THE JOURNAL OF FINANCE • VOL. XLVI, NO. 4 • SEPTEMBER 1991

Structural and Return Characteristics of Small and Large Firms

K. C. CHAN AND NAI-FU CHEN*

ABSTRACT

We examine differences in structural characteristics that lead firms of different sizes to react differently to the same economic news. We find that a small firm portfolio contains a large proportion of marginal firms—firms with low production efficiency and high financial leverage. We construct two size-matched return indices designed to mimic the return behavior of marginal firms and find that these return indices are important in explaining the time-series return difference between small and large firms. Furthermore, risk exposures to these indices are as powerful as log(size) in explaining average returns of size-ranked portfolios.

WHY DO SMALL CAPITALIZATION stocks earn higher mean returns than large capitalization stocks? One view is that small and large stocks have different sensitivities to the risk factors important for pricing assets (see Chan, Chen, and Hsieh (1985) and Huberman, Kandel, and Karolyi (1987)).[1] This view emphasizes that the risk differences between small and large stocks arise from the differences in their time series responses to changes in the underlying risk factors. Chan, Chen, and Hsieh (1985) find that small firms are more exposed to production risk and changes in the risk premium. Huberman, Kandel, and Karolyi (1987) find that returns of firms within the same size range tend to respond to risk factors in similar ways, and their returns tend to move together. Although these studies have shown that there are risk differences between small and large firms, they do not suggest why. Smallness by itself does not necessarily imply higher risk, and differences in market capitalizations do not explain why small and large firms have different responses to economic news.

This study suggests that the small firms examined in the empirical litera-

*Chan is with Ohio State University. Chen is with the University of California, Irvine and Hong Kong University of Science and Technology. We are grateful to Tom Berglund, George Constantinides, Doug Diamond, Eugene Fama, Wayne Ferson, Ken French, Mike Gibbons, Shmuel Kandel, Ron Masulis, Merton Miller, Marc Reinganum, Jay Shanken, Rob Stambaugh, René Stulz, Rob Vishny, Arnold Zellner, workshop participants at Aarhus, Austin, Brussels, Chicago, Copenhagen, Helsinki, Iowa, Irvine, Koblenz, Leuven, SMU, UCLA-USC, Urbana, Vanderbilt, and the European Finance Association meeting in Madrid for helpful comments and suggestions, Raymond Kan for computational assistance, and the Center for Research in Security Prices for support.

[1]A partial list of explanations for the size effect (Banz (1981) and Reinganum (1981)) includes: misestimation of risks (Roll (1981), Reinganum (1982), Chan and Chen (1988)), misestimation of return (Blume and Stambaugh (1983), Roll (1983)), inadequacy of the CAPM (Chen (1983), Chan, Chen, and Hsieh (1985)), and transaction costs (Stoll and Whaley (1983), Schultz (1983)).

ture tend to be what we call marginal firms. They have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems. They are marginal in the sense that their prices tend to be more sensitive to changes in the economy, and they are less likely to survive adverse economic conditions. For example, in a competitive economy with continuing technological changes, firms that become relatively inefficient or have higher costs will decrease in relative size. While a more efficiently run firm may do well and even prosper if the aggregate economy is growing slowly, a less efficiently run firm may not survive a low growth rate for very long. Furthermore, firms that suffer from past misfortunes tend to be smaller in size. If they do not change their capital structure accordingly, they have higher financial leverage. In addition, if information is imperfect in the capital market, poor past performance and high current financial leverage may restrict the firms' accessibility to external financing, especially during *tight* credit periods.[2] Consequently the same piece of economic news affects the return of a portfolio of small firms, which tends to contain a higher proportion of these marginal firms, more than it affects the return of a portfolio of large firms.

Our economic interpretation of why small firms on average are riskier is thus based on the characteristics that cause the marginal firms to react differently from the healthy firms to the same piece of macroeconomic news. Since small firms as a group are heavily populated by marginal firms, they tend to behave like marginal firms. We provide information about the time profile of the market values as well as their financial conditions to show that small firms tend to have more of these marginal firm characteristics.

To show that it is the marginal firm characteristics but not size that explain the difference in return behavior of large and small stocks, we construct two *size-matched* return indices of marginal firms. The first index is intended to capture the return behavior of firms in distress as inferred from recent substantial reductions in dividend payouts. Since firms are known to be reluctant to cut dividends, a substantial reduction is a clear signal of a firm with cash flow problems, whether as a consequence of poor profitability or of difficulties in obtaining external financing. The return index is constructed by taking the average returns of firms that have recently cut dividends substantially and subtracting from them the average returns of firms that have not cut dividends but are strictly smaller in size. The second return index is constructed to be the return difference between a portfolio of high-leverage firms and a portfolio of low-leverage firms that are strictly smaller in size.

These two size-matched marginal firm indices have many of the return characteristics of the documented size effect. Their time series have strong January seasonals and are reliably correlated with the return difference between a small and a large firm portfolio over time. In time series regressions, we find that the responses of size portfolio returns to these two indices

[2]See, e.g., Stiglitz and Weiss (1981), Myers and Majluf (1984), and Fazzari, Hubbard, and Peterson (1988).

are inversely related to their size ranking. Furthermore, these response differences between small and large firms are as powerful as log(size) in explaining the cross-sectional average return differences in size portfolios.

The rest of our paper is divided into three sections. Section I provides descriptive statistics about the firms in the largest and smallest size quintiles —how they differ in terms of their entries into the two extreme size quintiles and how they differ in terms of some accounting ratios, dividend policy, and financial leverage. In Section II, we describe how we form our size-matched return indices to mimic the fluctuations of firms that are in distress and firms that are highly levered. We then apply these two return indices to examine the return characteristics of small and large firms. The results indicate that our measurements of risk are important in explaining the return differences both in the time series and in the cross section between small and large firms. Section III briefly summarizes the results.

I. Structural Characteristics of Small and Large Firms

A. The Composition Characteristics by Entry Type

We hypothesize that an important reason why small and large firms react differently to economic news is that small firms tend to be marginal firms that have not been doing well. To find out if this is true, we classify firms by how they enter the top (largest) and bottom (smallest) size quintile over the 30 years' sample period from 1956 to 1985. Based on the most recent entry, the firms in the top and bottom size quintiles are categorized according to when and how they entered the size quintile (by falling, rising, or being listed into). The result is reported in Table I.

The most revealing statistic from the bottom quintile is that typically about 66% of the firms have fallen from the higher quintiles and only about 14% were listed directly into that quintile over the past 10 years. This indicates that indeed the bottom quintile contains a high fraction of firms that have not been doing well. The remaining 20% of the firms have been in the bottom quintile for over 10 years, suggesting that most firms in the bottom quintile do not tend to stay there for a long time. They either do well subsequently and move to a higher quintile or exit from the NYSE (see Queen and Roll (1987) for a discussion of a firm's mortality rate as a function of its size). In contrast, about 51% of the firms in the top size quintile have been there over 10 years. Of the remaining 49%, about 41% have gone up from the lower quintiles, and 8% were listed into the top quintile over the past 10 years. Thus, the top quintile contains a substantial fraction of firms that are successful.[3]

[3]There is evidence that betas of common stocks change following large price changes. Chan (1988) shows that betas of losers tend to go up and betas of winners tend to go down. These changes in risks explain the returns of the strategy of buying losers and selling winners (see DeBondt and Thaler (1985)). While our marginal firm argument has a prediction similar to Chan's findings, our marginal firms differ from the losers studied by Chan and by DeBondt and Thaler. Losers are often stocks that were large to begin with. Thus, even if they fall in value and have increased risk, they are not as "marginal" as a typical firm in the NYSE bottom size quintile.

Table I

Frequency Distribution (in Percentage) of NYSE Firms in the Top and Bottom Size Quintiles Classified by the Most Recent Entry Type

Data is for 1956-1985. Size is measured by the market value of equity at the end of the previous year.

Bottom (Smallest) Quintile				
Most Recent Entry	Over Past 2 Years	2-5 Years Before	6-10 Years Before	Has been in the Quintile more than 10 years
Fallen from Higher Quintile	32.2	18.7	15.1	19.8
Newly Listed into the Quintile	5.8	4.8	3.6	
Top (Largest) Quintile				
Most Recent Entry	Over Past 2 Years	2-5 Years Before	6-10 Years Before	Has been in the Quintile more than 10 Years
Gone Up from Lower Quintile	19.8	12.0	9.6	50.9
Newly Listed into the Quintile	2.0	2.4	3.3	

Size Distribution (in Percentage) of Newly Listed NYSE Firms by Decile (1956-1985)

(Smallest)	1	2	3	4	5	6	7	8	9	10	(Largest)
	4.5	16.0	16.7	16.8	15.0	11.7	6.7	6.3	3.2	3.1	

Table I also reports the size distribution by decile of newly listed NYSE firms. Interestingly, these firms do not enter disproportionately into the bottom quintile, with only 4.5% of them listed into the bottom decile. From the listing requirement of the NYSE, newly listed firms are likely to be firms that have been successful. When they enter, they tend to enter into the lower middle size range of the NYSE. These statistics suggest that the return behavior of the bottom quintile is not primarily driven by an overrepresentation of newly listed firms in the quintile. (See also Barry and Brown (1984).)

B. Characteristics of Small and Large Firms in Terms of Selected Accounting Ratios

Marginal firms are likely to have lower returns on assets. If their problems are further compounded by high financial leverage, they are likely to have a lower interest expense coverage too. If marginal firms tend to be smaller in size within each (broadly defined) industry, these characteristics should also be reflected in the average small firm and the average large firm within each industry. Table II provides some direct evidence.

The NYSE firms in COMPUSTAT are classified into 19 industry groups (as in Stambaugh (1982)) on the basis of the SIC codes. We compute the average return to asset ratio (operating income before depreciation/total asset) and the interest expense ratio (interest expense/operating income before depreciation)[4] using the annual data *following* the size ranking. While we recognize that accounting figures do not always correspond to economic values, we hope

Table II

Average Return to Asset and Interest Expense Ratios for Firms in the Top and Bottom Size Quintiles

Data is for 1966–1984. Ratios are computed from COMPUSTAT data the year following the size ranking. The ratios are the averages of the annual median ratios for firms in the industry and size group from 1966 to 1984. Q1 is the smallest size quintile and Q5 is the largest size quintile. The size ranking is based on the capitalization value at the end of the previous year.

	Operating Income before Depreciation / Total Asset		Interest Expenses / Operating Income before Depreciation	
Industry Group	Q1	Q5	Q1	Q5
Mining	.143	.207	.153	.101
Food	.131	.221	.180	.094
Textiles	.124	.206	.210	.106
Paper Products	.131	.159	.235	.133
Chemical	.120	.228	.211	.084
Petroleum	.184	.210	.163	.084
Stone, Clay & Glass	.106	.159	.202	.141
Primary Metals	.134	.120	.166	.205
Fabricated Metals	.139	.192	.159	.115
Machinery	.132	.200	.161	.121
Appliances	.131	.208	.141	.091
Transportation Equipment	.134	.158	.169	.110
Misc. Manufacturing	.114	.238	.087	.067
Railroads	.026	.101	1.032	.212
Other Transporation	.151	.168	.288	.148
Utilities	.132	.126	.277	.264
Department Stores	.110	.168	.291	.149
Other Retail	.124	.228	.181	.078
Banking & Finance	.042	.084	.452	.437
Average	.121	.178	.250	.144

[4]The average ratio is the average of the median ratio for the industry in the size group from 1966 to 1984. The median ratio is used here to avoid averaging over some extreme accounting ratios and averaging over negative interest expense ratios which are difficult to interpret. If we use the mean rather than the median, the average return to asset ratio would be 0.166 for Q5 and 0.113 for Q1. If we include only those firms with positive operating income before depreciation, the average of the mean interest expense ratios would be 0.490 for Q1 and 0.168 for Q5.

that the average ratios are nevertheless informative of the economic values that we are interested in.

Among the numbers reported for the top and bottom size quintiles, there are only two industries (Primary Metals and Utilities) whose return to asset ratios and one industry (Primary Metals) whose interest expense ratio are opposite to what we expect. There are some outliers in the Railroads (where the number of firms is relatively small) and the Banking and Finance (where the interpretation of the interest expense ratio may be more ambiguous) industries. The relative size of the cross-sectional averages, however, are not affected by the exclusion of those two industries. Although the statistics for the middle three size quintiles are not reported, they are generally monotonic as a function of size. Overall, the pattern is consistent with our hypothesis regarding the differences in characteristics of small and large firms.

C. The Relation between Firm Size, Leverage and Dividend Changes

The accounting ratios reported above are suggestive but not exhaustive indicators of the differences between small and large firms. There are other indicators that can better capture the market and the management's expectation of the uncertainty facing the marginal firms in the future. These indicators will guide us later in constructing indices that mimic the return responses of these firms. In this study, we select two forward-looking measures: one based on dividend policy and one based on financial leverage.

It is well known that firms are reluctant to cut their dividends. Consequently, firms that cut their dividends drastically are likely to have done poorly and face a very uncertain future. Furthermore, a cut in dividends can also signal the management's expectation of lower future cash flows or increasing difficulties in relying on external financing. This motivates the choice of using a dividend-cut criterion to measure the overall health of a firm.

Financial leverage affects the risk of equity return of firms of every size, but its influence is likely to be felt more strongly among firms that are not doing well. This motivates the choice of using a financial leverage criterion to examine the riskiness of a firm. Financial leverage can compound the problems of a marginal firm or it can exert a separate effect—a cost inefficient firm may be in distress without debt and a highly financially levered firm may be run very efficiently and competitively, and their responses to changes in production costs and financing costs can be very different. Financial leverage is defined as the sum of book value of current liabilities, long term debt, and preferred stock over market value of equity. The book value data are from the COMPUSTAT database if available. If the NYSE company is not on COMPUSTAT, we collect the data from Moody's Manuals. This is to avoid the survivorship bias in the COMPUSTAT database, especially in the earlier years.

Table III describes the frequency distribution of the two-way classifications according to (i) size/dividend-change and (ii) size/leverage. The patterns are

Table III

Frequency Distribution of NYSE Securities Assigned to Size/Leverage and Size/Dividend-Change Classification

Data is for 1956–1985. The dividend change classification in year t is based on the percentage dividend change of the stock from year $t-2$ to year $t-1$. The dividend change information is updated every year from 1956 to 1985 based on stocks that paid dividends in year $t-2$. Stocks that did not pay dividends in year $t-2$ are excluded. The size classification in year t is based on the market value of equity at the end of year $t-1$. Leverage is defined as the ratio of the sum of the book value of current liabilities, long-term debt and preferred stock over the market value of equity as of the end of the previous year. Size is the market value of equity.

Panel A. Size/dividend change

	Dividend Change					
	−100%	(−100%, −50%)	(−50%, 0%)	0%	(0%, 50%)	More than 50%
Smallest	460	368	928	1883	2433	555
Size 2	131	152	695	1624	3418	614
Size 3	66	85	555	1501	4010	422
Size 4	22	54	442	1445	4358	325
Largest	9	27	361	1238	4805	210
Total	688	686	2981	7691	19024	2126

Panel B. Size/leverage

	Leverage				
	Low	2	3	4	High
Smallest	566	797	1115	1416	1904
Size 2	843	1156	1254	1163	1393
Size 3	1045	1251	1215	1178	1121
Size 4	1241	1194	1191	1247	936
Largest	2103	1411	1035	805	439
Average Leverage	0.18	0.49	0.88	1.49	4.49

immediately obvious. Among firms that have cut their dividends in half or more the year before, over 50% are in the bottom size quintile. There are also more highly levered firms in the bottom quintile and vice versa. Overall, with the appropriate caveat regarding the leverage measure, the patterns in the two-way classification are consistent with our hypothesis about why a small firm portfolio is riskier.

D. Evidence from the NASDAQ Firms

The recently available NASDAQ data set provides an interesting way to test our marginal firm hypothesis. We argue that the portfolio of small firms listed on the exchanges is risky because it contains a disproportionate share of firms that have lost market value. In the NASDAQ sample, however, most of the firms within the range defined by the NYSE smallest size quintile are less likely to be "fallen angels" than their NYSE counterparts. This is because firms on the NASDAQ are on the whole smaller than those on the NYSE to start with, and firms that are small by the NYSE standards are not necessarily firms in distress. If our marginal firm hypothesis is valid, we should observe significant risk and return differences between the small firms listed on the NYSE and firms of similar size on the NASDAQ.

We collect data on the NASDAQ firms over the period of 1973 to 1985. Our results provide supportive evidence for the marginal firm explanation. We find that the NASDAQ firms that are considered to be small by the NYSE standards do not have the marginal firm characteristics. First, they are almost twice as likely (2941 versus 1730 over the sample period) to have gone up than to have fallen into this size range. Second, they are half as likely to have cut their dividends drastically as their NYSE counterparts (7.15% versus 14.4%, the proportion of firms that have cut their dividend yields 50% or more). Their return to asset and interest expense ratios (0.135 and 0.125, respectively) are more favorable than their NYSE counterparts (0.115 and 0.284, respectively, over this period). Over the sample period, the average monthly compounded equally weighted portfolio return for the NYSE bottom size quintile is higher than that corresponding to the NASDAQ firms of similar size.[5] The difference is 0.00644/month ($t = 2.55$). In sum, the small firms on the NYSE are riskier and earn higher average returns than the NASDAQ firms of similar size. This suggests, as we contend, that the riskiness of the small firms documented in the empirical literature has more to do with what we call the marginal firm characteristics than smallness per se.

II. Return Characteristics of Small and Large Firms

A. The Construction of Size-Matched Return Indices

We want to construct two indices mimicking the return behavior of marginal firms that have cut their dividends drastically and the behavior of firms with high financial leverage. Given the patterns in Table III, if we simply selected firms with these characteristics, the portfolios would be dominated by firms with low market value. Since it is our purpose to explain the return behavior of small firms, we do not wish to use small firms to explain small firms. Therefore, in order to avoid inadvertently including a factor in the construction of the portfolios that is size-related but independent of our intuition about the marginal firms and the financial leverage, we create the return indices by taking the difference between our dividend-

[5]The average returns of firms belonging to the second smallest and the middle size quintile of the NYSE are also reliably higher than those of the NASDAQ of similar size. For the largest two size quintiles, however, the differences are indistinguishable from zero. See related results in Lamoureux and Sanger (1989).

decrease portfolio, our high leverage portfolio, and their appropriate matching portfolios of smaller firms.

For each year t, we collect all the firms on the NYSE that cut their dividends by 50% or more from year $t - 2$ to year $t - 1$. For each of these firms, we find a matching firm that (i) is *smaller* in the market value of equity as of December of year $t - 1$, (ii) did not decrease it dividends from year $t - 2$ to year $t - 1$, and (iii) has been newly listed on the NYSE during the past 5 years. The first two criteria ensure that the matching firm would still be smaller in size despite the nondecrease in dividends. Among these firms, the third criterion is designed to pick out those that have been doing well recently (and exclude those struggling firms that are already paying little dividends), and we rely on the listing requirement of the NYSE as an indicator. This process is updated once every year from 1956 to 1985. We then take the difference between the return on the dividend-decrease portfolio and this matching portfolio and call the resultant index DIV.

The construction of the leverage effect index is similar. For each firm in the top leverage quintile, we select a firm that (i) is smaller in market equity value as of December of year $t - 1$ and (ii) belongs to the bottom leverage quintile. This process is again updated once every year from 1956 to 1985. We subtract the return of the matching portfolio from the high leverage portfolio and call the series LEV. In creating the matched series DIV and LEV, the composition is held constant until the next update.

B. The Size Portfolios

To examine the return characteristics of small and large firms, we form twenty size portfolios. Return and firm size data are collected from the CRSP monthly file. For each year, firms on the NYSE that have available prices on December of the previous year are chosen and ranked according to the market value of equity as of that December. The firms are then put into one of twenty portfolios arranged in order of increasing size, each containing the same number (within one) of securities. The composition of the portfolio is then held constant through the year except for missing returns or delisting of the security. We repeat this process each year over the period from 1956 to 1985, generating 360 non-overlapping, monthly rebalanced, equally-weighted rates of return for each portfolio.[6] Portfolio P1 contains the smallest size vigintile and P20 the largest; Q1, Q5, and QDIFF are returns on the bottom quintile, the top quintile, and their difference, respectively.

[6]See Roll (1983) and Blume and Stambaugh (1983) for a discussion of possible problems involved in computing the average returns of small firm portfolios. Using a method suggested by Blume and Stambaugh (1983) to correct for possible biases arising from the bid-ask effect, we find that the average returns thus computed and the average returns computed using monthly rebalance intervals are essentially indistinguishable for our portfolios over this period. The maximum difference in average monthly returns is 0.00089 (portfolio 3), and the average difference is 0.00020.

Table IV reports the correlations between DIV, LEV, the return difference of the two extreme size quintiles = Q1 − Q5, and the value-weighted NYSE index. Perhaps the most interesting numbers are the positive correlations of QDIFF = Q1 − Q5 with DIV and LEV which are 0.47 and 0.49, respectively.[7] In contrast, the correlation between QDIFF and the value-weighted index is only 0.18.

Note that in constructing the indices DIV and LEV, the marginal firms are always *bigger* than the control group; thus the correlations between these portfolios and QDIFF would be negative if they were driven by the empirical regularity that firms within the same size range tend to move together. The fact that these correlations are reliably positive suggests that the concept of marginal firm is capturing the important differences in return behavior between small and large firms over time.

C. Return Characteristics of Selected Portfolios

Table V provides the contrast in return characteristics between the value-weighted NYSE index and stocks that we consider to be relatively risky. Firms with high leverages and firms that have cut their dividends by 50% or more (based on the previous year) generally have higher returns than the market index. Both the return difference between high leverage firms and the market and the return difference between dividend-decrease firms and the market exhibit a strong January seasonal.

Table IV

Correlations of Stock Portfolios Returns. Data are for 1956–1985.

DIV = Return on Dividend Decrease (50% or more) Portfolio less the return on Matching Portfolio of newly listed smaller firms that had no dividend decrease in the previous year.

LEV = Return on High Leverage (the top 20%) Portfolio less the return on Matching Portfolio of smaller firms with low leverage (the bottom 20%). Leverage is measured at the end of the year prior to inclusion into the portfolio.

QDIFF = Return on Smallest Size Quintile less the return on Largest Size Quintile (NYSE Firms).

VWNYS = Return on the Value-Weighted NYSE Market (in excess of T-bill rate).

	LEV	QDIFF	VWNYS
DIV	.2083	.4714	.2860
LEV		.4923	.0587
QDIFF			.1841

[7] If we subtract the value-weighted NYSE index (representing the relatively safe firms) rather than the matching portfolios of smaller firms in the construction of DIV and LEV, the correlations with QDIFF are 0.87 and 0.93, respectively.

Table V

Monthly Return Statistics for Selected Stock Return Indices

Data is for 1956–1985. DIV is the difference in return between the dividend-decrease (50% or more) firms and the matching newly listed smaller firms with no dividend decrease in the previous year. LEV is the difference between a portfolio of high leverage (top 20%) firms and a portfolio of matching firms of low leverage and smaller size, where leverage is measured at the end of the year prior to inclusion in the portfolio.

	Mean[a]	January
Value-weighted NYSE	.00868	.0136
Stocks with dividend decrease (50% or more)	.01422	.1034
Stocks with high leverage	.01356	.0788
Stocks with dividend decrease – value-weighted NYSE	.00553*	.0898**
Stocks with high leverage – value-weighted NYSE	.00488**	.0652**
Size-matched series and their components		
DIV	.00191	.0419**
(a) dividend decrease	.01343	.0933
(b) matching portfolio	.01151	.0513
LEV	.00162	.0291**
(a) high leverage	.01305	.0649
(b) matching portfolio	.01143	.0358

[a] For the return differences.
*denotes significance at the 10% level.
**denotes significance at the 5% level for two-tail t tests.

Table V also reports the return characteristics of the two size-matched series DIV and LEV constructed in Section II. A.[8] As expected, the average returns of these two series, though positive, are substantially smaller than the previous two difference series when we subtract the value-weighted market index rather than the matching portfolios of smaller firms from the portfolios of dividend-decrease firms and high leverage firms. While this may suggest that DIV and LEV will not be as strong in their abilities to mimic the return fluctuations of small firms relative to large firms, these *size-matched* series still exhibit a strong January seasonal. The average is 0.0419 (t = 4.10) for DIV and 0.0291 (t = 4.59) for LEV. Recall that in the construction of DIV and LEV, the firms in the matching portfolios are *strictly smaller* in size. The above evidence indicates that the economic reasoning underlying the construction of DIV and LEV to mimic the return behaviors of small and

[8] The returns of the dividend-decrease portfolio and the high leverage portfolio in the construction of DIV and LEV are different from the similar series described in the top part of Table V because we have to discard those very small marginal firms that we cannot match with smaller firms with no dividend cut or low leverage. Consequently, the portfolios in DIV and LEV contain fewer firms than the other portfolios described in Table V.

large firms, rather than size itself, dictates the relative magnitude of the realized January seasonal.[9] As Keim (1983) points out, a strong January seasonal is a distinctive characteristic of the return difference between small and large firms over the last several decades. This common seasonal pattern in the realized return adds credibility to our marginal firm interpretation of the small firm effect.

D. The Return Characteristics of Portfolios Ranked on the Basis of the Multiple Betas

In the remainder of the paper, we shall measure the risk of a stock (or a portfolio) by its sensitivities (betas) to the fluctuations of (i) the value-weighted market (VWNYS), (ii) LEV, and (iii) DIV in a multiple regression. The following experiment indicates that sorting firms (within the same size quintile) on the basis of their LEV-β and DIV-β allows us to identify firms with higher risks.

For each year from 1961 to 1985, we group firms that have been on the NYSE for the previous 5 years into five size quintiles based on their market capitalization as of December of the previous year. Within each quintile, we estimate the multiple betas (VWNYS, LEV, DIV) for all the stocks using their return data over the previous 5 years. We then classify the stocks according to their estimated LEV-β and DIV-β and form three equally weighted portfolios.[10] The first one, called H, consists of stocks with high (top half within the size quintile) LEV-β and high DIV-β. The second one, called L, consists of stocks with low LEV-β and low DIV-β. The third one, called M, contains all the remaining stocks from that size quintile. The mean returns and the January returns of H, L, and their difference, H − L, for each quintile are reported in Table VI.

All the differences are positive, and they are reliably so for the mid-size quintiles. The difference for the smallest quintile Q1, 0.00287/month or approximately 3.5%/year, is larger than that corresponding to the next larger quintile Q2, but the high return variances of firms in the smallest quintile produce a lower t-statistic (1.54 versus 1.83 for the H − L in Q2). Overall, the F-statistic rejects the null hypothesis that all five differences are jointly zero. The evidence of return difference between H and L from the same size quintile is much stronger in January. The return for H is reliably higher for all five size quintiles in January. Thus, *within each size quintile*, we are able to create portfolios that mimic the difference in return character-

[9] We are not proposing an economic explanation here for the realized January seasonal in this sample period. What we demonstrate here is that the size-matched indices we use to mimic the response differences between small and large firms share the same return characteristics over the same sample period.

[10] Note that we are ranking stocks partly according to their multiple beta estimation errors. In the presence of this errors-in-variable problem in the inclusion criteria, the procedure that follows is not as powerful as it would be without such a problem.

Table VI

Return Characteristics of Portfolios Formed on the Basis of Multiple Betas Within Each Size Quintile

Data is for 1961–1985. DIV is the difference in return between the dividend decrease (50% or more) firms and the matching newly listed smaller firms with no dividend decrease in the previous year. LEV is the difference between a portfolio of high leverage (top 20%) firms and a portfolio of matching firms of low leverage and smaller size, where leverage is measured at the end of the year prior to inclusions into the portfolio. Q1, Q2, Q3, Q4, and Q5 are, from the smallest to the largest, size quintiles in NYSE. H (vice versa for L) denotes the portfolio of stocks with high (top half) DIV-beta and high (top half) LEV-beta estimated in multiple regressions over the previous 5 years with the excess return of the value-weighted NYSE, DIV, and LEV as independent variables.

		Mean[a]	January
Q1 (smallest)	H	.01825	.1193
	L	.01538	.0873
	H − L	.00287	.0320**
Q2	H	.01588	.0808
	L	.01322	.0574
	H − L	.00266*	.0234**
Q3	H	.01487	.0565
	L	.01129	.0434
	H − L	.00358**	.0131**
Q4	H	.01321	.0397
	L	.00920	.0292
	H − L	.00401**	.0104**
Q5 (largest)	H	.01045	.0233
	L	.00849	.0101
	H − L	.00196	.0131**
		$F(5,295) = 2.84$ [p-value = 0.016]	

[a]For the return differences. The F-statistic is for the test of the H − L returns being jointly zero for the five quintiles.

*denotes significance at the 10% level.

**denotes significance at the 5% level for two-tail t-tests.

istics of small and large firms or, as we hypothesize, the difference between relatively risky and relatively safe firms.

E. The Risk and Return of Size Portfolios

The average monthly returns (1956 to 1985) and the average log(size) of the 20 size portfolios are reported in Table VII. The "size effect" is apparent from the near monotonicity of the average return as a function of size. The last three columns contain the multiple regression coefficients of the size portfolio return on the value-weighted NYSE index, the size-matched index mimicking the leverage effect (LEV) and the size-matched index mimicking the marginal firms with dividend decrease (DIV). Almost all the regression

Table VII

Multiple Portfolio Betas and Returns

Data is for 1956–1985. Portfolio 1 contains the smallest 5% NYSE firms. Portfolio 20 contains the largest 5% NYSE firms. Estimated VWNYS, LEV, DIV-betas are multiple regression coefficients of portfolio returns (in excess of T-bill) on the value-weighted NYSE index (in excess of T-bill), the difference between the high leverage portfolio and the matching portfolio, the difference between the dividend-decrease (50% or more) firms and the matching portfolio, respectively.

Portfolio	Average Monthly Return	Average Log of Equity Value	Estimated VWNYS-Beta[a]	Estimated LEV-Beta	Estimated DIV-Beta
1	.01821	9.04	1.07(.074)	0.86(.148)	0.52(.096)
2	.01492	9.68	1.06(.057)	0.75(.112)	0.35(.066)
3	.01571	10.05	1.04(.051)	0.62(.106)	0.33(.063)
4	.01413	10.34	1.08(.047)	0.57(.086)	0.28(.048)
5	.01415	10.59	1.06(.042)	0.51(.072)	0.23(.039)
6	.01327	10.82	1.05(.046)	0.44(.083)	0.25(.045)
7	.01332	11.04	1.08(.038)	0.47(.064)	0.18(.038)
8	.01335	11.26	1.07(.033)	0.37(.057)	0.19(.035)
9	.01144	11.47	1.02(.035)	0.37(.062)	0.16(.034)
10	.01242	11.68	1.05(.038)	0.38(.066)	0.16(.031)
11	.01090	11.88	1.04(.030)	0.31(.048)	0.14(.030)
12	.01139	12.09	1.07(.031)	0.29(.046)	0.09(.027)
13	.01096	12.31	1.08(.027)	0.22(.054)	0.10(.031)
14	.01126	12.55	1.06(.024)	0.21(.042)	0.06(.022)
15	.01012	12.80	1.05(.022)	0.27(.037)	0.05(.021)
16	.00990	13.06	1.03(.019)	0.19(.032)	0.04(.019)
17	.00953	13.31	1.03(.019)	0.15(.037)	0.03(.021)
18	.00898	13.61	0.99(.020)	0.03(.031)	−.02(.022)
19	.00755	14.03	1.03(.019)	−.02(.033)	−.01(.016)
20	.00748	15.44	1.00(.014)	−.15(.031)	−.04(.015)

[a] Heteroskedasticity consistent standard errors (White (1980)) are in parentheses.

slope coefficients are more than two standard errors away from zero, indicating that some of the return fluctuations of the size portfolios can be explained by their covariations with our return indices along with the market index. In other words, the risk of the size portfolios, especially for the smaller firms, cannot be completely captured by the market index.

The pattern of the partial market betas is interesting. Most of the partial market betas are statistically indistinguishable from 1, suggesting that firms of every size are affected by the aggregate market, but the differential responses of small and large firms can be captured much better by our size-matched portfolios LEV and DIV. Since both LEV and DIV are positively correlated with the value-weighted market, the above observation is also suggestive of why smaller firms have higher market betas in univariate regressions (not reported here).

The near monotonicity of the LEV-betas and the DIV-betas is also rather striking. Given that the matching firms in LEV and DIV are smaller in size, the pattern of regression coefficients (risk exposures) is opposite to what is expected if size is a sufficient statistic for risk but, as we emphasized before, is consistent with the economic interpretation underlying the construction of LEV and DIV.

F. Cross-Sectional Results

In this section, we want to examine whether our multiple risk exposures can explain mean returns reflected in the explanatory power of the size proxy (log(size)) in a multiple cross-sectional regression. The functional form of the size proxy is based on the approximate linear relation between average return and log(size) observed in Brown, Kleidon, and Marsh (1983). The equation we use is

$$E(\tilde{r}_i) = \lambda_0 + \lambda_1\beta_i(\text{VWNYS}) + \lambda_2\beta_i(\text{LEV}) + \lambda_3\beta_i(\text{DIV}) + \lambda_4\overline{\log(\text{size})}_i \quad (1)$$

where $\tilde{r}_i$ is the return of portfolio i; λ_j, $j = 0, \cdots, 4$ are constants; $\beta_i(VWNYS)$, β_i(LEV) and β_i(DIV) are the unconditional risk exposures[11] of portfolio i to VWNYS (the value-weighted NYSE index), LEV and DIV; and $\overline{\log(\text{size})}_i$ is the time average of the logarithm of the average firm size in portfolio i. Here, we are not proposing that the three betas can capture all the risks relevant to the equity market but rather that the three betas are sufficient to capture the risk-return relation reflected in the explanatory power of log(size) within the subspace spanned by the 20 size portfolios.

We estimate the pricing equation by a two-step method (see, e.g., Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), and Chan and Chen (1988)). In the first step, we estimate the unconditional betas (risk exposures) using monthly returns over the entire sample period from 1956 to 1985. In the second step, we perform cross-sectional regressions of realized returns of the 20 size portfolios on the estimated betas[12] and the log(size) variable month by month over 1956 to 1985, using a generalized least square method that takes into account the heteroskedasticity of the residuals. Consequently, in each month from 1956 to 1985, we obtain an estimate of the intercept $\hat{\lambda}_{ot}$, an estimate of the slope coefficient $\hat{\lambda}_{kt}$ associated with the beta corresponding to each factor, and an estimate of the slope coefficient $\hat{\lambda}_{st}$ associated with the size variable. If the "size effect" is captured by the multiple betas, the mean $\hat{\lambda}_S = 1/T\sum_{t=1}^{T}\hat{\lambda}_{st}$ should be statistically indistinguishable from zero.

Without the multiple risk exposures, the cross-sectional results are (t-statistics in parentheses):

$$\underset{(4.27)}{r_i = 0.03149} - \underset{(-3.44)}{0.00166}\ \overline{\log(\text{size})}_i + \epsilon_i. \qquad (1956{:}1\text{–}1985{:}2)$$

[11]The approach in Chan and Chen (1988) can be generalized to cover the multiple betas case studied here.

[12]We have also estimated the betas with data outside of the year in which we run the cross-sectional regressions. We have also estimated the betas excluding the January observations. The results are essentially the same.

When we include the multiple risk exposures,[13] the cross-sectional results are (t-statistics in parentheses):[14]

$$\begin{aligned} r_i = \underset{(1.02)}{0.01252} - \underset{(-0.90)}{0.00058}\, \overline{\log(\text{size})}_i + \underset{(0.54)}{0.00420}\, \hat{\beta}_i(\text{VWNYS}) \\ + \underset{(0.16)}{0.00066}\, \hat{\beta}_i(\text{LEV}) + \underset{(1.65)}{0.01094}\, \hat{\beta}_i(\text{DIV}) + \epsilon_i. \qquad (1956{:}1\text{–}1985{:}12) \end{aligned}$$

The evidence suggests that neither the log(size) proxy nor our multiple risk exposures[15] dominate the other in explaining the cross-sectional dispersion of average returns.[16] This is encouraging, given that we have carefully controlled for size in the two return indices and that the value-weighted NYSE index is heavily weighted in large firms. In other words, the economics underlying the construction of the two size-matched return indices is successful in capturing the differential risk exposures of small and large firms to the extent that the size proxy, log(size), does not have additional explanatory power for average returns conditional on those risk exposures.[17]

III. Conclusion

We argue that there are important economic reasons why small firms and large firms have different risk and return characteristics. Small firms on the

[13] If we include only the value-weighed market beta (estimated with the value-weighted market as the only independent variable in time-series regressions) as an additional variable in the cross-sectional regressions, the slope coefficient for the size variable is -0.00129 ($t = -2.56$) while the slope coefficient for the market beta is 0.00916 ($t = 1.27$).

[14] The standard errors are computed with Shanken's (1985) suggested adjustments. The results are qualitatively the same with or without the adjustments because the estimated adjustments are minor.

[15] The simple cross-sectional correlations between average return and log(size), LEV-beta and DIV-beta are -0.966, 0.967, 0.971, respectively. The estimated market betas are all close to one and one must be cautious in interpreting the beta slope coefficient and the intercept. We have also run the cross-sectional regressions without the market beta and the results for the other coefficients are essentially the same.

[16] We have also reestimated the cross-sectional results with split samples. We arbitrarily split the universe of stocks into two mutually exclusive groups, use the stocks from the first group to form the return indices and the stocks from the second group to form the size portfolios in the cross-sectional tests. The results are similar. We have also used the portfolios constructed on section II.D for the testing, and the results are similar.

[17] The evidence also suggests that investors who are willing to invest in small marginal firms are compensated with higher average returns over time. It turns out that empirically future aggregate consumption growth is more highly correlated with the return of small marginal firms than with the return of the value-weighted NYSE index (results not reported here but available from the authors upon request). Thus the higher average returns of the small marginal firms have an appealing economic interpretation. Investors whose levels of consumption fluctuate more with the aggregate consumption rate are more likely to invest less than the market proportions in small marginal firms. Their levels of consumption are then partially "insured" by those who are willing to invest more than the market proportions in those small marginal firms in exchange for the higher potential reward.

NYSE tend to be firms that have not been doing well, and, consequently, they tend to be firms that are less efficiently run and have higher financial leverage. As a result of the difference in production efficiency, difference in leverage, and perhaps the resultant difference in accessibility to external financing, small firms tend to be riskier than large firms, and the risk of the smaller firms are not likely to be captured by a market index heavily weighted toward large firms.

We propose and show that the time series of the return difference between small and large firms can be captured by the responses of high leverage firms and marginal firms to economic news. In the cross-sectional tests, the size proxy, log(size), has reliable explanatory power on the dispersion of returns among the size portfolios. However, it loses its explanatory power after we introduce the multiple risk exposures corresponding to the market index, the leverage index, and the dividend-decrease index mimicking the marginal firms. In other words, the explanatory power of the size proxy is reflected in the risk exposures to the *size-matched* return indices. Both the time-series and the cross-sectional evidence are consistent with our hypothesis regarding the risk and return of small and large firms.

REFERENCES

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

Barry, C., and S. Brown, 1984, Differential information and the small firm effect, *Journal of Financial Economics* 13, 283–294.

Black, F., M. Jensen, and M. Scholes, 1972, The capital asset pricing model: Some empirical tests, in M. Jensen, ed., *Studies in the Theory of Capital Market* (Praeger, New York).

Blume, M. and R. Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics* 12, 387–404.

Brown, P., A. Kleidon, and T. Marsh, 1983, New evidence on the nature of size related anomalies in stock prices, *Journal of Financial Economics* 12, 33–56.

Chan, K., 1988, On the Contrarian investment strategy, *Journal of Business* 61, 147–163.

——— and N. Chen, 1988, An unconditional asset pricing test and the role of firm size as an instrumental variable for risk, *Journal of Finance* 43, 309–325.

———, N. Chen and D. Hsieh, 1985, An exploratory investigation of the firm size effect, *Journal of Financial Economics* 14, 451–471.

Chen, N., 1983, Some empirical tests of the theory of arbitrage pricing, *Journal of Finance* 28, 401–418.

DeBont, W. and R. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 795–805.

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

Fazzari, S., R. Hubbard, and B. Petersen, 1988, Financing constraints and corporate investment, *Brookings Papers on Economic Activity*, pp. 141–195.

Huberman, G., S. Kandel, and Karolyi, 1987, A size-based stock returns model, CRSP Working paper, University of Chicago.

Keim, D., 1983, Size related anomalies and stock return seasonality: Empirical evidence, *Journal of Financial Economics* 14, 13–32.

Lamoureux, C. and G. Sanger, 1989, Firm size and turn of the year effects in the OTC/NASDAQ market, *Journal of Finance* 44, 1219–1245.

Myers, S. and N. Majluf, 1984, Corporate financing decisions when firms have investment information that investors do not, *Journal of Financial Economics* 13, 187–220.

Queen, M. and R. Roll, 1987, Firm mortality: Using market indicators to predict survival, *Financial Analysts Journal* 3, 9-26.

Reinganum, M., 1981, Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values, *Journal of Financial Economics* 9, 19-46.

———, 1982, A direct test of Roll's conjecture on the firm size effect, *Journal of Finance* 37, 27-35.

Roll, R., 1981, A possible explanation of the small firm effect, *Journal of Finance* 36, 879-888.

———, 1983, On computing mean returns and the small firm premium, *Journal of Financial Economics* 12, 371-386.

Schultz, P., 1983, Transaction costs and the small firm effect: A comment, *Journal of Financial Economics* 12, 81-88.

Shanken, J., 1985, Multivariate tests of the zero-beta CAPM, *Journal of Financial Economics* 14, 327-348.

Stambaugh, R., 1982, On the exclusion of assets from tests of the two-parameter model: A sensitivity analysis, *Journal of Financial Economics* 10, 237-268.

Stiglitz, J., and A. Weiss, 1981, Credit rationing in markets with imperfect information, *American Economic Review* 71, 393-410.

Stoll, H. and R. Whaley, 1983, Transaction costs and the small firm effect, *Journal of Financial Economics* 12, 57-79.

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, *Econometrica*, 817-838.