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Dissecting Anomalies

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ABSTRACT

The anomalous returns associated with net stock issues, accruals, and momentum are pervasive; they show up in all size groups (micro, small, and big) in cross-section regressions, and they are also strong in sorts, at least in the extremes. The asset growth and profitability anomalies are less robust. There is an asset growth anomaly in average returns on microcaps and small stocks, but it is absent for big stocks. Among profitable firms, higher profitability tends to be associated with abnormally high returns, but there is little evidence that unprofitable firms have unusually low returns.

THERE ARE PATTERNS IN AVERAGE stock returns that are considered anomalies because they are not explained by the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). For example, Banz (1981) finds that stocks with low market capitalization (small stocks) have abnormally high average returns. Stocks with high ratios of book value to the market value of equity also have unusually high average returns (Rosenberg, Reid, and Lanstein (1985), Chan, Hamao, and Lakonishok (1991), Fama and French (1992)). Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002) find that more profitable firms have higher average stock returns, while Fairfield, Whisenant, and Yohn (2003) and Titman, Wei, and Xie (2004) show that firms that invest more have lower stock returns. A literature initiated by Sloan (1996) finds that higher accruals predict lower stock returns. Pulling together earlier evidence that returns after stock repurchases are high (Ikenberry, Lakonishok, and Vermaelen (1995)) and returns after stock issues are low (Loughran and Ritter (1995)), Daniel and Titman (2006) and Pontiff and Woodgate (2008) show that there is a negative relation between net stock issues and average returns. The premier anomaly is momentum (Jegadeesh and Titman (1993)): Stocks with low returns over the last year tend to have low returns for the next few months and stocks with high past returns tend to have high future returns. Like the patterns in average returns associated with net stock issues, accruals, profitability, and asset growth, return momentum is left unexplained by the three-factor model of Fama and French (1993) as well as by the CAPM.

We revisit the size, value, profitability, growth, accruals, net stock issues, and momentum anomalies. Each presents a path traveled by earlier work, but

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there are gains in studying them together to see which have information about average returns that is missed by the others.

There are also methodology issues. Two approaches are commonly used to identify anomalies, (i) sorts of returns on anomaly variables, and (ii) regressions, in the spirit of Fama and MacBeth (1973), that use anomaly variables to explain the cross-section of average returns. Each approach has advantages and disadvantages.

The main advantage of sorts is a simple picture of how average returns vary across the spectrum of an anomaly variable. There are, however, potential pitfalls. For example, a common approach is to form equal-weight (EW) decile portfolios by sorting stocks on the variable of interest. Though the detailed results for deciles are typically shown, it is common to focus on the hedge portfolio return obtained from long-short positions in the extreme deciles. A potential problem is that the returns on EW hedge portfolios that use all stocks can be dominated by stocks that are tiny (microcaps, which we define as stocks with market cap below the 20th NYSE percentile), not just small. Microcaps can be influential in EW hedge portfolio returns for two reasons. First, though microcaps are on average only about 3% of the market cap of the NYSE-Amex-NASDAQ universe, they account for about 60% of the total number of stocks. Second, the cross-section dispersion of anomaly variables is largest among microcaps, so they typically account for more than 60% of the stocks in extreme sort portfolios. To circumvent this problem, value-weight (VW) hedge portfolio returns are often shown along with EW returns. But VW hedge returns can be dominated by a few big stocks, resulting again in an unrepresentative picture of the importance of the anomaly.

To attack these problems, we examine the average returns from separate sorts of microcaps, small stocks, and big stocks on each anomaly variable, where the breakpoints separating micro from small and small from big are the 20th and 50th percentiles of market cap for NYSE stocks. Examining sort returns for the three size groups is a simple way to evaluate the pervasiveness of the abnormal returns associated with an anomaly.

Sorts have two shortcomings that do not afflict cross-section regressions. First, sorts are awkward for drawing inferences about which anomaly variables have unique information about average returns. Multiple regression slopes provide direct estimates of marginal effects. Moreover, with our large samples, marginal effects are measured precisely for many explanatory variables. Second, sorts are clumsy for examining the functional form of the relation between average returns and an anomaly variable. In contrast, simple diagnostics on the regression residuals allow us to judge whether the relations between anomaly variables and average returns implied by the regression slopes show up across the full ranges of the variables.

The regression approach also faces potential problems. First, regressions estimated on all stocks can be dominated by microcaps because they are so plentiful and because they tend to have more extreme values of the explanatory variables and more extreme returns. We avoid this problem by estimating separate regressions for microcaps, small stocks, and big stocks, as well as for a sample that includes all-but-microcap stocks. Difference of means tests on the average slopes from the regressions for different size groups then provide formal inferences about whether the relations between average returns and an anomaly variable differ across size groups. Second, because the returns on individual stocks can be extreme, the potential for influential observation problems lurks in FM regressions. The sorts provide a cross-check. If the regressions and the sorts suggest contradictory inferences, influential observation problems in the regressions are a likely culprit. Fortunately, we never face this problem; the sorts and regressions sometimes differ on nuances, but they support the same general conclusions.

The pervasiveness of anomaly returns across size groups, which we address with both sorts and cross-section regressions, is an important issue. From a practical perspective, if the extreme returns associated with an anomaly variable are special to microcaps, they are probably not realizable because of the high costs of trading such stocks. From a general economic perspective, it is important to know whether anomalous patterns in returns are marketwide or limited to illiquid stocks that represent a small portion of market wealth.

We proceed as follows. Section I presents summary statistics for returns and the anomaly variables we use to predict returns. Section II examines abnormal returns (average returns adjusted for the effects of size and book-to-market equity) from sorts of stocks on the anomaly variables. We find that, at least in the extremes, net stock issues, accruals, and momentum produce strong abnormal returns for microcaps, small stocks, and big stocks. For net stock issues and accruals, however, there are chinks in the armor. Specifically, though extreme positive stock issues and accruals are followed by negative abnormal returns, abnormal returns after less extreme positive issues and accruals are typically positive. The profitability and asset growth sorts also produce mixed pictures. Higher positive profitability tends to be associated with higher abnormal returns, but there is no evidence that negative profitability is associated with abnormally low returns. Even in the extremes, there is no asset growth anomaly in the average returns on the big stocks that account for more than 90% of total market cap.

Section III presents the cross-section regressions to identify which variables have information about average returns missed by the rest. The two clear winners, in terms of strong average regression slopes for all size groups, are net stock issues and momentum. The evidence is weaker, but the regressions also suggest that for positive accruals there is a pervasive negative relation between accruals and average returns, and among profitable firms there is a pervasive positive relation between profitability and average returns. For big stocks the regressions again fail to find any reliable relation between average returns and asset growth. Finally, analysis of the regression residuals uncovers minor functional form problems for extreme values of the anomaly variables, but in general average returns seem to vary across values of the anomaly variables largely in the manner predicted by the regression slopes.

Section IV summarizes the results and interprets them from the perspective of the standard valuation equation used, for example, in Fama and French

(2006a). The valuation equation says that controlling for book-to-market equity, higher expected net cash flows (earnings minus investment, per dollar of book value) imply higher expected stock returns. We argue that all the anomaly variables are at least rough proxies for expected cash flows. We also argue that the observed relations between average returns and the anomaly variables (positive for momentum and profitability, negative for net stock issues, accruals, and asset growth) are at least roughly in line with the valuation equation.

I. Summary Statistics

At the end of each June from 1963 to 2005, we allocate NYSE, Amex, and (after 1972) NASDAQ stocks to three size groups—microcaps, small stocks, and big stocks. The breakpoints are the 20th and 50th percentiles of end-of-June market cap for NYSE stocks. The three size groups are roughly in line with the definitions used by investment managers, but our big group is sometimes split between megacaps and midcaps, where megacaps are, for example, the 200 stocks with the highest market capitalization. For perspective, at the end of June 2005 (the last portfolio formation point) the market cap breakpoints separating micro from small and small from big are $610 million and $2.3 billion, respectively.

Table I shows averages and standard deviations of returns for the value-weight and equal-weight micro, small, and big portfolios for July 1963 to December 2005, along with time-series averages of the number of stocks and the percent of aggregate market cap in each portfolio. Results are also shown for the market portfolio of all sample stocks and for a sample that includes all-but-micro (small plus big) stocks.

On average, microcaps are 60% of all sample stocks, but they account for only about 3% of the market cap of stocks in the sample. (During the pre-NASDAQ period, from July 1963 to December 1972, the fraction of sample stocks that are microcaps varies between 42% and 48%, and these stocks account for 1.2% to 3.6% of total market cap. After 1972, microcaps are between 48% and 69% of firms and between 1.0% and 5.0% of total market cap.) Because microcaps are so plentiful, they are influential in the EW market return. With their high average EW return (1.56% per month, versus 1.07% for big stocks), microcaps pull the average EW market return up to 1.36% per month. The EW microcap portfolio also has by far the highest return volatility, and it is influential in the volatility of the EW market return. In contrast, big stocks average more than 90% of total market cap, and they dominate VW market returns. The average monthly return and the standard deviation of the monthly return on the VW market (0.94% and 4.44%) are close to those of the VW big stock portfolio (0.92% and 4.36%).

Table I also shows time-series averages of the standard deviations of the annual cross-sections of returns and the anomaly variables we use to predict returns. (Detailed descriptions of the variables and the sample of firms are in the Appendix.) For returns and all anomaly variables, cross-section dispersion is largest for microcaps and declines from microcaps to small and then to big

Table I

Value- and Equal-Weight Average Monthly Returns, and Averages and Cross-Section Standard Deviations of Anomaly Variables, 1963–2005

The table shows averages of monthly value-weight (VW) and equal-weight (EW) average stock returns, and monthly cross-section standard deviations of returns for all stocks (Market) and for Micro, Small, Big, and All but Micro stocks. It also shows the average number of stocks and the average percent of the total market capitalization (market cap) in each size group each month. Finally, it shows the averages of annual EW average values and annual cross-section standard deviations of the anomaly variables used to sort stocks into portfolios (Table II) and as independent variables in regressions (Table IV). Here and in the tables that follow, we assign stocks to size groups at the end of June each year. Microcap stocks (Micro) are below the 20th percentile of NYSE market cap at the end of June, Small stocks are between the 20th and 50th percentiles, and Big stocks are above the NYSE median. All but Micro combines Small and Big stocks. The anomaly variables, which are used to predict the monthly returns for July of t to June of $t+1$ in the tables that follow, are: *MC*, the natural log of market cap (in millions) in June of t; *B/M*, the ratio of book equity for the last fiscal year-end in $t-1$ divided by market equity in December of $t-1$; *NS* (net stock issues), the change in the natural log of the split-adjusted shares outstanding from the fiscal year-end in $t-2$ to $t-1$; *Ac/B* (accruals), the change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split-adjusted share in $t-1$; *Mom* (momentum), the cumulative stock return from month $j-12$ to $j-2$; *dA/A* (growth in assets), the change in the natural log of assets per split-adjusted share from $t-2$ to $t-1$; and *Y/B* (profitability), equity income in $t-1$ divided by book equity for $t-1$. *Zero NS* is a dummy variable that is one if *NS* is zero and zero otherwise. *Neg Y* is one if equity income is negative and zero otherwise. *Neg Ac/B* is *Ac/B* for firms with negative accruals (zero otherwise) and *Pos Ac/B* is *Ac/B* for firms with positive accruals. Except for *MC*, *B/M*, *Zero NS*, and *Neg Y*, the variables are multiplied by 100. The Appendix gives more detailed definitions of the anomaly variables.

Average Monthly Values, July 1963–December 2005

	Firms	Percent of Total Market Cap	VW Average Return: Ave	VW Average Return: Std Dev	EW Average Return: Ave	EW Average Return: Std Dev	Cross-Section Std Dev of Returns
Market	3060	100.00	0.94	4.44	1.36	6.14	15.14
Micro	1831	3.07	1.29	6.84	1.56	6.99	17.51
Small	603	6.45	1.22	6.03	1.21	6.26	11.41
Big	626	90.48	0.92	4.36	1.07	5.10	8.77
All but Micro	1229	96.93	0.94	4.42	1.13	5.57	10.22

	MC	*B/M*	*Mom*	*Zero NS*	*NS*	*Neg Ac/B*	*Pos Ac/B*	*dA/A*	*Neg Y*	*Y/B*
Average of Annual EW Average Values, 1963–2005										
Market	4.22	−0.47	16.64	0.24	3.55	−8.06	9.50	11.45	0.22	−3.65
Micro	2.89	−0.34	14.62	0.33	3.67	−10.53	11.45	9.88	0.30	−11.86
Small	5.09	−0.59	21.20	0.18	3.58	−5.17	8.03	15.29	0.12	7.08
Big	7.01	−0.70	19.00	0.09	2.92	−3.26	5.18	12.06	0.07	11.99
All but Micro	6.09	−0.65	20.01	0.13	3.26	−4.21	6.56	13.70	0.10	9.51
Average of Annual Cross-Section Standard Deviations, 1963–2005										
Market	1.92	0.87	56.07	0.41	10.83	28.98	20.50	30.62	0.38	60.60
Micro	1.04	0.89	60.89	0.45	11.50	34.17	23.58	33.76	0.42	71.66
Small	0.37	0.77	50.99	0.37	10.06	20.27	15.70	27.61	0.29	33.64
Big	0.96	0.74	38.90	0.27	8.63	12.41	10.69	19.65	0.21	23.19
All but Micro	1.21	0.76	45.57	0.32	9.41	17.08	13.58	24.10	0.26	29.75

stocks. And for returns and all anomaly variables, the cross-section standard deviations for microcaps dominate those for all stocks. This result is important because it implies that microcaps have even more influence in marketwide anomaly tests (like FM regressions estimated on all stocks and EW average hedge returns from the extremes of sorts of all stocks) than their large numbers would imply.

II. Sorts

Table II shows average monthly value-weight and equal-weight returns for July 1963 through December 2005 for sorts of microcaps, small stocks, and big stocks on each anomaly variable. For all variables except momentum, the sorts are done once a year at the end of June, and monthly returns are calculated from July through June of the following year. The monthly return on a stock is measured net of the return on a matching portfolio formed on size and book-to-market equity (B/M). The matching portfolios are the updated 25 VW size-B/M portfolios of Fama and French (1993), formed at the end of June each year, based on independent sorts of firms into market cap and B/M quintiles, using NYSE breakpoints for the quintiles.

We refer to the adjusted average returns from the sorts as abnormal returns. They show the portion of anomaly average returns left unexplained by market cap and book-to-market equity. Skipping the details, we can report that these portfolio-adjusted average returns are similar to the intercepts from the three-factor regression model of Fama and French (1993) estimated on the portfolio returns from the anomaly sorts. Thus, Table II in effect shows average returns that cannot be explained by the three-factor model.

We make two choices when setting sort breakpoints. First, to have meaningful comparisons of returns across size groups, the sorts for a variable use the same breakpoints for all size groups. The breakpoints are those for the all-but-micro group. The anomaly variables show more dispersion for microcaps, and if we include microcaps when setting sort breakpoints, we often have few small or big stocks in the extreme portfolios. Second, net stock issues, profitability, asset growth, and accruals take positive and negative values, and it is interesting to examine positives and negatives separately. But positives are more frequent than negatives. To produce cells that are more comparable in terms of number of stocks, negative values of these variables are allocated to two groups, using the median of negative values of the variable for the all-but-micro group as the breakpoint. Positive values are allocated to five groups, using quintile breakpoints for positive values of the variable for all-but-micro. Many firms have no net stock issues, especially during the early years of the sample, so the sorts for net issues have an additional cell, for zeros.

Except for size and momentum, the variables we use to forecast returns are measured with long lags relative to the returns. (This is also the case in earlier work.) For portfolios formed in June of year t, variables from Compustat (book equity, B, and earnings, Y) are for the fiscal year ending in calendar year $t-1$, and Compustat variables that involve changes (asset growth, dA/A, accruals,

Table II

Average Abnormal Returns and t-statistics for Portfolios Formed Using Sorts on Anomaly Variables: July 1963 to December 2005

For all variables except momentum, we sort stocks into portfolios in June of each year t, and compute value-weight and equal-weight average abnormal returns for July of t to June of $t+1$. We sort stocks on momentum monthly. We use All but Micro stocks to determine the sort breakpoints for all size groups. We sort firms with negative net stock issues (repurchases) into two portfolios each year; those with *NS* below the median for All but Micro stocks with negative *NS* are in Negative Low and those above the median are in Negative High. We sort firms with positive net stock issues into five quintiles. Zeros are firms with no change in split-adjusted shares. The sort portfolios for accruals, asset growth, and profitability are analogous to those for net stock issues, except we do not isolate Zeros. We combine positive and negative cumulative prior returns when forming momentum quintiles. The monthly return on a stock is measured net of the value-weight return on a matching portfolio formed on size and B/M. The 25 matching portfolios are formed at the end of June each year, based on independent sorts of stocks into market cap and B/M quintiles, using NYSE breakpoints for the quintiles. Pos H – Neg L compares the return on the portfolio of stocks with the highest positive values of a characteristic with the return on the portfolio of stocks with the most negative values. The comparison for momentum is between the highest and lowest prior return quintiles.

	All Firms						All Firms					
	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Sorting on Momentum, *Mom*												
	Average Value-Weight Returns						t-statistics for Average Value-Weight Returns					
Market	−0.31	−0.07	−0.10	0.06	0.43	0.74	−2.11	−0.91	−1.57	1.00	3.91	3.29
Micro	−0.64	−0.16	0.05	0.22	0.72	1.37	−5.26	−1.80	0.60	2.90	6.61	6.31
Small	−0.54	−0.10	0.01	0.11	0.62	1.16	−3.97	−1.38	0.14	1.87	5.89	5.28
Big	−0.25	−0.07	−0.11	0.05	0.41	0.66	−1.55	−0.79	−1.63	0.88	3.44	2.73
	Average Equal-Weight Returns						t-statistics for Average Equal-Weight Returns					
Market	−0.06	−0.05	0.12	0.25	0.69	0.75	−0.36	−0.70	2.22	4.88	8.64	3.57
Micro	0.08	−0.01	0.28	0.38	0.81	0.73	0.43	−0.14	3.43	5.06	9.27	3.39
Small	−0.47	−0.07	0.04	0.13	0.61	1.08	−2.71	−0.88	0.71	2.15	6.42	4.56
Big	−0.26	−0.09	−0.02	0.12	0.46	0.72	−1.45	−1.11	−0.42	2.43	4.54	2.96

	Negatives			Positives					Pos H –	Negatives			Positives					Pos H –
	Low	High	Zeros	Low	2	3	4	High	Neg L	Low	High	Zeros	Low	2	3	4	High	Neg L
Sorting on Net Stock Issues, *NS*																		
	Average Value-Weight Returns									t-statistics for Average Value-Weight Returns								
Market	0.26	0.11	−0.11	−0.03	0.08	0.11	−0.08	−0.29	−0.54	3.73	1.56	−1.34	−0.42	1.56	1.69	−0.98	−3.91	−4.78
Micro	0.26	0.10	−0.08	0.10	0.02	0.28	−0.13	−0.45	−0.71	3.24	1.26	−1.33	1.45	0.24	3.59	−1.91	−5.06	−4.98
Small	0.26	0.20	−0.08	0.11	0.15	0.12	0.11	−0.36	−0.62	3.29	2.47	−1.06	1.65	2.27	1.87	1.46	−4.44	−4.71
Big	0.26	0.11	−0.13	−0.04	0.08	0.11	−0.09	−0.27	−0.54	3.44	1.46	−1.27	−0.53	1.49	1.51	−0.97	−3.36	−4.30
	Average Equal-Weight Returns									t-statistics for Average Equal-Weight Returns								
Market	0.38	0.30	0.13	0.19	0.22	0.27	0.07	−0.27	−0.66	6.05	4.86	1.34	3.08	4.16	4.69	0.81	−2.55	−5.59
Micro	0.47	0.42	0.23	0.32	0.27	0.39	0.08	−0.22	−0.69	5.41	4.43	2.15	3.28	3.13	4.28	0.75	−1.54	−4.85
Small	0.26	0.15	−0.12	0.13	0.19	0.13	0.07	−0.35	−0.61	3.29	1.94	−1.06	1.92	2.89	1.91	0.85	−3.16	−4.28
Big	0.28	0.17	−0.07	0.09	0.14	0.14	−0.02	−0.34	−0.62	4.25	2.88	−0.65	1.76	2.83	2.46	−0.20	−3.74	−5.02

(*continued*)

Table II—*Continued*

	Negatives		Positives					Pos H−	Negatives		Positives					Pos H−
	Low	High	Low	2	3	4	High	Neg L	Low	High	Low	2	3	4	High	Neg L
Sorting on Accruals, Ac/B																
			Average Value-Weight Returns								t-statistics for Average Value-Weight Returns					
Market	0.19	0.05	0.00	0.01	−0.02	−0.07	−0.34	−0.54	2.82	1.13	0.00	0.23	−0.24	−1.12	−4.39	−5.29
Micro	0.12	0.05	−0.05	0.07	0.05	0.07	−0.25	−0.37	2.55	0.86	−0.65	0.90	0.78	1.37	−4.50	−4.56
Small	0.17	0.16	0.11	0.04	0.10	−0.03	−0.20	−0.37	2.79	2.84	1.70	0.71	1.51	−0.46	−2.78	−4.00
Big	0.20	0.05	−0.00	0.01	−0.03	−0.09	−0.37	−0.56	2.62	0.93	−0.02	0.17	−0.40	−1.16	−3.82	−4.70
			Average Equal-Weight Returns								t-statistics for Average Equal-Weight Returns					
Market	0.33	0.20	0.13	0.14	0.15	0.14	−0.08	−0.41	4.00	3.80	2.57	2.56	2.94	2.27	−0.90	−6.76
Micro	0.44	0.27	0.27	0.20	0.20	0.26	−0.00	−0.44	4.23	3.12	3.21	2.30	2.43	3.05	−0.04	−6.12
Small	0.14	0.19	0.10	0.10	0.05	−0.04	−0.27	−0.42	1.82	3.17	1.46	1.39	0.80	−0.57	−2.87	−4.83
Big	0.12	0.06	−0.00	0.07	0.08	0.03	−0.18	−0.30	1.71	1.34	−0.10	1.46	1.50	0.44	−2.01	−3.30
Sorting on Asset Growth, dA/A																
			Average Value-Weight Returns								t-statistics for Average Value-Weight Returns					
Market	−0.04	0.03	−0.00	0.09	0.07	−0.01	−0.14	−0.10	−0.46	0.51	−0.04	1.55	1.46	−0.19	−1.20	−0.74
Micro	0.17	0.12	0.05	0.06	0.07	−0.01	−0.39	−0.57	1.86	1.82	0.84	0.97	0.99	−0.12	−5.45	−4.42
Small	−0.01	0.21	0.10	0.19	0.15	0.10	−0.32	−0.31	−0.15	2.88	1.71	3.46	2.39	1.70	−3.36	−2.43
Big	−0.07	0.01	−0.01	0.09	0.06	−0.03	−0.09	−0.02	−0.73	0.15	−0.13	1.42	1.27	−0.35	−0.67	−0.10
			Average Equal-Weight Returns								t-statistics for Average Equal-Weight Returns					
Market	0.53	0.27	0.17	0.16	0.19	0.04	−0.29	−0.82	4.36	4.10	3.20	3.33	3.34	0.61	−2.46	−7.42
Micro	0.68	0.34	0.25	0.15	0.24	0.05	−0.24	−0.92	4.73	3.73	3.26	1.98	2.72	0.60	−1.80	−7.31
Small	0.04	0.21	0.10	0.18	0.20	0.07	−0.38	−0.42	0.38	2.79	1.82	3.27	3.11	0.87	−2.77	−3.15
Big	−0.01	0.11	0.06	0.15	0.10	−0.03	−0.18	−0.17	−0.14	1.72	1.33	3.32	2.28	−0.41	−1.41	−1.16
Sorting on Profitability, Y/B																
			Average Value-Weight Returns								t-statistics for Average Value-Weight Returns					
Market	0.05	−0.14	−0.08	0.00	−0.01	0.03	0.06	0.01	0.30	−0.83	−1.24	0.07	−0.22	0.57	1.34	0.05
Micro	−0.14	−0.25	−0.07	0.01	0.12	0.10	0.23	0.36	−0.95	−2.46	−1.76	0.09	1.49	1.04	2.22	1.67
Small	−0.49	−0.13	−0.05	0.01	0.07	0.16	0.30	0.79	−2.03	−0.53	−0.84	0.29	1.11	2.37	3.72	2.87
Big	0.32	−0.28	−0.08	−0.00	−0.03	0.01	0.05	−0.27	1.01	−1.05	−1.12	−0.01	−0.49	0.29	0.98	−0.84
			Average Equal-Weight Returns								t-statistics for Average Equal-Weight Returns					
Market	0.41	0.15	0.13	0.08	0.11	0.16	0.22	−0.19	2.25	1.20	2.35	1.69	1.97	2.36	2.87	−0.97
Micro	0.49	0.21	0.21	0.14	0.15	0.20	0.27	−0.23	2.62	1.61	2.87	1.73	1.84	2.08	2.47	−1.07
Small	−0.44	−0.10	−0.06	0.06	0.08	0.15	0.25	0.68	−1.68	−0.40	−1.04	1.09	1.32	1.97	2.79	2.41
Big	0.05	−0.23	−0.00	0.00	0.07	0.09	0.11	0.05	0.17	−0.85	−0.06	0.08	1.40	1.67	1.76	0.16

Ac/B, and net stock issues, NS) are changes from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$. Since the portfolios are formed once a year, the Compustat sort variables are from 6 to 30 months old when the returns they are used to predict are measured. This suggests that the anomaly returns we observe are persistent, either risk-related characteristics of expected returns or the result of behavioral biases that persist for rather long periods after the variable that signals the bias is observed.

To separate out the effects of share issues and repurchases, the two accounting variables (accruals and asset growth) that are year-to-year changes are measured on a per share basis. The relation between average returns and share issues and repurchases is then captured by the net share issues variable, which is the change in the natural log of (split-adjusted) shares outstanding from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$.

Size (market cap) and momentum, which use CRSP data, are measured in a more timely fashion than other variables. Size is measured once a year, when portfolios are formed in June. Since momentum returns are short-term (Jegadeesh and Titman (1993)), we measure momentum monthly. The momentum variable to predict returns for month j is the 11-month return for $j-12$ to $j-2$. Like much of the literature on momentum, we skip the return for the month before the return to be explained because of Jegadeesh's (1990) evidence of negative correlation (reversal rather than continuation) of month-to-month returns.

A. *Perspective*

In Table I, big stocks dominate VW market returns and microcaps are influential in EW returns. These conclusions carry over when portfolios are formed by sorting stocks on the anomaly variables, and when returns on individual stocks are measured net of the returns on portfolios matched on size and B/M. With one exception, VW abnormal returns from the sorts of all stocks in Table II are close to VW abnormal returns from the sorts of big stocks. The exception is profitability, Y/B. Few big firms are highly unprofitable, so the VW abnormal return for the left cell of the profitability sorts of all stocks is not close to the corresponding VW abnormal return for unprofitable big firms. But for quintiles of positive profitability, VW abnormal returns in the sorts of all stocks are close to those for big stocks.

Table II also says that EW abnormal returns for sort portfolios that are limited to microcaps are typically much higher than VW abnormal returns. This is due to a strong size effect among microcaps (documented later): Within the micro group, tinier stocks have higher average returns. In contrast, EW and VW abnormal returns are more similar in the sorts of small stocks and in the sorts of big stocks. This reflects the fact (discussed later) that the size effect is weaker within the small and big groups.

B. Hedge Portfolio Returns

The anomalies literature tends to emphasize hedge portfolio returns from long/short positions in the extreme portfolios from sorts of all stocks. The focus is often on average EW hedge returns, though VW returns are typically also shown. Table II says that the EW hedge returns observed in such studies are heavily influenced by stocks that are tiny (microcaps), not just small. The average EW hedge returns from sorts of all stocks are typically closer to those for microcaps than to those for small or big stocks.

There are two reasons why microcaps are influential in EW hedge returns for all stocks. (i) On average, about 60% of sample stocks are microcaps, so even if we formed portfolios randomly, about 60% of the stocks in each portfolio would be microcaps. (ii) But the extreme portfolios from sorts of all stocks on the anomaly variables are not random. The average cross-section standard deviations of the anomaly variables (Table I) are highest for microcaps, so they are more likely than small or big stocks to end up in the extreme portfolios obtained from sorts of all stocks. As a result, microcaps are likely to dominate EW hedge returns from sorts of all stocks.

Which anomalies produce strong average hedge returns for all three size groups (micro, small, and big)? The clear winners in Table II are net stock issues, accruals, and momentum. The sorts on net issues produce negative average hedge returns (due to negative abnormal returns for extreme issues and positive abnormal returns for large repurchases) that range from −0.54% to −0.71% per month and are more than 4.25 standard errors from zero for all size groups and for EW and VW returns. Though smaller than net issue abnormal hedge returns, the negative average EW and VW hedge returns in the sorts on accruals are also large (−0.30% to −0.56% per month and at least 3.30 standard errors from zero) for microcaps, small stocks, and big stocks. Finally, momentum sorts produce strong positive average VW and EW hedge returns for all size groups. The average monthly hedge returns for micro, small, and big are 1.37%, 1.16%, and 0.66% per month ($t = 6.31$, 5.28, and 2.73) when we value weight stocks and 0.73%, 1.08%, and 0.72% ($t = 3.39$, 4.56, and 2.96) when we equal weight.

Our momentum results complement those in Hong, Stein, and Lim (2000). They use different portfolio formation rules and a shorter time period (1980 to 1996), but they find a similar humped pattern in their EW hedge portfolio returns; specifically, their momentum strategy produces the highest hedge returns for NYSE size deciles 3, 4, and 5, which comprise our small category. Their evidence that the extreme losers in the smallest decile actually have high average returns may also explain why we observe a slightly positive EW abnormal return for the extreme losers in our microcap group. Their results, however, do not predict the strong negative VW abnormal return we observe for this portfolio (−0.64% per month, $t = -5.26$) or our finding that microcaps produce the largest VW abnormal hedge return.

Since stock issues, accruals, and momentum produce large average EW and VW abnormal hedge returns in all size groups, at least in terms of hedge returns, these three anomalies are pervasive. Anomalous returns are less pervasive for asset growth. Sorts on asset growth produce large negative average hedge returns (strong negative abnormal returns for large increases in assets and weak to positive abnormal returns for large declines) for microcaps and small stocks, but not for the big stocks that account for more than 90% of total market cap. The average VW spreads for microcaps and small stocks are −0.57% and −0.31% per month ($t = -4.42$ and –2.43), but the average spread for big stocks is near zero (−0.02%, $t = -0.10$). For all size groups, average EW hedge returns from sorts on asset growth are larger than VW returns, but the average EW hedge return for big stocks is still just −1.16 standard errors from zero.

Profitability sorts produce the weakest average hedge portfolio returns. Only the small group produces EW and VW abnormal hedge returns more than two standard errors from zero. Thus, hedge returns do not provide much basis for the conclusion that, with controls for market cap and B/M, there is a positive relation between average returns and profitability.

C. The Spectrum of Anomaly Returns

Theoretical explanations for anomalous returns do not say that the relations between average returns and anomaly variables should be linear. Behavioral models are not precise enough to predict a linear relation and risk-based explanations predict that expected returns vary linearly with a portfolio's sensitivity to risk factors in returns, not with the magnitude of the anomaly variables. For a full picture of the average returns associated with an anomaly variable, however, results for the full spectrum of the variable are pertinent. In particular, do average returns vary systematically across values of an anomaly variable or are return differences apparent only in the extreme portfolios used to create hedge portfolio returns?

The spectrum of average returns from a sort is difficult to judge without information about how the anomaly variable itself varies across the cells of the sort. Table III shows time-series averages of the annual averages and standard deviations of the anomaly variables within the cells of the Table II sorts. Clearly, much of the action in anomaly variables is in the extremes. The jumps in the average values of the variables from the extreme cells of the sorts to adjacent interior cells dwarf the changes across interior cells. The standard deviations of the anomaly variables within the extreme cells are several times those of interior cells. These results are not surprising. They just say that the distributions of anomaly variables are not uniform; they are thinner in the tails, so the extreme cells of the sorts cover wider ranges of the variables. We shall see, however, that most (but not all) anomaly variables have interesting variation across interior cells of the sorts. And for some variables, firms in the extremes are quite unusual.

Which anomalies are present in all size groups and produce returns that vary systematically from the low to the high ends of the sorts? Momentum satisfies both criteria. Abnormal VW momentum returns are strongest for microcaps and weakest for big stocks, but they are impressive in all size groups, and they increase rather systematically from strongly negative for extreme losers

Table III

Average Values and Standard Deviations of Anomaly Variables for the Cells of Sorts on the Variables, 1963 to 2005

For all variables except momentum, we sort stocks into portfolios in June of each year t. We sort stocks on momentum monthly. We use All but Micro stocks to determine the sort breakpoints for all size groups. We sort firms with negative net stock issues (i.e., repurchases) into two portfolios each year; those with *NS* below the median for All but Micro firms with negative *NS* are in Negative Low and those above the median are in Negative High. We sort firms with positive net stock issues into five quintiles. Zeros are firms with no change in split-adjusted shares. The sort portfolios for accruals, asset growth, and profitability are analogous to those for net stock issues, except we do not isolate Zeros. We combine positive and negative cumulative prior returns when forming momentum quintiles. The table shows average values across years of (i) EW averages of the variables within the cells of the sorts and (ii) the standard deviations of the variables within the cells of the sorts.

	Average of Annual EW Average Values All Stocks					Average of Annual Cross-Section Standard Deviations All Stocks				
	Low	2	3	4	High	Low	2	3	4	High
Sorting on Momentum, *Mom*										
Market	−32.83	−3.36	12.48	31.22	97.89	15.56	4.82	4.51	6.81	61.57
Micro	−34.76	−3.60	12.36	31.29	104.34	16.00	4.81	4.49	6.81	65.95
Small	−29.12	−3.22	12.56	31.31	91.90	13.49	4.84	4.52	6.83	53.43
Big	−25.21	−2.90	12.60	30.93	80.46	11.15	4.77	4.50	6.74	41.73

	Average of Annual EW Average Values								Average of Annual Cross-Section Standard Deviations							
	Negatives			Positives					Negatives			Positives				
	Low	High	Zeros	Low	2	3	4	High	Low	High	Zeros	Low	2	3	4	High
Sorting on Net Stock Issues, *NS*																
Market	−5.73	−0.48	0.00	0.14	0.57	1.48	4.50	24.04	5.24	0.38	0.00	0.09	0.17	0.41	1.67	16.93
Micro	−6.20	−0.46	0.00	0.14	0.58	1.48	4.47	26.03	5.51	0.38	0.00	0.09	0.17	0.40	1.65	18.19
Small	−5.48	−0.48	0.00	0.15	0.58	1.48	4.50	22.18	4.91	0.40	0.00	0.09	0.17	0.41	1.68	15.00
Big	−4.82	−0.51	0.00	0.15	0.57	1.49	4.56	20.29	4.52	0.39	0.00	0.09	0.17	0.41	1.71	13.61

	Average of Annual EW Average Values							Average of Annual Cross-Section Standard Deviations						
	Negatives		Positives					Negatives		Positives				
	Low	High	Low	2	3	4	High	Low	High	Low	2	3	4	High
Sorting on Accruals, *Ac*/*B*														
Market	−30.23	−1.92	1.02	3.24	6.12	10.78	37.72	50.65	1.23	0.60	0.71	1.00	1.82	34.61
Micro	−34.74	−1.97	1.00	3.25	6.14	10.87	39.93	55.38	1.24	0.61	0.70	0.99	1.82	36.37
Small	−22.73	−1.91	1.03	3.26	6.15	10.71	32.43	38.78	1.25	0.59	0.71	0.98	1.81	26.82
Big	−15.94	−1.83	1.02	3.22	6.07	10.62	28.47	25.48	1.21	0.60	0.70	1.01	1.81	23.18
Sorting on Asset Growth, *dA*/*A*														
Market	−21.91	−2.36	2.65	7.24	12.06	19.82	59.08	18.49	1.48	1.45	1.29	1.57	3.25	35.16
Micro	−23.19	−2.42	2.57	7.22	12.03	19.89	61.68	19.09	1.47	1.46	1.30	1.56	3.27	36.86
Small	−18.04	−2.27	2.69	7.26	12.11	19.82	56.48	15.75	1.50	1.45	1.29	1.58	3.25	32.01
Big	−14.89	−2.26	2.76	7.26	12.05	19.65	49.54	12.24	1.47	1.42	1.28	1.58	3.21	26.13
Sorting on Profitability, *Y*/*B*														
Market	−76.77	−4.83	5.12	10.22	13.33	16.90	29.23	112.57	3.24	2.35	0.95	0.89	1.30	12.38
Micro	−79.57	−4.86	4.83	10.17	13.30	16.95	30.17	115.11	3.20	2.37	0.95	0.89	1.30	13.00
Small	−60.60	−4.93	5.56	10.25	13.34	16.94	28.55	85.33	3.19	2.19	0.95	0.89	1.31	11.39
Big	−49.69	−4.68	5.87	10.27	13.37	17.01	28.01	71.08	3.18	2.09	0.96	0.88	1.30	11.26

to strongly positive for extreme winners. EW momentum returns in all size groups also vary smoothly from losers to winners.

For net stock issues, average EW and VW hedge returns from the extremes of the sorts are strong for all size groups, but abnormal returns do not vary much across interior cells of the sorts. For judging the spectrum of abnormal returns, weighting stocks equally seems more relevant than weighting by market cap. In all size groups, extreme negative net issues (percent repurchases above the median for the all-but-micro group) are followed by strong positive EW abnormal returns (0.47%, 0.26%, and 0.28% per month for micro, small, and big stocks). EW abnormal returns are smaller (0.42%, 0.15%, and 0.17%), but still statistically reliable ($t = 4.43$, 1.94, and 2.88) for less extreme repurchases. Thus, positive abnormal returns after repurchases are pervasive. The problem is that for all size groups, the first three quintiles of positive stock issues have positive EW abnormal returns that are nearly as large as those for smaller repurchases. EW abnormal returns decline for the fourth quintile of positive net issues, but only stocks in the highest quintile of issues produce average returns reliably below those of portfolios matched on size and B/M.

Our positive EW abnormal returns for repurchases are consistent with existing event studies, and our new result that abnormal returns are more extreme for larger repurchases fits nicely with earlier evidence. But our positive EW abnormal returns over most of the range of positive net issues seem to contradict previous studies. Except for Daniel and Titman (2006) and Pontiff and Woodgate (2008), however, previous papers on returns after stock issues are event studies that focus on seasoned equity offerings (SEOs) or stock issues to complete mergers. These events likely fall into the fourth and fifth quintiles of positive net issues, which show large average values of issues (Table III), and they probably account for the strong negative abnormal returns of the fifth quintile (Table II).

Fama and French (2005) find that though SEOs and stock-financed mergers are infrequent, net issues of stock are common. Other ways of issuing stock include executive options, grants, and other employee benefit plans; conversions of debt and preferred stock; warrants; rights issues; and direct purchase plans. The positive abnormal returns after less extreme net stock issues are probably associated with these more common activities. Whatever the source, the novel finding in Table II is that consistent negative abnormal returns are limited to the extreme quintile of issues.

Table III provides additional perspective on these results. Repurchases above the median average about 5% of stock outstanding, but repurchases below the median average only 0.5% of outstanding stock. The first three quintiles of positive net issues also involve small amounts of stock (on average about 0.1%, 0.6%, and 1.5% of stock outstanding). Thus, the positive abnormal returns for the first three quintiles are associated with rather minor issuing events. But net stock issues average a substantial 4.5% of stock outstanding in the fourth quintile of positive net issues. The fact that EW abnormal returns for this quintile are positive for microcaps and close to zero for small and big stocks is a problem for theoretical models that predict negative returns after stock issues.

The strong negative abnormal returns for stock issues predicted by these stories are limited to the fifth quintile of positive net issues, where issues average an impressive 20% to 26% of shares outstanding.

Like momentum and net stock issues, accruals sorts lead to large EW and VW abnormal hedge returns for all size groups. Like net stock issues, however, the spectrum of average returns from accruals sorts suggests a more nuanced story. Extreme negative accruals are followed by positive abnormal returns, and extreme positive accruals are typically followed by negative abnormal returns. For small and big stocks, however, the positive EW abnormal returns for extreme negative accruals are less than two standard errors from zero. For microcaps, the EW abnormal return for extreme positive accruals is zero to two decimal places. Thus, even in the extremes the abnormal returns from accruals sorts are not always statistically reliable without the added emphasis provided by long-short hedge portfolios. And less extreme accruals, positive or negative, tend to be followed by positive abnormal EW returns that do not decline much across the cells of the sorts. Except for microcaps, however, the EW abnormal returns associated with less extreme accruals are rather close to zero.

The details of the sorts on asset growth confirm the inference from hedge returns that this candidate anomaly is not associated with pervasive abnormal returns. In the asset growth sorts, microcaps and small stocks produce rather large average EW and VW hedge portfolio returns, but only microcaps produce abnormal returns that fall systematically from extreme declines to extreme increases in assets. Thus, only microcaps produce a systematic negative relation between asset growth and abnormal returns.

Finally, since profitability sorts produce weak results for hedge returns, it is not surprising that the details of the sorts also produce little evidence of pervasive abnormal returns. Only the sorts for small stocks produce average returns that increase systematically from unprofitable to extremely profitable firms. There is no consistent pattern for big stocks, and for microcaps the order of abnormal returns changes from decreasing for EW returns (the most unprofitable firms have the highest subsequent returns) to increasing for VW returns. Note, however, that if we restrict attention to firms with positive profitability, abnormal returns in all size groups tend to increase with profitability. This result is important in evaluating the regression evidence that follows.

III. Cross-Section Regressions

Which anomalies are distinct and which have little marginal ability to predict returns? We use the cross-section regression approach of Fama and MacBeth (1973) to answer this question.

FM regressions face potential problems. Unlike sorts, regressions impose a functional form on the relation between anomaly variables and returns. This structure is what gives regressions the power to disentangle the return effects of multiple anomalies. The functional form may, however, be incorrect. To explore this issue, we examine sorts of regression residuals on each explanatory variable. The residual sorts allow us to examine whether average returns vary across the spectrum of an anomaly variable in the manner predicted by the regression slopes, with controls for the effects of other anomaly variables. The residual sorts thus address a more complicated question about how average returns vary with anomaly variables than the sorts in Table II.

Another problem is that, as in marketwide sorts (and for similar reasons), microcaps are likely to dominate FM regressions estimated on all stocks. For a more balanced picture, we fit FM regressions separately for microcaps, small stocks, and big stocks, as well as for all stocks and a sample that excludes microcaps. Estimating separate regressions for size groups also allows difference-of-means tests of whether the relations between average returns and an anomaly variable differ across size groups.

The regression setup is similar to that of the sorts. We estimate the regressions monthly, but we again update most of the explanatory variables once a year. Thus, we explain the cross-section of monthly returns from July of year t to June of $t+1$ using anomaly variables observed in June of t or earlier. The exception to this rule is the momentum variable, which we update monthly. The results of Fama and French (2006a) lead us (i) to estimate profitability slopes using only positive values of profitability, covering negative values with a dummy variable, and (ii) to estimate separate slopes for positive and negative accruals. Finally, net stock issues are zero for many firms, especially during the early years of the sample, and all regressions that include net issues use a dummy variable to isolate zeros.

The regressions (Table IV) include market cap and B/M (both in logs) as explanatory variables. They are thus in line with the sorts, which also control for market cap and B/M. The rationale is that the two variables proxy for loadings on the size (*SMB*) and book-to-market (*HML*) factors of the three-factor model of Fama and French (1993). Indeed, the results of Fama and French (1997) suggest that because the *SMB* and *HML* loadings of individual firms vary over time, current size and B/M are more timely proxies for the loadings than three-factor regression slopes estimated as constants. The three-factor model also calls for estimates of market betas. In general, however, the betas of the three-factor model tend to be much less disperse (closer to 1.0) than the betas of the CAPM (Fama and French (1993)). Moreover, Davis, Fama, and French (2000) estimate that the premium for the three-factor beta is much smaller than the average market return in excess of the risk-free rate. Finally, there is little reason to expect that individual firm betas are correlated with the anomaly variables. Given the imprecision of beta estimates for individual stocks, we judge that little is lost in omitting them from the cross-section regressions (in effect assuming they are all equal to 1.0).

A. Size and Book-to-Market

As a warm up, we examine the average regression slopes for market cap and B/M. Like previous work, the regressions that use all stocks produce strong average slopes, negative for market cap (-0.18, $t = -4.36$) and positive for B/M (0.26, $t = 3.77$). The novel evidence is that the market cap (*MC*) result draws

Table IV

Average Slopes and *t*-statistics from Monthly Cross-Section Regressions, July 1963–December 2005

The table shows average slopes and their t-statistics from monthly cross-section regressions to predict stock returns. The variables used to predict returns for July of t to June of $t+1$ are: *MC*, the natural log of market cap in June of t (in millions); B/M, the natural log of the ratio of book equity for the last fiscal year-end in $t-1$ divided by market equity in December of $t-1$; *NS* (net stock issues), the change in the natural log of split-adjusted shares outstanding from the fiscal year-end in $t-2$ to $t-1$; Ac/B (accruals), the change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split-adjusted share in $t-1$; *Mom* (momentum) for month j, the cumulative return from month $j-12$ to $j-2$; dA/A (growth in assets), the change in the natural log of assets per split-adjusted share from $t-2$ to $t-1$; and Y/B (profitability), equity income in $t-1$ divided by book equity in $t-1$. *Zero NS* is one if *NS* is zero and zero otherwise. *Neg Y* is one if equity income is negative (zero otherwise). *Pos* Y/B is Y/B for profitable firms and zero otherwise. Similarly, *Neg* Ac/B and *Pos* Ac/B are Ac/B for firms with negative and positive accruals, respectively. Each regression includes all the anomaly variables. *Int* is the average regression intercept and the average regression R^2 is adjusted for degrees of freedom. The t-statistics for the average regression slopes (or for the differences between the average slopes) use the time-series standard deviations of the monthly slopes (or the differences between the monthly slopes).

	Int	*MC*	*B/M*	*Mom*	*Zero NS*	*NS*	*Neg Ac/B*	*Pos Ac/B*	*dA/A*	*Neg Y*	*Pos Y/B*	R^2
Market												
Average	1.81	−0.18	0.26	0.50	−0.11	−1.90	0.03	−0.34	−0.81	0.06	0.92	0.04
t-statistic	5.36	−4.36	3.77	3.24	−2.41	−8.59	0.20	−2.72	−7.37	0.55	3.19	
Micro												
Average	2.63	−0.46	0.23	0.41	−0.16	−1.94	0.00	−0.28	−0.83	−0.01	0.55	0.03
t-statistic	7.41	−6.95	3.19	2.51	−2.83	−6.74	0.03	−2.02	−6.82	−0.11	1.50	
Small												
Average	1.01	−0.03	0.30	0.82	−0.04	−1.49	−0.09	−0.45	−0.57	0.01	1.19	0.05
t-statistic	2.02	−0.37	3.41	4.65	−0.55	−4.42	−0.28	−2.24	−3.10	0.03	2.36	
Big												
Average	1.06	−0.08	0.17	0.78	−0.12	−1.71	0.12	−0.38	−0.17	0.11	0.75	0.08
t-statistic	2.61	−1.96	1.79	3.92	−1.59	−5.28	0.32	−1.49	−0.86	0.46	1.56	
All but Micro												
Average	1.12	−0.08	0.23	0.81	−0.09	−1.65	−0.05	−0.49	−0.43	0.02	0.93	0.06
t-statistic	2.87	−1.92	2.73	4.60	−1.41	−6.28	−0.19	−2.87	−2.80	0.12	2.35	
Micro – Small												
Difference	1.62	−0.43	−0.07	−0.41	−0.11	−0.45	0.09	0.17	−0.26	−0.02	−0.64	
t-statistic	4.02	−5.11	−0.93	−3.64	−1.23	−1.12	0.29	0.79	−1.35	−0.09	−1.13	
Micro – Big												
Difference	1.57	−0.38	0.06	−0.38	−0.03	−0.23	−0.11	0.10	−0.66	−0.12	−0.20	
t-statistic	4.02	−4.99	0.61	−2.42	−0.34	−0.57	−0.29	0.38	−2.97	−0.52	−0.33	
Micro – All but Micro												
Difference	1.51	−0.38	0.00	−0.40	−0.07	−0.29	0.05	0.21	−0.40	−0.03	−0.38	
t-statistic	4.44	−5.28	0.00	−3.41	−0.88	−0.83	0.19	1.14	−2.35	−0.20	−0.76	
Small – Big												
Difference	−0.05	0.05	0.12	0.04	0.08	0.22	−0.20	−0.06	−0.39	−0.11	0.44	
t-statistic	−0.12	0.71	1.72	0.31	0.84	0.55	−0.48	−0.23	−1.72	−0.36	0.78	

much of its power from microcaps. The average MC slope for all–but-micro (small plus big) stocks (-0.08, $t = -1.92$) is less than one-fifth that produced by microcaps (-0.46, $t = -6.95$), and the average slope for microcaps is more than five standard errors below the average for all–but-micro stocks. In short, microcaps are influential in the size effect observed in tests on all stocks.

The relation between average returns and B/M is more consistent across size groups. The average slopes for B/M are similar for microcaps and small stocks, 0.23 ($t = 3.19$) and 0.30 ($t = 3.41$), but the average slope for big stocks (0.17, $t = 1.79$) is less impressive. The average B/M slope for big stocks is, however, within two standard errors of the slopes for microcaps and small stocks. Moreover, Fama and French (2006b) find that the weaker relation between average returns and B/M for big stocks is specific to the post-1962 period and to U.S. stocks.

B. Results for Anomaly Variables

Among the remaining variables, only net stock issues and momentum show strong marginal explanatory power in all size groups in the regressions of Table IV. The consistency of the slopes for nonzero net stock issues is impressive. The average slopes range from -1.49 to -1.94 for microcaps, small stocks, and big stocks, all are more than -4.4 standard errors from zero, and they differ by less than 1.15 standard errors. Table IV thus says that larger net issues of stock are associated with lower future returns, and the marginal relation between issues and returns is much the same for microcaps, small stocks, and big stocks.

The average slopes for the dummy variable for zero net stock issues range from -0.04 ($t = -0.55$) for small stocks to -0.16 ($t = -2.83$) for microcaps, and the two slopes differ by -1.23 standard errors. Thus, zero net stock issues do not seem to be associated with unusual returns, except perhaps for microcaps, where they might be bad news.

Like the sorts, the regressions say that the positive relation between average returns and momentum is strong for all size groups. But average momentum slopes differ across groups. The average slope for microcaps (0.41, $t = 2.51$) is about half the size and more than 2.5 standard errors below the slopes for small and big stocks (0.82, $t = 4.65$, and 0.78, $t = 3.92$). These results suggest that if the momentum anomaly is due to a risk factor in returns, the relation between our momentum variable and sensitivity to the factor varies across size groups.

The much smaller average momentum regression slope for microcaps in Table IV seems at odds with the near identical spreads in average EW momentum returns for microcaps and big stocks in the sorts of Table II. Table I shows, however, that the cross-section standard deviation of the momentum variable is on average about 50% larger for microcaps than for big stocks. Table III confirms that average values of the momentum variable in the extreme cells of the sorts are more extreme for microcaps. Larger spreads in the momentum variable for microcaps combine with similar spreads in EW average sort returns for microcaps and big stocks to produce lower average momentum slopes in the cross-section regressions for microcaps. All approaches (regressions and EW and VW sort returns) agree, however, that there are strong relations between momentum and average returns in all size groups.

In contrast, the relations between average returns and accruals in the Table IV regressions are not consistently strong. The average slopes for positive accruals are all negative, but their t-statistics range from -1.49 for big stocks to -2.24 for small stocks. This is in line with the EW sort returns in Table II, which also say that for positive accruals the negative relation between accruals and average returns is not strong. The average slopes for positive accruals are, however, similar across size groups, and they differ by less than 1.15 standard errors. We can then look to the average slope from the regressions for all stocks, which is –2.72 standard errors from zero. Thus, with the power of the full sample we can infer that higher positive accruals are indeed associated with lower future returns.

The average slopes for negative accruals are within 0.32 standard errors of zero. This is puzzling given the evidence from the sorts (Table II) that negative accruals are followed by rather strong positive average EW returns. Inspection of the sorts suggests an explanation. As the level of negative accruals rises toward zero, average returns do not drop off enough to generate a reliably negative average regression slope. If this is correct, the regressions might be improved by replacing negative accruals with a dummy variable.

The regressions in Table IV confirm the inference from the sorts in Table II that the negative relation between asset growth and average returns is not pervasive. The relation is strong for microcaps, weaker but statistically reliable for small stocks, and probably nonexistent for big stocks. The average slopes for asset growth rise from -0.83 ($t = -6.82$) for microcaps, to -0.57 ($t = -3.10$) for small stocks, and -0.17 ($t = -0.86$) for big stocks, and the average slope for big stocks is –2.97 standard errors from the average slope for microcaps. Thus, like the sorts, the regressions for big stocks do not identify a reliable relation between average returns and asset growth.

Finally, like the sorts, the regressions say that profitable small stocks produce a reliable positive relation between profitability and average returns; the average *Pos* Y/B slope for small stocks is 2.36 standard errors from zero. But the regressions also suggest positive relations between profitability and future returns for profitable microcap and big stocks. The average *Pos* Y/B slope for microcaps, though about half the slope for small stocks, is 1.50 standard errors above zero, and the slope for big stocks is 1.56 standard errors from zero. Moreover, the differences between the average slopes for the size groups are within 1.2 standard errors of zero. Given this result, it is reasonable to point to the average slope estimated from all stocks (0.92, $t = 3.19$) as reliable evidence of an overall positive relation between positive profitability and average returns. (The average slopes for the dummy variable for unprofitable firms are essentially zero.)

Is the regression evidence on profitability in conflict with the sorts? The positive relation between profitability and average returns observed in the regressions is estimated using firms with positive profitability. The absence of profitability effects for microcap and big stocks in the sorts comes from hedge returns from extremely profitable and extremely unprofitable firms. As noted earlier, if we look only at profitable firms, the sorts also suggest positive relations between profitability and average returns in all size groups. The absence of evidence that negative profitability is associated with lower average returns nevertheless suggests that the positive relation between profitability and average returns observed for profitable firms does not hold across the full spectrum of profitability.

C. Regression Diagnostics

Except for profitability, accruals, and dummy variables, the explanatory variables in the regressions are natural logs (market cap, B/M, momentum) or changes in logs (asset growth, net stock issues). The regression explanatory variables are also winsorized at the 0.5 and the 99.5 percentiles. Are the resulting regressions well specified, or is there evidence that returns do not vary with our versions of the anomaly variables in the manner implied by the regression slopes? To answer this question, we use sorts on the anomaly variables to assign firms to groups and then examine each group's EW average residual from the multiple regressions in Table IV. This is analogous to the sorts that look at EW abnormal returns in Table II. In fact, since we again use all-but-microcap stocks to determine the breakpoints for the anomaly variables in the residual tests, firms are assigned to the same groups in the residual sorts (Table V) and the return sorts (Table II).

Note first that the average residuals from the sorts are estimated precisely. For example, in the regression for microcaps, the average monthly residual for the highest quintile of accruals, −0.09% (about 1% per year), seems modest, but it is –3.14 standard errors from zero.

The average residuals in Table V say that the regressions in Table IV largely absorb the abnormal returns observed in the sorts in Table II. But the average residuals do identify a minor functional form problem. Three variables (net stock issues, momentum, and accruals) produce large spreads in abnormal returns in the sorts for all size groups in Table II. The average residuals in the extremes of the sorts on these variables in Table V are typically much closer to zero than the abnormal returns in Table II but they almost always have the same sign. Given their high precision, the average residuals in the extremes of the sorts are sometimes large relative to their standard errors (for example, for extreme positive momentum and accruals). Mild failures to absorb returns in the extremes are also observed in the sorts of regression residuals on profitability and asset growth.

We noted earlier that much of the action in anomaly average returns and in the anomaly variables themselves is in the extremes (see Tables II and III). Thus, the regressions in Table IV put lots of weight on absorbing returns in the extremes, and Table V says the effort is largely (but not entirely) successful. The minor failures in the extremes are probably due to the fact that the regressions also attempt to move unexplained returns closer to zero for less extreme values of the anomaly variables, with considerable success. Across the spectrum of

Table V

Equal-Weight Average Residuals from the Cross-Section Regressions of Table IV, July 1963–December 2005

The table shows equal-weight average monthly residuals from the cross-section return regressions in Table IV, for residuals sorted on each of the regression explanatory variables. The explanatory variables in the return regressions for July of t to June of $t+1$ are: MC, the natural log of market cap in June of t (in millions); B/M, the log of the ratio of book equity for the last fiscal year-end in $t-1$ divided by the market equity in December of $t-1$; NS (net stock issues), the change in the natural log of split-adjusted shares outstanding from the fiscal year-end in $t-2$ to $t-1$; Ac/B (accruals), the change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split-adjusted share in $t-1$; Mom (momentum) for month j, the cumulative return from month $j-12$ to $j-2$; dA/A (growth in assets), the change in the natural log of assets per split-adjusted share from $t-2$ to $t-1$; and Y/B (profitability), equity income in $t-1$ divided by book equity in $t-1$. *Zero NS* is one if NS is zero and zero otherwise. *Neg Y* is one if equity income is negative (zero otherwise). *Pos Y/B* is Y/B for profitable firms and zero otherwise. Similarly, *Neg Ac/B* and *Pos Ac/B* are Ac/B for firms with negative and positive accruals, respectively. We sort stocks into portfolios using the same breakpoints for the explanatory variables used in the sorts in Table II. Thus, we exclude Micro stocks when determining the portfolio breakpoints. We sort firms with negative net stock issues (repurchases) into two portfolios each year; those with NS below the median of All but Micro firms with negative NS are in Negative Low and those above the median are in Negative High. We sort firms with positive net stock issues into five quintiles. Zeros are firms with no change in split-adjusted shares. The sort portfolios for accruals, asset growth, and profitability are analogous to those for net stock issues, except we do not isolate Zeros. We combine positive and negative cumulative prior returns when sorting firms into momentum portfolios.

	Average of Monthly EW Average Residuals All Stocks					t-statistic for Average of Monthly EW Average Residuals All Stocks				
	Low	2	3	4	High	Low	2	3	4	High
Sorting on Momentum, *Mom*										
Market	−0.03	−0.13	0.00	0.04	0.15	−0.64	−3.04	0.02	0.92	4.19
Micro	−0.04	−0.20	0.04	0.07	0.20	−0.86	−3.25	0.69	1.31	3.70
Small	−0.08	0.03	0.02	−0.03	0.09	−1.31	0.60	0.41	−0.62	2.36
Big	0.08	−0.03	−0.05	−0.02	0.06	1.07	−0.74	−1.31	−0.47	1.62
All but Micro	−0.02	−0.01	−0.02	−0.02	0.07	−0.35	−0.31	−0.59	−0.47	2.27

(*continued*)

Table V—*Continued*

	Average of Monthly EW Average Residuals								t-statistic for Average of Monthly EW Average Residuals							
	Negatives			Positives					Negatives			Positives				
	Low	High	Zeros	Low	2	3	4	High	Low	High	Zeros	Low	2	3	4	High
Sorting on Net Stock Issues, *NS*																
Market	0.00	0.04	0.00	−0.02	0.02	0.09	−0.08	−0.03	−0.04	0.98	−0.58	−0.60	0.54	2.25	−2.11	−1.33
Micro	−0.05	0.02	0.00	0.04	0.00	0.16	−0.14	−0.04	−0.83	0.27	−1.63	0.64	−0.03	2.61	−2.24	−0.95
Small	0.04	0.02	0.00	0.00	0.03	0.03	−0.01	−0.06	0.66	0.27	−1.22	0.09	0.59	0.44	−0.18	−1.68
Big	0.04	0.05	0.00	−0.02	0.05	0.05	−0.02	−0.06	0.89	1.09	−0.57	−0.66	1.25	1.04	−0.47	−1.78
All but Micro	0.03	0.03	0.00	−0.02	0.03	0.04	−0.03	−0.05	0.87	0.77	−0.81	−0.49	1.15	1.11	−0.79	−2.16

	Average of Monthly EW Average Residuals							t-statistic for Average of Monthly EW Average Residuals						
	Negatives		Positives					Negatives		Positives				
	Low	High	Low	2	3	4	High	Low	High	Low	2	3	4	High
Sorting on Accruals, Ac/B														
Market	0.04	0.04	0.01	0.00	0.02	0.00	−0.10	1.75	1.25	0.35	0.01	0.47	0.07	−4.08
Micro	0.04	0.01	0.06	−0.03	−0.01	0.03	−0.09	1.35	0.14	0.95	−0.53	−0.20	0.66	−3.14
Small	0.04	0.10	0.03	−0.00	−0.03	−0.06	−0.10	1.09	1.92	0.61	−0.08	−0.55	−1.09	−2.46
Big	0.07	−0.02	−0.06	0.02	0.05	0.01	−0.06	2.00	−0.45	−1.55	0.51	1.11	0.26	−1.41
All but Micro	0.05	0.03	−0.04	0.01	0.02	−0.02	−0.07	1.75	0.98	−1.21	0.25	0.44	−0.44	−2.35
Sorting on Growth in Assets, dA/A														
Market	0.10	−0.03	−0.05	−0.02	0.04	−0.04	−0.01	2.67	−0.62	−1.46	−0.69	1.31	−1.30	−0.32
Micro	0.11	−0.03	−0.04	−0.08	0.00	−0.08	−0.00	2.84	−0.45	−0.77	−1.49	0.07	−1.80	−0.12
Small	−0.03	0.06	−0.02	0.03	0.06	0.01	−0.04	−0.54	0.89	−0.43	0.71	1.19	0.27	−1.23
Big	0.07	0.01	−0.02	0.04	0.01	−0.05	−0.01	1.07	0.21	−0.54	1.22	0.37	−1.20	−0.35
All but Micro	−0.01	0.02	−0.03	0.04	0.04	−0.01	−0.02	−0.14	0.52	−1.01	1.26	1.24	−0.17	−0.73
Sorting on Profitability, Y/B														
Market	0.09	−0.10	−0.04	−0.02	0.00	0.05	0.04	1.79	−1.34	−1.46	−0.74	0.08	1.81	1.92
Micro	0.05	−0.09	−0.03	0.03	0.03	0.06	−0.01	0.98	−1.10	−1.20	0.61	0.60	1.16	−0.39
Small	0.01	0.03	−0.08	0.00	0.00	0.03	0.05	0.08	0.28	−1.91	0.04	−0.04	0.61	1.38
Big	0.12	−0.11	0.00	−0.03	−0.02	0.00	0.04	0.74	−0.78	0.13	−0.82	−0.63	0.06	1.95
All–but-Micro	−0.20	0.10	−0.05	−0.03	0.00	0.03	0.05	−1.41	1.00	−1.48	−0.83	0.02	0.89	2.42

every anomaly variable, the EW average residuals in Table V are closer to zero than the EW abnormal returns in Table II.

For net stock issues and accruals, this result is a bit surprising. In Table II, EW abnormal returns (net of market cap and B/M effects) for net stock issues and accruals are mostly positive and only turn strongly negative for the fifth quintiles of the variables. It might then seem puzzling that the negative slopes on these variables reduce abnormal returns across the board, not just in the extremes. Adding variables to regressions, however, affects all coefficients, including intercepts. The average residuals in Table V tell us that despite negative slopes for net issues and accruals, the full regressions actually predict higher average returns across most of the spectrum of positive net issues and accruals than regressions that control for market cap and B/M alone.

We could fiddle with functional form to try for a better explanation of average returns in the extremes of anomaly variables. In the absence of theoretical directives, however, this is pointless, and the minor failures of the regression specification are in any case inconsequential for our inferences. We rest with the conclusion that much of the action in anomaly returns is in the extremes and that this is largely, but perhaps not entirely, due to the fact that much of the action in the anomaly variables themselves is in the extremes.

IV. Conclusions and Interpretation

Previous work finds that net stock issues, accruals, momentum, profitability, and asset growth are associated with anomalous average returns. We explore the pervasiveness of these return anomalies via sorts and cross-section regressions estimated separately on microcaps, small stocks, and big stocks. Does close examination of the results for the three size groups produce fresh insights? We judge that the answer to this question is positive. Here is our case.

The cross-section regressions are easiest to interpret since regression slopes measure marginal effects and calibrate returns against the values of anomaly variables. The regressions say that the size effect (the original center-stage anomaly) owes much of its power to microcaps and is marginal among small and big stocks. In contrast, the relation between momentum (the center-stage anomaly of recent years) and average returns is similar for small and big stocks, but only about half as strong among microcaps. The negative relation between average returns and asset growth is powerful among microcaps, weaker but statistically reliable among small stocks, and probably nonexistent among big stocks.

The book-to-market ratio, net stock issues, accruals, and profitability all produce average regression slopes that are indistinguishable across size groups. We are thus justified in looking to the regressions that use all stocks for inferences about reliability. This is unnecessary for net stock issues; the negative average slopes for net issues are more than four standard errors from zero for all size groups. But B/M and accruals produce average regression slopes within two standard errors of zero for big stocks, and the average slopes for profitability are within two standard errors of zero for microcaps and big stocks. Thus, the power of the full sample and the fact that average regression slopes are not reliably different across size groups must be invoked to infer that these variables probably have unique information about average returns in all size groups.

There are also interesting results in the univariate sorts. Like previous work that examines the extremes of sorts, we find that, measured net of the effects of size and B/M, the equal- and value-weight abnormal hedge portfolio returns associated with momentum, net stock issues, and accruals are strong for all size groups (and thus pervasive). For profitability and asset growth, however, even hedge portfolio abnormal returns seem to be nonexistent for big stocks.

The more interesting results from the sorts are in the details, specifically, for net stock issues and accruals. Repurchases of stock are followed by strong positive abnormal returns and the most extreme quintile of stock issues shows strong negative abnormal returns. But measured net of the effects of size and B/M, abnormal returns for less extreme positive stock issues tend to be positive—a clear challenge for theories that attempt to explain returns after stock repurchases and issues. Similarly, negative accruals are followed by positive abnormal returns, but only the extreme quintile of positive accruals shows strong negative abnormal returns. In short, at least when measured net of the effects of size and B/M, anomalous returns after net stock issues and accruals seem to be limited to the extremes.

There is a more serious stain on the net stock issues anomaly. This variable can be calculated from CRSP data, so the tests are easily extended back to 1926. Pontiff and Woodgate (2008) find that the earlier period produces no evidence that net stock issues (including repurchases and positive net issues) are associated with unusual returns. (See also Fama and French (2006c).) This, of course, is a more serious challenge for stories that attempt to explain the anomalous returns of 1963 to 2005.

Our regressions say that, at least for 1963 to 2005, each of the anomaly variables we consider seems to have unique information about future returns. This does not mean we lack a unifying logic for the anomalies. In fact, the evidence from the sorts and the regressions is consistent with the standard valuation equation that says that controlling for B/M, higher expected net cash flows (earnings minus investment, per dollar of book value) imply higher expected stock returns—whether the pricing of securities is rational or irrational. (See Fama and French (2006a) for details.)

All the anomaly variables are at least rough proxies for expected cash flows. For example, firms that repurchase stock tend to have higher net cash flows (high earnings relative to investment), and the reverse is true for firms that issue stock (Fama and French (2005)). The negative relation between net stock issues and average returns is thus consistent with the valuation equation. Many papers (e.g., Fairfield, Whisenant, and Yohn (2003)) find that firms with more accruals tend to have lower net cash flows (high investment relative to earnings), so the negative relation between average returns and accruals is also consistent with the valuation equation. It seems reasonable that high returns over the last year signal high expected cash flows, so the positive relation between momentum and average returns is consistent with the valuation equation. Profitability and asset growth tend to be persistent (Fama and French (1995)), so the positive relation between average returns and profitability and the negative relation between asset growth and average returns are in line with the valuation equation.

Finally, researchers commonly interpret the average returns associated with anomaly variables as evidence of market inefficiency. The valuation equation says, however, that controlling for the book-to-market ratio, proxies for expected net cash flows will identify differences in expected returns whether they are due to irrational pricing or rational risks. Thus, evidence that variables that predict future cash flows also predict returns does not, by itself, help us determine how much variation in expected returns is caused by risk and how much is caused by mispricing.

Appendix

The data are from the Center for Research in Security Prices (CRSP) and Compustat. We measure most of the variables used to forecast returns once a year. Thus, we use information available in June of year t to forecast the returns in July of t to June of $t+1$. The exception is the momentum variable, which we measure every month. Time t for the Compustat variables in the descriptions below is the fiscal year end in calendar year t. The forecasting (anomaly) variables are:

- MC: Market cap, the natural log of price times shares outstanding at the end of June of year t, from CRSP.
- B/M: Book-to-market equity, the natural log of the ratio of the book value of equity to the market value of equity. Book equity is total assets (Compustat data item 6) for year $t-1$, minus liabilities (181), plus balance sheet deferred taxes and investment tax credit (35) if available, minus preferred stock liquidating value (10) if available, or redemption value (56) if available, or carrying value (130). Market equity is price times shares outstanding at the end of December of $t-1$, from CRSP.
- NS: Net stock issues, the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in $t-1$ divided by the split-adjusted shares outstanding at the fiscal year end in $t-2$. The split-adjusted shares outstanding is Compustat shares outstanding (25) times the Compustat adjustment factor (27).
- Ac/B: Accruals, the change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split-adjusted share at $t-1$. Operating working capital is current assets (4) minus cash and short-term investments (1) minus current liabilities (5) plus debt in current liabilities (34). We use operating working capital per split-adjusted share to adjust for the effect of changes in the scale of the firm caused by share issuances and repurchases.

Mom: Momentum, the cumulated continuously compounded stock return from month $j-12$ to month $j-2$, where j is the month of the forecasted return. We measure the momentum variable monthly.

dA/A: Growth in assets, the natural log of the ratio of assets per split-adjusted share at the fiscal year end in $t-1$ divided by assets per split-adjusted share at the fiscal year end in $t-2$. This is equivalent to the natural log of the ratio of gross assets at $t-1$ (6) divided by gross assets at $t-2$ minus net stock issues from $t-2$ to $t-1$.

Y/B: Profitability, equity income (income before extraordinary (18), minus dividends on preferred (19), if available, plus income statement deferred taxes (50), if available) in $t-1$ divided by book equity for $t-1$.

We exclude financial firms (Standard Industrial Classification codes between 6000 and 6999) and firms with negative book equity in $t-1$. We also exclude firms if we do not have the data required to compute accruals, book equity, growth in assets, profitability, or market cap for June of t or December of $t-1$. If the Compustat shares or adjustment factors needed to compute *NS* are missing, we set *NS* to zero. We also set NS to zero if the fiscal year end for $t-2$ precedes the firm's first appearance on CRSP. We exclude a firm in month j from tests involving momentum if we are unable to compute the cumulative prior return for months $j-12$ to $j-2$. Since CRSP reports the cumulative return over intervals with missing data, the critical variable for us is the reported return for the last month in a compound period. Thus, if the CRSP return for month $j-2$ is missing, we drop the firm from any portfolio sorts or regressions for month j that use momentum. We do not require good CRSP returns for months $j-12$ to $j-3$, but we do require the firm to be on CRSP by month $j-12$.

REFERENCES

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Chan, Louis K.C., Yasushi Hamao, and Josef Lakonishok, 1991, Fundamentals and stock returns in Japan, *Journal of Finance* 46, 1739–1789.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409–462.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

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

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–156.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, Eugene F., and Kenneth R. French, 2005, Financing decisions: Who issues stock? *Journal of Financial Economics* 76, 549–582.

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

Fama, Eugene F., and Kenneth R. French, 2006b, The value premium and the CAPM, *Journal of Finance* 61, 2163–2185.

Fama, Eugene F., and Kenneth R. French, 2006c, Average returns, B/M, and share issues, Working paper, Graduate School of Business, University of Chicago, forthcoming in the *Journal of Finance*.

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

Haugen, Robert A., and Nardin L. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401–439.

Hong, Harrison, Jeremy Stein, and Terrence Lim, 2000, Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Ikenberry, David, Josef Lakonishok, and Theo Vermelean, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921–945.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–17.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

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

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.