor significantly increasing the risk of failure of IPO firms, even upon controlling for potential endogeneity of the decision to engage in CS around the time of the issue.

7. Conclusion

In this study, we examine for the first time the effect of earnings management by CS on firm success by focusing on the survival of IPO firms. Although CS represents a form of earnings management long-considered not to possess any important negative and reversing consequences for future bottom-line performance, we anticipate that shifting income-decreasing expenses from core to SIs in order to artificially inflate core performance should be negatively associated with the future success of IPO firms. This can be due to false signaling and inaccurate indications of a firm's actual prospects when it comes to sustaining and repeating operating or core profitability and the ability to generate cash flows. We examine our research question for US IPO firms during 1990–2018. Our results show that CS undertaken through the use of income-decreasing SIs in the issue year is positively associated with IPO failure over the five years following the offering, and negatively associated with the long-term survival of the IPO firm. In addition to controlling for the non-classification-shifted portion of negative SIs, our evidence is robust to the application of a number of controls frequently used in IPO survival analysis as well as CS research, including industry and year fixed effects, controls for bottom-line forms of earnings management, and participation in high-tech industries. Importantly, our findings are unaffected upon controlling for an alternative explanation, related to restructuring events that may have triggered the generation of corresponding SIs around the IPO issue. This control was imposed in order to alleviate concerns that a negative signal arising from an eventual underlying corporate event could have driven SIs, rather than the decision to engage in CS. Our evidence further remains unchanged when controlling for the potential endogeneity of the decision to engage in CS around the time of the issue by repeating our analysis for classification-shifter and propensity score-matched non-shifter IPO firms.

Importantly, we identify potential underlying mechanisms that could provide an explanation for our results. We find that the existence of external corporate governance mechanisms, which should discipline a firm's leadership and make it refrain from value-destroying decisions as well as business factors, which favor the operating sustainability of firms, mitigates the negative effect of any CS undertaken around the time of the IPO on future firm survival. This is because in the absence of such mechanisms, lower than reported core firm performance because of CS should revert and associate with reduced survival for IPO firms. However, the existence of stronger external corporate governance with a disciplining effect on managers as well as focusing firm operations in a single business segment, keeping business geographically concentrated, and facing less product market competition are all observed to mitigate the effect of CS in the IPO year on future IPO survival. Thus, the existence of efficient external governance and business factors that facilitate firm survivability results in weaker than reported sustainable performance not materializing in terms of decreased firm survival, thus protecting the firm from IPO failure.

Our supplementary analyses provide additional indications about why CS, which has generally been considered a "soft" method of earnings manipulation, is found to have significant adverse consequences for firm success. Upon isolating the opportunistic component of SIs by employing a modified approach introduced by Cain et al. (2020), we observe that such SIs are strongly and negatively associated with future earnings and cash flows for our sample of IPO firms engaging in CS. Therefore, our IPO research context provides the opportunity to empirically validate the propositions and evidence of Cain et al. (2020) as to the adverse consequences of opportunistic SIs for future firm performance. This validation is performed within a research context where firm survival is considered as proof of corporate success.

Our research explores, in the context of IPO success, whether CS really is a method that is as innocuous for future performance as has long been perceived. Our evidence to the contrary has obvious repercussions in terms of the need for more efficient monitoring of firms, so that this softer earnings-management method is not pervasively used in the absence of opportunities to engage in other, bottom-line profit-altering forms of earnings manipulation. Finally, our evidence underlines the importance of strong governance and business factors in firm survival, to the extent that such factors can function as protective mechanisms against the negative effect of managerial financial reporting opportunism on firm success.

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Appendix A: Variable definitions
(Source: Compustat North America, unless otherwise indicated)

Variables for measuring classification shifting	
ACCRUALS	Total accruals, defined as net income before extraordinary items minus cash flows from operations, scaled by sales.
ATO	Asset turnover ratio, defined as $\text{Sales}_{i,t}/((\text{NOA}_{i,t} + \text{NOA}_{i,t-1})/2)$, where NOA (net operating assets) is calculated as the difference between operating assets and operating liabilities.
CE	Core earnings, defined as operating income before depreciation divided by sales.
CS	Classification shifting, equal to unexpected core earnings if unexpected core earnings are positive and special items are income-decreasing, and zero otherwise.
NCS	The proportion of income-decreasing special items which is not classification-shifted. It is calculated as the difference between *SI* and *CS*.
NEG_ΔSALES	Percentage change in sales if the latter is negative, and zero otherwise.
ΔSALES	Percentage change in sales, calculated as $(\text{Sales}_t - \text{Sales}_{t-1})/\text{Sales}_{t-1}$.
SI	Income-decreasing special items, defined as special items multiplied by negative one scaled by sales when special items are income-decreasing, and zero otherwise.
UE_CE	Unexpected core earnings, estimated based on the model developed by McVay (2006). Measurement details are specified in Section 3.
Variables for real and accrual-based earnings management	
A_CFO	Abnormal levels of cash flows from operations multiplied by negative one, where abnormal levels of cash flows from operations are calculated as the difference between actual and normal levels of cash flows from operations following Roychowdhury (2006). The normal levels of cash flows from operations are measured using the following regression estimated cross-sectionally for each industry-year (2-digit SICs) for all non-IPO firms: $\frac{CFO_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{S_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta S_{i,t}}{AT_{i,t-1}} + e_{i,t}$, where $CFO_{i,t}$ is cash flows from operations for firm *i* in year *t*. $AT_{i,t-1}$ is total assets. $S_{i,t}$ is sales revenue.
A_DISX	Abnormal levels of discretionary expenses multiplied by negative one, where abnormal levels of discretionary expenses are calculated as the difference between actual and normal levels of discretionary expenses following Roychowdhury (2006). The normal levels of discretionary expenses are measured using the following regression estimated cross-sectionally for each industry-year (2-digit SICs) for all non-IPO firm: $\frac{DISX_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{S_{i,t-1}}{AT_{i,t-1}} + e_{i,t}$, where $DISX_{i,t}$ is discretionary expenses, calculated as selling, general, and administrative expenses plus advertising expenses plus R&D expenses. $AT_{i,t-1}$ is total assets. $S_{i,t}$ is sales revenues.

A_PROD	Abnormal levels of production costs, calculated as the difference between actual and normal levels of production costs following Roychowdhury (2006). The normal levels of production costs are measured using the following regression estimated cross-sectionally for each industry-year (2-digit SICs) for all non-IPO firm: $\frac{PROD_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{S_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta S_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta S_{i,t-1}}{AT_{i,t-1}} + e_{i,t}$, where $PROD_{i,t}$ is production costs, calculated as the sum of cost of sales and change in inventory. $AT_{i,t-1}$ is total assets. $S_{i,t}$ is sales revenue.
A_TA	Abnormal levels of total accruals, calculated as the difference between actual and normal levels of accruals. The normal levels of accruals are measured using the modified cross-sectional Jones model (Dechow, Sloan, and Sweeney 1995). This model is estimated by adding return-on-assets as an additional regressor to control for extreme cases of operating performance (Kothari, Leone, and Wasley 2005). Thus, normal accruals are estimated cross-sectionally for each industry-year (2-digit SICs) for all non-IPO firms as follows: $\frac{TA_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{\Delta SAR_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{AT_{i,t-1}} + \beta_4 ROA_{i,t} + e_{i,t}$, where $TA_{i,t}$ is total accruals for firm *i* in year *t*, calculated as the difference between net income before extraordinary items and cash from operations. $AT_{i,t-1}$ is total assets. $\Delta SAR_{i,t}$ is the change in sales revenue minus the change in accounts receivable. $PPE_{i,t}$ is gross property, plant, and equipment. $ROA_{i,t}$ is return-on-assets.
Variables for firm and offering characteristics	
BIG_4	Big Four audit, indicator variable equals to one if the firm is audited by a Big Four audit firm, and zero otherwise. *(Source: SDC)*
FAILURE	An indicator variable that is set to one if the IPO firm is delisted for negative reasons by the end of 2018, and zero otherwise. *(Source: CRSP)*
FAILURE_5	An indicator variable that is set to one if the IPO firm is delisted for negative reasons within five years after the offering, and zero otherwise. *(Source: CRSP)*
FIRM_AGE	Firm age, calculated as the logarithm of one plus the difference between the firm's IPO year and its founding year. Company founding years are collected from the Field-Ritter dataset.[15] *(Source: SDC, Jay Ritter dataset)*
INITIAL_RET	Initial returns, measured as the stock return on the first day of trading. *(Source: CRSP)*
LEV	Leverage, calculated as the ratio of total debt to total assets in the issue year.
MTB	Market-to-book ratio, calculated as the ratio of market value (price at fiscal year-end multiplied by the number of shares outstanding) to book value in the issue year.
PROCEEDS	Proceeds, calculated as the logarithm of total proceeds of the IPO. *(Source: SDC)*
ROA	Return on assets, calculated as earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets in the issue year.
SIZE	Firm size, calculated as the natural log of total assets in the issue year.
UND_WRIT	Underwriter prestige, indicator variable set to one if the IPO is underwritten by reputable underwriters, and zero otherwise. Reputable underwriters are those with a ranking score of 9.0 or above based on Jay Ritter's underwriter rakings[16]. *(Source: SDC, Jay Ritter dataset)*
VC	Venture-capital financing, indicator variable set to one if the firm is venture backed, and zero otherwise. *(Source: SDC)*
Variables for channel, supplementary, and robustness analyses	
HIGH_TOIND	High takeover susceptibility index, indicator variable set to one if the takeover index by Cain et al. (2017) is greater than the sample median, and zero otherwise. We thank Cain et al. (2017) for making takeover index data available to us.
HIGH_OCONC	High ownership concentration, indicator variable set to one if the concentration of institutional ownership, as measured by the Herfindahl-Hirschman index is greater than the sample median, and zero otherwise. (*Source: Thomson 13f*).

[15] The Field-Ritter dataset is available on Jay Ritter's webpage: https://site.warrington.ufl.edu/ritter/ipo-data/
[16] IPO underwriter reputation rankings are available on Jay Ritter's webpage: https://site.warrington.ufl.edu/ritter/ipo-data/

S_BSEG	Firms with a single business segment, indicator variable set to one if the firm has one business segment, and zero otherwise.
BCONC	Business concentration, measured as the degree of a firm's geographic dispersion, where the latter is computed as the normalized Herfindahl–Hirschman index (HHI), as follows: $SS_{i,t} = \left(\frac{\#Alabama_{i,t}}{\#Total\ US\ states_{i,t}}\right)^2 + \cdots + \left(\frac{\#New\ York_{i,t}}{\#Total\ US\ states_{i,t}}\right)^2 + \cdots + \left(\frac{\#Wyoming_{i,t}}{\#Total\ US\ states_{i,t}}\right)^2$ $Concentration_{i,t} = \frac{SS_{i,t} - 1/50}{1 - 1/50}$ where $SS_{i,t}$ is the aggregated value of the squared ratio of each state count divided by total state citations, and $Concentration_{i,t}$ is the normalized HHI of the degree of geographic dispersion across different states. Higher *Concentration* values indicate that a firm has more geographically concentrated business interests. We thank García and Norli (2012) for making the state citations data available on their website.
MCOMP	Product market competition, calculated as the median value of a firm's Lerner index in an industry-year using all firms in Compustat.
A_ACCRUALS	Total accruals adjusted for income-decreasing special items, calculated as net income before extraordinary items minus cash flows from operations plus special items.
CFO	Cash from operations scaled by sales.
HIGH-TECH	High-tech IPO, indicator variable set to one if the IPO firm is in a high-tech industry. High-tech industries are identified as those with the following SIC codes: 357 (computer equipment), 366 (communications equipment), 367 (electronics), 381 (navigation equipment), 382 (measuring and controlling instruments), 384 (medical instruments), 481 (telephone equipment), 489 (communications services), 737 (software), and zero otherwise. *(Source: SDC).*
NIBTSI	Net income before taxes and special items, calculated as net income before taxes adjusted for income-decreasing special items, divided by sales.
PredSI	Predicted special items, estimated based on the model developed by Cain et al. (2020). Measurement details are specified in Appendix B.
OppSI	Opportunistic special items, estimated based on the model developed by Cain et al. (2020). Measurement details are specified in Appendix B.
REST	Restructuring firms, indicator variable set to one if the firm engages in restructuring either in the year before the IPO or in the issue year.

Appendix B: Measuring opportunistic special items

We measure opportunistic special items by employing the Tobit model estimation developed by Cain et al. (2020). Notably, we make two modifications to the model to account for data constraints in an IPO setting. First, prior stock returns and change in the book-to-market ratio are excluded from the model, as these market-based variables are not available for pre-IPO years. Second, Cain et al. (2020) use three-year changes for some of their variables, while we only consider one-year changes to maximize the number of usable observations as financial data for two to three years before the issue is limited. The model is estimated as follows:

$$\begin{aligned} SI_{i,t} = \eta + {} & \lambda_1 \Delta ROA_{i,t-1,t} + \lambda_2 Merger_{i,t-1,t} + \lambda_3 Employee\ decline_{i,t-1,t} + \lambda_4 DiscontinuedOp_{i,t} \\ & + \lambda_5 LargeSalesDecline_{i,t} + \lambda_6 \Delta Sales_{i,t-1,t} \\ & + \lambda_7 Loss_{i,t} + \lambda_8 PctLoss_{i,t-1,t} + \lambda_9 \Delta CFO_{i,t-1,t} \\ & + \lambda_{10} CapitalIntensity_{i,t-1} + \lambda_{11} IntangibleIntensity_{i,t-1} + \lambda_{12} \ln(assets)_{i,t-1} \\ & + \mu_{i,t} \end{aligned} \quad \text{(A.1)}$$

where

ΔROA	=	The change in return on assets from year *t*-1 to *t*.
$Merger$	=	An indicator variable set to one if the firm undertakes merger and acquisition (M&A) activity in year *t* or *t*-1, and zero otherwise.
$Employee\ decline$	=	An indicator variable set to one if the firm has a decline in the number of employees from year *t*-1 to *t*, and zero otherwise.
$DiscontinuedOp$	=	An indicator variable set to one if the firm reports income from discontinued operations in year *t*, and zero otherwise.
$LargeSalesDecline$	=	An indicator variable set to one if the firm is in the lowest industry-year sales growth quintile, and zero otherwise.
$\Delta Sales$	=	The change in net sales from year *t*-1 to *t*.
$Loss$	=	An indicator variable set to one if the firm reports net pre-tax loss before special items, extraordinary items and discontinued operations in year *t*, and zero otherwise.
$PctLoss$	=	Percentage of years where *Loss* = 1 over the specified measurement period.
ΔCFO	=	The change in cash flow from operations from year *t*-1 to *t*, measured as cash from operations minus operating cash flows attributable to extraordinary items and discontinued operations.
$CapitalIntensity$	=	Property, plant, and equipment scaled by total assets.
$IntangibleIntensity$	=	Intangible assets scaled by total assets.
$\ln(assets)$	=	The natural logarithm of total assets.

We estimate the above Tobit regression for each industry-year with data availability for at least 50 observations. The predicted (*PredSI*) (opportunistic (*OppSI*)) component of income-decreasing special items is identified as the fitted value (error term). Following Cain et al. (2020), two adjustments are made to address the deferred reporting of income-decreasing special items and the combination of both income-increasing and income-decreasing components in the special items figure reported in Compustat. Specifically, *PredSI* and *OppSI* are set to zero if the firm does not report income-decreasing special items for the period. *OppSI* is also set to zero if the error term is negative and the firm reports income-decreasing special items. To validate our modifications, we compare the results obtained by our modified model to the Cain et al. (2020) results for all Compustat firms. Particularly, our results of the association of special items components with future firm performance (presented in Appendix C) are similar to those by Cain et al. (2020).

Appendix C: Opportunistic special items and future performance (All Compustat firms)

Panel A: Future earnings and opportunistic special items

Variable	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$
	Full sample	*SI sample*	*OppSI sample*
$OppSI_t$	-0.132	-0.936***	-1.106***
	(-1.46)	(-8.08)	(-8.25)
$PredSI_t$	1.725***	0.818***	1.812***
	(6.53)	(2.95)	(4.75)
$NIBTSI_t$	1.753***	1.675***	1.691***
	(152.62)	(89.46)	(83.95)
$\Delta SALES_t$	-0.112***	-0.101***	-0.069***
	(-11.08)	(-5.90)	(-3.65)
Constant	-0.606**	-0.254	-0.390
	(-2.17)	(-0.36)	(-0.51)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	94,866	36,466	30,347
Adjusted R-squared	0.257	0.255	0.269

Panel B: Future cash flows and opportunistic special items

Variable	$\Sigma^{t+3}{}_{t+2}\ CFO_t$	$\Sigma^{t+3}{}_{t+2}\ CFO_t$	$\Sigma^{t+3}{}_{t+2}\ CFO_t$
	Full sample	*SI sample*	*OppSI sample*
$OppSI_t$	-0.039	-0.423***	-0.505***
	(-0.64)	(-5.32)	(-5.49)
$PredSI_t$	0.623***	0.170	0.570**
	(3.47)	(0.90)	(2.18)
CFO_t	1.5[illegible]7***	1.610***	1.609***
	(14[illegible].71)	(88.95)	(82.68)
$\Delta SALES_t$	-0.051***	-0.046***	-0.026**
	(-7.38)	(-3.88)	(-1.99)
$A\_ACCRUALS_t$	0.683***	0.567***	0.572***
	(32.91)	(17.30)	(15.97)
Constant	-0.170	0.002	-0.084
	(-0.89)	(0.00)	(-0.16)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	94,682	36,408	30,296
Adjusted R-squared	0.288	0.289	0.302

Panels A(B), columns (1)-(3) show the effect of opportunistic special items on future earnings (cash flows from operations) for all firms, firms with special items, and firms with opportunistic special items. $NIBTSI_t$ is net income before taxes and special items; SI_t is income-decreasing special items scaled by sales, multiplied by negative one; $OppSI_t$ is opportunistic special items; $PredSI_t$ is predicted special items; $\Delta SALES_t$ is sales growth; CFO_t is cash flows from operations; $A\text{-}ACCRUALS_t$ is total accruals adjusted for income-decreasing special items. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two tailed) levels, respectively.

Table 1: IPO distribution by issue year and industry

Panel A: Distribution by issue year

Year	All IPOs		Failed (tracked for 5 years post-IPO)		Failed (tracked until 2018)		Survived (tracked until 2018)	
	N	%	*N*	%	*N*	%	*N*	%
1990	29	1.47	3	1.37	7	1.83	7	1.86
1991	66	3.35	3	1.37	16	4.19	8	2.12
1992	129	6.55	8	3.65	25	6.54	16	4.24
1993	171	8.68	15	6.85	42	10.99	25	6.63
1994	143	7.26	14	6.39	30	7.85	14	3.71
1995	168	8.53	10	4.57	26	6.81	16	4.24
1996	243	12.39	42	19.63	55	14.66	23	6.10
1997	159	8.07	29	13.24	48	12.57	16	4.24
1998	103	5.23	19	8.68	28	7.33	13	3.45
1999	169	8.58	35	15.98	43	11.26	23	6.10
2000	114	5.79	17	7.76	22	5.76	16	4.24
2001	22	1.12	4	1.83	5	1.31	6	1.59
2002	30	1.52	0	0.00	0	0.00	11	2.92
2003	21	1.07	3	1.37	3	0.79	9	2.39
2004	62	3.15	2	0.91	6	1.57	17	4.51
2005	63	3.20	3	1.37	5	1.31	22	5.84
2006	61	3.10	4	1.83	6	1.57	26	6.90
2007	67	3.40	1	0.46	6	1.57	29	7.69
2008	7	0.36	1	0.46	1	0.26	3	0.80
2009	24	1.22	1	0.46	2	0.52	11	2.92
2010	31	1.57	3	1.37	3	0.79	20	5.31
2011	26	1.32	0	0.00	1	0.26	11	2.92
2012	31	1.57	1	0.46	1	0.26	17	4.51
2013	30	1.52	0	0.00	0	0.00	18	4.77
Total	1,969	100.00	218	100.00	381	100.00	377	100.00

Panel B: Distribution by industry

Industry (two-digit SIC codes)	All IPOs		Failed (tracked for 5 years post-IPO)		Failed (tracked until 2018)		Survived (tracked until 2018)	
	N	%	*N*	%	*N*	%	*N*	%
Chemical products (28)	71	3.60	8	3.65	14	3.66	18	4.77
Computer equipment and services (35, 73)	637	32.34	71	32.42	97	25.39	85	22.55
Electronic equipment (36)	192	9.75	14	6.39	30	7.85	43	11.41
Entertainment services (70, 78, 79)	48	2.44	6	2.74	8	2.09	8	2.12
Food products (20)	41	2.08	5	2.28	9	2.36	7	1.86
Health services (80)	54	2.74	5	2.28	8	2.09	7	1.86
Manufacturing (30 - 34)	74	3.76	9	4.11	22	5.76	19	5.04
Oil and gas (13)	51	2.59	3	1.37	7	1.83	12	3.18
Scientific instruments (38)	157	8.02	4	2.28	8	2.36	33	8.75
Transportation and public utilities (41, 42, 44 - 49)	120	6.09	24	10.96	36	9.42	24	6.37
Wholesale and retail trade (50 - 59)	283	14.37	37	16.89	70	18.32	62	16.45
Others (01, 10, 12, 15-17, 22-27, 29, 37, 39, 65, 67, 72, 82, 83, 87, 99)	241	12.23	32	14.61	72	18.85	59	15.65
Total	1,969	100.00	218	100.00	381	100.00	377	100.00

Panel A(B) presents the distribution of the overall sample and the two groups of failed and survived IPO firms by year (industry). Survived firms are those that are still trading (CRSP delisting code of 100). Failed firms are those that are delisted for negative reasons (CRSP delisting code greater than or equal to 300). *N* denotes the number of observations.

Table 2: Descriptive statistics

Panel A: Summary statistics for the full sample

Variables	*N*	Mean	*p25*	Median	*p75*	SD
UE_CE	1,969	-0.029	-0.060	0.000	0.041	0.253
SI	1,969	0.022	0.000	0.000	0.007	0.079
CS	1,969	0.016	0.000	0.000	0.000	0.064
A_CFO	1,969	0.041	-0.140	-0.013	0.150	0.328
A_DISX	1,969	-0.367	-0.704	-0.138	0.083	0.645
A_TA	1,969	0.021	-0.082	0.006	0.116	0.204
NCS	1,969	0.005	0.000	0.000	0.000	0.076
ROA	1,969	0.080	0.031	0.119	0.190	0.202
MTB	1,969	3.134	1.071	2.013	3.597	4.448
LEV	1,969	0.165	0.003	0.058	0.278	0.212
VC	1,969	0.468	0.000	0.000	1.000	0.499
BIG_4	1,969	0.919	1.000	1.000	1.000	0.273
UND_WRIT	1,969	0.356	0.000	0.000	1.000	0.479
PROCEEDS	1,969	1.670	1.387	1.644	1.938	0.444
FIRM_AGE	1,969	1.061	0.778	1.000	1.301	0.401
INITIAL_RET	1,969	0.226	0.008	0.107	0.271	0.419

Panel B: Means for IPO firms delisted for negative reasons and survivor IPO firms

Variables	Delisted for negative reasons (*N* = 218)	Survivors (*N* = 377)	Differences in means (*t*-test)
UE_CE	-0.096	-0.016	***
SI	0.042	0.015	***
CS	0.026	0.012	**
A_CFO	0.244	-0.007	***
A_DISX	-0.432	-0.242	***
A_TA	0.091	-0.004	***
NCS	0.015	0.003	*
ROA	-0.045	0.126	***
MTB	2.683	2.992	
LEV	0.205	0.172	*
VC	0.431	0.377	
BIG_4	0.835	0.891	**
UND_WRIT	0.284	0.424	***
PROCEEDS	1.497	1.886	***
FIRM_AGE	0.910	1.200	***
INITIAL_RET	0.262	0.179	**

This table shows descriptive statistics for the main variables used in the study. Panels A and B report descriptive statistics for the main variables for the full sample (panel A) and for IPO firms that are delisted for negative reasons within five years post-IPO, and those that have survived by the end of the sample period (panel B). *UE_CE* is unexpected core earnings; *SI* is income-decreasing special items scaled by sales, multiplied by negative one; *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the logarithm of total proceeds of the IPO; *FIRM_AGE* is the logarithm of one plus firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively. *N* denotes the number of observations.

Table 3: Classification shifting of IPO firms delisted for negative reasons during the offer year

Variables	(1) *UE_CE*	(2) *UE_CE*	(3) *UE_CE*
SI	0.193***	0.027	-0.111
	(2.723)	(0.341)	(-1.268)
FAILURE_5		-0.039**	
		(-2.026)	
SI× FAILURE_5		0.719***	
		(4.412)	
FAILURE			-0.039**
			(-2.548)
SI× FAILURE			0.848***
			(5.966)
ROA	0.259***	0.261***	0.262***
	(4.834)	(4.8[illegible]2)	(4.917)
MTB	-0.001	-0.001	-0.001
	(-0.694)	(-0.6[illegible]7)	(-0.704)
LEV	0.020	0.026	0.022
	(0.656)	(0.851)	(0.724)
SIZE	0.004	0.004	0.004
	(0.688)	(0.661)	(0.628)
CFO	0.243***	0.236***	0.241***
	(4.000)	(3.871)	(3.978)
Constant	-0.011	-0.014	0.026
	(-0.04[illegible])	(-0.059)	(0.106)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	1,969	1,969	1,969
Adjusted R-squared	0.119	0.127	0.135

This table shows classification shifting regression results of IPO firms delisted for negative reasons relative to their counterparts that are not delisted for negative reasons during the offer year. *UE_CE* is unexpected core earnings; *SI* is income-decreasing special items scaled by sales, multiplied by negative one; *FAILURE_5* is equal to one if the IPO firms delisted for negative reasons within 5 years after the IPO date and zero otherwise; *FAILURE* is equal to one if the IPO firms delisted for negative reasons by the end of 2018 after the IPO date and zero otherwise; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *SIZE* is the natural log of total assets in the issue year; *CFO* is cash flows from operations in the issue year. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 4: Logistic regression estimation: prediction failure within 5 years of IPO

Variables	(1) *FAILURE_5*	(2) *FAILURE_5*	(3) *FAILURE_5*	(4) *FAILURE_5*
CS	3.082***	3.037***	3.818***	3.069***
	(2.929)	(2.764)	(3.524)	(2.707)
A_CFO		1.708***		1.680***
		(5.350)		(4.165)
A_DISX		0.133		0.131
		(0.815)		(0.793)
A_TA			1.330***	0.054
			(3.595)	(0.113)
NCS	1.359	0.941	1.872**	0.971
	(1.461)	(0.984)	(2.026)	(0.980)
ROA	-2.367***	-0.863*	-2.014***	-0.873*
	(-5.605)	(-1.699)	(-4.647)	(-1.692)
MTB	-0.052**	-0.052**	-0.049*	-0.052**
	(-2.060)	(-1.983)	(-1.924)	(-1.978)
LEV	1.324***	1.131***	1.307***	1.134***
	(3.173)	(2.649)	(3.128)	(2.652)
VC	-0.192	-0.263	-0.203	-0.262
	(-1.024)	(-1.353)	(-1.077)	(-1.349)
BIG_4	-0.907***	-0.924***	-0.929***	-0.926***
	(-3.225)	(-3.267)	(-3.302)	(-3.269)
UND_WRIT	0.055	0.140	0.086	0.140
	(0.260)	(0.653)	(0.405)	(0.653)
PROCEEDS	-1.066***	-1.119***	-1.050***	-1.117***
	(-3.829)	(-3.918)	(-3.743)	(-3.907)
FIRM_AGE	-0.663***	-0.694***	-0.702***	-0.695***
	(-2.801)	(-2.874)	(-2.935)	(-2.876)
INITIAL_RET	0.049	-0.019	0.046	-0.018
	(0.254)	(-0.095)	(0.236)	(-0.090)
Constant	2.770**	3.050***	2.834**	3.048***
	(2.525)	(2.739)	(2.559)	(2.736)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Pseudo R^2	0.199	0.223	0.209	0.222
N failures within 5 years	218	218	218	218
N	1,828	1,828	1,828	1,828

This table provides logistic regression results for testing whether classification shifting of IPO firms during the offer year affects the probability of IPO failure in the subsequent years. *FAILURE_5* is equal to one if the IPO firms delisted for negative reasons within 5 years after the IPO date, and zero otherwise; *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the logarithm of total proceeds of the IPO; *FIRM_AGE* is the logarithm of one plus firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 5: Coefficient estimates from Cox hazard models, time to failure

Variables	(1) Coefficient	(1) Hazard ratio	(2) Coefficient	(2) Hazard ratio	(3) Coefficient	(3) Hazard ratio	(4) Coefficient	(4) Hazard ratio
CS	2.152***	8.60	1.839***	6.29	2.409***	11.12	1.871***	6.50
	(3.274)		(2.887)		(3.716)		(2.860)	
A_CFO			1.203***	3.33			1.157***	3.18
			(5.491)				(3.771)	
A_DISX			0.107	1.11			0.104	1.11
			(0.907)				(0.872)	
A_TA					1.048***	2.85	0.078	1.08
					(4.039)		(0.214)	
NCS	0.655		0.195		[illegible]		0.229	
	(1.081)		(0.319)		[illegible]		(0.364)	
ROA	-2.278***		-1.293***		-2.012***		-1.312***	
	(-8.180)		(-3.578)		(-6.959)		(-3.519)	
MTB	-0.066***		-0.062***		-0.066***		-0.062***	
	(-2.970)		(-2.692)		(-2.926)		(-2.693)	
LEV	1.230***		1.086***		1.248***		1.092***	
	(4.510)		(3.855)		(4.556)		(3.856)	
VC	-0.113		-0.090		-0.072		-0.088	
	(-0.908)		(-0.720)		(-0.578)		(-0.696)	
BIG_4	-0.583***		-0.604***		-0.597***		-0.604***	
	(-3.199)		[illegible]		(-3.277)		(-3.317)	
UND_WRIT	-0.165		[illegible]		-0.134		-0.105	
	(-1.135)		(-0.714)		(-0.917)		(-0.715)	
PROCEEDS	-0.778***		[illegible]		-0.768***		-0.786***	
	(-4.397)		(-4.372)		(-4.340)		(-4.358)	
FIRM_AGE	-0.400**		[illegible]		-0.425***		-0.426***	
	(-2.511)		[illegible]		(-2.659)		(-2.666)	
INITIAL_RET	-0.057		-0.137		-0.047		-0.133	
	(-0.362)		(-0.901)		(-0.299)		(-0.865)	
Industry effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes	
Chi-square	410.59		440.22		426.38		440.27	
Chi-square test Prob	0.000		0.000		0.000		0.000	
N	1,969		1,969		1,969		1,969	

This table shows the results of the Cox proportional hazard model for testing whether high levels of classification shifting in the IPO year decrease the likelihood of survival. *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the logarithm of total proceeds of the IPO; *FIRM_AGE* is the logarithm of one plus firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 6: Channel analysis - External corporate governance

	Takeover index		Ownership concentration	
Variables	Coefficient	Coefficient	Coefficient	Coefficient
CS × HIGH_TOIND		-2.511**		
		(-1.992)		
CS × HIGH_OCONC				-3.198**
				(-2.144)
CS	2.790***	4.358***	1.596**	3.438***
	(3.525)	(4.415)	(2.148)	(3.399)
HIGH_TOIND	-0.043	0.001		
	(-0.305)	(0.010)		
HIGH_OCONC			0.004	0.074
			(0.027)	(0.439)
A_CFO	1.019***	1.034***	1.215***	1.222***
	(3.182)	(3.230)	(3.326)	(3.349)
A_DISX	0.164	0.194	0.096	0.117
	(1.317)	(1.544)	(0.672)	(0.815)
A_TA	0.238	0.237	0.285	0.292
	(0.623)	(0.619)	(0.680)	(0.694)
NCS	1.018	1.038	0.575	1.143*
	(1.464)	(1.497)	(0.848)	(1.710)
ROA	-1.499***	-1.535***	-1.224**	-1.255***
	(-3.904)	(-3.991)	(-2.560)	(-2.631)
MTB	-0.057**	-0.055**	-0.061**	-0.061**
	(-2.438)	(-2.348)	(-2.201)	(-2.215)
LEV	1.030***	1.020***	1.228***	1.269***
	(3.447)	(3.424)	(3.324)	(3.462)
VC	-0.062	-0.069	-0.167	-0.187
	(-0.471)	(-0.526)	(-1.089)	(-1.212)
BIG_4	-0.600***	-0.594***	-0.550**	-0.504**
	(-3.164)	(-3.136)	(-2.390)	(-2.172)
UND_WRIT	-0.078	-0.042	-0.091	-0.050
	(-0.506)	(-0.268)	(-0.515)	(-0.281)
PROCEEDS	-0.815***	-0.835***	-1.100***	-1.125***
	(-4.350)	(-4.460)	(-4.146)	(-4.205)
FIRM_AGE	-0.366**	-0.384**	-0.481**	-0.491**
	(-2.215)	(-2.320)	(-2.288)	(-2.329)
INITIAL_RET	-0.182	-0.155	-0.163	-0.102
	(-1.092)	(-0.908)	(-0.906)	(-0.542)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Chi-square	407.40	411.18	353.51	357.97
Chi-square test Prob	0.000	0.000	0.000	0.000
N	1,898	1,898	1,542	1,542

This table shows the results of the Cox proportional hazard model for testing whether external governance factors, proxied by the takeover index and institutional ownership concentration, explain the negative effect of classification shifting on firm survival. *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *HIGH_TOIND* is equal to one if the takeover susceptibility index by Cain et al. (2017) is greater than the sample median, and zero otherwise; *HIGH_OCONC* is equal to one if the concentration of institutional ownership, as measured by the Herfindahl-Hirschman index of institutional ownership concentration, is greater than the sample median, and zero otherwise; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the natural log of total proceeds of the IPO; *FIRM_AGE* is the natural log of firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 7: Channel analysis - Business factors

	Business segments		Geographic concentration		Market competition	
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
CS × *S_BSEG*		-4.973**				
		(-2.361)				
CS × *BCONC*				-10.486*		
				(-1.743)		
CS × *MCOMP*						-7.976**
						(-2.036)
CS	1.965***	6.670***	3.009***	6.241***	2.017***	2.321***
	(3.014)	(3.259)	(3.244)	(3.22[illegible])	(3.081)	(3.574)
S_BSEG	-0.120	-0.026				
	(-0.661)	(-0.138)				
BCONC			-0.828**	-0.[illegible]28*		
			(-2.389)	(-1.[illegible]48)		
MCOMP					-0.719***	-0.702***
					(-3.742)	(-3.551)
A_CFO	1.103***	1.109***	0.970**	0.885**	1.140***	1.082***
	(3.595)	(3.624)	(2.544)	(2.303)	(3.715)	(3.546)
A_DISX	0.098	0.107	0.043	0.052	0.096	0.114
	(0.822)	(0.897)	(0.[illegible]74)	(0.331)	(0.806)	(0.953)
A_TA	0.145	0.158	0.[illegible]63	0.256	0.112	0.199
	(0.394)	(0.431)	(0.[illegible])	(0.591)	(0.306)	(0.543)
NCS	0.317	0.480	1.171	1.253	0.231	0.322
	(0.504)	(0.766)	(1.277)	(1.359)	(0.369)	(0.523)
ROA	-1.299***	-1.321***	-1.280***	-1.386***	-1.209***	-1.276***
	(-3.493)	(-3.566)	(-2.693)	(-2.886)	(-3.225)	(-3.385)
MTB	-0.064***	-0.066***	-0.060**	-0.061**	-0.059**	-0.053**
	(-2.762)	(-2.8[illegible])	(-2.280)	(-2.285)	(-2.554)	(-2.278)
LEV	1.080***	1.040***	1.393***	1.358***	1.113***	1.138***
	(3.817)	([illegible].[illegible]55)	(3.158)	(3.066)	(3.929)	(4.019)
VC	-0.108	-0.097	-0.038	-0.038	-0.095	-0.084
	(-0.862)	(-0.770)	(-0.211)	(-0.207)	(-0.753)	(-0.669)
BIG_4	-0.655***	-0.626***	-0.744***	-0.779***	-0.615***	-0.628***
	(-3.604)	(-3.422)	(-2.988)	(-3.121)	(-3.370)	(-3.438)
UND_WRIT	-0.106	-0.094	-0.120	-0.090	-0.124	-0.088
	(-0.719)	(-0.636)	(-0.598)	(-0.448)	(-0.843)	(-0.599)
PROCEEDS	-0.[illegible]14***	-0.812***	-1.059***	-1.061***	-0.754***	-0.763***
	(-4.5[illegible])	(-4.510)	(-4.080)	(-4.083)	(-4.167)	(-4.214)
FIRM_AGE	-0.460***	-0.481***	-0.348	-0.337	-0.433***	-0.430***
	(-2.856)	(-2.977)	(-1.452)	(-1.407)	(-2.701)	(-2.686)
INITIAL_RET	-0.145	-0.140	0.085	0.099	-0.159	-0.253*
	(-0.943)	(-0.899)	(0.476)	(0.552)	(-1.034)	(-1.672)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Chi-square	440.35	444.92	304.37	307.93	448.66	453.20
Chi-square test Prob	0.000	0.000	0.000	0.000	0.000	0.000
N	1,937	1,937	1,008	1,008	1,969	1,969

This table shows the results of the Cox proportional hazard model for testing whether business factors, including business segments, geographic business concentration and product market competition, explain the negative effect of classification shifting on firm survival. *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *S_BSEG* is equal to one if the firm has one business segment, and zero otherwise; *BCONC* is the level of a firm's geographic dispersion, where larger values for *BCONC* indicate that a firm has more concentrated business interests, so is less dispersed, and vice versa; *MCOMP* is the median value of a firm's Lerner index in an industry-year calculated using all firms in Compustat, where smaller values for *MCOMP* indicate a more intense competitive environment, and vice versa; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the natural log of total proceeds of the IPO; *FIRM_AGE* is the natural log of firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 8 Opportunistic special items and future performance

Panel A: Opportunistic and predicted special items for IPO firms delisted for negative reasons vs. survivor IPO firms

	Delisted for negative reasons	Survivors	Difference in
	Mean	Mean	Mean (*t*-test)
OppSI	0.087	0.053	0.034**
PredSI	0.003	0.004	-0.001

Panel B: Future earnings and opportunistic special items

Variables	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$	$\Sigma^{t+3}{}_{t+2}NIBTSI_t$
	Full sample	*SI sample*	*OppSI sample*
$OppSI_t$	15.711	-2.371***	-2.729***
	(1.24)	(-3.49)	(-3.75)
$PredSI_t$	11.506	-0.420	9.448**
	(0.14)	(-0.14)	(2.11)
$NIBTSI_t$	2.283***	0.886***	0.897***
	(4.14)	(9.48)	(9.27)
$\Delta SALES_t$	-0.140	0.091**	0.084**
	(-0.52)	(2.46)	(2.21)
Constant	-0.706	0.427	0.503
	(-0.02)	(0.33)	(0.38)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	1,685	522	485
Adjusted R-squared	0.008	0.339	0.327

Panel C: Future cash flows and opportunistic special items

Variables	$\Sigma^{t+3}{}_{t+2}\,CFO_t$	$\Sigma^{t+3}{}_{t+2}\,CFO_t$	$\Sigma^{t+3}{}_{t+2}\,CFO_t$
	Full sample	*SI sample*	*OppSI sample*
$OppSI_t$	11.648	-2.313**	-2.506**
	(0.99)	(-2.00)	(-2.01)
$PredSI_t$	3.738	-0.938	8.527
	(0.05)	(-0.18)	(1.07)
CFO_t	-0.231	0.435**	0.510**
	(-0.33)	(2.08)	(2.27)
$\Delta SALES_t$	0.377	0.082	0.078
	(1.46)	(1.34)	(1.23)
$A\_ACCRUALS_t$	14.205***	0.989*	0.800
	(6.68)	(1.90)	(1.43)
Constant	2.497	1.289	1.271
	(0.06)	(0.62)	(0.59)
Industry effects	Yes	Yes	Yes

Year effects	Yes	Yes	Yes
N	1,678	516	479
Adjusted R-squared	0.032	0.208	0.200

Panel A shows the difference in mean opportunistic and predicted special items during the offer year for IPO firms delisted for negative reasons, and survivor IPO firms. Panel B(C), columns (1)-(3) show the effects of opportunistic special items on future earnings (cash flows from operations) for all IPO firms, IPO firms with special items, and IPO firms with opportunistic special items. $OppSI_t$ is opportunistic special items; $PredSI_t$ is predicted special items; $NIBTSI_t$ is net income before taxes and special items; SI_t is income-decreasing special items scaled by sales, multiplied by negative one; $\Delta SALES_t$ is sales growth; CFO_t is cash flows from operations; $A\_ACCRUALS_t$ is total accruals adjusted for income-decreasing special items. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 9 Special items and future performance

Panel A: Future earnings and special items

Variables	$\Sigma^{t+3}_{t+2}NIBTSI_t$	$\Sigma^{t+3}_{t+2}NIBTSI_t$	$\Sigma^{t+3}_{t+2}NIBTSI_t$	$\Sigma^{t+3}_{t+2}NIBTSI_t$
	Full sample	*SI sample*	*SI sample with positive UE_CE*	*SI sample with negative UE_CE*
SI_t	17.532***	-1.456**	-1.564***	-1.287
	(6.64)	(-2.41)	(-[illegible].30)	(-0.97)
$NIBTSI_t$	7.526***	0.336***	0.3[illegible]3***	0.482***
	(39.09)	(3.90)	([illegible])	(2.62)
$\Delta SALES_t$	0.632***	0.036	0.020	0.153
	(7.60)	(1.07)	(1.01)	(1.45)
Constant	-0.142	0.206	0.483	0.744
	(-0.02)	(0.23)	(1.12)	(0.51)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	1,581	505	259	246
Adjusted R-squared	0.524	0.339	0.223	0.284

Panel B: Future cash flows and special items

Variables	$\Sigma^{t+3}_{t+2}CFO_t$	$\Sigma^{t+3}_{t+2}CFO_t$	$\Sigma^{t+3}_{t+2}CFO_t$	$\Sigma^{t+3}_{t+2}CFO_t$
	Full sample	*SI sample*	*SI sample with positive UE_CE*	*SI sample with negative UE_CE*
SI_t	3.26[illegible]	-2.137	-1.551***	-2.610
	(1.1[illegible])	(-1.62)	(-4.15)	(-0.87)
CFO_t	-0.529	0.138	0.213**	0.078
	(-1.58)	(0.61)	(2.39)	(0.16)
$\Delta SALES_t$	0.534***	0.063	-0.002	0.294
	(6.54)	(0.94)	(-0.15)	(1.29)
$A\_ACCRUALS_t$	24.962***	-0.238	-0.153	-0.198
	(60.25)	(-0.42)	(-0.93)	(-0.15)
Constant	-0.149	0.918	1.167***	1.656
	(-0.02)	(0.51)	(3.67)	(0.53)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	1,573	499	257	242
Adjusted R-squared	0.760	0.279	0.280	0.195

Panel A(B), columns (1)-(4) show the effects of special items on future earnings (cash flows from operations) for all IPO firms, IPO firms with special items, IPO firms with special items but with positive unexpected core earnings, and IPO firms with special items but with negative unexpected core earnings, respectively. $NIBTSI_t$ is net income before taxes and special items; *SI* is income-decreasing special items scaled by sales, multiplied by negative one; *UE_CE_t* is unexpected core earnings; $\Delta SALES_t$ is sales growth; CFO_t is cash flows from operations; $A\_ACCRUALS_t$ is total accruals adjusted for income-decreasing special items. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Table 10: Robustness controls

Variables	(1) Coefficient	(2) Coefficient	(3) Coefficient	(4) Coefficient	(5) Coefficient
CS	1.907***	1.877***	1.880***	2.121*	3.997***
	(2.880)	(2.862)	(2.881)	(1.817)	(3.552)
REST		0.814**			
		(2.021)			
HIGH-TECH			0.185		
			(1.039)		
A_PROD				0.548	
				(1.352)	
A_CFO	1.144***	1.155***	1.147***	2.930***	-0.237
	(3.704)	(3.765)	(3.741)	(3.736)	(-0.308)
A_DISX	0.102	0.097	0.126	0.307	0.233
	(0.842)	(0.809)	(1.041)	(0.848)	(0.688)
A_TA	0.111	0.092	0.091	-1.550*	1.934**
	(0.301)	(0.252)	(0.249)	(-1.842)	(1.968)
NCS	0.172	0.176	0.186	0.517	-0.033
	(0.266)	(0.277)	(0.296)	(0.480)	(-0.026)
ROA	-1.377***	-1.313***	-1.306***	-0.869	-3.857***
	(-3.655)	(-3.515)	(-3.483)	(-1.192)	(-3.880)
MTB	-0.058**	-0.062***	-0.063***	-0.034	-0.025
	(-2.507)	(-2.701)	(-2.724)	(-0.586)	(-0.460)
LEV	1.126***	1.076***	1.126***	1.010*	1.968***
	(3.868)	(3.784)	(3.951)	(1.728)	(2.576)
VC	-0.057	-0.070	-0.096	-0.278	0.318
	(-0.446)	(-0.557)	(-0.764)	(-1.042)	(0.863)
BIG_4	-0.626***	-0.632***	-0.620***	0.075	-1.441***
	(-3.362)	(-3.469)	(-3.392)	(0.213)	(-2.787)
UND_WRIT	-0.142	-0.098	-0.106	-0.051	-0.709*
	(-0.946)	(-0.670)	(-0.722)	(-0.188)	(-1.908)
PROCEEDS	-0.783***	-0.798***	-0.779***	-1.451***	-0.903*
	(-4.262)	(-4.434)	(-4.321)	(-3.459)	(-1.703)
FIRM_AGE	-0.376**	-0.450***	-0.417***	-0.601*	-0.068
	(-2.312)	(-2.811)	(-2.608)	(-1.874)	(-0.164)
INITIAL_RET	-0.128	-0.133	-0.140	-1.066**	0.009
	(-0.826)	(-0.868)	(-0.915)	(-2.261)	(0.031)
Industry effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Chi-square	440.42	443.86	441.36	225.44	203.37
Chi-square test Prob	0.000	0.000	0.000	0.000	0.000
N	1,889	1,969	1,969	752	482

This table shows our main results of the Cox proportional hazard model after excluding firms that engage in restructuring activities in the year before the IPO or in the issue year (column 1), when including an explicit control variable for restructuring activities and perform the estimation for the full sample (column 2), when controlling for high-tech industry participation (column 3), and also for abnormal levels of production costs (column 4), and finally, when imposing controls for potential endogeneity concerns about the decision to engage in CS around the time of the IPO (column 5). For results reported in column 5, we apply propensity score matching by matching classification shifter IPO firms with non-classification shifter IPOs according to several firm characteristics as described in text. Classification shifter (non-shifter) IPO firms are defined as the firm-year observations with a *CS* value greater than (equal to) zero in the year of the IPO. *CS* is equal to unexpected core earnings if unexpected core earnings are positive and special items are negative, and zero otherwise; *REST* is equal to one if the firm engages in restructuring either in the year before the IPO or in the issue year; *HIGH-TECH* is equal to one if an issuer is a high-technology firm, and zero otherwise; *A_PROD* is abnormal levels of production costs; *A_CFO* is abnormal levels of cash flows from operations multiplied by negative one; *A_DISX* is abnormal levels of discretionary expenses multiplied by negative one; *A_TA* is abnormal levels of total accruals; *NCS* is the proportion of special items which is not classification-shifted; *ROA* is the profitability ratio in the issue year; *MTB* is the market-to-book ratio in the issue year; *LEV* is the leverage ratio in the issue year; *VC* is equal to one if the firm is venture backed, and zero otherwise; *BIG_4* is equal to one if the firm is audited by a Big Four audit firm, and zero otherwise; *UND_WRIT* is equal to one if the IPO is underwritten by reputable underwriters, and zero otherwise; *PROCEEDS* is the logarithm of total proceeds of the IPO; *FIRM_AGE* is the logarithm of one plus firm age; *INITIAL_RET* is initial returns. See Appendix A for detailed variable definitions and calculations. The test statistics are shown in parentheses below coefficient estimates. ***/**/* indicate significance at 1%/5%/10% (two-tailed) levels, respectively.

Highlights

- Classification shifting undertaken using income-decreasing SIs in the issue year is positively associated with IPO failure over the five years following the offering, and negatively associated with the long-term survival of the firms.
- Negative effect of Classification Shiftin on IPO success is mitigated for IPO firms with stronger vs. weaker business factors (i.e. firms with registered patents, and firms with more geographically concentrated business interests).
- Special Items are strongly and negatively associated with future earnings and cash flows for companies engaging in Classification Shifting.
- Higher levels of SIs, particularly opportunistic ones, adversely affect future performance, leading to lower IPO survival.
- We underline the importance of strong business factors in firm survival, to the extent that such factors can function as protective mechanisms.