The predictive power of investment and accruals

Jonathan Lewellen
Dartmouth College and NBER
jon.lewellen@dartmouth.edu

Robert J. Resutek
Dartmouth College
robert.j.resutek@dartmouth.edu

This version: May 2013
First draft: December 2011

JEL codes: G14, M41

Key words: Earnings persistence, accruals, investment, stock returns, anomalies

We are grateful to Asher Curtis, Mozaffar Khan, Joshua Livnat, John McInnis, Richard Sansing, Phillip Stocken, and workshop participants at the 2012 AAA Annual Meeting for helpful comments and suggestions.

The predictive power of investment and accruals

Abstract

We provide a direct test of whether investment explains the accrual anomaly by decomposing a firm's total accruals into investment-related and so-called 'nontransaction' accruals, those such as depreciation and asset write-downs that do not represent new investment expenditures. We find that nontransaction accruals predict earnings and stock returns as strongly as working-capital accruals and long-term investment, contrary to the predictions of the investment hypothesis. A long-short portfolio based on nontransaction accruals has a significant average return of 0.71% monthly from 1972–2010, comparable to the returns on working-capital accrual and investment portfolios. Our results suggest that investment cannot explain a significant portion of the accrual anomaly.

1. Introduction

The accrual anomaly is one of the strongest and most striking asset-pricing anomalies. Sloan (1996) shows that accruals, measured in his paper as working-capital accruals minus depreciation, are strongly negatively related to subsequent stock returns after controlling for a firm's size, beta, and other characteristics. Stocks in the bottom accrual decile outperform those in the top accrual decile by roughly 10% annually, a result that has been confirmed in numerous follow-up studies.

The source of the accrual anomaly continues to be the subject of much debate. Two competing explanations have been offered in the literature, one emphasizing the link between accruals and earnings and the other emphasizing the link between accruals and investment. Distinguishing between the two is important both to clarify the economic forces underlying the anomaly and to understand better how investors use, and possibly misuse, accounting numbers.

Sloan (1996) proposes the first explanation, based on the idea that accruals inject 'distortions' into the earnings process. He shows that the accrual component of earnings is less persistent than the cashflow component, i.e., given the same level of total earnings today, firms with higher accruals tend to have lower subsequent profits. Sloan suggests that investors do not understand this relation and, hence, overvalue stocks with high accruals and undervalue stocks with low accruals. The strongest version of this hypothesis says that investors fixate on a firm's total earnings and do not differentiate at all between cashflows and accruals, so this hypothesis is often referred to as the 'earnings-fixation' hypothesis.

Fairfield, Whisenant, and Yohn (2003) propose the second explanation, based on the link between accruals and investment (or growth). FWY observe that Sloan's accrual variable is a component not only of earnings but also of growth in net operating assets (NOA). They show that changes in working capital and long-term NOA have similar predictive power for firm performance, implying that the total change in NOA subsumes the predictive ability of Sloan's measure. Thus, FWY argue that the accrual anomaly reflects a general 'growth effect' arising from the fact that investors do not understand diminishing marginal returns from investment. An alternative interpretation, emphasized by Fama and French (2006) and Wu, Zhang, and Zhang (2010), is that investment simply covaries with rational variation in expected stock returns, i.e., a low cost of equity (expected stock returns) should natuarlly lead to higher current investment and accruals. In either case, both interpretations of the 'investment hypothesis' suggest that accruals predict stock returns only because they are closely tied to investment.

To date, the empirical literature has not distinguished directly between the two hypotheses above, though a number of papers provide evidence consistent with one hypothesis or the other. For example, Xie (2001) and Richardson et al. (2005) show that 'discretionary' and 'less reliable' accruals are the least persistent and most mispriced types of accruals, consistent with idea that investors do not fully understand the earnings-generating process. Dechow and Ge (2006) find that special items help explain the mispricing of low-accrual firms, and Richardson et al. (2006) show that accruals unrelated to sales growth contribute to the low persistence of accruals, again consistent with the earnings-fixation hypothesis (though the latter paper does not look at returns). On the other hand, Zhang (2007) finds that the accrual anomaly is stronger when accruals are more highly correlated with employee growth, consistent with the argument that growth explains the accrual anomaly. Dechow, Richardson, and Sloan (2008) find that accruals and retained cash are similarly mispriced and 'conjecture that the accrual anomaly could be driven by … a combination of diminishing marginal returns to new investment and agency-related overinvestment' (p. 539). Khan (2008) and Wu, Zhang, and Zhang (2010) conclude that the accrual anomaly might be explained by risk, consistent with the idea that the anomaly may be driven by rational variation in investment and expected returns.

An important limitation of the papers above is that none explicitly tests whether investment does (or does not) explain their results. For example, changes in long-term NOA—the long-term accrual measure used by FWY (2003), Richardson et al. (2005, 2006), and Dechow, Richardson, and Sloan (2008)—reflect both investment expenditures made by the firm as well as accruals such as depreciation, asset write-downs, and deferred taxes that are not tied to current investment. Thus, their findings could reflect the predictive power of new investment or of non-investment accounting charges. Similarly, the accrual and investment variables considered by Wu, Zhang, and Zhang (2010) combine both investment-related and non-investment-related changes in balance-sheet accounts and, therefore, do not enable a clean interpretation of whether investment really explains their results.

Our goal in this paper is to provide the first direct test of whether investment explains the accrual anomaly. The key empirical challenge comes from the tight link between investment and accruals, since most investment expenditures have an immediate one-to-one impact on accruals under the principles of historical cost accounting. As noted above, however, investment and accruals are not identical: while many accruals represent new investments made by the firm, others such as depreciation, asset write-downs, deferred taxes, and the earnings of unconsolidated subsidiaries represent purely accounting-based changes in the capitalized value of existing assets (we refer to the second group as 'nontransaction' accruals becaue they are not tied to current investment transactions). We exploit this wedge between investment and accruals in order to test whether investment truly explains the accrual anomaly. As far as we know, our paper is the first to distinguish explicitly between investment-related and non-investment-related accruals.

To be more specific, we decompose a firm's total accruals (change in net operating assets) into working-capital accruals (change in non-cash net working capital), long-term investment accruals (representing new expenditures on long-term net operating assets), and an estimate of nontransaction accruals obtained from the Statement of Cash Flows and earlier flow-of-funds statements. Nontransaction accruals are probably measured with error, but we argue that the decomposition provides an effective way to isolate a component of accruals that is linked primarily to accounting rather than current investment decisions. The earning-fixation hypothesis says that nontransaction accruals should predict returns after controlling for investment, while the investment hypothesis says that investment alone explains the accrual anomaly. Thus, our decomposition allows us to distinguish directly between the two hypotheses.[1]

Our central empirical result is that nontransaction accruals contribute significantly to the accrual anomaly, both to the low persistence of accruals and to the predictive power of accruals for future stock returns. In fact, the predictive slopes on nontransaction accruals are larger (in absolute value) than the slopes on working-capital

[1] To be clear, we use the term 'earnings fixation' broadly to capture the idea that investors misjudge the persistence of the different components of earnings. Some authors use the term more narrowly to refer only to the idea that investors do not distinguish at all between the different components (i.e., investors look only at total earnings). The narrow definition has been rejected in the literature (e.g., Dechow, Richardson, and Sloan, 2008).

accruals and long-term investment. In persistence regressions from 1972–2009 (earnings regressed on prior-year earnings and accruals), the slope on working-capital accruals is -0.13, the slope on long-term investment accruals is -0.08, and the slope on nontransaction accruals is -0.45, all with Fama-MacBeth (1973) t-statistics greater than eight in absolute value. Similarly, in predictive regressions for stock returns, the slope on non-transaction accruals is more than 70% greater than the slopes on working-capital accruals and long-term investment. These results provide strong evidence that investment alone does not explain the accrual anomaly: accruals that are not directly tied to current investment expenditures have stronger predictive power for earnings and returns than investment-related accruals.[2]

Stock portfolios formed on nontransaction accruals exhibit a large spread in average returns. Specifically, we sort stocks based on the component of nontransaction accruals that is uncorrelated with working-capital accruals and long-term investment (we focus on the orthogonal component of nontransaction accruals in order to isolate the portion that is unrelated to investment). From 1972–2010, the bottom decile outperforms the top decile by a significant 0.71% monthly, comparable in magnitude to the return spread when stocks are sorted by working-capital accruals (0.61% monthly) or long-term investment (1.10% monthly). The nontransaction-accrual strategy remains profitable even at the end of the sample, with average returns from 2001–2010 that are actually higher than in the full sample. In short, accruals that affect earnings but are uncorrelated with current investment have strong predictive power for future stock returns, consistent with the general version of the earnings-fixation hypothesis.

Our tests also contribute to the literature in a number of additional ways:

First, we show that working-capital accruals are negatively related not only to future earnings but also to future cashflow, defined here as cashflow from operations before working-capital investment. In fact, high working-capital accruals are a bad signal for future earnings because they predict lower cashflow, not lower accruals.

[2] Of existing studies, Dechow and Ge's (2006) results probably have the most overlap with ours because accruals associated with special items are likely to be part of nontransaction accruals. However, special items explain less than 20% of the variation in nontransaction accruals and adding special items to our return regressions has only a modest impact on the results (the slope on nontransaction accruals is significant while the slope on special items is not). Separately, we show that nontransaction accruals have strong predictive power even controlling for prior-year investment; nontransaction accruals do not simply capture an investment effect carried over from early years.

This result seems to contradict the idea that transitory measurement error in (or manipulation of) working capital might explain the accrual anomaly.

Second, we find that earnings positively predict stock returns and, depending on the exact specification, the slope on earnings can be nearly as large in magnitude as the negative slope on accruals. The implication is that a single combined measure—earnings minus accruals—predicts stock returns nearly as well as the two separate variables do when used together in a regression. The combined measure is, of course, simply the firm's free cashflow. Thus, our evidence suggests that a pure cashflow variable can explain a significant portion of the accrual anomaly (see, also, Desai, Rajgopal, and Venkatachalam, 2004; Dechow, Richardson, and Sloan, 2008). However, nontransaction accruals continue to have strong predictive power for returns even controlling for a firm's free cashflow.

Third, our tests show that accruals and external-financing measures have distinct predictive power for returns: In Fama-MacBeth regressions, accruals, net debt issuance, and net stock issuance are all significant predictors of returns when used in the same regression. Thus, neither the accrual nor the external-financing anomaly appears to subsume the other (consistent with the results of Fama and French, 2008, and Resutek, 2010, but contrary to Dechow, Richardson, and Sloan, 2008).

Finally, we provide the most comprehensive evidence to date on the predictive power of accruals among larger firms. Most studies in the literature pool all firms together, without distinguishing between large and small firms. In contrast, we repeat all of our tests using the roughly 1,500 firms that remain, on average, after we drop micro-cap stocks from the regressions (micro-cap stocks—those smaller than the NYSE 20th percentile ranked by market value—represent 61% of firms in the sample but only 3% of total market value from 1972–2009). We find significant differences between the full-sample and large-firm regressions, but our main conclusions hold in both groups.

The remainder of the paper is organized as follows. Section 2 describes our accrual decomposition and further motivates our tests. Section 3 describes the data. Sections 4 and 5 report predictive regressions for earnings and stock returns, respectively. Section 6 concludes.

2. Accruals vs. investment

One of the main difficulties in interpreting the accrual anomaly comes from the fact that accruals typically represent investments made by the firm, so it is often impossible to say whether the stock market's reaction reflects the underlying investment expenditure (the investment hypothesis) or the way the expenditure has been accounted for in the firm's financial statements (the earnings-fixation hypothesis). Our empirical strategy in this paper comes from the simple observation that the connection between accruals and investment is imperfect. Thus, we attempt to isolate accruals that are not directly linked to current investment expenditures and to test whether these 'nontransaction' accruals have different implications for subsequent earnings and returns compared with other accruals.

Our analysis starts with the broad measure of accruals considered by FWY (2003), Richardson et al. (2006), and Dechow, Richardson, and Sloan (2008):

$$\text{Total accruals} = \text{change in net operating assets } (\Delta\text{NOA}). \quad (1)$$

NOA can be defined as non-cash assets minus non-debt liabilities, or equivalently, as the sum of non-cash net working capital (WC) and long-term net operating assets (LTNOA), the latter defined as long-term assets minus long-term operating liabilities. Thus, total accruals can be expressed as:

$$\Delta\text{NOA} = \Delta\text{WC} + \Delta\text{LTNOA}. \quad (2)$$

Optimally, we would like to break each term in this equation into a component that reflects new investment expenditures and a component that reflects changes in the capitalized value of investments made in prior years. Our main tool for doing so is to use information about the second component—i.e., nontransaction accruals—from the Statement of Cash Flows (SCF) and earlier flow-of-funds statements on Compustat (we refer to these flow-of-funds statements collectively as the Statement of Cash Flows, but the variables are available on Compustat prior to the adoption of SFAS 95). In particular, using Compustat's variable names, we define nontransaction accruals (NTAcc) as:

$$
\begin{aligned}
-\text{NTAcc} = &+ \text{Depreciation and Amortization (SCF account)} \\
&+ \text{Deferred Taxes (SCF account)} \\
&+ \text{Equity in Net Loss (of unconsolidated subsidiaries)} \\
&+ \text{Loss on Sale of Property, Plant, and Equipment and Sale of Investments} \\
&+ \text{Funds from Operations–Other (including accruals related to special items)} \\
&+ \text{Extraordinary Items and Discontinued Operations (SCF account – Income Statement account).} \quad (3)
\end{aligned}
$$

These items include all non-working-capital adjustments made in the SCF to reconcile earnings with cashflow from operations and, thus, represent all accruals identified as distinct from investments in working-capital and long-term assets—precisely what we want to measure. Notice that the terms on the right-hand side of the equation represent negative accruals, so their sum defines the negative of NTAcc. Also, the final item in the list is defined as the difference between the value of Extraordinary Items and Discontinued Operations (EIDO) reported in the SCF and the value reported in the Income Statement. This is because Compustat reconciles income before extraordinary items, not net income, with cashflow from operations. As a result, the value of EIDO in the SCF reflects the cashflow implications of EIDO, while the difference between the Income Statement and SCF values represents accruals associated with EIDO (which is what we want).

A limitation of the SCF is that it does not specify whether the items included in NTAcc affect short-term or long-term assets and liabilities. However, since most of the items relate to long-term accruals, we assume that NTAcc primarily affects LTNOA. The remaining component of ΔLTNOA then provides a measure of long-term investment expenditures (InvAcc):

$$\text{InvAcc} = \Delta\text{LTNOA} - \text{NTAcc}. \quad (4)$$

The logic is that changes in long-term NOA reflect either new investments made by the firm, such as acquisitions or purchases of plant and equipment, or changes in the capitalized value of investments made in prior years that are reflected in NTAcc through items such as depreciation, deferred taxes, and asset write-downs (the last of these might be included in either EIDO or Funds from Operations–Other). Therefore, the portion of ΔLTNOA remaining after taking out nontransaction accruals should provide a better measure of new investment than the total change. The separation of ΔLTNOA into investment and nontransaction accruals then implies the following decomposition of total accruals:

$$\Delta\text{NOA} = \Delta\text{WC} + \text{InvAcc} + \text{NTAcc}. \quad (5)$$

This decomposition serves as the basis for our empirical tests. It allows us to explore the differential predictive power of working-capital accruals, long-term investment, and nontransaction accruals for future earnings and stock returns. Our central thesis is that NTAcc should not predict subsequent returns, controlling for the other two components, if investment explains the accrual anomaly.

An attractive feature of our accrual decomposition is that it also leads to a novel decomposition of earnings into accruals and cashflows. In particular, earnings adjusted for nontransaction accruals provide a measure of operating cashflow (CF) before working capital and long-term investment:

$$\text{CF} = \text{NI} - \text{NTAcc}, \tag{6}$$

where NI is net income. (Prior to the adoption of SFAS 95, this measure is precisely what Compustat reports as 'Funds from Operations–Total'.) The firm's free cashflow can then be defined in two equivalent ways. First, following Dechow, Richardson, and Sloan (2008), free cashflow can be expressed as the difference between net income and total accruals:

$$\text{FCF} = \text{NI} - \Delta\text{NOA}. \tag{7}$$

Second, subtracting NTAcc from both terms on the right-hand side of this equation, we can re-express FCF as:

$$\text{FCF} = \text{CF} - \Delta\text{WC} - \text{InvAcc}. \tag{8}$$

In other words, free cashflow can be interpreted as either the difference between earnings and accruals or as cashflow left over after investments in working capital and long-term assets. The second interpretation illustrates why ΔWC and InvAcc together provide a better measure of new investment than does ΔNOA: the sum of ΔWC and InvAcc can be expressed as the difference between CF and FCF, which is exactly what we mean by a firm's investment expenditures.

3. Data and descriptive statistics

Our primary source of data is the Compustat annual file, merged with stock prices and returns from the Center for Research in Security Prices (CRSP). Since our initial tests focus on accounting performance, we describe the Compustat data here and discuss the return data later.

3.1. Sample

The sample includes all nonfinancial firms on Compustat that have data for net income, total accruals, and average total assets in a given year (financial firms are identified using historical SIC codes from CRSP). Our tests start in 1971, the first year that Compustat has the data items used to calculate nontransaction accruals. In addition, because we repeat all of our tests using firms larger than the NYSE 20th percentile ranked by market value (price times shares outstanding), we require firms to have beginning-of-year market value on CRSP. Our final sample has an average of 4,036 stocks per year from 1971–2009, for a total of 157,411 firm-years. The sample of 'all-but-tiny' firms (those larger than the NYSE 20th percentile) has 1,542 firms per year, for a total of 60,149 firm-years.

The all-but-tiny sample essentially drops 'micro-cap' stocks from the regressions. For example, at the start of 2009, the NYSE 20th percentile is $308 million, close to the popular cutoff between micro-cap and small-cap stocks (e.g., Investopedia.com; Fama and French, 2008). From 1971–2009, micro-caps make up slightly more than 61% of the sample but only 3% of total market value. (In 2009, the largest stock in the sample, Exxon, has a market value twice as large as the combined value of all micro-cap stocks.) Thus, the all-but-tiny sample provides a simple check of whether our results are driven by the large number of economically small firms on Compustat. To our knowledge, our study is the first to provide a comprehensive analysis of the accrual anomaly among larger firms.

3.2. Variable definitions

The variable definitions are consistent with our analysis in Section 2. We begin with the following variables:

NOA = net operating assets (total assets – cash – total liabilities + debt),
WC = net working capital (current assets – cash – current liabilities + short-term debt),
LTNOA = long-term net operating assets (NOA – WC).

Accruals are calculated using the annual changes in these variables, supplemented with nontransaction accruals from the SCF (and its antecedents):

dNOA = annual change in NOA,
dWC = annual change in WC,

dLTNOA = annual change in LTNOA.

NTAcc = nontransaction accruals from the SCF (see Section 2 for the full definition),

InvAcc = long-term investment accruals (dLTNOA – NTAcc),

Depr = depreciation and amortization accruals (negative of expense) from the SCF,

OthAcc = NTAcc – Depr.

Notice that the final two items above break nontransaction accruals into depreciation accruals and other accruals, a decomposition that allows us to test whether depreciation differs from other types of nontransaction accruals. Accruals therefore satisfy the following identities:

dNOA = dWC + dLTNOA,

dNOA = dWC + InvAcc + NTAcc,

dNOA = dWC + InvAcc + Depr + OthAcc.

Our tests also use information about a firm's earnings, cashflows, and external-financing choices:

NI = net income,

CF = operating cashflow before working-capital investments (NI – NTAcc),

FCF = free cash flow (NI – dNOA).

dDebt = change in total debt (short-term + long-term debt),

Issues = change in shareholders' equity minus the change in retained earnings.

Following the convention in the literature, all flow variables are scaled by a firm's average total assets for the year (i.e., the average of start-of-year and end-of-year asset value). The variables are then winsorized annually at their 1st and 99th percentiles to reduce the impact of extreme outliers on the regressions. A consequence of this winsorization is that the various accounting identities do not hold exactly in the data for a small subset of firms (those for which the winsorization affects one variable but not another). We show later, however, that this has a minimal impact on our results.

3.3. Descriptive statistics

Table 1 reports summary statistics for the sample. The statistics represent the average from 1971–2009 of the annual cross-sectional mean, standard deviation, minimum, and maximum for each of the variables (after being

Table 1
Descriptive statistics, 1971–2009
This table reports the time-series average of the annual cross-sectional mean, standard deviation (Std), 1st percentile (Min), and 99th percentile (Max) for the variables listed, all of which are scaled by average total assets for the year and winsorized annually at their 1st and 99th percentiles. The sample includes all nonfinancial firms on Compustat that have data for average total assets, net income, net operating assets, and beginning-of-year market value (from CRSP), for an average of 4,036 firms per year and a total sample of 157,411 firm-years. The 'all-but-tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value, leaving 1,542 firms per year and a total sample of 60,149 firm-years.

		All firms				All-but-tiny firms			
Variable	Description	Mean	Std	Min	Max	Mean	Std	Min	Max
NI	Net income	-0.03	0.21	-1.10	0.28	0.05	0.10	-0.41	0.27
CF	Operating cashflow[a]	0.05	0.17	-0.78	0.35	0.11	0.09	-0.22	0.34
FCF	Free cashflow[b]	-0.07	0.24	-1.13	0.45	-0.03	0.16	-0.68	0.33
dNOA	Change in NOA[c]	0.04	0.21	-0.71	0.73	0.07	0.15	-0.34	0.62
dWC	Change in WC[d]	0.01	0.10	-0.38	0.34	0.01	0.06	-0.18	0.24
dLTNOA	Change in LTNOA[e]	0.03	0.16	-0.54	0.64	0.06	0.12	-0.27	0.56
InvAcc	Long-term investment[f]	0.11	0.16	-0.38	0.81	0.12	0.13	-0.16	0.68
NTAcc	Nontransaction accruals[g]	-0.08	0.09	-0.55	0.12	-0.07	0.06	-0.34	0.05
Depr	Depr. and amort.[h]	-0.05	0.04	-0.22	0.00	-0.05	0.03	-0.16	-0.01
OthAcc	NTAcc – Depr	-0.02	0.07	-0.42	0.17	-0.02	0.04	-0.24	0.09
dDebt	Change in debt[i]	0.02	0.13	-0.42	0.57	0.03	0.10	-0.21	0.49
Issues	Share issuance[j]	0.07	0.18	-0.15	1.05	0.03	0.10	-0.14	0.56

[a] CF = Cashflow before investments in working capital and long-term assets = NI – NTAcc
[b] FCF = NI – dNOA
[c] NOA = Total assets – cash – non-debt liabilities
[d] WC = Current assets – cash – non-debt current liabilities
[e] LTNOA = NOA – WC
[f] InvAcc = dLTNOA – NTAcc
[g] NTAcc = Non-working-capital operating accruals from the Statement of Cash Flows (SCF) and its antecedents
[h] Depr = Depreciation and amortization accruals (negative of expense) from the SCF and its antecedents
[i] Debt = Short-term debt + long-term debt
[j] Issues = Change in shareholders equity – change in retained earnings

winsorized). We report the average of annual cross-sectional numbers to be consistent with the Fama-MacBeth regressions discussed below.

In the full sample, average operating cashflow is positive (5.0%) but average net income and free cashflow are both negative (-2.7% and -7.1%, respectively). Working-capital accruals average 1.0% of assets and changes in long-term NOA average 3.4% of assets, implying that total accruals (dNOA) equal 4.3% of assets. The change in LTNOA reflects 11.0% of new investment (InvAcc) and -7.6% of nontransaction accruals (NTAcc), where the latter item consists of depreciation accruals of -5.1% and other nontransaction accruals of -2.4%. Long-term investment is the most volatile component of accruals, with a cross-sectional standard deviation equal to 16.4%, but variation in working-capital accruals (10.3%) and nontransaction accruals (9.0%) is also large in relation to typical earnings or cashflow. These volatilities imply that our tests have reasonable power to detect the predictive ability of the different accrual components.

The right-hand columns in Table 1 show that earnings, accruals, and investment behave much differently among larger firms. Average net income becomes positive (4.5%) and average operating cashflow grows to 11.2% of assets. Working-capital accruals (1.5%) and long-term investment (12.4%) also increase relative to the full sample, while nontransaction accruals drop slightly (-6.6% of assets). As a result, dNOA is nearly twice as high among larger firms, 7.2% of assets compared with 4.3% of assets in the full sample. The cross-sectional dispersion in all variables is lower than in the full sample, but the variability of accruals is still substantial relative to earnings and cashflow. Long-term investment is again the most volatile component of accruals (13.0%), while working-capital accruals and nontransaction accruals have standard deviations that are about half as large (6.3% and 5.7%, respectively).

Correlations between the variables, in Table 2, are similar in the two samples. Focusing on the full sample, net income is highly correlated with cashflow (0.88) and reasonably strongly correlated with total accruals (0.37), working-capital accruals (0.29), changes in LTNOA (0.27), and nontransaction accruals (0.46) (but not with long-term investment). The components of accruals tend to be positively correlated with each other, with the exception of long-term investment and nontransaction accruals (-0.33). The latter correlation implies that firms with large depreciation expense and asset write-downs tend to have high investment expenditures. The table also shows that free cashflow is positively correlated with net income (0.50) and operating cashflow (0.48) but negatively correlated with total accruals (-0.57), working-capital accruals (-0.31), and long-term investment (-0.62). The correlation between ΔLTNOA and InvAcc is high (0.82), but, as we observed above, the difference between the variables is sufficiently great—reflected in the volatility of NTAcc in Table 1—to allow us to distinguish between accruals and investment.

4. Earnings and cashflow persistence

Our tests start with standard 'persistence' regressions, i.e., we study how the different components of earnings

Table 2
Correlations, 1971–2009
This table reports the time-series average of the annual cross-sectional correlations among the variables listed, all of which are scaled by average total assets for the year and winsorized annually at their 1st and 99th percentiles. (The variables are defined in Table 1.) The sample includes all nonfinancial firms on Compustat with data for average total assets, net income, net operating assets, and beginning-of-year market value (from CRSP), for an average of 4,036 firms per year and a total sample of 157,411 firm-years. The 'all-but-tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value, leaving 1,542 firms per year and a total sample of 60,149 firm-years. Bold indicates correlations that are greater than 0.30 in absolute value.

	NI	CF	FCF	dNOA	dWC	dLTNOA	InvAcc	NTAcc	Depr	OthAcc	dDebt	Issues
Panel A: All firms												
NI	-	**0.88**	**0.50**	**0.37**	0.29	0.27	-0.02	**0.46**	0.18	**0.45**	-0.04	**-0.35**
CF	**0.88**	-	**0.48**	0.28	0.26	0.19	0.13	0.05	-0.06	0.10	-0.04	**-0.33**
FCF	**0.50**	**0.48**	-	**-0.57**	**-0.31**	**-0.51**	**-0.62**	0.20	0.09	0.18	**-0.58**	**-0.52**
dNOA	**0.37**	0.28	**-0.57**	-	**0.61**	**0.83**	**0.64**	0.25	0.09	0.24	**0.58**	0.20
dWC	0.29	0.26	**-0.31**	**0.61**	-	0.10	0.02	0.14	0.08	0.12	0.28	0.07
dLTNOA	0.27	0.19	**-0.51**	**0.83**	0.10	-	**0.82**	0.21	0.05	0.22	**0.54**	0.20
InvAcc	-0.02	0.13	**-0.62**	**0.64**	0.02	**0.82**	-	**-0.33**	-0.24	-0.25	**0.53**	**0.32**
NTAcc	**0.46**	0.05	0.20	0.25	0.14	0.21	**-0.33**	-	**0.58**	**0.84**	-0.01	-0.19
Depr	0.18	-0.06	0.09	0.09	0.08	0.05	-0.24	**0.58**	-	0.10	-0.01	-0.08
OthAcc	**0.45**	0.10	0.18	0.24	0.12	0.22	-0.25	**0.84**	0.10	-	0.00	-0.18
dDebt	-0.04	-0.04	**-0.58**	**0.58**	0.28	**0.54**	**0.53**	-0.01	-0.01	0.00	-	0.01
Issues	**-0.35**	**-0.33**	**-0.52**	0.20	0.07	0.20	**0.32**	-0.19	-0.08	-0.18	0.01	-
Panel B: All-but-tiny firms												
NI	-	**0.81**	**0.36**	0.26	0.22	0.19	0.02	**0.34**	0.09	**0.36**	-0.08	-0.16
CF	**0.81**	-	**0.31**	0.19	0.17	0.14	0.22	-0.23	-0.28	-0.10	-0.07	-0.12
FCF	**0.36**	**0.31**	-	**-0.78**	**-0.38**	**-0.70**	**-0.72**	0.11	0.04	0.11	**-0.65**	**-0.46**
dNOA	0.26	0.19	**-0.78**	-	**0.54**	**0.87**	**0.75**	0.12	0.02	0.14	**0.62**	**0.35**
dWC	0.22	0.17	**-0.38**	**0.54**	-	0.10	0.05	0.11	0.09	0.06	0.27	0.12
dLTNOA	0.19	0.14	**-0.70**	**0.87**	0.10	-	**0.89**	0.08	-0.03	0.13	**0.59**	**0.34**
InvAcc	0.02	0.22	**-0.72**	**0.75**	0.05	**0.89**	-	**-0.35**	-0.30	-0.23	**0.56**	**0.37**
NTAcc	**0.34**	-0.23	0.11	0.12	0.11	0.08	**-0.35**	-	**0.65**	**0.80**	-0.02	-0.08
Depr	0.09	-0.28	0.04	0.02	0.09	-0.03	-0.30	**0.65**	-	0.12	-0.01	-0.02
OthAcc	**0.36**	-0.10	0.11	0.14	0.06	0.13	-0.23	**0.80**	0.12	-	-0.02	-0.09
dDebt	-0.08	-0.07	**-0.65**	**0.62**	0.27	**0.59**	**0.56**	-0.02	-0.01	-0.02	-	0.05
Issues	-0.16	-0.12	**-0.46**	**0.35**	0.12	**0.34**	**0.37**	-0.08	-0.02	-0.09	0.05	-

correlate with a firm's subsequent performance. An important way we deviate from the literature is that we consider not only the predictability of future earnings, but also the predictability of future accruals and cashflow. As discussed below, the behavior of these variables helps us to understand what drives the relation between accruals and subsequent earnings.

4.1. Accruals, investment, and subsequent performance

Table 3 reports average slopes and R^2s when earnings, cashflow, and accruals are regressed cross-sectionally on prior-year earnings and accruals. In particular, for each dependent variable Y_t, we report three sets of Fama-MacBeth (1973) regressions:

Model 1: $Y_t = a_0 + a_1\, NI_{t-1} + a_2\, dNOA_{t-1} + e_t$,

Model 2: $Y_t = b_0 + b_1\, NI_{t-1} + b_2\, dWC_{t-1} + b_3\, InvAcc_{t-1} + b_4\, NTAcc_{t-1} + e_t$,

Model 3: $Y_t = c_0 + c_1\, NI_{t-1} + c_2\, dWC_{t-1} + c_3\, InvAcc_{t-1} + c_4\, Depr_{t-1} + c_5\, OthAcc_{t-1} + e_t$.

The goal, following Sloan (1996) and others, is to explore the differential predictive ability of accruals and cashflow, or equivalently, to test whether accruals help to predict a firm's future performance after controlling for current profits. These two interpretations are equivalent, as noted by FWY (2003) and Richardson et al. (2005), because the models can be estimated with either earnings or cashflow in the regression. For example, Model 1 could be estimated as:

Model 1*: $Y_t = d_0 + d_1\, FCF_{t-1} + d_2\, dNOA_{t-1} + e_t$,

with slopes that are mechanically linked to those in Model 1: $a_1 = d_1$ and $a_2 = d_2 - d_1$. Thus, in our specification, the slope on NI captures the predictive power of free cashflow ($a_1 = d_1$) and the slope on dNOA captures the difference in the predictive slopes of free cashflow and accruals ($a_2 = d_2 - d_1$). The contribution of Model 2 is to test whether investment-related and nontransaction accruals have different implications for future performance (equivalent models could be estimated with either CF or FCF replacing NI). Model 3 tests whether depreciation is different from other nontransaction accruals.

Predicting earnings. Consider, first, the earnings regressions in the shaded columns. Model 1 replicates the earnings predictability results in prior studies: earnings are persistent but, controlling for NI_{t-1}, higher accruals forecast lower subsequent profits. The slope on NI_{t-1} is 0.75 in both samples of firms, while the slope on $dNOA_{t-1}$ is -0.11 in the full sample and -0.09 in the all-but-tiny subsample (both are more than eight standard errors below zero). The implication is that the accrual component of earnings is significantly less persistent than the cashflow component. Our estimates are close to the slopes reported by Richardson et al. (2006) and Dechow, Richardson, and Sloan (2008).

Model 2, new to this paper, shows that working-capital accruals (dWC), long-term investment (InvAcc), and nontransaction accruals (NTAcc) all contribute to the predictive power of total accruals, with slopes that are more than six standard errors below zero. The slopes on dWC and InvAcc range from -0.08 to -0.13 across the

Table 3
Persistence regressions, 1972–2009
This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets for the year and winsorized annually at their 1st and 99th percentiles. The sample includes all nonfinancial firms on Compustat with beginning-of-year market value (from CRSP) and data for all variables within each panel. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value. The variables are defined in Table 1.

	Dependent variables (Y_t)					Dependent variables (Y_t)				
	NI	CF	dWC	InvAcc	NTAcc	NI	CF	dWC	InvAcc	NTAcc
	All firms					All-but-tiny firms				
Model 1: $Y_t = b_0 + b_1 NI_{t-1} + b_2 dNOA_{t-1} + e_t$										
NI_{t-1}	0.75	0.63	0.13	0.02	0.11	0.75	0.67	0.17	0.11	0.07
t	51.43	40.04	3.31	0.55	6.43	46.95	21.00	4.30	2.64	4.26
$dNOA_{t-1}$	-0.11	-0.08	0.01	0.14	-0.03	-0.09	-0.05	0.03	0.18	-0.03
t	-11.77	-9.63	2.07	14.54	-3.58	-8.09	-7.83	4.05	8.40	-2.87
R^2	0.474	0.471	0.035	0.052	0.073	0.496	0.439	0.051	0.071	0.035
Model 2: $Y_t = b_0 + b_1 NI_{t-1} + b_2 dWC_{t-1} + b_3 InvAcc_{t-1} + b_4 NTAcc_{t-1} + e_t$										
NI_{t-1}	0.82	0.77	0.13	0.10	0.05	0.80	0.79	0.16	0.23	-0.01
t	29.10	47.84	3.57	2.44	3.33	67.34	64.18	4.19	6.84	-0.56
dWC_{t-1}	-0.13	-0.12	-0.02	0.05	0.00	-0.08	-0.09	0.07	-0.02	0.02
t	-13.28	-15.82	-1.55	2.36	0.06	-8.84	-12.97	3.14	-1.43	4.53
$InvAcc_{t-1}$	-0.08	-0.01	0.03	0.23	-0.06	-0.08	-0.03	0.01	0.27	-0.05
t	-8.75	-1.65	4.60	10.92	-8.59	-6.69	-9.07	1.93	7.97	-4.75
$NTAcc_{t-1}$	-0.45	-0.82	0.02	-0.30	0.37	-0.30	-0.82	0.07	-0.47	0.52
t	-8.92	-52.20	1.49	-4.11	6.24	-6.63	-39.19	3.94	-9.57	9.93
R^2	0.492	0.580	0.041	0.120	0.252	0.513	0.621	0.066	0.182	0.337
Model 3: $Y_t = b_0 + b_1 NI_{t-1} + b_2 dWC_{t-1} + b_3 InvAcc_{t-1} + b_4 Depr_{t-1} + b_5 OthAcc_{t-1} + e_t$										
NI_{t-1}	0.82	0.76	0.13	0.09	0.06	0.81	0.77	0.16	0.20	0.03
t	28.94	45.73	3.55	2.23	4.58	64.86	58.44	4.37	6.02	2.49
dWC_{t-1}	-0.13	-0.12	-0.02	0.06	-0.01	-0.09	-0.09	0.06	-0.01	0.00
t	-13.46	-15.73	-1.74	2.61	-1.08	-9.60	-11.81	2.98	-0.54	0.11
$InvAcc_{t-1}$	-0.07	-0.01	0.03	0.22	-0.05	-0.07	-0.03	0.01	0.27	-0.04
t	-8.32	-1.66	4.89	11.62	-7.16	-6.54	-9.08	2.59	8.11	-4.22
$Depr_{t-1}$	-0.14	-1.01	0.11	-0.62	0.89	-0.08	-1.03	0.18	-0.81	0.96
t	-5.44	-51.50	4.58	-9.05	39.57	-3.30	-55.78	6.44	-11.96	43.84
$OthAcc_{t-1}$	-0.60	-0.76	-0.03	-0.16	0.16	-0.43	-0.70	0.00	-0.23	0.27
t	-14.69	-40.25	-2.50	-2.88	4.60	-7.65	-35.53	-0.28	-6.97	5.88
R^2	0.496	0.581	0.043	0.127	0.314	0.520	0.625	0.071	0.192	0.409

two samples, similar to the slope on dNOA in Model 1. The slope on nontransaction accruals is many times larger, -0.45 for the full sample and -0.30 for the all-but-tiny sample. Thus, NTAcc is the least persistent component of earnings, with an implied persistence slope (the slope on NI_{t-1} plus the slope on $NTAcc_{t-1}$) of 0.37 in the full sample and 0.50 among larger stocks, compared with persistence slopes of 0.69–0.74 for dWC and InvAcc. (NTAcc's slope is significantly smaller than the other two, with t-statistics testing equality that range from -4.50 to -7.53.) The slope on dWC is also statistically different from the slope on InvAcc in the full sample (t-statistic of -4.69). This finding shows that, contrary to the hypothesis of FWY (2003), working-capital accruals and long-term investment have different predictive power for subsequent profitability.

Model 3 shows that the strong predictive power of NTAcc is driven primarily by nontransaction accruals other than depreciation. The slope on depreciation accruals is similar to the slopes on working capital and long-term investment (and significantly negative), while the slope on other nontransaction accruals (OthAcc) is -0.60 in the full sample and -0.43 among larger firms. The implied persistence of OthAcc, adding the slopes on NI_{t-1} and $OthAcc_{t-1}$, equals 0.22 in the full sample and 0.38 for larger firms, substantially less than the implied slopes of roughly 0.70 for other types of accruals and 0.80 for cashflow.

Other dependent variables. The remaining columns in Table 3 provide new insight into why accruals are negatively related to subsequent earnings (controlling for current earnings). The dependent variables include the different components of earnings, so the results allow us to trace earnings predictability to its constituent parts. For example, NI equals CF + NTAcc, implying that the slopes when CF and NTAcc are used as dependent variables mechanically sum to the slopes in the NI column (except for the small 'slippage,' noted earlier, caused by winsorization). More generally, the different columns can be combined in various ways to explore the predictability of other accounting measures.[3]

Focusing on Model 2 in the middle of the table, working-capital accruals have nearly the same predictive power for future operating cashflow (CF) as they do for future net income. In other words, high dWC is a bad signal for future earnings not because it predicts lower accruals—i.e., not because accruals reverse—but because high dWC signals a drop in cashflow. This result seems to contradict the idea that transitory movements in working-capital accruals explain the accrual anomaly. Further, in unreported tests, we find that high dWC is associated with high future sales (scaled by average total assets), so the decline in subsequent profits comes from higher costs, not lower sales.

[3] The predictability of operating cashflow after working-capital investment can be found by subtracting the slopes in the dWC column from those in the CF column; the predictability of free cashflow can be found by subtracting the slopes in the dWC, InvAcc, and NTAcc columns from those in the NI column.

In contrast, InvAcc is more negatively related to subsequent earnings (a slope of -0.08 in both samples) than to subsequent cashflow (a slope of -0.01 in the full sample and -0.03 for all-but-tiny firms). Thus, high long-term investment is a bad signal for future profits largely because it predicts subsequent nontransaction accruals (column 5) rather than a decline in cashflow.

Interestingly, the slopes on NTAcc exhibit the opposite pattern: Controlling for current earnings, NTAcc predicts future cashflow (a slope of -0.82 in both samples) much more strongly than it predicts future profits (a slope of -0.45 in the full sample and -0.30 for all-but-tiny firms). The easiest way to interpret the relation between NTAcc and future CF is to recall that the total impact of NTAcc can be found by adding the slopes on NI_{t-1} and $NTAcc_{t-1}$, giving a combined slope that is close to zero (-0.05 for all firms, -0.03 for all-but-tiny firms). This result implies that, controlling for a firm's current cashflow and investment, nontransaction accruals have essentially no predictive power for future cashflow.

Summary. Overall, Table 3 conveys three broad messages. First, controlling for current profits, all three components of accruals—working capital, long-term investment, and nontransaction accruals—are negatively related to subsequent earnings. The negative slope on NTAcc provides a powerful setting in which to test the earnings-fixation and investment hypotheses: NTAcc have strong predictive ability for future earnings but represent a component of accruals that is driven primarily by accounting, not investment, decisions. The earnings-fixation hypothesis, but not the investment hypothesis, suggests that NTAcc should also predict subsequent returns.

Second, Table 3 shows that our decomposition captures statistically and economically important differences between the different types of accruals. Prior studies that lump these components together, into either dNOA or dLTNOA, miss these differences. Moreover, dWC, InvAcc, and NTAcc differ not only in their predictive ability for future earnings but also in their predictive ability for future cashflow and accruals. Perhaps most interesting, we find that dWC is as strongly related to future operating cashflow as it is to future earnings. Thus, dWC seems to predict earnings not because of transitory measurement error in working capital that reverses in the future, but because high dWC signals lower future cashflow. The predictive power of dWC for future cashflow, and the absence of any reversal in dWC, is hard to reconcile with the idea that measurement error in working capital explains the relation between dWC and subsequent earnings.

Third, Table 3 shows that earnings persistence and the predictive power of accruals are similar in the full and all-but-tiny samples, despite the significant differences in the univariate properties of earnings and cashflows reported for the two samples in Table 1. The evidence implies that the many micro-cap stocks in the sample do not drive our persistence results.

4.2. External financing and subsequent performance

Investment expenditures—and accruals more generally—should be related to a firm's demand for external capital. Indeed, the descriptive statistics in Table 2 show that InvAcc and dNOA are correlated with changes in a firm's debt (dDebt) and with new equity issuance (Issues). The correlations, ranging from 0.20 to 0.62 for the different variables and samples, suggest that it could be important to control for a firm's external financing in our persistence regressions. The underlying question is whether accruals or external financing have stronger predictive power for subsequent performance.

Table 4 reports two sets of regressions using the external-financing variables, dDebt and Issues. The top panel establishes a baseline relation between external financing and a firm's subsequent performance, controlling only for NI_{t-1} to capture the basic persistence of earnings. The bottom panel adds our full set of accrual components (dWC, InvAcc, Depr, and OthAcc) to the regressions, to test whether the accruals and external financing have distinct predictive power for future performance. As in Table 3, we report regressions using earnings, cash-flow, accruals, and sales as different dependent variables.

The top panel shows that, controlling for current earnings, debt and equity issuance are both negatively related to a firm's subsequent earnings. The slopes are similar to but somewhat smaller than the slope on total accruals in Table 3: a one percentage point increase in dDebt or Issues is associated with a -0.04 to -0.08 percentage point drop in subsequent earnings (relative to total assets), with strong statistical significance in both samples of firms (the t-statistics range from -3.77 to -12.24). The external-financing variables have about

Table 4
Persistence regressions: Accruals vs. external financing, 1972–2009
This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets for the year and winsorized annually at their 1st and 99th percentiles. The sample includes all nonfinancial firms on Compustat with beginning-of-year market value (from CRSP) and data for all variables within each panel. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value. The variables are defined in Table 1.

	Dependent variables (Y_t)					Dependent variables (Y_t)				
	NI	CF	dWC	InvAcc	NTAcc	NI	CF	dWC	InvAcc	NTAcc
	All firms					All-but-tiny firms				
Model 1: $Y_t = b_0 + b_1 NI_{t-1} + b_2 dDebt_{t-1} + b_3 Issues_{t-1} + e_t$										
NI_{t-1}	0.67	0.58	0.14	0.13	0.09	0.70	0.63	0.18	0.23	0.06
t	41.30	32.30	3.86	3.63	6.46	35.46	18.73	4.67	7.79	4.01
$dDebt_{t-1}$	-0.04	-0.02	-0.01	0.09	-0.01	-0.06	-0.05	0.00	0.13	-0.01
t	-3.77	-2.09	-2.40	7.51	-2.63	-12.24	-7.97	-0.16	6.07	-2.07
$Issues_{t-1}$	-0.08	-0.06	0.08	0.21	-0.02	-0.06	-0.04	0.08	0.27	-0.02
t	-6.03	-4.04	3.44	6.78	-3.12	-7.36	-4.68	4.25	8.33	-2.91
R^2	0.470	0.470	0.043	0.067	0.070	0.491	0.439	0.061	0.088	0.031
Model 2: $Y_t = b_0 + b_1 NI_{t-1} + b_2 dDebt_{t-1} + b_3 Issues_{t-1} + b_4 dWC_{t-1} + b_5 InvAcc_{t-1} + b_6 Depr_{t-1} + b_7 OthAcc_{t-1} + e_t$										
NI_{t-1}	0.81	0.74	0.15	0.14	0.06	0.80	0.75	0.17	0.26	0.03
t	30.12	44.29	4.06	4.82	5.42	79.55	56.04	4.61	12.13	3.43
dWC_{t-1}	-0.13	-0.10	-0.04	0.02	-0.02	-0.08	-0.07	0.05	-0.07	-0.01
t	-13.60	-17.35	-3.35	0.93	-2.86	-9.23	-9.95	2.48	-4.45	-1.50
$InvAcc_{t-1}$	-0.07	0.01	0.01	0.18	-0.07	-0.06	-0.01	0.00	0.19	-0.05
t	-6.87	0.72	2.08	8.48	-8.70	-4.92	-1.34	-0.34	5.26	-5.06
$Depr_{t-1}$	-0.13	-0.99	0.08	-0.69	0.88	-0.05	-0.99	0.16	-0.93	0.96
t	-4.95	-45.63	3.87	-11.15	40.90	-2.23	-46.82	6.16	-19.06	47.74
$OthAcc_{t-1}$	-0.59	-0.75	-0.04	-0.20	0.15	-0.41	-0.68	-0.01	-0.28	0.27
t	-14.79	-41.65	-2.75	-4.21	4.35	-7.57	-35.19	-0.95	-8.57	5.87
$dDebt_{t-1}$	0.04	0.00	-0.01	-0.02	0.03	0.00	-0.03	-0.01	0.02	0.02
t	3.15	0.42	-2.20	-2.93	4.85	-0.36	-8.67	-2.94	1.28	3.22
$Issues_{t-1}$	-0.03	-0.04	0.08	0.14	0.01	-0.02	-0.02	0.08	0.19	0.00
t	-2.10	-3.13	3.34	9.19	1.98	-2.33	-4.16	3.88	12.10	0.61
R^2	0.499	0.584	0.051	0.147	0.317	0.524	0.627	0.082	0.214	0.413

the same predictive power for earnings and operating cashflow, implying that high debt and equity issuance mostly signal a drop in cashflow not a drop in future accruals (though they do have some predictive power for future nontransaction accruals).

The bottom panel of Table 4 shows that accruals largely subsume the predictive power of dDebt and Issues for subsequent earnings. With all variables included in the regression, working-capital accruals, long-term investment, and nontransaction accruals continue to have strong negative slopes, similar in magnitude to our estimates without the external-financing measures in the model (see Table 3). In contrast, the slope on dDebt becomes either insignificant (all-but-tiny firms) or even somewhat positive (full sample), while the slope on Issues drops by more than half and becomes only marginally significant (-0.03 in the full sample and -0.02 in the all-but-tiny subsample). In addition, the R^2s in the bottom panel of Table 4 are only slightly greater than the corresponding estimates in Table 3 without the external-financing measures in the regressions. Thus, the accrual variables seem to contain more information about subsequent firm performance than either of the external-financing measures.

5. Predicting stock returns

The regressions above show that investment-related and nontransaction accruals both have strong predictive power for subsequent earnings. We now test whether this predictive power extends to stock returns. FWY (2003) and Richardson et al. (2005) find that changes in LTNOA help to predict returns, but neither paper tests whether this predictability comes from investment expenditures, nontransaction accruals, or both. Our central thesis is that nontransaction accruals should not predict returns if investment explains the accrual anomaly, as proposed by FWY and Wu, Zhang, and Zhang (2010).

5.1. Return data

The return regressions use nearly the same sample of firms as our persistence regressions, with a few minor differences. In our earlier tests, a firm must have Compustat data in both the current and prior fiscal years, since we regress year t performance on year t–1 earnings and accruals. The return regressions instead require a firm to have return data on CRSP for year t and accounting data for fiscal year t–1. Thus, a firm can be included in the return regressions even if it does not have Compustat data for fiscal year t. The motivation for this approach is to avoid introducing any survival bias into the sample: we want the sample to include any firm that could enter an investor's portfolio at the start of the year, not just firms that survive until the end of the year on Compustat.

We assume that accounting data become publicly available within four months of the end of the fiscal year and, therefore, define return year t as the 12-month period starting in the fifth month after fiscal year t–1. We regress monthly stock returns during this period on accruals for fiscal year t–1. We focus on monthly returns to avoid making any assumptions about what to do with firms that drop off CRSP during return year t. Our tests simply include a firm up until the month it drops off CRSP, including any delisting return.

The return regressions include an average of 4,082 stocks per month from May 1972 through December 2010 (464 months), compared with an average of 4,036 firms in the persistence regressions. The subsample of all-but-tiny stocks has 1,595 stocks per month, compared with an average of 1,542 firms in the persistence regressions. The monthly average stock return is 1.24% in the full sample and 1.09% for all-but-tiny stocks, with cross-sectional standard deviations of 16.9% and 11.1%, respectively.

5.2. Accruals, investment, and stock returns

Table 5 reports Fama-MacBeth regressions of monthly stock returns (in percent) on lagged earnings, accruals, and investment. We include a firm's market value (LogSize) as a control variable in all regressions, following standard practice in the literature. We also include book-to-market (LogB/M) and past 12-month stock returns (Ret_{Yr-1}) as additional controls in some regressions, since they are well-known predictors of returns. (We do not expect Ret_{Yr-1} to add much explanatory power because momentum is weaker at the annual horizon, but we include it for completeness.)[4]

Table 5 shows three main results. First, columns (1) and (4) show that total accruals have strong predictive power for subsequent returns after controlling for a firm's size, B/M, past returns, and profitability. The slope on dNOA is more than eight standard errors below zero in both samples, regardless of whether B/M and past returns are added as controls. The point estimates, -2.34 in the full sample and -2.28 in the all-but-tiny sample when size and net income are in the regressions, are similar to the slopes on dWC and long-term NOA reported by Richardson et al. (2005, Table 8) (dividing their annual coefficients by 12). The primary new finding concerning total accruals in our paper is that the slope on dNOA is strong not only in the full sample, but also

[4] The control variables are defined as follows: $LogSize_{t-1}$ is the natural log of the firm's market value at the start of return year t; $LogB/M_{t-1}$ is the natural log of the book value of common equity for fiscal year t–1 minus $LogSize_{t-1}$; and Ret_{Yr-1} is the return in the 12 months leading up to the start of return year t, skipping the final month (following the convention in the momentum literature). Adding $LogB/M_{t-1}$ and Ret_{Yr-1} as controls reduces the full sample to an average of 3,969 stocks per month and the all-but-tiny subsample to 1,495 stocks per month.

Table 5
Predicting monthly stock returns, May 1972–December 2010
This table reports average slopes and R^2s from cross-sectional regressions of monthly stock returns (in %) on lagged earnings, accruals, and other firm characteristics (the regression intercepts are omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates. All predictor variables are winsorized annually at their 1st and 99th percentiles and updated once per year, four months after the end of the firm's prior fiscal year. Prior-year earnings and accruals (NI, dNOA, dWC, InvAcc, NTAcc, Depr, OthAcc) are scaled by average total assets for that year and are defined in Table 1. LogSize is the natural log of market value; LogB/M is natural log of book equity minus LogSize; and Ret_{Yr-1} is the prior-year stock return, skipping the final month. Accounting data come from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns and lagged LogSize, NI, and dNOA. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on LogSize.

	All firms						All but tiny firms					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$LogSize_{t-1}$	-0.15	-0.15	-0.15	-0.11	-0.11	-0.11	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07
t	-3.62	-3.66	-3.65	-2.68	-2.72	-2.67	-1.79	-1.88	-1.83	-1.61	-1.60	-1.57
$LogB/M_{t-1}$				0.26	0.27	0.27				0.21	0.24	0.24
t				4.22	4.38	4.45				2.56	3.04	2.97
Ret_{Yr-1}				0.05	0.04	0.04				0.29	0.28	0.28
t				0.44	0.32	0.31				2.16	2.10	2.08
NI_{t-1}	1.43	1.52	1.46	1.07	1.29	1.21	1.37	1.68	1.57	2.11	2.71	2.62
t	3.38	3.44	3.31	2.56	2.98	2.79	2.38	2.89	2.70	3.75	4.82	4.63
$dNOA_{t-1}$	-2.34			-2.16			-2.28			-2.01		
t	-12.85			-13.10			-8.42			-8.64		
dWC_{t-1}		-2.34	-2.31		-2.12	-2.09		-3.06	-2.99		-2.54	-2.50
t		-8.68	-8.60		-8.07	-7.95		-6.69	-6.56		-6.14	-6.02
$InvAcc_{t-1}$		-2.33	-2.37		-2.16	-2.19		-1.98	-1.99		-1.71	-1.72
t		-11.06	-11.32		-10.83	-11.03		-7.07	-7.05		-6.78	-6.75
$NTAcc_{t-1}$		-3.99			-4.15			-4.03			-4.43	
t		-7.70			-8.19			-5.59			-6.31	
$Depr_{t-1}$			-5.70			-5.86			-5.86			-5.50
t			-6.42			-6.68			-5.07			-4.81
$OthAcc_{t-1}$			-3.61			-3.90			-3.35			-4.28
t			-6.20			-6.75			-4.04			-5.28
R^2	0.019	0.021	0.022	0.028	0.030	0.031	0.028	0.033	0.035	0.046	0.052	0.054

among larger stocks (see, also, Richardson, Tuna, and Wysocki, 2010).

The second key result in Table 5 is that working-capital accruals, long-term investment expenditures, and nontransaction accruals all contribute to the predictive power of dNOA, with slopes that are more than -5.50 standard errors from zero in both samples (with or without B/M and past returns in the regression). In the full sample, the slopes on dWC and InvAcc are nearly identical to each other (-2.33 and -2.34 without B/M and momentum in the regression) and to the slope on dNOA in column (1). The slope on NTAcc is more than 70% larger than the other two, equal to -3.99 with a t-statistic of -7.70. Moreover, in untabulated tests, the slope on NTAcc is statistically different from the others, with t-statistics of -2.93 and -3.10 when we test equality with the slopes on dWC and InvAcc. This evidence supports the earnings-fixation hypothesis: accruals that are not directly tied to current investment expenditures have strong predictive power for stock returns. (Of course, the negative slope on InvAcc suggests that investment may also play a role.)[5]

The results among larger stocks are similar: all three accrual terms are significant and nontransaction accruals have the most negative slope. In this sample, the slopes on dWC (-3.06) and NTAcc (-4.03) are significantly different from the slope on InvAcc (-1.98) when size and profitability are included the regression (t-statistics testing equality of -2.81 and -2.37), and all three slopes are significantly different from each other when B/M and past returns are added as controls (t-statistics testing equality ranging from -1.86 to -3.96).

Columns (3) and (6) in Table 5 show that, when we break NTAcc into depreciation and other nontransaction accruals, both components are significantly related to subsequent returns. Depreciation accruals have the most negative slopes in both samples, with point estimates ranging from -5.50 to -5.86 (t-statistics of -4.81 to -6.68), depending on the specification. This result is surprising because prior studies find that depreciation contributes little to the accrual anomaly (e.g., Sloan, 1996; Thomas and Zhang, 2002). The strong depreciation effect in

[5] Several readers have asked whether NTAcc might capture the impact of prior-period investment on returns. The argument is that investment may predict returns for several years and, while our tests control for contemporaneous investment, they do not control for prior-period investment. Recall, however, that NTAcc is negatively correlated with investment—high investment tends to be associated with more negative depreciation accruals, write-downs, and the other components of NTAcc—so excluding lagged investment from the regressions tends to reduce, not explain, the predictive power of NTAcc. Indeed, if we add $InvAcc_{t-2}$ to the regression in column (2), the slope on NTAcc becomes bigger and more significant (-4.30 with a t-statistic of -8.06 in the full sample).

our tests can be explained by the fact that our regressions include not just working-capital accruals, but also earnings and long-term investment (the latter, in particular, is important). Depreciation accruals are positively correlated with NI and negatively correlated with InvAcc (see Table 2), so controlling for those variables significantly strengthens the slope on Depr. For example, in the full sample, the slope on Depr drops roughly in half, to -2.76 with t-statistics of -2.92, if we omit InvAcc from the regression in column (3) and becomes insignificant if we also omit net income. In essence, the predictive power of depreciation is typically masked in the literature because of its correlation with profits and investment.

The significance of Depr illustrates an important result: the predictive power of nontransaction accruals is not just driven by special items. More explicitly, if we either replace NTAcc with special items in the regression in column (3) or include special items as an additional regressor, special items are never significant and, when added to the regression, have little impact on the slope on NTAcc (the slope drops from -3.99 to -3.74 in the full sample and from -4.03 to -3.64 among all-but-tiny stocks; the slope remains more than five standard errors below zero in both samples).

The strong negative slope on Depr is also interesting because we found Depr to have a weaker relation than OthAcc to subsequent earnings (controlling for current profits; see Table 3). This suggests that investors understand the link between OthAcc and future earnings better than the link between Depr and future earnings. An alternative interpretation is that investors react not only to earnings but also to cashflow, and they may be surprised by the strong negative relation between Depr and cashflow found in Table 3.

The third key result in Table 5 is that, controlling for accruals, earnings are significantly positively related to subsequent returns. Across the different specifications, the slope on NI_{t-1} varies from 1.07 to 1.52 in the full sample (t-statistics of 2.56 to 3.44) and from 1.37 to 2.71 in the all-but-tiny sample (t-statistics of 2.38 to 4.82). The slopes tend to be higher for larger stocks, particularly if B/M and Ret_{Yr-1} are included in the regressions. The positive slope on earnings is consistent with post-earnings-announcement drift in returns (as well as the evidence in Fama and French, 2006, 2008), though the accrual literature has often missed this effect. In fact, the lack of a reliably positive slope on earnings has been one of the problems for the earnings-fixation hypothesis: if investors fixate on total earnings, they should be just as surprised by the higher persistence of cashflows as they are by the lower persistence of accruals (see, e.g., Sloan, 1996). Thus, our positive slope on NI_{t-1} provides new support for the earnings-fixation hypothesis.

Depending on the specification, the positive slope on earnings can be nearly as large in magnitude as the negative slope on total accruals (the slope on NI varies from 50% less to 5% greater than the slope on dNOA across the different regressions). If the magnitudes were identical, a single combined measure, earnings minus accruals, would encompass the predictive power of the individual variables (i.e., two variables with identical regression slopes can be merged with no loss of explanatory power). As noted in Section 2, the combined variable equals a firm's free cashflow, FCF = NI – dNOA. The evidence in Table 5 therefore suggests that a pure cashflow variable—the cashflow remaining after new investment expenditures—might capture a significant portion of the accrual anomaly.

Table 6 tests that hypothesis directly. The table is identical to Table 5 except that FCF_{t-1} is used in place of NI_{t-1} in the regressions. Note that, if the relation FCF = NI – dNOA held exactly in the data, the change in variables would have no impact on the regressions except that the slope on dNOA would now equal the difference between the slopes on NI and dNOA estimated in Table 5 (the slope on FCF would be the same as the slope on NI in Table 5). In practice, the relation does not hold exactly in the data because we winsorize each of the variables separately, but the impact of this slippage is relatively small.[6]

Table 6 shows that the slopes on accruals shrink significantly when we control for a firm's FCF rather than its earnings, but accruals—especially nontransaction accruals—have some incremental predictive power. In the full sample, the slope on dNOA declines by about a half relative to the estimate in Table 5 but remains roughly three standard errors below zero. The slopes on dWC and InvAcc are marginally significant, with t-statistics ranging from -1.77 to -2.22, while the slope on NTAcc and its components (Depr and OthAcc) remains highly

[6] We view the benefits of winsorization as outweighing the benefits of having the accounting identities hold perfectly in the data. An alternative approach would be to winsorize only net income and the components of accruals and to construct dNOA and FCF from the winsorized variables. However, it is not clear which variables to winsorize first and which to construct after, so we prefer the simpler approach of just winsorizing all of the predictors separately. The key goal, in our view, is to ensure that all of the variables capture what they intend to capture and that the results are not driven by a few extreme data points. Our approach satisfies both requirements.

Table 6
Predicting monthly stock returns: Accruals vs. FCFs, May 1972–December 2010

This table reports average slopes and R^2s from cross-sectional regressions of monthly stock returns (in %) on lagged cashflow, accruals, and other firm characteristics (the regression intercepts are omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates. All predictor variables are winsorized annually at their 1st and 99th percentiles and updated once per year, four months after the end of the firm's prior fiscal year. Prior-year cashflow and accruals (FCF, dNOA, dWC, InvAcc, NTAcc, Depr, OthAcc) are scaled by average total assets for that year and are defined in Table 1. LogSize is the natural log of market value; LogB/M is natural log of book equity minus LogSize; and Ret_{Yr-1} is the prior-year stock return, skipping the final month. Accounting data come from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns and lagged LogSize, NI, and dNOA. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on LogSize.

	All firms						All but tiny firms					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$LogSize_{t-1}$	-0.15	-0.15	-0.15	-0.11	-0.11	-0.11	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07
t	-3.51	-3.61	-3.58	-2.63	-2.71	-2.65	-1.71	-1.86	-1.81	-1.51	-1.58	-1.53
$LogB/M_{t-1}$				0.25	0.27	0.27				0.21	0.23	0.23
t				4.13	4.35	4.41				2.63	2.95	2.91
Ret_{Yr-1}				0.04	0.04	0.03				0.28	0.28	0.28
t				0.32	0.30	0.29				2.07	2.08	2.07
FCF_{t-1}	1.32	1.51	1.45	1.04	1.32	1.24	1.37	1.60	1.49	2.15	2.52	2.44
t	3.36	3.84	3.67	2.67	3.34	3.12	2.56	3.05	2.84	4.01	4.81	4.63
$dNOA_{t-1}$	-1.03			-1.14			-0.92			0.12		
t	-2.70			-3.00			-1.63			0.23		
dWC_{t-1}		-0.81	-0.83		-0.80	-0.85		-1.38	-1.41		0.05	0.02
t		-1.89	-1.95		-1.77	-1.87		-1.99	-2.03		0.08	0.03
$InvAcc_{t-1}$		-0.80	-0.91		-0.82	-0.93		-0.39	-0.52		0.83	0.73
t		-1.87	-2.13		-1.97	-2.22		-0.68	-0.91		1.56	1.38
$NTAcc_{t-1}$		-2.28			-2.73			-2.26			-1.71	
t		-3.96			-4.93			-2.68			-2.13	
$Depr_{t-1}$			-4.14			-4.55			-4.33			-2.90
t			-4.17			-4.60			-3.35			-2.27
$OthAcc_{t-1}$			-1.87			-2.49			-1.61			-1.54
t			-2.97			-4.17			-1.77			-1.77
R^2	0.019	0.021	0.022	0.028	0.030	0.031	0.027	0.033	0.035	0.046	0.052	0.054

significant (t-statistics of -2.97 to -4.93). Thus, FCF absorbs a significant portion of the accrual anomaly but cannot explain the predictive power of nontransaction accruals.

The same conclusions hold even more strongly in the all-but-tiny sample. Among larger firms, FCF fully drives out the significance of both dNOA and investment expenditures, and largely absorbs the predictive power of working capital. Again, nontransaction accruals continue to have incremental predictive power, with t-statistics ranging from -1.77 to -3.35 on NTAcc and its components.

5.3. Accruals, external financing, and stock returns

We noted earlier that accruals are correlated with a firm's demand for external funds, measured in our data by changes in debt (dDebt) and net new equity issuance (Issues). The literature finds that external financing, like accruals, is negatively related to subsequent returns, but there is some disagreement about the connection between the anomalies. For example, Fama and French (2008) and Resutek (2010) find that share issuance and accruals have distinct predictive power for returns, but Dechow, Richardson, and Sloan (2008) conclude that accruals subsume the external-financing anomaly. It seems worthwhile, then, to consider the joint predictive power of accruals, investment, and external financing.

Table 7 reports three sets of return regressions using the external-financing variables: the first includes only earnings, dDebt, and Issues as predictor variables; the second adds the full set of accrual variables to the regressions; and the third replaces NI with FCF, mirroring our tests in Table 6. We also include size, B/M, and past returns in all regressions as control variables.

The first column shows that, controlling for size, B/M, past returns, and NI, the external-financing variables have strong predictive power for returns in both samples of stocks. The slopes on dDebt and Issues are between -5.68 and -13.43 standard errors from zero and comparable in magnitude (-1.85 to -2.31) to the slope on total accruals in Table 5.

The slopes drop significantly when accruals are added to the regressions but dDebt and Issues both remain

Table 7

Predicting monthly stock returns: Accruals vs. external financing, May 1972–December 2010

This table reports average slopes and R^2s from cross-sectional regressions of monthly stock returns (in %) on lagged earnings, accruals, and other firm characteristics (the regression intercepts are omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates. All predictor variables are winsorized annually at their 1st and 99th percentiles and updated once per year, four months after the end of the firm's prior fiscal year. Prior-year earnings, cashflow, and accruals (NI, FCF, dNOA, dWC, InvAcc, NTAcc, Depr, OthAcc) are scaled by average total assets for that year and are defined in Table 1. LogSize is the natural log of market value; LogB/M is natural log of book equity minus LogSize; and Ret_{Yr-1} is the prior-year stock return, skipping the final month. Accounting data come from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns and lagged LogSize, NI, and dNOA. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on LogSize.

	All firms			All but tiny firms		
	(1)	(2)	(3)	(1)	(2)	(3)
$LogSize_{t-1}$	-0.10	-0.11	-0.11	-0.06	-0.07	-0.07
t	-2.43	-2.60	-2.58	-1.49	-1.68	-1.63
$LogB/M_{t-1}$	0.25	0.25	0.25	0.18	0.21	0.21
t	4.10	4.23	4.20	2.32	2.76	2.73
Ret_{Yr-1}	0.07	0.04	0.04	0.31	0.28	0.28
t	0.62	0.35	0.34	2.29	2.17	2.16
NI_{t-1}	-0.42	0.66		0.81	2.10	
t	-1.04	1.48		1.51	3.72	
FCF_{t-1}			0.69			1.95
t			1.65			3.65
dWC_{t-1}		-1.44	-0.80		-1.98	-0.00
t		-5.03	-1.78		-4.45	-0.04
$InvAcc_{t-1}$		-1.33	-0.68		-1.03	0.87
t		-5.47	-1.68		-3.64	1.68
$Depr_{t-1}$		-4.78	-4.11		-4.50	-2.48
t		-5.50	-4.23		-3.96	-1.97
$OthAcc_{t-1}$		-3.12	-2.37		-3.58	-1.42
t		-5.36	-4.02		-4.35	-1.64
$dDebt_{t-1}$	-2.31	-0.99	-0.94	-1.85	-0.59	-0.50
t	-13.43	-4.42	-3.99	-8.14	-2.12	-1.72
$Issues_{t-1}$	-1.96	-1.26	-1.22	-2.09	-1.40	-1.33
t	-6.81	-4.70	-4.57	-5.68	-3.65	-3.48
R^2	0.029	0.032	0.032	0.049	0.058	0.058

significant. Similarly, the slopes on all components of accruals are smaller than the corresponding estimates in Table 5, without external financing in the regressions, but all components remain roughly four to five standard errors below zero in both samples (controlling for NI; the slopes are more modest if we control for FCF, as in Table 6). Thus, Table 7 shows that accruals and external-financing variables capture correlated, but distinct, predictability in stock returns.

Table 8
Average returns on accrual-sorted portfolios, 1972–2010
This table reports average monthly returns (in %) for four sets of accrual-sorted portfolios, formed based on (1) total accruals (dNOA), (2) working-capital accruals (dWC), (3) long-term investment (InvAcc), and (4) the component of non-transaction accruals that is uncorrelated with dWC and InvAcc (this component is labeled NTAcc*). Low–High is the average return on decile 1 minus decile 10. Portfolios are equal-weighted and formed monthly using NYSE breakpoints. The accrual variables, defined in Table 1, are updated once per year, four months after the firm's fiscal-year end. Accounting data come from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns, dNOA, and net income. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value.

	All firms				All-but-tiny firms			
Portfolio	dNOA	dWC	InvAcc	NTAcc*	dNOA	dWC	InvAcc	NTAcc*
Low accruals	1.76	1.44	1.60	1.42	1.45	1.25	1.30	1.24
2	1.67	1.48	1.55	1.43	1.39	1.26	1.23	1.23
3	1.58	1.36	1.52	1.48	1.32	1.22	1.31	1.29
4	1.42	1.36	1.44	1.37	1.31	1.19	1.25	1.23
5	1.45	1.34	1.36	1.41	1.28	1.14	1.19	1.19
6	1.34	1.33	1.28	1.22	1.24	1.17	1.21	1.12
7	1.33	1.36	1.32	1.17	1.19	1.20	1.21	1.02
8	1.15	1.26	1.22	1.21	1.07	1.15	1.12	1.08
9	0.95	1.12	1.01	1.10	0.85	1.02	0.94	0.91
High accruals	0.41	0.82	0.50	0.71	0.43	0.62	0.58	0.70
Low–High	1.35	0.61	1.10	0.71	1.03	0.64	0.73	0.54
t-stat	10.48	6.99	8.77	6.19	7.87	6.04	5.07	5.07

5.4. Portfolios

To provide additional perspective on the predictive power of accruals, Table 8 reports average monthly returns for accrual-sorted portfolios. We form four sets of portfolios, based on (1) total accruals, (2) working-capital accruals, (3) long-term investment, and (4) nontransaction accruals. The first three sets are constructed simply by sorting stocks based on dNOA, dWC, and InvAcc. For the final set, we sort stocks not on NTAcc directly, but on the component of NTAcc that is uncorrelated with the dWC and InvAcc, i.e., we regress NTAcc each month on dWC and InvAcc and sort stocks based on residuals from the regression (labeled NTAcc*). The idea is that we want to isolate the component of accruals that is uncorrelated with investment in order to provide a clean test of whether non-investment-related accruals have predictive power.

Like our cross-sectional regressions, Table 8 shows that total accruals and all three components are strongly related to subsequent stock returns. Total accruals have the strongest predictive power, with an average-return spread (decile 1 minus decile 10) of 1.35% in the full sample and 1.03% among all-but-tiny stocks (with t-statistics of 10.48 and 7.87, respectively). The return spreads are lower but still economically and statistically strong when we sort based on dWC, InvAcc, and NTAcc*. Most important, Table 8 shows that sorting stocks based on accruals constructed to be uncorrelated with investment creates a large spread in portfolio returns, with a long-short return of 0.71% monthly in the full sample and 0.54% in the all-but-tiny stock sample (with t-statistics of 6.19 and 5.07). Again, these results provide strong evidence that investment does not explain a significant portion of the accrual anomaly.

Fig. 1 explores how returns on the long-short portfolios change through time. Specifically, the figure plots average monthly returns over 10-year rolling windows (the x-axis identifies the final month of the window) for the four long-short portfolios described in Table 8, based on dNOA (dark solid line), dWC (dotted line), InvAcc (dashed line), and NTAcc* (light solid line).

Similar to Richardson, Tuna, and Wysocki (2010) and Green, Hand, and Soliman (2011), our results suggest that strategies based on dNOA and dWC have become less profitable in recent years, dropping markedly in the last 10 years of the sample. For example, focusing on results for all stocks (Panel A), the average monthly return on the dNOA strategy drops from 2.39% in the ten years ending December 2000 (close to its all-time peak) to 0.94% in the ten years ending December 2010. The average return on the dWC strategy drops from 1.13% to 0.13% during the same period. In contrast, the 10-year average return on the nontransaction accrual portfolio is relatively stable at the end of the sample—indeed, the return from January 2001–December 2010 is slightly higher than the average return over the whole period: The 10-year rolling average equals 0.80% for the first ten years of the sample, peaks at 1.28% in the ten years ending January 2004, and equals 0.76% over the final ten years. These results suggest that our NTAcc strategy has been affected less by whatever forces have reduced the profitability of other accrual strategies.

6. Conclusions

The accrual anomaly remains one of the most challenging asset-pricing anomalies to interpret because of the close link not only between accruals and earnings, but also between accruals and investment. The second link makes it hard to test whether the market's reaction to accruals is due to the underlying investment expenditure or to the way the expenditure is recorded in the firm's financial statements.

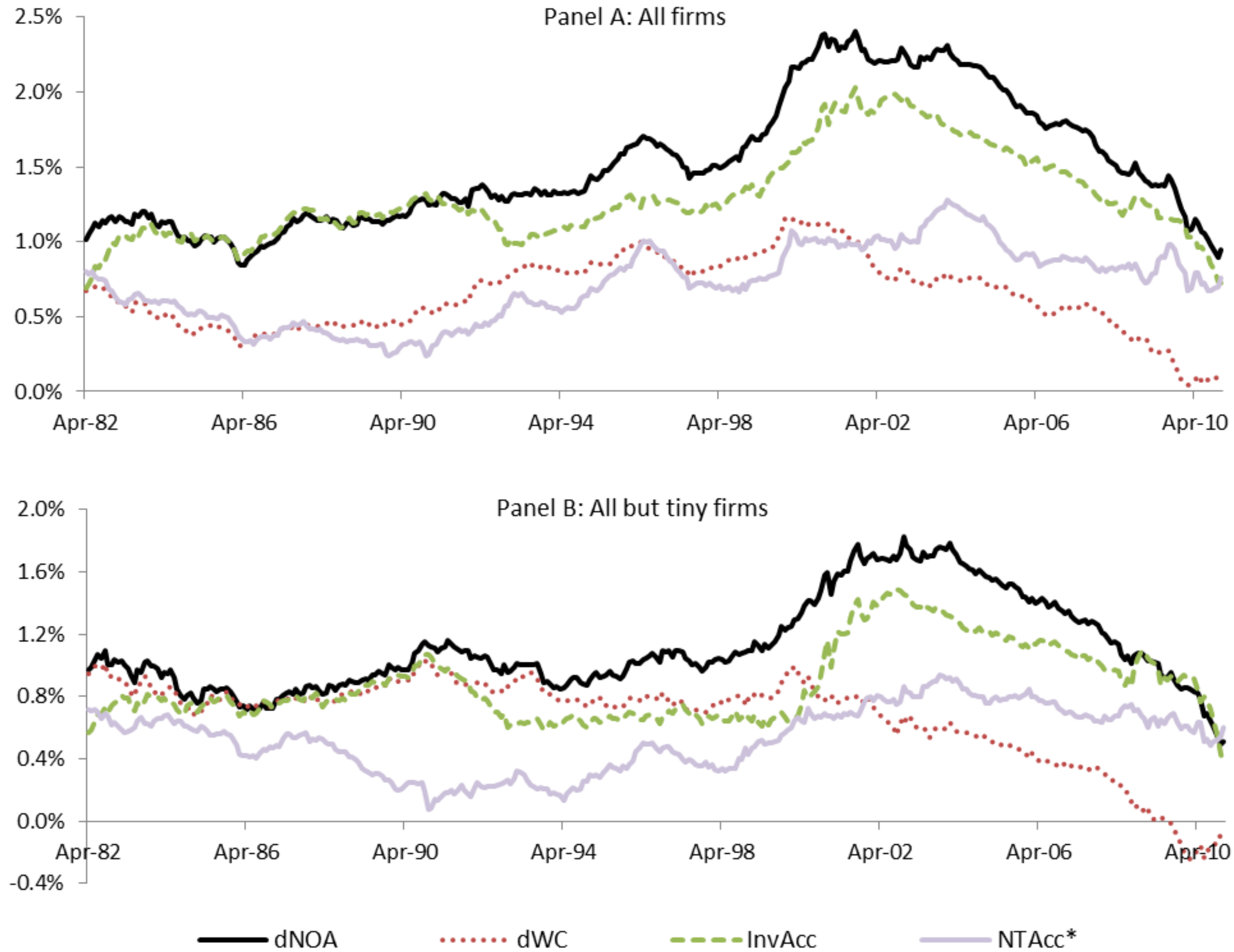

Fig. 1. Average monthly returns (ten-year rolling windows) on long-short accrual strategies, 1982–2010
The figure plots ten-year average monthly returns, ending in the month indicated on the x-axis, for investment strategies based on total accruals (dNOA; dark solid line), working-capital accruals (dWC; dotted line), long-term investment (InvAcc; dashed line), and the component of nontransaction accruals that is uncorrelated with dWC and InvAcc (NTAcc*; light solid line). Each strategy invests in an equal-weighted portfolio of low-accrual stocks (bottom decile) and shorts an equal-weighted portfolio of high-accrual stocks (top decile) based on one of the four accrual measures. The variables, defined in Table 1, are updated once per year, four months after the firm's fiscal-year end. Accounting data come from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns, dNOA, and net income. The 'all but tiny' sample drops firms below the NYSE 20th percentile based on beginning-of-year market value.

Our paper is the first to distinguish between accruals and investment by isolating accruals that are not tied to current investment expenditures. These accruals, which we label nontransaction accruals, include items such as depreciation, amortization, asset write-downs, and other accounting charges that impact earnings but do not reflect new investment expenditures. Our central thesis is that nontransaction accruals should help to predict returns if investors fixate on earnings and fail to appreciate the differential predictive power of nontransaction accruals for future performance; they should not be significant, however, if investment drives the accrual anomaly, as proposed by FWY (2003) and Wu, Zhang, and Zhang (2010).

Our empirical results show that nontransaction accruals have strong predictive power for subsequent stock returns, consistent with the earnings-fixation hypothesis. In Fama-MacBeth regressions, working-capital accruals, long-term investment expenditures, and nontransaction accruals all have slopes that are more than 5.50 standard errors below zero, even when we drop micro-cap stocks from the regressions. The most negative slopes are found on nontransaction accruals, with point estimates that are up to twice as large as the estimates on working-capital accruals and investment. Our results provide strong evidence that investment does not fully explain the accrual anomaly.

It is useful to note that we have not explicitly tried to distinguish between risk and mispricing explanations for the accrual anomaly. However, the risk-based explanations proposed in the literature predict a link between investment accruals and stock returns (e.g., Khan, 2008; Wu, Zhang, and Zhang, 2010), not a link between nontransaction accruals and stock returns. Our evidence that investment does not (fully) explain the accrual anomaly seems to be most consistent with Sloan's (1996) mispricing-based earnings-fixation hypothesis. But, again, our main conclusion is more basic: investment-based stories for the accrual anomaly—rational and irrational—do not fully explain the data.

References

Dechow, Patricia and Weili Ge, 2006. The persistence of earnings and cash flows and the role of special items: Implication for the accrual anomaly. Review of Accounting Studies 11, 253–296.

Dechow, Patricia, Scott Richardson, and Richard Sloan, 2008. The persistence and pricing of the cash component of earnings. Journal of Accounting Research 46, 537–566.

Desai, Hemang, Shivaram Rajgopal, and Mohan Venkatachalam, 2004. Value-glamour and accruals mispricing: One anomoly or two? The Accounting Review 79, 355–385.

Fairfield, Patricia, J. Scott Whisenant, and Teri Yohn, 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. The Accounting Review 78, 353–371.

Fama, Eugene and Kenneth French, 2006. Profitability, investment, and average returns. Journal of Financial Economics 82, 491–518.

Fama, Eugene and Kenneth French, 2008. Dissecting anomalies. Journal of Finance 63, 1653–1678.

Fama, Eugene and James MacBeth, 1973. Risk, return and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Green, Jeremiah, John Hand, and Mark Soliman, 2011. Going, going, gone? The apparent demise of the accrual anomaly. Management Science 57, 797–816.

Khan, Mozaffar, 2008. Are accruals mispriced? Evidence from tests of an intertemporal capital asset pricing model. Journal of Accounting and Economics 45, 55–77.

Resutek, Robert, 2010. Intangible returns, accruals and return reversal: A multiperiod examination of the accrual anomaly. The Accounting Review 85, 1347–1374.

Richardson, Scott, Richard Sloan, Mark Soliman, and İrem Tuna, 2005. Accrual reliability, earnings persistence, and stock prices. Journal of Accounting and Economics 39, 437–485.

Richardson, Scott, Richard Sloan, Mark Soliman, and İrem Tuna, 2006. The implications of accounting distortions and growth for accruals and profitability. The Accounting Review 81, 713–743.

Richardson, Scott, İrem Tuna, and Peter Wysocki, 2010. Accounting anomalies and fundamental analysis: A review of recent research advances. Journal of Accounting and Economics 50, 410–454.

Sloan, Richard, 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289–315.

Thomas, Jacob, and Huai Zhang, 2002. Inventory changes and future returns. Review of Accounting Studies 7, 163–187.

Wu, Jin, Lu Zhang, X. Frank Zhang, 2010. The *q*-theory approach to understanding the accrual anomaly. Journal of Accounting Research 48 , 177–223.

Xie, Hong, 2001. The mispricing of abnormal accruals. The Accounting Review 76, 357–373.

Zhang, X. Frank, 2007. Accruals, investment, and the accrual anomaly. The Accounting Review 82, 1333–1363.