Understanding the Asset Growth Anomaly

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Abstract

Components of balance sheet asset growth driven by earnings management contributed to the asset growth anomaly in the past. These components of balance sheet asset growth are no longer related to returns and this has contributed to the disappearance of the asset growth anomaly. I provide evidence that the Sarbanes-Oxley Act reduced earnings management induced mispricing which I relate to the asset growth anomaly. More broadly, these findings point towards changes in the regulatory environment as a novel driver of equity market anomalies.

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1 Introduction

Firms with high growth in balance sheet assets today have lower equity returns on average going forward, this "asset growth anomaly" and the associated asset growth factor has emerged as a key feature of modern empirical asset pricing models. The five-factor model of Fama and French (2015) and the q-factor model of Hou et al. (2014) feature a factor which is constructed using a long-short portfolio based on the growth in balance sheet assets. Fama and French (2016) and Hou et al. (2017) show that the asset growth factor is crucial for summarizing the cross-section of equity returns by explaining patterns that were anomalous to the three-factor model of Fama and French (1992).

Theories that explain the relationship between asset growth and stock returns fall into two broad categories. One category of theories feature heterogeneous producers that each use the marginal utility of a representative consumer to choose their optimal investment policy. In these models, firms with relatively limited ability to turn capital goods into consumption goods due to capital investment frictions have values that covary more with marginal utility, and the return relationship is explained by this risk. For this reason, the asset growth anomaly is often called an investment factor. Another category of theories tie asset growth to systematic investor mistakes about the prospects of high growth firms relative to low growth firms.

I forward an explanation for the anomaly that relies on systematic investor mistakes. In contrast to assuming that investors are too optimistic in general about the prospects of high growth firms relative to low growth firms, I show how these systematic errors can be related to distortions in the accounting information provided to investors. I use the fact that the asset growth anomaly is fundamentally tied to the accrual anomaly of Sloan (1996). Since asset growth is defined as the percentage growth in balance sheet assets, I can trace asset growth to variation in different accounts on the balance sheet. I use the insight that some of the "accrual" accounts that contribute to asset growth are also used to manage earnings. I show that variation in these accrual accounts contributes to the asset growth anomaly. To provide further evidence that earnings management drives the asset growth anomaly I exploit the enactment of the Sarbanes-Oxley Act (SOX) of 2002, which was intended to reduced earnings management and improve the integrity of accounting information. I show that the anomaly significantly weakens in the post-SOX period and that the reduction can be attributed to accounts related to earnings management. Empirical evidence supports this explanation of the anomaly.

I show that components of asset growth that are related to earnings management are related to returns. Variations in working capital accruals and nontransaction accrual accounts used to manage earnings are important drivers of the asset growth anomaly. Coefficients on components of asset growth related to these accrual accounts are significant in Fama and MacBeth (1973) cross-sectional regressions and sorts on the unique variation associated with these components of asset growth result in abnormal portfolio returns. This suggests that incorrect projections about future profitability embedded in earnings and capitalized into the price by investors could contribute to the anomaly. This motivates a test of these relationships in the post-SOX period.

I show that the relationship between total asset growth and returns has disappeared in the post-SOX period. Specifically, the returns to a value-weighted strategy based on asset growth decrease from 0.81% per month (t-value of 3.61) to -0.19% per month (t-value 0.80). The returns to an equal-weighted strategy decrease by almost two-thirds from 1.63% per month (t-value 7.91) to 0.58% per month (t-value 2.58). The results are consistent across methods (parametric Fama and MacBeth (1973) regressions, Hou and Loh (2016) decompositions of the Fama MacBeth regression coefficients, and non-parametric results using portfolio returns) and size groups (for both equal-weighted and value-weighted returns). I show that much of these reductions are found in components of asset growth related to accrual accounts. This suggests that the change in environment post-SOX could explain the change in the asset growth anomaly.

I further explore why the asset growth anomaly has decreased after SOX and find that the information environment has changed since 2002: earnings management has decreased, analyst forecast errors have decreased, and statistical expectations of earnings are more accurate. Specifically, the discontinuity in the surprise earnings per share distribution used as a measure of earnings management has decreased by 80%, analyst forecast errors decreased on average by 0.65%, and statistical estimates of a linear conditional expectation function can explain more of the variance in earnings in the recent period (R^2 of earnings predictability regressions increase between 5% and 15%). Furthermore, using measures of misconduct such as class action lawsuits, accounting enforcement actions, and irregularities in accounting statements, I find that the incidence of misconduct is highest in the period after a firm enters the higher asset growth portfolios.

Finally, I distinguish between theories of rational valuation and mispricing by relating accruals to stock returns through the probability assessments of sell-side analysts. I show that the accrual accounts that are related to earnings management explain the cross-section of forecast errors in a direction consistent with the asset growth anomaly - analysts are relatively more optimistic about firms with higher growth in accrual accounts related to earnings management in the pre-SOX period. This relationship has significantly reduced in the post-SOX period.

This empirical evidence is open to alternative interpretations, for example, the passage of the Sarbanes Oxley Act coincided with changes in the trading environment for institutions which could raises the question of whether mispricing was reduced by sophisticated traders. However, theories that relate returns to mispricing do not speak to changes in variables such as the predictability of profits, the subjective expectations of analysts, or the decrease in earnings manipulation. I show that the channel goes from forecast errors to returns through variation in the components of asset growth that are related to earnings management. This suggests the mispricing no longer exists to be exploited by sophisticated traders. I support this view with evidence that the anomaly is weaker in firms with lower ability to manage earnings in the pre-SOX period and that there is is no significant change in the trading of institutions in the post-SOX period. Collectively these results suggest that the regulatory environment, rather than the trading of sophisticated institutions, was the key determinant of the anomaly.

Another interpretation is that the variation in asset growth is related to high-frequency changes in risk, so that the asset growth anomaly reflected loadings on an asset growth risk factor in the past, and that the loadings or price of this risk factor has diminished. My tests using returns have low power against an alternative in which all these patterns in returns are driven by a persistent change in the price of an asset growth risk factor. Keloharju et al. (2018) point out that since long-term discount rates do not vary, we need econometric techniques which can identify high-frequency variation in conditional covariance functions to specify powerful alternative tests. However, the set of stylized facts related to the decline in the anomaly, and the relationship of the anomaly decline to changes in the quality of the information environment pose a difficult set of stylized facts for a risk based theory to explain.

I contribute to several strands of literature. I contribute to the literature that focuses on explanations for the asset growth anomaly. There is a large theoretical and empirical literature on the topic and the paper most closely related to this is Cooper et al. (2017)

who also point out that some components of asset growth - such as noncash current assets - that seem least connected to investment as imagined in theoretical models are the most important for pricing anomaly portfolios. I suggest that these components are related to asset growth through earnings manipulation, providing an explanation for why such components would be most important for pricing anomaly portfolios. Likewise, Cao (2016) points out that the net operating asset component of asset growth drives the negative relationship between asset growth and future profitability and returns, while Lewellen and Resutek (2016) show that non-investment components of net operating asset growth are related to returns. This paper suggests that the power of net operating assets to predict returns and profitability comes from earnings management, offering a mechanism to explain the relative importance of different components.

I also contribute to the literature on anomaly decay, both Chordia et al. (2014) and McLean and Pontiff (2016) provide large-scale studies focusing on multiple anomalies. Both studies show that anomalies seem to decay after discovery and suggest that data mining or the elimination of mispricing by arbitrageurs are potential explanations for such anomaly decay.[1] I provide a novel explanation for the decline of a single important asset pricing anomaly related to changes in the regulatory environment, and provide stylized facts that are hard to reconcile with anomaly decay due to institutional trading or data mining. Chordia et al. (2014) also focus on a gradual decay where this paper suggests that discrete changes in the market environment are responsible for the decay of the asset growth anomaly in particular.

I also contribute to the literature on managerial incentives and trading around corporate events such as seasoned equity offers. Teoh et al. (1998) and Teoh and Wong (2002) relate returns around equity issues to earnings management, and Fu and Huang (2015)

[1]Since factor models provide a useful data reduction, once a satisfactory low dimensional factor model that summarizes the anomaly portfolios has been found, we can focus on explaining the individual factors.

suggests that the post-event abnormal returns after seasoned equity offers have declined since 2002. Fu (2014) shows that external equity issuance is high in firms with high asset growth, and Bradshaw et al. (2006) show that analyst forecast errors vary systematically with the incidence of financing. Equity issues influence the asset growth signal so that my evidence can be seen as reinforcing the message of these papers, and adding evidence that managerial manipulation of the information to investors contributes to these event-return relationships.

2 Asset growth decomposition

I motivate the asset growth decomposition through the lens of valuation and managerial incentives. First, I describe accruals and show how accruals affect earnings. Second, I show that managerial discretion exercised in forecasting accrual account values combined with incentives to distort earnings may skew the ability of earnings to reflect the economic situation of any given firm. Third, I show how the accruals used to distort earnings feature in asset growth.

2.1 The relationship between earnings and accruals

In general we can write

$$\text{Earnings} = \text{Operating Cash Flows} + \text{Accruals}.$$

"Accruals" are adjustments of cash flows used to arrive at earnings. In finance, we consider valuation on a cash basis, the discounted cash flow model finds the value of a firm's equity as the net present value of the free cash flows to equity holders discounted at an appropriate rate. However, much of our data is given on an accrual basis, under the accrual method income items are recorded when they are earned (as opposed to when they are actually received) and expenses are deducted when incurred (as opposed to when they are actually paid). We can think of accrual accounting as a two-step process: accruals are first originated to account for timing differences between the economic transaction and its cash realization, and accruals are then reversed when either the cash flow is realized or the estimation error in the amount of expected cash is realized. Under accrual accounting, earnings should reflect firm performance better than cash flows, especially for firms with more volatile operating investment and financing activities where large receipts and payments of cash in one period can drive economic value for many future periods.

Accruals are typically defined as a measure capturing the difference between cash flows and earnings, reflecting all the non cash adjustments to operating cash flows to arrive at earnings. For example, on the statement of cash flows data available on Compustat there are 11 items between Operating Activities, net cash flow (OANCF) and Income Before Extraordinary Items (IBC). [2]

2.2 Earnings misrepresentation through accruals

From the perspective of an investor, standard free cash flow valuation helps to purge all of the accrual adjustment from earnings. There is no sense in which accrual accounts (essentially shifting recognition of receipts and payments around in time) should influence

[2]The items are accounts payable and accrued liabilities (change), accounts receivable (change), assets and liabilities - other (change), deferred taxes, depreciation and amortization, equity in net loss (earnings), extraordinary items & discontinued operations, funds from operations - other, income taxes - accrued (change), inventory (change), and sale of property, plant, equipment and investments.

valuation and stock returns if the accounting is fully appreciated by investors. However, managers need to forecast the timing and receipt of payments, and these forecasts are embedded in accrual accounts. The trade-off at the heart of accrual accounting is that the discretion which allows for earnings to be a better measure of a firms' economic performance requires managerial manipulation. The irrelevance of accruals for valuation is conditional on managers getting their forecasts correct on average. If investors trust managers forecasts embedded in accrual accounts and capitalize these gains or losses, then we would expect a correction if forecast errors are realized. In this way estimation errors or accrual account manipulation will be reflected in prices when accruals reverse.

The fact that accruals embed expectations about future payments and receipts is important in light of the relationship between accruals and earnings, and the huge focus investors and managers put on earnings. Precisely because earnings are intended to be a superior measure of firm performance they have become a key focus in three particular areas. First, people outside the firm such as investors, analysts, and regulators measure and use earnings to evaluate the economic performance and potential of the firm. Second, people inside the firm use earnings for internal performance measurement. Third, earnings are used in contracts for managerial compensation and debt covenants.

The importance of earnings suggests that managers have an incentive to manipulate them. This raises three key questions: why would managers manage earnings?, do they manage earnings?, and if so, how do they manage earnings?

Graham et al. (2005) survey 401 financial executives and find that the majority of these managers view earnings-per-share as they key metric used by people outside the firm, focus heavily on meeting or beating earnings benchmarks because they want to influence stock prices, and are concerned about their careers. Managers also admit that they are willing to sacrifice economic value to hit earnings benchmarks. Graham et al. (2005) also perform 20 one-on-one interviews and find that several CFOS argue that: “you have to start with the premise that every company manages earnings”.

Managers can benefit from managing earnings up or down and examples of how managers manipulate earnings can be found from survey evidence with managers in Dichev et al. (2013), survey evidence with auditors in Nelson et al. (2002), and enforcement actions of the SEC (Dechow et al. (2011) collects evidence from over 2,000 Accounting and Auditing Enforcement Releases).

Levitt (1998) highlighted the technique of “Big Bath” accounting, where a manager can overestimate reserves in one period and take a large hit to earnings, which allows for the creation of reserves which management can then add back into earnings in bad years. This evidence is corroborated by interview evidence from Dichev et al. (2013) where a manager comments that: “I've watched numerous managements earn big incentives through being able to manage a balance sheet accrual, they set up big accruals and (then do) not meet them”. This is a particularly attractive technique for new managers who can blame the large negative hit to earnings on the past management team.[3]

Managers may also manage earnings upward, by bringing payments forward in time (overestimating assets) or delaying costs (underestimating liabilities). This is a more difficult manipulation to hide, since the absence of cash flows must eventually be revealed. However, in a growing firm the manager can hope that the reversals of past optimistic

[3]Examples of downward earnings management include a technique called “Cookie Jar Accounting” exemplified by Beazer Homes, USA. Their Chief Accounting Officer was accused of using the cookie jar accounting method to hide over US$56 million in cash by increasing land inventory accounts then reversing these accruals in declining years to increase income (link:secactions.com). Xerox Corp settled with the SEC without admitting wrongdoing in a similar case. The SEC charged that Xerox created reserves for liabilities including vacation pay that the company knew were too high so it could draw on reserves in years when it needed a boost to meet earnings estimates (link:sec.gov).

estimates of accruals are hidden by strong future growth.[4] Career concerns mean that if low earnings today can result in termination or lost compensation, the prospect of high future earnings may not be a strong incentive to invest efficiently, indeed Graham et al. (2005) find that managers will forgo a positive NPV project if investment would result in a missed earnings benchmark. Bens et al. (2012) explore the idea that changes in managerial horizon can affect the incentives to misreport earnings. They find that managers with career concerns driven by badly received merger and acquisition investments are more likely to misreport earnings.

Questions raised by issues at the intersection of managerial incentives and managerial discretion have not been missed by researchers that try to understand returns around corporate events. Teoh et al. (1998) report that seasoned equity issuers manage earnings upward (measured as positive abnormal accruals) and have lower future earnings and lower future stock returns. Teoh and Wong (2002) suggest that accruals management affects analysts forecasts of firms earnings. Cheng and Warfield (2005) and Bergstresser and Philippon (2006) give evidence that chief executive officer equity incentives are associated with accruals management and the likelihood of beating analyst forecasts. Jiang et al. (2010) provide evidence that chief financial officer equity incentives are related to the probability of meeting or beating analyst forecasts, and that the magnitude of accruals is related to equity incentives in the pre-SOX period only.

A large literature in accounting and finance also considers the effects of accruals and earnings management for stock prices in general. Dechow et al. (1995) rejects the null

[4]Examples of upward earnings management include a practice called "Channel Stuffing" exemplified by SEC litigation against Sunbeam. The SEC claim that at year-end 1997, at least $62 million of Sunbeam's reported income of $189 million came from accounting fraud, such as parking merchandise with a wholesaler and inducing customers to place orders they could cancel at will (link:sec.gov). Bristol-Myers Squibb ("BMS") also engaged in channel stuffing, selling excessive amounts of products to wholesalers ahead of demand near the end of every quarter (they guaranteed the wholesalers a return on investment until they sold the products), and recognizing $1.5 billion in revenue from these sales upon shipment, rather than on acceptance, to meet earnings targets (link:sec.gov).

that there is no earnings management in a sample of firms with extreme performance while Sloan (1996) show that accruals are less persistent than cash flows and can predict equity returns going forward. Allen et al. (2013) demonstrate that the returns and earnings following extreme accruals are explained by accrual estimation error reversals unanticipated by the stock markets. Ball et al. (2015) highlight the success of measures like gross profitability in predicting returns is due to removing accruals from earnings. Ball et al. (2016) and Lewellen and Resutek (2016) point out that a combined measure of earnings less accruals predict the cross-section of stock returns, they attribute the success of their measure to the fact that firms who are less profitable on a cash basis - i.e. high accrual firms - tend to be less profitable going forward.

2.3 The relationship between accruals and balance sheet asset growth

When the income statement and balance sheet articulate, net operating asset changes record the differences between cash and accounting profitability (accruals).[5] For example, a manager could record a sale as a receivable before the cash flow is received to increase earnings, and this would mechanically increase net operating assets. This is perfectly reasonable if the cash flow is expected to be realized, and not embedding manipulation or optimistic expectations. Barton and Simko (2002) point out that the balance sheet records all past accounting choices, so the level of assets can then reflect past earnings management. Hirshleifer et al. (2004) call this increase in net operating assets that comes from generous assumptions in earnings "balance sheet bloat" and point out that high cumulative working capital accruals contain negative information about future earnings

[5] Some non-operating events such as mergers and acquisitions or discontinued operations cause non-articulating accruals. I follow Allen et al. (2013) and include them in the definition of accruals.

if they derive from unusually high unpaid receivables or low deferred revenues.

The asset growth decomposition presented below highlights the fact that asset growth contains two important accrual accounts that affect earnings.

I start with total assets (AT) on the balance sheet and decompose total assets into operating assets (OA) and cash

$$AT = OA + CASH.$$

Operating assets can be further divided into operating assets financed by operating liabilities (OA_OL) and operating assets financed by debt and equity (NOA),

$$\begin{aligned} NOA =& (AT - CASH) - (LT - (DLTT + DLC)) \\ =& OA - OA\_OL, \end{aligned}$$

where LT is total liabilities, DLTT is debt in long-term liabilities, and DLC is debt in short-term liabilities. Using the above definition I can write

$$\begin{aligned} AT =& (OA - OA\_OL) + OA\_OL + CASH \\ =& NOA + OA\_OL + CASH. \end{aligned}$$

Using the decomposition of Lewellen and Resutek (2016) we can further decompose NOA into working capital (WC) and long term net operating assets (LTNOA)

$$NOA = LTNOA + WC.$$

Working capital is defined as the difference between non-cash current assets and non-debt current liabilities. This is defined as

$$WC = (ACT - CASH) - (LCT - DLC).$$

where ACT represents current assets, LCT current liabilities, and DLC is debt in short term liabilities. The total change in assets can be written as

$$\Delta AT = \Delta LTNOA + \Delta WC + \Delta OA\_OL + \Delta CASH.$$

Long term net operating assets can be decomposed into Investment accruals (InvAcc) and Nontransaction accruals (NTAcc),

$$\Delta LTNOTA = InvAcc + NTAcc,$$

where NTAcc are defined as

$$\begin{aligned}
-NTAcc = {} & \text{Depreciation and Amortization (SCF account)} \\
& + \text{Deferred Taxes (SCF account)} \\
& + \text{Equity in Net loss (earnings) of unconsolidated subsidiaries} \\
& + \text{Loss (gain) on sale of property, plant and equipment and investments} \\
& + \text{Funds from operations -Other (including accruals related to special items)} \\
& + \text{Extraordinary items and discontinued operations (cash flow-income statement account)}
\end{aligned}$$

Using the definition for NTAcc I can write

$$\Delta NOA = NTAcc + \Delta WC + InvAcc = dAcc + InvAcc$$

Where dAcc combines NTAcc and ΔWC for convenience. Using the above definitions I arrive the decomposition of balance sheet asset growth used in the rest of the paper

$$\begin{aligned}\Delta AT &= \Delta WC + NTAcc + InvAcc + \Delta OA\_OL + \Delta CHE \\ &= dAcc + InvAcc + \Delta OA\_OL + \Delta CHE\end{aligned}$$

This equation says that asset growth must come from changes in working capital, investment accruals, nontransaction accruals, changes in operating assets funded by operating liabilities, or changes in cash and short term investments. Some components of this decomposition are subject to managerial discretion, and rather than reflecting the operations of the firm in the current period they reflect accruals. I combine ΔWC and $NTAcc$ to create a composite accrual measure $dAcc$. This variable collects accounts that directly impact earnings. These accounts are more susceptible to manipulation and highlight how earnings management can affect asset growth.[6]

Returning to the earlier decomposition of earnings into cash flows and accruals we can now show formally the link between earnings, accruals, and asset growth.

[6] This decomposition also allows one to account for deficiencies encountered using asset growth as an investment measure, for example, using ΔAT alone, an investment in operating assets using cash would result in zero asset growth. Unfortunately, the expensing of research and development costs still makes this a less than complete measure of investment, since research and development costs are expensed, an investment in research and development using cash could reduce assets on the balance sheet so investment would increase while total assets decrease. One could capitalize some expenses into organization capital as in Eisfeldt and Papanikolaou (2013), I abstain from this as my decomposition involves making use of a balance sheet identify that would be disturbed by such a change.

We have that

$$NI = OANCF + \Delta WC + NTAcc = dAcc + InvAcc$$

which says that earnings are cash flow from operations plus working capital accruals plus nontransaction accruals. These working capital accrual and nontransaction accrual accounts enter directly into asset growth.[7]

The key takeaway from the asset growth decomposition is that firms can grow or shrink their asset base through accrual accounts, and that they have a strong motivation to do this as accrual accounts directly impact earnings. The variation in asset growth is related to the variation in these accrual accounts by definition, and thus incorporates managerial forecasts and incentives. I use this decomposition to explore the relationships between earnings, accruals, and asset growth. It's also important to note the additional contribution of earnings management to growth through asset growth financed by external funds that would not have been raised if investors had seen the true earnings process.

3 Data and descriptive statistics

I start with all nonfinancial firms in the monthly CRSP database between January 1975 and December 2017 having share codes 10 and 11. I keep only firms listed on NYSE, Amex, or Nasdaq that can be matched with Compustat. I adjust for delisting returns

[7]There is a large literature that distinguishes between different types of accruals, making groupings such as reliable/unreliable accruals, and discretionary/nondiscretionary accruals. In this paper I use an existing decomposition and do not try to search for the perfect specification, for example, within investment accrual changes (invacc) one could distinguish between changes in accounts such as property plant and equipment (Compustat item ppent) vs. investments and advances/other (Compustat item ivao) which can contain long-term receivables and other investments and advances such as investments in unconsolidated companies in which there is no control.

using CRSP, and if a delisting return is missing and due to performance I impute the delisting return as the average delisting return for that exchange.

I use analyst level earnings-per-share (EPS) forecasts from the I/B/E/S Detail History file (unadjusted). I calculate firm level consensus forecasts for a given time period by taking the median of all forecasts within that period, taking care to use only the most recent forecast for each analyst. I use forecasts for the current fiscal year and match the forecast EPS with a measure of the actual EPS which is adjusted for stock splits using the number of shares outstanding from CRSP. [8]

For empirical tests I scale asset growth and its components by the lagged value of total assets in the prior fiscal year. This is the measure of total balance sheet asset growth used to construct factors in Fama and French (2015) and Hou et al. (2017).

Table 1 contains descriptive statistics for the price and accounting data in my sample. Table 1 panel A contains information on the distribution of each variable. Considering the full decomposition of asset growth, $tag = dwc + invacc + ntacc + doa\_ol + dche$, we can see that changes in working capital (dwc) have a moderate standard deviation relative to asset growth, and that it contributes to both positive and negative asset growth. Nontransaction accruals ($ntacc$) contribute mostly to negative asset growth, with the 95th percentile being less than zero. The composite measure of accruals $dacc = dwc + ntacc$ inherits the properties of both dwc and $ntacc$. Investment accruals has a mean close to that of asset growth but a tighter distribution, suggesting that the extremes of asset growth cannot be driven by this component alone. Operating assets funded by operating liabilities (doa_ol) and changes in cash ($dche$) also contribute to the changes in asset

[8] Robinson and Glushkov (2006) point out that if the number of shares on the announcement date differs from that on the date an analyst made a forecast then the EPS forecast can be stated on a different basis than the actual EPS which can bias the forecast error measure.

growth.

Table 1 Panel B contains Spearman (above diagonal) and Pearson (below diagonal) correlation coefficients between total asset growth (tag) and its components. Looking at the first row, and the first column, we can see how individual components of total asset growth are correlated with asset growth, considering the full decomposition of $tag = dwc + invacc + ntacc + doa\_ol + dche = dacc + invacc + doa\_ol + dche$ we can see that the components such as invacc, *doa_ol*, and dche have moderately high correlation, while the components *dwc* and *ntacc* (and their combination *dacc*) have lower correlation. This indicates that there is unique variation in components of asset growth which will allow us to distinguish the contributions of different components to earnings and return predictability. Considering the correlations of the individual components of the decomposition with each other, we can see that they all have moderate to low correlations with each other. Note that variables with high correlations (e.g. *dnoa* and *dltnoa*) are never included in the same regression, since they are both included in different decompositions of asset growth.

[Table 1 about here]

4 Empirical results

For Fama and MacBeth (1973) regressions I winsorize all characteristics at the 1st and 99th percentiles of their monthly distributions to reduce the impact of outliers. In both the dividend discount model, and the q-theory model, the relationship between investment and expected returns is conditional on expected profitability, so I include the lag of net income scaled by lag total assets as a measure of expected profitability as in Fama and

French (2006). I also include the following control variables in all regressions where returns are the dependent variable: the natural logarithm of the book-to-market ratio, the natural logarithm of the market value of equity, past returns for the prior month, and for the prior 12-month period excluding the prior month.

I consider the influence of small stocks by running Fama and MacBeth (1973) regressions on the full sample of firms, as well as using a sample that excludes microcap stocks, which are defined as stocks with a market capitalization less than the 20th percentile of the NYSE distribution in each month. Regressions are run monthly, and there is a minimum lag of 6 months between accounting information and returns to ensure the accounting information was available to investors.

I calculate equal and value-weighted portfolio excess returns and alphas relative to a market model and the Fama and French (1996) three-factor model. Each month I sort stocks into 10 deciles based on NYSE breakpoints of each characteristic and calculate returns for the following month. Portfolios are rebalanced monthly and I ensure there is a lag of 6 months between the last fiscal year end and the portfolio construction to ensure accounting data for each firm was available to investors.

When using components of asset growth for portfolio construction I remove variation associated with the other components. I do this by projecting asset growth onto each individual component and retaining part of asset growth predicted by that component. For example, when sorting on the change in accruals (dacc), I regress total asset growth each month on accruals and sort stocks using the predicted value from the cross sectional regression, thus sorting on the unique variation in asset growth related to the composite measure of accruals (dacc).

4.1 Full sample and replication of the anomaly

Table 2 column 1 presents the baseline Fama and MacBeth (1973) regression which shows that the total asset growth effect is economically and statistically significant (coefficient of -0.87 with a t-value of -11.02). Columns (2)-(4) present results for the decomposition of asset growth into its components. The coefficient on the growth in working capital (dwc) and the composite accrual measure (dacc) are about two times the magnitude of the coefficient on the total asset growth effect (coefficient of -1.62, -1.76 with t-values of -6.39, -7.76 respectively). The results highlight that the individual components of asset growth contribute to its ability to predict returns and are consistent with the idea that variation in accrual accounts that affect earnings are related to future stock returns.

Table 2 columns (5)-(8) show the same coefficients and t-values for the sample of firms excluding microcap firms. The coefficient on total asset growth is reduced by excluding microcap firms (coefficient of -0.59 with a t-value of -5.88), The coefficients on the growth in working capital (dwc) and composite accruals (dacc) are again about 2 times the magnitude of the coefficient on total asset growth (coefficients of -1.09, -1.46 with t-values of -3.34,-5.09 respectively). Regressions excluding microcap firms suggest that the effect is weaker for large firms.

Taken together, these results suggest that individual components of asset growth are significantly related to returns, especially those related to changes in composite accruals (dacc). Since these components are related to accrual accounts and subject to managerial discretion, they suggest that variation in accounts that are associated with earnings management contribute to the relationship between returns and asset growth.

We can also see in column (8) that the coefficient on investment accruals (the measure most associated with capital investment) is still strong when we purge the effect of other variables (coefficient -0.78 t-value -5.49). This suggests that the conventional investment return relationship implied by the dividend discount model, and the q-theory model, may still exist once variation in other components of asset growth unrelated to investment are accounted for.

[Table 2 about here]

Table 3 contains equal and value-weighted portfolio excess returns and alphas relative to a market model and a three factor model, showing that the results from Table 2 are robust to an alternative methodology. Looking at the first row we can see that the average monthly returns are 1.25% for the equal-weighted asset growth strategy and 0.44% for the value-weighted asset growth strategy. Looking down the rows in the first column we can see that portfolios formed on separate components of asset growth contribute to its predictive power, unique variation associated with the individual components (dwc, invacc, and dacc) are all statistically and economically significant. Looking at the last three columns we can see that returns on value-weight portfolios are smaller on average. The results in the last column show that using only the unique variation associated with working capital or investment accruals results in larger returns than the total asset growth measure, suggesting that total balance sheet asset growth mixes variation that may serve to weaken its returns when focusing on large firms.

[Table 3 about here]

In summary, the results using Fama and MacBeth (1973) cross-sectional regressions and portfolio sorts reveal that components of asset growth such as working capital and non-transaction accruals provide independent information about the cross section of stock returns and contribute to the balance sheet asset growth effect. Motivated by the relationship between asset growth and earnings management, in the next section I explore how changes in the regulatory environment affect the ability of these components of asset growth to predict returns.

4.2 Predictability: pre-SOX relative to post-SOX

In remarks delivered at the NYU Center for Law and Business in 1998, Arthur Levitt, then chairman of the Securities and Exchange Commission (SEC), expressed his concern about corporations playing "The Numbers Game" (see Levitt (1998)). His speech highlighted that some corporate managers were misrepresenting their firms' business situations by taking advantage of discretionary judgments allowed in the accounting system. His remarks foreshadowed large corporate failures such as Enron and Worldcom. The Sarbanes-Oxley Act (SOX) was signed into law in July 2002 in reaction to these events and the perceived deterioration in the quality of information available to investors in accounting statements.

The Sarbanes-Oxley Act created the Public Company Accounting Oversight Board (PCAOB) to oversee and enforce regulatory changes. The key implications for corporations are that top management now have to individually certify the accuracy of financial information, they face increased penalties for fraudulent financial activity, there is an increased oversight role for boards of directors, and outside auditors of corporate financial statements are now required to act more independently of the firm. Clawback provisions outlined in the SOX also mean that the CEO or CFO can now be forced to return any executive compensation (such as bonus pay or proceeds from stock sales) earned within a year of misconduct that results in an earnings restatement. As a result of SOX, in November

2002, the SEC shortened the deadline for filing 10-K forms after the fiscal year end from 90 to 75 days. SOX also required the SEC to address conflicts of interest involving research analysts and investment bankers, which led to NASD Rule 2711 and the amended NYSE Rule 472 intended to improve capital market transparency through decreased analyst forecasting biases.

These far-reaching changes in the corporate environment motivate the tests in this section. I empirically assess the ability of balance sheet asset growth and its components to predict returns in the period prior to, and after, July 2002, which is the month SOX was signed into law. The results are not sensitive to the choice of cutoff (for example, excluding all of the year 2002).

Before turning to formal statistical tests I present a graph of the average annual return and cumulative returns for a strategy based on total asset growth from 1975 to 2017. Figure 1 Panel A contains a graph of the average annual return, and cumulative return to an equal-weighted strategy that takes a long position in the low asset growth portfolio and a short position in the high asset growth portfolio. One can see that until 2002 the strategy enjoys almost uninterrupted positive returns. Figure 1 Panel B contains the same graph for value-weighted portfolios, although less consistently positive the strategy has positive returns for all holding periods of four years or more. For both Panel A, and Panel B, we can see that the strategy returns attenuate from 2002 onward.[9]

[Figure 1 about here]

[9]The structural break in the return series can be statistically detected, unreported results (available upon request) using a supremum Wald test indicates that we reject the null hypothesis of no structural break at a 1% level and that the estimated structural break date is December 2002. For clarity, I choose the date the Sarbanes-Oxley act was signed into law as the date to split the sample in later tests, but this choice does not have a material effect on results.

Results in Table 4 show that the relationship between asset growth and returns has diminished in the post-SOX period. Table 4 columns (1)-(4) give Fama and MacBeth (1973) regression results for the pre-SOX period from January 1975 to July 2002 while columns (5)-(8) show the regressions for the post-SOX period from August 2002 to December 2017. Comparing columns (1) and (5) the regression coefficient on total asset growth (tag) in the pre-SOX period is stronger than the full sample (coefficient -1.03 with t-value -10.54) however, the economic and statistical significance is diminished in the post SOX period (coefficient -0.50 with t-value -4.15). Comparing columns (4) and (8) one can see that much of decline in the returns of the asset growth strategy can be attributed to the individual components related to changes in the composite measure of accruals.

[Table 4 about here]

Table 5 repeats the regressions in Table 4 excluding microcap firms. One can see that the results echo those in Table 4 with the returns to the asset growth characteristic deteriorating, where changes in the predictive power of composite accruals (*dacc*) (the sum of working capital changes (*dwc*) and nontransaction accruals (*ntacc*)) contribute to the reduction. These results for regressions excluding microcap firms emphasize that small firms do not drive the reduction. We can also see that the results are not due to a lack of power in the second period as the coefficient decreases as well as the t-value. The magnitude of the coefficient on total asset growth decreases from -0.74 to -0.24 with that of the t-value decreasing from -5.91 to -1.54. We can see that the coefficient on *invacc* remains statistically and economically significant in the post-SOX period while the coefficient on the composite measure of accruals declines almost to zero. This suggests the pure capital investment effect may remain strong, while the accrual component drives the decline of the total asset growth anomaly.

[Table 5 about here]

An alternative way of understanding how different components of asset growth contribute to return predictability involves using a decomposition of the Fama and MacBeth (1973) cross-section regression coefficient as in Hou and Loh (2016). I give a simple overview of the method here and refer interested readers to details in Hou and Loh (2016). The insight that allows us to determine the amount of variation in an anomaly return that is accounted for by another variable starts with the Fama and MacBeth (1973) regression. For each month t run a cross-sectional regression

$$R_{it} = \alpha_t + \gamma_t X_{i,t-1} + \varepsilon_{it}$$

next, run a regression of $X_{i,t-1}$ on some candidate predictor

$$X_{i,t-1} = a_{t-1} + b_{t-1} CANDIDATE_{i,t-1} + \mu_{i,t-1}$$

Finally we can use the linearity of covariances to decompose the estimated regression coefficient

$$\begin{aligned}
\gamma_t =& \frac{Cov_t[R_{i,t}, X_{i,t-1}]}{Var_t[X_{i,t-1}]} \\
=& \frac{Cov_t[R_{i,t}, a_{t-1} + b_{t-1} CANDIDATE_{i,t-1} + \mu_{i,t-1}]}{Var_t[X_{i,t-1}]} \\
=& \frac{Cov_t[R_{i,t}, b_{t-1} CANDIDATE_{i,t-1}]}{Var_t[X_{i,t-1}]} + \frac{Cov_t[R_{i,t}, a_{t-1} + \mu_{i,t-1}]}{Var_t[X_{i,t-1}]} \\
\gamma_t =& \gamma_t^C + \gamma_t^R
\end{aligned}$$

I use the asset growth decomposition to apportion the total asset growth coefficient to the different components of asset growth. The results can be seen in Table 6. I report the total coefficient in column b and the percentage of the covariation with returns explained by each component in the remaining columns. Note that the coefficients on asset growth are not exactly equal to those in previous tables since those regressions contained control variables in addition to asset growth, while the decomposition focuses on the univariate regression coefficient.

In Table 6 panel A we can see that *dacc* and *invacc* are the most important explanatory variables in the pre-SOX period, collectively accounting for 74% of the coefficient. Although all these variables can change contemporaneously, we can gain some insight from understanding which variables have the largest change in predictive power between the two periods. In the post-SOX period the percentage of the coefficient due to *dacc* decreases from 29% to 9% while the other components have the same or higher impact on returns. This suggests that the decline of the anomaly is linked to the accrual component of asset growth that also enters into earnings. The results in Table 6 panel B are qualitatively similar and in line with the results in table 4 that shows the decline is less severe when micro cap firms are included.

Table 7 shows the portfolio realized returns and alphas in the pre-SOX period (Panel A) the post-SOX period (Panel B) and provides a statistical test of the difference in returns between the two periods (Panel C). Comparing the results in Panel A to those in Table 3 you can see that the coefficients are larger in the period pre-SOX for equal and value-weighted returns and for all factor models. Results in Panel B indicate that the returns to strategies formed using asset growth and its components have economically and statistically lower returns in the post-SOX period. Panel C provides a formal statistical test for the difference in returns between the two periods. In columns (1) and (4) the statistics are exactly the difference in means, in columns (2)-(3) and (5)-(6) the statistics are not exactly equal to the difference as I assume that the factor adjustment does not differ across periods. These results confirm that there is an economically and statistically significant difference in returns to these strategies between the pre- and post-SOX periods.[10] Looking at the individual components of asset growth such composite accruals (dacc) confirms the insight of the Fama and MacBeth (1973) regressions that changes in the predictive power of accrual accounts contribute to changes in the predictive power of balance sheet asset growth. The results on the changing predictive power of accruals are consistent with the results in Green et al. (2011) that the accrual anomaly has diminished in recent years, I show that these accruals are a key driver of the asset growth anomaly.

[Table 7 about here]

Results in this section showed that the asset growth anomaly has weakened in the post-SOX period. Further, components of asset growth that are related to accrual accounts and earnings management are no longer related to returns in the post-SOX period. Given the link between accruals accounts and earnings management, this suggests that earnings management was a potential mechanism driving the anomaly in the pre-SOX period. The regulatory changes of the SOX act were intended to reduce earnings management and increase the quality of accounting information. I consider the question of whether SOX reduced earnings manipulation and increased the quality of accounting information as an empirical question which I answer in the next section.

[10]The results are similar using a 15 year sample for the pre-SOX period (equal to the length of the post-SOX period).

5 Understanding the decline

Estimating expected profitability is fundamental for valuation and the accounting system facilitates the process by ensuring the integrity of financial statement information. Sarbanes-Oxley was intended to improve the information environment and prevent managerial manipulation of the information flow to investors. However, it is important to assess whether the regulations did increase transparency and reduce manipulation, if this is to be interpreted as contributing to the decline of the anomaly.

In this section, I provide evidence that - relative to the pre-SOX period - earnings management has decreased in the post SOX-period, subjective (analyst) expectations of earnings are more accurate in the post-SOX period, and statistical expectations of earnings are more accurate in the post SOX period.

5.1 Misrepresentation of earnings

Section 3 emphasized the relationship between asset growth and earnings management through accrual accounts. In this section, I perform a statistical test that attempts to estimate the degree of earnings manipulation in the data, and estimate if this has changed in the recent, post-SOX period.

Although much of the evidence of earnings management comes from anecdotal accounts in survey evidence (Graham et al. (2005), Dichev et al. (2013), and Nelson et al. (2002)) and enforcement action by the SEC, using past accounting data alone one can also see evidence of earnings manipulation. The advantage of using accounting data from the full sample of firms is the inclusion of firms that are not surveyed by researchers or detected by regulatory bodies. For example, Hayn (1995) pointed out that there is a sharp discontinuity in the earnings-per-share to price ratio distribution, interpreting the discontinuity as evidence that managers who are close to reporting a loss engage in earnings management to cross the zero threshold. Hayn (1995) perform statistical tests of the earnings discontinuity under the null of a normal distribution of earnings in the absence of manipulation. Burgstahler and Dichev (1997) find that both cash flow from operations and working capital are used to find the extra income for earnings and extend the test of Hayn (1995) to a more general null of a "smooth" distribution in the absence of manipulation. Degeorge et al. (1999) find evidence that managers manipulate earnings around the threshold of analyst consensus forecasts, and provide a statistical test that relies on the idea of the distribution under the null of no earnings management being smooth and continuous.

I use a method that tests for earnings management while avoiding strong assumptions about the distribution of earnings variables in the absence of earnings management. I use the insight of McCrary (2008) that one can test for manipulation of the running variable in a regression discontinuity design by testing for a discontinuity of the distribution of the running variable at the cutoff for program assignment. In the context of earnings management we can imagine the "treatment" program to be the market reaction to *Surprise EPS*, and we can test for a discontinuity of the running variable around the cutoff of Surprise EPS=0. I use the methodology of Bird et al. (2016) and estimate a flexible parametric form for the earnings surprise distribution, allowing the functional form to vary on each side of the cutoff. This has the advantage of estimating the discontinuity without making strong assumptions about the data generating process as I allow the data to determine the functional form of the distribution. Specifically, I estimate the regression

$$nb_i = a + b \times \mathbb{1}_{\text{Surprise EPS}\geq 0} + f^k(\text{Surprise EPS}_i) + g^k(\mathbb{1}_{\text{Surprise EPS}\geq 0} \times \text{Surprise EPS}_i) + v_i$$

where nb_i represents the proportion of firm year observations in earnings surprise bin i (I use bin widths of one cent), $\mathbb{1}_{SurpriseEPS\geq 0}$ is an indicator function that is equal to one when the earnings surprise is positive and zero otherwise, $f^k(.)$ and $g^j(.)$ are order-k and order-j polynomial functions of *Surprise EPS*$_i$. I choose j and k using the Akaike Information Criterion and Bayesian Information Criterion. The estimate $\hat{b}$ of b, measures the discontinuity in the distribution of Surprise EPS around the cutoff point (*Surprise EPS=0*), and I interpret this as a measure of earnings management.

Figure 2 shows the fit of the regression specification for the pre- and post-SOX periods. The estimate of the discontinuity ($\hat{b}$) represents the difference in the functions at each side of the cutoff evaluated at the cutoff. Formal statistical tests are presented in Table 8, column (1) shows that the estimate of the discontinuity at the zero Surprise EPS cutoff is an economically significant 3.92% (t-statistic 7.04), column (2) shows that the estimate of the discontinuity falls to 0.70% in the post-SOX period. Column (3) provides an estimate of the difference in the discontinuity between the two periods which is 3.22% (t-statistic 5.04). These results echo those in Bird et al. (2016) and Gilliam et al. (2015) who find that earnings manipulation has decreased in the post-SOX period. In contrast to Bird et al. (2016), I show the result holds in an extended pooled sample containing the entire pre-SOX and post-SOX sample. If the earnings management was driven by a small window before SOX we would expect the noise in the other years to reduce the statistical and economic significance of the results. These results are also consistent with Iliev (2010) who provides causal evidence from a regression discontinuity experiment that SOX affected earnings management. This suggests that the information in earnings available to investors subject to less manipulation in the post-SOX period, so that prices that capitalize information in earnings will reflect the future firm value more accurately.

[Figure 2 about here]

[Table 8 about here]

Figure **??** gives further evidence on the relationship between accounting manipulation and asset growth. Since earnings management is unobservable I use information about the raw number of misconduct events from four commonly used financial misconduct databases: The Audit Analytics (AA) restatements datbase; the Government Accounting Office (GAO) database with classifications of irregularities as in Hennes et al. (2008); the Securities Class Action (SCA) database; and the Accounting Auditing Enforcement (AAER) database. Panel A contains the raw number of misconduct events over time in each database, we can see that the SCA ,GAO, and AAEER data all reveal a peak near the passage of Sarbanes Oxley. Likewise the restatements from the AA database peak a few years later as past accounting mistakes or misrepresentations are corrected. Figure **??** Panel B contains the number of misconduct events recorded for each firm within 5 years of entering a given asset growth portfolio, we can see that the number of events in the GAO, AAER, and SCA databases are much higher for the high asset growth portfolios. This reflects the fact that investors and regulatory agencies are more likely to take action against firms that underperform after suspected earnings misconduct. The restatements (which are not categorized into errors vs irregularies) are slightly higher for the very high and low asset growth portfolios.

[Figure ?? about here]

5.2 Analyst forecast errors

The previous section presented evidence that managers, given the consensus EPS in the month before earnings, are now less likely to manage earnings to meet or beat the consensus forecast. This suggests a more nuanced understanding of the generally observed optimistic bias of analysts - when managers act to beat the analyst forecast, then the analyst will look biased even if the manipulation free forecast was correct. Next, I investigate if this is visible in the magnitudes of analyst forecast errors in the pre- and post-SOX periods.

Figure 4 shows the difference in average analyst forecast errors for fiscal year t earnings as a function of the number of months from the announcement of fiscal year t-1 earnings. For both the pre- and post-SOX periods we can see that the well documented analyst optimism bias is present. We can see that the consensus forecast error is higher in magnitude for every period in the pre-SOX period relative to the post-SOX period. This level effect could be driven by the reduction in manipulation as well as analysts becoming more accurate in their forecasts due to the increased accuracy of available accounting information. The dynamics of forecast errors show us that the optimism is strongest after the report of prior fiscal year earnings and gradually reduce throughout the year. The forecast errors move closer to zero as the distance to the earnings announcement becomes closer and quarterly earnings information becomes available. This suggests that even investors who rely only on information from analyst earnings forecasts will have more accurate information regarding future earnings.

[Figure 4 about here]

5.3 Earnings predictability

In sections 5.1 and 5.2 I provided evidence that analyst forecast errors are more accurate post-SOX, and that this could be driven by a reduction in managerial manipulation of earnings. If earnings are not manipulated, then the accounting information available to investors should be of higher quality, and it should be easier to forecast earnings. In this section, I use cross sectional regressions to identify rational statistical expectations of earnings conditional on an information set of accounting variables that would have been available to investors at the time of their expectation formation. I estimate cross sectional regressions of earnings in year t on earnings and accruals in year t-1. These earnings persistence regressions are a measure of the predictability of firm performance, and allow me to identify changes in the predictability of earnings between different periods while holding the model constant.

Table 9 contains results for earnings predictability regressions (earnings in year t are regressed on prior year accounting variables). Columns (1)-(4) contain results of regressions in the pre-SOX sample. In column (1) we can see that earnings are predictable by prior earnings and that asset growth typically predicts lower earnings going forward. Moving from column (1) to column (4) we can see that decomposing asset growth into accrual and investment components allows for better predictability of earnings. The fact that accrual components of earnings have lower persistence than other components can be seen by looking at the coefficient on *dacc* (-0.16). This reflects the fact that accruals are the least reliable component of earnings, and are not expected to contribute to earnings going forward. Columns (5)-(8) contain the results of regressions in the post-SOX sample. Comparing columns (4) and (8) we can see that the amount of explained variation in the cross section of earnings is significantly higher in the post-SOX period (the R^2 increases from 44% to 59%). This suggests that a simple estimate of a linear conditional expectation function using publicly available conditioning information can explain more variation in the post-SOX period relative to the pre-SOX period.

[Table 9 about here]

[Table 10 about here]

Table 10 contains results for regressions of earnings predictability using a sample excluding microcap firms. The results are similar to those presented in Table 9. Focusing on the explained variation in earnings the change in R^2 between the pre- and post-SOX period is 5%, which suggests the increase in predictability is also present in the sample excluding microcap firms.

In summary, results suggest that relative to the pre-SOX period, statistical expectations of earnings using a linear model are more accurate post-SOX, analyst forecast errors have decreased on average post-SOX, and that earnings management is less prevalent post-SOX. The implication is that any variation in asset growth driven by variation in accrual accounts used to manipulate earnings has decreased in the post-SOX period.[11]

6 Is the relationship explained by risk or mispricing?

Results in section 4 show that the components of asset growth that managers used to manipulate earnings in the past are no longer related to returns, while results in section 5 suggest that the information environment has changed and that earnings manipulation

[11]This includes externally financed variation in asset growth that would not have been financed if investors had seen unmanaged earnings.

has decreased. In this section, I try to understand if the accrual accounts that are related to returns - and connect asset growth with earnings management - can be related to mispricing or risk. First I review the literature that attempts to connect asset growth to risk or mispricing, and then I provide a test that attempts to distinguish between the two explanations.

The risk based mechanism must tie the asset growth characteristic to returns through covariation with states of nature that are unfavorable to investors, either using optimal production or consumption decisions. Cochrane (1996) shows that a pure production based asset pricing model is impossible with the current production technology specifications, so that in general equilibrium in a complete market, these models will inherit all of the challenges of consumption based asset pricing. In fact, problems are multiplied because when dividends are endogenous as the representative investor uses firms as bank of capital to smooth consumption so that one needs adjustment costs of capital to maintain risk. Gomes et al. (2003) generate cross sectional risk premia in general equilibrium and Chen (2016) extends this to a model with endogenous time variation in risk though habit utility.

A large class of partial equilibrium models take the preferences/probability assessments of the representative consumer as given and explore the ability of models with production to explain the link between characteristics and returns (through covariance with investor preferences/probability assessments), these models are framed as neoclassical investment models (examples include Zhang (2005), Li et al. (2009), Livdan et al. (2009), Lin and Zhang (2013), Belo et al. (2016), and Bazdrech et al. (2008)) or real options models (examples include Berk et al. (1999), Carlson et al. (2006), Novy-Marx (2011), and Cooper (2006)). The main takeaway from these models is that (conditional on expected profitability) firms invest when ex-ante expected returns are low, so that in the data we see that ex-post average returns to high investment portfolios are low.[12]

A second set of "behavioral" explanations emphasize the idea that investors make systematic mistakes in their probability assessments, which are related to firm characteristics and thus drive characteristic return relationships. Lakonishok et al. (1994) use valuation ratios such as book-to-market as a proxy for expected growth and suggest that investors overestimate future growth rate differences between firms sorted on valuation ratios. Porta (1996) ties value characteristics directly to expectations thought analyst forecast errors. Lipson et al. (2011) tie asset growth to analyst forecast errors and find that the returns to asset growth are higher on earnings announcement days. These theories often implicitly assume that managers invest optimally, but that investors are overly optimistic about the prospects of growing firms relative to shrinking firms. Polk and Sapienza (2008) also assume optimal behavior of management and systematic mistakes on the side of investors, they use accruals as a measure of mispricing, and suggest that managers accommodate the preferences of sentiment investors in the sense of Stein (1996). In such models investment is a proxy for ex-ante probability belief distortions and prices reverse when the probability mistakes are revealed ex-post.

In contrast to the above theories, I suggest that managers create the mispricing, rather than accommodating it, and suggest that investors are deceived rather than mistaken. Managers internalize the enormous importance investors place on earnings, and given discretion in accounting they try to guide the stock price through earnings manipulation.

[12] While some of these models focus on size and book-to-market effects rather than pure asset growth effects, empirical work has shown that asset growth is behind the success of the book-to-market factor. Xing (2007) shows that investment is behind the book to market effect and considers it consistent with q-theory Anderson and Garcia-Feijóo (2006) consider the same question from a real options perspective. The intuition is that low investment firms are those with high book value who can not convert capital to consumption due to investment frictions so they have high risk and low investment, however, operating leverage and high irreversibility of investment are needed to make assets in place riskier than growth options. Clementi and Palazzo (2015) provides a critique that Aretz and Pope (2018) and Gu et al. (2017) also emphasize: even a small amount of investment reversibility may reduce the operating leverage effect needed to explain this risk premium.

Thus, investors who neglect the propensity for earnings to incorporate manipulation will capitalize this information into prices, and prices will be corrected when manipulation is reversed. Such behavior of investors can be rationalized by the need to focus on a small set of information variables when attention is limited, as in Hirshleifer et al. (2011).

Early empirical attempts to distinguish between different explanations for the asset growth anomaly include Li and Zhang (2010) and Lam and Wei (2011) who exploit cross sectional variation in constructs related to either limited arbitrage or producer investment frictions to assess the time periods, and firms, for which the anomaly is strongest. A difficulty discovered by these authors is that the investment friction and limited arbitrage measures are correlated, making it hard to say the anomaly exists exclusively for one group of firms or another. Lin and Zhang (2013) and Kozak et al. (2018) make the point (one from the side of production and the other from the side of trading) that tests that draw a distinction between "characteristics" and "covariances" relying only on market data does not inform us about investor preferences or beliefs. Kozak et al. (2018) emphasize the point that models must make assumptions about investor beliefs and preferences that result in restrictions on the stochastic discount factor to deliver testable predictions that potentially help discriminate between competing models of how investors price assets.[13] For this reason, I try to identify a channel between accruals and returns using data on the probability assessments of sell-side analysts.

[13] That is, arbitrary projections of returns onto the subspace of marketed returns have no economic content - which they did in the case of the classic CAPM as the projection was motivated by assumptions about investor behavior.

6.1 Evidence from analyst forecast errors

In this section, I tie variation in accrual components of earnings (and asset growth) to analyst forecast errors. This suggests that the channel of mispricing goes from accruals to prices through the mistaken probability assessments of investors. A crucial assumption to make the link from accruals to mispricing through the probability distortions of investors is that investors' expectations are the same as those of analysts. While they are unlikely to be exactly the same, So (2013) show that prices do not reflect the predictable component of analyst forecast errors, which provides evidence that investors systematically overweight analyst forecasts.

Bradshaw et al. (2001) suggest that neither auditors nor analysts respond to information in accruals and show that analysts forecast errors can be predicted using information in accruals. I use a similar methodology and examine the relationship between the cross section of firm accrual characteristics in year t-1 and the series of monthly forecast errors for fiscal year earnings of year t to understand if accruals can predict forecast errors. A finding that accruals can predict forecast errors would suggest that analysts do not completely incorporate information in accruals into their return forecasts. I follow the methodology in Bradshaw et al. (2001) to understand if the relationship between accruals and forecast errors has changed.

Table 11 shows the results of a series of cross sectional regressions of analyst forecast errors (in percent) on accruals using a composite measure of accruals which is the sum of working capital accruals and nontransaction accruals.[14] The accrual component of asset growth (*dacc*) that are related to returns in the pre-SOX period, are also related to the cross section of analyst forecast errors. In Table 11 you can see that the coefficient on

[14] I also replicate the results of Bradshaw et al. (2001) and results are qualitatively similar, with slight differences due to the fact that I use the detail file from I/B/E/S rather than the summary file.

PortAcc (which is the nyse decile portfolio ranking of the firm-year accruals scaled by the lag of total assets in year t) is negative and significant for almost all horizons (Panel A), and that this relationship weakens in the post-SOX period (Panel B). I show a test of the difference in coefficients in Panel C, the relationship between accruals and forecast errors is significantly lower for most forecast horizons in the post-SOX period relative to the pre-SOX period. The results are economically significant. The forecast errors are scaled by price so multiplying by, for example, a price-to-earnings ratio of 20 suggests that moving from the bottom decile to the top decile of accruals results in an additional error of 6% ($20 \times -0.30\%$) in earnings forecasts in the pre-SOX period, an effect which dissipates in the post-SOX period. These results suggest that expectational errors related to accruals can drive accrual related mispricing in the following way: analysts and investors expect higher earnings in year t+1 for firms with relatively higher accruals in year t and thus bid up the prices of these stocks, however, firms with relatively higher accruals tend to have lower earnings than expected in year t+1.

[Table 11 about here]

7 Alternative explanations

The shock to the corporate environment due to the Sarbanes-Oxley act provided changes that were exogenous to the circumstances of individual firms. This provides an almost ideal context to understand the impact of earnings management on the asset growth anomaly. However, as SOX applied to all firms one might be concerned that contemporaneous changes in the corporate environment could have caused the effects detailed in this paper.[15] Additional tests can distinguish between alternative hypotheses. A key impli-

[15] Firms with a public float of less than US$75 million were excepted from section 404(a) until 2007 and remain excepted from section 404(b). Section 404(a) requires a public reporting company to file a management report on the effectiveness of internal accounting controls while section 404(b) requires firms to obtain an auditor attestation regarding the management report.

cation of the idea that strengthening regulation reduced earnings management induced mispricing is that firms with ex-ante strong lower ability to manage earnings will have a weaker relationship between asset-growth and returns. The hypothesis that the anomaly could be reduced by institutional trading is agnostic about the source of the anomaly but makes strong predictions about changes in the trading of institutions. In this section I provide tests that show the anomaly was stronger in firms with weaker corporate governance and that there was no significant increase in the institutional trading of anomaly portfolios in the post-SOX period. This supports the hypothesis that the anomaly was driven by earnings management induced mispricing in the past, and that the reduction in earnings management caused by SOX caused the decline of the anomaly.

7.1 The anomaly and corporate governance

Results so far suggest that earnings management contributes to the asset growth anomaly, and that the decline of earnings management after SOX has driven some of the decline of the asset growth anomaly. However, using SOX as a shock to identify changes in earnings management poses some challenges, as it was enacted at one point in time. This raises the concern that other contemporaneous changes in the market could drive the observed changes in the data. In this section I exploit cross sectional variation in the propensity of managers to manage earnings to add further support to the hypothesis that changes in earnings management drive the changes in the returns to the asset growth strategy.

I rely on variables that proxy for the propensity of managers to manage earnings. The idea that managerial entrenchment can affect earnings management is explored by Zhao and Chen (2008) who show that entrenchment reduces abnormal accruals and increases loss recognition. Di Meo et al. (2017) use exogenous variation in entrenchment to identify the causal effect of entrenchment on earnings management. Likewise Klein (2002) and Xie et al. (2003) both show a negative relationship between board independence and sophistication and measures of earnings management.

To design a test of the relationship between asset growth and the likelihood of earnings management I use proxy variables for managerial entrenchment and board independence. I measure entrenchment using the Entrenchment Index of Bebchuk et al. (2008) and governance using the fraction of independent directors from the ISS directors legacy database. Under the hypothesis that earnings management is negatively related to managerial entrenchment (governance) I would expect to see the strength of the asset growth anomaly weaken as a function of entrenchment (governance). I use a sample period pre-SOX and all stocks that have data for entrenchment (governance). There are 47,594 firm year observations in the full data set for the period from 1990-2002. Conditional on the availability of the measure of entrenchment (governance) there are (12,745) 8,126 firm year observations. These firms tend to be much larger on average, and the asset growth anomaly exists only on an equal weighted basis in this sample so I proceed by understanding the variation in the equally-weighed asset growth anomaly as a function of entrenchment (governance). I sort stocks first into terciles based on entrenchment (governance) and then conditional on the level of entrenchment (governance) I sort firms into terciles based on asset growth. The monthly returns of these portfolios are then calculated going forward and rebalanced annually. The results can be seen in table 12.

Table 12 Panel A shows the relationship between the asset growth anomaly and entrenchment. In the low entrenchment portfolio the asset growth anomaly has monthly returns of 0.80% which is statistically significant. The portfolio returns decrease as entrenchment increases, and firms in the high tercile of entrenchment have anomaly returns of 0.43% per month which are almost half that of the return spread in the low entrenchment tercile.

Table 12 Panel B shows the relationship between the asset growth anomaly and governance as measured by the fraction of independent directors. In the low governance portfolio the asset growth anomaly has monthly returns of 1.05% which are statistically significant. The portfolio returns decrease as governance increases, and firms in the high tercile of governance have insignificant anomaly returns of 0.36% per month which is almost one third that of the return spread in the low governance tercile.

These results suggest that mechanisms that lessen the incentive to manage earnings (entrenchment) or the ability to manage earnings due to increased oversight (governance) decrease the strength of the asset growth anomaly.

[Table 12 about here]

7.2 The anomaly and institutional trading

A key alternative hypothesis that can explain the decline (but not the source) of the asset growth anomaly relates to the activities of institutional traders. McLean and Pontiff (2016) show evidence from many anomalies that institutional trading of anomalies in the post-publication period can explain their decline. Chordia et al. (2014) also give evidence on the diminishing returns of multiple anomalies and suggest that it is related to institutional trading and easing of arbitrage limits by capital markets developments such as decimalization. As decimalisation occurs in 2002, and many anomalies related to asset growth (e.g. accruals) were well known around that time. It is important to understand if institutional trading is driving the decline of the asset growth anomaly.

I attempt to answer the question of whether sophisticated investors arbitrage away the anomaly by focusing on the trading of institutional investors. I calculate the percentage of share ownership accounted for by institutional investors at the stock level, and then analyse how the patterns of institutional ownership in anomaly decile portfolios change around the anomaly portfolio formation period. Figure 5 shows equal- and value-weighted quarterly institutional ownership changes in the months prior to portfolio formation for the low asset growth portfolio in the pre-SOX period (blue line) and post-SOX period (red line). I focus on the low asset growth portfolio for expositional purposes. Table A.3 further shows that most of the anomaly decline can be attributed to the long-side of the portfolio which means that the decline can be attributed to the easiest position for long-only institutional investors to exploit. We can see that for both equal weighted and value weighted institutional ownership, institutional investors build up positions in low asset growth anomaly stocks in the months before portfolio formation. If institutions were trading the anomaly more aggressively in the post-SOX period, we would expect to see the red line above the blue line. However, the figure points towards the opposite effect. In the post-SOX period, institutional investors invest less in the low asset growth portfolio.

I test the difference formally in Table 13 where I regress the changes in average institutional ownership in the six quarters prior to portfolio formation for the low asset growth portfolio, the high asset growth portfolio, and the difference between the two on a post-

SOX dummy.[16] If institutional investors were trading on the anomaly we would expect the average changes in ownership on low asset growth firms to be positive overall (positive coefficient on *Intercept*) and to see this effect increase in the post-SOX period (positive coefficient on *Post-Sox Indicator*. Likewise, we would expect to see institutional ownership changes at a lower level in the low asset growth firms as funds avoid these firms, and we would expect this to decrease further as funds exploit the anomaly more in the post-SOX period.

Results in Table 13, show precisely the opposite. For the equal weighted institutional ownership changes in Panel A, the difference in institutional ownership goes in the opposite direction than would be expected if funds were investing more in the anomaly in the post-SOX period. Funds invest less in high asset growth firms while investing more in low asset growth firms. The coefficent of 1.25% on the high minus low difference of *Intercept* means that, on average, funds invest more in high asset growth firms than low asset growth firms in the post-SOX period. The coefficient of 1.43% on *Post-SOX Indicator* means that the extent to which institutions purchase more high asset growth firms than low asset growth firms is increasing in the post-SOX period. In Panel B the results for value-weighted percentage changes in institutional ownership are presented. I am unable to reject the null hypothesis that value-weighted institutional trading behavior in the anomaly portfolios is unchanged in the post-SOX period. These results are consistent with Edelen et al. (2016) who show that institutional investors often build up positions that run in the opposite direction to the prescriptions of anomaly portfolios.

[Figure 5 about here]

[Table 13 about here]

8 Conclusion

I document that the asset growth anomaly of Cooper et al. (2008) is related to the accrual anomaly of Sloan (1996). Variation in accrual accounts which affect asset growth

[16]Portfolios are formed monthly with a minimum lag of 6 months, which means the oldest possible data-point used in the portfolio is 18 months old. The 6-quarter lag captures this effect. Results are similar using changes over 2 and 4 quarters.

contribute to the returns of the asset growth anomaly. The returns on the asset growth anomaly have diminished, and the reduction can be linked to changes in accrual accounts used for earnings management. Wide ranging changes in the corporate governance environment since the Sarbanes-Oxley Act of 2002 seem to have reduced earnings management. Evidence on earnings manipulation, analyst forecast errors, and the relationship between forecast errors and accruals suggest that the relationship between asset growth and returns was driven by mispricing in the past, and that this mispricing has dissipated. This mispricing hypothesis explains both the source and the decline of the asset growth anomaly. These findings point towards changes in the regulatory environment as a novel way in which equity market anomalies can rise and fall over time.

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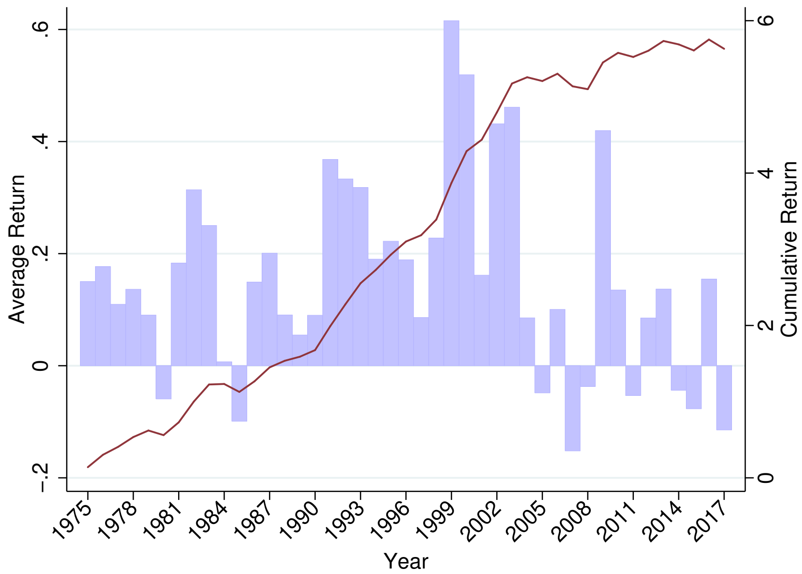
Figure 1: Annual and cumulative returns of the asset growth strategy

This figure shows the yearly returns and logarithm of cumulative returns to the total asset growth portfolio considered in Table 3 from 1975 to 2017. Panel A contains results for equally weighted returns and Panel B contains results for value-weighted returns.

Panel A: Equal-weighted returns



Panel B: Value-weighted returns

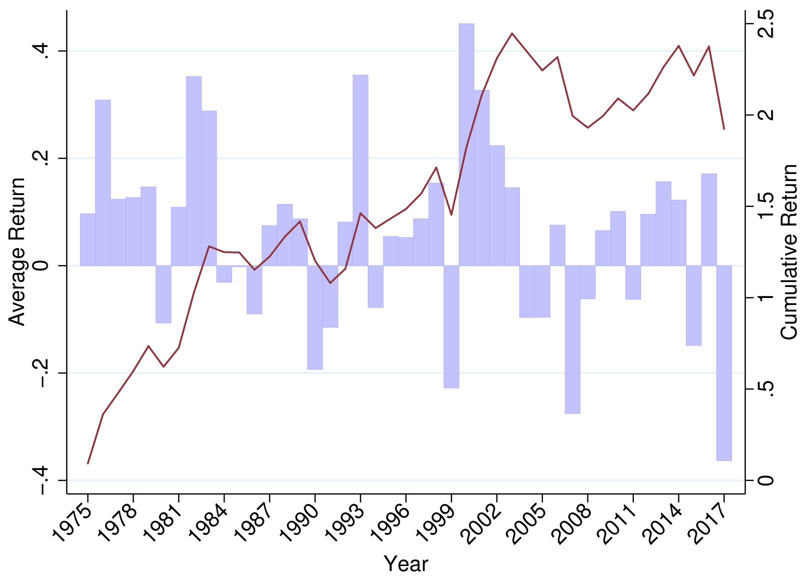


Figure 2: Parametric distribution fits to surprise EPS frequencies

This figure contains the points of a scatter plot that give the frequency of each observation of Surprise EPS in each bin (nb_i) (bin width of one cent) as well as a polynomial function fit on each side of the cutoff of *Surprise EPS*=0 separately for the period pre- and post-SOX. The running variable is *Surprise EPS*, which is defined as actual earnings minus analysts consensus earnings forecast in the month prior to the announcement of fiscal year earnings, and the dependent variable is the frequency of firm-year observations in each earnings surprise bin (nb_i). The estimate of the distribution discontinuity can be seen as the intersection of the fitted polynomials at *Surprise EPS*=0.

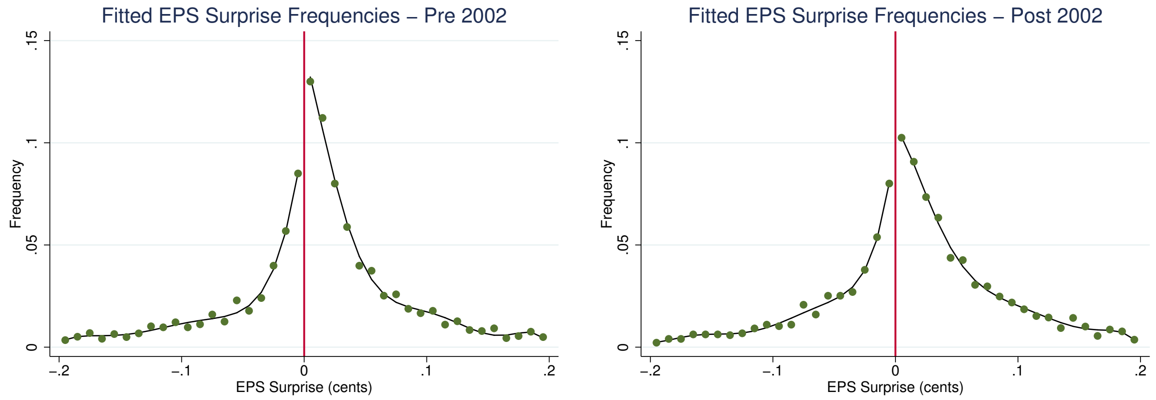
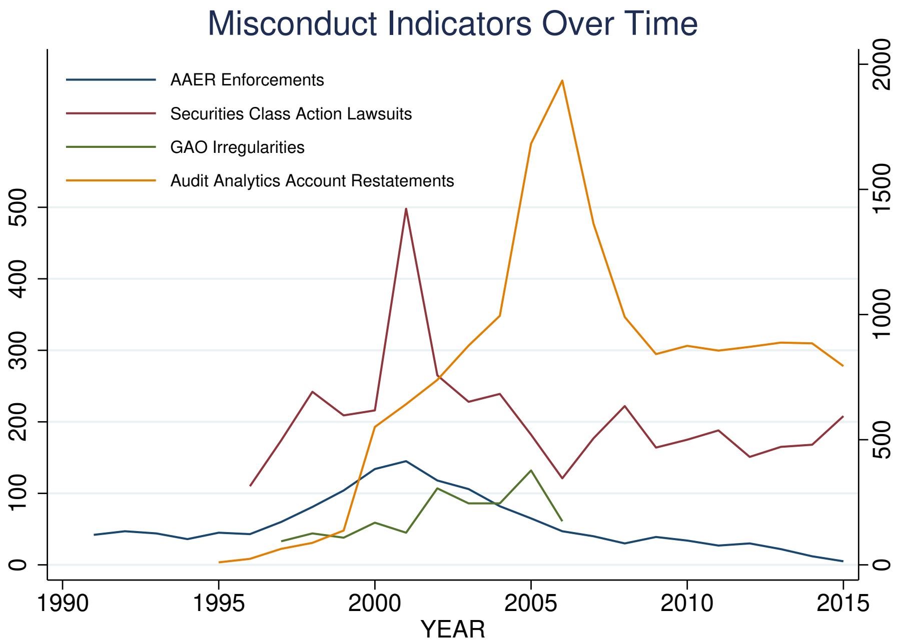


Figure 3: Misconduct indicators over time and within asset growth portfolio firms

This figure contains information about the raw number of misconduct events from four commonly used financial misconduct databases: The Audit Analytics restatements database; the Government Accounting Office (GAO) database with classifications of irregularities as in Hennes et al. (2008); the Securities Class Action (SCA) database; and the Accounting Auditing Enforcement (AAER) database. Panel A contains the raw number of misconduct events over time in each database. Panel B contains the number of misconduct events recorded for each firm within 5 years of entering a given asset growth portfolio.



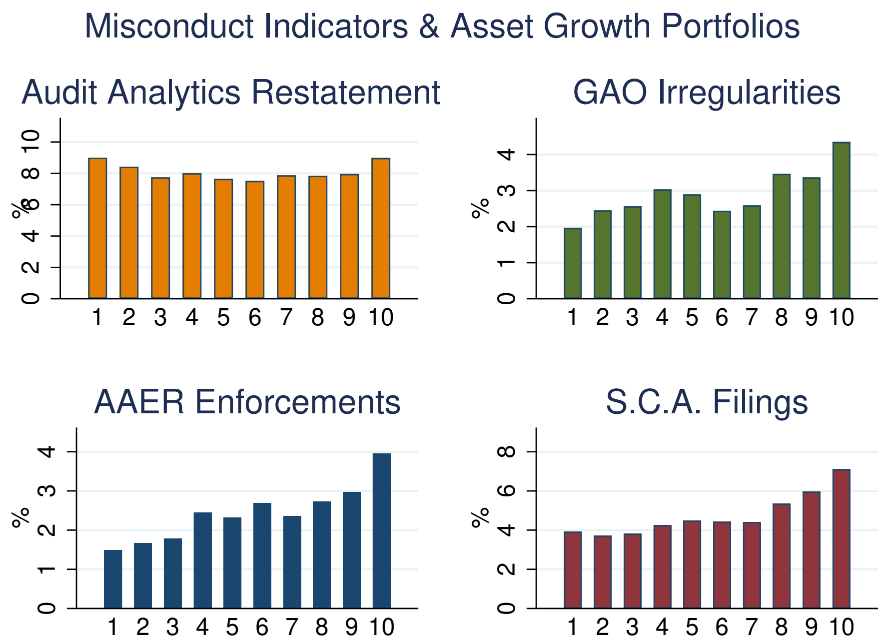


Figure 4: Average analyst forecast errors

Analyst forecast errors pre- and post-SOX. This figure contains the average of firm level analyst consensus forecast errors over various horizons both pre- and post-2002. The forecast error (FE) for each firm is calculated as the actual earnings minus the current analyst consensus forecast (so that negative numbers reflect analyst optimism). The forecast error is recalculated for each firm in each month after the announcement of the firms prior year fiscal earnings announcement until the announcement of the firms actual fiscal year earnings. These firm month forecast errors are then averaged for each month. This procedure is done separately for the period from 1988-2002 and the period from 2003-2017. Appendix A provides the variable definitions.

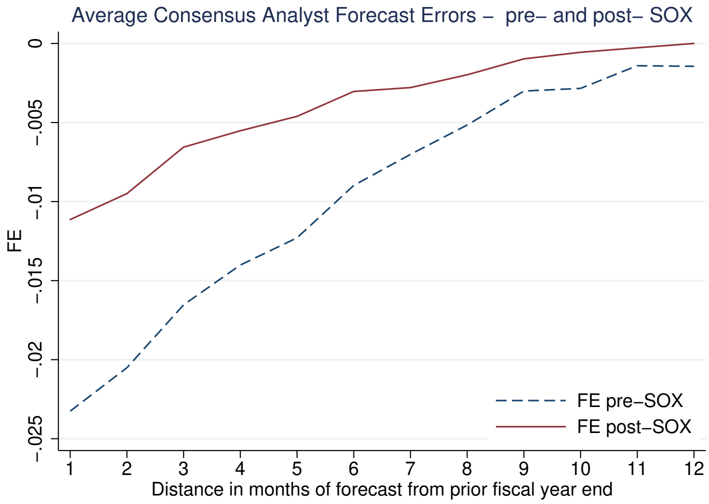
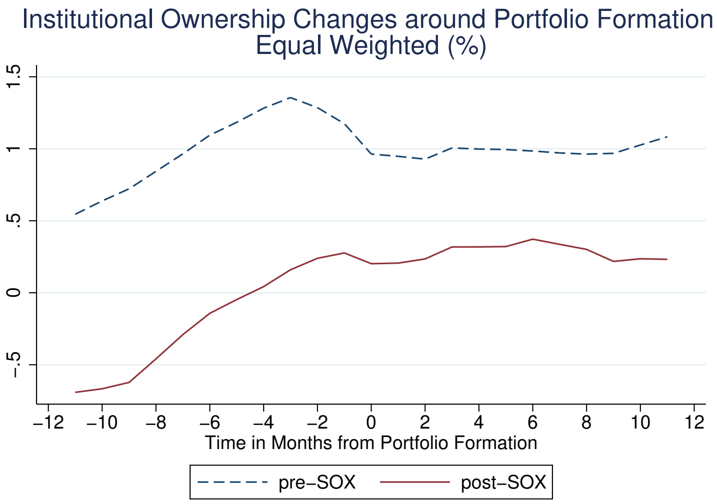


Figure 5: Institutional ownership changes in the months around total asset growth portfolio formation

This figure contains quarterly changes in the percentage of shares owned by 13F institutions in the months prior to portfolio formation in the low asset growth decile portfolio. The values are annualized percentage changes. Value weighted ownership is calculated by weighting the 13F ownership of each stock in the anomaly portfolio by the overall weight of that stock in the anomaly portfolio. The values are presented separately for the pre-SOX period (January 1982- July 2002) and post-SOX period (August 2002-December 2017). Appendix A provides the variable definitions.



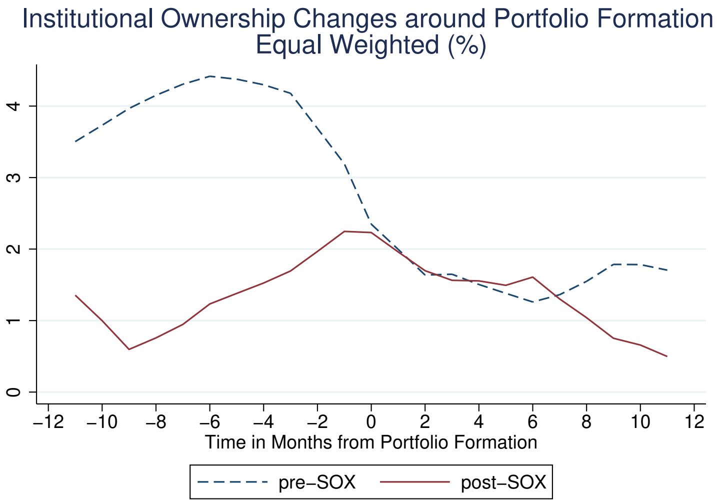


Table 1: Data Description

Panel A contains information about the distributions of the variables used in the paper. Percentile values are time series averages of the percentiles. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=accruals, ntacc=non-transaction accruals, *doa_ol*=change in operating assets funded by operating liabilities, dche=change in cash (all of which are scaled by total assets at the end of the prior fiscal year). Control variables include earnings scaled by assets, log size, log book to market, returns from month t-12 to t-2 and returns in month t-1. Panel B contains Spearman (above diagonal) and Pearson (below diagonal) correlation coefficients. All independent variables are winsorized at the 1st and 99th percentiles. Appendix A provides the variable definitions. The sample is from January 1975 to December 2017.

Panel A: Univariate distribution statistics

Variable	mean	sd	p5	p25	p50	p75	p95
tag	0.19	0.43	-0.11	0.02	0.10	0.22	0.78
dnoa	0.10	0.26	-0.11	-0.01	0.05	0.14	0.48
dltnoa	0.09	0.23	-0.08	-0.00	0.03	0.10	0.41
dwc	0.02	0.08	-0.09	-0.02	0.01	0.04	0.15
dacc	-0.06	0.12	-0.22	-0.10	-0.05	-0.01	0.10
invacc	0.16	0.26	-0.01	0.05	0.10	0.18	0.53
ntacc	-0.07	0.08	-0.18	-0.09	-0.06	-0.04	-0.01
doa_ol	0.04	0.10	-0.05	0.00	0.03	0.06	0.19
dche	0.04	0.20	-0.11	-0.01	0.00	0.04	0.24
ni	0.06	0.22	-0.11	0.03	0.07	0.11	0.21
ls	6.77	1.65	4.29	5.58	6.68	7.77	9.74
lbm	-0.78	0.80	-2.15	-1.22	-0.72	-0.25	0.37
r12_2	0.19	0.56	-0.44	-0.10	0.11	0.36	0.99
r1_1	0.02	0.13	-0.16	-0.04	0.02	0.08	0.21

Panel B: Correlation coefficients

	tag	dnoa	dltnoa	dwc	dacc	invacc	ntacc	doa_{ol}	dche
tag	1.00	0.71	0.69	0.29	0.19	0.61	-0.10	0.65	0.35
dnoa	0.81	1.00	0.85	0.56	0.41	0.73	-0.05	0.32	-0.17
dltnoa	0.81	0.93	1.00	0.15	0.08	0.86	-0.08	0.38	-0.08
dwc	0.30	0.50	0.17	1.00	0.76	0.10	0.06	0.00	-0.21
dacc	0.08	0.24	-0.03	0.77	1.00	-0.19	0.59	-0.05	-0.16
invacc	0.78	0.88	0.95	0.15	-0.21	1.00	-0.48	0.38	-0.07
ntacc	-0.27	-0.25	-0.28	-0.02	0.60	-0.54	1.00	-0.13	-0.03
doa_{ol}	0.66	0.48	0.52	0.08	-0.06	0.51	-0.21	1.00	0.16
dche	0.60	0.12	0.16	-0.07	-0.10	0.17	-0.10	0.25	1.00

Table 2: Fama and MacBeth regressions

This table contains average Fama and MacBeth (1973) regression slopes and their t-values from cross sectional regressions that predict monthly returns. The regressions are estimated monthly using data from January 1975 through December 2017. Columns (1)-(4) contain results the full sample of firms, and columns (5)-(8) contain results for the sample excluding microcap firms. Microcaps are defined as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals. Control variables include earnings scaled by assets, log size, log book to market, prior returns from month t-12 to t-2, prior returns in month t-1, and remaining components of the asset growth decomposition (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year). All independent variables are winsorized at the 1st and 99th percentiles. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	full sample				no microcap sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tag	-0.87***				-0.59***			
	(-11.02)				(-5.88)			
dnoa		-1.25***				-0.99***		
		(-11.51)				(-7.69)		
dltnoa			-1.24***				-0.83***	
			(-9.73)				(-5.51)	
dwc			-1.62***				-1.09***	
			(-6.39)				(-3.34)	
dacc				-1.76***				-1.46***
				(-7.76)				(-5.09)
invacc				-1.11***				-0.78***
				(-9.14)				(-5.49)
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.035	0.037	0.038	0.038	0.060	0.064	0.066	0.067

Table 3: Portfolio returns

This table contains equal- and value-weighted average excess returns ($\bar{r}^e$), market model alphas (CAPM), and Fama-French three-factor model alphas (FF3) for portfolios sorted by asset growth and its components. I sort stocks into deciles based on NYSE breakpoints at the end of each month and hold the portfolio for the following month. The sample extends from January 1975 through December 2017. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=accruals (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year), and for each component the sort is based on the variation unrelated to the other components as described in section 4. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Equal-Weight			Value-Weight		
Sort Variable	$\bar{r}^e$	CAPM	FF3	$\bar{r^e}$	CAPM	FF3
tag	1.25***	1.33***	1.15***	0.44***	0.55***	0.24*
	(8.06)	(8.87)	(8.21)	(2.66)	(3.26)	(1.69)
dnoa	1.21***	1.27***	1.13***	0.36**	0.43***	0.25*
	(9.50)	(10.28)	(9.73)	(2.53)	(3.05)	(1.91)
dltnoa	1.20***	1.25***	1.12***	0.33**	0.39***	0.22
	(9.14)	(9.80)	(9.35)	(2.27)	(2.71)	(1.61)
dwc	0.49***	0.51***	0.45***	0.66***	0.65***	0.63***
	(6.00)	(6.28)	(5.79)	(4.67)	(4.49)	(4.27)
dacc	0.25**	0.29***	0.24**	0.28*	0.34**	0.30*
	(2.27)	(2.71)	(2.27)	(1.84)	(2.25)	(1.93)
invacc	1.03***	1.15***	1.03***	0.33**	0.45***	0.30**
	(9.04)	(10.77)	(10.08)	(2.33)	(3.25)	(2.35)

Table 4: Fama and MacBeth regressions

This table contains average Fama and MacBeth (1973) regression slopes and their t-values from cross sectional regressions that predict monthly returns. Columns (1)-(4) contain results for regressions estimated in the pre-SOX period, and columns (5)-(8) in the post-SOX period. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=accruals. Control variables include earnings scaled by assets, log size, log book to market, prior returns from month t-12 to t-2, prior returns in month t-1, and remaining components of the asset growth decomposition (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year). All independent variables are winsorized at the 1st and 99th percentiles. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Pre-SOX				Post-SOX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tag	-1.03***				-0.50***			
	(-10.54)				(-4.15)			
dnoa		-1.50***				-0.68***		
		(-11.40)				(-3.53)		
dltnoa			-1.49***				-0.56***	
			(-9.44)				(-2.76)	
dwc			-1.92***				-1.31**	
			(-7.40)				(-2.19)	
dacc				-2.16***				-1.07**
				(-8.81)				(-2.14)
invacc				-1.29***				-0.64***
				(-8.27)				(-3.43)
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.04

Table 5: Fama and MacBeth regressions - sample excluding microcap firms

This table contains average Fama and MacBeth (1973) regression slopes and their t-values from cross sectional regressions that predict monthly returns in which Microcap firms are excluded. Microcaps are defined as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. Columns (1)-(4) contain results for regressions estimated on the sample from the pre-SOX period, and columns (5)-(8) from the post-SOX period. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=accruals. Control variables include earnings scaled by assets, log size, log book to market, prior returns from month t-12 to t-2, prior returns in month t-1 and remaining components of the asset growth decomposition (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year). All independent variables are winsorized at the 1st and 99th percentiles. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Pre-SOX				Post-SOX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tag	-0.74***				-0.24			
	(-5.91)				(-1.54)			
dnoa		-1.26***				-0.41**		
		(-7.95)				(-1.99)		
dltnoa			-0.98***				-0.48**	
			(-5.22)				(-2.26)	
dwc			-1.97***				0.38	
			(-5.65)				(0.50)	
dacc				-2.27***				0.14
				(-7.48)				(0.22)
invacc				-0.95***				-0.46**
				(-5.32)				(-2.23)
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.06	0.07	0.07	0.07	0.06	0.06	0.07	0.07

Table 6: Fama and MacBeth coefficient decompositions

This table contains Hou and Loh (2016) decompositions of the Fama and MacBeth (1973) regression coefficient for total asset growth. Microcaps are defined as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. tag=total asset growth, dacc=change in accruals, invacc = investment accruals, doaol=change in operating assets financed by operating liabilities, dche=change in cash and cash equivalents (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year). Appendix A provides the variable definitions.

Panel A - All but microcap firms

Full Sample

	b	dacc	invacc	doaol	dche	resid
coefficient	-0.63	-0.16	-0.30	-0.10	-0.07	-0.01
percent	1	26%	48%	16%	11%	1%
t-stat	-5.35	3.60	7.27	4.23	1.92	0.98

Pre-SOX

	b	dacc	invacc	doaol	dche	resid
coefficient	-0.82	-0.24	-0.37	-0.13	-0.09	-0.02
percent	1	29%	46%	15%	11%	2%
t-stat	-4.95	4.46	8.81	4.40	2.42	1.80

Post-SOX

	b	dacc	invacc	doaol	dche	resid
coefficient	-0.29	-0.025	-0.16	-0.06	-0.03	0.01
percent	1	9%	57%	21%	10%	-1%
t -stat	-2.09	0.85	4.02	4.42	0.87	-0.48

Panel B - All firms

Full Sample

	b	dacc	invacc	doaol	dche	resid
coefficient	-1.11	-0.21	-0.53	-0.21	-0.18	-0.01
percent	1	19%	48%	19%	16%	1%
t-stat	-9.55	5.79	12.9	11.7	6.21	0.71

Pre-SOX

	b	dacc	invacc	doaol	dche	resid
coefficient	-1.32	-0.27	-0.64	-0.24	-0.14	-0.00
percent	1	21%	49%	18%	11%	0%
t-stat	-8.51	7.35	17.6	11.4	5.35	0.091

Post-SOX

	b	dacc	invacc	doaol	dche	resid
coefficient	-0.72	-0.08	-0.29	-0.16	-0.25	-0.02
percent	1	11%	40%	22%	35%	7%
t-stat	-4.38	1.97	6.42	11.6	10.2	1.75

Table 7: Portfolio returns

This table contains equal- and value-weighted average excess returns ($\bar{r}^e$), market model alphas (CAPM), and Fama-French three-factor model alphas (FF3) for portfolios sorted by asset growth and its components. I sort stocks into deciles based on NYSE breakpoints at the end of each month and hold the portfolio for the following month. Panel A contains results from January 1975 to July 2002. Panel B contains results from August 2002 to December 2017. Panel C contains statistical tests of the difference in each return measure between the two periods. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=accruals (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year), and for each component the sort is based on the variation unrelated to the other components as described in section 4. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pre-SOX

	Equal-Weight			Value-Weight		
Sort Variable	$\bar{r}^e$	CAPM	FF3	$\bar{r}^e$	CAPM	FF3
tag	1.63***	1.73***	1.51***	0.81***	0.94***	0.43**
	(7.91)	(8.85)	(7.87)	(3.61)	(4.26)	(2.23)
dnoa	1.62***	1.71***	1.54***	0.61***	0.72***	0.45**
	(9.64)	(10.66)	(9.72)	(3.22)	(3.97)	(2.57)
dltnoa	1.59***	1.66***	1.50***	0.54***	0.62***	0.31*
	(9.04)	(9.81)	(9.05)	(2.77)	(3.21)	(1.68)
dwc	0.75***	0.78***	0.71***	0.90***	0.91***	0.90***
	(6.83)	(7.23)	(6.67)	(4.79)	(4.73)	(4.41)
dacc	0.50***	0.53***	0.37***	0.58***	0.65***	0.64***
	(3.62)	(3.96)	(2.78)	(2.92)	(3.38)	(3.23)
invacc	1.34***	1.46***	1.25***	0.63***	0.74***	0.43***
	(8.57)	(10.16)	(8.69)	(3.42)	(4.15)	(2.67)

Panel B: Post-SOX

	Equal-Weight			Value-Weight		
Sort Variable	$\bar{r}^e$	CAPM	FF3	$\bar{r^e}$	CAPM	FF3
tag	0.58**	0.52**	0.56***	-0.19	-0.22	-0.16
	(2.58)	(2.43)	(2.68)	(-0.80)	(-0.94)	(-0.79)
dnoa	0.48***	0.43**	0.44**	-0.08	-0.18	-0.16
	(2.68)	(2.42)	(2.59)	(-0.38)	(-0.91)	(-0.83)
dltnoa	0.50***	0.47**	0.49***	-0.05	-0.06	-0.04
	(2.81)	(2.57)	(2.81)	(-0.24)	(-0.31)	(-0.19)
dwc	0.05	0.01	0.01	0.25	0.18	0.17
	(0.43)	(0.05)	(0.10)	(1.25)	(0.87)	(0.85)
dacc	-0.18	-0.12	-0.13	-0.23	-0.25	-0.24
	(-0.99)	(-0.69)	(-0.70)	(-0.97)	(-1.07)	(-1.00)
invacc	0.49***	0.57***	0.60***	-0.19	-0.08	-0.03
	(3.31)	(3.85)	(4.21)	(-0.91)	(-0.37)	(-0.17)

Panel C: Pre-Post Difference

	Equal-Weight			Value-Weight		
Sort Variable	$\bar{r}^e$	CAPM	FF3	$\bar{r^e}$	CAPM	FF3
tag	-1.06***	-1.03***	-0.90***	-0.99***	-0.94***	-0.68**
	(-3.51)	(-3.37)	(-3.12)	(-3.07)	(-2.93)	(-2.50)
dnoa	-1.15***	-1.12***	-1.02***	-0.69**	-0.65**	-0.50*
	(-4.71)	(-4.56)	(-4.36)	(-2.47)	(-2.34)	(-1.91)
dltnoa	-1.09***	-1.07***	-0.98***	-0.59**	-0.56**	-0.41
	(-4.37)	(-4.24)	(-4.08)	(-2.11)	(-2.01)	(-1.54)
dwc	-0.69***	-0.69***	-0.65***	-0.63**	-0.64**	-0.62**
	(-4.43)	(-4.38)	(-4.18)	(-2.29)	(-2.31)	(-2.24)
dacc	-0.68***	-0.67***	-0.62***	-0.81***	-0.78**	-0.74**
	(-2.96)	(-2.89)	(-2.63)	(-2.61)	(-2.52)	(-2.39)
invacc	-0.86***	-0.80***	-0.71***	-0.82***	-0.76***	-0.63**
	(-4.00)	(-3.86)	(-3.50)	(-2.92)	(-2.80)	(-2.41)

Table 8: Estimates of the discontinuity in the Surprise EPS distribution

This table contains coefficient estimates of the discontinuity in the distribution of earnings-per-share (EPS) Surprises. The running variable is EPS Surprise, which is defined as actual earnings minus analysts consensus earnings forecast in the month prior to the announcement of fiscal year earnings, and the dependent variable is nb_i, the frequency of firm-year observations in each earnings surprise bin. I use bin sizes of one cent. I estimate the discontinuity in nb_i at the point where Surprise EPS=0 and use global polynomial controls. t-values are calculated using robust standard errors. Appendix A provides variable definitions.

	pre-SOX	post-SOX	difference
EPS $\geq$0	3.92	0.70	3.22
	(7.04)	(2.26)	(5.04)
Polynomial degree	6	6	6
R^2	99.38%	99.39%	99.38%

Table 9: Fama and MacBeth regressions - all firms

This table contains average Fama and MacBeth (1973) regression slopes and their t-values from cross sectional regressions that predict net income. Columns (1)-(4) contain results for regressions estimated on the sample from 1975-2002, and columns (5)-(8) from 2003-2017. ni=net income, tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=total accruals, dche=change in cash, and *doa_ol*=change in operating assets funded by operating liabilities (all of which are scaled by total assets at the end of the prior fiscal year and lagged by one year for predictor variables). All independent variables are winsorized at the 1st and 99th percentiles. Regressions include a constant term which is suppressed for brevity. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Pre-SOX				Post-SOX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ni	0.67***	0.67***	0.68***	0.71***	0.74***	0.75***	0.75***	0.82***
	(43.40)	(43.25)	(43.25)	(42.19)	(42.93)	(37.86)	(36.50)	(48.09)
tag	-0.02***				0.01			
	(-3.81)				(1.77)			
dnoa		-0.06***				-0.07***		
		(-15.52)				(-5.14)		
dwc			-0.09***				-0.09**	
			(-11.29)				(-3.84)	
dltnoa			-0.06***				-0.07***	
			(-11.09)				(-4.68)	
dacc				-0.16***				-0.29***
				(-12.14)				(-11.59)
invacc				-0.04***				-0.02
				(-7.15)				(-2.15)
doa_ol		0.10***	0.09***	0.07***		0.14***	0.13***	0.06*
		(7.28)	(7.08)	(6.76)		(7.04)	(7.75)	(3.01)
dche		0.01	0.00	-0.01		0.08**	0.08**	0.05**
		(0.88)	(0.50)	(-0.67)		(3.53)	(3.32)	(3.46)
r2	0.42	0.43	0.44	0.44	0.56	0.57	0.57	0.59

Table 10: Fama and MacBeth regressions - all but microcap firms

This table contains average Fama and MacBeth (1973) regression slopes and their t-values from cross sectional regressions that predict net income in which Microcap firms are excluded. Microcaps are defined as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. Columns (1)-(4) contain results for regressions estimated on the sample from 1975-2002, and columns (5)-(8) from 2003-2017. ni=net income, tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=total accruals, dche=change in cash, and *doa_ol*=change in operating assets funded by operating liabilities (all of which are scaled by total assets at the end of the prior fiscal year and lagged by one year for predictor variables). All independent variables are winsorized at the 1st and 99th percentiles. Regressions include a constant term which is suppressed for brevity. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Pre-SOX				Post-SOX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ni	0.74***	0.73***	0.74***	0.76***	0.71***	0.72***	0.72***	0.77***
	(38.50)	(38.60)	(38.52)	(41.84)	(23.75)	(21.91)	(21.82)	(23.04)
tag	-0.02***				-0.01			
	(-5.06)				(-1.01)			
dnoa		-0.06***				-0.06***		
		(-12.63)				(-5.57)		
dwc			-0.08***				-0.06**	
			(-8.05)				(-3.14)	
dltnoa			-0.06***				-0.06***	
			(-10.55)				(-5.11)	
dacc				-0.14***				-0.23***
				(-10.07)				(-10.40)
invacc				-0.05***				-0.04**
				(-7.98)				(-3.38)
doa_ol		0.06***	0.06***	0.03*		0.07**	0.07**	0.02
		(3.97)	(4.01)	(2.49)		(3.38)	(3.29)	(0.93)
dche		-0.00	-0.00	-0.01		0.04*	0.04*	0.03
		(-0.08)	(-0.17)	(-1.16)		(2.53)	(2.55)	(1.79)
r2	0.51	0.52	0.52	0.52	0.54	0.56	0.56	0.57

Table 11: Regressions of analyst forecast errors on accruals

This table contains regression coefficients from regressions of the form

$$FE_{i,s,t+1} = \beta_0 + \beta_1 PortAcc_{i,t} + \varepsilon_{i,t+1}$$

where $FE_{i,s,t+1}$ is the monthly percentage forecast error for firm i in month s following the announcement of year t earnings (i.e. prior year). s indicates the distance (in months) following the prior year's earnings announcement, so that $FE_{i,s,t+1}$ is calculated as realized earnings for year t + 1 less the consensus earnings forecast in month s, scaled by the stock price in month 1. *PortAcc* the nyse decile portfolio ranking of the firm-year based on accruals $(dwc + ntacc)$ scaled by the lag of total assets in year t, scaled to a [0,1] range. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Panel A: Pre-SOX period

Months	1	2	3	4	5	6	7	8	9	10	11	12
β_0	-1.06***	-0.96***	-0.77***	-0.77***	-0.57***	-0.38***	-0.32***	-0.21***	-0.07***	-0.07***	-0.01	0.03**
	(-27.06)	(-21.66)	(-22.23)	(-19.71)	(-15.33)	(-14.73)	(-11.30)	(-9.14)	(-4.26)	(-3.83)	(-0.65)	(2.10)
β_1	-0.30***	-0.30***	-0.22***	-0.09	-0.20***	-0.13***	-0.12***	-0.08**	-0.08***	-0.06**	-0.03	-0.04
	(-4.77)	(-4.23)	(-3.94)	(-1.42)	(-3.31)	(-3.26)	(-2.62)	(-2.03)	(-3.07)	(-2.28)	(-1.37)	(-1.50)

Panel B: Post-SOX period

Months	1	2	3	4	5	6	7	8	9	10	11	12
β_0	-0.42***	-0.40***	-0.27***	-0.31***	-0.22***	-0.06***	-0.07***	-0.06***	-0.01	-0.01	0.04**	0.05***
	(-12.63)	(-9.03)	(-9.00)	(-7.38)	(-6.07)	(-2.62)	(-2.62)	(-2.63)	(-0.59)	(-0.75)	(2.54)	(3.18)
β_1	0.08	0.11	0.08	0.20***	0.10	-0.05	0.03	0.06	0.05*	0.06**	0.03	0.05*
	(1.52)	(1.48)	(1.57)	(2.85)	(1.59)	(-1.19)	(0.53)	(1.50)	(1.88)	(2.33)	(1.15)	(1.82)

Panel C: Pre-Post Difference in coefficients

Months	1	2	3	4	5	6	7	8	9	10	11	12
$d\beta_0$	0.64***	0.56***	0.50***	0.46***	0.35***	0.32***	0.25***	0.15***	0.06***	0.05**	0.05**	0.02
	(12.56)	(8.96)	(10.86)	(7.91)	(6.69)	(8.97)	(6.22)	(4.65)	(2.63)	(2.27)	(2.24)	(0.75)
$d\beta_1$	0.38***	0.41***	0.30***	0.29***	0.30***	0.09	0.15**	0.13**	0.13***	0.13***	0.06*	0.08**
	(4.60)	(4.01)	(3.99)	(3.08)	(3.46)	(1.48)	(2.21)	(2.49)	(3.50)	(3.26)	(1.78)	(2.35)

Table 12: Portfolio returns

This table contains equal-weighted CAPM alphas for portfolios double sorted by variables related to earnings management and asset growth. I first sort stocks into terciles of the earnings management variable, and then into terciles of asset growth at the end of each fiscal year, portfolios are rebalanced annually. Panel A contains results from a double sort on the Entrenchment Index (Entrenchment) and Asset Growth. The sample period is from 1990 to 2002 and contains all firms with information on the Entrenchment Index from the webpage of Lucian Bebchuck. Panel B contains results from a double sort on the fraction of independent directors (Governance) and Asset Growth. The sample period is from 1996 to 2002 and contains all firms with information on the fraction of independent directors which is calculated using data from the ISS director legacy file. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Relationship between the Asset Growth Anomaly and Entrenchment

	Lowest AG Tercile	Medium AG Tercile	Highest AG Tercile	Diff. in means (Lowest-Highest)
Low Entrenchment	1.34***	1.02***	0.54**	0.80***
	(4.32)	(4.63)	(2.37)	(3.26)
Medium Entrenchment	1.17***	0.76***	0.50**	0.67***
	(3.94)	(3.15)	(2.13)	(2.74)
High Entrenchment	0.89***	0.83***	0.46*	0.43*
	(3.18)	(3.09)	(1.89)	(1.92)

Panel B: Relationship between the Asset Growth Anomaly and Governance

	Lowest AG Tercile	Medium AG Tercile	Highest AG Tercile	Diff. in means (Lowest-Highest)
Low Governance	1.18**	1.12***	0.13	1.05***
	(2.47)	(3.04)	(0.30)	(2.74)
Medium Governance	1.51***	1.25***	0.55	0.97***
	(3.13)	(3.39)	(1.20)	(2.68)
High Governance	0.84**	1.07***	0.49	0.36
	(2.02)	(2.68)	(1.33)	(1.09)

Table 13: Institutional trading in asset growth anomaly deciles

This table contains average results of regressions that measure institutional trading in asset growth anomaly portfolios and the changes in this trading in the post-SOX period. The change in percentage of institutional ownership is measured using the change in percentage of shares held by 13F institutional investors. The changes are measured in the six quarters prior to portfolio formation. The regression is run on quarterly data from 1982 - 2017. Appendix A provides the variable definitions. Standard errors are adjusted for autocorrelation due to overlapping observations using Newey and West (1986) standard errors with a lag of 6 quarters. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Changes in Percentage Institutional Ownership (equal weighted)

	Low decile	High Decile	High Minus Low
Post-SOX Indicator	-0.68	0.75	1.43***
	(-0.71)	(0.80)	(3.94)
Intercept	0.44**	1.69***	1.25***
	(2.40)	(9.23)	(5.83)

Panel B: Changes in Percentage Institutional Ownership (value weighted)

	Low decile	High Decile	High Minus Low
Post-SOX Indicator	-0.21	-0.03	0.18
	(-0.88)	(-0.13)	(0.90)
Intercept	0.56***	0.15**	-0.41***
	(5.37)	(1.99)	(-3.27)

A Appendix

Table A.1: Description of Variables

Variable	Definition and source
tag	Annual growth in total balance sheet assets from Compustat.
dwc	The annual growth in working capital defined as the change in noncash current assets less non short term debt current liabilities scaled by the lag of total balance sheet asset from Compustat.
dnoa	The percentage growth in net operating assets defined as the change in noncash assets less nondebt liabilities scaled by the lag of total balance sheet assets from Compustat.
dltnoa	The percentage growth in long term net operating assets defined as dnoa-dwc.
ntacc	Defined as in Lewellen and Resutek (2016) as the negative of the sum of the following Compustat variables: depreciation and amortization, deferred taxes, qquity in net loss (earnings) of unconsolidated subsidiries, loss (gain) on sale of property, plant and equipment and investments, funds from operations -Other and extraordinary items and discontinued operations.
dacc	The change in accruals scaled by lag total assets defined as dwc+ntacc.
invacc	The change in investment accruals scaled by lag total assets defined as dltnoa-ntacc.
dche	The growth in cash and cash equivalents, defined as the annual change in cash and cash equivalents scaled by the lag of total balance sheet assets.
doaol	The growth in operating assets funded by operating liabilities defined as the annual change in nondebt total liabilities scaled by the lag of total balance sheet assets from Compustat
ls	The natural logarithm of the market value of equity calculated using price multiplied by common shares outstanding from CRSP.
lbm	The natural logarithm of the book value of equity divided by the market value of equity. Book value of equity is defined as the sum of stockholders equity and deferred taxes and investment tax credit less preferred stock.
r(t-1)	The prior month stock return.
r(12,2)	The cumulative stock return from t-12 to t-2.
Surprise EPS	Earnings minus analysts consensus earnings forecast in the month prior to the announcement of fiscal year earnings
FE	The forecast error (FE) for each firm, for each fiscal year, is calculated as the actual earnings minus the current analyst consensus forecast divided by the beginning of period price.
Institutional Ownership	Percentage of shares held by 13F institutions from Thomson Reuters.
Entrenchment	Entrenchment Index from the webpage of Lucian Bebchuck
Governance	Fraction of independent directors from the ISS director legacy file.

Table A.3: Portfolio returns - long and short portfolios

This table contains equal- and value-weighted excess market model alphas (CAPM) for portfolios sorted by asset growth and its components. I sort stocks into deciles based on NYSE breakpoints at the end of each month and hold the portfolio for the following month. The table contains statistical tests of the difference in each return measure between the pre-SOX and post-SOX period. The pre-SOX period is from January 1975 to July 2002. The post-SOX period is from August 2002 to December 2017. tag=total asset growth, dnoa=change in net operating assets, dltnoa=change in long term net operating assets, dwc=change in working capital, invacc = investment accruals, dacc=total accruals (all of which are measured 6 months before returns and are scaled by total assets at the end of the prior fiscal year), and for each component the sort is based on the variation unrelated to the other components as described in section 4. Appendix A provides the variable definitions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

pre-SOX to post-SOX difference in CAPM-alphas

	Equal-Weight			Value-Weight		
Sort Variable	LS	L	S	LS	L	S
tag	-1.06***	-1.16**	-0.10	-0.98***	-1.01***	-0.03
	(-3.49)	(-2.42)	(-0.32)	(-3.06)	(-4.17)	(-0.13)
dnoa	-1.10***	-1.15***	-0.06	-0.65**	-0.76***	-0.11
	(-4.52)	(-2.74)	(-0.17)	(-2.36)	(-3.63)	(-0.51)
dltnoa	-1.06***	-1.09**	-0.03	-0.60**	-0.83***	-0.23
	(-4.27)	(-2.56)	(-0.09)	(-2.18)	(-3.85)	(-1.09)
dwc	-0.66***	-0.85**	-0.19	-0.61**	-0.59***	0.02
	(-4.26)	(-2.30)	(-0.56)	(-2.21)	(-2.73)	(0.09)
dacc	-0.66***	-0.83**	-0.17	-0.76**	-0.66***	0.10
	(-2.89)	(-2.39)	(-0.44)	(-2.46)	(-2.98)	(0.40)
invacc	-0.82***	-0.97***	-0.15	-0.82***	-0.89***	-0.07
	(-3.98)	(-2.79)	(-0.44)	(-3.01)	(-4.97)	(-0.33)