Does corporate governance matter? Evidence from the AGR governance rating

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ABSTRACT

Poor corporate governance facilitates unreliable financial reporting. The AGR governance rating is based on the premise that a more accurate assessment of corporate governance can be formulated by taking this output of corporate governance into account. We document that time series variation in a firm's AGR rating reliably forecasts measures of firm operating performance. A long/short strategy based on the AGR rating generates a risk-adjusted return of approximately 5% per year but, consistent with learning by the market, this abnormal performance has been declining over time. Most of this return differential originates with firms having poor corporate governance.

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1 Introduction

Academic research as well as numerous commercial endeavors attempt to quantify the effectiveness of a firm's corporate governance. The resultant metrics allow users to investigate potential links between corporate governance and a firm's subsequent operating performance and its stock price behavior.

In a seminal contribution, Gompers, Ishii, and Metrick (2003) propose the so-called G score which enumerates the number of anti-takeover measures adopted by a firm and document that a portfolio long shares of firms with strong shareholder rights (five or fewer measures and labelled as "democracies") while shorting shares of firms with weak shareholder rights (fourteen or more measures and labelled as "dictatorships") generates abnormal returns of 8.5% per year over the sample period 1990 to 1999. Subsequently, Bebchuk, Cohen, and Ferrell (2009) put forward the E or entrenchment index which relies on a subset of six of the twenty-four provisions considered in the G score that are most highly correlated with firm value and stockholder returns. They find that buying a portfolio of stocks of firms with non-entrenched management (a zero E index score) and selling short a portfolio of stocks of firms with entrenched management (a five or six E index score) earned abnormal returns of 7% annually over the 1990 to 2003 sample.

Although both the G and E measures have been widely cited and used, unfortunately the effects of governance on a firm' operating performance and stock returns remain unresolved. For example, Johnson, Moorman, and Sorescu (2009) argue that the significant abnormal return spreads earned by strategies relying on these measures is a statistical artifact of ignoring industry clustering. That is, industry instead of governance is the source of variation in returns across these governance portfolios. Once statistical tests are properly adjusted for these industry effects, Johnson, Moorman, and Sorescu (2009) find that the significance of the abnormal return spreads based on either the E or G measures is eliminated. Relatedly, Bebchuk, Cohen, and Wang (2013) put forward a learning explanation for the reduced profitability of portfolios that load on these corporate governance measures and argue that while this profitability may be waning, the link between governance and firm performance has been stable over time. Furthermore, statistical inference when dealing with corporate governance measures based on takeover provisions is complicated by the fact that these metrics show limited time variation. This then makes it difficult to establish a causality link between corporate governance and firm performance because the effects of corporate governance cannot be separated from those of other time-invariant firm characteristics, such as, for example, a firm's culture.

In addition to these academic studies, numerous commercial corporate governance measures have also been introduced. Firms such as Risk Metrics/ISS, Governance Metrics International, and The Corporate Library have provided institutional investors with the ratings of the quality of firm governance. Given their greater access to data and potentially more sophisticated models, it would be expected that these commercial measures would perform favorably against simple count scores like the G or E measures. To the contrary, Daines, Gow, and Larcker (2010) find that the governance ratings of these commercial providers bear little empirical relation to either a firm's subsequent operating performance, the likelihood of shareholder litigation, or the probability of financial restatements. However, they find somewhat stronger predictive evidence for MSCI's AGR governance rating[1] that uses information on financial statements in addition to observable corporate governance measures such as board structure. In contrast to other commercial corporate governance measures, Daines, Gow, and Larcker (2010) also find that AGR has modest ability to forecast excess stock returns, at least as of December 31, 2005. As argued by Daines, Gow, and Larcker (2010), AGR views a firm's financials as an output of its governance. That is, poor corporate governance facilitates unreliable financial reporting by a firm's management. Therefore, a more accurate assessment of the effects of corporate governance may be formulated by taking into account both corporate governance outputs as well as inputs.

[1]The AGR methodology was developed by Audit Integrity. In August 2014, MSCI acquired Governance Holdings Inc. which was formed by the merger of Audit Integrity, Governance Metrics International, and The Corporate Library. MSCI is now responsible for AGR ratings.

The purpose of this paper is to investigate the links between the quality of a firm's corporate governance as measured by its AGR score and its subsequent operating performance and stock price behavior. No systematic analysis of the AGR metric is available in the literature. To fill this void, we rely on an extensive database of AGR scores that ranks approximately 8,300 firms over the January 1997 to December 2011 sample period. This comprehensive panel data set affords us the opportunity to more carefully examine the links by which corporate governance impacts firm performance.

The AGR metric differs importantly from the G and E measures because a firm's AGR score exhibits non-trivial variation over time. For example, for the poorly governed firms that fall in the bottom 10% of the AGR distribution in a given month, only about 35%, on average, remain in this decile twelve months later. Similarly, about 40% of firms in the top 15% of AGR scores remain in this group after twelve months. We find little or no correlation between AGR scores and G and E measures. These findings confirm that AGR scores capture a dimension of governance that is distinct from that reflected by the number of anti-takeover provisions in place.

In light of this evidence, we ask whether corporate governance as captured by AGR is associated with higher future firm operating performance. We find that higher AGR-rated firms are indeed characterized by better future operating performance as measured by the firm's Return on Assets (ROA). In particular, a 10-point increase in AGR rating is accompanied by a 0.15% expected increase in that firm's 2-year ahead industry-adjusted ROA. A similar positive relation is found when relating the AGR score to other measures of a firm's output previously used in the literature such as Tobin's Q, net margin, and sales growth. In the cross-section, the effect is more pronounced for firms in the lower AGR decile, i.e. poorly managed firms. We also find that over time, the relation between AGR and operating performance is actually stronger in more recent years. Importantly, these results hold even after controlling for firm fixed effects and time-varying firm characteristics. While our tests cannot completely address the endogeneity of a firm's corporate governance structure, they increase the odds in favor of a causal link that runs from changes in a firm's governance to future profitability.

We also construct a portfolio that is long the stocks of better governed firms (i.e. Conservative, top 15% of AGR scores) and short the stocks of poorly governed firms (i.e. Very Aggressive, bottom 10% of AGR scores). We find that this portfolio delivers an abnormal return or alpha as large as 50 basis points per month when benchmarked against the 5-factor Fama and French (2014) model augmented by momentum as well as two accounting factors that load on the accrual and earnings surprise "anomalies". This result is robust to alternative portfolio formation strategies (value- versus equal-weighted, monthly versus annual rebalancing) and holds whether we use excess or industry-adjusted returns. Most of the profitability of this strategy originates with the portfolio of stocks having low AGR scores which delivers a negative and significant alpha of about 40 basis points. The significance of the loading on the AGR metric is further confirmed in Fama and MacBeth (1973) cross-sectional regressions that include a wide array of firm-level controls. Interestingly, we find that the premium for governance has been declining almost monotonically over time. This pattern is consistent with the learning argument of Bebchuk, Cohen, and Wang (2013) who find that the alpha associated with trading strategies based on the G and E measures has been waning in recent years.

Overall, these findings suggest that firms with poor corporate governance as captured by a low AGR score tend to be subsequently characterized by abnormally low returns and poor operating performance. Since a low AGR score also reflects an increased likelihood of shareholder litigation and financial restatements, our paper also contributes to the recent literature on unethical corporate behavior. For example, Biggerstaff, Cicero, and Puckett (2015) document that CEOs who backdate their options are more likely to engage in corporate misbehavior and to induce an unethical corporate culture. This behavior eventually results in more value-destroying acquisitions, more extensive reliance on accounting manipulations, and lower stock returns. Corporate fraud and misbehavior may ultimately undermine investors' trust in financial markets and have an overall detrimental effect on stock market participation (Giannetti and Wang (2016)). We contribute to this discussion by showing that a firm's AGR score aggregates valuable warning signals and reliably allows investors to identify firms at risk of corporate fraud.

2 The AGR Metric

A firm's AGR score measures the overall risk that the firm engages in fraudulent or misleading accounting and governance activities. Using publicly available information, MSCI's objective is to discriminate between fraudulent and non-fraudulent firms. To do so, it ranks firms by their AGR scores and then groups them ranging from Very Aggressive (bottom 10%) to Conservative (top 15%), with the bulk of firms being classified as Aggressive (25%) or Average (50%).

Being proprietary, the exact algorithm by which a firm's AGR score is calculated is not publicly available. However, in general, the following five risk categories are considered: (*i*) corporate governance, (*ii*) high risk events, (*iii*) revenue recognition, (*iv*) expense recognition, and (*v*) asset-liability valuation. Within each of these risk categories, multiple issues (or "games") are tabulated. There can be as many as twenty-five issues per category. For example, issues within the revenue recognition category include high operating revenues, large accounts receivables, large inventory, and small unearned revenues. Each issue, in turn, is measured by one or more metrics. For example, corporate governance metrics include the percentage of board directors who are officers, incentive compensation over total compensation for both the firm's CEO and CFO, and the ratio of CFO to CEO total compensation.

These metrics are the fundamental ingredients of an AGR score. In particular, firms that exhibit extreme values in these measures are hypothesized to be of higher risk of fraudulent accounting and governance activities. To that end, each metric is examined for unusual behavior according to (i) an industry comparison (number of inter-quartile ranges from the industry median), (ii) it's one year change (percentage change from previous year), as well as (iii) it's volatility (variance over the previous eight quarters). *Only* if a firm's particular metric exhibits unusual behavior, defined to be in the corresponding extreme 20% of all observed values, is that metric included in a firm's AGR score.

A firm's AGR score is then constructed as a weighted average of its extreme metrics. The weight assigned to a particular extreme metric value is determined by its importance in detecting fraudulent behavior. In particular, this weight is given by the estimated odds ratio associated with whether extreme values of the metric explain particular examples of fraudulent behavior. The scores are then transformed to fit a curve with the above predefined percentile cutoffs corresponding from Very Aggressive, with a minimum AGR score of 1, to Conservative firms, with a maximum AGR score of 100.

3 Data and descriptive statistics

We rely on a comprehensive database of AGR scores that ranks approximately 8,300 firms during the January 1997 to December 2011 sample period. AGR scores are generally updated after the public release of new quarterly or yearly financial statements. Because of this, changes in AGR scores may occur at any point in calendar time. In our analyses, we rely on monthly observations and only update AGR scores at the end of the month following a score change. We apply this lag to ensure that our regression results are not subject to any potential look-ahead biases. Once a firm's AGR score is updated, we retain this score until when it is updated once again. We match our AGR dataset to the Center for Research in Security Prices (CRSP) dataset using a firm's CUSIP number. Balance sheet and other fundamental data are collected from COMPUSTAT.

The original sample consists of 611,838 firm-month observations. Following the literature, we apply a series of filters to these data. First, we retain only stocks with a CRSP share code equal to 10 or 11, thereby eliminating companies incorporated outside the US, trusts, closed-end funds, and REITs. Next, we remove dual-class shares owing to their peculiar governance structure (see Gompers, Ishii, and Metrick (2010)). Finally, we remove stocks with a price lower than \$1 ("penny stocks"), and drop observations with a monthly return greater than 300% (16 observations) to avoid exceptionally high returns that may exert undue influence on our results. These filters leave us with a reference sample of 529,833 firm-month observations on 7,189 firms.

Next, we turn our attention to the time-series and cross-sectional characteristics of the AGR scores themselves. For each year in the sample period, Table 1 summarizes the distribution of AGR scores. After a few initial years, we see that both the number of observations as well as firms being followed remains stable. The distribution of AGR scores is also fairly stable over time, with median and mean AGR scores varying within the 45 to 54 range. The same observation applies to the 10th, 35th, and 85th percentiles that serve as cut-off points for AGR rankings from 'Conservative' to 'Very Aggressive'.

Johnson, Moorman, and Sorescu (2009) point out that particular care must be paid to control for industry composition when investigating corporate governance. To offer a first glimpse into this issue, Figure 1 displays the average number (blue bars) and market capitalization (grey bars) of AGR-rated firms as a fraction of the CRSP universe for each of the 30 Fama and French industries. We see that each industry appears to be equally represented in our sample, with average market capitalization fractions ranging from a low of 0.56% (the residual industry) to a high of nearly 1% ("Tobacco Products"). In what follows, based on the findings of Johnson, Moorman, and Sorescu (2009), we use the finer 3-digit SIC code to take into account industry clustering.

Table 2 examines the characteristics of the firms in our sample. In particular, the first set of rows report summary statistics for four measures of firm value and operating performance that have been related to corporate governance metrics in prior research, e.g. Daines, Gow, and Larcker (2010) and Bebchuk, Cohen, and Wang (2013). These include return on assets (ROA), Tobin's Q, net margin, and 3-year sales growth. All measures are industry-adjusted by subtracting the median value of the corresponding measure for all firms with non-missing COMPUSTAT data in the same industry in that fiscal year. The subsequent set of rows displays analogous statistics for the control variables that we use and that have also been relied upon in the prior literature: the market value of equity (Market Value); total assets (Assets); the ratio of capital expenditures to total assets (CAPEX/Assets); the debt-to-assets ratio (Leverage); and the ratio of R&D expenses to sales (R&D/Sales). The construction of these variables is detailed in the Appendix. For each year, we record all variables as of the fiscal year ending on or before December and match them to the firm's AGR score as of December of that year. Thus, a firm whose COMUSTAT last fiscal year entry for 2005 is recorded on May 2006 would be matched with its AGR score as of December 2005. We provide statistics for both levels and logs of equity and total assets as the log values will be used in our regressions to account for the high skewness of these variables.

At the median, the industry-adjusted characteristics of the firms in our sample are close to zero. This implies that AGR-rated firms are fairly representative of the universe of CRSP companies across each industry. The contemporaneous correlations of the firm performance measures with AGR, reported in the fourth column, indicate that highly rated firms tend to have, on average, a lower Tobin's Q, higher net margins, and to have experienced lower sales growth in the past three years. The correlations are, however, quite modest and never exceed 0.10 in absolute value. Turning to the controls, highly rated AGR firms appear to be significantly smaller in size, whether measured by equity or total asset value, and to be less levered.[2]

In our subsequent analyses, we report results using all AGR-rated firms as well as restricting attention to only those firms in the two extreme groupings, 'Conservative' and 'Very Aggressive'. For this reason, the last three columns of Table 2 report the average values of the performance measures and controls for these two groups and their differences. To properly account for potential time-series and cross-sectional correlations, statistical significance for

[2]These results are clearly not independent, as leverage is on average positively correlated with size.

the differences are based on doubly-clustered standard errors at both the year and firm level. The signs of the differences are consistent with the correlations reported across all firms. In particular, 'Conservative' firms tend to be characterized by higher net margins, lower sales growth in the prior 3 years, smaller size, and lower leverage. There is also some evidence, albeit economically more modest, that 'Conservative' firms have lower Tobin's Q. We note that the large difference in size is partly due to the impact of outliers. Median differences in Market Value and Assets appear less dramatic at $306 million and $363 million, respectively. Nevertheless, taken together, the evidence indicates that the two sets of firms appear *ex-ante* quite dissimilar. This suggests that including the controls in our analysis is key to ensuring that the AGR classification is not merely reflecting observables such as firm size.

The last two rows of Table 2 relate the AGR scores to the G and E measures. We focus on the data from the 1998, 2000, 2002, 2004, and 2006 Investor Responsibility Research Center (IRRC) publications that overlap with our sample period, and contrast the G and E measures with the last AGR score available for a firm in each of these years. The combined dataset consists of about 7,000 observations on about 2,400 firms. As a preliminary, we note that the mean (median) market capitalization of these firms is much larger, at about $7.5 billion ($1.5 billion), when compared to the corresponding results presented in Table 2. These values are comparable to those reported in Core, Guay, and Rusticus (2006) and highlight that corporate governance measures based on anti-takeover provisions tend to be available for larger firms. Turning to their correlations with corresponding AGR scores, they are nearly zero for the G score and slightly positive for the E index. This implies that the type of corporate governance information contained in AGR scores is distinct from that conveyed by indices based on anti-takeover provisions. If anything, firms in the 'Conservative' segment of AGR scores feature somewhat *higher* G and E measures as compared to the 'Very Aggressive', but the differences are not significant.

We next analyze the time-series properties of AGR scores. The top Panel of Table 3 reports the autocorrelation coefficients of AGR scores at the firm level at lags of 1, 2, 3, 6, and 12 months. AGR scores are characterized by significant time-variation, as can be gleaned by the 12-month autocorrelation of 0.47. This is in line with the 0.55 figure documented by Daines, Gow, and Larcker (2010) when working with their 2005 AGR snapshot. Panel B of the Table presents persistence statistics across the AGR groups. We assign groups at the beginning of each month and then track the firms within each group (from "Very Aggressive"= 1 to "Conservative"= 4) in the subsequent 1, 2, 3, 6, and 12 months. We then compute the average group value, the average AGR score, and the fraction of firms that remains in the same group after each period (Retention %). We see that the ordering in AGR groups is preserved even after a year. However, we also observe a convergence toward the average, which is consistent with the above-documented autocorrelation in AGR scores. For the group of 'Very Aggressive' AGR firms, about 35% of firms remain in that group after a year. The same statistic is slightly higher at 41% for firms in the other extreme, 'Conservative'. Similar conclusions hold when focusing on AGR deciles rather than groups in Panel C of the Table.[3]

4 The AGR metric and Operating Performance

In this section, we correlate AGR scores to measures of firm value and operating performance. Our goal is to investigate whether corporate governance, as captured by a firm's AGR score, is a reliable predictor of future operating performance. A distinct feature of our estimation approach is that, given the documented time-variation in the AGR score of a given firm, we are able to include firm fixed effects in our regression framework. This is in contrast with much of the previous research that relies on corporate governance indices that exhibit little or no time variation.

[3]While AGR data are available beginning in 1996, ratings were first released to the public in October 2004. In light of a potential look-ahead bias, we test the relation between AGR and operating performance at an annual frequency using the full sample of data and test for robustness in the post-2004 data. For the return analysis, we restrict our attention to the post-2004 period to ensure that our results represent that of a truly implementable trading strategy.

4.1 Return on Assets (ROA)

We begin by analyzing the relation between AGR scores and ROA. In the corporate governance literature, this measure has been used by, among others, Core, Guay, and Rusticus (2006) and Daines, Gow, and Larcker (2010). Under the hypothesis that good governance results in more value-enhancing decisions, we expect a positive relation between AGR scores and operating performance.

In Panel A of Table 4, we estimate pooled regressions of contemporaneous and future ROA on AGR scores. To capture the direct and indirect effects of governance, we investigate this relation both with and without including cross-sectional controls. As discussed above, ROA is industry-adjusted by its median value in the same three-digit SIC code industry. Future ROA is computed as the firm's ROA in fiscal year $t + 2$, thereby avoiding any potential overlap with the timing of our dependent variables.[4] All regressions include both year and industry fixed effects and ROA is expressed in percentage terms.

Column (1) of Table 4 shows that, consistent with Table 2, the contemporaneous relation between AGR and ROA is slightly negative, but not statistically significant. After controlling for firm characteristics (column (2)), however, we see that AGR scores appear to be positively and significantly related to ROA. In the next two columns, we include firm fixed effects. This amounts to asking whether variation in AGR scores for the same firm correlates with variation in its ROA. The loading on AGR is now much smaller at 0.012, and is significant only at the 10% level. In sum, there is some evidence that firms with higher AGR scores display better current performance than otherwise comparable firms.[5]

In columns (5)-(8) of Table 4, the dependent variable is now future ROA. Here the results indicate that AGR scores represent a reliable predictor of future firm profitability. The loadings are 0.011 (no controls) and 0.030 (with controls) when excluding firm fixed

[4] This implies that since a great majority of firms report financials in December of each year, we use the last available AGR score in, say, 2003 to predict ROA computed as of December 2005.

[5] The reduction in the number of observations (Obs.) when adding controls other than AGR is mainly due to R&D/Sales being often missing. When excluding R&D/Sales, the number of observations in specification (8) increases to 30,200, and the loading on AGR is smaller at 0.008 but again statistically significant (t-ratio of 2.03). Given the significance of R&D/Sales, we decided against excluding it from the set of regressors.

effects, both significant at the 1% level. The significance and magnitude of this relation are preserved when including firm fixed effects, implying that time-series variation in AGR scores for the same firm is indeed capturing future operating performance. To put these numbers in perspective, the 0.015 estimate in column (4) implies that a one-standard deviation increase in AGR, which is about 28 from Table 1, is associated with an expected increase in the firm's future ROA of about 0.42%.

In the bottom Panel of Table 4, we present estimates in analogous regressions where now the AGR score is replaced by dummies for firms in the "Aggressive", "Average", and "Conservative" groups of AGR scores. For contemporaneous ROA, we see that the relation with these AGR groups is not clear. For example, it is humped in specifications (1) and (4), increasing in specification (2), and decreasing in specification (3). This is in contrast with columns (5)-(8), where the loadings on AGR groups are monotonically increasing. From the estimates in column (6) that include time and industry fixed effects, we see that better firm governance is accompanied by improved ROA in the three groups of 0.241%, 1.247%, and 2.376%, respectively. A similar pattern is observed when including firm fixed effects, although the estimates are generally lower and are significant only for the 'Conservative' group.

4.2 Other operating performance measures

It is natural to ask whether the association between AGR scores and operating performance is restricted to ROA as a measure of firm performance. To address this question, we follow prior research that looks at whether governance metrics are useful determinants of future firm value (Tobin's Q), financial profitability (Net Margin), and operating growth (3-year sales growth).

Panel A of Table 5 presents the corresponding estimates for the specifications that include time, industry, and firm fixed effects. When entering alone as a predictor, we see that high AGR scores are associated with higher Tobin's Q, higher net margin, and higher sales growth.

The point estimates are 0.117, 0.049, and 0.056, respectively, and all are significant at the 5% level or better. When conditioning on our set of controls, however, the significance is preserved only for Net Margin, while for the other two measures the relations become insignificant (and negative in the case of sales growth). Overall, the evidence that AGR scores also reliably predict other dimensions of a firm' performance is indicative that the link between corporate governance and firm output is rather robust.

4.3 Additional analyses

We also conduct additional analyses to investigate the stability of our findings with respect to various dimensions of our dataset. In particular, we check whether our results are sensitive to the definition of the AGR groups by relying on AGR score deciles to form groups. We also work on sub-samples by excluding firms in the "Very Aggressive" group. Finally, we test for time-variation in these effects by introducing separate dummies for the pre- and post-2003 periods. The results for the predictive regressions of the four dependent variables on AGR with year and firm fixed effects are presented in Table 6. Overall, we find reliable evidence that AGR scores are related to future operating performance.

4.3.1 Deciles

Akin to the standard portfolio formation approach, we investigate the dependence between operating performance measures and AGR deciles, instead of the ratings *per se*. Working with deciles may increase the power of the tests while making identification stronger as the inclusion of firm fixed effects effectively restricts the sample to firms whose AGR decile changes over time. Results are reported in Panel A of Table 6. We see that AGR is an economically and statistically robust predictor of future performance, irrespective of how the latter is measured. For example, a one-decile increase in AGR is associated with a 0.55% increase in 2-year ahead sales growth.

4.3.2 Excluding low AGR firms

We test to what extent the results are driven by firms in the very low, i.e. tenth decile (D1) of AGR scores. In Panel B of Table 6, we repeat our analysis relating future performance to AGR scores while excluding firms in D1. The results show that AGR continues to predict future performance, although the statistical significance and the magnitude of the effects are weaker than compared to the evidence in Tables 4 and 5. From these results, we conclude then that AGR is a particularly valuable predictor for firms with weak corporate governance that are more prone to management misconduct. However, our evidence does not appear to be confined only to these firms in particular.

4.3.3 Subsample results

Finally, we investigate the time-variation in AGR predictability by estimating the operating performance regressions but including a separate interaction term of the AGR score with a pre- versus post-2003 dummy. The bottom panel of the Table indicates that the relation between AGR scores and firm performance is not confined to the 1997-2003 period. If anything, the relation is stronger in the latter subsample as the coefficient remains significant across all four operating performance measures (as opposed to the pre-2003 period, where it is insignificant in the case of 3-Year Sales Growth). Since AGR ratings became available to subscribers starting only in October 2003, these results also reassure us that our conclusions are not spuriously arising from any look-ahead bias in the dataset.

5 Stock returns and AGR scores

We next investigate whether corporate governance, as measured by AGR, is priced in stock returns. Initial but limited work by Daines, Gow, and Larcker (2010) suggests that a significant spread can be earned by going long well governed (high AGR) firms and shorting poorly governed ones (low AGR). The panel nature of our dataset allows us to investigate the returns obtained when loading on AGR over an extended period of time. In particular, as firms' AGR scores change over time, our analysis will be able to isolate the extent to which stock returns' react to changes in governance as opposed to company-specific attributes that otherwise cannot be controlled for with a single snapshot view of governance.

5.1 Portfolio performance regressions

We first analyze the performance of AGR-sorted portfolios. The portfolio formation is in the spirit of Fama and French (1993) and Hirshleifer, Hou, and Teoh (2012). As mentioned previously, for this analysis we restrict our attention to the post-2004 period to ensure that our results represent that of an implementable trading strategy. Specifically, at the end of each month starting in January 2005, we group firms into thirds based on their end-of-month market capitalization (from Small to Large) and, separately, by the four AGR groups (from Very Aggressive to Conservative). The intersection of these size and AGR groups yields twelve portfolios, ranging from S&VA (Small & Very Aggressive) to L&C (Large & Conservative). We compute each corresponding portfolio return in the subsequent month as, alternatively, the value-weighted (VW) or equal-weighted (EW) average returns to stocks within the portfolio, where the weights in the former case equal the relative market capitalization of a firm's stock as of the formation date. The portfolios are subsequently rebalanced every month. We construct returns to a given AGR group as the simple average across portfolios with different sizes.[6] Similarly to Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009), we also investigate the performance of a portfolio that is long better governed, high AGR stocks (Conservative) and short stocks in the bottom AGR group (Very Aggressive), AGR_p = (S&C+M&C+L&C)/3 - (S&VA+M&VA+L&VA)/3.

To assess whether AGR-based portfolios produce average returns that cannot be attributed to exposure to well-known risk factors, we rely on the following performance attri-

[6] So, for example, the Very Aggressive portfolio is constructed as (S&VA+M&VA+L&VA)/3.

bution model:

$$r_{p,t} = \alpha + \beta_1 \text{RMRF}_t + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \beta_4 \text{UMD}_t + \beta_5 \text{RMW} + \beta_6 \text{CMA} + \beta_7 \text{ACC}_t + \beta_8 \text{SUE}_t + \epsilon_{p,t} \quad (1)$$

where $r_{p,t}$ is the return to a given AGR-sorted portfolio, $p = \{Very\,Agg, Agg, Avg, Cons\}$, in excess of the 3-month T-Bill rate. The first four regressors are the standard Fama and French (1993) factors measuring zero-investment returns for exposure to market risk (RMRF), size (SMB), and book-to-market ratio (HML), plus the momentum portfolio UMD as constructed by Fama and French (1996). This is the benchmark model used in prior studies that investigate the performance of governance-sorted portfolios. Given the nature of AGR, however, we augment this list with four additional factors capturing trading strategies (risk factors) that are either related to operating performance or based on accounting information. The first two additional factors, RMW and CMA, have been recently proposed by Fama and French (2014) based on the evidence that profitability and investment have a significant role in explaining the cross-section of expected returns. RWA is constructed as the difference between the returns on diversified portfolios of stocks with robust and weak profitability. CMA is defined as the difference between the returns on diversified portfolios of the stocks of low and high investment firms. The final two factors are the accrual factor (ACC) of Hirshleifer, Hou, and Teoh (2012), constructed as the return difference to portfolios of stocks with low versus high accruals, and a portfolio based on standardized earning surprises (SUE). By including these two additional factors, we attempt to differentiate the corporate governance information contained in AGR from exposure to previously documented accounting-based "anomalies".[7]

Panel A of Table 7 presents the OLS estimates of the time-series regression, equation (1), for portfolios ranging from Very Aggressive to Conservative as well as for the AGR_p portfolio

[7] The ACC and SUE factors are characterized by the highest monthly Sharpe Ratio of 0.17 and 0.10, respectively, during our sample period. This too underlines the importance of including them in the analysis.

that is long Conservative firms and short Very Aggressive firms. The left-hand side of the Table is based on value-weighted returns, while the right-hand side is based on equal-weighted returns. As can be seen, the unexplained average monthly return or *Alpha* for the value-weighted Very Aggressive group is -0.451% and is significant at the 1% level. For the equal-weighted Very Aggressive portfolio, its *Alpha* is slightly lower at -0.337% but still significant at the 5% level. Thus, firms in the low AGR group deliver significant average risk-adjusted returns. High AGR firms also tend to outperform the benchmark model. However, the corresponding *Alpha* is quite small in absolute value, ranging from 0.090% (Conservative in the value-weighted case with a t-stat of 1.26) to 0.179% (Conservative in the equal-weighted case with a t-stat of 2.51). Taken together, the spread between Conservative and Very Aggressive firms for both value-weighted and equal-weighted portfolios is approximately 50 bps per month and is highly significant. This spread originates primarily from the group of Very Aggressive firms suggesting that the AGR score is particularly able to identify poorly managed firms. It is also noteworthy that this spread is greater when portfolio returns are computed in value-weighted rather than equal-weighted terms, and so is not the result of loading on smaller, and potentially more difficult to short shares.

Looking across risk exposures, we see that Very Aggressive firms load significantly and positively on the market, size, and book-to-market ratio risk factors. Interestingly, the Very Aggressive portfolio loads negatively on the momentum and RMW factors, confirming the view that these firms have recently experienced negative returns and suffered weak profitability. Across all portfolios and specifications, we find very limited exposures to the two accounting factors, the sole exception being the value-weighted Conservative portfolio with a -0.065 loading on the earnings surprise factor, albeit only marginally significant with a t-statistic of -1.71. In addition, Conservative firms appear to load only on the market and book-to-market ratio factors. The returns of the AGR_p portfolio that goes long Conservative firms while shorting Very Aggressive firms are only weakly related to the Fama and French (1993) factors but load positively and significantly on momentum and negatively but not significantly on the SUE factor.

In Panel B of the Table, we repeat this empirical analysis but now using industry-adjusted returns. Industry-adjusted returns are obtained by subtracting from each stock return its corresponding value-weighted three-digit SIC code industry return. Accounting for this industry effect now increases the AGR spread to 68 bps (value-weighted) and 71 bps (equal-weighted). As before, the large bulk of this spread is attributable to low AGR firms underperforming with respect to their peers. Interestingly, industry-adjusted *Alpha*s are now monotonically increasing across AGR groups. Overall, the significance of the risk factor exposures is similar to that documented in Panel A.

In addition to industry adjustment, we also investigate whether this unexplained return originates in specific industries. To that end, Figure 2 displays our estimates for *Alpha* when stocks from a given Fama and French industry are removed from the original sample. Notice that the numbers vary within a rather narrow range, from 0.525% (when excluding "Personal and Business Services") to 0.749% (when excluding "Business Equipment"), and are all highly statistically significant. These results confirm that the spread attributable to AGR is broad based and not particular to a specific industry.

In sum, the strategy of going long firms with high AGR scores while shorting firms with low AGR scores delivers a positive return even after adjusting for an extensive set of risk factors. These results are consistent with AGR capturing an important dimension of the effectiveness of corporate governance that is not fully reflected in contemporaneous stock valuations.

5.2 Fama and MacBeth regressions

As an alternative to AGR-sorted portfolios, we further evaluate the robustness of our findings by estimating monthly firm-level regressions using the approach of Fama and MacBeth (1973). This cross-sectional framework has the benefit of allowing the inclusion of a relatively large number of firm characteristics that is impractical to do in the time-series portfolio approach. We find that AGR's economic and statistical significance persists even when accounting for these additional dimensions of risk.

Specifically, each month t from January, 2005 to December, 2011 we estimate the following cross-sectional model:

$$r_{i,t+1} = \gamma_{0,t} + \gamma'_{1,t}\mathbf{X}_{i,t} + \epsilon_{i,t+1} \tag{2}$$

where $r_{i,t+1}$ is the return to stock i at the end of month $t+1$, and $\mathbf{X}_{i,t}$ is a collection of firm-specific control variables that are observed at the end of month t. The average coefficient, $\overline{\gamma}'_1 = 1/T\sum_t \gamma'_{1,t}$, measures the expected return (risk premium) to a zero-cost portfolio that loads on a given characteristic. Our interest is in the premium for AGR. Since AGR scores are hypothesized to be increasing in the effectiveness of governance, we expect a positive estimate of this premium reflecting positive returns to better governed firms. The comprehensive list of the conditioning variables in $\mathbf{X}_{i,t}$ follows from Hirshleifer, Hou, and Teoh (2012), and is based on evidence in the prior asset pricing and accounting literatures. These controls include the market beta (β) estimated on the prior 60-month period; log market capitalization; log book-to-market ratio; the stock return in month t (*Ret(t)*) and the cumulative return in months $t-12$ through $t-1$ (*Ret(t-12:t-1)*); idiosyncratic volatility (iv), as measured by the square root of average squared residuals from a 3-factor Fama and French (1993) model estimated using daily returns in month t, following Ang, Hodrick, Xing, and Zhang (2006); the value of the accrual *Accrual*, computed as in Hirshleifer, Hou, and Teoh (2012); and the most recent standardized earning surprise, *SUE*. In order to maintain comparability of the results across specifications, we restrict the sample to firms with at least 60 months of available return data.

Table 8 reports the average coefficients for the regression (2), along with their corresponding time-series t-statistics. Five different specifications of $\mathbf{X}_{i,t}$ are explored. In the first column, the AGR score enters alone as a determinant. The corresponding coefficient is positive at 0.006, and is strongly significant with a t-statistic of 2.93. In the second column, we add a first set of control variables. The coefficient on AGR is now slightly lower at 0.005, but with a larger t-statistic of 4.11. For the other regressors, we note that the weak relation between expected returns and market betas and book-to-market is consistent with Boyer, Mitton, and Vorkink (2010). In specification (3), we see that the coefficient on AGR remains stable at 0.005 when including Accrual and earning surprises.

Finally, we run a kitchen-sink regression in which we include all controls first excluding (column (4)), and then including (column (5)) the AGR score. In this specification, the loading on AGR remains positive at 0.005 and is significant at the 1% level with a t-statistic of 3.86. Among other factors, momentum and accrual stand out as the most robust predictors. The statistical significance of AGR goes hand in hand with its economic significance. The 0.005% monthly premium in Table 8 implies that an average difference of 83 points between the Very Aggressive and Conservative groups (from Table 3) translates into a monthly average return differential of 0.415%, or about 5% annually.

5.3 Time-series variation in AGR premium

From an asset pricing perspective, the fact that well governed firms persistently deliver higher risk-adjusted returns than poorly governed firms is puzzling. If differences between firms' future governance, and hence performance, are already incorporated in current valuations, it should not be possible to generate abnormal profits by trading on governance metrics.

A possible explanation for the documented profitability of our AGR trading strategy is that it reflects a slow adjustment towards equilibrium expected returns. As argued by Bebchuk, Cohen, and Wang (2013), if this is the case, we should detect a decline in abnormal returns as market participants begin to more aggressively trade on AGR even as we have observed that the relation between AGR and firm operating performance has actually become stronger with time. To investigate this possibility, we explore the time variation in the AGR premium. Specifically, Figure 3 displays the 24-month trailing average of the slope of the AGR metric from the full specification of the Fama-MacBeth regression (column 5 of Table 8). The plot reveals a distinct downward trend in the premium. From a peak of approximately

80 basis points (monthly) during the 2005 to 2006 time period, the premium declines almost monotonically and actually turns negative in 2009 before returning to zero by the end of the sample. Thus it appears that the declining profitability of corporate governance-based trading strategies, first evidenced by Bebchuk, Cohen, and Wang (2013), also extends to the AGR score.

6 Conclusions

Does the market reward well governed firms? How can we identify these well governed firms? Several academic papers have relied on anti-takeover provisions and other governance inputs to identify weakly governed firms. Johnson, Moorman, and Sorescu (2009) find that while the G and E measures have some correlation with poor operating performance and low Tobin Q values, they do not generate excess returns when industry clustering is accounted for. Similarly, commercial governance rankings have largely struggled in spite of their much better datasets and sophisticated models.

This paper focuses on MSCI's AGR governance rating that, unlike other governance ratings, relies on both governance inputs as well as outputs. We document that over the 1997-2011 sample period, a firm's AGR rating is economically and statistically related to future operating performance as measured by either ROA, sales growth, Tobin's Q, or net margin. The rating is especially valuable in tracking the performance of firms in the bottom AGR decile, that is, firms with poor corporate governance. In addition to operating performance, we investigate whether loading on AGR ratings generates abnormal stock returns. We document that a long-short portfolio that goes long better governed firms while shorting poorly governed ones delivers approximately a 5% risk-adjusted return even after controlling for an extensive set of risk factors. However, consistent with learning by the market, this abnormal performance has been declining over time. Taken together, our results confirm that corporate governance does systematically affect a firm's operating performance and its stock price behavior.

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Table 1: Descriptive statistics of AGR scores by year

We provide the following summary statistics for the annual distribution of AGR scores over our sample period January 1997 to December 2011: mean; standard deviation; minimum; 10th, 35th, 50th (Median), and 85th percentiles; maximum; number of firm-month observations; and number of firms (permnos).

Year	Mean	Median	Std Dev	Min	p10	p35	p85	Max	Obs.	# of Firms
1997	52.76	54	27.17	1	14	41	85	99	22,321	2,494
1998	53.78	55	27.41	1	15	41	85	99	28,678	3,010
1999	51.96	53	27.25	1	14	38	84	99	31,820	3,181
2000	48.12	47	27.09	1	11	34	81	99	33,384	3,380
2001	47.00	46	26.94	1	11	33	80	99	33,973	3,348
2002	46.62	45	26.77	1	11	32	79	99	35,271	3,373
2003	46.56	46	26.60	1	10	32	78	99	36,995	3,403
2004	47.02	46	26.73	1	11	33	79	99	39,484	3,628
2005	48.26	49	26.57	1	12	34	80	99	40,163	3,673
2006	48.33	49	26.62	1	12	35	81	99	40,633	3,739
2007	48.58	48	27.28	1	11	34	81	99	40,836	3,789
2008	47.25	47	27.10	1	11	33	81	99	37,251	3,548
2009	47.42	46	27.88	1	10	33	81	99	32,110	3,048
2010	50.99	51	28.13	1	11	37	85	100	36,324	3,711
2011	52.02	53	28.10	1	12	38	85	100	40,590	3,668

Table 2: Summary statistics of characteristics of AGR-rated firms

We provide the following summary statistics for characteristics of AGR-rated firms measured at year end: the number of firm-year observations for a characteristic; mean value of a characteristic; median value of a characteristic; the Pearson correlation of a characteristic with the firm's last AGR score available that year; the mean value of a characteristic for Conservative firms whose AGR score ranked in the top 15% of AGR scores that year; the mean value of a characteristic for Very Aggressive firms whose AGR scores ranked in the bottom 10% of AGR scores that year; the difference in mean values between characteristics of Conservative and Very Aggressive firms. See the Appendix for the definition of the variables. For the G score and E Index, the summary statistics are based on values observed in the years 1998, 2000, 2002, 2004, and 2006. For the other variables, the sample period is 1997 to 2011.

	Obs.	Mean	Median	Corr. with AGR	Mean Conservative	Mean Very Aggressive	Difference
ROA, Ind. Adj.	48,139	0.005	0.004	-0.002	-0.002	-0.007	0.008
Tobin's Q, Ind. Adj.	42,497	0.448	0.052	-0.040	0.345	0.477	-0.107*
Net margin, Ind. Adj.	48,001	-0.154	0.006	0.074	-0.088	-0.339	0.257***
3-Year Sales growth	39,285	0.245	0.003	-0.087	0.135	0.438	-0.303***
Market Value (in millions of $)	48,320	3,601	423.135	-0.126	1,181	8,877	-7,688***
Log(Market Value)	48,320	6.233	6.048	-0.172	5.714	6.626	-0.892***
Assets (in millions of $)	48,352	6,984	615.498	-0.099	2,398	26,397	-24,053***
Log(Assets)	48,352	6.506	6.422	-0.135	6.155	6.932	-0.769***
CAPEX/Assets	45,600	0.050	0.031	0.014	0.049	0.046	0.003*
Leverage	46,244	0.188	0.129	-0.055	0.163	0.206	-0.044***
R&D/Sales	24,384	4.923	0.049	-0.007	2.590	16.247	-13.642
G Score	7,002	9.192	9.000	-0.002	9.142	9.067	0.075
E Index	7,002	2.416	2.000	0.015	2.510	2.416	0.095

Table 3: Persistence in AGR scores

We tabulate the persistence of AGR scores (Panel A), AGR groups (Panel B), and AGR deciles (Panel C). At the beginning of each month, firms are grouped into deciles based on their AGR score reported at the end of the prior month. For each decile, from lowest (D1) to highest (D10), we report the average AGR score and the equal-weighted average return (in percentage) computed in the formation month M. We then track the firms in each decile in the subsequent 1, 2, 3, 6, and 12 months and compute the corresponding average AGR score, the equal-weighted average return (in percentage), and the fraction of stocks that remains in the decile (Retention %). The sample period is January 1997 to December 2011.

Panel A: AGR scores

	Statistic	M	M+1	M+2	M+3	M+6	M+12
AGR score	Autocorr.	1.00	0.93	0.86	0.79	0.66	0.47

Panel B: AGR groups

Group	Statistic	M	M+1	M+2	M+3	M+6	M+12
	Group	1.00	1.17	1.31	1.44	1.67	1.99
Very Aggressive	AGR	6.61	9.12	11.42	13.53	18.44	26.37
	Retention %	100	86.48	74.84	64.84	50.18	34.66
	Group	2.00	2.07	2.14	2.20	2.30	2.42
Aggressive	AGR	23.46	25.72	27.80	29.68	33.34	38.22
	Retention %	100	84.25	70.76	59.41	46.17	36.61
	Group	3.00	2.98	2.95	2.94	2.90	2.84
Average	AGR	57.08	56.48	55.91	55.39	54.29	52.45
	Retention %	100	90.43	82.23	75.22	65.97	58.42
	Group	4.00	3.86	3.74	3.64	3.47	3.27
Conservative	AGR	89.23	86.16	83.37	80.82	75.50	68.13
	Retention %	100	87.24	76.41	67.09	53.77	40.57

Panel C: AGR deciles

Decile	Statistic	M	M+1	M+2	M+3	M+6	M+12
	Decile	1.00	1.28	1.54	1.76	2.28	3.11
D1	AGR	6.61	9.12	11.42	13.53	18.44	26.37
	Retention %	100	86.48	74.84	64.84	50.18	34.66
	Decile	2.00	2.30	2.58	2.82	3.32	3.99
D2	AGR	17.08	19.78	22.27	24.51	28.93	35.05
	Retention %	100	77.16	58.28	42.68	28.54	20.08
	Decile	3.00	3.24	3.46	3.66	4.02	4.50
D3	AGR	26.65	28.72	30.62	32.38	35.61	39.90
	Retention %	100	74.87	54.52	37.54	23.58	17.13

Table 3 - continued from previous page

Decile	Statistic	M	M+1	M+2	M+3	M+6	M+12
	Decile	4.00	4.15	4.28	4.41	4.65	4.92
D4	AGR	35.81	37.10	38.30	39.41	41.53	43.87
	Retention %	100	73.89	52.48	34.92	21.28	15.76
	Decile	5.00	5.07	5.12	5.17	5.25	5.33
D5	AGR	44.91	45.46	45.94	46.40	47.10	47.68
	Retention %	100	73.20	51.52	34.57	20.81	15.13
	Decile	6.00	5.96	5.93	5.91	5.83	5.73
D6	AGR	54.06	53.77	53.53	53.25	52.53	51.42
	Retention %	100	72.85	51.02	33.84	19.85	14.56
	Decile	7.00	6.86	6.74	6.63	6.42	6.10
D7	AGR	63.18	61.98	60.93	59.95	58.07	54.95
	Retention %	100	74.07	53.05	35.69	21.15	14.66
	Decile	8.00	7.77	7.55	7.36	6.99	6.48
D8	AGR	72.50	70.45	68.54	66.78	63.43	58.53
	Retention %	100	74.97	54.51	37.80	23.77	16.42
	Decile	9.00	8.70	8.42	8.17	7.66	6.99
D9	AGR	82.39	79.62	77.06	74.71	69.91	63.48
	Retention %	100	76.99	58.38	42.81	28.39	20.32
	Decile	10.00	9.66	9.35	9.07	8.51	7.72
D10	AGR	93.07	89.91	87.02	84.38	78.81	70.88
	Retention %	100	85.00	72.58	61.54	46.78	32.77

Table 4: AGR score and operating performance: ROA

We tabulate OLS estimates of the pooled annual regression of return on assets (ROA) on the AGR score and additional cross-sectional controls. Panel A uses AGR scores and Panel B uses AGR groups. AGR(t) is the last rating available in year t. In specifications (1) to (4), the dependent variable is the contemporaneous ROA, ROA(t). In specifications (5) to (8), the dependent variable is the ROA in fiscal year $t+2$, ROA($t+2$). ROA is computed as ratio of Operating Income After Depreciation in the current fiscal year to Assets at the end of the prior fiscal year. For a given firm-year, ROA is then adjusted by subtracting the median ROA in the industry, as defined by its three-digit SIC code. Delaware is a dummy that equals one for firms incorporated in Delaware. t-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. Sample period is January 1997 to December 2011.

Dep. Var.	ROA(t)				ROA($t+2$)			
Panel A: AGR score								
Variable (t)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGR score	-0.002	0.056***	-0.003	0.012*	0.011***	0.030***	0.010***	0.015**
	(0.004)	(0.008)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.006)
Log(Market Value)		3.729***		1.743**		-0.880		-2.264***
		(0.818)		(0.789)		(0.562)		(0.680)
Log(Assets)		1.633*		3.641***		2.530***		2.275**
		(0.856)		(1.184)		(0.576)		(1.084)
CAPEX/Assets		7.224		1.926		6.685*		3.425
		(6.175)		(4.750)		(3.753)		(4.846)
Leverage		-10.469***		-6.165**		0.910		0.139
		(1.982)		(2.403)		(1.471)		(2.330)
R&D/Sales		-0.004*		-0.001		-0.003***		-0.001**
		(0.002)		(0.001)		(0.001)		(0.000)
Log(Tobin's Q)		-3.344**		4.081***		1.672**		5.466***
		(1.314)		(1.268)		(0.831)		(1.046)
Delaware		-4.319***				-1.188***		
		(0.685)				(0.359)		
ROA, Ind. Adj.					0.624***	0.593***		
					(0.012)	(0.015)		
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Obs.	47,896	22,094	47,896	22,094	36,116	16,640	36,116	16,640
R^2	0.002	0.191	0.695	0.725	0.004	0.520	0.729	0.752
Panel B: AGR groups								
Variable (t)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggressive	1.398***	3.016***	0.522*	1.201**	0.399	0.241	0.580**	0.461
	(0.413)	(0.661)	(0.303)	(0.536)	(0.287)	(0.509)	(0.288)	(0.519)
Average	1.592***	5.198***	0.516*	1.765***	0.772***	1.247**	0.769***	0.729
	(0.423)	(0.685)	(0.309)	(0.556)	(0.275)	(0.493)	(0.296)	(0.536)
Conservative	0.519	5.593***	0.074	1.379**	0.987***	2.376***	1.027***	1.276**
	(0.467)	(0.805)	(0.350)	(0.654)	(0.312)	(0.563)	(0.345)	(0.622)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Obs.	48,139	22,214	48,139	22,214	36,551	16,942	36,661	16,996
R^2	0.043	0.185	0.665	0.698	0.465	0.494	0.706	0.728

Table 5: AGR score and operating performance: other measures

We tabulate OLS estimates of pooled annual regressions of operating performance measures on the AGR score and additional cross-sectional controls. The measures are Tobin's Q, Net Margin, and 3-Year Sales Growth. The dependent variable is industry-adjusted by subtracting its median value in the industry, as defined by three-digit SIC code. Delaware is a dummy that equals one for firms incorporated in Delaware. t-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. Sample period is January 1997 to December 2011.

Dep. Var.	Tobin's Q($t+2$)		Net Margin($t+2$)		3-Year Sales growth($t+2$)	
	Panel A: AGR score					
Control (t)	(1)	(2)	(3)	(4)	(5)	(6)
AGR score	0.117***	0.061	0.049***	0.081***	0.056**	-0.049
	(0.029)	(0.046)	(0.015)	(0.030)	(0.025)	(0.040)
Log(Market Value)		10.998***		-5.284		8.379
		(2.483)		(4.211)		(6.840)
Log(Assets)		-67.312***		-0.073		-60.082***
		(4.490)		(5.808)		(8.558)
CAPEX/Assets		-47.523		52.545**		6.338
		(34.920)		(26.180)		(35.826)
Leverage		30.420***		36.168**		4.809
		(10.633)		(17.516)		(17.572)
R&D/Sales		0.001		-0.011		-0.009
		(0.010)		(0.012)		(0.007)
Log(Tobin's Q)				4.878		-18.179*
				(6.014)		(9.846)
ROA						
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	32,465	16,897	36,456	16,930	27,390	12,671
R^2	0.631	0.640	0.722	0.734	0.453	0.498
	Panel B: AGR groups					
Control (t)	(1)	(2)	(3)	(4)	(5)	(6)
Aggressive	2.010	-1.954	2.630*	3.321	4.275*	2.526
	(2.360)	(3.786)	(1.470)	(2.812)	(2.314)	(3.860)
Average	8.078***	3.764	3.581**	4.731	6.593***	2.131
	(2.429)	(3.829)	(1.524)	(2.927)	(2.326)	(3.771)
Conservative	9.277***	1.460	5.547***	8.251**	4.522*	-4.245
	(2.883)	(4.575)	(1.697)	(3.369)	(2.550)	(4.152)
Controls	No	Yes	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	32,465	16,897	36,456	16,930	27,390	12,671
R^2	0.631	0.640	0.722	0.734	0.453	0.498

Table 6: AGR score and operating performance: additional analyses

We tabulate the results of the OLS pooled annual regression of future industry-adjusted operating performance measures. In Panel A, the independent variable is the year-t AGR decile. In Panel B, the independent variable is the year-t AGR rating when companies in the lowest AGR decile (D1) in that year are removed from the sample. In Panel C, the independent variable is the year-t AGR rating interacted with dummies for the three subsamples 1997-2001, 2002-2006, and 2007-2012. t-statistics based on heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. All regressions include a constant term, whose coefficient is omitted. The sample period is January 1997 to December 2011.

Panel A: AGR deciles

	ROA$(t+2)$	Tobin's Q$(t+2)$	Net Margin$(t+2)$	3-Year Sales growth$(t+2)$
AGR decile (t)	0.089***	1.051***	0.465***	0.550**
	(0.030)	(0.262)	(0.142)	(0.231)
Obs.	36,661	32,465	36,456	27,390
R^2	0.706	0.631	0.722	0.453

Panel B: Dropping firms in AGR decile D1

	ROA$(t+2)$	Tobin's Q$(t+2)$	Net Margin$(t+2)$	3-Year Sales growth$(t+2)$
AGR (t)	0.006*	0.109***	0.031**	0.044
	(0.003)	(0.031)	(0.015)	(0.000)
Obs.	32,768	29,055	32,600	24,446
R^2	0.711	0.640	0.733	0.487

Panel C: Subsamples

	ROA$(t+2)$	Tobin's Q$(t+2)$	Net Margin$(t+2)$	3-Year Sales growth$(t+2)$
AGR (t) $\times \mathbb{1}_{1997-2003}$	0.009*	0.079*	0.062***	-0.011
	(0.005)	(0.042)	(0.023)	(0.031)
AGR (t) $\times \mathbb{1}_{2004-2011}$	0.011***	0.153***	0.036*	0.160***
	(0.004)	(0.034)	(0.020)	(0.034)
Obs.	36,661	32,465	36,456	27,390
R^2	0.700	0.620	0.716	0.443

Table 7: Performance analysis of AGR sorted portfolios

At the beginning of each month, stocks are grouped into Very Aggressive, Aggressive, Average, and Conservative groups based on their AGR score reported at the end of the prior month. We compute value-weighted (VW) and equal-weighted (EW) returns to these portfolios as well as the portfolio which goes long shares of Conservative firms and short share of Very Aggressive firms. The groups are then rebalanced every month. We report estimates of the following regression:

$$r_{p,t} = \alpha + \beta_1 \mathrm{RMRF}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{UMD}_t + \beta_5 \mathrm{RMW} + \beta_6 \mathrm{CMA} + \beta_7 \mathrm{ACC}_t + \beta_8 \mathrm{SUE}_t + \epsilon_{p,t}$$

The risk factors are the following zero-investment portfolios: the three Fama and French (1993) factors capturing exposure to the market (RMRF), size (SMB), and book-to-market (HML); the momentum factor UMD of Fama and French (1996); RWA is the difference between the returns on diversified portfolios of stocks with robust and weak profitability; CMA is the difference between the returns on diversified portfolios of the stocks of low and high investment firms; CMA is the accrual factor of Hirshleifer, Hou, and Teoh (2012); SUE is a portfolio based on standardized earning surprises. t-statistics based on Newey and West (1987) standard errors with 3 lags are reported in parentheses. *Alpha* is the intercept estimate and measures the monthly abnormal return, in percentage terms. Panel A uses returns in excess of the 3-month T-bill rate, while Panel B uses industry-adjusted returns. The sample period is January 2005 to December 2011.

Panel A: Excess returns

	VW					EW				
	VeryAgg	Agg	Avg	Cons	Cons - VeryAgg	VeryAgg	Agg	Avg	Cons	Cons - VeryAgg
Alpha	-0.451	0.004	0.155	0.090	0.541	-0.337	0.013	0.141	0.179	0.516
	(-2.74)	(0.05)	(2.60)	(1.26)	(3.03)	(-2.07)	(0.16)	(2.23)	(2.51)	(3.25)
RMRF	1.043	1.005	0.960	0.940	-0.102	1.022	0.976	0.952	0.911	-0.111
	(22.26)	(44.91)	(50.04)	(38.51)	(-1.55)	(24.25)	(30.53)	(55.02)	(48.25)	(-2.10)
SMB	0.508	0.627	0.667	0.624	0.117	0.626	0.766	0.750	0.657	0.031
	(6.87)	(18.86)	(21.63)	(14.67)	(1.29)	(8.60)	(16.56)	(22.26)	(14.11)	(0.34)
HML	0.230	0.130	0.146	0.173	-0.057	0.171	0.145	0.154	0.145	-0.026
	(3.56)	(4.34)	(3.69)	(3.76)	(-0.69)	(2.79)	(3.59)	(4.35)	(2.69)	(-0.37)
UMD	-0.195	-0.112	-0.083	0.025	0.219	-0.203	-0.158	-0.107	-0.027	0.176
	(-4.62)	(-3.95)	(-4.15)	(1.07)	(5.63)	(-4.60)	(-5.50)	(-5.14)	(-0.93)	(4.39)
RMW	-0.333	-0.055	-0.104	-0.052	0.281	-0.411	-0.174	-0.131	-0.116	0.294
	(-3.00)	(-0.97)	(-2.04)	(-0.84)	(2.24)	(-3.76)	(-2.53)	(-2.50)	(-1.75)	(2.37)
CMA	-0.066	-0.121	-0.128	-0.062	0.004	-0.090	-0.162	-0.154	-0.036	0.054
	(-0.51)	(-2.15)	(-2.24)	(-1.04)	(0.03)	(-0.81)	(-2.41)	(-2.77)	(-0.48)	(0.54)
ACC	-0.064	-0.045	0.015	0.037	0.101	0.088	0.047	0.073	0.016	-0.072
	(-0.50)	(-0.63)	(0.30)	(0.77)	(0.74)	(0.64)	(0.56)	(1.52)	(0.31)	(-0.47)
SUE	0.060	-0.024	-0.020	-0.065	-0.125	0.057	-0.023	-0.028	-0.040	-0.098
	(1.09)	(-0.92)	(-0.67)	(-1.71)	(-1.89)	(0.93)	(-0.92)	(-1.09)	(-0.95)	(-1.22)
R^2	0.963	0.988	0.991	0.987	0.49	0.964	0.986	0.991	0.987	0.515

Panel B: Industry-adjusted returns

	VW					EW				
	VeryAgg	Agg	Avg	Cons	Cons - VeryAgg	VeryAgg	Agg	Avg	Cons	Cons - VeryAgg
Alpha	-0.431	-0.043	0.126	0.132	0.562	-0.403	-0.023	0.144	0.177	0.580
	(-2.46)	(-0.62)	(2.19)	(1.87)	(3.27)	(-2.32)	(-0.32)	(2.23)	(2.68)	(3.73)
RMRF	0.017	-0.045	-0.074	-0.066	-0.083	-0.017	-0.077	-0.093	-0.096	-0.079
	(0.34)	(-2.50)	(-3.31)	(-3.54)	(-1.38)	(-0.38)	(-2.91)	(-4.11)	(-4.68)	(-1.61)
SMB	0.371	0.458	0.449	0.415	0.044	0.438	0.529	0.492	0.430	-0.009
	(4.30)	(20.49)	(18.44)	(13.53)	(0.50)	(4.97)	(16.47)	(16.89)	(11.14)	(-0.09)
HML	0.193	0.147	0.148	0.127	-0.066	0.170	0.131	0.139	0.100	-0.070
	(2.70)	(6.29)	(4.04)	(3.45)	(-0.81)	(2.53)	(4.27)	(4.28)	(2.39)	(-0.99)
UMD	-0.124	-0.032	-0.024	0.046	0.170	-0.127	-0.053	-0.035	0.011	0.138
	(-3.23)	(-1.81)	(-1.54)	(2.61)	(4.63)	(-3.33)	(-2.81)	(-2.40)	(0.47)	(3.62)
RMW	-0.296	-0.043	-0.045	-0.030	0.266	-0.343	-0.129	-0.092	-0.064	0.279
	(-2.66)	(-0.94)	(-1.01)	(-0.57)	(2.31)	(-3.20)	(-2.63)	(-1.99)	(-1.24)	(2.42)
CMA	-0.017	-0.043	-0.018	0.028	0.045	-0.039	-0.058	-0.043	0.052	0.091
	(-0.13)	(-0.81)	(-0.32)	(0.60)	(0.40)	(-0.33)	(-1.01)	(-0.75)	(0.77)	(0.98)
ACC	0.091	-0.064	-0.013	0.049	-0.042	0.168	0.035	0.080	0.042	-0.126
	(0.67)	(-1.04)	(-0.24)	(1.05)	(-0.32)	(1.15)	(0.45)	(1.38)	(0.73)	(-0.92)
SUE	0.100	-0.008	-0.016	-0.007	-0.107	0.098	-0.008	-0.011	0.033	-0.064
	(1.77)	(-0.39)	(-0.56)	(-0.22)	(-1.67)	(1.70)	(-0.39)	(-0.48)	(0.96)	(-0.87)
R^2	0.588	0.798	0.817	0.761	0.444	0.607	0.799	0.827	0.708	0.476

Table 8: Fama-MacBeth regressions

We provide the results of the OLS cross-sectional regression of stock returns:

$$r_{i,t+1} = \gamma_{0,t} + \gamma'_{1,t}\mathbf{X}_{i,t} + \epsilon_{i,t+1}$$

on various combinations of the regressors in $\mathbf{X}$. AGR is the AGR score at the end of month t. MV and *Book-to-Market* denote, respectively, the log of stock market capitalization and book-to-market ratio at the end of the prior fiscal year. *Ret(t)* is the return in month t, while *Ret(t-12:t-1)* denotes the cumulative return in months $t-12$ through $t-1$. β is the slope coefficient in the regression of excess stock returns on a constant and RMRF estimated on the 60-month period ending in month t. Idiosyncratic volatility iv is measured by the square root of average squared residuals from a 3-factor Fama and French (1993) model estimated using daily returns in month t as in Ang, Hodrick, Xing, and Zhang (2006). *Accrual* is the most recent accrual. *SUE* is the most recent earnings surprise. The regressions are estimated separately each month from January 2005 to December 2011. We tabulate average coefficients with the corresponding t-statistic based on Newey and West (1987) standard errors with 3 lags in parentheses. Returns are expressed in percentage.

Control	(1)	(2)	(3)	(4)	(5)
AGR	0.006	0.005	0.005		0.005
	(2.93)	(4.11)	(2.79)		(3.86)
β		0.179		0.163	0.180
		(0.75)		(0.69)	(0.76)
log(MV)		-0.083		-0.100	-0.088
		(-1.43)		(-1.76)	(-1.52)
log(Book-to-Market)		-0.002		0.013	0.006
		(-0.03)		(0.22)	(0.11)
Ret(t)		-2.871		-2.896	-2.905
		(-4.02)		(-4.06)	(-4.07)
Ret(t-12:t-1)		0.032		0.028	0.018
		(0.12)		(0.11)	(0.07)
iv		-5.373		-6.224	-5.736
		(-0.91)		(-1.05)	(-0.98)
Accrual			-1.952	-1.851	-1.763
			(-3.64)	(-3.98)	(-3.79)
SUE			0.019	0.025	0.023
			(1.15)	(2.26)	(2.09)

Figure 1: Industry concentration of AGR-rated companies

The figure reports the percentage of AGR rated firms within the 30 Fama and French industries computed as a fraction of the universe of CRSP stocks in each industry.

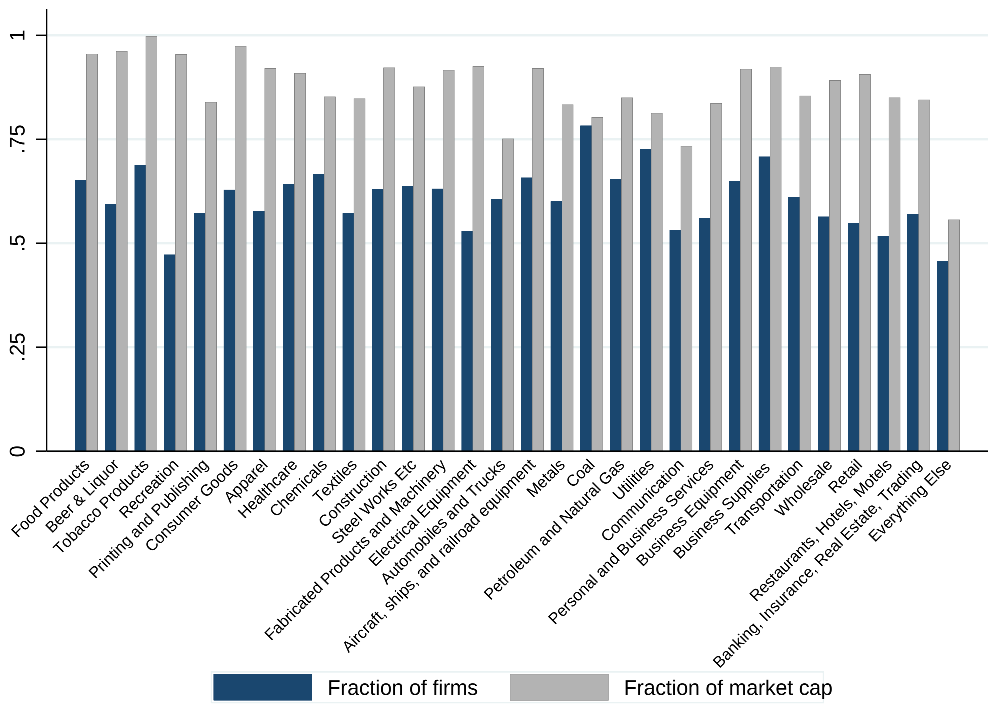

Figure 2: Performance regressions and industry concentration

The grey bars (left Y-axis) are the *Alpha* to the AGR factor (Conservative minus Very Aggressive) using the factor model of Table 7, when firms from the corresponding industry in the X-axis have been removed from the original sample. The grey bars (right Y-axis) are the corresponding *t*-statistics. The sample period is January 2005 to December 2011.

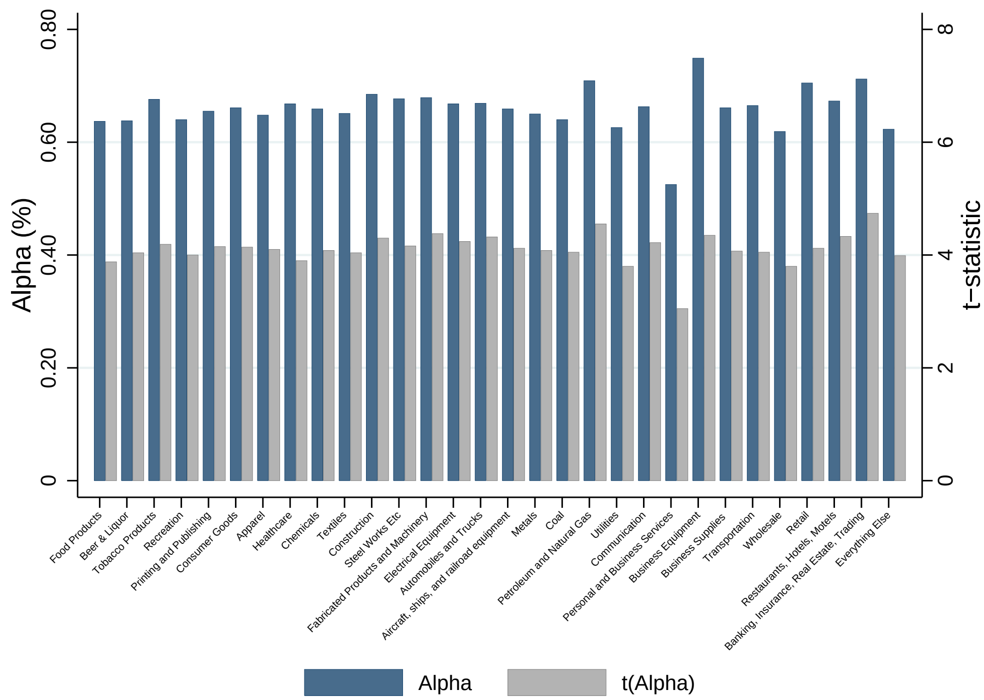

Figure 3: Time variation in AGR premium

We estimate monthly OLS Fama-MacBeth cross-sectional regression of stock returns of the AGR metric and firm-level controls, using the model in column 5 of Table 8. The Figure displays the trailing 24-month average of the slope on the AGR metric. The sample period is January 2005 to December 2011.

Appendix: Variables construction

From the CRSP database, we obtain the **Market Value of equity (Size)** as the natural log of the product of number of shares outstanding (item *shrout*) times the absolute value of price per share (*prc*) times 1,000.

From the CRSP/Compustat merged database, we construct the following variables:

Assets Total assets (*at*).

Debt Sum of financial debt in current liabilities (*dlc*) and long-term financial debt (*dltt*).

Return On Assets (ROA) Ratio of Operating Income After Depreciation in the current fiscal year (*oiadp*) to Assets at the end of the prior fiscal year.

Leverage Ratio of the sum of long-term financial debt (*dltt*) plus long-term debt due in one year (*dd1*) to Assets.

Tobin's Q Numerator is the sum of Assets and Market Value of Equity minus the sum of Book Value of Equity and Deferred Taxes (*txdb*). Denominator is Assets.

3-Year Sales growth Ratio between total sales in current fiscal year (*sale*) to the total sales of three fiscal years ago.

Net Margin Ratio between Income Before Extraordinary Items (*ib*) to Sales.

CAPEX/Assets Ratio of Capital Expenditures (*capx*) to Assets.

R&D/Sales Ratio of R&D expenses (*xrd*) to Sales.

Following Daines, Gow, and Larcker (2010), ROA is winsorized to have an absolute value not greater than one. All other variables are winsorized at the 2.5% and 97.5% to reduce the impact of outliers.