Is Sunlight the Best Disinfectant?
Window Dressing in a Transaction-Level Disclosure Regime

This study examines whether firms strategically window dress year-end reports in a regime requiring transaction-level investment disclosure. Proponents of mandatory transaction-level disclosure argue such granularity will prevent window dressing, thereby improving financial reporting quality. Using CUSIP-level transaction data, we examine whether U.S. insurance companies manage period-end portfolio composition to reduce potential regulatory scrutiny over investment risk-taking during the period. Results are consistent with insurance companies increasing risk during the period, "reaching for yield," and subsequently decreasing risk at the reporting date to reduce potential regulatory consequences. Such window dressing appears to be successful as we document no incremental adverse regulatory outcomes among firms engaging in window dressing. Our evidence suggests the existence of fixation on period-end balances, even when transaction-level data is available. It appears transaction-level data does not fully eliminate window dressing, likely due to processing costs and budgetary constraints of the regulator.

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1. Introduction

Using insurance company investment transaction data, this study examines whether year-end window dressing occurs in a reporting regime in which all transaction-level data is available to financial statement users. Window dressing describes the process of engaging in real activities towards the end of a reporting period to improve the appearance of reported financial condition (Roychowdhury, 2006). In our setting, insurance companies have incentives to increase returns by purchasing higher risk assets throughout a given year, but then reduce their risky assets at year-end to minimize the reported risk of their investment portfolio to comply with regulatory reviews. We examine whether the availability of transaction-level detail eliminates these incentives to engage in this window dressing behavior.

Window dressing behavior has been shown to occur in a variety of industries, most of which have limited transaction-level data available to investors and regulators. For instance, mutual fund managers strategically buy and sell certain investments towards period-end with the apparent objective of appearing more successful to their clientele and other market participants (Lakonishok et al., 1991; Agarwal et al., 2014). Similarly, banks reported quarter-end repurchase liability levels are lower than within-quarter averages, consistent with potential window dressing of liabilities (Owens and Wu, 2015).

Unraveling window dressing behavior is difficult for financial statement users provided only with period-end balances. Regulators have attempted to reduce information asymmetry for certain regulated companies by mandating disclosure of transaction-level or investment-level data, thereby providing a more transparent view into changes in financial condition between period-ends.[1] The rationale behind such *sunlight* rules is that more complete disclosure will prevent reporting manipulation and deter harmful management actions manipulated reports are intended to conceal (e.g. SEC, 2009).[2] If sunlight rules work as intended, broadening the scope of transaction-level disclosure to more firms and/or providing more financial statement line items should not only increase the quality of information available to investors by reducing reporting manipulation and information asymmetry (Yu, Lin, and Tang 2018), but should also result in real effects as managers constrain potentially undesirable actions (Dye, 1990).

Technological advances, including blockchain and development of real-time open-source data systems, have accelerated the debate surrounding informational transparency. Public blockchain transactions are recorded instantaneously, can not be altered, and can be viewed by anyone with internet access. Such transparency can increase trust and theoretically eliminate the need for public company audits (Morehouse, 2017). However, opponents of mandatory transaction-level disclosure cite potential costs of requiring this level of granularity. Types of costs include direct costs, proprietary costs, and systemic costs. Although technology has reduced direct costs associated with disseminating, accessing, and processing data, more complete disclosure can result in indirect proprietary and systemic costs. In the context of investment data, transaction-level disclosure by investment companies and insurance firms permits other firms to copy proprietary trading strategies and extract profits (Cao et al., 2021). Such behavior not only adversely affects the firm's competitive position, but also has broader market-wide consequences such as increasing systemic risk (Hagenberg, 2022).

[1] For example, insurance companies are required by regulators to provide transaction-level data for each investment, while the SEC requires certain investment companies to provide unaggregated investment-level balances at period-end.

[2] Citing Louis Brandies, whose ideas were a major influence on the disclosure philosophy of regulation, SEC Commissioner Paredes explained that "[p]ublicity is justly commended as a remedy for social and industrial diseases. *Sunlight* [emphasis added] is said to be the best of disinfectants; electric light the most efficient policeman (SEC Commissioner Troy A. Paredes, October 16, 2009)."

The focus of this study is to examine the impact of sunshine disclosure laws on manager behavior. These sunshine laws exist in a variety of settings. For instance, among state and local governments, open meeting sunshine laws exist to constrain self-dealing and assure accountability to the public. Similarly, for insurance companies, the purpose of mandatory transaction-level disclosure is to aid regulators and promote public monitoring of intra-period investment risk (NAIC, 1906). However, to be effective, users of financial information must have sufficient incentives to expend personal effort to monitor, sufficient expertise to process information provided, and some control mechanism by which to influence management decisions. There is some evidence that these necessary conditions are not present in the insurance industry.[3] Given this tension, our aim is to examine the premise that full disclosure eliminates window dressing. Thus, our research question is equivalent to asking whether sunlight is indeed the best disinfectant in the context of transaction-level disclosure.

There are several reasons full disclosure by itself may not curtail window dressing. First, shareholders may benefit from risk-taking while regulators, consumers, and other creditors wish to constrain it. Therefore, disclosures targeted to equity investors that have incentives for additional risk taking may not work to reduce risk. Second, insurance company creditors may not be effective monitors. The primary creditors of insurance companies are customers with claims on loss reserves. Thus, insurance company customers are similar to bank depositors, representing a diffuse base of claimants without the clear control mechanisms available to traditional creditors. While customers can theoretically "vote with their feet," consumer purchase of insurance is frequently required, and alternatives may be limited. Similar to bank depositors, insurance

[3] Despite the granularity of investment disclosure, regulators continue to express concern that insurance companies may be taking on excessive idiosyncratic investment risk to maximize short-term returns, a term known as "reaching for yield" (NAIC, 2018; Ellul et al., 2018).

customers may be financially unsophisticated or limited in their individual processing capabilities; however, unlike depositors, insurance company customers do not benefit from government indemnification of their claims. Therefore, whether insurance company customers can respond to disclosure and constrain company risk-taking is an open question.

Reflecting these market frictions, both banks and insurance companies are regulated with the objective of protecting consumers and capital markets from adverse consequences related to failure. In this sense, regulators "stand in" for customer claimants and are granted a direct statutory control mechanism over the company and its managers. However, research suggests field-level regulators may not be consistent or effective risk monitors because they lack incentives or expertise, or are captured by the industry (U.S. Government Accountability Office, 2020). Regulatory frictions may be exacerbated in the insurance industry relative to banking because insurance companies are regulated at the state level with variable levels of oversight and examination frequencies. Due to time and budgetary constraints, insurance regulators often perform reviews of ratios on an annual basis to determine whether the insurance company meets the regulatory requirements or requires a more thorough level of investigation (NAIC, 2018). If insurance regulators primarily focus on year-end reported numbers, transaction-level disclosure may go unused by those who could most effectively monitor.

To examine whether insurance companies engage in opportunistic window dressing in the presence of full disclosure, we exploit insurance company transaction-level disclosure to create a novel measure of window dressing that captures intra-period portfolio risk during our sample period, 2009 to 2017. This measure reflects the weighted portfolio risk after adjusting risk for size of the asset and the number of days within the reporting window it is held. Our measure is based on National Association of Insurance Commissioners (NAIC) assigned credit ratings for each fixed income and preferred equity held in the portfolio.[4] We compare the average portfolio risk during the period to the period-end risk to assess the extent of window dressing at period end. We believe our approach improves on measures of window-dressing used in prior research, which relies on more indirect assessments of period-end restructuring.[5]

We begin our empirical analysis by comparing the association between the intra-period weighted portfolio risk measures and the point-in-time portfolio risk at year-end. Univariate evidence suggests industry wide intra-period weighted portfolio risk is significantly higher than the end of year point-in-time portfolio risk. These results are consistent with managers window dressing at year-end to reduce their perceived portfolio risk. In cross-sectional analyses, we examine whether insurance companies with the greatest incentives to window dress are most likely to reduce the risk of their portfolio at year-end. In particular, we expect that insurance companies that face greater regulatory risk will be more likely to make the largest increases in their portfolio risk during the year and then lower the portfolio risk at the end of year to reduce the likelihood of regulatory scrutiny. To quantify regulatory risk, we exploit Insurance Regulatory Information System (IRIS) ratios. These IRIS ratios focus on items like capital adequacy and liquidity and are utilized by insurance regulators to monitor insurance company. Consistent expectations, we find that window dressing is positively associated with regulatory risk.

Next, we provide direct evidence related to firms' asset sales and repurchases. If firms are window dressing, they should risk up at the beginning of the fiscal year to reach for yield, and then risk down at year-end to present a less concerning portfolio to regulators. Our results reveal that

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[4] Insurance companies primarily invest in fixed-income securities, matching investment cash inflows with expected cash outflows for insurance claims. Insurance companies are significant institutional asset owners, holding over 1/3rd of the corporate bond market and 1/10th of the estimated Russell 3000.

[5] Prior literature relies on period-end adjustments and correlation with investment returns to conjecture the existence of window dressing. In contrast, our approach finds a precise change in risk between year-end and the during-period portfolio.

the highest-risk assets carried in the insurance industry are generally purchased in the first two weeks of the year and sold in the last two weeks of the year. All of this additional trading activity at year-end is not without cost. We estimate (untabulated) that in the 30 days surrounding the end of the year (i.e., the 15 days before and after year-end), there is approximately $73 billion dollar in abnormal trading relative to other 30-day periods throughout the year. Assuming transaction costs related to trading commissions, bid ask spreads, and price pressure range between 0.2% to 0.5% of the transaction amount, the incremental transaction costs at year-end would be between $147 and $368 million dollars each year.

Additional analyses show that window dressing is limited to year-end reporting (i.e., we find no evidence of this buying and selling pattern during any of the other three quarters). Our quarterly comparisons help mitigate concerns that the results are driven by routine quarterly portfolio rebalancing and help to tie the window dressing behavior to regulatory concerns. Although regulators are most focused with portfolio composition at year-end, other market participants concerned with excessive risk taking throughout the year would be equally concerned at other quarterly reporting cut-offs. Thus, our results suggest that the window dressing activity appears to be driven primarily by year-end regulatory concerns.

Taken together, our results suggest the mere existence of transaction-level disclosure even in a highly regulated industry does little to eliminate window dressing behavior and highlight potential limitations of transaction-level disclosure as an effective solution to agency problems (Yermack, 2017; Kaal, 2020). Our results have implications for regulatory policy and academic research. Given documented proprietary and systemic costs, the absence of benefits of mandatory transaction-level disclosure suggests such policies may impose net costs on preparers and the financial system. For academic research, our results suggest full disclosure may not effectively constrain managerial actions. One plausible explanation for the existence of this window dressing behavior is that the sheer volume of investment transactions today leads to too high of processing costs for regulators to properly address the intra-period risk. As such, our findings extend literature suggesting the utility of financial information is limited by user processing costs of financial reports (Blankespoor et al., 2020).

2. Background and Hypothesis Development

2.1 Insurance Regulatory Background

The McCarran-Ferguson Act of 1945 delegated insurance company oversight exclusively to states. This is in sharp contrast to banking institutions that are regulated by the Federal government. In subsequent decades, Congress has questioned the efficacy of state regulation by commissioning studies by the Government Accountability Office (GAO), holding public hearings to address concerns that states are not adequately funding insurance regulation, and finding that monitoring is frequently deficient (Subcommittee on Oversight and Investigations, 1990). At a minimum, the efficacy of insurance regulation varies greatly across states given different levels of emphasis and funding.

The primary mechanism for routine regulatory solvency surveillance consists of Financial Analysis Solvency Tools (FAST) maintained by the NAIC. As described by the NAIC, "FAST is intended to assist regulators in prioritizing resources to those insurers in greatest need of regulatory attention" (NAIC 2012). Key tools within FAST include ratios computed by the Insurance Regulatory Information System (IRIS) that are reviewed by state examiners and analysts.[6] In the

[6] The Insurance Regulatory Information System (IRIS) financial ratios are a collection of analytical solvency tools and databases designed to provide state insurance regulators with an "integrated approach to screening and analyzing the financial condition of insurers operating within their respective states" (NAIC Financial Analysis Handbook, 2018). Regulators calculate these ratios at year-end for an 'efficient' assessment of insurance company financial condition.

analysis review stage, computer-generated lists of potential problems are reviewed and validated, and a supervisory plan is developed for each insurer detailing the need for any increased surveillance, including special scope examinations. In the absence of any system-generated red flags, periodic scheduled regulatory examinations, occurring as infrequently as every 3 to 5 years, provide the only independent check on solvency.

Investment portfolio holdings are a significant source of risk and solvency in the insurance industry. Insurance company investment policies focus on providing a steady stream of long-term asset cash inflows that ideally are matched to actuarially-determined expected liability cash outflows. As a result of holding premium collections in reserve for future expected claims, insurance companies are among the largest investors in fixed income securities in the economy. Prudent investments include potentially illiquid investments with long duration and low credit risk. While an insurance company's core business is underwriting insurance policies, excess cash from underwriting invested in the capital markets is a core source of profitability. Regulators increasingly express concern that lower underwriting margins incentivize increased risk-taking to generate higher investment yields, a term called "reaching-for-yield," without adequate capitalization (NAIC, 2018; Ellul et al., 2018). Firms performing poorly on the underwriting dimension have significant incentives to increase the risk of their portfolios to achieve higher yields without holding additional capital. This can be achieved by "managing" reported risk metrics used to determine required regulatory capital.

Because investments are such an important component of capital preservation, regulations require insurance firms to report extensively on portfolio composition and transactions. Despite mandatory transaction-level investment reporting, investment losses have been at least partially responsible for several notable insurance company failures.[7] Existing regulation adopts defined limits and defined standards approaches. The former places limits on proportions of investment types, while the latter relies on insurers adopting a “prudent person” approach to investment. In addition to complying with portfolio restrictions, insurance companies with risky portfolios must hold capital greater than regulatory minimum standards. Although regulatory capital compliance is arguably the most significant determinant of costly regulatory intervention, the Insurer Receivership Model Act has broad provisions for regulatory action including not acting in the best interests of policy holders, operating in a hazardous financial condition, or concealing or altering financial records.

Due to limited resources at the state level, regulators tend to rely on reviews of period-end statutory report balances in lieu of more costly regulatory monitoring activities. This environment creates incentives for window dressing periodend reports, despite the availability of detailed portfolio transactions that theoretically make possible the unwinding of window dressing. Transaction-level (flow) data is not aggregated into user-friendly summary statistics as are the end of period reports. Thus, this setting is one in which a class of financial information users has a defined objective of downside risk monitoring but face high processing costs and constrained resources. If monitoring is not credible, we predict managers will window dress at year-end despite the regulators’ theoretical ability to unravel the behavior.[8]

[7] For example, National Heritage Life Insurance Company failed and was liquidated in 1996 amid claims of unsafe investments and fraud. At the time, it was considered one of the larger insurance company failures in history. More recently, despite extensive reporting and credit-grading, at least 15% of 2000-2017 insurance company failures were attributable to significant investment losses (A.M. Best,(2018).

[8] This is analogous to the lack of efficacy of signs on the roadway stating that speed limits are enforced by aircraft in the absence of credible enforcement (see Bittel, J. 2013. “Do Police Really Use Aircraft to Enforce Speed Limits?” Slate Magazine. Future Tense Column May 30, 2013. https://slate.com/technology/2013/05/speed-limit-enforced-by-aircraft-do-police-really-do-that.html).

Initial regulatory standards on investment portfolio composition, dating back to at least the mid-1800s, required companies to report a list of investments owned. When the number of investments was small, the investment portfolio could easily be reconciled to ensure compliance with regulatory limitations on ownership of risky asset types. As options for investment grew over time, regulatory standards shifted from a list of owned securities to more granular financial reporting. Insurance companies were initially required to report individual holdings at year-end by CUSIP. This was followed several decades later by the requirement to report individual transactions taking place during the year (NAIC, 1906). The motivation for requiring transaction-level reporting was to ensure that between periods, insurance companies were holding only acceptable investments. Currently, the number of investments available for purchase is in the hundreds of thousands, limiting the feasibility of manual review. At the same time, investment in technological regulatory infrastructure has not kept pace (Grace and Klein, 2009).

2.2 Window Dressing

In retail businesses, window dressing is the practice of arranging goods in the store window to make them seem more attractive. Although successful window dressing can result in significant consequences for firms (Bartov et al., 2002), relatively few studies investigate whether changes in accounting standards and disclosure influence management decisions to engage in earnings management. In finance, the practice has been examined in the context of fund managers selling losers and buying winners to appear more attractive on period-end statements (Lakonishock et al., 1991). However, results are mixed. Hu et al. (2014) find little evidence of window dressing. In contrast, Agarwal et al. (2014) find evidence that poorly- performing managers engage in window dressing, and such activities are value-destroying and contribute to lower future performance. He et al. (2004) examines whether window dressing behavior is more prevalent among certain types of fund managers and finds support for the hypothesis that external money managers are more likely to engage in window dressing than internal money managers (e.g., pension fund or endowment managers). From a regulatory perspective, prior literature finds evidence of window dressing to minimize the perceived risk of bank short-term borrowings (Owens and Wu, 2012). In insurance companies, window dressing and other reporting manipulation occurs to circumvent unwanted regulatory scrutiny (Petroni, 1992; Gaver and Paterson, 2004).

A predominant assumption in the window dressing literature is that periodic aggregate reporting without detailed intra-period transaction data affords the opportunity to window dress. This is consistent with literature suggesting transparency is critical to the monitoring process (Bushman and Smith, 2001; Lambert, 2001; Armstrong et al., 2010; Stephanou, 2010) and underlies recent calls to mandate transaction-level disclosure (Yermack, 2017; Kaal, 2020) through distributed automated ledgers (e.g., blockchain). Empirical literature addressing whether greater transparency constrains opportunistic reporting typically uses frequency of disclosure as a proxy for transparency and finds mixed results. Jo and Kim (2007) argue that more frequent disclosure increases transparency and reduces incentives to manage earnings because increased transparency helps investors detect earnings management. Consistent with their predictions, proxies for earnings management are inversely associated with disclosure frequency. However, Ernstberger et al. (2017) find that real activities manipulation increases as mandatory periodic reporting frequency increases from semi-annual to quarterly and attribute the results to increased short-termism arising from more frequent reporting.

Our study differs from this stream of literature because we do not examine the effect of transparency on financial statement manipulation in the context of more frequent disclosure of aggregated amounts. Instead, we examine whether costly real activities designed to improve reported performance are constrained by complete disclosure throughout the period. Thus, our study holds constant the potential confounding effects of increased short-termism documented by Ernstberger et al. (2017) in which transparency is measured in terms of reporting frequency. Closest to our research question is literature examining whether new mandatory disclosure reduces earnings management of specific accruals. However, this research is both limited and provides mixed results. For example, Cazier et al. (2015) find no evidence that enhanced disclosures of tax reserves mandated by Financial Accounting Standards Board Interpretation 48 (FIN48) reduced excess accruals through the reserve for income taxes.

2.3 Hypothesis Development

As previously discussed, insurance companies' main source of income stems from investing. In order to achieve larger returns, many companies invest in higher-risk investments. However, regulators are concerned about insurance companies' solvency and thus perform annual reviews of investment risk at year-end. The state insurance regulators' limited resources make period-end statutory report balances a focal point of annual reviews. Although investment transaction detail is available to regulators wherein, theoretically, real risk exposure can be quantified and monitored, the primary regulatory process appears to focus on aggregate year-end ratios in assessing financial condition and solvency. Further, due to processing costs (Blankespoor et al. 2021) a full review of detailed transactions is likely to occur only when insurers significantly violate aggregate regulatory ratios. Combined, these incentives suggest that managers will reduce the risk of their portfolios at year-end to avoid regulatory scrutiny. These arguments lead to our primary hypothesis, stated in the alternative form:

H1: ***Insurance firms are likely to decrease the riskiness of their investment portfolio at year-end relative to the risk taken during the year.***

3. Measuring Risk-Taking

Prior literature seeking to identify window dressing typically associates period-end investment levels with intra-period investment income. For example, increased holdings in winners and decreased holdings in losers without the respective investment income to match would indicate potential period-end window dressing. In this study, we exploit the reported granularity of the investment portfolios to calculate both during period aggregate risk through an intra-period weighted portfolio risk measure as well as various point-in-time value weighted security holdings. These metrics provide a way to compare the actual portfolio risk held during the reporting periods to point-in-time portfolio risk at particular reporting dates. We primarily compare to year-end given rhetoric in regulator policies and procedures. We discuss our design of each risk measure below.

3.1 Regulatory Risk

In all of our measures of portfolio risk, we rely on an assessment of credit risk. In particular, each fixed income and preferred stock held by an insurance company is evaluated by the NAIC and given a credit risk measure between 1 and 6. A value of 1 represents a low-risk security (i.e., AAA bonds), and a value of 6 represents a security near or in default (i.e., C or below bonds). While credit risk is only assigned to certain asset types, it is representative of over 80% of most insurance company portfolios. This measure can then be value weighted across an insurer's portfolio to ascertain a depiction of aggregate portfolio risk.

3.1 Intra-Period Portfolio Risk

We begin by measuring the intra-period portfolio risk held during the reporting period, labeled as *Portfolio Risk (Intra-Period)*. For this measure, we multiply the security value by the number of days it was held during the year. We then multiply this measure by the credit risk factor.

We then scale by the total intra-period portfolio value to find an aggregate portfolio risk assessment. This provides a portfolio risk value between 1 and 6, where lower numbers are associated with lower risk. The *Portfolio Risk (Intra-Period)* measure provides for an assessment of the annualized during period-risk, accounting for intra-period behavior.

$$Portfolio\ Risk\ (Intra - Period)_{\ i,t}$$
$$= \frac{\Sigma(Security\ Value_{i,t} * Security\ Risk\ Assessment_t * Days\ Held_{i,t})}{\Sigma(Security\ Value_{i,t} * Days\ Held_{i,t})}$$

where *Portfolio Risk (Intra-Period)*$_{i,t}$ is the days-weighted, value-weighted portfolio risk for firm *i* in reporting year *t. Security Value* is the most recently reported carrying value of the security within the reporting year. *Security Risk Assessment* is the NAIC assigned credit assigned to that particular CUSIP. *Days Held* is the total number of days within the reporting period that the insurance company held the security in year *t*.

This measure would weight a credit risk security with a risk rating of 6 held from January 2nd to December 30th more than a credit risk security with a risk rating of 1 held from November 30th to December 2nd. In the first case, the insurance company holds a security in near default for 363 days, and in the second case, the insurance company holds the security that is likely a federal treasury bill for only the four days during the year.

3.2 Point-in-Time Portfolio Risk

The point-in-time portfolios value weight the security by the assigned credit risk measure at a specific date during the reporting period. By definition, these measures are somewhat limited as they reflect the risk on only one particular date during the reporting period. In contrast to the intra-period portfolio risk measure, we simply calculate the weighted value risk for every security held on that specific date. The portfolio is scaled by the total portfolio value to again have a measure of credit risk between 1 and 6 for all holdings.

$$Portfolio\ Risk\ (PIT)_{i,t} = \frac{\Sigma(Security\ Value_{i,t} * Security\ Risk\ Assessment_t)}{\Sigma(Security\ Value_{i,t})}$$

where *Portfolio Risk (PIT)* is the point-in-time value weighted portfolio risk for firm *i* at time *t*. *PIT* can take the form of any date during the reporting year. Security *Value* is the most recently reported carrying value of the security as of the point-in-time date. *Security Risk Assessment* is the NAIC assigned credit risk assigned to that particular CUSIP in year *t*.

3.3 Window Dressing

After calculating the intra-period portfolio risk and the point-in-time portfolio risk we then compare these measures to the year-end 12/31 point-in-time portfolio risk. We deem window dressing as the difference between the calculated risks and what is reflected on 12/31 scaled by what is reflected on 12/31. A decrease in portfolio risk for year-end reporting purposes can be considered the extent of window dressing.

$$Window\ Dressing_{i,t} = \frac{Portfolio\ Risk\ (Intra - Period)_{i,t} - Portfolio\ Risk\ (PIT)_{i,t}}{Portfolio\ Risk\ (PIT)_{i,t}}$$

where *Window Dressing* is the difference between the *Portfolio Risk (Intra-Period)*$_{i,t}$ measure and the *Portfolio Risk (PIT)*$_{i,t}$ measure, scaled by the *Portfolio Risk (PIT)*$_{i,t}$ measure.

4. Data and Empirical Results

4.1 Data and Sample Construction

The data used in this study comes from SNL Global Market Intelligence (SNL). For CUSIP-level data, we use a unique dataset derived from the mandatory regulatory filings of U.S.

Life and P&C insurance companies.[9] These supporting schedules present a disaggregated list of individual debt and equity securities included in aggregated balance sheet captions, as well as any acquisitions and disposals during the reporting period. The regulatory reports are centrally filed with the NAIC, who then provides the regulatory reports to SNL for broad dissemination. SNL is a data aggregator that makes the data available to subscribers in a structured, electronic form for a fee. From annual and quarterly regulatory filings accessible through SNL, we create a firm-year CUSIP data panel spanning from 2008 to 2017.

The granularity of the supporting schedules allows us to construct portfolios at any time during the year, capturing portfolio composition and underlying idiosyncratic investment risk over the reporting period and at any point in time. Upon calculating measures of portfolio risk, we refine the transaction-level sample to a firm-year data panel and a credit rating-year sample spanning from 2008-2017. For the firm-year data panel, we take several steps to remove certain observations. We remove any firms that are headquartered outside the U.S. due to variation in international insurance regulation. Next, we remove firms with missing data needed for analyses. Lastly, we remove observations from 2008 used to create lag variables. To remove the potential for extreme data errors influencing our results we winsorize all continuous variables at the 1st and 99th percentile. During the sample period, we observe 23,713 firm-year observations.

<Insert Table 1, Panel A Here>

For the credit rating-year data panel, we remove observations from 2008 to be consistent with the firm-year sample. This panel examines timing of trading volume based on credit rating of each security. During the sample period, we observe 54 rating-year observations (6 possible ratings per year, for 9 years).

[9] We do not consider the health line of insurance companies due to the significant variation in regulatory protocols and horizon of investment strategy.

<Insert Table 1, Panel B Here>

4.2 Summary Statistics

We report summary statistics for the overall sample of individual insurance companies at the firm-year level in Table 2. The mean individual company has an asset size of $1.7 billion with a portfolio size of $1.1 billion and a return on assets of 1.89%. The average portfolio risk at year-end is 1.35. The intra-period portfolio risk is 1.36. This suggests the average insurance company carries relatively low idiosyncratic investment risk at year-end and throughout the year. However, the range of portfolio risk is more vast ranging from 1 up to the 3.55 for point-in-time year-end risk and 3.66 for the days weighted intra-period risk. This is consistent with the notion that risk is higher during the year for certain insurance companies seeking to carry more risk. The average insurance company has a mean dollar trading volume of almost $963 million, and median dollar trading volume of $71.3 million. Lastly, the average insurance company violates about one IRIS ratio, equivalent to the median of 7.7% shown, ranging from 0% up to 53.8%. The wide variation in IRIS ratio violations provides some justification to suspect that number of violations may trigger further regulatory scrutiny and/or intervention.

<Insert Table 2 Here>

4.3 Univariate Correlations

Table 3 presents a correlation matrix of variables used in analyses at the firm-year level. Pearson correlation coefficients are shown below the diagonal and Spearman rank correlation coefficients appear above the diagonal. *Size* is positively associated with *Portfolio Risk (PIT) 12/31 (Pearson Corr. = 0.36)* measures suggesting larger insurance companies carry higher risk investment portfolios at year-end, consistent with the notion that larger insurers have more sophisticated investment arms. However, *IRIS Score* is also positively associated with *Portfolio*

Risk (PIT) 12/31 (Pearson corr. = 0.06), consistent with the notion that regulatory scrutiny considers investment risk. Additionally *Trading Volume (Dollars)* is positively associated with *Portfolio Risk (PIT) 12/31 (Pearson corr. = 0.02)* suggesting that more active investors also carry more risk at year-end.

<Insert Table 3 Here>

4.4 Window Dressing Evidence

4.4.1 Univariate Evidence

To test our hypothesis, we begin by examining the intra-period risk with the risk at the end of various reporting periods. We predict that managers will be likely to window dress at year-end to avoid regulatory scrutiny. Table 4 provides univariate comparisons of intra-period portfolio risk with year-end portfolio risk. Consistent with our expectations, we find in Panel A of Table 4 that *Portfolio Risk (PIT) 12/31*$_{i,t}$ is significantly lower than the *Portfolio Risk (intra-period)*$_{i,t}$ measure (0.002, t-statistic = 1.82). This is consistent with managers reducing their portfolio risk at year-end.

As previously discussed, we expect window dressing to be greater when firms face higher regulatory scrutiny. To capture likely regulatory scrutiny, we rely on a compositive measure of ratios that regulators most likely consider in their assessment of financial condition. These ratios, known as the Insurance Regulatory Information System (IRIS) ratios, are designed to measure solvency and liquidity. They are calculated using the year-end regulatory reports issued by individual insurance companies. Insurance companies that fail one or more of the ratios (12 total for Life and 13 total for P&C) can be placed under the supervision of their state regulator. Thus, an insurance company is incentivized to (1) meet these ratios, or (2) clean up their financial such that if a regulator does decide to look based on a violation, everything else will appear to meet regulatory standards. We create a composite score of these ratios we call the "IRIS Score" which is a percentage of ratios violated.

We examine window dressing across high and low regulatory scrutiny based on the top and bottom terciles of *IRIS Score*. Consistent with managers being more likely to window dress when regulatory risk is high, we find in Panel B of Table 4 that the intra-period portfolio risk is statistically higher than portfolio risk at year-end (0.006; t-statistic = 2.77) for insurance companies that are in the top tercile of *IRIS Score*. In contrast, in Panel C of Table 4, we find no statistical difference when regulatory risk is low (-0.000, t-statistic = -0.70). Collectively, the evidence in Table 4 suggests insurance companies window dress their portfolio risk at year-end, and this is concentrated in firms with higher regulatory risk.

<Insert Table 4 Here>

4.4.2 Incentives for Window Dressing

Next, we re-examine the expectation that insurance companies with greater regulatory risk will be more likely to window dress. In particular, we examine the association of *IRIS Score* with the extent of window dressing in the following OLS regression, Equation 1, below:

$$Window\ Dressing_{i,t} = \beta_0 + \beta_1 IRIS\ Score_{i,t} + \Sigma Controls_{i,t} + Fixed\ Efects + \epsilon_{i,t} \quad (1),$$

where *Window Dressing* in this analysis is the difference between the *Portfolio Risk (intra-period)* and *Portfolio Risk (PIT) 12/31* for firm *i*, in year *t*, scaled by *Portfolio Risk (PIT) 12/31* in year *t*. *IRIS Score* is the percentage of IRIS ratios violated by firm *i* in year *t*. *Controls* is a vector of commonly used controls for the insurance industry, including *Size* calculated as the natural log of net total assets, *ROA* calculated as net income divided by net total assets, *RBC* calculated as ratio of adjusted capital to minimum authorized control level capital, *Liquidity* calculated as cash and short-term equivalents to total liabilities, and *Public* which is an indicator variable equal to one if the insurance company or its parent is publicly traded, and zerootherwise. [10] We also include firm and year fixed effects to control for time-invariant omitted firm characteristics and time-dependent economy-wide factors. More detailed variable definitions are available in Appendix A.

The coefficient $\beta_1$examines the association of likely regulatory scrutiny with the propensity to window dress the year-end repots. Consistent with our prediction that firms that are most likely to receive regulatory scrutiny and/or intervention are most likely to window dress their year-end reports, we predict β_1 to be significantly positive. We present the results of estimating Equation 1, in Table 5.[11] We find significant evidence of firms with a greater risk of regulatory intervention being more likely to window dress across both specifications presented in Table 5. In our most restrictive analysis presented in Column (2), where the results are presented with controls and firm and year fixed effects, we find a positively significant coefficient on *IRIS Score* (0.029, t-statistic = 2.74). The evidence in Table 5 suggests that firms with the greatest risk of regulatory intervention are most likely to have the greatest amount of window dressing.

4.5 Purchase and Sale of Risky Assets

4.5.1 Purchase and Sale of Risky Assets at Year-end

Lastly, we provide evidence of a potential mechanism for the window dressing of year-end reports. In particular, if insurance companies are attempting to increase risk during the year to reach for yield it is likely that they are purchasing their higher risk assets in the first part of the year and selling them in the last part of the year. To test this mechanism, we examine the

[10] Risk based capital (RBC) is a ratio of capital the insurance company has to a statutory minimum level of capital based on the company's size and the inherent risk of its financial assets and operations. Insurance companies are considered healthy when capital on hand is sufficient to cover any potential losses, as calculated by its risk. RBC is a primary metric monitored by insurance regulators.

[11] For brevity, we report results from only the strictest specifications going forward. In unablated analyses, all specifications with and without controls and with and without firm fixed effects are statistically similar.

association between a security's credit risk and its likelihood of being purchased or sold in the following OLS regression, Equation 2, below:

$$Dollar\ Sales\ (Purchase)\ Volume\ (Time\ Period)_t = \beta_0 + \beta_1 Credit\ Rating_{\ i,t} + Fixed\ Efects + \epsilon_{i,t} \tag{2}$$

where *Dollar Sales Volume* is the dollar volume of sales during a specific time period in year *t*. This takes the form of both sales volume and purchase volume and is examined at various half-month periods throughout the year. *Credit Rating* takes the form of an integer between 1 and 6 depending on the NAIC's assessed credit risk for the particular security. We also run specifications comparing a credit rating of 4 or above, relative to a credit rating 3 and below.

If managers are reaching for yield and then window dressing at year end, we would expect them to purchase risky assets at the beginning of the year and sell these risky assets at the end of the year. Consistent with this notion we begin by considering relative sales volume based on credit rating from 12/16 to 12/31 and relative purchase volume based on credit rating from 1/1 to 12/15. The coefficient β_1 examines the association between volume and credit rating. We predict $\beta_1$will be positively significant for both time periods, consistent with our prediction that insurance companies sell their high-risk assets at year-end and purchase their high-risk assets in the beginning of the year to reach for yield while simultaneously giving the perception that risk is lower at year-end than during the year.

Table 6 presents the results of estimating Equation 2. Column (1) presents results using an integer between 1 and 6 as assigned by the NAIC. Column (2) presents results using higher credit risk securities, a credit rating of 4 or over, relative to 3 and under. The dependent variable in these columns is *Dollar Sales Volume* between 12/16 and 12/31. In both columns, we find positively significant results (0.826, t-statistic = 2.84) and (3.216, t-statistic = 3.41). This evidence suggests that securities with higher credit risk tend to be sold in the final half of December relative to securities with lower credit risk.

Columns (3) and (4) replicate this test using *Dollar Purchase Volume* between 1/1 and 1/15. Again, we find positively significant results (0.972, t-statistic = 1.96) and (2.098, t-statistic = 1.70). Collectively, results from Table 6 suggest that insurance companies tend to sell higher risk securities at year-end and purchase them in the beginning of the year. This is consistent with reaching for yield only to window dress for year-end reporting.

4.5.2 Purchase and Sale of Risky Assets at Other Quarter Ends

We next perform several falsification tests using the credit rating year data panel around each of the first three quarter-ends of each year. If window dressing is primarily driven by concerns over year-end regulatory scrutiny, as opposed to scrutiny from other stakeholders or quarterly rebalancing, we would not expect β_1 to be significant in any of these first three quarter specifications.

We present the results of estimating Equation 2 in and around the first three quarters of the year in Table 7. As expected, we do not find statistically significant results across any of the purchases or sales in any of the first three quarters of a firm's reporting regime. This lack of evidence is consistent with managers window dressing specifically to avoid regulatory scrutiny. In particular, if the year-end result is simply a matter of portfolio rebalancing, we would expect this general pattern to also occur at each quarter. Further, if other stakeholders are monitoring the firm are worried about risk, and relying on quarterly reports, we would expect the same pattern to be seen. Since we do not observe this pattern, our results suggest the motivation is primarily due to the regulator focusing primarily on year-end.

5. Conclusion

The impact of intra-period transaction data on the likelihood of window dressing is anopen question. Our study uses the unique regulatory setting of U.S. insurance industry, where intra-period transaction period is available, to address whether the existence of this transaction data eliminates managers' window dressing behavior. Our evidence suggests that managers continue to window dress even with the availability of this detailed transaction data. Further, evidence shows that managers appear to buy higher-risk assets at the beginning of the period to "reach for yields" and then sell risky assets in the last few weeks of the year to de-risk the perception of the companies perceived portfolio risk. Our estimates (untabulated) suggest that all of this additional trading activity at year-end results in a significant transaction costs every year.

The evidence in this study is pertinent to regulators in the U.S. insurance industry, but perhaps more importantly speaks to a larger question of the implications of full ledger transparency. Such ledger transparency has been touted in blockchain-like registries to provide financial statement users with information on transactions that occur in the period between required reports. The evidence from this study suggests that such level of granularity may not prevent unwanted behavior even in a highly regulated environment. One potential reason for this behavior is that it remains costly for investors to process such large amounts of data (Blankespoor et al., 2020).

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Appendix A

Variable Definitions

VARIABLE NAME	DEFINITION
Measures of Window Dressing	
Window Dressing	The difference between calculated intra-period portfolio risk and point-in-time portfolio risk where the point-in-time is a reporting period, scaled by the point-in-time portfolio risk.
Variables to Construct Measures of Window Dressing	
Portfolio Risk (Intra-Period)	The annualized portfolio risk weighted by the number of days each security is held during the reporting period and its overall value to the total portfolio multiplied by its credit rating, scaled by the annualized total portfolio size.
Portfolio Risk (Point-In-Time)	Value-weighted portfolio risk where each security value is multiplied by its credit rating, scaled by the total portfolio size.
Other Variables Used in Analyses	
Net Total Assets (000s)	Total assets minus any valuation allowance, as of year-end
Size	Natural log of net toal assets
Net Income (000s)	Net income, as of year-end
ROA	Net income, scaled by net total assets
Net Invested Assets (000s)	Total value of portfolio holdings invested in the debt and equity markets
Risk Based Capital	The ratio of total adjusted capital to authorized control level capital, reported as a percentage, as of year-end
Liquidity	The ratio of cash and short-term equivalents to total liabilities, as of year-end
Public	An indicator variable equal to 1 if the firm or its parent was pulibcaly traded during the year
Credit Risk Rating	An integer between 1 and 6 that corresponds to the NAIC's Securities Valuation Office (SVO) designation of a security as reported by the insurer. Higher numbers imply greater expected losses (e.g., 1 = low risk, 6 = at or near default).
Credit Risk Rating = 1	An indicator variable equal to 1 if the security is rated a 1 by the NAIC, 0 otherwise.
Credit Risk Rating = 2	An indicator variable equal to 1 if the security is rated a 2 by the NAIC, 0 otherwise.
Credit Risk Rating = 3	An indicator variable equal to 1 if the security is rated a 3 by the NAIC, 0 otherwise.
Credit Risk Rating = 4	An indicator variable equal to 1 if the security is rated a 4 by the NAIC, 0 otherwise.
Credit Risk Rating = 5	An indicator variable equal to 1 if the security is rated a 5 by the NAIC, 0 otherwise.
Credit Risk Rating = 6	An indicator variable equal to 1 if the security is rated a 6 by the NAIC, 0 otherwise.
Trading Volume (Dollars) (000s)	Total dollars of trading volume during the period
IRIS Score	The number of IRIS ratios in violation, as of year-end
Capitally Constrained	An indicator variable equal to 1 if the insurer is in the bottom decile of capital, by line, as of year-end.

Table 1
Sample Selection

Panel A: Individual Company - Year Sample

Steps Taken	*Observations*
Raw Data from SNL, 2008-2017	32,922
Less Observations with HQ Outside the U.S.	-1,918
Less Observations with Missing Data	-4,084
Less Observations to Construct Lag Variables	-3,207
Final Sample, 2009-2017	**23,713**

Panel B: Credit Rating - Year Sample

Steps Taken	*Observations*
Raw Data from SNL, 2008-2017	60
Less Observations in 2008	-6
Final Sample, 2009-2017	**54**

Table 2
Descriptive Statistics

VARIABLES	*n*	*mean*	*sd*	*p1*	*p25*	*p50*	*p75*	*p99*
Window Dressing	23,713	0.005	0.106	-0.202	-0.018	0.000	0.018	0.303
Portfolio Risk (Intra-Period)	23,713	1.36	0.42	1.00	1.09	1.23	1.49	3.64
Portfolio Risk (PIT) 12/31	23,713	1.35	0.42	1.00	1.08	1.23	1.49	3.55
Net Total Assets (000s)	23,713	$1,689,604	$6,165,001	$2,538	$26,999	$100,873	$460,658	$45,200,000
Size	23,713	11.78	2.14	7.84	10.20	11.52	13.04	17.63
Net Income (000s)	23,713	$22,945	$87,481	-$64,240	$87	$1,313	$8,750	$616,320
ROA	23,713	1.89%	9.17%	-16.33%	0.28%	1.70%	3.65%	18.16%
Net Invested Assets (000s)	23,713	$1,069,483	$3,598,586	$988	$16,805	$69,988	$350,591	$25,000,000
Risk Based Capital	23,713	4876.78	24430.57	116.89	616.18	997.62	2007.21	53464.82
Liquidity	23,713	39.42	88.22	-2.59	3.79	11.09	32.32	556.26
Public	23,713	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Trading Volume (Dollars) (000s)	23,713	$963,526	$3,333,047	$380	$15,839	$71,277	$350,913	$24,300,000
IRIS Score	23,713	12.8%	12.7%	0.0%	7.7%	7.7%	16.7%	53.8%

Table 3

Pearson/Spearman Correlation Matrix

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	VARIABLES	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*10*	*11*	*12*	*13*	*14*
1	Window Dressing		**0.11**	**-0.14**	**-0.03**	**-0.03**	**-0.03**	0.00	**-0.04**	**0.02**	**0.02**	-0.01	**-0.04**	0.00
2	Portfolio Risk (Intra-Period)	**0.22**		**0.94**	**0.35**	**0.35**	**0.20**	**-0.03**	**0.36**	**-0.23**	**-0.23**	**0.02**	**0.36**	**0.07**
3	Portfolio Risk (PIT) 12/31	**-0.11**	**0.94**		**0.36**	**0.36**	**0.20**	**-0.03**	**0.38**	**-0.24**	**-0.24**	**0.02**	**0.37**	**0.06**
4	Net Total Assets	**-0.01**	**0.18**	**0.19**		**1.00**	**0.58**	**0.02**	**0.97**	**-0.24**	**-0.56**	**0.09**	**0.91**	**-0.08**
5	Size	**-0.04**	**0.21**	**0.22**	**0.59**		**0.58**	**0.02**	**0.97**	**-0.24**	**-0.56**	**0.09**	**0.91**	**-0.08**
6	Net Income	**0.00**	**0.15**	**0.15**	**0.68**	**0.50**		**0.66**	**0.59**	**0.03**	**-0.29**	**0.09**	**0.55**	**-0.35**
7	ROA	0.01	0.00	0.00	**-0.02**	**0.03**	**0.13**		**0.05**	**0.19**	**0.07**	**0.08**	**0.05**	**-0.35**
8	Net Invested Assets	-0.01	**0.19**	**0.19**	**0.94**	**0.61**	**0.71**	-0.01		**-0.22**	**-0.56**	**0.09**	**0.92**	**-0.14**
9	Risk Based Capital	0.01	**-0.10**	**-0.10**	**-0.04**	**-0.12**	**-0.04**	0.00	**-0.05**		**0.21**	0.00	**-0.25**	**-0.27**
10	Liquidity	0.05	**-0.07**	**-0.08**	**-0.10**	**-0.33**	**-0.09**	**0.02**	**-0.11**	**0.15**		**-0.03**	**-0.51**	**0.07**
11	Public	0.00	**-0.02**	**-0.02**	**0.03**	**0.09**	**0.09**	**0.04**	**0.04**	-0.02	0.00		**0.09**	0.00
12	Trading Volume (Dollars)	0.00	**0.18**	**0.18**	**0.88**	**0.57**	**0.66**	0.00	**0.89**	**-0.04**	**-0.11**	**0.04**		**-0.06**
13	IRIS Score	**0.04**	**0.10**	**0.09**	0.00	**-0.08**	**-0.10**	**-0.20**	**-0.03**	**-0.04**	**-0.04**	0.00	0.00	

Bold denotes statistical significance at .05

Table 4
Portfolio Risk Univariates

Panel A: Full Sample

VARIABLES	*n*	*mean*	*sd*	Portfolio Credit Risk (Intra-Period) Differences	(T-Statistic)
Portfolio Risk (Intra-Period)	23,713	1.356	0.420		
Portfolio Credit Risk (PIT) 12/31	23,713	1.354	0.416	0.002*	1.82

Panel B: High IRIS Score

VARIABLES	*n*	*mean*	*sd*	Portfolio Credit Risk (Intra-Period) Differences	(T-Statistic)
Portfolio Risk (Intra-Period)	6738	1.449	0.508		
Portfolio Credit Risk (PIT) 12/31	6738	1.443	0.504	0.006***	2.77

Panel C: Low IRIS Score

VARIABLES	*n*	*mean*	*sd*	Portfolio Credit Risk (Intra-Period) Differences	(T-Statistic)
Portfolio Risk (Intra-Period)	11489	1.302	0.345		
Portfolio Credit Risk (PIT) 12/31	11489	1.302	0.344	-0.000	-0.70

Table 4 reports univariate statistics of portfolio risk and the difference in means between the intra-period portfolio risk and the point-in-time portfolio at year-end. Variables are defined in Appendix A. ***, **, * indicate two-tailed statistical significance of coefficient estimates at 1%, 5%, and 10%.

Table 5
Incentives for Window Dressing

VARIABLES	Pred.	Window Dressing	
		(1)	(2)
IRIS Score	(+)	0.038***	0.029***
		(4.04)	(2.74)
Size		-0.001***	-0.010***
		(-3.20)	(-2.80)
ROA		0.020	0.023
		(0.99)	(0.95)
RBC		0.000	0.000*
		(1.23)	(1.87)
Liquidity		0.000***	0.000
		(3.02)	(1.43)
Public		0.000	-0.005**
		(0.10)	(-2.04)
Constant		0.015**	0.122***
		(2.53)	(2.81)
Year Fixed Effects		Yes	Yes
Line Fixed Effects		Yes	No
Firm Fixed Effects		No	Yes
Observations		23,713	23,544
R-Squared		0.009	0.190
Adjusted R-Squared		0.009	0.061

Table 5 reports OLS regression results where window dressing is the dependent variable and IRIS Score is the independent variable. Column 1 reports results with year and line fixed effects. Column 2 reports results with firm and year fixed effects. Standard errors are clustered by year. Variables are defined in Appendix A. ***, **, * indicate two-tailed statistical significance of coefficient estimates at 1%, 5%, and 10%.

Table 6
Dollar Volume Patterns by Riskiness of Security

Abnormal Volume by NAIC Rating Around Year-End

VARIABLES	Pred.	Dollar Sales Volume (From 12/16 to 12/31) (1)	(2)	Dollar Purchase Volume (From 1/1 to 1/15) (3)	(4)
NAIC Rating (1 to 6)	(+)	0.826**		0.972**	
		(2.84)		(1.96)	
NAIC Rating (>=4)	(+)		3.216***		2.098*
			(3.41)		(1.70)
Constant		5.334***	6.619***	4.869**	7.222***
		(5.24)	(14.04)	(2.80)	(11.72)
Year Fixed Effects		Yes	Yes	Yes	Yes
Observations		54	54	54	54
R-Squared		0.425	0.479	0.230	0.175
Adjusted R-Squared		0.307	0.373	0.072	0.006

Table 6 reports OLS regression results where abnormal dollar volume is the dependent variable and NAIC credit rating is the independent variable. Columns (1) and (2) report abnormal dollar sales volume. Columns (3) and (4) report abnormal dollar purchase volume. Standard errors are clustered by year. Variables are defined in Appendix A. ***, **, * indicate two-tailed statistical significance of coefficient estimates at 1%, 5%, and 10%.

Table 7
Dollar Volume Patterns by Riskiness of Security – Falsification

Panel A: Abnormal Volume by NAIC Rating Around Quarter 1 End

VARIABLES	Dollar Sales Volume (From 3/16 to 3/31)		Dollar Purchase Volume (From 4/1 to 4/15)	
	(1)	(2)	(3)	(4)
NAIC Rating (1 to 6)	0.758		0.079	
	(1.20)		(0.26)	
NAIC Rating (>=4)		2.534		0.307
		(1.21)		(0.37)
Constant	9.016***	10.401***	6.414***	6.538***
	(4.08)	(9.97)	(6.07)	(15.75)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	54	54	54	54
R-Squared	0.252	0.250	0.377	0.378
Adjusted R-Squared	0.099	0.097	0.250	0.251

Panel B: Abnormal Volume by NAIC Rating Around Quarter 2 End

VARIABLES	Dollar Sales Volume (From 6/16 to 6/30)		Dollar Purchase Volume (From 7/1 to 7/15)	
	(1)	(2)	(3)	(4)
NAIC Rating (1 to 6)	-0.013		0.015	
	(-0.07)		(0.06)	
NAIC Rating (>=4)		-0.392		-0.139
		(-0.87)		(-0.16)
Constant	10.198***	10.350***	6.543***	6.666***
	(15.44)	(45.85)	(7.26)	(14.92)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	54	54	54	54
R-Squared	0.083	0.090	0.202	0.202
Adjusted R-Squared	-0.105	-0.097	0.038	0.039

Panel C: Abnormal Volume by NAIC Rating Around Quarter 3 End

VARIABLES	Dollar Sales Volume (From 9/16 to 9/30)		Dollar Purchase Volume (From 10/1 to 10/15)	
	(1)	(2)	(3)	(4)
NAIC Rating (1 to 6)	-0.312		0.064	
	(-1.07)		(0.43)	
NAIC Rating (>=4)		-0.416		0.096
		(-0.57)		(0.22)
Constant	11.246***	10.361***	4.138***	4.314***
	(11.03)	(28.59)	(8.01)	(20.06)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	54	54	54	54
R-Squared	0.346	0.319	0.406	0.402
Adjusted R-Squared	0.213	0.180	0.285	0.279

Table 7 reports OLS regression results where abnormal dollar volume is the dependent variable and NAIC credit rating is the independent variable. Columns (1) and (2) report abnormal dollar sales volume. Columns (3) and (4) report abnormal dollar purchase volume. Standard errors are clustered by year. Variables are defined in Appendix A. ***, **, * indicate two-tailed statistical significance of coefficient estimates at 1%, 5%, and 10%.