Time-Varying Expected Small Firm Returns and Closed-End Fund Discounts

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This article describes the relation between closed-end fund discounts and time-varying expected excess returns on small firms. The results indicate that closed-end fund discounts forecast future excess returns on small firms. The information in discounts is independent of that in other commonly used forecasting variables such as the dividend yield on the market, the default spread, and the term spread. Furthermore, the closed-end fund discount forecasts only the small firm factor return and is the only variable that forecasts the small firm factor return. Additional tests indicate that the information in discounts is related to expectations of future earnings growth and expectations of future inflation. These results provide significant support for a rational explanation of the time-series relationship between discounts and expected returns on small firms.

In this article, we examine the time-series relationship between closed-end fund discounts and small firm expected returns and explore the implications of the relationship for the economic behavior of individual investors. In a recent article, Lee, Shleifer,

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I thank Paul Alapat, Warren Bailey, Peter Carr, Bhagwan Chowdhry, Yehning Chen, Tarun Chordia, Laura Field, Narasimhan Jegadeesh, Roni Michaely, Avanidhar Subrahmanyam, an anonymous referee, Rick Green (the editor), participants of workshops at Carnegie-Mellon, Cornell, London Business School, Penn State, UCLA, University of Southern California, University of Texas at Austin, and especially Michael Brennan for their helpful comments and suggestions. I thank Charles Lee for providing me with the data on closed-end fund discounts and Ken French for providing me with the data on factor proxies. All errors are my own.

and Thaler (1991) report that changes in closed-end fund discounts are negatively correlated with small firm returns. Since both small firms and closed-end funds are typically owned by individual investors, Lee, Shleifer, and Thaler interpret their results as evidence that stock prices are affected by nonfundamental factors such as investor sentiment or noise trading.[1] While their results suggest that there is common variation in small firm and closed-end fund prices, it remains unclear whether this variation is due to economic fundamentals or investor sentiment. In this article, we cast discounts on closed-end funds in a time varying expected return framework and show that the Lee, Shleifer, and Thaler results are just one facet of the relation between discounts and time-varying small firm expected returns. This raises the issue of whether this time-series relationship is due to investor expectations about future macroeconomic conditions or is due to nonfundamental risks such as investor sentiment.

We investigate this issue empirically using the long horizon regression framework. The empirical results indicate that closed-end fund discounts forecast future excess returns on small firms. The forecasting power of discounts is robust even in the presence of other forecasting variables such as the dividend yield on the market, the default spread, and the term spread. Additional tests show that the relationship between discounts and small firm expected returns arises from positive covariance between discounts and the small firm factor risk premium. Furthermore, the discount does not contain information about any other factor risk premia and is the only variable we examine that covaries with the small firm factor risk premium. Finally, we find that discounts contain information about future expected real earnings growth of both small firms and large firms and future expected inflation.

The relation between discounts and future economic conditions suggests that there may be a rational explanation for the time-series relationship between discounts and expected returns on small firms. Specifically, the time variation in discounts may be related to changing (rational) expectations or risk aversion of individual investors. The relation between discounts and future economic conditions also suggests that there may be rational reasons for the existence of discounts. However, this issue is not directly addressed in this work.

This article is organized as follows. Section 1 analyzes the information content of discounts using a log-linear framework. Section 2 describes the empirical tests and the data, Section 3 presents evidence

[1] See De Long et al. (1990) for a model of noise trading.

of time variation in expected small firm returns tracked by closed-end fund discounts. Section 4 ties the time variation in small firm expected returns to time variation in underlying factor risk premia. Section 5 examines the relationship between discounts and future economic indicators. Section 6 interprets the empirical results and Section 7 concludes.

1. Information Content of Discounts

In this section we derive a relation between discounts and stock returns using the approximate log-linear relation among prices, dividends, and returns proposed by Campbell and Shiller (1988). We use this relation to compare two types of regression tests that can be used to analyze the correlation between discounts and small firm returns.

Consider an arbitrary security (portfolio) i. Let $p_{i,t}$ be the log real stock price of this arbitrary security i, $d_{i,t}$ be the log real dividend, and $e_{i,t}$ be the excess return. The excess stock return is defined as the difference between log real stock return and log real interest rate.[2] Let r_t be the log real interest rate. Now, denote the closed-end fund by the subscript $i = f$ and the net asset value by the subscript $i = n$. Then, using the ex ante version of the log-linear relationship, we can write the dividend yields corresponding to the net asset value and the closed-end fund share price as follows:

$$d_{n,t} - p_{n,t} = E_t \sum_{k=0}^{\infty} \rho_n^k (e_{n,t+1+k} + r_{t+1+k} - \Delta d_{n,t+1+k}) - K_n, \quad (1)$$

$$d_{f,t} - p_{f,t} = E_t \sum_{k=0}^{\infty} \rho_f^k (e_{f,t+1+k} + r_{t+1+k} - \Delta d_{f,t+1+k}) - K_f, \quad (2)$$

where ρ_n $(0 < \rho_n < 1)$ is the average ratio of the net asset value to the sum of the net asset value and the dividend, ρ_f $(0 < \rho_f < 1)$ is the average ratio of the closed-end fund share price to the sum of the share price and the dividend, and K_n and K_f are nonlinear functions of ρ_n and ρ_f, respectively. Since $d_{n,t} = d_{f,t} = d_t$ for closed-end funds,

[2] Since $e_{i,t}$ is the difference between two real quantities, the inflation term cancels out and we can measure $e_{i,t}$ as the difference between log nominal returns.

we can compute the log discount $\delta_t = p_{n,t} - p_{f,t}$ from Equations (1) and (2):[3]

$$\delta_t = (K_n - K_f) + \sum_{k=0}^{\infty} \rho_f^k E_t(e_{f,t+1+k}) - \sum_{k=0}^{\infty} \rho_n^k E_t(e_{n,t+1+k}) + \sum_{k=0}^{\infty} (\rho_f^k - \rho_n^k) E_t(r_{t+1+k}) - \sum_{k=0}^{\infty} (\rho_f^k - \rho_n^k) E_t(\Delta d_{t+1+k}). \quad (3)$$

Equation (3) says that discounts vary with the differential variation in the conditional expected excess returns of the closed-end fund share price and the net asset value, and fluctuations in dividend growth rates and real interest rates. The effect of terms involving real interest rate and dividend growth on the time-series variation in discounts depends on how close ρ_n is to ρ_f. For a portfolio of domestic stock closed-end funds, during the time period 1965 to 1985 (the Lee, Shleifer, Thaler data set), we find that the average ratio of stock price to the sum of stock price and the dividend for the closed-end fund and the net asset value are, respectively, $\rho_f = 0.99056$ and $\rho_n = 0.99154$. The difference between ρ_n and ρ_f is 0.00094.[4]

This suggests that the direct effect of terms involving real interest rates and real dividend growth on closed-end fund discounts is likely to be small relative to that of terms involving conditional expected excess returns.[5] Ultimately, how much contribution these terms make to the time-series variation in discounts is an issue that can only be empirically determined. The correlation between closed-end fund discounts and 1-month real T-bill return is approximately −0.30, which is not very large. Table 1, panel D shows that there is very little correlation between closed-end fund discounts and the nominal 1-month T-bill yield. The same is true with respect to the average yield on a portfolio of AAA bonds and the spread between the AAA yield and the 1-month T-bill yield. The standard deviation of the monthly dividend yield on the closed-end fund share price is 0.19% and the standard deviation of the monthly dividend yield on the net asset value is 0.16%.

[3] We abstract away from issues such as capital gains tax liabilities and management fees that lead to differences in dividends between closed-end funds and the underlying securities. These differences may be a source of average discounts. However, since we are interested in this article only in the time-series variation in discounts, these approximations are not expected to be major sources of error. In addition, we assume that closed-end funds pay out dividends as soon as they become available on the underlying assets. This is not an unreasonable assumption since most closed-end funds pay quarterly dividends. Also, federal law requires closed-end funds to pay out the collected dividends within a year if they want to maintain their beneficial tax status [see Anderson and Born (1992)].

[4] $\rho_f < \rho_n$ because the closed-end fund has a higher dividend yield than the net asset value. The higher dividend yield is due to the fact that historically domestic stock closed-end funds have sold on average at a discount.

[5] These terms will, however, have a significant effect on average discounts.

Since dividends are much less volatile than stock prices, it is unlikely that the term involving dividend growth will have a big influence on the time-series variation in discounts.

Therefore, we may think of discounts as a noisy proxy of the differential variation in conditional expected excess returns of the closed-end fund share price and the net asset value. Thompson (1978) reports that discounts contain information about the future expected returns of closed-end funds but not the net asset value. This suggests that discounts track some independent sources of variation in the conditional expected excess returns of closed-end funds. If the expected return components tracked by discounts also affect the conditional expected excess returns of other securities then there will be common variation between discounts and the conditional expected excess returns of other securities. To see this more clearly, assume that discounts follow an AR(1) process with AR(1) coefficient λ $(0 < \lambda < 1)$. Consider a security (for instance, the small firm portfolio) whose conditional expected excess return is correlated with the expected return components affecting closed-end fund discounts. Let us denote this security with the subscript $i = s$. Suppose that the conditional expected excess return on security s follows an AR(1) process with AR(1) coefficient γ $(0 < \gamma < 1)$. Thus

$$\delta_t \;=\; g + \lambda\delta_{t-1} + v_{\delta,t}, \tag{4}$$

$$E_t(e_{s,t+1}) \;=\; h + \gamma E_{t-1}(e_{s,t}) + v_{s,t}, \tag{5}$$

where $v_{\delta,t}$ is the shock to discounts which depends primarily on shocks to $E_t(e_{f,t+1})$ and $E_t(e_{n,t+1})$ and $v_{s,t}$ is the shock to conditional expected excess returns of security s. Consider now the expression for the excess return of security s using the log-linear framework of Campbell (1991):

$$e_{s,t} = E_{t-1}(e_{s,t}) + v_{s,d,t} - v_{s,r,t} - v_{s,e,t}. \tag{6}$$

where $v_{s,d,t} = (E_t - E_{t-1})\sum_{k=0}^{\infty}\rho_s^k\Delta d_{s,t+k}$ represents new information about dividends, $v_{s,r,t} = (E_t - E_{t-1})\sum_{k=0}^{\infty}\rho_s^k r_{t+k}$ represents new information about real interest rates and $v_{s,e,t} = (E_t - E_{t-1})\sum_{k=1}^{\infty}\rho_s^k e_{s,t+k}$ represents new information about conditional expected excess returns.[6] Using Equation (5), the expression for $v_{s,e,t}$ can be simplified to $v_{s,e,t} = \rho_s v_{s,t}/(1-\rho_s\gamma)$.

There will be common variation between closed-end fund discounts and the conditional expected excess returns of security s, if $v_{\delta,t}$ and $v_{s,t}$ [and therefore δ_t and $E_t(e_{s,t+1})$] are correlated. There

[6] $v_{s,d,t}$, $v_{s,r,t}$, and $v_{s,e,t}$ can be contemporaneously correlated with one another.

Table 1
Summary statistics for monthly returns and forecasting variables

Panel A: Returns

Variable	Mean	Standard deviation	Minimum	Maximum	Sum of autocorrelations up to lag 1	3	12	36	60	84
VW	0.22	4.63	−24.91	15.04	0.07	0.00	−0.08	−0.46	−0.21	−0.36
EW	0.40	5.68	−30.12	25.64	0.16	0.08	0.04	−0.25	−0.16	−0.44
*P*1–*P*10	0.31	5.61	−19.77	33.57	0.07	0.05	0.70	1.11	1.14	1.03
Vwcef	0.42	4.53	−21.30	15.45	0.11	−0.02	0.09	−0.27	−0.06	−0.42
Vwnav	0.25	4.37	−21.90	12.51	0.08	0.07	−0.07	−0.52	−0.26	−0.45
Vwdiff	0.17	2.39	−7.01	10.20	−0.07	−0.07	−0.02	0.01	−0.26	−0.45
SMB	0.23	2.98	−10.64	10.48	0.18	0.26	0.82	1.30	1.03	0.18
HML	0.41	2.64	−10.26	8.54	0.17	0.19	0.26	0.15	−0.47	−0.77
Defret	0.05	1.97	−6.16	5.58	−0.24	−0.36	−0.30	−0.52	−0.40	−0.48
Termret	−0.02	3.13	−9.62	12.92	0.04	−0.11	0.26	0.01	−0.05	−0.13

Panel B: Forecasting Variables

Variable	Mean	Standard deviation	Minimum	Maximum	Autocorrelation at lag 1	3	12	36	60	84
D/P	3.95	0.83	2.57	6.27	0.97	0.91	0.66	0.46	0.15	−0.11
Def	0.57	0.34	−0.27	1.46	0.88	0.73	0.47	−0.02	0.22	0.20
Term	2.29	1.67	−2.67	6.88	0.86	0.69	0.38	−0.08	−0.07	−0.10
Tbyld	6.88	2.66	2.52	16.82	0.94	0.83	0.61	0.14	0.01	−0.15
Vwdsc	10.88	8.49	−10.91	25.28	0.96	0.92	0.72	0.07	−0.17	−0.26
$\Delta Vwdsc$	−0.02	2.14	−7.76	7.24	−0.11	0.14	0.17	0.09	0.08	0.07

Panel C: Correlation among returns

Name	*VW*	*EW*	*P*1–*P*10	*SMB*	*HML*	*Defret*	*Termret*
EW	0.93						
*P*1–*P*10	0.20	0.52					
SMB	0.32	0.62	0.83				
HML	−0.38	−0.24	0.23	−0.09			
Defret	−0.12	−0.04	0.20	0.17	0.10		
Termret	0.24	0.28	−0.09	−0.06	−0.04	−0.81	
Δ *Vwdsc*	0.17	0.07	−0.18	−0.09	−0.31	−0.01	0.01

Panel D: Correlation among forecasting variables

Name	*D/P*	*Def*	*Term*	*Tbyld*	*AAAyld*
Def	0.37				
Term	0.04	0.20			
Tbyld	0.67	0.31	−0.43		
AAAyld	0.75	0.47	0.21	0.79	
Vwdsc	0.27	−0.14	−0.21	0.12	−0.01

The data is of monthly frequency and expressed in percent. The time period covered is 7/65 to 12/90. All returns are continuously compounded excess returns. The factor proxy returns are also continuously compounded. *VW* and *EW* are, respectively, the CRSP NYSE value weighted and equal weighted monthly returns. *P1* and *P10* are, respectively, the monthly returns on the smallest and the largest size decile portfolios of NYSE stocks. *Vwcef* and *Vwnav* are, respectively, the monthly closed-end fund share price and net asset value returns on a value-weighted portfolio of domestic stock closed-end funds and *Vwdiff* = *Vwcef*– *Vwnav*. *SMB*, *HML*, *Defret* and *Termret*, respectively, are proxies of firm size, book-to-market, default, and term risk factors. *D/P* is the annualized value weighted dividend yield, *Def* is the annualized default spread, *Term* is the annualized term spread, *Tbyld* is the nominal annualized yield on 1-month T-bills, *AAAyld* is the nominal annualized yield on a portfolio of AAA bonds, and *Vwdsc* is the value weighted closed-end fund discount, all measured end-of-month. Δ *Vwdsc* is the change in *Vwdsc*.

are two ways of testing for common variation in closed-end fund discounts and stock returns: using contemporaneous regressions and using forecasting regressions. First, consider the contemporaneous regression approach of Lee, Shleifer, and Thaler (1991) in which excess returns of security s are regressed on the change in discounts:

$$e_{s,t} = a + b\,\Delta\delta_t + u_t. \tag{7}$$

The slope coefficient from this regression is given by

$$\begin{aligned} b = \ & \frac{1}{\operatorname{var}(\Delta\delta_t)}\left[\operatorname{cov}(v_{s,d,t},\, v_{\delta,t}) - \operatorname{cov}(v_{s,r,t},\, v_{\delta,t}) - \frac{\rho_s \operatorname{cov}(v_{s,t},\, v_{\delta,t})}{1-\rho_s\gamma}\right. \\ & \left. - (1-\lambda)\operatorname{cov}(E_{t-1}(e_{s,t}),\ \delta_{t-1})\right]. \end{aligned} \tag{8}$$

Suppose, that δ_t and $E_t(e_{s,t+1})$ are positively correlated. This ensures that the last two terms inside the square brackets on the right-hand side of Equation (8) are negative. However, whether the slope coefficient b is positive or negative will depend on the other covariance terms on the right-hand side of Equation (8), which can be positive or negative. Consider now a multiperiod forecasting regression of future excess returns on the current level of discounts:

$$\sum_{k=1}^{K} e_{s,t+k} = a_K + b_K\,\delta_t + u_{t,t+K}. \tag{9}$$

The slope coefficient from this regression is given by

$$b_K = \frac{1-\gamma^K}{1-\gamma} \times \frac{\operatorname{cov}[E_t(e_{s,t+1}),\, \delta_t]}{\operatorname{var}(\delta_t)}. \tag{10}$$

If the conditional expected excess return of security s and the closed-end fund discount are positively (negatively) correlated then the slope coefficient b_K will be positive (negative). The advantage of the forecasting regression test is that it provides unambiguous inference about the correlation between the conditional expected excess return of security s and the closed-end fund discount. To the extent that discounts proxy for expected return components that are unique to the closed-end fund, the forecasting regression also provides unambiguous inference about common variation between the conditional expected excess returns of security s and the closed-end fund share price.

Let us examine the Lee, Shleifer, and Thaler (1991) regression results in the context of Equation (8). Lee, Shleifer, and Thaler report that changes in discounts covary negatively with small firm returns. Does this imply that the conditional expected excess returns of closed-end funds and small firms covary positively with one another? Not necessarily, since a negative covariance may arise even if shocks to discounts, $v_{\delta,t}$, and shocks to conditional expected excess returns of security s, $v_{s,t}$, are independent. For instance, if shocks to discounts, $v_{\delta,t}$, is positively correlated with new information about real interest rates, $v_{s,r,t}$, but uncorrelated with new information about dividends, $v_{s,d,t}$, and new information about conditional expected excess returns, $v_{s,t}$, then the slope coefficient b can be negative. This, however, does not imply that there is common variation in the conditional expected excess returns of small firms and closed-end funds.

Even if the multiperiod forecasting regression test confirmed the Lee, Sheleifer, and Thaler results, it is not apparent whether discounts capture some independent sources of variation in the conditional expected excess returns on small firms or simply proxy for other expected return variables such as the dividend yield on the market, the default spread, and the term spread. It is also possible that the correlation between discounts and conditional expected returns of other securities is due to common interest rate effects [see Equation (3) which contains an interest rate term on the right-hand side]. The final issue is, even if discounts do track some independent source of variation in the conditional expected excess returns on small firms, whether such variation is consistent with rational models of asset pricing.

In order to address these issues, our empirical tests proceed as follows: (1) we test whether discounts forecast future excess returns on small firms and closed-end fund share price returns; (2) we test whether the forecasting power of discounts (if any) is related to the forecasting power of variables such as the dividend yield, the default spread, and the term spread; (3) we test whether discounts forecast variables that arguably proxy for risk factors in the economy; and (4) we test whether closed-end fund discounts have information about future macroeconomic variables.

2. Methodology

The primary empirical test we use to examine the relation between discounts and future returns is the multiperiod forecasting regression test of Fama and French (1988a,b, 1989): Consider the OLS regression:

$$\sum_{k=1}^{K} R_{t+k} = X_t\theta + u_{t+K,t}, \tag{11}$$

where R_t is the continuously compounded excess return per month, X_t is a $1 \times m$ row vector of explanatory variables (including the intercept) known by the end of month t, $u_{t+K,t}$ is the regression residual, θ is an $m \times 1$ vector of slope coefficients, and K is the return horizon. For convenience, henceforth, we refer to excess returns simply as returns.

The above regression is usually run with overlapping observations. This implies that the regression residual will be serially correlated up to lag $K-1$ under both the null hypothesis and alternate hypotheses that fully account for time-varying expected returns.[7] In addition, the regression residuals may be conditionally heteroskedastic. To correct for both the induced autocorrelation due to the regression overlap and the conditional heteroskedasticity, we use the GMM standard errors with Newey–West correction [see Hansen (1982), Hansen and Hodrick (1980), and Newey and West (1987)]. The forecasting regressions are run for eight horizons, $K = 1, 12, 24, 36, 48, 60, 72, 84$. Since the regressions corresponding to different horizons use the same data, the corresponding regression slopes will be correlated. Therefore, we use the average slope statistic suggested by Richardson and Stock (1989) to test the hypothesis that the slopes at various horizons are jointly equal to zero.

2.1 Econometric considerations

In our empirical tests we report asymptotic Z-statistics computed using the GMM standard errors. These asymptotic Z-statistics, although consistent, may be biased in finite samples. The bias arises from three sources: the first two are small sample biases, while the last is due to the degree of overlap in the sample. First, since the independent variables in the OLS regressions are not strictly exogenous but only predetermined, the OLS estimators of the slope coefficients would be biased in small samples [see Stambaugh (1986)]. Second, as observed by Richardson and Smith (1991), although the GMM standard errors consistently estimate the asymptotic variance-covariance matrix, they are biased in small samples due to the sampling variation in estimating the autocovariances. Third, as noted by Richardson and Stock (1989), the asymptotic distribution of the OLS estimators may not work well if the degree of overlap is high relative to the sample size, that is, if K is large relative to T. As a result of these biases, the null hypothesis of no forecastability tends to get rejected too often for a given significance level. In order to overcome this problem, we generate small sample distributions of the OLS statistics using Monte Carlo simulations [see Hodrick (1992) and Nelson and Kim (1993)]. Appendix A explains the Monte Carlo simulation methodology.

[7] The regression residual may be autocorrelated beyond lag $K-1$ under the alternate hypothesis if the regressors do not capture all of the time variation.

2.2 Data

The return data includes size decile returns; value weighted and equal weighted market portfolio returns; returns on mimicking portfolios for size; book-to-market, default, and term risk factors; and 1-month T-bill returns. The data on the explanatory variables includes the dividend yield on the value weighted market portfolio, the default spread, the term spread, and the value weighted closed-end fund discount. The macroeconomic data includes quarterly growth rates in real gross domestic product, real consumption and aggregate corporate earnings, quarterly inflation rates, and annual growth rates of real earnings of manufacturing firms based on asset size. These variables are explained in detail below.

2.2.1 Stock returns. The stock return data is obtained from the Center for Research in Security Prices (CRSP) New York Stock Exchange (NYSE) stock files for the sample period July 1965 to December 1990. We use returns on 10 size-ranked portfolios and value weighted and equal weighted market indices. The size decile portfolios are formed as follows. In December of each year, all stocks trading on the NYSE are ranked based on the market value of their equity (size) and divided into 10 portfolios with an approximately equal number of stocks. Only firms with ordinary common shares are included in these portfolios. In addition, all closed-end funds and real estate investment trusts are excluded. This will minimize any spurious association between closed-end fund discounts and small firm returns. Once the size decile portfolios are formed in this manner, membership in the portfolios is kept constant over the following year and equal weighted monthly returns are computed. This process is repeated every year and a time series of monthly returns on the decile portfolios is obtained. The smallest size decile portfolio return is denoted *P1* and the largest size decile portfolio return is denoted *P10*. The two market portfolio returns are the NYSE value weighted market return and the NYSE equal weighted market return, denoted *VW* and *EW*, respectively. All returns are converted to monthly continuously compounded excess returns. The monthly excess return is defined as the difference between the continuously compounded 1-month stock portfolio return and the continuously compounded 1-month T-bill return. The 1-month T-bill return is obtained from the Fama CRSP files and is computed from the 1-month T-bill yield at the end of the previous month.

2.2.2 Factor returns. The mimicking portfolio returns for size and book-to-market factors are the ones used by Fama and French (1993).[8] The two returns proxy for risk factors associated with size and book-to-market and are denoted *SMB* and *HML*, respectively. *SMB* is the return on a portfolio that longs small firms and shorts large firms of approximately the same book-to-market value. *HML* is the return on a portfolio that longs high book-to-market firms and shorts low book-to-market firms of approximately the same size. They are converted into continuously compounded returns. The mimicking portfolio returns for default and term factors are computed according to the definition in Fama and French (1993). The default factor, *Defret*, is defined as the difference between the continuously compounded return on a market portfolio of long-term corporate bonds (obtained from Ibbotson Associates) and the continuously compounded returns on a portfolio of long-term government bonds (obtained from CRSP SBBI series). The term factor, *Termret*, is defined as the difference between the continuously compounded return on a portfolio of long-term government bonds and the continuously compounded 1-month T-bill return. The corporate bond returns are obtained from the Corporate Bond Module of Ibbotson Associates. The government bond returns are obtained from the CRSP Stocks, Bonds, Bills, and Inflation (*SBBI*) series. The 1-month T-bill returns are obtained from Fama CRSP files.

2.2.3 Business cycle variables. The dividend yield on the market is constructed according to the procedure suggested by Fama and French (1988a). An annualized dividend yield, denoted *D/P*, is computed at the end of each month by summing the previous 12 months' dividends on the CRSP NYSE value weighted stock portfolio and then dividing the sum by the value of the portfolio at the end of the month. The use of annualized dividends avoids the seasonal in monthly dividends. The default spread, *Def*, is a measure of the default risk premium in the economy and is defined as the difference between the end-of-month yield on a market portfolio of corporate bonds and the end-of-month yield on a portfolio of AAA bonds. The term spread, *Term*, is a measure of the term risk premium in the economy and is defined as the difference between the end-of-month yield on a portfolio of AAA bonds and the end-of-month yield on a 1-month T-bill. The corporate bond yields are obtained from the Corporate Bond Module of Ibbotson and Associates.

[8] We thank Ken French for permitting us to use this data. For detailed information on how the size and book-to-market factors are constructed see Fama and French (1993).

2.2.4 Closed-end fund discounts and returns. The closed-end fund discount data for the period July 1965 to December 1985 are the same as those used by Lee, Shleifer, and Thaler (1991). The data for the 1985 to 1990 time period was hand collected from the *Wall Street Journal* (WSJ) using the procedure described by Lee, Shleifer, and Thaler in their article. First, a list of 33 domestic stock funds was compiled from the Wiesenberger Investment Companies Services annual survey of mutual funds.[9] For these 33 funds, end-of-month stock prices, net asset values, and discounts were collected from the WSJ. This data was then combined with the number of shares outstanding data from the CRSP NYSE stock files to obtain the net asset value of the fund, NAV. This data was then used to construct a monthly value weighted index of closed-end fund discounts, *Vwdsc*. Defining the net asset value of fund i at time t as NAV_{it} and the share price of fund i at time t as P_{it}, we have

$$Vwdsc_t = \sum_{i=1}^{N_t} w_{it} Disc_{it}.$$

where $w_{it} = \frac{\mathrm{NAV}_{it}}{\sum_{i=1}^{N_t} \mathrm{NAV}_{it}}$ and $Disc_{it} = \frac{\mathrm{NAV}_{it} - \mathrm{P}_{it}}{\mathrm{NAV}_{it}} \times 100$. w_{it} is the weight assigned to fund i at time t based on its NAV relative to the total NAV of all funds at time t and N_t is the number of funds available at time t. The changes in *Vwdsc* are obtained after controlling for common membership in adjacent months,[10] thus, $\Delta Vwdsc_t = Vwdsc_t - Vwdsc_{t-1}$. These definitions are the same as those used by Lee, Shleifer, and Thaler (1991).[11] *Vwnav* is the monthly net asset value return on a value weighted portfolio of domestic stock closed-end funds and *Vwcef* is the corresponding share price return. *Vwnav* and *Vwcef* are converted to continuously compounded excess returns. $Vwdiff = Vwcef - Vwnav$ is the difference between closed-end fund share price returns and net asset value returns. The dividends on closed-end funds were obtained from the CRSP stock files.

2.2.5 Macroeconomic variables. The macroeconomic variables used in this study include the growth rates in quarterly real gross domestic product, *Ggdpq*, quarterly real aggregate consumption, *Gcq*,

[9] We use only domestic stock funds to be consistent with the original Lee, Shleifer, and Thaler data set. The number of funds available each month during this period varied from 9 to 30.

[10] In other words, each fund should have discounts available in the current month and the past month to be included in the portfolio of funds used in the computation of the change in discount.

[11] We also constructed an equal weighted index of domestic stock fund discounts and value weighted and equal weighted indices of domestic plus foreign stock fund discounts. All these indices had time-series properties similar to that of *Vwdsc*.

quarterly real durables consumption, *Gcdq*, quarterly real nondurables consumption plus services, *Gcnq*, quarterly aggregate corporate profits, *Gpatq*, and quarterly inflation rate measured from the consumer price index for all urban consumers, *Gcpiq*. All growth rates are computed as log differences. The data on gross domestic product, consumption, and aggregate corporate profits are seasonally adjusted and are obtained from the CITIBASE files. The data runs from the third quarter of 1965 to the fourth quarter of 1990. The inflation data is not seasonally adjusted and is obtained from the CRSP SBBI files. In addition, annual earnings growth rates of manufacturing firms by asset size are also used. *Gpata1* is the annual growth rate of real earnings of manufacturing firms with total assets (book value) less than \$100 million, *Gpata2* is the annual growth rate of real earnings of manufacturing firms with total assets of \$100 to \$1,000 million, and *Gpata3* is the annual growth rate of real earnings of manufacturing firms with total assets greater than \$1,000 million. The data on the earnings of manufacturing firms is taken from the *Quarterly Financial Report* (QFR) published by the Commerce Department.[12] The annual real earnings growth rates are computed by subtracting the continuously compounded annual inflation rate from the annual nominal earnings growth rate. Using annual earnings growth rates avoids the seasonal in quarterly earnings growth rates.

2.3 Descriptive statistics

Table 1 presents summary statistics for the data described above. The average return difference *Vwcef-Vwnav* is positive, which implies that discounts must be narrowing over the sample period. The negative correlation in the return data at long horizons (see panel A) are indicative of mean reversion in stock prices. The small firm premium defined as $P1 - P10$ and the small firm factor, *SMB*, exhibit similar patterns of autocorrelation. The autocorrelations of the explanatory variables, the dividend yield, the default spread, the term spread, and the discount (see panel B) are high and decline slowly over longer lags. Since these variables move slowly over time, return forecastabil-

[12] The data was hand collected from the *Quarterly Financial Report* (QFR) published by the Economics and Statistics Administration of the U.S. Department of Commerce. The QFR publishes estimated balance sheet and income statement information for all manufacturing corporations based on a stratified (on size and industry) sample survey. A major portion of the sample is chosen from the Internal Revenue Service (IRS) file of corporate entities that file Form 1120 or 1120S and have their principal activity in manufacturing, mining, or wholesale or retail trade. In addition, a separate sample is drawn from applications for a federal Social Security Employer's Identification Number filed with the Social Security Administration (SSA) during the previous quarter by new corporations. According to the QFR, "the composition of the sample changes each quarter to reflect the effects of corporate births, deaths, acquisitions, divestitures, mergers, consolidations, and the like." There does not seem to be any survivorship bias in this data.

ity by these variables would indicate a slowly moving expected return component in stock returns. Panel C presents correlations among the return variables. Not surprisingly, the small firm factor, *SMB*, is very highly correlated with $P1-P10$. The high correlation (83%) indicates that the small firm premium $P1 - P10$ may well be used as a proxy of the small firm factor. There is very little correlation between the change in discounts, $\Delta\,Vwdsc$, and the other return variables. However, the change in discounts, $\Delta\,Vwdsc$, is negatively correlated with $P1-P10$, *SMB*, and *HML* even though the correlations are small. This suggests that there may be some common variation among all four variables. Panel D presents correlations among the explanatory variables. The correlations between discount and the dividend yield, the default spread, the term spread, the 1-month T-bill yield, and the AAA yield are quite small.

3. The Relation Between Small Firm Expected Returns and Discounts

In this section we examine the link between discounts and future expected returns. Specifically, we test if discounts forecast future small firm returns. We first run univariate forecasting regressions as a preliminary test of the results reported by Lee, Shleifer, and Thaler (1991). Then we run multivariate forecasting regressions involving other explanatory variables to ensure that discounts have independent explanatory power.

3.1 Univariate forecasting regressions

The specification for the univariate forecasting regression is as follows:

$$\sum_{k=1}^{K} R_{t+k} = a + b\; Vwdsc_t + u_{t+K,t}. \tag{12}$$

The returns we examine are closed-end fund share price returns, *Vwcef*, closed-end fund net asset value returns, *Vwnav*, the difference between closed-end fund share price returns and net asset value returns, *Vwdiff*, NYSE value weighted excess returns, *VW*, NYSE equal weighted excess returns, *EW*, and the small firm premium, $P1-P10$.[13] We first present results with respect to closed-end fund share price returns and closed-end fund net asset value returns since this allows us to determine whether discounts are associated with time-varying expected returns of closed-end fund share price or net asset value.

[13] The small firm premium is an ex post measure of the small firm risk premium.

We expect high discounts to forecast high expected closed-end fund returns and/or low expected net asset value returns. If the results of Brauer (1988) and Thompson (1978) are any indication, then discounts should forecast only future closed-end fund share price returns. Since negative correlation between changes in discounts and small firm returns suggest positive correlation between discounts and conditional expected small firm returns (see the discussion in Section 1), we expect high discounts to forecast high expected small firm returns. Thus, for all regressions, a one-sided test of the null hypothesis is appropriate.

Table 2 presents the regression results. Panels A, B, and C present the forecasting regression results for fund share price returns, fund net asset value returns, and the difference between share price and net asset value returns. The results indicate that while discounts forecast future expected share price returns, they do not forecast future expected net asset value returns as well. While five out of eight Z-statistics are significant at the 5% or 10% level for the share price regressions, only one out of eight Z-statistics is significant for the net asset value regressions. Also, the joint slope statistic, $\bar{b}$, is significant (at the 10% level) only for the closed-end fund share price returns. In addition, while the signs of OLS slopes are as expected for the share price return regressions, they are mixed for the net asset value return regressions. We find that discounts very strongly forecast the difference between share price and net asset value returns. The OLS slopes are all positive and all of the Z-statistics and the average slope statistic are significant at the 1% level. It appears that by subtracting the net asset value returns from the share price returns we are able to minimize the influence of common expected return components and isolate expected return components that are unique to closed-end fund share price returns. However, it should be noted that there is some evidence that discounts forecast future net asset value returns at longer horizons ($K = 72$ and $K = 84$). While the evidence is weak, it is at least suggestive of a straightforward rational explanation for changing discounts. Overall, these results are consistent with Thompson (1978).

Panels D–F examine the relation between discounts and time-varying expected returns of large and small firms. The results indicate that while discounts forecast future expected small firm returns, they do not forecast future expected large firm returns. In regressions involving the value weighted market returns (see panel D), only one out of eight Z-statistics is significant, and that too at the 10% level. In contrast, in regressions involving the equally weighted market returns (see panel E), three out of eight Z-statistics are significant at the 5% level and one at the 10% level. The R^2s are also higher. The regressions

Table 2
Univariate forecasting regressions of stock portfolio returns on closed-end fund discounts

Panel A: $\sum_{k=1}^{K} Vwcef_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.05	.00	1.43[10]	−2.22	−1.58	−1.21	1.43	1.83	2.58	.41
12	.39	.05	1.41	−3.46	−2.14	−1.64	1.96	2.56	3.77	4.01
24	.70	.09	1.58	−4.08	−2.44	−1.78	2.21	2.87	4.37	7.74
36	.85	.13	1.99	−4.39	−2.65	−1.96	2.44	3.22	5.19	10.81
48	1.51	.17	3.14[10]	−5.22	−2.99	−2.13	2.73	3.65	5.71	28.93
60	2.13	.19	3.40[10]	−5.64	−3.37	−2.38	2.99	4.04	6.39	38.05
72	2.61	.22	4.73[5]	−6.03	−3.70	−2.59	3.23	4.54	7.46	44.12
84	2.99	.25	9.11[5]	−7.22	−4.11	2.87	3.77	5.14	9.33	50.44
$\bar{b}$	1.40[10]			−2.15	−1.40	−1.02	1.32	1.65	2.30	

Panel B: $\sum_{k=1}^{K} Vwnav_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.00	.01	.15	−2.24	−1.55	−1.18	1.51	1.88	2.64	−.32
12	.01	.06	.04	−3.33	−2.14	−1.59	2.03	2.64	3.80	−.34
24	−.13	.11	−.29	−3.90	−2.41	−1.76	2.30	2.95	4.41	−.01
36	−.32	.15	−.88	−4.16	−2.65	−1.97	2.53	3.26	5.15	1.85
48	.16	.19	.37	−4.96	−2.92	−2.11	2.72	3.61	5.99	.13
60	.67	.22	1.11	−5.32	−3.34	−2.35	2.98	4.07	6.88	6.01
72	1.12	.25	2.07	−5.93	−3.67	−2.57	3.34	4.64	7.98	14.41
84	1.51	.27	6.22[5]	−7.03	−4.17	−2.89	3.84	5.25	8.96	25.09
$\bar{b}$	.38			−2.16	−1.34	−.99	1.31	1.66	2.38	

Panel C: $\sum_{k=1}^{K} Vwdiff_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.04	.00	2.65[1]	−2.35	−1.71	−1.34	1.24	1.59	2.20	1.80
12	.37	−.01	3.49[1]	−3.63	−2.43	−1.90	1.66	2.21	3.31	22.46
24	.83	−.02	5.27[1]	−4.30	−2.80	−2.14	1.91	2.57	3.87	47.17
36	1.17	−.02	6.56[1]	−4.88	−3.06	−2.28	2.19	2.85	4.67	63.38
48	1.36	−.02	8.21[1]	−5.66	−3.35	−2.51	2.35	3.25	5.30	74.35
60	1.46	−.02	11.50[1]	−6.38	−3.77	−2.80	2.59	3.62	5.90	82.54
72	1.49	−.02	10.81[1]	−7.06	−4.30	−3.03	2.94	4.03	6.91	82.89
84	1.48	−.02	9.88[1]	−8.34	−4.81	−3.42	3.31	4.68	7.80	78.67
$\bar{b}$	1.02[1]			−.86	−.62	−.48	.45	.59	.88	

Panel D: $\sum_{k=1}^{K} VW_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.00	.01	−.15	−2.18	−1.51	−1.17	1.47	1.87	2.58	−.32
12	−.08	.06	−.26	−3.20	−2.16	−1.60	1.97	2.60	3.83	−.15
24	−.30	.11	−.63	−3.76	−2.46	−1.76	2.21	2.95	4.33	1.34
36	−.52	.16	−1.24	−4.28	−2.70	−1.93	2.50	3.26	5.11	4.68
48	−.04	.21	−.07	−4.74	−2.92	−2.10	2.75	3.63	6.07	−.37
60	.49	.26	.64	−5.34	−3.08	−2.27	3.07	4.18	6.86	2.28
72	.97	.29	1.39	−5.88	−3.51	−2.49	3.40	4.75	7.79	8.10
84	1.44	.33	4.34[10]	−6.61	−3.91	−2.82	3.86	5.46	9.57	16.27
$\bar{b}$	.24			−2.15	−1.37	−1.03	1.39	1.78	2.46	

Table 2
continued

Panel E: $\sum_{k=1}^{K} EW_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.02	.01	.58	−2.24	−1.52	−1.15	1.48	1.86	2.53	−.21
12	.29	.08	.77	−3.20	−2.15	−1.59	2.01	2.62	3.99	1.22
24	.59	.16	1.11	−3.84	−2.40	−1.77	2.29	2.92	4.52	3.42
36	.89	.22	2.02	−4.30	−2.58	−1.87	2.49	3.33	5.24	7.18
48	1.84	.28	3.81^{5}	−4.64	−2.88	−2.05	2.79	3.68	5.92	28.34
60	2.60	.34	4.06^{10}	−5.13	−3.11	−2.23	3.06	4.07	6.79	41.56
72	2.96	.38	5.71^{5}	−5.78	−3.42	−2.43	3.33	4.70	8.39	42.91
84	3.00	.43	7.91^{5}	−6.86	−3.87	−2.65	3.90	5.53	9.39	38.35
$\bar{b}$	1.52			−2.54	−1.66	−1.21	1.73	2.17	3.04	

Panel F: $\sum_{k=1}^{K} P1 - P10_{t+k} = a + b\ Vwdsc_t + u_{t+K,t}$

				Fractiles of statistics						
K	b	Bias	$Z(b)$	.01	.05	.10	.90	.95	.99	Adj. R^2
1	.05	.01	1.41^{10}	−2.20	−1.56	−1.20	1.40	1.73	2.40	.20
12	.78	.05	3.09^{5}	−3.28	−2.19	−1.62	1.91	2.47	3.63	10.03
24	1.98	.10	4.19^{5}	−3.74	−2.45	−1.80	2.15	2.83	4.24	26.90
36	3.16	.14	5.11^{1}	−4.24	−2.80	−2.01	2.40	3.07	4.84	47.86
48	4.08	.17	5.77^{1}	−4.91	−3.10	−2.20	2.66	3.48	5.41	63.68
60	4.35	.18	4.83^{5}	−5.60	−3.30	−2.35	2.97	4.02	6.79	58.18
72	3.90	.20	3.67^{10}	−6.41	−3.70	−2.65	3.29	4.41	7.32	41.77
84	2.70	.24	3.11	−7.05	−4.30	−2.91	3.67	5.07	8.95	18.71
$\bar{b}$	2.62^{5}			−2.79	−1.82	−1.36	1.59	2.05	2.86	

Regressions for $K > 1$ use overlapping observations. b is the slope coefficient from the OLS regression. $Z(b)$ is the asymptotic Z-statistic computed using the generalized method of moments (GMM) standard errors with Newey–West correction. These standard errors correct for the induced sample auto-correlation in $u_{t+K,t}$ due to overlapping observations as well as for generalized conditional heteroskedasticity. Adj. R^2 is the adjusted coefficient of determination (in percent). Bias is the mean of the empirical distribution of b generated under the null hypothesis $b = 0$ from 5,000 trials of a Monte Carlo simulation. $\bar{b}$ is the average slope statistic. The columns labeled fractiles represent the empirical distribution of $Z(b)$ and $\bar{b}$ obtained under the null hypothesis from the same Monte Carlo simulation. Superscripts: 10 = significant at the 10% level; 5 = significant at the 5% level; 1 = significant at the 1% level.

involving the small firm premium, $P1 - P10$, in panel F provides the strongest evidence linking discounts and small firm expected returns. Two out of eight Z-statistics are significant at the 1% level, three at the 5% level, and two at the 10% level. The average slope statistic is significant at the 5% level. The adjusted R^2 first increases with K reaching a maximum at $K = 48$ and then decreases. The slope coefficients have the right sign at all horizons, indicating that high discounts are associated with high small firm expected returns.[14] These results confirm

[14] We have also examined the forecasting power of discounts with respect to individual decile portfolio returns (not reported here) and have found that the forecasting power of discounts declines with size.

the Lee, Shleifer, and Thaler results and provide preliminary evidence that the conditional expected returns of small firms and closed-end funds covary positively with one another.

A brief discussion of the economic magnitude of the slope coefficients is in order here. Focusing on the regression involving the small firm premium, $P1 - P10$, we find that at the 60-month horizon, an increase of 1% in discounts is associated with an increase of 0.07% per month in the expected small firm premium. Therefore, a one standard deviation change in discounts (8.49%) will cause a change of about 0.60% per month in the expected small firm premium. This is almost twice as large as the mean small firm premium of 0.31% over the time period, 1965 to 1990 (see Table 1, panel A). These numbers suggest that the time variation in the expected small firm premium is economically significant.

Since changes in discounts and small firm returns are contemporaneously correlated (see Table 1, panel C) and small firm returns are autocorrelated at long horizons (see Table 1, panel A), it is possible that discounts are simply proxying for lagged small firm returns. Therefore, in our forecasting regressions, it would be interesting to know if discounts have explanatory power for future small firm returns beyond that associated with lagged small firm returns. Table 3 presents the empirical results from regressing future small firm returns on lagged discount and lagged small firm returns. We use two proxies of small firm excess returns: excess returns on the smallest size decile in NYSE, *P1*, and excess returns on the NYSE equally weighted market portfolio, *EW*. We use the sum of 12 lags of small firm returns as a proxy for lagged small firm returns.[15] The evidence presented in panels A and B of Table 3 indicates that discounts have *independent* explanatory power beyond that associated with lagged small firm returns.

3.2 Multivariate forecasting regressions

A potential problem with the results presented in the previous section is the possibility that the forecasting power of closed-end fund discounts might disappear in the presence of other commonly used forecasting variables such as the dividend yield on the market, the default spread, and the term spread. Therefore, we repeat the regressions in the previous section by including other forecasting variables on the right-hand side. The specification for the multivariate forecast-

[15] We have also run these regressions using the sum of 24, 36, 48, or 60 lags of small firm returns and the results are similar. Since the use of 12 lags provides the largest Z-statistics for lagged small firm returns we have chosen to report those results.

Table 3
Forecasting power of discounts in the presence of lagged returns

Panel A: $\sum_{k=1}^{K} P1_{t+k} = a + b\ Vwdsc_t + c\ \sum_{l=1}^{12} P1_{t-l+1} + u_{t+K,t}$

K	b	$Z(b)$	c	$Z(c)$	Adj. R^2
1	0.03	0.51	0.02	1.02	−0.02
12	0.66	1.47	−0.08	−0.50	3.76
24	1.51	2.76	−0.33	−2.11	15.78
36	2.25	4.37	−0.38	−4.96	28.64
48	3.62	9.22	−0.31	−2.73	57.68
60	4.46	12.66	−0.51	−6.74	69.72
72	4.60	13.17	−0.77	−5.12	70.61
84	4.06	7.24	−0.92	−5.78	63.61

Panel B: $\sum_{k=1}^{K} EW_{t+k} = a + b\ Vwdsc_t + c\ \sum_{l=1}^{12} EW_{t-l+1} + u_{t+K,t}$

K	b	$Z(b)$	c	$Z(c)$	Adj.R^2
1	0.02	0.53	0.00	0.11	−0.56
12	0.37	0.91	−0.16	−0.92	3.49
24	0.68	1.22	−0.40	−2.71	11.79
36	0.95	1.91	−0.40	−4.04	13.88
48	1.97	3.91	−0.24	−2.19	31.75
60	2.84	4.31	−0.39	−4.60	48.50
72	3.33	5.61	−0.69	−3.25	55.98
84	3.40	10.60	−0.77	−3.74	55.03

Regressions for $K > 1$ use overlapping observations. b and c are the slope coefficients from the OLS regression. $Z(b)$ and $Z(c)$ are the asymptotic Z-statistics computed using the generalized method of moments (GMM) standard errors with Newey–West correction. These standard errors correct for the induced sample autocorrelation in $u_{t+K,t}$ due to overlapping observations as well as for generalized conditional heteroskedasticity. Adj. R^2 is the adjusted coefficient of determination (in percent).

ing regression is as follows:

$$\sum_{k=1}^{K} R_{t+k} = a + b\, D/P_t + c\, Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}. \quad (13)$$

Panels A–F in Table 4 present the multivariate forecasting regression results. The columns labeled p-value in Table 4 represent the observed significance levels obtained from the Monte Carlo simulation of corresponding test statistics to the left. The table also presents p-values for adjusted R^2 in order to test whether the forecasting variables jointly predict future returns.

Panels A–C present multivariate forecasting regression results for closed-end fund share price returns, net asset value returns, and their difference. The results indicate that discounts forecast future share price returns even in the presence of other commonly used expected

Table 4
Multivariate forecasting regressions of stock portfolio returns

Panel A: $\sum_{k=1}^{K} Vwcef_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.54	1.52	.177	.15	.18	.450	.42	2.68	.007	.05	1.44	.108	3.09	.015
12	7.01	2.47	.127	5.73	1.04	.234	1.49	1.13	.233	.30	1.39	.193	25.62	.048
24	12.69	2.43	.185	6.03	1.22	.215	−.67	−.42	.670	.37	.92	.315	35.78	.065
36	17.06	3.10	.145	−.87	−.13	.564	−.98	−.50	.699	.35	.93	.331	49.23	.035
48	17.94	4.18	.099	−1.20	−.23	.590	1.05	.63	.408	1.09	4.28	.037	65.71	.006
60	21.81	5.77	.060	.66	.14	.509	3.24	3.06	.053	1.68	5.74	.023	81.20	.000
72	25.47	6.51	.056	−3.51	−.85	.706	2.01	1.78	.199	1.94	6.80	.019	84.65	.001
84	26.53	5.75	.111	−14.63	−2.16	.877	1.18	.66	.448	2.07	8.74	.016	83.01	.002
Mean	16.13		.113	−.95		.580	.97		.388	.98		.166		

Panel B: $\sum_{k=1}^{K} Vwnav_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.64	1.76	.154	−.08	−.09	.534	.49	3.26	.001	.01	.25	.414	3.89	.005
12	8.29	3.37	.061	1.86	.32	.398	2.41	1.80	.111	−.09	−.38	.623	27.85	.037
24	14.03	3.25	.114	−1.37	−.28	.570	.41	.31	.459	−.49	−1.31	.798	33.89	.088
36	17.24	4.23	.077	−9.04	−1.53	.846	.65	.41	.448	−.80	−2.93	.938	50.97	.032
48	16.51	5.19	.066	−3.52	−1.01	.742	2.68	1.97	.136	−.17	−.79	.682	54.66	.044
60	17.68	4.81	.111	8.26	1.49	.196	3.87	3.78	.029	.36	1.19	.323	66.90	.015
72	20.28	5.08	.131	7.43	1.19	.262	1.97	1.53	.243	.61	1.82	.254	71.48	.012
84	21.77	6.27	.107	−2.74	−.46	.594	.70	.39	.515	.74	4.49	.079	74.85	.010
Mean	14.55		.170	.10		.515	1.65		.255	.02		.527		

Table 4
continued

Panel C: $\sum_{k=1}^{K} Vwdiff_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	−.11	−.62	.644	.23	.52	.346	−.07	−.89	.885	.04	2.51	.008	1.21	.110
12	−1.28	−1.11	.719	3.87	1.68	.153	−.92	−2.57	.976	.39	3.70	.008	29.80	.014
24	−1.34	−.65	.595	7.40	2.48	.075	−1.08	−1.64	.889	.86	5.25	.004	53.40	.002
36	−.18	−.08	.449	8.17	3.25	.032	−1.64	−2.14	.924	1.15	5.69	.005	70.41	.000
48	1.43	.87	.263	2.32	.79	.368	−1.63	−2.53	.947	1.26	7.26	.004	78.60	.000
60	4.14	4.51	.023	−7.60	−3.61	.983	−.63	−1.83	.867	1.32	19.42	.000	86.68	.000
72	5.19	5.41	.018	−10.93	−3.91	.984	.04	.07	.482	1.33	17.44	.000	89.67	.000
84	4.76	2.70	.110	−11.89	−5.13	.989	.48	.69	.349	1.32	8.81	.009	85.38	.001
Mean	1.58		.248	−1.05		.682	−.68		.821	.96		.004		

Panel D: $\sum_{k=1}^{K} VW_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.70	1.75	.171	.04	.04	.484	.52	3.44	.001	.00	−.02	.504	4.15	.005
12	8.30	3.42	.066	3.73	.63	.320	3.06	2.49	.055	−.15	−.64	.674	33.96	.013
24	14.16	3.53	.104	3.88	.91	.272	1.15	.89	.321	−.60	−1.64	.846	41.04	.041
36	17.92	4.90	.061	−.21	−.05	.513	1.09	.69	.399	−.95	−3.45	.958	59.23	.011
48	17.51	5.21	.074	8.48	1.43	.187	2.81	2.25	.113	−.35	−1.45	.785	62.48	.020
60	19.74	5.38	.097	20.54	3.20	.039	3.88	3.40	.045	.14	.35	.468	74.74	.004
72	24.38	6.94	.064	16.66	2.10	.123	1.69	1.40	.292	.35	.77	.409	78.62	.003
84	28.09	8.91	.043	3.22	.47	.392	.55	.32	.557	.45	2.36	.223	81.37	.003
Mean	16.35		.152	7.04		.265	1.84		.256	−.14		.598		

Table 4
continued

Panel E: $\sum_{k=1}^{K} EW_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.87	1.83	.135	.20	.19	.449	.57	3.08	.003	.03	.59	.319	3.64	.008
12	11.34	3.44	.055	2.51	.40	.400	2.93	2.03	.103	.14	.42	.420	31.60	.017
24	17.79	2.83	.163	1.34	.21	.464	−.72	−.33	.672	.10	.17	.494	33.88	.097
36	21.27	3.39	.140	−3.60	−.70	.698	−.93	−.31	.665	.26	.56	.420	42.73	.083
48	20.58	3.84	.146	1.74	.23	.469	1.53	.67	.413	1.38	4.12	.046	62.82	.016
60	21.07	5.24	.096	10.04	1.70	.183	3.37	1.75	.200	2.19	6.37	.017	76.48	.002
72	24.00	4.57	.161	2.55	.34	.452	2.72	1.53	.264	2.36	8.55	.012	73.28	.010
84	26.14	3.16	.343	−8.26	−.65	.657	2.84	1.51	.298	2.10	4.50	.083	65.19	.049
Mean	17.88		.201	.82		.504	1.54		.362	1.07		.211		

Panel F: $\sum_{k=1}^{K} P1 - P10_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.07	.17	.471	.28	.29	.429	.12	.71	.271	.05	1.48	.094	−.59	.696
12	4.98	1.18	.232	−5.43	−.80	.765	−.65	−.43	.665	.59	1.89	.115	12.45	.282
24	4.10	.57	.403	−12.06	−.80	.749	−5.53	−2.01	.941	1.56	3.01	.053	36.09	.046
36	1.64	.21	.496	−13.50	−.78	.746	−6.86	−1.95	.934	2.75	5.06	.014	57.23	.010
48	−1.39	−.24	.600	−16.33	−1.03	.789	−5.63	−1.65	.889	3.83	8.00	.002	69.41	.002
60	−7.64	−1.64	.813	−16.13	−1.73	.892	−4.76	−1.15	.808	4.37	6.32	.015	64.53	.010
72	−13.18	−1.37	.763	−25.56	−1.36	.828	−1.56	−.39	.653	4.20	4.12	.075	51.85	.081
84	−19.38	−1.50	.761	−15.67	−.79	.736	2.04	.39	.481	3.41	2.85	.174	31.57	.366
Mean	−3.85		.689	−13.05		.873	−2.85		.898	2.59		.013		

The asymptotic Z-statistics are computed using the GMM standard errors with Newey–West correction. The columns labeled p-value refer to the upper tail observed significance levels of the corresponding test statistics to the left. The observed significance levels are obtained by comparing the test statistics to their empirical distributions generated from 5,000 trials of a Monte Carlo simulation. The artificial data for the simulation are generated under the null hypothesis using the VAR approach. Mean represents the average slope statistic.

return variables.[16] Furthermore, while the dividend yield and the term spread forecast both the share price returns and the net asset value returns, the discount forecasts only the share price returns. This can be seen more clearly from regressions involving the difference between fund share price returns and net asset value returns in panel C. The variable that forecasts the difference in returns, *Vwdiff*, the best is the closed-end fund discount. All of the Z-statistics and the average slope statistic corresponding to discounts are significant at the 1% level. On the other hand, relatively few of the statistics associated with the other explanatory variables are significant and none of the average slope statistics are significant. This suggests that while the dividend yield and the term spread may proxy for expected return components that are common to both the fund share price return and the fund net asset value return, the closed-end fund discount may proxy for expected return components that are unique to the fund share price return.

The results in panels D–F examine whether discounts forecast small firm returns in the presence of other forecasting variables. We skip discussion of panel D since it basically confirms our univariate forecasting regression results that discounts do not forecast large firm returns. The results in panels E and F confirm the univariate forecasting regression results that discounts forecast small firm returns. This is consistent with our prior that discounts track some independent sources of variation in conditional expected small firm returns. Also, as expected, we find that the dividend yield, the default spread, and the term spread forecast both small firm and large firm returns. However, these commonly used expected return variables are not able to forecast the difference between small firm and large firm returns, $P1 - P10$. Considering the results in panel F with respect to the small firm premium, we find that the only variable that forecasts the small firm premium is the closed-end fund discount. Examining the Z-statistics with respect to discounts, we find that one out of eight Z-statistics is significant at the 1% level, two at the 5% level, and three at the 10% level. In addition, the average slope statistic is significant at the 5% level. On the other hand, very few of the Z-statistics corresponding to the dividend yield, the default spread, and the term spread are significant and none of the average slope statistics are significant. These results suggest that while the dividend yield, the default spread and the term spread track components of time-varying expected returns common to both small firms and large firms, discounts track components of time-varying expected

[16] These results are consistent with Pontiff (1995) who finds that discounts predict future closed-end fund share price returns even in the presence of other variables that affect expected returns.

returns unique to small firms. By subtracting the largest size decile stock return from the smallest size decile stock return, we are able to eliminate expected return components that are common to both small firms and large firms and isolate components that are unique to small firms and closed-end funds.

4. Discounts and Factor Risk Premia

Fama and French (1993) decompose stock and bond returns into five empirical factors: three stock market factors and two bond market factors. The stock market factors are the market factor, *VW*, the small firm factor, *SMB*, and the book-to-market factor, *HML*. The bond market factors are the default risk factor, *Defret*, and the term risk factor, *Termret*. In this section we examine the forecasting power of closed-end fund discounts by examining whether discounts forecast one or more of these factor returns. This would allow us to determine what kind of risks discounts are associated with and shed some light on the determinants of the time-series relationship between conditional expected excess returns of small firms and closed-end fund discounts.

Since we have already shown that discounts do not forecast the value weighted market returns (the market factor), we perform the forecasting regressions only for the remaining four factors. Panels A–D in Table 5 report the results of multivariate forecasting regressions for the small firm factor, the book-to-market factor, the default risk factor, and the term risk factor. The results with respect to the small firm factor, *SMB*, indicate that only the discount, and to a lesser extent the default spread, forecast the small firm factor. All of the slope coefficients with respect to the discount have the right sign and five out of eight Z-statistics are significant. The average slope statistic is significant at the 1% level, indicating that discounts strongly forecast expected small firm factor risk premium. The results with regard to the default spread provide some weak evidence that the default spread forecasts small firm risk premium. However, when we ran univariate forecasting regressions of the small firm factor on the default spread (not reported), we found that the default spread had no explanatory power for the small firm factor. We suspect that the weak significance of the slope coefficients corresponding to the default spread is due to the high R^2 of these regressions arising from the explanatory power of discounts.

Panel B presents regression results with respect to the book-to-market factor, *HML*. The results indicate that none of the forecasting variables, including the discount, have any explanatory power for the

Table 5
Multivariate forecasting regressions of factor returns

Panel A: $\sum_{k=1}^{K} SMB_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.24	1.01	.210	−.10	−.18	.609	.04	.41	.366	.03	1.34	.107	.10	.374
12	5.36	1.87	.141	− 4.22	−.98	.800	−.54	−.51	.683	.31	1.32	.198	19.22	.101
24	6.63	1.28	.280	−7.33	−1.15	.823	−3.09	−1.51	.886	.85	2.04	.125	36.20	.048
36	6.88	1.23	.321	−8.98	−1.54	.878	−3.03	−1.13	.812	1.57	3.46	.043	51.87	.017
48	7.68	1.32	.327	−13.23	−2.73	.967	−2.39	−.83	.753	2.32	5.35	.017	65.52	.006
60	5.80	1.00	.405	−19.35	−3.17	.975	−1.58	−.50	.672	2.92	6.19	.013	68.82	.006
72	3.42	.53	.500	−24.89	−2.36	.928	.70	.23	.504	3.09	6.26	.018	62.33	.028
84	.74	.09	.588	−24.12	−2.04	.884	2.76	.92	.351	2.87	4.52	.066	47.94	.132
Mean	4.59		.310	−12.78		.964	−.89		.803	1.74		.002		

Panel B: $\sum_{k=1}^{K} HML_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	−.18	−.85	.698	.08	.16	.451	−.06	−.67	.727	.01	.46	.381	−.85	.849
12	−3.11	−1.69	.806	1.69	.47	.376	.72	.67	.283	.23	1.35	.209	5.21	.687
24	−5.27	−1.31	.691	7.72	.98	.267	1.45	1.18	.182	.52	2.11	.128	12.69	.548
36	−6.32	−1.08	.616	16.40	1.21	.228	−.03	−.02	.462	.72	2.76	.095	16.68	.521
48	−5.85	−.88	.560	18.18	1.20	.245	−.82	−.49	.579	.53	1.61	.251	9.95	.781
60	−7.17	−.96	.559	17.60	1.66	.180	−1.40	−.66	.613	.25	.65	.438	8.79	.844
72	−5.88	−.84	.514	7.67	.90	.341	−.44	−.17	.495	−.08	−.23	.595	5.37	.933
84	−4.25	−.89	.504	12.53	2.63	.109	.70	.25	.393	−.47	−1.83	.808	15.50	.735
Mean	−4.75		.706	10.23		.066	.01		.441	.21		.403		

Table 5
continued

Panel C: $\sum_{k=1}^{K} Defret_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	−.28	−1.97	.951	.33	.87	.226	.03	.32	.406	.01	.96	.174	−.17	.487
12	−.52	−.78	.621	1.24	.75	.339	.35	.90	.278	.13	1.94	.096	4.34	.741
24	−.61	−.49	.529	2.34	1.00	.287	.16	.36	.425	.24	1.97	.120	11.34	.577
36	−.48	−.42	.498	2.85	.93	.315	−.20	−.40	.636	.22	1.59	.189	12.61	.636
48	−1.39	−.95	.592	.05	.01	.556	−.35	−.64	.700	.25	1.63	.198	19.67	.499
60	−1.52	−1.61	.680	−4.30	−1.51	.849	.15	.29	.467	.33	1.91	.181	28.80	.345
72	−1.63	−1.24	.591	−3.55	−.89	.741	.70	1.62	.198	.31	2.39	.154	23.55	.504
84	−2.57	−1.85	.659	−2.50	−.91	.740	1.19	2.27	.137	.21	2.75	.146	28.02	.448
Mean	−1.13		.484	−.44		.610	.25		.429	.21		.278		

Panel D: $\sum_{k=1}^{K} Termret_{t+k} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	p-value	c	$Z(c)$	p-value	d	$Z(d)$	p-value	e	$Z(e)$	p-value	Adj. R^2	p-value
1	.49	2.04	.057	.12	.19	.406	.30	2.15	.013	−.02	−.71	.779	3.48	.008
12	2.53	1.51	.266	3.55	.91	.239	2.31	2.86	.016	−.30	−1.75	.895	26.53	.032
24	3.78	1.03	.410	9.61	1.20	.193	2.35	1.50	.115	−.76	−2.54	.938	34.68	.060
36	5.18	.96	.455	16.04	1.16	.216	2.11	1.57	.112	−1.06	−3.62	.975	42.77	.052
48	5.78	.83	.515	30.09	1.76	.132	1.52	.88	.238	−1.07	−2.57	.920	46.31	.069
60	6.30	1.14	.478	40.04	3.34	.030	1.24	.50	.323	−1.13	−1.82	.842	48.16	.092
72	9.40	1.60	.432	34.86	2.51	.083	.09	.03	.438	−1.12	−1.99	.833	44.47	.167
84	14.88	2.60	.317	27.00	2.49	.098	−1.03	−.42	.526	−1.14	−4.30	.947	48.44	.153
Mean	6.04		.330	20.16		.010	1.11		.176	−.82		.926		

The asymptotic Z-statistics are computed using the GMM standard errors with Newey–West correction. The columns labeled p-value refer to the upper tail observed significance levels of the corresponding test statistics to the left. The observed significance levels are obtained by comparing the test statistics to their empirical distributions generated from 5,000 trials of a Monte Carlo simulation. The artificial data for the simulation are generated under the null hypothesis using the VAR approach. Mean represents the average slope statistic.

book-to-market factor.[17] Panels C and D present regression results with respect to the default risk factor and the term risk factor. None of the forecasting variables predict the default risk factor (see panel C), including the default spread variable.[18] Relevant to this article is the result that discounts do not forecast future default risk factor returns. The results corresponding to the term risk factor (see panel D) indicate that the dividend yield, the default spread, the term spread, and the closed-end fund discount all predict the term risk factor. It is interesting to note that while the default spread predicts the term risk factor, it does not forecast the default risk factor. The slope coefficients corresponding to the discount are uniformly negative in sign and provide some weak evidence that discounts forecast expected term risk premium.

Overall the evidence suggests that discounts track the risk premium associated with a single empirical factor, namely, the small firm factor. The question now is whether the information in discounts is related to fundamental risks or to some nonfundamental factors such as investor sentiment. One way to address this is to test if discounts have any information about future macroeconomic conditions. We turn to this issue in the next section.

5. Discounts and Macroeconomic Risks

The results in the previous section suggest that the information in closed-end fund discounts is mostly related to the small firm factor risk premium. However, it is not clear whether this risk premium results from fundamental risks or from nonfundamental risks such as the noise trading risks of De Long et al. (1990). If the risk premium tracked by discounts is the result of fundamental risks in the economy, then it should respond to news about future economic conditions. We examine this issue by testing if discounts forecast indicators of future economic activity. We use quarterly growth rates in real gross domestic product, *Ggdpq*, real aggregate consumption, *Gcq*, real durables con-

[17] Breen and Korajczyk (1994) report that the book-to-market cross-sectional asset pricing effect is halved when data that is free of selection biases is used. While this result is not directly related to our time-series evidence, it is plausible that if the book-to-market effect is subject to biases in the data, then the mimicking portfolio returns will also be subject to such biases. Whether these biases can explain why commonly used forecasting variables such as the dividend yield, the default spread, and the term spread are unable to predict the book-to-market factor is an interesting avenue for future research.

[18] This result is also puzzling since one would expect the ex ante default risk variable to predict the ex post default risk variable. Note that the ex ante default risk variable, *Def*, is constructed as the difference between the yield on a market portfolio of corporate bonds and the AAA yield, while the ex post default risk variable, *Defret*, is constructed as the difference between the monthly returns on a market portfolio of corporate bonds and long-term government bond returns.

Table 6

Panel A: Quarterly growth rates and inflation summary statistics for macroeconomic variables

Variable	Mean	Standard deviation	Minimum	Maximum	Autocorrelation at lag 1	2	3	4	8	16
Gpatq	0.22	6.79	−20.75	16.99	0.31	0.05	0.00	0.00	−0.30	0.10
Ggdpq	0.67	0.96	−2.60	3.16	0.27	0.15	0.03	0.03	−0.28	−0.01
Gcq	0.77	0.72	−2.07	2.46	0.20	0.17	0.24	0.03	−0.23	0.01
Gcdq	1.00	3.83	−12.72	10.25	−0.13	0.11	0.01	0.01	−0.13	0.12
Gcnq	0.74	0.48	−0.78	2.36	0.32	0.18	0.30	0.05	−0.20	−0.10
Gcpiq	1.43	0.86	−0.43	4.22	0.62	0.51	0.57	0.53	0.16	0.08

Panel B: Annual earnings growth rates of manufacturing firms

Variable	Mean	Standard deviation	Minimum	Maximum	Autocorrelation at lag 1	2	3	4	5	6
*Gpata*1	−2.24	22.29	−51.77	35.58	−0.08	−0.24	−0.16	0.00	0.16	−0.23
*Gpata*2	−4.74	20.05	−46.73	30.83	0.09	−0.29	−0.07	−0.01	0.02	−0.43
*Gpata*3	2.29	18.14	−35.18	33.23	−0.13	−0.35	0.00	0.04	0.22	−0.31
Gcpia	5.74	2.96	1.13	12.49	0.64	0.14	−0.05	0.05	0.11	−0.03

The table presents summary statistics for macroeconomic variables. The data is of quarterly frequency and in percent. The time period covered is from the third quarter of 1965 to the fourth quarter of 1990. *Gdpq* refers to the quarterly growth rate of real gross domestic product, *Gcq* refers to the quarterly growth rate of real aggregate consumption, *Gcdq* refers to the quarterly growth rate of real durables consumption, *Gcnq* refers to the quarterly growth rate of real nondurables consumption and services, *Gpatq* refers to the quarterly growth rate of real aggregate corporate profits after taxes, and *Gcpiq* refers to the quarterly inflation rate measured from the consumer price index for all urban consumers. *Gpata1* is the annual growth rate of real earnings of manufacturing firms of asset size (book value) less than \$100 million, *Gpata2* is the annual growth rate of real earnings of manufacturing firms of asset size (book value) \$100 to \$1,000 million, and *Gpata3* is the annual growth rate of real earnings of manufacturing firms of asset size greater than \$1,000 million. *Gcpia* refers to the annual inflation rate measured from the consumer price index for all urban consumers.

sumption *Gcdq*, real nondurables and services consumption, *Gcnq*, real aggregate after-tax corporate profits, *Gpatq*, and quarterly inflation rate, *Gcpiq*, as measures of future economic activity. The summary statistics for these macroeconomic variables are provided in panel A of Table 6. The forecasting regression specification is given by

$$Growth_{t+K} = a + bVwdsc_t + u_{t,t+K}. \tag{14}$$

Note that this regression is different from the multiperiod regression specification used so far. Here we are simply testing if discounts track expectations about economic activity K quarters ahead. The regressions are run for $K = 1, 2, \ldots, 16$, which is up to 16 quarters ahead.

The regression results are reported in Table 7.[19] The evidence indicates that high discounts forecast low real growth rates in gross domestic product, consumption, and after-tax corporate earnings. The results are the strongest for after-tax corporate earnings and indicate that high discounts forecast lower than average earnings growth rates from quarters 3–15. The Z-statistics are most significant for quarters 9–15. While the results corresponding to real growth rates in gross domestic product and consumption are not as strong, the slopes have the right sign. The reason for the weak results may be that growth rates in gross domestic product and consumption are noisy proxies of the growth rate in after-tax corporate earnings.[20]

The results in column 7 of Table 7 indicate that high discounts also forecast higher than average inflation from quarters 3–11, which is 1–3 years ahead. What significance do expectations of higher inflation have for economic growth? Fama (1981) argues that higher inflation expectations may reflect information about lower expected economic growth. This suggests that the information contained in discounts about future expected inflation may be indirectly related to expectations of future economic growth. The fact that discounts have information about future earnings growth and inflation suggests that discounts respond to fundamental information. Specifically, the results imply that expectations of worsening economic conditions are associated with higher small firm and closed-end fund risk premia, lower small firm and closed-end fund prices, and higher discounts.

In Table 8 we regress the quarterly growth rate in real after-tax aggregate corporate profits, *Gpatq*, on the dividend yield, the default spread, the term spread, and the closed-end fund discount. The results in Table 8 indicate that discounts have information beyond what is contained in other expected return variables. These results are similar to the univariate forecasting regression results and suggest that high discounts now are associated with lower than average earnings growth in quarters 5–16. Interestingly, in the near term (one and two quarters ahead), discounts seem to forecast future earnings growth with a positive sign. This is suggestive of pro-cyclical movement on the part of discounts.

The results above indicate that discounts are negatively correlated with future expected economic growth. An examination of the slope

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[19] We use GMM standard errors to correct for heteroskedasticity and autocorrelation. We have also run these regressions using the Cochrane–Orcutt procedure and the results are similar. In addition, we have checked for coefficient stability by conducting Chow's analysis of variance tests and predictive failure tests by splitting the sample arbitrarily into two halves. We cannot reject the null of coefficient stability.

[20] The correlations between growth rate in earnings, *Gpatq*, and growth rates in gross domestic product and consumption, *Ggdpq, Gcq, Gcdq, Gcnq*, range from about 40–60%.

Table 7
Univariate forecasting regressions of quarterly growth rates of macroeconomic variables on closed-end fund discounts

K	*Ggdpq*	*Gcq*	*Gcdq*	*Gcnq*	*Gpatq*	*Gcpiq*	*N*
1	0.003	−0.003	−0.007	−0.003	0.067	0.037	101
	(0.25)	(−0.35)	(−0.15)	(−0.46)	(0.81)	(1.66)	
	−0.95	−0.88	−0.99	−0.78	−0.32	12.25	
2	0.003	−0.006	−0.014	−0.005	0.047	0.041	100
	(0.27)	(−0.72)	(−0.31)	(−0.95)	(0.50)	(1.85)	
	−0.95	−0.47	−0.93	−0.11	−0.68	15.30	
3	0.003	−0.007	−0.033	−0.004	0.014	0.046	99
	(0.24)	(−0.87)	(−0.72)	(−0.73)	(0.16)	(2.03)	
	−0.97	−0.23	−0.49	−0.55	−1.00	20.24	
4	−0.002	−0.010	−0.040	−0.006	−0.030	0.048	98
	(−0.17)	(−1.09)	(−0.80)	(−1.10)	(−0.32)	(2.25)	
	−1.00	0.46	−0.25	0.29	−0.91	21.91	
5	−0.012	−0.013	−0.052	−0.008	−0.099	0.044	97
	(−0.89)	(−1.40)	(−1.07)	(−1.39)	(−1.02)	(2.49)	
	0.09	1.53	0.34	1.33	0.47	18.49	
6	−0.011	−0.013	−0.055	−0.008	−0.128	0.046	96
	(−0.91)	(−1.48)	(−1.29)	(−1.27)	(−1.35)	(2.94)	
	0.00	1.62	0.46	1.31	1.50	20.34	
7	−0.012	−0.013	−0.038	−0.010	−0.106	0.049	95
	(−0.95)	(−1.42)	(−0.92)	(−1.46)	(−1.24)	(3.55)	
	0.05	1.56	-0.33	2.57	0.68	23.72	
8	−0.014	−0.015	−0.054	−0.010	−0.124	0.049	94
	(−1.06)	(−1.66)	(−1.35)	(−1.44)	(−1.38)	(4.12)	
	0.51	2.30	0.42	2.46	1.34	23.31	
9	−0.017	−0.014	−0.062	−0.008	−0.157	0.044	93
	(−1.36)	(−1.68)	(−1.70)	(−1.18)	(−1.87)	(4.33)	
	1.18	1.97	0.89	1.44	2.79	19.22	
10	−0.019	−0.014	−0.069	−0.007	−0.217	0.039	92
	(−1.48)	(−1.57)	(−2.07)	(−0.98)	(−2.71)	(3.49)	
	1.85	1.95	1.36	0.80	6.30	14.44	
11	−0.024	−0.014	−0.062	−0.008	−0.251	0.037	91
	(−1.92)	(−1.53)	(−1.73)	(−1.14)	(−3.04)	(2.85)	
	3.62	2.10	0.87	1.50	8.83	13.16	
12	−0.024	−0.009	−0.031	−0.007	−0.263	0.029	90
	(−1.92)	(−0.88)	(−0.74)	(−0.92)	(−3.25)	(1.93)	
	3.61	0.23	−0.62	0.77	9.83	7.49	
13	−0.021	−0.006	−0.032	−0.003	−0.221	0.022	89
	(−1.58)	(−0.52)	(−0.72)	(−0.35)	(−2.68)	(1.26)	
	2.53	−0.57	−0.61	−0.80	6.58	4.07	
14	−0.011	−0.003	−0.019	−0.001	−0.201	0.014	88
	(−0.71)	(−0.21)	(−0.40)	(−0.07)	(−2.55)	(0.67)	
	−0.23	−1.05	−0.97	−1.15	5.26	0.90	
15	−0.004	0.003	0.009	0.002	−0.141	0.010	87
	(−0.27)	(0.22)	(0.17)	(0.25)	(−1.74)	(0.44)	
	−1.03	−1.04	−1.13	−0.96	1.97	−0.07	
16	0.006	0.007	0.030	0.004	−0.091	0.005	86
	(0.32)	(0.51)	(0.56)	(0.45)	(-0.96)	(0.20)	
	−0.93	−0.38	−0.71	−0.46	0.12	−0.96	

This table presents the OLS slope coefficient, b, the asymptotic Z-statistic computed using the GMM standard errors (in parentheses), and the adjusted R^2. The GMM standard errors are computed with 4 Newey–West lags except for *Gcpiq* for which the standard errors are computed with 16 Newey–West lags. N represents the number of observations.

Table 8
Multivariate forecasting regression of quarterly real growth rate in aggregate corporate profit on dividend yield, default spread, term spread, and closed-end fund discounts

$Gpatq_{t+K} = a + b\ D/P_t + c\ Def_t + d\ Term_t + e\ Vwdsc_t + u_{t+K,t}$

K	b	$Z(b)$	c	$Z(c)$	d	$Z(d)$	e	$Z(e)$	Adj. R^2	N
1	−3.30	−3.57	1.55	0.74	1.00	1.98	0.19	3.20	15.61	101
2	−2.61	−3.39	0.76	0.31	1.18	3.77	0.15	2.10	12.29	100
3	−1.35	−1.54	2.35	0.82	1.58	3.29	0.11	1.46	12.95	99
4	−0.89	−0.89	3.30	1.17	1.10	2.36	0.05	0.53	6.20	98
5	−0.40	−0.49	0.95	0.39	1.10	2.17	−0.05	−0.57	4.64	97
6	−0.36	−0.39	1.04	0.52	0.80	1.81	−0.09	−0.94	2.40	96
7	−0.75	−0.73	1.58	0.66	0.41	0.94	−0.07	−0.77	−0.71	95
8	−0.93	−0.84	0.71	0.24	0.34	0.53	−0.09	−0.99	−0.31	94
9	−0.84	−0.80	1.31	0.53	0.18	0.37	−0.12	−1.38	0.57	93
10	−0.75	−0.71	3.48	1.47	−0.06	−0.13	−0.18	−2.02	5.38	92
11	−0.71	−0.67	2.84	1.21	−0.09	−0.22	−0.22	−2.38	7.22	91
12	0.28	0.27	−2.81	−1.15	0.30	0.76	−0.28	−3.26	8.43	90
13	0.12	0.10	−1.52	−0.49	−0.08	−0.15	−0.23	−2.74	3.74	89
14	0.23	0.20	−2.09	−0.73	−0.24	−0.43	−0.23	−2.63	2.98	88
15	−0.63	−0.47	0.11	0.03	0.22	0.41	−0.12	−1.44	−0.88	87
16	−1.41	−1.07	3.19	1.09	−0.20	−0.33	−0.05	−0.51	−0.87	86

This table presents OLS slope coefficients, the asymptotic Z-statistic computed using the GMM standard errors, and the adjusted R^2. The GMM standard errors are computed with four Newey–West lags. K represents the number of lags and N represents the number of observations.

coefficients in the regressions (both univariate and multivariate) involving real corporate earnings growth, *Gpatq*, reveals that a 1% increase in discounts is associated with a decrease in expected real quarterly earnings growth rate (from quarters 5–16) of 0.10–0.30%. This suggests that if discounts were to rise above their historical average by one standard deviation (about 8.5%), then the real quarterly earnings growth rate would fall below its average by 0.9–2.6%. Since the average quarterly real earnings growth rate over 1965 to 1990 is 0.22% (see Table 6), this amounts to a substantial contraction in real earnings.

Since discounts forecast small firm returns better than they do large firm returns, the logical question to ask is whether there are any differences in the way discounts forecast small firm and large firm earnings growth. In order to examine this issue, we consider the annual real earnings growth rates of three groups of manufacturing firms based on asset size. Annual earnings growths are used to avoid the seasonal in the quarterly earnings growth rates. The three groups of manufacturing firms are those with (1) total assets (book value) less than \$100 million, (2) total assets in the range \$100 to \$1,000 million, and (3) total assets greater than \$1,000 million. Panel B in Table 6 presents summary statistics on the earnings growth rates of the three groups. It shows that the earnings of firms in the bottom two asset size groups shrank in real terms.[21]

The univariate forecasting regression results involving annual earnings growth rates of manufacturing firms are presented in panel A of Table 9. The results indicate that discounts forecast all three future real earnings growth 3–4 ahead. This is consistent with the regression results for the real growth rate in after-tax corporate profits reported in Table 7. The results in panel A of Table 9 also indicate that discounts forecast the earnings growth rate of small firms more strongly than they do that of large firms. However, it is important to note that discounts also have information about future earnings growth rates of large firms (most closed-end funds hold large firm stocks as their underlying assets). This fact will be helpful in understanding the link between expected returns on small firms and closed-end fund discounts.

5.1 The instrumental variable regressions

The empirical results presented in the previous sections provided indirect evidence on the link between the small firm risk premium and future economic activity. In this section we provide direct tests of the relation between the small firm risk premium and measures of future economic activity. If the small firm risk premium responds to information about future economic activity, then the predictable part of the difference between smallest size decile returns and largest size decile returns, $P1-P10$, should be correlated with expectations of future earnings growth and inflation. Furthermore, since discounts also forecast the difference between closed-end fund share price returns and net asset value returns, *Vwdiff*, we expect the predictable part of *Vwdiff* to respond to expectations of future earnings growth and inflation. Finally, we expect the predictable part of $P1 - P10$ to be positively correlated with the predictable part of *Vwdiff*.

We test these hypotheses using the following instrumental variable regression:[22]

$$Y_{t,t+K} = a + b\,X_{t,t+K} + u_{t,t+K}, \tag{15}$$

where $Y_{t,t+K} = \sum_{k=1}^{K} Y_{t+k}$ and $X_{t,t+K} = \sum_{k=1}^{K} X_{t+k}$. $Y_{t,t+K}$ represents multiperiod returns and $X_{t,t+K}$ represents multiperiod earnings

[21] The negative real earnings growth observed in the bottom two size groups is not necessarily inconsistent with small firms having a higher return than large firms. If the stocks are risky, realized returns can be high at the same time as earnings growth is low or negative. While current earnings reflect assets in place, stock prices reflect expectations of future earnings growth.

[22] This regression is similar to a two-stage least squares (2SLS) regression. The modified 2SLS approach used by us corrects for induced autocorrelation and generalized heteroskedasticity, while the conventional 2SLS approach assumes homoskedasticity and no autocorrelation.

Table 9
Regressions involving annual earnings growth rates and instrumental variables

Panel A: Univariate forecasting regressions of annual earnings growth rates of manufacturing firms on closed-end fund discounts
$Growth_{t+K} = a + b\ Vwdsc_t + u_{t,t+K}$

K	*Gpata1*	*Gpata2*	*Gpata3*	*N*
1	0.202	−0.021	0.147	25
	(0.38)	(−0.06)	(0.74)	
	−3.65	−4.34	−3.79	
2	−0.161	−0.467	−0.065	24
	(−0.42)	(−1.01)	(−0.25)	
	−4.09	0.16	−4.44	
3	−0.554	−0.479	−0.224	23
	(−2.70)	(−2.19)	(−1.42)	
	0.75	0.22	−3.45	
4	−1.037	−0.673	−0.499	22
	(−3.42)	(−2.40)	(−2.26)	
	14.28	4.80	1.66	
5	−0.382	−0.278	−0.183	21
	(−1.14)	(−1.23)	(−0.84)	
	−2.76	−3.66	−4.40	

Panel B: Instrumental variable regressions
$Y_{t,t+K} = a + b\ X_{t,t+K} + u_{t,t+K}$
Instruments: D/P_t, Def_t, $Term_t$, $Vwdsc_t$

K	$Y = Vwdiff$		$Y = P1 - P10$		$Y = P1 - P10$	*N*
	$X = Gpatq$	$X = Gcpiq$	$X = Gpatq$	$X = Gcpiq$	$X = Vwdiff$	
1	0.04	1.00	−0.01	1.11	1.35	101
	(0.37)	(1.57)	(−0.02)	(0.63)	(1.15)	
2	0.07	1.10	−0.27	2.62	1.07	100
	(0.71)	(1.93)	(−1.03)	(1.83)	(1.32)	
4	−0.01	1.25	−0.34	3.29	1.11	98
	(−0.14)	(2.54)	(−1.31)	(2.14)	(1.77)	
6	−0.16	1.34	−0.51	3.82	1.53	96
	(−1.12)	(2.48)	(−1.84)	(2.01)	(2.46)	
8	−0.15	1.33	−1.00	4.84	1.92	94
	(−1.87)	(2.30)	(−2.33)	(2.08)	(3.11)	
10	−0.24	1.39	−1.16	4.88	2.15	92
	(−4.83)	(2.26)	(−2.31)	(2.19)	(3.58)	
12	−0.35	1.35	−1.31	4.80	2.49	90
	(−4.41)	(2.26)	(−2.32)	(2.40)	(3.61)	
14	−0.42	1.37	−1.34	4.87	2.63	88
	(−3.91)	(2.52)	(−2.48)	(2.54)	(3.69)	
16	−0.41	1.27	−1.31	4.72	2.99	86
	(−4.50)	(2.56)	(−2.76)	(2.69)	(3.68)	

Panel A presents the OLS slope coefficient, b, the asymptotic Z-statistic computed using the GMM standard errors (in parentheses), and the adjusted R^2. In each row corresponding to K, the slope coefficient is presented at the top, the Z-statistic in the middle, and the adjusted R^2 at the bottom. The GMM standard errors are computed with six Newey–West lags. Panel B presents the slope statistic, b, and the Z-statistic (within parentheses) from the instrumental variable regressions. The Z-statistics are computed using the GMM standard errors with $K - 1$ Newey-West lags. $Y_{t,t+K} = \sum_{k=1}^{K} Y_{t+k}$ and $X_{t,t+K} = \sum_{k=1}^{K} X_{t+k}$ represent K period returns or growth rates.

growth rates, inflation, or returns. The use of multiperiod returns and growth rates allows us to examine the long-term relation between expected returns and economic conditions. Since our intention is to test whether $E(X_{t,t+K})$ and $E(Y_{t,t+K})$ covary with one another, we use ex ante predictor variables as instruments to extract the expected part of $X_{t,t+K}$. The instruments used are the dividend yield, the default spread, the term spread, and the closed-end fund discount.

The instrumental variable regression results are presented in panel B of Table 9. Columns 2 and 3 of panel B present results obtained by regressing the difference between the fund share price returns and the net asset value returns, *Vwdiff*, on quarterly growth rate in real after-tax corporate profits and quarterly inflation rate, respectively. The results indicate that *Vwdiff* responds to expectations of future earnings growth and inflation. Specifically, expectations of lower than average earnings growth or higher than average inflation results in a higher *Vwdiff*. This relation is much stronger at longer horizons, indicating that expectations of earnings growth and inflation, and the expected return premium of closed-end funds over the net asset value, *Vwdiff*, move together slowly over time.

Columns 4 and 5 of panel B present the empirical results generated by regressing the small firm premium, $P1 - P10$, on quarterly growth rate in real after-tax corporate profits and quarterly inflation rate, respectively. These results are similar to those with respect to *Vwdiff* and provide direct evidence that the small firm risk premium responds to information about future earnings growth and inflation. Furthermore, they also indicate that the risk premia contained in *Vwdiff* and $P1 - P10$ respond to fundamental information in a similar fashion. Finally, the results in column 6 confirm that the risk premia contained in $P1-P10$ and *Vwdiff* covary positively with one another.

The instrumental variable regression results reported in panel B of Table 9 are obtained by estimating the instrumental variable regression (simultaneous equation) for each horizon individually. However, this does not take into account the fact that the instrumental variable regressions and the corresponding regression coefficients are correlated across horizons. Therefore, in order to determine whether $E(X_{t,t+K})$ and $E(Y_{t,t+K})$ covary with one another, we have to test the joint hypothesis that the slope coefficients at various horizons are equal to zero. We do this by estimating the simultaneous equations at various horizons as a system of equations using GMM.[23] From the joint es-

[23] Estimating the regression equations jointly using GMM is similar to the three-stage least squares (3SLS) approach. While the GMM approach corrects for induced autocorrelation and generalized heteroskedasticity, the conventional 3SLS approach assumes homoskedasticity and no autocorrelation. Since the joint estimation approach uses the information available in the whole system, it is asymptotically more efficient than the two-stage least squares approach (2SLS), which estimates the simultaneous equation corresponding to each horizon individually. This implies that the structural parameters will be estimated more precisely by the joint estimation approach (3SLS) than by the individual estimation approach (2SLS). See Judge et al. (1988) for more details.

timation, we compute a chi-square test statistic to test the joint null hypothesis that the slope coefficients at all horizons are zero. Since there are nine instrumental variable slope coefficients corresponding to nine horizons the chi-square test statistic will have nine degrees of freedom. The five chi-square statistics corresponding to the five systems — *(Vwdiff, Gpatq), (Vwdiff, Gcpiq), (P1-P10, Gpatq),* ($P1-P10$, *Gcpiq)*, and ($P1 - P10$, *Vwdiff)* — are, respectively, 2383.55, 419.50, 356.77, 328.53, and 633.53. Since the joint estimation is more efficient, all of the chi-square statistics are large and significant at the 1% level.

6. Interpretation of the Results

In this section, we explore rational explanations for the time-series relationship between discounts and small firm expected returns in light of the empirical evidence that discounts may be related to fundamental risks in the economy. Specifically, we are interested in examining whether discounts capture fundamental information.

6.1 Implications for rational asset pricing

The relation between closed-end fund discounts and future earnings growth and inflation suggests that discounts respond to information about future macroeconomic conditions. Since discounts forecast both the small firm and the large firm earnings growth, it appears that the macroeconomic information contained in discounts is common to both small firms and large firms. However, small firm risk premia seem more responsive to this information than do large firm risk premia. One possible explanation for this result is that small firm earnings are more sensitive to macroeconomic conditions than are large firm earnings, in which case, small firm risk premia could be more responsive to ex ante economic information than large firm risk premia. However, the empirical evidence provided in this article showed that the small firm risk premia responds only to discounts, and not to other commonly used expected return variables. Therefore, this argument is not satisfactory in explaining what is unique about discounts in relation to the small firm risk premia.

Our evidence showed that the expected returns on the closed-end fund share price, *Vwcef*, were more responsive to the information in discounts than were the expected returns on the net asset value, *Vwnav*. However, the fundamental cash flows are essentially the same for the net asset value and the fund share price. This implies that the cash flows with respect to the net asset value and the fund share price should also have the same sensitivity to macroeconomic conditions. Therefore, it is not clear why the fund share price returns and the net asset value returns respond differently to the information in discounts.

It is difficult to address these issues within the framework of perfect markets. Hence, we consider an explanation based on market imperfections, specifically *market segmentation*. According to Lee, Shleifer, and Thaler (1991), in 1988, the average institutional ownership in the largest 10% of the firms on the NYSE was 52.1%, the average institutional ownership in the smallest 10% of the firms on the NYSE was 26.5%, and the average institutional ownership in domestic stock closed-end funds was 6.6%. While the large firm shares are predominantly held by institutional investors, both the small firm and the closed-end fund shares are predominantly held by individual investors.[24] This suggests that markets for large firms and small firms may be segmented. This in turn suggests that closed-end funds, which are small firms themselves, and their underlying assets, which are predominantly large firms, may also be segmented.

Market segmentation can lead to common macroeconomic risks being priced differently in the closed-end fund (small firm) and the net asset value (large firm) markets. This is because security prices in a market will mostly be determined by the expectations and the risk characteristics of the investors who are predominant in that security market. For instance, if the individual investors are more risk averse to macroeconomic risks than are the institutional investors, then the risk premia for these macroeconomic risks will be higher in the closed-end fund market than in the net asset value market. This can potentially explain the existence of discounts. Since the time variation in factor risk premia is related to the time variation in perceived risk or risk aversion of investors, the time variation in factor risk premia can be different in the fund and the net asset value markets. Consequently, the risk premia tracked by discounts need not be related to the expected returns on the net asset value. Under the same reasoning, the risk premia tracked by discounts need not be related to the expected returns on large firms either.

The link between discounts and small firm expected returns arises from common individual investor ownership. Since the cash flows of closed-end funds (whose underlying assets are large firms) are less sensitive to macroeconomic conditions than the cash flows of small firms, investing in small firm stocks is likely to be more risky than investing in closed-end funds. However, both types of securities are

[24] The reason institutional investors do not invest in small firms and closed-end funds may have to do with monitoring difficulties, and liquidity and legal constraints. For instance, pension funds have their own investment managers and may not want to invest in other mutual funds over whom they have very little control. In addition, institutional investors may choose to invest only in securities they know about [see Merton (1987)]. These and other market frictions such as limitations on short sales, transaction costs, etc., may give rise to market segmentation between small firms and large firms and, therefore, between closed-end funds and their underlying assets.

predominantly owned by individual investors. In addition, while the cash flows of large firms may be less sensitive to macroeconomic risks than the cash flows of small firms, they are still affected by adverse economic conditions. Therefore, while the risk premium demanded by individual investors in the closed-end fund market may be lower than that for a firm of similar size that is not a closed-end fund, it will still be higher than the risk premium demanded by the investors in the net asset value market. This will give rise to an average discount. How low the risk premium in closed-end funds will be relative to small firms depends on how less sensitive closed-end fund earnings are to economic conditions relative to small firm earnings. Since investors in small firms and closed-end funds have expectations and risk characteristics that move together over time, the risk premia associated with small firms and closed-end funds will be correlated. This could explain the time-series relationship between discounts and expected returns on small firms.

6.2 The investor sentiment hypothesis

According to the investor sentiment hypothesis, individual investors who trade in small firms and closed-end funds often misperceive future cash flows. Trading by individual investors based on these misperceptions or sentiment causes small firm and closed-end fund prices to be more volatile than usual. The risk due to the fluctuating sentiment will be priced if all investors have finite horizons [see De Long et al. (1990)]. This causes the required rate of return on closed-end funds to be higher than that on their underlying assets and gives rise to an average discount. The actual discount will fluctuate with individual investors' misperceptions. Thus, discounts may be a proxy of the investor sentiment or noise trading risk premium that varies over time.

A mean reverting investor sentiment will give rise to a negative covariance between changes in discounts and small firm returns, and a positive covariance between the level of discounts and future small firm returns. If the individual investors are optimistic, they will push the small firm and closed-end fund prices up, resulting in higher small firm returns and lower discounts. This gives rise to the negative covariance between small firm returns and changes in discounts. However, current investor optimism also suggests that stock prices, on average, will be lower in the future. This gives rise to the positive covariance between current discounts and future small firm returns. Therefore, both the Lee, Shleifer, and Thaler (1991) results and the results in this article, that discounts forecast future small firm returns, are consistent with the investor sentiment hypothesis. The fact that none of the other forecasting variables have any explanatory power for the conditional expected small firm risk premium is also consistent with the investor sentiment story. However, the evidence that discounts have information about future earnings growth and inflation is not consistent with the investor sentiment hypothesis. If investors are responding to fads in the stock market it is unlikely that closed-end fund discounts will move with future expected earnings growth and inflation. However, if fads are correlated with some observable variable in the economy, that could explain the link between discounts and future economic activity.

Can the sentiment story be ruled out as a possible explanation of the results in this article? Not easily, given the level of market segmentation that is needed to rationalize the empirical results presented in this article. Thus, there may still be a role for a sentiment-based explanation. However, the results presented in this article rule out any straightforward sentiment stories. In summary, the evidence presented in this article relating discounts to future economic activity suggests that discounts may be a proxy of individual investors' rational expectations about future economic conditions and/or their risk aversion to macroeconomic risks. Thus, discounts on closed-end funds may provide important fundamental information that is not contained in any of the commonly used expected return variables.

7. Conclusions

Since closed-end fund discounts contain information about time-varying expected returns of closed-end fund share prices, any relation between discounts and the returns of other securities must arise from common variation in conditional expected returns. This suggests that if there is common variation in the conditional expected returns of closed-end funds and small firms, then discounts should forecast small firm returns. This article examines the relation between closed-end fund discounts and small firm returns using multiperiod forecasting regression tests. The empirical results show that discounts forecast future small firm returns and that discounts have independent information about the conditional expected returns of small firms. Furthermore, the empirical tests show that discounts forecast only the small firm factor return out of the five risk factor returns suggested by Fama and French (1993). Additional tests indicate that discounts forecast future earnings growth rates, especially small firm earnings growth rates and future inflation. This suggests that discounts contain fundamental economic information. The basic conclusion of this article is that closed-end fund discounts may be a proxy of individual investors' rational expectations about future economic conditions and/or their risk aversion to macroeconomic risks. Thus, they may provide important fundamental information that is not contained in any of the commonly used expected return variables.

Appendix

A. Monte Carlo Simulation Methodology

The simulation methodology used by us closely follows the one used by Hodrick (1992) and Nelson and Kim (1993). We discuss the simulation methodology below.

A.1 VAR data generating process for state variables

Define $Z_t = (VW_t, SMB_t, HML_t, Defret_t, Termret_t, D/P_t, Def_t, Term_t, Vwdsc_t)'$ where Z_t is a 9×1 column vector. We fit a first-order VAR to Z_t using the following specification:

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1}, \tag{16}$$

where A_0 is a 9×1 vector of intercepts, A_1 is a 9×9 coefficient matrix and u_{t+1} is a 9×1 vector of forecast errors. The VAR results are presented in Table A-1.

A.2 Contemporaneous regressions for portfolio returns

The following time-series regression is fit for the portfolio returns used in our regressions: *EW*, *P1*, *P2*, *P3*, *P10*, *Vwcef*, and *Vwnav*:

$$R_t = a + bVW_t + cSMB_t + dHML_t + eDefret_t + f\,Termret_t + v_t, \tag{17}$$

where R_t is the appropriate portfolio return. The contemporaneous regression results are presented in Table A-2.

A.3 Artificial data generation

The point estimates in Tables A-1 and A-2 are used to generate artificial data for the Monte Carlo simulations. We first impose the null hypothesis of no predictability on the factor returns, *VW, SMB, HML, Defret, Termret*, in the VAR. This is done by setting the slope coefficients on the explanatory variables to zero for all of the factor returns and by setting the intercepts equal to the unconditional means. We use the fitted VAR under the null hypothesis of no predictability to generate artificial data 5,000 times. Each time, we generate 306 observations of the state variable vector, *VW, SMB, HML, Defret, Termret, D/P, Def, Term, Vwdsc*. The initial observation for this vector is drawn from a multivariate normal distribution with mean equal to the historical mean and variance-covariance matrix equal to the historical estimated variance-covariance matrix of the vector of state variables. Once the

Table A-1
First-order vector autoregressions

Dep.	Intpt.	VW_t	SMB_t	HML_t	$Defret_t$	$Termret_t$	D/P_t	Def_t	$Term_t$	$Vwdsc_t$	χ^2_9	Adj. R^2
VW_{t+1}	−3.271	−0.071	0.163	−0.125	0.303	0.375	0.678	−0.066	0.418	−0.006	28.16	5.71
	(−2.557)	(−0.793)	(2.003)	(−1.306)	(1.091)	(1.956)	(1.725)	(−0.070)	(2.679)	(−0.186)		
SMB_{t+1}	−1.326	0.181	0.095	0.042	−0.113	-0.031	0.388	−0.314	−0.023	0.016	33.27	8.19
	(−1.544)	(2.919)	(1.452)	(0.597)	(−0.617)	(−0.252)	(1.650)	(−0.604)	(−0.243)	(0.750)		
HML_{t+1}	1.185	−0.009	−0.063	0.171	−0.106	0.007	−0.233	0.093	−0.059	0.016	11.84	2.11
	(1.537)	(−0.185)	(−1.014)	(2.261)	(−0.660)	(0.074)	(−1.170)	(0.184)	(−0.568)	(0.849)		
$Defret_{t+1}$	0.798	0.064	0.033	0.105	−0.180	0.049	−0.253	0.153	−0.013	0.012	28.10	8.08
	(1.505)	(2.220)	(0.802)	(2.174)	(−1.662)	(0.690)	(−1.856)	(0.411)	(−0.179)	(0.836)		
$Termret_{t+1}$	−2.210	−0.124	−0.052	−0.119	0.219	0.170	0.418	0.148	0.285	−0.010	25.20	4.83
	(−2.681)	(−2.319)	(−0.822)	(−1.435)	(1.130)	(1.226)	(1.815)	(0.240)	(2.129)	(−0.465)		
D/P_{t+1}	0.143	0.004	−0.005	0.006	−0.015	−0.019	0.968	0.011	−0.016	0.001	4341.70	94.51
	(2.488)	(1.116)	(−1.355)	(1.494)	(−1.164)	(−2.112)	(56.217)	(0.268)	(−2.307)	(0.956)		
Def_{t+1}	−0.009	−0.002	−0.004	−0.002	−0.003	−0.007	0.032	0.849	−0.003	−0.002	1187.60	77.49
	(−0.224)	(−0.584)	(−1.386)	(−0.610)	(−0.331)	(−1.139)	(2.531)	(27.371)	(−0.453)	(−1.957)		
$Term_{t+1}$	0.260	−0.031	−0.013	−0.016	0.171	0.146	0.002	0.441	0.800	−0.004	876.23	77.15
	(1.142)	(−2.309)	(−0.858)	(−0.747)	(3.522)	(4.080)	(0.035)	(2.581)	(21.335)	(−0.911)		
$Vwdsc_{t+1}$	−0.384	−0.011	0.107	0.091	−0.175	−0.170	0.068	0.166	0.131	0.966	5199.82	93.49
	(−0.588)	(−0.269)	(2.268)	(1.624)	(−1.260)	(−2.015)	(0.413)	(0.388)	(1.517)	(57.096)		

The first column refers to the left-hand side variables in the VAR and columns 3–11 refer to the slope coefficients of the right-hand side variables. χ^2_9 is the chi-square test statistic with nine degrees of freedom testing the null hypothesis that the slope coefficients are jointly zero. $\bar{R}^2$ refers to the adjusted coefficient of determination. The numbers in parentheses are the asymptotic Z-statistics computed using the White heteroskedasticity consistent standard errors.

Table A-2
Time-series regressions of stock and bond portfolio returns for Monte Carlo simulation

Dep.	Intpt.	*VW*	*SMB*	*HML*	*Defret*	*Termret*	Adj. R^2
*P*1	−0.33	1.09	1.43	0.67	0.00	−0.05	89.11
	(−2.33)	(25.02)	(23.93)	(8.33)	(0.00)	(−0.66)	
*P*2	−0.21	1.10	1.14	0.45	0.04	0.01	96.18
	(−2.80)	(41.09)	(31.34)	(9.84)	(0.57)	(0.31)	
*P*3	−0.17	1.09	1.06	0.33	0.05	0.01	96.92
	(−2.50)	(39.91)	(38.15)	(10.34)	(0.82)	(0.32)	
*P*10	0.03	1.01	−0.14	−0.04	−0.03	0.01	98.29
	(0.68)	(64.36)	(−8.95)	(−2.23)	(−0.66)	(0.32)	
Vwcef	0.14	0.79	0.19	0.16	−0.09	0.00	68.42
	(0.91)	(17.65)	(3.04)	(2.27)	(−0.62)	(0.01)	
Vwnav	0.10	0.83	0.07	−0.12	−0.13	−0.03	86.93
	(1.06)	(29.21)	(1.93)	(−2.67)	(−1.56)	(−0.49)	
EW	−0.09	1.04	0.68	0.25	0.04	0.06	98.31
	(−2.33)	(69.89)	(32.83)	(9.00)	(0.84)	(2.16)	

VAR is initiated, shocks for subsequent observations are generated by randomizing [sampling without replacement, see Nelson and Kim (1993) and Noreen (1989)] among the actual VAR residuals. The VAR residuals for *VW, SMB, HML, Defret*, and *Termret* are scaled so that the standard errors computed from these residuals will be equal to the historical standard errors of *VW, SMB, HML, Defret*, and *Termret*, respectively.

The artificially generated factor returns, *VW, SMB, HML, Defret, Termret*, are now fed to the fitted time-series regression models in Table A-2. The residuals for the time-series regression models are obtained by randomizing (using the same randomization order as for the VAR residuals) the actual residuals from the regressions in Table A-2 with two exceptions. For *Vwcef* and *Vwnav*, we use the residuals from regressions that also include the change in discounts as a regressor on the right-hand side so that the residuals we use in our simulations for generating *Vwcef* and *Vwnav* are free of the influence of changes in discounts, Δ *Vwdsc*. These residuals are also scaled so as to reflect the standard errors of residuals from the regressions with respect to *Vwcef* and *Vwnav* in Table A-2. Using the artificial factor returns and regression residuals, we generate artificial data for the portfolio returns, *EW, P1, P2, P3, P10, Vwcef*, and *Vwnav*. This artificial data is then used to run regressions and generate regression statistics. This process is repeated 5,000 times and empirical distributions of univariate and multivariate regression statistics are obtained. The FORTRAN numerical recipes subroutine, *ran1*, is used to generate uniform random numbers in the interval 0 to 1. The uniform random numbers are converted to standard normal random numbers using the FORTRAN numerical recipes subroutine, *gasdev*. See *Numerical Recipes in Fortran: The Art of Scientific Computing* by Press, et al. (1992).

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