Detection of Channel Stuffing

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Abstract

Based on a sample of firms that engaged in channel stuffing, we develop a model that predicts the probability of channel stuffing behavior in a broad cross-section of firms. Channel stuffing leads to accelerated revenue recognition by managing "real" activities to achieve short-term revenue and earnings targets. Given that channel stuffing is difficult to detect without the help of whistle-blowers, we control for undetected cases by estimating a bivariate probit model with partial observability. The model simultaneously estimates the effect of incentives, opportunities, and financial performance measures on the probability that a firm engages in channel stuffing and the probability that the channel stuffing activity is detected. Our results show that smaller firms, firms with higher growth opportunities, higher profit margins, and limited accrual management ability are more likely to engage in channel stuffing. A slow-down in receivables collection in the affected quarter serves as a significant indictor of channel stuffing. At the same time, we find that firm size, institutional holdings, Big-4 auditor, and tighter accounting regulation increase the detection probability and in turn reduce the probability of channel stuffing. Further analysis shows that firms that engage in channel-stuffing experience declining sales, production and profitability in future periods, suggesting that this activity achieves short-term benefits only at the price of long-term adverse consequences. Our results show that the power and specification of the bivariate probit prediction model is superior to that of the simple probit model. In an ex post validation analysis, we find that a sub-sample of the population of firms identified as having a high likelihood of channel stuffing by the bivariate probit model (but not by the simple probit model) exhibits future performance reversals that closely parallel those of the actual channel stuffing sample. These results highlight the need to control for the probability of detection to minimize misclassification in studies predicting accounting irregularities that are hard to detect.

1. Introduction

The accounting scandal at Enron, followed by allegations of accounting fraud at WorldCom, Xerox, HealthSouth and others, has triggered a closer scrutiny of potential managerial manipulation of reported earnings. The business press includes numerous anecdotes suggesting that companies engage in irregular accounting practices and other dubious methods to meet short-term investor expectations. While a significant body of research has examined the manipulation of accounting accruals as a means to manage earnings, recent attention has been directed towards yet another device used to manage earnings – the manipulation of "real" activities, i.e., managers' operating and investing decisions made expressly for the purpose of meeting earnings targets (Roychowdhury 2006, and Gunny 2010). In this paper, we focus on a particular "real" activity that companies are known to manage for the purpose of achieving a desired earnings goal – "channel stuffing".

In the past two decades, many companies were alleged to have engaged in a practice called "channel stuffing," which accelerates revenue recognition and provides a short-term boost to their bottom line. Channel stuffing refers to the practice of shipping more goods to distributors and retailers along the distribution channel than end-users are likely to buy in a reasonable time period. This is usually achieved by offering lucrative incentives, including deep discounts, rebates, and extended payment terms, to persuade distributors and retailers to buy quantities in excess of their needs. Usually, distributors retain the right to return any unsold inventory which calls into question whether a final sale has actually occurred. "Stuffing" the distribution channel is frowned upon by the Securities and Exchange Commission (SEC) as a practice used by companies to accelerate revenue recognition to reach short-term revenue and earnings targets, and as such misleading to investors.[1] Usually, cases of channel stuffing come to light either due to actions of whistle-blowers or through observed performance reversals in future periods in the form of declining revenues, increasing sales returns, shrinking production and inventory build-up. The difficulty in uncovering cases of channel stuffing suggests that this activity may be more widespread than currently believed. Our goal in this study is to develop a model that can predict the

[1] The SEC investigated more than 40% of our sample firms in relation to their alleged channel stuffing activities.

probability of channel stuffing behavior in a broad cross-section of firms. Such a model will be useful in identifying potential cases of channel stuffing without having to wait until the scheme unravels in future periods or if and when an insider or a major distributor blows the whistle.

We examine a sample of firms for which allegations of channel stuffing were reported in the business press during the period 1994 to 2006.[2] By comparing these firms to the broader population of firms, we predict the probability of channel stuffing based on characteristics that capture (i) earnings management incentives, (ii) opportunities for channel stuffing, (iii) ex ante financial indicators of channel stuffing, and (iv) external monitoring. Since our sample includes firms where channel stuffing was detected, we directly observe the probability of *detected* channel stuffing. This probability is the product of the probability of a firm engaging in channel stuffing and the probability of detection. Examining the joint probability of detected channel stuffing using a simple probit model can lead to biased inferences, since the common predictors may have opposite effects on the two latent probabilities. To overcome this partial observability problem, we follow Poirier (1980) and Feinstein (1990) to incorporate the detection process into the statistical analysis of the observed data. This procedure accounts for the fact that channel stuffing behavior may have occurred but may not have been detected, i.e., some observations of channel stuffing may be "missing". This estimation technique is especially important in the channel stuffing case where timely detection without whistle-blower intervention is difficult, leading to many missing or undetected observations.

Using a sample of firms that engaged in channel stuffing and a sample of firms with no channel stuffing allegations, we estimate parameters of the prediction model after controlling for the probability of detection. We then validate the efficacy of our model by examining both in-sample and out-of-sample predictive ability. Based on relative predicted probabilities, we identify firms in the general population that exhibit a high likelihood of channel stuffing. While ex ante detection of channel stuffing is difficult, an interesting feature of this activity is the potential for unraveling it ex post based on performance

[2]Our sample excludes firms for which channel stuffing allegations were later discovered to be unfounded as indicated by dismissed lawsuits or absolution from liability announced by the SEC in a public disclosure.

reversals in future periods. This feature provides us with a useful tool to ex post validate whether firms that we identify as having a high likelihood of channel stuffing indeed suffer performance reversals in future periods comparable to that experienced by the channel stuffing sample.

The results of estimating the partial observability bivariate probit model reveal that the channel stuffing activity is more likely to be detected when it is undertaken by large firms, firms with high institutional ownership, Big-4 auditors, and high litigation risk, due to greater external monitoring and public scrutiny of these firms. Further, we find that, while the probability of *detection* significantly increases with greater external monitoring and in the period after revenue recognition rules were tightened (due to the SEC Staff Accounting Bulletin (SAB) 101), the probability of channel stuffing in fact decreases. Thus, the high detection probability acts as a deterrent for these firms to engage in channel stuffing. The shortcomings of the simple probit model estimating the joint probability of detected channel stuffing become apparent from our findings. When we do not separately control for the probability of detection (i.e., when we use the simple probit model), we find that firm size and institutional ownership reflect an *increase* in the likelihood of channel stuffing in contrast with the results of the bivariate probit model. In addition, based on the simple probit model, we find that Big-4 auditors and stringent revenue recognition rules have an insignificant effect on the probability of channel stuffing. Our results emphasize the need to incorporate the detection process in the analysis, if the goal is to estimate the probability of channel stuffing as opposed to the probability of detected channel stuffing.

Further examination of the results of the bivariate probit model shows how ex ante factors that capture incentives and opportunities for channel stuffing and other financial indictors relate to the probability of channel stuffing. We find that firms with high prior sales growth and low book-to-market ratios exhibit a high likelihood of channel stuffing suggesting that these firms may be trying to maintain superior growth potential relative to industry peers rather than simply mimicking industry peers' performance. In examining opportunities for channel stuffing, we find that firms with limited accrual management ability (high beginning net operating assets) are more likely to engage in channel stuffing. Also, firms with higher gross and net margins are associated with a higher probability of channel stuffing, since higher margins applied to inflated revenues translate into higher profits. In addition, we find that an increase in the receivables collection period serves as a useful financial indicator of channel stuffing.

Overall, the model performs well in terms of both in-sample and out-of-sample predictive ability. A comparison of the performance of the bivariate with the simple probit model yields some noteworthy insights. First, focusing on the probability of detected channel stuffing, we find that, on average, the predicted probability of channel stuffing is significantly higher based on the bivariate probit model relative to the probit model for the sample of channel stuffing firms, that is, the bivariate probit model provides a more powerful test. On the other hand, the predicted probability of channel stuffing is on average significantly lower based on the bivariate probit model for the sample of non-channel stuffing firms, that is, the bivariate probit model results in lower Type I errors (i.e., the model is better specified). This result holds in the out-of-sample analysis as well. Second, while the average fit of the bivariate and simple probit models is comparable (pseudo-R^2 of 0.35 versus 0.32), cross-sectional differences in their predicted probabilities are significant. The correlation between predicted probabilities of detected channel stuffing of the two models is high as expected (0.75); however, the correlation between the simple probit model's predicted probability of detected channel stuffing and the bivariate model's predicted probability of channel stuffing (i.e., detected and undetected) is negative at -0.04. An implication of this result is that, when identifying channel stuffing in the general population, it is possible that the simple probit model will identify a different set of firms as likely to have engaged in channel stuffing compared to the bivariate model.

Given that the channel stuffing setting to some extent allows us to ex post validate our out-of-sample prediction, we examine the future performance of firms in the general population that are identified by our model as potential channel stuffing firms to test whether these firms experience future performance reversals to the same degree as the actual (detected) channel stuffing firms. We first track the performance of firms in the channel stuffing sample over a period of four subsequent quarters. We find that these firms experience a significant decline in sales growth and return on assets (ROA) and the trend worsens over the four future quarters. Consistent with the slowing down of sales, we find that these firms experience a significant inventory build-up and consequent shrinkage in production following the channel stuffing quarter. Overall, our results show that managing revenues and earnings via channel stuffing is a costly alternative that is followed by long-lasting adverse consequences for the firm.

We next compare the observed subsequent performance reversals of the channel stuffing sample with a sample of firms identified by our model as having a high likelihood of channel stuffing. We form 20 portfolios of the non-channel stuffing sample of firms by sorting on the predicted probability of channel stuffing and designate firms in the top portfolio as those identified by our model to be likely to have engaged in channel stuffing. Our results show a significant decline in sales, ROA, and production, and a significant increase in inventory levels in the subsequent four quarters for the top portfolio of firms with a high likelihood of channel stuffing, which is comparable to the trends observed for the actual channel stuffing sample. In contrast, the decline in future sales, ROA, and production, and the increase in inventory levels indicated for the top portfolio based on the simple probit model are significantly lower than that for the top portfolio based on the bivariate probit model as well as for the actual channel stuffing sample. Overall, based on the ex post validation results, our identification of potential channel stuffing cases from the bivariate probit model appears to be reasonable. Naturally, since these are undetected cases, perfect ex post validation is not possible. However, we believe that the observed consistent future performance reversals provide at least persuasive evidence validating our identification.

Our paper makes contributions to the accounting literature along several dimensions. First, we link the literature on aggressive revenue recognition with that on “real” activities management. Prior studies on revenue manipulation mostly focus on accounting maneuvers that pull revenues forward in time (see Altamuro et al. 2005, Zhang 2009, and Forester 2009). Our paper is perhaps one of the first to examine revenue manipulation via managerial policy rather than via accounting. Second, we examine a specific form of revenue manipulation which has the advantage of narrowing down the set of specific financial indicators that are impacted (in the spirit of McNichols and Wilson 1988). This feature provides us with a more powerful tool to predict potential cases of manipulation compared to settings such as accounting restatements that involve manipulation of both accruals and real activities whose effects are hard to disentangle.

Our third contribution relates to our prediction methodology which is broader in scope and applicability than the channel stuffing setting. Our results highlight that failing to control for the probability of detection may lead to classification errors, which is of special concern when the accounting irregularity or other wrong-doing is harder to detect. We recommend that researchers engaged in estimating the probability of an accounting irregularity or earnings management use the partial observability bivariate probit model to control for the "missing" or undetected observations.

Finally, we offer a detection model for practitioners that can assist in the prediction of the likelihood of channel stuffing. Our model should be of considerable interest to analysts and investors who currently have difficulty detecting such behavior and are hence misled into believing that these companies did meet their revenue and earnings targets. Our out-of-sample results indicate that at least 5% (the top 20^{th} portfolio) of firms that did not face channel stuffing allegations had an estimated probability of channel stuffing as high as that of firms facing allegations and moreover showed comparable ex post sales, production and profitability reversal patterns. Thus, it appears quite likely that a number of cases of channel stuffing may have escaped detection. Of course, as in any prediction model, misclassification is always a potential explanation. Therefore, while we cannot and do not make assertions regarding the behavior of these firms, we do stress that further investigation by analysts and investors into these firms' business practices and financial statements may be warranted.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 discusses the empirical methodology, model specification, data and sample selection. Empirical results are reported in Section 4, followed by concluding remarks in Section 5.

2. Review of Related Literature

Researchers have used alternative approaches to infer earnings management (e.g., Burgstahler and Dichev 1997, Degeorge, Patel, and Zeckhauser 1999, and Das, Shroff, and Zhang 2009). Evidence of earnings management is generally linked with managers' incentives to attain certain earnings benchmarks, in particular, to avoid losses, or to meet prior-period earnings or analysts' earnings expectations. Such evidence is largely based upon inferences about the extent to which managers have made use of discretionary choices in financial reporting that are available under GAAP to overstate the "true" level of earnings and/or to hide unfavorable earnings realizations. While much of the earnings management literature has generally focused on manipulations of accounting accruals, recent research has started examining cases of "real" earnings management.

The fundamental distinction between the two types of earnings management is that while management of "real" activities directly impacts a firm's operations and hence typically requires action prior to the end of a fiscal period, accrual management has no direct effect on a firm's operations and typically such actions can be taken at the end of a fiscal period. Accrual-based actions merely shift earnings between periods, i.e., they result in either borrowing from or saving for future earnings. On the other hand, real earnings management warrants managers to change the timing of operations, resource allocation, and investment decisions, thereby having a direct impact on cash flows.

In a survey of managers, Graham, Harvey, and Rajgopal (2005) find that managers are more likely to make real economic decisions that affect operations to manage firm earnings than to take accounting-based actions. 78% of the managers surveyed stated that they may take actions which sacrifice long-term value and choose real operating and investing actions over accounting actions to meet earnings benchmarks. Indeed, a study by Bruns and Merchant (1990) showed that only 13% of managers surveyed considered a typical channel stuffing scenario to be unethical. Further, these authors also found that the surveyed managers in general preferred manipulating operating decisions or procedures rather than accounting methods to meet short-term earnings targets. A recent study by Cohen, Day, and Lys (2007) documents that, in the post-SOX period, managers have shifted away from accrual manipulation to real earnings management for meeting earnings benchmarks.

Studies that examine techniques of real earnings management find evidence suggesting that managers may accelerate the timing of sales, overproduce, reduce discretionary expenditures, and strategically time the disposal of long-lived assets and investments to meet their earnings goals (Bartov

1993, Hermann, Inoue, and Thomas 2003, Roychowdhury 2006, and Gunny 2010). The use of R&D as a tool for real earnings management has been the focus of many research studies (e.g., Baber, Fairfield, and Haggard 1991, Dechow and Sloan 1991, and Perry and Grinaker 1994).

Attention has recently been directed towards examining potential earnings management via revenue recognition practices. The Deloitte Forensic Center (2007) examined all Accounting and Auditing Enforcement Releases (AAERs) by the SEC between January 2000 and December 2006, identifying 344 AAERs related to financial statement fraud. These 344 AAERs encompassed 1,240 different fraud schemes, of which 41% related to revenue recognition. Recording fictional revenue was the most common type of revenue-recognition fraud, followed by recognizing inappropriate revenue from swaps, round-tripping, or barter arrangements. More recently, a study on corporate fraudulent reporting (2010), sponsored by the Committee of Sponsoring Organizations (COSO) of the Treadway Commission, noted that there were 347 alleged cases of public company fraudulent financial reporting from 1998 to 2007 versus 294 cases from 1987 to 1997. Consistent with the high-profile scandals at Enron, WorldCom and others, the dollar magnitude of fraudulent financial reporting soared in the last decade, with total cumulative misstatement or misappropriation of nearly $120 billion across 300 fraud cases with available information (mean of nearly $400 million per case). More relevant to our setting, the most common fraud technique involved improper revenue recognition accounting for over 60% of the cases, over 48% of which represented those recording fictitious revenues.

Several empirical studies have examined the use of revenue manipulation in earnings management. Feroz, Park, and Pastena (1991) find that more than half of SEC enforcement actions issued between 1982 and 1989 involved overstatement of receivables resulting from premature revenue recognition. Similarly, Dechow, Sloan, and Sweeney (1996) find a greater likelihood of revenue manipulation among firms that are investigated by the SEC. Research based on a survey of managers also supports the hypothesis that managers often use revenue recognition as a means to manage earnings upward (Nelson, Elliott, and Tarpley 2002, 2003). Plummer and Mest (2001) replicate the distributional tests in Burgstahler and Dichev (1997) using earnings components and find evidence suggesting that firms overstate revenues and understate expenses to meet analysts' earnings forecasts. Caylor (2010) finds that managers use discretion in both accrued revenue (i.e., accounts receivable) and deferred revenues (i.e., customer advances) to avoid negative earnings surprises. Marquardt and Wiedman (2004) find that new firms manipulate revenues or expenses rather than special items to achieve their earnings goals.

Recently, Callen, Robb, and Segal (2008) examine the use of revenue manipulation by loss firms. Their evidence, based on a sample of firms with revenue restatements, suggests that the ex ante likelihood of firms manipulating their revenues increases as past losses and expected future losses increase. Zhang (2009) uses a sample of accounting restatements to examine managers' choice in using revenues versus other accruals for earnings management. She finds that the flexibility for revenue recognition provided by the magnitude of receivables and the firm's business model affects the likelihood of using revenues to manage earnings. Stubben (2009) focuses on the use of discretionary revenues as a tool for detecting earnings management and its superiority over accrual-based models. His findings suggest that relative to accrual-based models, the discretionary revenue model is less likely to falsely indicate earnings management and more likely to detect earnings management when it does occur.

In general, studies on revenue manipulation focus on revenue-related discretionary accruals as the means to shift revenues forward or backward in time. One exception is Chapman and Steenburgh (2008) who find that firms increase marketing promotions at the fiscal year-end to boost their revenue. Similar to Chapman and Steenburgh (2008), we focus on a specific tool for revenue manipulation through the management of real activities, i.e., "channel stuffing". Different from Chapman and Steenburgh (2008), we do not focus on *how* firms stuff the channel. Instead, we focus on predicting channel stuffing using publicly available data.

There are several distinguishing features of channel stuffing that raise interesting issues. First, channel stuffing involves operating decisions that may disrupt the business and have long-term consequences to the detriment of the firm. Managing revenues through accruals, on the other hand, may not be as costly in terms of its effect on operations and profitability. Second, the nature of the activity narrows down the set of specific financial indicators that are impacted (e.g., sales growth, margins, receivables collection, inventory levels, operating cash flow). This feature provides us with a setting for a more powerful prediction model based on specific indicators relative to settings such as accounting misstatements which could involve accruals as well as real activities manipulation and hence harder to model effectively. Third, channel stuffing is hard to detect except with the help of whistle-blowers or ex post by inference from future performance reversals. Thus, developing a prediction model to detect channel stuffing ex ante would be useful in identifying potential cases that would otherwise go undetected. Finally, channel stuffing in most cases is followed by reversals in future sales, operations, and profitability. This provides us with a means to ex post validate whether our identified cases of potential channel stuffing have future performance patterns that are consistent with what is typically observed for firms that actually engaged in channel stuffing. The next section describes how we estimate our prediction model after incorporating the detection process in our analysis.

3. Empirical Research Design

3.1 Data and sample selection

To identify firms that engaged in channel stuffing, we first conduct a keyword search in *Factiva* for the period of 1987-2007.[3] We then identify the fiscal periods that a firm is alleged to have stuffed the distribution channel by using various information sources including the SEC's Accounting and Auditing Enforcement Releases (AAER), class actions lawsuits, and media coverage. Because the I/B/E/S coverage of analysts' revenue forecasts is incomplete until the mid-1990s, we restrict our sample period to 1994 and onward. Our sample selection procedure results in the identification of 528 firm-quarters for 102 publicly traded companies that are alleged to have engaged in channel stuffing. The requirement of data availability in Compustat further reduces our sample to 510 firm-quarters for 90 firms.

Table 1 describes our sample. Panel A of Table 1 reports the inter-temporal sample distribution. The number of firms facing channel stuffing allegations in a given quarter increases from 9 in 1994 to 17 in 1996 and then increases sharply to 44 in 1997, reaching its peak of 92 in 2001. This pattern is consistent with the idea that firms are more likely to manage revenues and earnings in periods of

[3]We use "channel-stuffing" and various combinations of "stuff" and "channel" as our keywords.

economic boom when capital market pressure is high. It is also consistent with the explanation that the general awareness of the practice of channel stuffing increased in the late 1990s. After 2001, the number of firm-quarters with channel stuffing allegations reduces gradually from 57 in 2002 to 9 in 2006. The reduction in the post-2002 period could be due to a decrease in the channel stuffing activity itself and/or in its detection.

Panel B reports the number of quarters during which firms in our sample were alleged to have engaged in the channel stuffing activity. Since it is fairly costly (and physically impossible) for a company to stuff the channel over an extended period of time, most of our sample firms were alleged to have engaged in channel stuffing for less than 2 years (8 quarters). Only 12 firms (13.3%) were alleged to have engaged in channel stuffing for over 2 years.

Panel C reports that 44.4% of firms in the channel stuffing sample were investigated by the SEC and 68.9% were sued in class actions on account of their revenue manipulation activities.

Table 2 reports the industry distribution of our sample firms. 15.6% of sample firms belong to the drugs and pharmaceutical industry, 13.3% to the computer software industry, 13.3% to the computer and office equipment industry, and 13.3% to other electrical equipment industry. The industry distribution is consistent with expectations based on prior anecdotal evidence.

3.2 Bivariate probit model

We compare a sample of firms for which allegations of channel stuffing were reported in the business press during the period 1994 to 2006 with the broader population of firms to predict the probability of channel stuffing. The prediction model is based on firm and industry characteristics that capture (i) managerial incentives, (ii) opportunities for channel stuffing, (iii) ex ante financial indicators of channel stuffing, and (iv) external monitoring. A simple probit model would predict the probability of *detected* channel stuffing, since our estimation is based on firms in which channel stuffing was detected or alleged. This probability is the product of the probability of a firm engaging in channel stuffing and the probability of detection. Studying the compound probability of detected channel stuffing can lead to biased inferences, since the common predictors may have opposite effects on the two latent probabilities.

For example, high institutional ownership may be negatively associated with the likelihood of channel stuffing, but positively associated with the probability of detection of channel stuffing if institutional investors serve as effective external monitors. When many violations go undetected as in the case of channel stuffing, the bias in parameter estimates and inferences may be quite severe (see Feinstein 1990). To address this issue, we incorporate the detection process into the statistical analysis of the observed data on detected channel stuffing; this method is referred to as "detection controlled" estimation by Feinstein (1990). The procedure controls for the non-observability of channel stuffing that may have occurred but was not detected. A brief discussion of the methodology following Poirier (1980), Feinstein (1990), and Wang (2010) is provided below.

Let CS_i denote firm i's decision to engage in channel stuffing (CS_i equals 1 or 0) and D_i denote the detection of channel stuffing (D_i equals 1 or 0) given that channel stuffing occurs.

$$CS_i^* = X_{CS,i}\beta_{CS} + \mu_i \tag{1}$$

where $CS_i = 1$ if $CS_i^* > 0$ and $CS_i = 0$ if $CS_i^* \leq 0$. $X_{CS,i}$ is a vector of economic factors that affect firm i's likelihood of engaging in channel stuffing. μ_i is a mean-zero random variable that is drawn from the distribution $F(\ )$. Note that equation (1) is different from a conventional binary choice model because the choice variable CS_i is not directly observable. The occurrence of channel stuffing will be observed only if it is detected. To incorporate the detection process into the analysis, we supplement equation (1) with the following equation (2). Conditional on $CS_i = 1$, set

$$D_i^* = X_{D,i}\beta_D + \nu_i \tag{2}$$

where $D_i = 1$ if $D_i^* > 0$ and $D_i = 0$ if $D_i^* \leq 0$. $X_{D,i}$ is a vector of economic factors that affect the detection process. υ_i is a mean-zero random variable that is drawn from the distribution $G(\ )$.

Equation (1) and (2) form a complete model for the channel-stuffing detection system. Although CS_i and D_i are both unobservable, we can observe the product of the two processes and consistently estimate β_{CS} and β_D using the maximum-likelihood technique. The probability of observing detected channel stuffing is represented by $F(X_{CS,i}\beta_{CS}) * G(X_{D,i}\beta_D)$ and the probability of not observing detected channel stuffing is represented by $[1 - F(X_{CS,i}\beta_{CS}) * G(X_{D,i}\beta_D)]$, which equals the sum of $[1 - F(X_{CS,i}\beta_{CS})]$ and $F(X_{CS,i}\beta_{CS}) * [1 - G(X_{D,i}\beta_D)]$. Therefore, the log likelihood of the observations equals

$$L = \sum_{i \in S} \log[F(X_{CS,i}\beta_{CS})G(X_{D,i}\beta_D)] + \sum_{i \in S^c} \log[1 - F(X_{CS,i}\beta_{CS})G(X_{D,i}\beta_D)] \tag{3}$$

where S represents the set of detected cases of channel stuffing and S^c represents the set of remaining cases in which no channel stuffing is detected. Assuming both F and G follow standard normal distributions, we can estimate model (3) with a bivariate probit model with partial observability. Wang (2010) shows that estimating detected fraud with a simple probit model without separately accounting for factors that affect the probability of fraud commission and factors that affect the probability of detection leads to biased inferences. According to Poirier (1980) and Feinstein (1990), the identification condition for the above specification is that $X_{CS,i}$ and $X_{D,i}$ do not contain exactly the same set of variables and that the explanatory variables exhibit sufficient variation. The bivariate probit model can be estimated using the maximum-likelihood method.

The extant literature typically uses the simple probit model to examine the likelihood of different types of accounting irregularities, including earnings management (see for e.g., Dechow, Ge, Larson, and Sloan 2010). The use of the simple probit model implicitly assumes perfect detection of the irregularity. Modeling the interaction between the commission of the irregularity and its detection by using the bivariate probit model alleviates the problem of incorrect inferences when the purpose of the analysis is to predict the probability of the occurrence of the irregularity rather than the probability of its detection.[4]

[4]Recent applications of the bivariate probit model can be found in Wang (2010) who examines the relation between a firm's investment decision and its decision to commit fraud using the setting of securities lawsuits, and Callen et al. (2008) who document the association between the likelihood of revenue manipulation and past and expected future losses and negative cash flows.

3.3 Model specification

3.3.1 Factors that affect the probability of detection

We use a number of ex ante variables that capture a firm's visibility, public profile, and external scrutiny as determinants of the likelihood of detecting channel stuffing behavior. We expect SIZE to be positively associated with the probability of detection especially for our sample firms since large publicly traded companies are often more likely to be scrutinized by investors, the SEC, and the popular press. We measure SIZE as the natural log of total assets at the beginning of the channel stuffing quarter *t*. In the detection model, we also include institutional ownership based on the findings of prior research suggesting that institutional investors serve as effective external monitors (e.g., Bushee 1998, and Gillan and Starks 2000). We measure institutional holdings (INST_HOLD) as the percentage of shares held by institutional investors at the beginning of the quarter. We expect INST_HOLD to be positively associated with the probability of detecting channel stuffing. We include the number of analysts that issue a revenue forecast (REV_ANA) for the firm in quarter *t-1* in the detection model and expect it to be positively associated with the probability of detection because analysts with expertise in forecasting revenue are more likely to detect the channel stuffing activity.[5] In December 1999, the SEC issued SAB 101 – *Revenue Recognition in Financial Statements*, which significantly tightened the rules for revenue recognition. To capture the time-varying regulation environment for revenue recognition, we construct an indicator variable, SAB101, which equals one for years after 2000 and zero otherwise. We expect SAB101 to be positively associated with the likelihood of detecting channel stuffing. We also include an indicator variable, BIG4, which equals one if one of the Big-4 public accounting firms served as the external auditor for the year, zero otherwise. We expect Big-4 auditors to be more likely to detect channel stuffing behavior through high quality audits. For each industry-quarter, we examine the percentage of firms in each industry that were sued in class actions in the previous quarter (PCT_LIT). Since firms that belong to industries with high litigation risk are more likely to be subject to public scrutiny, we expect a

[5]We set REV_ANA to zero when a firm is not included in the I/B/E/S database.

positive association between detection probability and PCT_LIT. Finally, we include return volatility measured over the twelve months, RETVOL, in the detection model, because firms with higher return volatility are more likely to experience large negative stock returns, which often trigger class action lawsuits.

3.3.2 Factors that affect the probability of channel stuffing

We include four sets of variables that affect the likelihood of a firm engaging in channel stuffing. These include incentives for channel stuffing, opportunities for channel stuffing, financial indicators of channel stuffing, and measures of external scrutiny.

Incentives for channel stuffing:

We first focus on managerial motivations that explain why firms may engage in channel stuffing. These include factors that managers may regard as important to enhance shareholder value by boosting revenues and earnings. First, previous literature on earnings management identifies analysts' earnings forecast, past earnings, and zero earnings as three benchmarks that managers attempt to meet or just beat. Since revenue manipulation is shown by prior research to be a device used to increase net income, we construct indicator variables, BEAT_CHEPS and BEAT_EPS that capture firms' incentives to meet or beat past earnings and zero earnings, respectively.[6] For each firm-quarter, BEAT_CHEPS equals one if the firm's earnings per share (EPS) of quarter t is greater than the EPS of the same quarter of the previous year by 0 to 3 cents and zero otherwise. BEAT_EPS equals one if the firm's EPS of quarter t is between 0 and 3 cents and zero otherwise. Second, we include LEVERAGE, measured as long-term debt divided by total assets at the beginning of quarter t, to capture earnings management incentives related to debt covenants. Third, Callen, Robb, and Segal (2008) document that firms with a string of losses have incentives to overstate revenues, because investors often use revenue as a basis of valuation for these firms (e.g., they use the price-to-revenue ratio). Similar to Callen et al. (2008), we include LOSS_RATIO to capture a firm's incentive to overstate revenues due to investor valuation concerns. For each firm-

[6]We do not include an indicator variable capturing analysts' earnings forecast as the third benchmark, because the requirement of *I/B/E/S* data further reduces the size of our channel stuffing sample.

quarter, we define LOSS_RATIO as the percentage of quarters with reported losses over of the previous eight quarters. Fourth, prior research has documented that investors focus more on revenues for valuing high growth firms (Ertimur, Livnat, and Martikainen 2003; Ertimur and Stubben 2005). We include SALES_GROWTH and the book-to-market (BM) ratio to capture the firm's growth potential. We calculate SALES_GROWTH for quarter *t-1* as the net revenue for quarter *t-1* divided by the net revenue for the same quarter of the previous year. We calculate the BM ratio as the book value of equity divided by the market value of equity at the beginning of the quarter. Both variables, SALES_GROWTH and BM, are industry-adjusted by subtracting the industry median. Finally, we use an indicator variable EXTERNAL to capture capital market pressure. EXTERNAL equals one if, in quarter *t*, the firm issues new debt or new equity, or carries out a merger or acquisition, and zero otherwise.

Opportunities for channel stuffing:

We next focus on circumstances in which a firm will choose to manage earnings through real activities and when efforts to manage earnings will have a substantial impact. We include profit margin (PM) and gross margin (GM) in the model, since the impact of revenue on net income is higher for firms with higher profit margins and higher gross margins. We measure PM and GM of quarter *t-1*, where PM equals operating income divided by net sales and GM equals gross margin divided by net sales, both adjusted by the respective industry median. We also include net operating assets (NOA) at the beginning of quarter *t* to capture constraints on earnings management through accrual adjustments. We define NOA as the difference between operating assets and operating liabilities scaled by total assets, where operating assets equal total assets minus cash and short-term investments, and operating liabilities equal total assets minus (common equity + long-term debt + current portion of long-term debt + preferred stock + minority interest). We conjecture that, if a firm has exhausted its ability to manage earnings via accrual manipulation, it is more likely to engage in earnings management via real activities. Thus, higher beginning NOA would result in a higher likelihood of channel stuffing.

Financial indicators of channel stuffing:

The third set of explanatory variables includes four accounting measures that represent financial indicators of channel stuffing. Since firms that engage in channel stuffing often ship products to distributors without receiving cash, we include the change in days to collect cash (CH_DAYS_COL) in our model to capture the build-up of receivables in quarter *t*. We calculate days to collect receivables as the average accounts receivables divided by net sales for each quarter, times 91. We then calculate the change in days to collect receivables relative to the same quarter of the previous year and subtract the industry median of this variable to exclude industry-specific inter-temporal changes. We expect CH_DAYS_COL to be positively associated with the probability of channel stuffing. We also include days to sell inventory (CH_DAYS_INV) in our model. Similar to CH_DAYS_COL, we calculate CH_DAYS_INV as the change in days to sell inventory adjusted by the industry median. Consistent with Kedia and Philippon (2009) who document that firms hire and invest excessively during periods of suspicious accounting, we expect firms engaging in channel stuffing to produce excessively and to stock extra inventory to corroborate their channel-stuffing activity. Thus, CH_DAYS_INV is expected to be positively associated with the probability of channel stuffing. Since the channel stuffing activity involves offering deep discounts to distributors or customers in order to promote products and services, we expect firms engaged in channel stuffing to experience lower operating cash flows and gross margins. We follow Roychowdhury (2006) to estimate abnormal operating cash flows for each firm quarter. Specifically, we regress cash flow from operations on the current quarter's sales and change in sales (all variables scaled by total assets at the beginning of the quarter) for each industry-quarter and use the signed residuals as the abnormal operating cash flow (AB_CFO) for the firm-quarter. For each firm-quarter, we define CH_GROSSM as the change in gross margin relative to the same quarter of the previous year adjusted by the industry median. We expect both AB_CFO and CH_GROSSM to be negatively associated with the probability of channel stuffing.

Measures of external scrutiny:

Since the strength of external monitoring is likely to be positively associated with the probability of detection, conditional on the occurrence of channel stuffing, we expect that firms with stronger external monitoring systems will anticipate the higher likelihood of detection and will therefore be less likely to engage in channel stuffing in the first place. Specifically, we expect a negative association between the probability of channel stuffing and SIZE, institutional ownership (INST_HOLD), number of analysts issuing revenue forecasts (REV_ANA), SAB101 post-issuance period (SAB101), and Big-4 as external auditors (BIG4).

4. Empirical Results

4.1 Descriptive statistics

Table 3 reports univariate statistics for the main variables used in our bivariate probit model. Panel A reports variable means and medians for our sample firms for (i) the channel-stuffing (CS) period covering the period of consecutive channel-stuffing quarters, (ii) pre-channel-stuffing (pre-CS) period including four quarters prior to the first channel-stuffing quarter, and (iii) post-channel-stuffing (post-CS) period including four quarters subsequent to the last channel-stuffing quarter.

In examining variables that capture channel-stuffing incentives, we find that the median industry-adjusted sales growth for the sample firms is 0.12 in the CS period, higher than the median sales growth of 0.07 in the pre-CS period. Notable is the fact that the median sales growth drastically declines to -0.01 after the CS period. We find that the sample firms' average BM ratio is lower than the industry BM in all periods indicating that these firms are high growth firms; however, the industry-adjusted BM ratio increases significantly after the CS period, suggesting that the capital market may have adjusted the growth potential of these firms downward. In addition, we find that leverage significantly increases during the CS and post-CS periods, suggesting a higher need to meet earnings goals to avoid violating debt covenants.

In relation to variables that capture channel-stuffing opportunities, we find our sample firms to have high median profit margins and gross margins in both the pre-CS and the CS periods. We also find significantly higher level of net operating assets for the sample firms at the beginning of the CS period, suggesting that these firms might have exhausted their accruals management ability and therefore are more likely to engage in real earnings management.

In examining accounting variables that represent channel-stuffing indicators, we find that it takes a longer time for the sample firms to collect cash and to sell inventory during the CS period. We find that the receivables collection period does not increase as much in the post-CS period as in the CS period perhaps because significant sales returns after the channel stuffing activity depresses the balance in receivables. On the other hand, days to sell inventory continues to increase in the post-period suggesting that the negative consequences of overproduction could last for an extended period. Consistent with firms using deep discounts to promote their product sales, we find significantly lower abnormal operating cash flows and change in gross margins for the CS period relative to the pre-CS period. As in the case of inventory turnover, the negative consequences of channel stuffing on operating cash flows and gross margins continue into the post-CS period.

Finally, for the set of variables that measure external monitoring, we find higher institutional ownership and a higher number of analysts issuing revenue forecasts for our sample in the CS period compared to the pre-CS period. However, we also observe high institutional ownership and number of analysts issuing revenue forecasts in the post-CS period. Thus, it seems more likely that the differences in these variables between the CS and non-CS periods are reflecting a time trend rather than the effects of the channel stuffing activity.

Table 3, Panel B, reports comparative mean and median values of the explanatory variables for the sample firms during the CS period and for other firms in the same industry for the corresponding period. For this comparison, we only report variables that are not industry-adjusted. We find that firms in the channel stuffing sample are larger, with higher leverage ratios and higher external financing needs. The higher level of net operating assets for the channel stuffing sample suggests that these firms have significantly lower flexibility to manipulate accruals relative to their industry peers. In addition, firms in the channel stuffing sample also have higher institutional holdings and higher number of analysts issuing revenue forecasts relative to their industry peers. Also, compared to industry peers, a higher number of firms in the channel stuffing sample have external auditors from the Big-4 accounting firms.

Table 4 presents Pearson correlations for the main explanatory variables. The sample comprises firm-quarters used to estimate the prediction model over the period 1994-2006. Specifically, we include firm-quarters in the channel stuffing sample and the remaining firm-quarters in the Compustat population of firms excluding financial firms and utilities.[7] Most correlation coefficients are statistically significant due to the large sample size. Consistent with prior research, we find that size is positively correlated with institutional ownership, number of analysts issuing revenue forecasts, profit margin, gross margin, and whether a firm uses a Big-4 auditor. Not surprisingly, we observe that firms with higher profit margin and gross margin experience fewer losses over the past two years. Since most accounting variables are measured as changes relative to the same quarter of the previous year and adjusted by the industry median, we do not observe unusually high correlations among the accounting variables. For example, the correlation between net operating assets and days to collect receivables (days to sell inventory) is 0.01 (0.05).

4.2 Model estimation

Results of the simple probit regression are reported in column (1) of Table 5. Since the probit model does not separately account for the probability of engaging in channel stuffing and the probability of detecting channel stuffing, the coefficient estimates could be interpreted as the impact of the explanatory variables on the probability of channel stuffing or on the detection of channel stuffing, or on both. For example, we find that the coefficient estimate on firm size is positive and significant in the probit model. However, it is unclear whether large firms are more likely to engage in channel stuffing or whether the market directs more scrutiny on these firms and therefore their channel stuffing activity is more likely to be detected. We also find the coefficient estimate on institutional ownership to be significantly positive in the probit model. But again, it is not clear whether institutional ownership encourages channel stuffing due to increased market pressure or whether it increases the detection probability due to the ability of sophisticated investors to understand complex accounting strategies.

[7] We also exclude firms in service industries (SIC code ≥ 8000) because the nature of their business does not afford them opportunities for channel stuffing. We refer to the sample of remaining firm-quarters in the Compustat population (i.e., other than channel-stuffing firm-quarters) as the non-channel stuffing sample.

To account for the probability of engaging in channel stuffing and detecting channel stuffing separately, we estimate the bivariate probit model and report its results in Table 5, columns 2 and 3. Similar to the results of the probit model estimation and the univariate analysis, we find that firms with higher sales growth in the previous quarter are more likely to engage in channel stuffing (although significance is weak). Since this variable is industry-adjusted, the result suggests that the channel stuffing firms may be trying to maintain superior growth potential relative to industry peers rather than simply mimicking the average industry performance. We also find firms with limited accrual management ability (high NOA) to be more likely to engage in real activities management via channel stuffing. Further, we find that firms with a higher level of gross margin and profit margin are more likely to engage in channel stuffing, consistent with our hypothesis that these firms can reap greater benefits from revenue manipulation since every dollar of inflated revenues would result in higher profitability. In terms of financial indicators of channel stuffing, we find that the receivables collection period increases significantly in the CS period. Further, firms that engaged in channel stuffing exhibit a lower gross margin and abnormal operating cash flow relative to the same quarter of the previous year (although significance is weak).

Different from the probit model, we find that firm size is negatively related with the probability of channel stuffing and positively correlated with the probability of detection, which is consistent with the higher likelihood of large firms with a public profile to be caught if they commit accounting fraud. Also different from the probit model, we find that institutional ownership, Big-4 auditor, and the passage of SAB 101 increase the probability of detecting channel stuffing and therefore reduce the probability of the channel stuffing activity itself. We find that the number of analysts issuing revenue forecasts decreases the probability of detecting channel stuffing and increases the probability of committing channel stuffing. While the result is consistent with analysts' revenue forecasts placing pressure on companies to manage their revenues, the negative coefficient estimate in the detection model casts some doubt on the monitoring role of security analysts. Finally, we find that, conditional on the occurrence of the channel stuffing activity, channel stuffing by firms in more litigious industries and firms with high prior return volatility is more likely to be detected.

4.3 Performance of the prediction model (within-sample)

4.3.1 Overall model fit

Both models exhibit high predictive power as indicated by the psuedo-R^2 of 32% for the probit model and 35% for the bivariate probit model. We further evaluate the models' ability to predict channel stuffing when it occurs and reject channel stuffing when it does not occur (i.e., the power and specification of the model). We follow Dechow et al. (2010) and construct a fitness score (F-Score) that equals the predicted probability of CS=1 and D=1 divided by the unconditional probability of including a specific firm-quarter in our sample. The unconditional probability is calculated as the number of observations (348 firm-quarters) in the channel-stuffing sample divided by the sum of the number of observations in the channel stuffing and non-channel stuffing samples (117,984 firm-quarters). An F-Score of one indicates that the predicted probability of channel stuffing equals the unconditional probability of channel stuffing. Values of F-Score higher (lower) than one indicate higher (lower) probability of channel stuffing. Figure 1 plots the distribution of F-Scores for the channel stuffing sample and the non-channel stuffing sample separately. The solid line (dashed line) depicts the cumulative distribution of F-Scores for non-channel stuffing firms based on the probit model (bivariate probit model) and the line with white squares (black circles) depicts the cumulative distribution of F-Scores for channel stuffing sample firms based on the probit model (bivariate probit model). Based on the bivariate probit model, it is clear from the figure that a higher number of firm-quarters are to the right of one for the channel stuffing sample (87.7%), while a lower number of firm-quarters are to the right of one for the non-channel-stuffing sample (21.7%). Since an F-Score of one is an arbitrary cut-off, we examine other cut-offs as well to check if the difference between the two groups holds consistently throughout the distribution. If we increase the F-Score cut-off to two, the percentage of firm-quarters to the right of two is 75.3% for the channel stuffing sample and 12.7% for the non-channel stuffing sample. These results suggest that our prediction model produces reasonably low Type I as well as Type II errors. Results based on the simple probit model are in general weaker than the bivariate probit model, i.e., the model produces marginally higher Type I and Type II errors in within-sample prediction.

4.3.2 Comparative predictive power of the probit and bivariate probit models

Table 6, Panel A, reports the correlations between the probability of detected channel stuffing based on the probit model (i.e., CS=1 & D=1) and (i) the probability of detected channel stuffing based on the bivariate probit model, (ii) the marginal probability of channel stuffing based on the bivariate probit model (i.e., CS=1), and (iii) the marginal probability of detection based on bivariate probit model (i.e., D=1). We find the probability of detected channel stuffing based on the probit model and the bivariate probit model to be highly positively correlated (0.7488). However, this correlation is significantly less than one (i.e., the null of ρ=1 is rejected at the 1% level), suggesting different prediction outcomes from the two models. In addition, we find that the probability of detected channel stuffing based on the probit model is negatively correlated with the marginal probability of channel stuffing based on the bivariate probit model (-0.0424) and positively correlated with the marginal probability of detection based on the bivariate probit model (0.3110). This suggests that the predicted outcomes based on the probit model are more likely to be affected by factors related to detection of channel stuffing rather than factors related to a firm engaging in channel stuffing. Consequently, it is likely that the simple probit model may identify a different set of firms as having a high likelihood of channel stuffing compared to the bivariate probit model.[8]

In Table 6, Panel B, we further evaluate the comparative fitness of the two models by examining whether the predicted probability of detected channel stuffing for the channel stuffing sample is higher based on the bivariate probit model relative to the probit model. Similarly, we examine whether the predicted probability of detected channel stuffing for the non-channel stuffing sample is lower based on the bivariate probit model relative to the probit model. We compute the ratio of the probability of detected

[8]We find that only 8% of firms in the top 5% of the predicted probability of detected channel stuffing estimated from the simple probit model also fall in the top 5% of the predicted probability of channel stuffing estimated from the bivariate probit model. The overlap increases to 17% and 40% when we examine firms in the top 25% and top 50% of the predicted probability of channel stuffing.

channel stuffing based on the bivariate probit model and the probability of detected channel stuffing based on the probit model for each firm-quarter. If the predictive ability of the bivariate probit model is superior to that of the probit model, we expect the mean ratio to be greater than one for the channel-stuffing firm-quarters and less than one for the remaining firm-quarters. In other words, we expect both Type I and Type II errors to be smaller for the bivariate probit model estimation results. We first calculate the ratio based on the estimation results presented in Table 5 (i.e., the within-sample analysis). We find the mean ratio to be significantly greater than one for the channel stuffing firm-quarters (1.3749) and significantly less than one for the non-channel stuffing firm-quarters (0.7460). To test the out-of-sample robustness of our results, we also estimate the two models using 50% of observations selected randomly. We then apply the estimated coefficients to the other half of the observations and compare the out-of-the-sample estimation results of the two models. We find that the mean ratio based on the out-of-sample estimation results is 1.3549 for the channel-stuffing firm-quarters and 0.5453 for the non-channel-stuffing firm-quarters, and further both ratios are significantly different from one. Overall, the results in Table 6 provide evidence that bivariate probit model obtains lower Type I and Type II prediction errors and hence provides a better fit relative to the simple probit model.

4.4 Impact on performance of subsequent quarters

Table 7 reports the performance of firms over a period of four quarters following the channel stuffing quarter.[9] We report the over-time industry-adjusted means of sales growth in Panel A, ROA in Panel B, days-to-sell inventory in Panel C, and change in production in Panel D. Column 1 of all panels documents the subsequent performance of the sample of channel stuffing firms. When a firm engages in channel stuffing in multiple consecutive quarters, we only retain the last quarter in the string for the analysis of subsequent performance.[10] We find that firms in the channel stuffing sample experience a significant decline in industry-adjusted sales growth after the channel stuffing quarter and this decline

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[9] Because our research objective is to predict channel-stuffing activity for a given firm quarter, we do not include performance reversal information in our prediction models. Instead, we use information on performance reversals in subsequent quarters to check the validity of our prediction models.

[10] We further require the retained firm to have no channel stuffing allegations in the subsequent four quarters that we examine in this table.

worsens over four quarters in the future. This finding confirms our conjecture that it is physically impossible for firms to engage in channel stuffing for an extended period of time. Further, firms that engage in channel stuffing experience a significant decline in industry-adjusted ROA after the channel stuffing quarter for the next four quarters. Consistent with the slowing down of sales, we find that these firms experience inventory build-up in the subsequent four quarters as indicated by the increase in the industry-adjusted days-to-sell inventory. Further, consistent with the inventory build-up, we find that the sample firms shrink their production following the channel stuffing quarter. Overall, our results indicate that firms that engage in channel stuffing in order to boost their revenues and earnings in the short-term, suffer long-lasting adverse effects on their operations and overall performance.[11] Thus, while this technique of managing earnings through real activities may be less costly in terms of litigation risk or regulatory penalties given its lower likelihood of detection, we observe that firms that engage in channel stuffing bear a huge cost in terms of adverse future operating performance.

To examine the reliability of the out-of-sample classification of channel stuffing based on the bivariate probit and probit models, we examine the future performance of firms that we identify as having a high likelihood of channel stuffing but that are not alleged to have engaged in channel stuffing. We expect the future performance for the non-detected firms with high probability of channel stuffing to follow the same pattern as the detected channel stuffing firms. We form 20 portfolios of the sample of non-channel stuffing firm-quarters by sorting on the predicted probability of channel stuffing estimated from the bivariate probit model and designate firm-quarters in the top portfolio as those identified by our model to have a high likelihood of channel stuffing (results reported in column 2 of Table 7). When a firm is identified as having a high likelihood of channel stuffing for multiple consecutive quarters, we only retain the last quarter of the string for the analysis of subsequent performance. We repeat the above identification procedure using the predicted probability of channel stuffing estimated from the simple probit model and designate firm-quarters in the top portfolio as those with a high likelihood of channel

[11]Of course, we cannot and do not claim that the channel stuffing activity per se led to the future adverse performance; it is possible that the firm would have experienced declining revenues and earnings regardless of the channel stuffing activity.

stuffing (reported in column 3 of Table 7).

When we compare the time-trend of performance variables of the detected channel stuffing sample (column 1) with the sample of firms identified by the bivariate probit model as having a high likelihood of channel stuffing (column 2), we find that the adverse trend of the latter sample closely follows that of the detected channel stuffing sample in the case of sales growth, ROA, production, and inventory build-up. From column 3, the decline in sales growth and ROA and the increase in days-to-sell inventory are significantly weaker for firms identified by the simple probit model as having a high likelihood of channel stuffing both relative to the detected channel stuffing sample and the sample identified by the bivariate probit model. Further, these firms experience no noticeable change in industry-adjusted production over the subsequent quarters. Thus, the bivariate probit model's classification of firms as having a high likelihood of channel stuffing is borne out by our ex post validation based on subsequent performance patterns similar to that of the detected channel stuffing sample.[12] On the other hand, firms classified as having a high likelihood of channel stuffing by the simple probit model have performance patterns in future quarters that are significantly different from those of the detected channel stuffing sample, implying that the simple probit model may be subject to greater classification errors than the bivariate probit model.

Overall, our results highlight the shortcomings of a simple probit model when predicting accounting irregularities, earnings management, or other wrong-doing that is hard to detect. In such cases, we recommend the use of the bivariate probit model that accounts for the probability of detection in the estimation process and results in superior predictive ability and lower classification errors.

5. Summary and Conclusion

[12] Since sales growth is also used as an explanatory variable in the prediction model, there may be a concern that the similar pattern of subsequent sales growth for the model-identified top 5% of firms and the actual channel stuffing firms simply reflects mean reversion in sales growth for both samples (since quarter *t*'s sales growth for the two samples are similar). To alleviate this concern, we match each of the model-identified firms in the top 5% with a matched firm with similar sales growth in quarter *t* and whose probability of channel stuffing falls below the median. We find that the matched-firm-adjusted future sales growth of the top 5% also follows the same pattern as that of the actual channel stuffing sample, implying that the result cannot be simply attributed to mean reversion.

We examine a sample of firms that engaged in channel stuffing. The practice of channel stuffing is a form of "real" activities management that leads to accelerated revenue recognition and provides a short-term boost to revenues and profits. Usually, cases of channel stuffing are revealed through the actions of whistle-blowers or ex post when future reversals in performance unravel the scheme. We develop a model that predicts the probability of channel stuffing after controlling for the fact that many cases of channel stuffing may have occurred but were not detected, i.e., we estimate a bivariate probit model that accounts for the partial observability problem. We find that smaller firms, firms with high growth opportunities, high profit margins and limited accrual management ability are more likely to engage in channel stuffing. Further, we find that an increase in the receivables collection period serves as a useful indicator of channel stuffing. At the same time, we find that larger firms, with high institutional ownership, high litigation risk, and facing a more stringent regulatory regime (post SAB 101) are more likely to be detected and hence are less likely to engage in channel stuffing. In addition, we find that firms that engage in channel stuffing experience declining sales, production, and profits and increasing inventory levels in subsequent periods. Thus, while this form of earnings management may be viewed by companies as less costly in that the risk of exposure is quite low, it imposes costs on the company's operations and profitability that persist over a long period of time.

We find that the bivariate probit model estimation results in lower Type I and Type II errors relative to the simple probit model. Moreover, we find that a subsample of undetected firms identified by the bivariate model (but not the simple probit) as having a high likelihood of channel stuffing exhibit patterns of future performance reversals that closely parallel those observed for the sample of detected channel stuffing. This ex post validation further supports the efficacy of the bivariate probit model. Overall, our results highlight the need to control for the probability of detection to minimize misclassification when predicting the likelihood of any accounting irregularity or earnings management behavior that is hard to detect.

The small sample size is of course a limitation of our study. However, the small sample size is partly due to the difficulty in detecting cases of channel stuffing. We believe that, particularly for such settings, it is necessary to shed light on factors associated with the activity which may help in the timely detection of many more cases.

An insight that arises from the results of the bivariate probit model is that large high profile firms are more likely to be detected but, after controlling for the detection probability, smaller firms are more likely to engage in this activity. We find that firms identified by us as having a high likelihood of channel stuffing but which escaped detection are significantly smaller than the detected channel stuffing firms (mean total assets of the channel stuffing sample 6 times higher) and have significantly lower institutional holdings (mean of channel stuffing sample 3 times higher). Since about 62% of firms in our channel stuffing sample were sued in class actions, it appears that litigators are effective monitors of large high profile companies likely because of their deep pockets. Assuming that the SEC's objective is to curb overall accounting abuse, it would make sense for the SEC to investigate smaller companies that are not subject to close public scrutiny rather than duplicate the efforts of litigators in pursuing large companies. On the other hand, perhaps the SEC acts on the belief that making an example of a large company deters wrong-doing by all companies.

Appendix:

Variable Definitions

AB_CFO	Abnormal operating cash flows. Following Roychowdury (2006), we regress cash flows from operations on the current quarter's sales and changes in sales. We run the regression within industry-quarter and use the residuals as the signed abnormal cash flows for each firm-quarter.
BEAT_CHEPS	Indicator variable that equals 1 if a firm's quarterly EPS is greater than the EPS of the same quarter of the previous year by 0 to 3 cents, 0 otherwise.
BEAT_EPS	Indicator variable that equals 1 if a firm's quarterly EPS is between 0 and 3 cents, 0 otherwise.
BIG4	Indicator variable that equals 1 if one of the big-4 public accounting firms served as the external auditor for a given firm-year, 0 otherwise.
BM	Book value of equity divided by the market value of equity at the beginning of quarter *t* minus the industry median.
CH_DAYS_COL	Percentage change in days to collect receivables relative to the same quarter last year minus the industry median.
CH_DAYS_INV	Percentage change in days to sell inventory relative to the same quarter last year minus the industry median.
CH_GROSSM	Changes in gross margin relative to the same quarter last year minus the industry median.
EXTERNAL	Indicator variable that equals 1 if a firm issues new debt, or new equity, or carries out a merger or acquisition, 0 otherwise, measured for each quarter.
GM	Gross margin divided by net sales, of quarter *t-1*, minus the industry median.
INST_HOLD	Percentage of shares held by institutional investors at the beginning of quarter *t*.
LEVERAGE	Long-term debt divided by total assets at the beginning of quarter *t*.
LOSS_RATIO	Number of loss quarters over the previous eight quarters divided by 8.
NOA	Net operating assets defined as the difference between operating assets and operating liabilities scaled by total assets, at the beginning of quarter *t*.
PCT_LIT	Percentage of firms in each industry that are sued in class actions in quarter *t-1*.
PM	Operating income divided by net sales, of quarter *t-1*, minus the industry median.
REV_ANA	Number of analysts that issue at least one revenue forecast for the firm in quarter *t-1*.
RET_VOL	Standard deviation of monthly stock returns over the previous year.
SAB101	Indicator variable that equals 1 for years after 2000 and 0 otherwise.
SALES_GROWTH	Net revenue for quarter *t-1* divided by the net revenue from the same quarter of the previous year minus 1, adjusted for industry median.
SIZE	Natural log of total assets at the beginning of quarter *t*.

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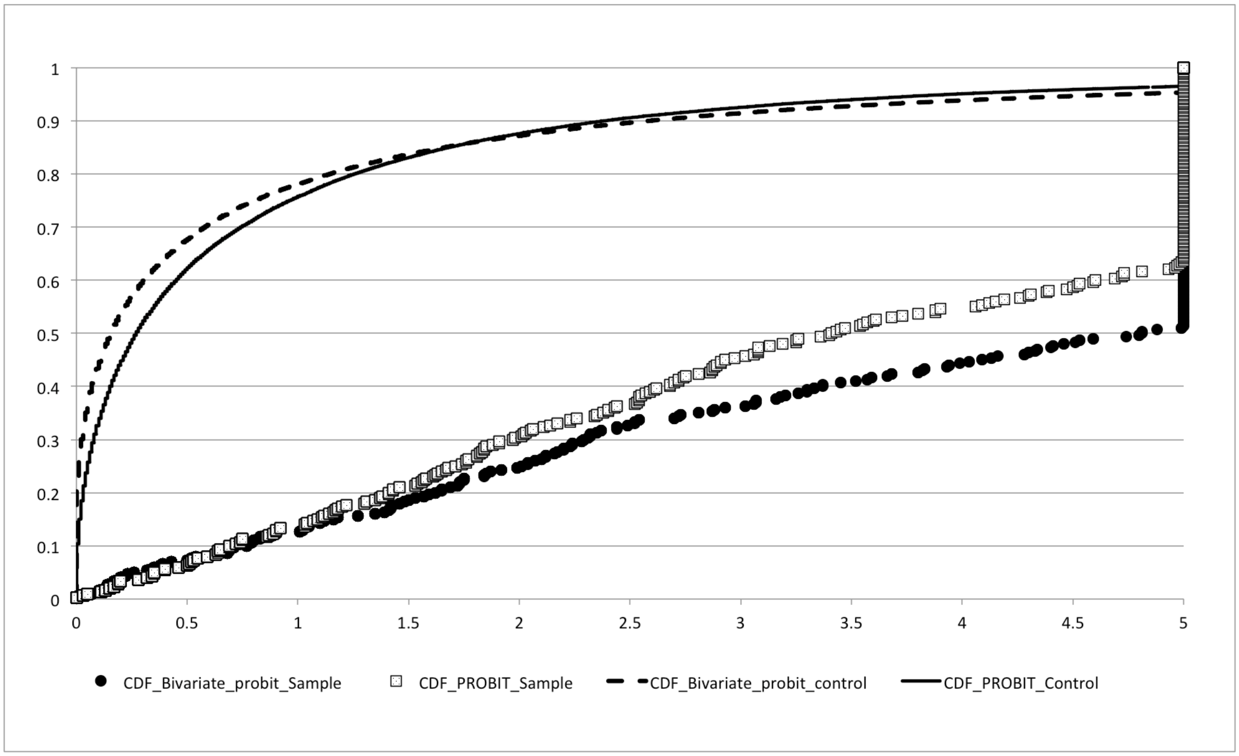
Figure 1: Cumulative distribution of predicted probability



Horizontal axis: fitness score calculated as predicted probability of detected channel stuffing divided by unconditional probability of the detected channel stuffing.

Vertical axis: cumulative distribution of the fitness score.

Table 1

Distribution of the sample of firms with channel stuffing allegations (CS firms)

Panel A: Year-wise frequency of firm-quarters and firm-years with channel stuffing allegations

Year	No. of CS firm-quarters	No. of CS firm-years
1994	9	3
1995	7	2
1996	17	6
1997	44	14
1998	54	14
1999	63	18
2000	84	25
2001	92	30
2002	57	21
2003	41	13
2004	23	10
2005	10	6
2006	9	3
Total	510	165

Panel B: Number of quarters during which the channel stuffing activity was undertaken by CS firms

No. of CS quarters	No. of CS firms
1	9
2	5
3	13
4	24
5	6
6	1
7	5
8	15
9	1
10	0
11	3
12	2
>12	6
Total	90

Panel C: Number of CS firms facing class action lawsuits and SEC investigations

	No. of firms
Involved in Class Actions	62
Investigated by SEC	40

Table 2
Industry distribution of the sample of channel stuffing firms (CS) based on the Fama-French 48 industry classification

Industry Name	No. of CS firms
Food and kindred products	5
Cigarettes	1
Apparel & other finished products	4
Lumber & wood products	1
Paper mills	1
Books	1
Commercial printing	1
Drugs & pharmaceutical	14
Soap, detergent, toilet preps	4
Fabricated metal, machinery	3
Farm machinery	2
Computer & office equipment	12
Other electrical equipment	12
Motorcycles	2
Measuring instruments, photo goods, watches	8
Pens, pencils, and artists' materials	1
Durable goods wholesale	2
Nondurable goods wholesale	3
Food stores	1
Computer programming, data processing	12
Total	90

Table 3
Descriptive statistics

Panel A: Characteristics of channel stuffing (CS) firms in pre-CS, CS, and post-CS periods

Variables	Pre-CS		CS period		Post-CS		Difference between pre-CS and CS		Difference between CS and post-CS	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Incentives for channel stuffing										
BEAT_CHEPS	0.18	0.00	0.17	0.00	0.09	0.00			***	***
BEAT_EPS	0.10	0.00	0.08	0.00	0.07	0.00				
LEVERAGE	0.20	0.14	0.27	0.22	0.27	0.25	***	***		
LOSS_RATIO	0.19	0.00	0.19	0.00	0.28	0.25			***	***
SALES_ GROWTH	0.22	0.07	0.28	0.12	0.08	-0.01	*	**	***	***
BM	-0.10	-0.12	-0.10	-0.11	-0.01	-0.05			***	***
EXTERNAL	0.90	1.00	0.96	1.00	0.89	1.00	**	**	***	***
Opportunities for channel stuffing										
PM	0.04	0.08	0.08	0.10	-0.01	0.07		*	*	***
GM	0.08	0.10	0.13	0.11	0.10	0.11	**		*	
NOA	0.002	0.012	0.10	0.11	0.03	0.03	***	***	***	***
Financial indicators of channel stuffing										
CH_DAYS_COL	0.07	0.03	0.13	0.14	0.06	0.02	***	***	***	***
CH_DAYS_INV	0.04	-0.03	0.14	0.03	0.11	-0.00	***	***		*
CH_GROSSM	0.06	0.01	0.01	-0.01	-0.03	-0.02	***	***	**	
AB_CFO	0.006	0.012	-0.01	0.00	-0.00	0.002	***	***		
Measures of external scrutiny										
SIZE	5.67	5.36	6.46	6.42	6.40	6.41	***	***		
INST_HOLD	0.22	0.21	0.35	0.36	0.37	0.36	**	***		
REV_ANA	3.51	0.00	3.82	2.00	7.24	3.00		***	***	***
BIG4	0.91	1.00	0.86	1.00	0.85	1.00	**	**		
Factors that affect detection probability but not the probability of channel stuffing										
PCT_LIT	0.07	0.04	0.09	0.05	0.07	0.04	**		**	*
RET_VOL	0.16	0.13	0.15	0.14	0.17	0.14			***	*

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Significance relates to p-values associated with t-test of difference in means and 2-sample median test of difference in distributions of the 2 samples.

CS period includes all quarters during which the firm is alleged to have engaged in channel stuffing. Pre-CS (Post-CS) is a period of four quarters preceding (following) the first (last) quarter of the CS period. Other variables are defined in the Appendix.

Table 3 continued…

Panel B: Comparison of firms in channel stuffing sample with industry-matched control firms

Variables	CS firm-periods		Industry Control		Difference	
	Mean	Median	Mean	Median	Mean	Median
Incentives for channel stuffing						
BEAT_CHEPS	0.17	0.00	0.17	0.00		
BEAT_EPS	0.08	0.00	0.11	0.00	**	**
LEVERAGE	0.27	0.22	0.23	0.16	***	***
LOSS_RATIO	0.19	0.00	0.38	0.25	***	***
EXTERNAL	0.96	1.00	0.78	1.00	***	***
Opportunities for channel stuffing						
NOA	0.10	0.11	0.01	0.02	***	***
Financial indicators of channel stuffing						
AB_CFO	-0.01	0.00	-0.01	-0.00		
Measures of external scrutiny						
SIZE	6.46	6.42	4.58	4.43	***	***
INST_HOLD	0.35	0.36	0.21	0.00	***	***
REV_ANA	3.82	2.00	1.50	0.00	***	***
BIG4	0.86	1.00	0.75	1.00	***	***
Factors that affect detection probability but not the probability of channel stuffing						
RET_VOL	0.15	0.14	0.16	0.14	*	*

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Significance relates to p-values associated with the t-test of difference in means and the two-sample median test of difference in distributions of the two samples.

Control firms include all firms in the same industry as the channel stuffing firm based on the Fama-French 48 industry classification. Variables are defined in the Appendix. Variables that are adjusted for the industry median are not reported in this table.

Table 4
Pearson correlations among variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
SIZE (1)	1.00																		
LEVERAGE (2)	**0.12**	1.00																	
EXTERNAL (3)	**0.20**	0.01	1.00																
SALES_GROWTH (4)	**-0.04**	**-0.03**	**0.07**	1.00															
BM (5)	-0.00	**-0.21**	**-0.10**	**-0.10**	1.00														
PM (6)	**0.23**	**0.05**	0.00	**-0.03**	**0.08**	1.00													
GM (7)	**0.14**	**0.02**	**0.01**	**-0.02**	**0.03**	**0.56**	1.00												
LOSS_RATIO (8)	**-0.44**	**-0.04**	**-0.07**	**0.06**	**-0.05**	**-0.36**	**-0.28**	1.00											
BEAT_CHEPS (9)	**-0.15**	**-0.05**	**-0.06**	**0.02**	**-0.07**	**-0.03**	-0.00	**-0.03**	1.00										
BEAT_EPS (10)	**-0.19**	**-0.01**	**-0.12**	**-0.00**	**0.00**	**0.03**	**0.03**	**-0.01**	**0.23**	1.00									
NOA (11)	**0.16**	**0.10**	**0.11**	**-0.01**	**0.24**	**0.18**	**0.12**	**-0.24**	-0.01	-0.00	1.00								
CH_DAYS_COL (12)	**-0.02**	-0.01	0.00	**-0.02**	-0.00	**-0.02**	**-0.02**	**-0.03**	-0.01	-0.00	0.01	1.00							
CH_DAYS_INV (13)	**-0.02**	**-0.02**	**0.02**	**-0.04**	0.01	**-0.03**	0.01	**-0.02**	-0.01	0.00	**0.05**	**0.18**	1.00						
CH_GROSSM (14)	**-0.05**	-0.01	0.00	**0.12**	**-0.04**	**-0.10**	**-0.05**	**0.12**	**0.02**	0.01	**-0.05**	**-0.10**	**0.15**	1.00					
AB_CFO (15)	**0.09**	**0.02**	**-0.05**	**0.01**	**0.03**	**0.13**	**0.10**	**-0.11**	**0.02**	**0.05**	**0.03**	**-0.03**	**-0.03**	-0.00	1.00				
INST_HOLD (16)	**0.44**	**-0.09**	**0.19**	**-0.02**	**-0.01**	**0.09**	**0.07**	**-0.19**	**-0.09**	**-0.11**	**0.09**	**-0.02**	-0.01	**-0.02**	**0.03**	1.00			
REV_ANA (17)	**0.40**	**-0.09**	**0.15**	0.00	**-0.06**	**0.06**	**0.05**	**-0.15**	**-0.06**	**-0.08**	**0.06**	-0.00	**0.01**	-0.01	**0.03**	**0.63**	1.00		
BIG4 (18)	**0.46**	**-0.02**	**0.17**	-0.01	**0.07**	**0.09**	**0.03**	**-0.19**	**-0.14**	**-0.18**	**0.08**	**-0.01**	**-0.01**	-0.01	**0.02**	**0.20**	**0.16**	1.00	
RET_VOL (19)	**-0.36**	0.00	**-0.05**	**0.04**	**0.05**	**-0.13**	**-0.08**	**0.40**	**-0.04**	**0.07**	**-0.04**	**0.01**	**0.02**	**0.03**	**-0.04**	**-0.16**	**-0.12**	**-0.14**	1.00
PCT_LIT (20)	**-0.03**	**-0.04**	**0.02**	**0.01**	0.01	**-0.02**	-0.01	**0.04**	0.00	**0.01**	**0.03**	**0.01**	0.01	0.01	-0.01	**0.05**	**0.05**	**-0.03**	**0.08**

Numbers in bold are significant at the 1% level. Variables are defined in the Appendix.

Table 5
Model estimation results: Probit and bi-variate probit models

VARIABLES	PROBIT	PROB. of CS	PROB. OF D
Constant	-4.6235***	2.3222***	-2.8947***
LEVERAGE	-0.0788	-0.0149	
EXTERNAL	0.4028***	0.1384**	
SALES_GROWTH	0.1535***	0.0371*	
BM	-0.2793***	-0.0775**	
LOSS_RATIO	-0.4393***	-0.0779*	
BEAT_CHEPS	0.1325**	0.0448*	
BEAT_EPS	0.1682*	0.0489	
PM	0.2863***	0.2151**	
GM	0.4335***	0.5504**	
NOA	0.6317***	0.1612**	
CH_DAYS_COL	0.3102***	0.1751***	
CH_DAYS_INV	-0.0322	-0.0042	
CH_GROSSM	-0.0769	-0.1440*	
AB_CFO	-0.4554	-0.2259*	
SIZE	0.1467***	-0.1390***	0.1732***
INST_HOLD	0.1679**	-0.7015**	0.6655**
REV_ANA	0.0400*	0.6601***	-0.5793***
SAB101	0.0199	-0.3183**	0.2825**
BIG4	0.0927	-1.2747***	1.1112***
RET_VOL	0.8884***		0.3091***
PCT_LIT	1.8770***		0.5792***
Pseudo R2	*0.3232*	*0.3460*	
# of Observations	117984	117984	

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Column (1) reports results of the probit model estimation of the probability of channel stuffing. Columns (2) report results of the joint estimation of the probability of channel stuffing (CS) and the probability of detect using the bivariate probit model. The models are estimated using the sample of firms that were alleged engaged in channel stuffing and industry-matched control firms. Variables are defined in the Appendix.

Table 6
Comparison of predictive power of the probit and the bivariate probit models

Panel A: Correlation between predicted probabilities

	Probit Pr (CS=1 & D=1)
Bivariate Probit Pr (CS=1 & D=1)	0.7488
Bivariate Probit Pr (CS=1)	-0.0424
Bivariate Probit Pr (D=1)	0.3110

Panel B: Predicted probability of detected channel stuffing based on bivariate probit model relative to that based on probit model

Ratio = Bivariate Probit Pr (CS=1 & D=1) / Probit Pr (CS=1 & D=1)

Estimated probability based on entire sample		
Channel stuffing sample	Mean Ratio = 1.3749	Larger than 1: t = 10.11
Control sample	Mean Ratio = 0.7460	Smaller than 1: t = -87.19
Estimated probability based on out- of-sample results[a]		
Channel Stuffing sample	Mean Ratio = 1.3549	Larger than 1: t = 4.6946
Control sample	Mean Ratio = 0.5453	Smaller than 1: t = -96.63

[a] Estimation is based on 50% of the sample drawn randomly; the estimated coefficients are then used to calculate the predicted probability for the other half of the sample.

Pr (CS=1 & D=1) = probability of detected channel stuffing; Pr (CS=1) = probability of channel stuffing; Pr (D=1) = probability of detection.

Table 7

Future performance of firms in the channel stuffing (CS) sample and firms identified by the bivariate probit and probit models as having a high likelihood of engaging in channel stuffing (top 5%).

Panel A: Sales growth adjusted for industry median

	CS Sample	High Prob of CS based on Bivariate Probit	High Prob of CS based on Probit	Difference between CS and Bivariate Probit	Difference between CS and Probit	Difference between Bivariate Probit and Probit
q_t	0.1523	0.1659	0.1323			**
q_{t+1}	0.1005	0.1094	0.1274			
q_{t+2}	0.0359	0.0743	0.1041		**	**
q_{t+3}	0.0201	0.0245	0.0899		**	***
q_{t+4}	-0.0058	-0.0075	0.0786		***	***

Panel B: ROA adjusted for industry median

	CS Sample	High Prob of CS based on Bivariate Probit	High Prob of CS based on Probit	Difference between CS and Bivariate Probit	Difference between CS and Probit	Difference between Bivariate Probit and Probit
q_t	0.0113	0.0093	0.0302		**	***
q_{t+1}	-0.0035	0.0078	0.0258		***	***
q_{t+2}	-0.0057	0.0005	0.0239		**	***
q_{t+3}	-0.0037	-0.0068	0.0299		***	***
q_{t+4}	-0.0142	-0.0072	0.0250		***	***

Panel C: Days to sell inventory adjusted for industry median

	CS Sample	High Prob of CS based on Bivariate Probit	High Prob of CS based on Probit	Difference between CS and Bivariate Probit	Difference between CS and Probit	Difference between Bivariate Probit and Probit
q_t	42.69	36.26	19.23		***	***
q_{t+1}	44.58	34.00	19.82		***	***
q_{t+2}	51.29	36.91	18.77	*	***	***
q_{t+3}	52.73	37.49	19.71	*	***	***
q_{t+4}	43.72	34.55	19.43		***	***

Panel D: Percentage change in production adjusted for industry median						
	CS Sample	High Prob of CS based on bivariate Probit	High Prob of CS based on Probit model	Difference between CS and Bivariate Probit	Difference between CS and Probit	Difference between Bivariate Probit and Probit
q_t	0.3047	0.1691	0.1961	*		*
q_{t+1}	0.2143	0.1272	0.1911			***
q_{t+2}	0.0671	0.0489	0.1914		**	***
q_{t+3}	0.0437	0.0339	0.1747		**	***
q_{t+4}	-0.0364	0.0370	0.2062	**	***	***

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Significance relates to p-values associated with the t-test of difference in means of the two stated samples.

The table reports means of variables in quarter *t* and subsequent four quarters. Columns (2) and (3) report results for firms in the top 5% of the distribution of predicted probability of channel stuffing based on the bivariate probit and probit models, respectively. Consistent with Roychowdhury (2006), we define production as the cost of goods sold plus the change in inventory. Change in production is measured relative to the same quarter of the previous year. Other variables are defined in the Appendix.