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The factor structure of time-varying conditional volume ☆

Eric C. Chang [a], Joseph W. Cheng [b], J. Michael Pinegar [c,*]

[a] *School of Business, The University of Hong Kong, Hong Kong, People's Republic of China*
[b] *Department of Finance, The Chinese University of Hong Kong, Shatin, New Territories, Hong Kong, People's Republic of China*
[c] *Marriott School of Management, Brigham Young University, Provo, UT 84602, United States*

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Abstract

We document a set of instruments that explain a large fraction of the time series variation in turnover between 1966 and 2003. We use these relations in latent variable tests that examine the number of predictable factors that drive conditional expected time-varying turnover. After refining the weighting matrix as suggested by Ferson and Foerster [Ferson, W. and S. Foerster, 1994. "Finite Sample Properties of the Generalized Method of Moments in Tests of Conditional Asset Pricing Models." Journal of Financial Economics 36, 29–55.] and Bekaert and Urias [Bekaert, G. and M.S. Urias, 1996. "Diversification, Integration and Emerging Market Closed-End Funds." Journal of Finance 51, 835–869.] and accounting for dimensionality as suggested by Gallant and Tauchen [Gallant, R. and G. Tauchen, 1991. "Seminonparametric Estimation of Conditionally Constrained Heterogeneous Processes: Asset Pricing Applications." Econometrica 57, 1091–1119.], we reject a one-factor model. However, this rejection is partially driven by non-stationarity. When we correct for non-stationarity by using normalized turnover, we reject a single-factor model in the second half of our sample but not in the first. Our work extends recent work by Tkac [Tkac, P.A., 1999. "A Trading Volume Benchmark: Theory and Evidence." Journal of Financial and Quantitative Analysis 34, 89–114.] and by Lo and Wang [Lo, A. and J. Wang, 2000. "Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory." Review of Financial Studies 13, 257–300.] who develop and test implications of share turnover for asset pricing relations.

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1. Introduction

Recent studies by Lo and Wang (2000) and Tkac (1999) develop and test implications for share turnover of asset pricing models. Lo and Wang focus on separation theorems. In particular, they show that two-fund separation implies

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* Corresponding author.
E-mail addresses: ecchang@business.hku.hk (E.C. Chang), Joseph@baf.msmail.cuhk.edu.hk (J.W. Cheng), jmp5@byu.edu (J.M. Pinegar).

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turnover will be identical for all securities while $(K+1)$-fund separation implies turnover will satisfy an approximately linear K-factor structure. Empirically, Lo and Wang find that two principal components explain approximately 90% of the variation in turnover of portfolios ranked by turnover betas over each of six five-year periods. The three-fund separation results appear robust to changes in the index against which turnover betas are measured and to the use of differences in or levels of turnover to measure betas.[1] These findings supplement returns-based tests in shedding light on which, if any, of the return generating processes implied by asset pricing models conform most closely to empirical predictions.

Tkac (1999) provides a theoretical rebalancing benchmark that connects trading of individual stocks to market-wide volume. Like Lo and Wang's (2000) two-fund separation, Tkac's result implies turnover will be identical for all securities if portfolio rebalancing is the sole motive for trade. To accommodate other motives, Tkac examines the idiosyncratic influences of institutional ownership, option availability, relative firm size, and membership in the S&P 500. Her findings support the hypotheses that both market-wide and firm-specific influences affect turnover and that market adjustments for turnover are important in filtering out anomalous trading.

Our paper extends Lo and Wang (2000) and Tkac (1999) by using GMM (Generalized Method of Moments) latent variable tests to determine the number of predictable factors that drive conditional expected time-varying turnover. Rouwenhorst (1999) demonstrates that turnover is positively related to the same attributes that drive cross-sectional differences in average returns. Other studies (e.g., Blume et al., 1994; Conrad et al., 1994; Gervais et al., 2001) suggest that volume is an important predictor of equity returns. Given these findings and those in numerous studies that support time-varying conditional expected returns (e.g., Gibbons and Ferson, 1985; Campbell, 1987; Campbell and Hamao, 1992; Chang and Huang, 1990), we conjecture that conditional expected turnover also varies predictably through time.

To examine this conjecture, we run time series regressions using monthly data between 1966 and 2003 with nine portfolios of US stocks based on two sorting schemes. The first uses double-sorted portfolios ranked first by market capitalization, then by the turnover betas. The second uses normalized turnover (defined below) that corrects for non-stationarity in the raw turnover data. Adjusted-R^2 estimates average approximately 60% in our raw turnover regressions and approximately 50% for normalized turnover. However, the signs of the coefficients are more consistent across portfolios in the normalized turnover regressions.

In our GMM tests that examine the number of latent variables that drive conditional expected turnover, we assume that conditional expectations of the latent turnover factors are linear in the instruments and that the factor loadings are constant through time. Because of the low power of GMM tests in finite samples, we also use procedures outlined in Ferson and Foerster (1994) and in Bekaert and Urias (1996) to improve the properties of the weighting matrix. We also vary the number of observations, portfolios, and instruments in our analysis to examine the effects of different saturation ratios on the number of factors detected (see Gallant and Tauchen, 1991).

The saturation ratio, defined as the number of observations divided by the number of parameters to be estimated including the parameters in the weighting matrix, relates directly to the power of our tests. For double-sorted portfolios with saturation ratios below 10, we fail to reject a single-factor model. For saturation ratios greater than 10, the number of factors depends on whether portfolios are equally weighted or value weighted. For value-weighted portfolios, we reject a one-but not a two-factor model in each case. For equally weighted portfolios, we fail to reject a single-factor model in some instances, but in one case we reject even a two-factor model. When we also correct for non-stationarity, we detect fewer factors than when we do not, even when saturation ratios exceed 10. In the first half of the sample, we fail to reject a single-factor model with both equally and value-weighted portfolios. In the second half, we reject a single-factor model with both weighting schemes.

In some but not all cases, our results are consistent with Lo and Wang (2000) in that we detect more than one factor. An important difference between their approach and ours, however, is that the principal components analysis tries to find all factors; whereas, the latent variable approach focuses only on factors that are predictable. If instruments we do not consider are important in predicting time-varying turnover, the number of factors we detect may understate the number of predictable factors. Even if all predictable factors can be identified, that number may understate the number of total factors if some factors that drive turnover cannot be forecasted.

However, latent variable tests also offer advantages over the principal components method. The process of identifying instruments for the latent variable tests may increase intuition about the time series properties of turnover that principal components tests cannot provide. The latent variable method also offers formal tests of the statistical

[1] Based on these results, Lo and Wang (2006) develop an intertemporal two-factor model.

significance of factors that drive conditional expected turnover cross-sectionally. In contrast, the number of factors in a principal components analysis must be determined subjectively. In using latent variable tests, therefore, we accept greater subjectivity in choosing the instruments, but we reduce subjectivity in discerning the number of factors.

The next section of the paper discusses the technical details of our tests. Sections 3 and 4 present our data and empirical results, and Section 5 concludes.

2. Latent variable tests for asset turnover

Lo and Wang (2000) show that when the risk-free security, the market portfolio, and $K-1$ constant hedging portfolios are the relevant separating funds, the turnover of stock j at time t can be approximated by a linear K-factor model of the following form:

$$\tau_{jt} = F_{1t} + \sum_{k=2}^{K} S_{jk}F_{kt} + \mu_{jt} \qquad j = 1, \ldots, J \tag{1}$$

in which F_{1t} is turnover for the market portfolio from time $t-1$ to time t; F_{kt} (for k=2,…, K) are factors that depend on the turnover of the corresponding hedged portfolio k; and S_{jk} is the number of shares of stock j held by fund k. Lo and Wang further demonstrate that the approximation error of Eq. (1) will be small when the amount of trading in the hedging portfolios is small.

Define the $T\times J$ turnover matrix τ with typical element τ_{jt}, j=1,…, J and t=1,…, T. Suppose τ is predictable using the information contained in Z, where Z is a $T\times L$ matrix of information variables: (z_{lt-1},…, z_{Lt-1}) where z_{lt-1} is a $T\times l$ column vector with l=1,…, L and t=1,…, T. We wish to test whether the time-varying expected turnover is driven by a small number of unobservable latent variables. With Eq. (1), the number of latent variables identified should equal K. To proceed with the latent variables and GMM tests for identifying the number of relevant factors that drive Eq. (1), we express the predictability or the conditional expectation τ^{K} for the first K reference assets (hedging portfolios), given Z, as:

$$E(\tau^K|Z) = Z\alpha \tag{2}$$

Where

$E(*|*)$ conditional expectation operator,
τ^{K} the $T\times K$ matrix of turnover for the first K reference assets, and
α the $L\times K$ matrix of coefficients with its kth column containing the projection coefficients of turnover of the kth reference portfolio onto the information variables in Z.

Conditional expectations are assumed to be linear in the elements of Z. We use the multifactor version of (1) to examine if time-varying turnover is governed by common factors. Within this framework, and with (2), Eq. (1) becomes:

$$E(\tau|Z) = Z\alpha\beta. \tag{3}$$

Where $E(\tau|Z)$ is the $T\times J$ matrix of expected turnover for t=1,…, T and j=1,…, J. β is the $K\times J$ matrix of constant regression coefficients corresponding to each factor k regarding the turnover for stock j in (1), i.e., with typical element β_{kj}, k=1,…, K and j=1,…, J. Following Hansen and Hodrick (1983), we express the system of J regression equations describing turnover as:

$$\tau = ZA + \mu \tag{4}$$

where

τ the $T\times J$ matrix of turnover volume
A $L\times J$ matrix of coefficients with typical elements δ_{lj}, l=1,…, L and j=1,…, J
μ a $T\times J$ matrix with typical element μ_{tj}, t=1,…, T and j=1,…, J.

Eq. (4) implies the following testable restrictions,

$A=\alpha\beta$ with typical element:

$$\delta_{lj} = \alpha_l \beta_j \tag{5}$$

where α_l is the $1\times K$ row vector containing the lth row of α with typical element α_{lk}, $k=1,\ldots, K$ and β_j is the $K\times 1$ column vector containing the jth column of β with typical element β_{kj}, $k=1,\ldots, K$. Neither β_j nor α_l is directly observable, since the turnover of hedge portfolios is assumed to be unobservable. Hence, we standardize by setting $\beta_{kj}=1$ for $j=k$ and j, $k\leq K$; and $\beta_{kj}=0$ for $j\neq k$ and j, $k\leq K$. Thus, there are $JK-K^2$ free β's and LK free α's. There are a total of JL coefficients in the matrix, A, resulting in $(J-K)(L-K)$ overidentifying restrictions on the data. Technically, the model places overidentifying restrictions on the data if the number of latent variables K is strictly less than the number of portfolios J and the number of information variables L. In addition, practical considerations require that K be a small number so that a parsimonious representation of changes in turnover is feasible. A natural progression of the tests is to start with the single latent variable model and move up to a higher number of variables if the lower dimensions are rejected.

In testing the predictability of turnover, we use ordinary least squares (OLS) estimates with standard errors adjusted by Newey and West (1987). To estimate and test the latent variable model (Eq. (4)), we use the GMM nonlinear estimation technique that allows for conditional heteroskedasticity and autocorrelation.

Eq. (4) implies that the conditional expectation of the elements of the $T\times J$ matrix of error terms from Eq. (4), given Z, are equal to zero, hence, $E(\mu'Z)=0$. Thus, the system consists of a $J\times L$ matrix of sample orthogonality conditions:

$$G_T = (\mu' Z/T). \tag{6}$$

G_T is partitioned into rows of length L and the transpose of these row vectors ($L\times 1$ column vectors) are further stacked into a $JL\times 1$ vector, g_T, where JL is the number of orthogonality conditions. Hence, g_T is a vector containing the sample estimate for the mean corresponding to the elements of the function in (6). The GMM estimator is obtained by searching for the parameter vector δ, consisting of the elements of α and β, that minimizes the quadratic form

$$L_T = (g_T{}' W g_T). \tag{7}$$

The $JL\times JL$ weighing matrix W is the inverse of a consistent estimate of the covariance matrix of the orthogonality conditions. We employ the sample weighting matrix suggested by Hansen (1982) with Newey and West (1987) adjustments for autocorrelation. Define the jth autocovariance matrix of the orthogonality conditions as:

$$\Gamma_j = [(1/T)\sum\nolimits_t (\mu_t \mu_{t-j}{}') \otimes (z_{t-1} z_{t-1-j}{}')]. \tag{8}$$

Where $\otimes$ denotes the Kronecker product; the column vector μ_t and z_{t-1} are respectively the time t elements of the matrix μ and Z. Let $q-1$ be the maximum lag length that receives a nonzero weight in the Newey and West (1987) estimator, we further define the weighting matrix:

$$W = \left[\Gamma_0 + \sum_{j=1}^{q} \left(\frac{q-j}{q}\right)(\Gamma_j + \Gamma_j{}')\right]^{-1}. \tag{9}$$

Hansen (1982) shows that T times the minimized value of the quadratic form, $L_T = g_T' W g_T$, is asymptotically distributed as χ^2 with degrees of freedom equal to $(J-K)(L-K)$. This χ^2-statistic regarding the overidentifying restrictions provides a goodness of fit test for Eq. (5).

To implement the estimation procedure, Hansen and Singleton (1982) suggest a two-stage method. In the first stage, an arbitrary or suboptimal weighting matrix W is used to minimize L_T to get an initial consistent estimate of δ. These δ estimates are then used to construct the optimal weighting matrix W^* that is used to minimize (7) and obtain a second-stage estimate of δ. Although a two-stage procedure is asymptotically efficient, the finite sample performance

Table 1
Summary statistics for turnover of size- and turnover-beta-ranked equally weighted portfolios of AMEX/NYSE stocks (1966–2003)

	(10^6US$) Average capitalization	Turnover beta	Monthly turnover				Autocorrelation coefficients				
			Mean	Standard Deviation	Maximum	Minimum	ρ_1	ρ_3	ρ_6	ρ_{12}	DF
Portfolio 1	29.16	0.426	0.0257	0.0105	0.0597	0.0075	0.835	0.672	0.597	0.518	−5.07**
Portfolio 2	28.71	0.334	0.0313	0.0137	0.1065	0.0081	0.827	0.654	0.542	0.390	−5.73**
Portfolio 3	31.70	0.718	0.0517	0.0234	0.1604	0.0105	0.856	0.715	0.624	0.533	−5.21**
Portfolio 4	250.87	0.777	0.0347	0.0171	0.0925	0.0095	0.936	0.901	0.857	0.852	−1.99
Portfolio 5	266.02	0.912	0.0436	0.0190	0.1139	0.0110	0.920	0.881	0.840	0.811	−2.21
Portfolio 6	263.82	1.542	0.0745	0.0319	0.1902	0.0145	0.898	0.854	0.799	0.794	−2.85*
Portfolio 7	5545.87	1.069	0.0405	0.0240	0.1182	0.0084	0.948	0.950	0.933	0.930	−1.70
Portfolio 8	4744.56	1.290	0.0451	0.0292	0.1559	0.0077	0.955	0.957	0.943	0.944	−1.58
Portfolio 9	2925.49	1.946	0.0731	0.0421	0.2208	0.0165	0.947	0.949	0.932	0.933	−1.83

The last column reports Dickey–Fuller (DF, 1979) tests of the hypothesis that turnover is non-stationary. Double (single) asterisks, ** (*), indicate rejection of that hypothesis at the .05 (.10) level.

of GMM can be improved when autocovariances of the orthogonality conditions are accounted for (see Bekaert and Urias, 1996) and further iterations are conducted (see Ferson and Foerster, 1994) to minimize the dependence of the estimator on the initial weighting matrix. Hence, in testing (4), we follow Andrews (1991) by selecting the bandwidth value of the weighting matrix and extending the two-stage process by sequentially updating the weighting matrix until convergence occurs. For the iterated GMM procedure, the criterion for convergence within a stage is a change in the objective function less than 0.00001. The criterion for convergence across stages is 0.0001.[2]

3. Data description

Table 1 summarizes turnover data for nine double-sorted portfolios of AMEX/NYSE stocks from the Center for Research in Securities Prices (CRSP) data base. For each month from March 1966 through December 2003, we sort securities into three size-ranked portfolios according to their previous year-end market capitalization.[3,4] Following Lo and Wang (2000), we then further partition each of these size-ranked portfolios into three turnover-beta-ranked portfolios according to the turnover betas of its component securities. The turnover beta of security j (b_j) for month t is estimated using data for the previous 36 months (i.e. from $t-36$ to $t-1$) according to Eq. (10):

$$\tau_{jt} = a_j + b_j\tau_{mt} + \varepsilon_{jt} \tag{10}$$

in which τ_{jt} (τ_{mt}) is the turnover of security j (the market portfolio) at time t. The double sorting process produces nine size-turnover-beta-sorted portfolios. We measure turnover betas relative to an equally and a value-weighted index of all AMEX/NYSE stocks. When we estimate betas relative to the equally (value) weighted index, the nine portfolios created through the sorting process are also equally (value) weighted. For brevity, we report only the equally weighted results in tables. In most cases, our results do not vary with the weighting scheme. However, for the GMM tests, interesting differences do occur; so, we report both sets of results.

Portfolios 1 through 3, 4 through 6, and 7 through 9 contain the small-, mid-, and large-cap firms in our sample. For medium- and large-cap firms, turnover betas increase with the portfolio number. For the small-cap portfolios, portfolio 1 has a larger beta (0.426) than portfolio 2 (0.334).[5] Overall, the relation between turnover betas and firm size is

[2] The convergence criterion is in terms of value (not in %).

[3] We sort by size because size has been shown to be a variable that is related to turnover (see, for example, Chordia and Swaminathan, 2000).

[4] We follow the common practice of excluding closed-end funds, REITs, ADRs, SBIs, unit trusts, ETFs etc. from our sample. Also, securities with an initial public offering in year t are excluded in the sample in year $t+1$. Because the CRSP tapes occasionally contain errors, with daily turnover rates exceeding 1,000% in some cases, we also exclude securities with daily turnover exceeding 50%. This threshold is arbitrary, but CRSP data providers confirm there are errors in some of the volume estimates. Because we are unsure whether all errors have been corrected, we use the 50% cutoff rate. Lo and Wang (2000) also use a filter in their analysis.

[5] The beta pattern for the full sample is not entirely monotonic since the "out-of-sample beta" pattern for the full sample does not always conform to the "in-sample beta" pattern. In subsequent GMM analysis, in the case when 6 assets are employed (J=6), we eliminate portfolios 1 to 3 to partially mitigate this potential small firm phenomenon.

positive because the unreported Spearman rank correlation coefficient (0.80) is significant at the .05 level. Turnover betas are also significantly positively associated with mean monthly turnover (Spearman rank correlation = .78).

According to Lo and Wang (2000), if turnover is driven by a single-factor model, turnover betas should be identical across all securities. That is, cross-sectional variation in turnover betas should not exist if two-fund separation holds. Differences in turnover betas in Table 1 are inconsistent with a single-factor model. We also reject the hypothesis of equal mean turnover betas across portfolios with more formal Wald tests (available upon request) over each five-year, ten-year, and twenty-year sub-period as well as over the full sample period. Hence, turnover is unlikely to be governed by a single latent variable model.[6]

The autocorrelation coefficients for turnover are high for all lags shown in the table. The coefficients are higher for larger firms. The Spearman rank correlation between firm size and the autocorrelation coefficients is at least 0.90 at every lag shown in the table. The slow decay of the autocorrelation coefficients suggests that turnover is non-stationary. Thus, it is not surprising that Dickey and Fuller (1979) tests reported in the last column of the table fail at the .10 level to reject the hypothesis that turnover is non-stationary for five of the nine portfolios.

Because of non-stationarity, Lo and Wang (2000, p. 281) divide their sample into six five-year sub-periods and use raw turnover data even though they recognize that "from a purely statistical point of view… shortening the sample period cannot induce stationarity." Nevertheless, they argue that the difficulty of choosing a generally accepted detrending method and the broader understanding provided by using raw turnover (as opposed to some detrended alternative) are sufficient reasons to use raw turnover for most of their tests. Lo and Wang then also do a robustness check of their main findings by examining principal components results based on first differenced turnover. We follow the same general procedure by first using raw turnover with its inherent non-stationarity problems, and then following those tests up with tests that correct for non-stationarity.

The first step in our investigation of the number of latent factors that drive conditional expected turnover is to show that portfolio turnover is predictable using currently observable information (instrumental variables). The instruments we use include lagged values of conditional volatility (CVOL), the relative short rate (RSR), the dividend price ratio (DPR), and the cross-sectional dispersion of turnover (TOD). The relative short rate and the dividend price ratio have been used in other studies to predict time-varying expected returns for latent variable tests.[7] Our motivation for using CVOL to predict turnover comes from Blume et al. (1994) who show why volume and absolute price changes correlate positively and how correlations change with changes in the precision of information. We estimate CVOL with procedures outlined in Schwert (1989).

Chang et al. (2006) also provide a model that motivates the use of a novel "volume dispersion" measure in studying the relation between trading volume and price change at the aggregate market level. The measure is designed to proxy for variability in the arrival of firm-specific information across securities in the market. Chang, Cheng, and Khorana show that introducing the dispersion measure significantly increases the explanatory power of the price-volume regressions at the market level. This volume dispersion measure is analogous to the return dispersion measure used by Bessembinder et al. (1996) to capture firm-specific information in their examination of the relation between trading volume and information flows regarding S&P 500 index futures contracts. The cross-sectional dispersion estimate for turnover is defined as

$$\mathrm{TOD}_t = \sum_{j=1}^{N} W_j |\tau_{j,t} - \tau_{m,t}| \tag{11}$$

where $\tau_{j,t}$ ($\tau_{m,t}$) is the turnover for stock j (the market) on day t; W_j is the weight used for the equally or value-weighted measure of TOD; and N is the number of securities in the portfolios.

[6] In the analysis that follows in this section, we fail to reject a single-factor model for turnover in several cases. However, the saturation ratios in these tests are very low, especially for sub-periods. Even for the full sample, with nine portfolios and five instrumental variables (including the intercept), the saturation ratio is approximately only six. In such cases, failing to reject a single-factor model with GMM tests may result from a lack of power. To maintain adequate power, we focus the GMM tests below mainly on the full sample period and on the 20-year sub-periods.

[7] Campbell (1987) uses four interest rate variables, including the one-month bill rate, the spread between the two-month and the one-month rate, the spread between the six-month and the one-month rate, and the one-period lagged excess return of the two-month bill over the one-month bill. Chang and Huang (1990) show that besides these interest rate variables a January dummy also helps predict bond and stock returns. Campbell and Hamao (1992) use the January dummy, the dividend-price ratio, the relative short rate, the lagged excess market return, and the long–short yield spread to predict stock returns in the US and Japan.

Table 2
Summary statistics for instrumental variables used to predict turnover for size-(equally weighted) and turnover-beta sorted AMEX/NYSE stocks (1966–2003)

	CVOL	RSR	DPR	TOD
Mean	0.04882	−0.000035	0.002363	0.031645
Standard Deviation	0.01605	0.001084	0.002814	0.013234
Maximum	0.12476	0.004467	0.015373	0.076186
Minimum	0.01178	−0.004942	0.000000	0.007844
Correlations				
CVOL	1.000			
RSR	0.082	1.000		
DPR	−0.015	0.049	1.000	
TOD	−0.334**	−0.167**	−0.182**	1.000

Note: The instruments include the conditional volatility (CVOL), the lagged value of the relative short rate (RSR), the lagged value of the dividend price ratio (DPR), the lagged cross-sectional dispersion of turnover for the market as a whole (TOD).
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 2 reports summary statistics for the instrumental variables we use to predict changes in turnover. TOD is negatively related to CVOL, RSR, and DPR. Thus, TOD may measure the same thing these other variables measure. However, even the most significant correlation (−.334, between TOD and CVOL) indicates that collinearity problems should be small. Thus, we now proceed to predict changes in time-varying turnover.

4. Results with raw turnover

Table 3 presents results of the following time series regression for each portfolio $j=1,\ldots,9$

$$\tau_{j,t} = \beta_{j,0} + \beta_{j,1}{*}\mathrm{CVOL}_{t-1} + \beta_{j,2}{*}\mathrm{RSR}_{t-1} + \beta_{j,3}{*}\mathrm{DPR}_{t-1} + \beta_{j,4}{*}\mathrm{TOD}_{t-1} + \varepsilon_{j,t} \tag{12}$$

in which $\tau_{j,t}$ is an equally weighted average of turnover at time t for portfolio j, and the instrumental variables are the time $t-1$ values of the variables defined above. The regressions use all the sample data from 1966 through 2003. Coefficients that are significant at the .05 (.10) level are marked with a double (single) asterisk. All t-statistics are calculated with standard errors based on Newey-West (1987) adjustments for heteroskedasticity and autocorrelation.

The coefficients on TOD_{t-1} (β_{j4}) are positive and significant at the .05 level for each of the nine portfolios. Coefficients on all the other variables are significant at the .10 level for at least five portfolios. However, the signs of these coefficients are not consistent across portfolios. For example, the coefficient on CVOL_{t-1} (β_{j1}) is negative and significant for portfolios 1 through 3, but positive and significant for portfolio 4 and for portfolios 7 through 9. Despite

Table 3
Regressions of equally weighted turnover on instrumental variables (1966 to 2003)

	Coefficients on instrumental variables					Adjusted-R^2
	β_{j0}	β_{j1}	β_{j2}	β_{j3}	β_{j4}	
Portfolio 1	0.014** (7.60)	−0.095** (−4.51)	−0.662** (−2.43)	−0.223** (−2.22)	0.532** (15.55)	0.566
Portfolio 2	0.030** (10.24)	−0.215** (−5.76)	−0.141 (−0.30)	−0.204 (−1.33)	0.387** (7.77)	0.268
Portfolio 3	0.040** (8.82)	−0.320** (−5.67)	0.930 (1.38)	−0.725** (−2.90)	0.910** (11.09)	0.400
Portfolio 4	−0.000 (−0.11)	0.060** (2.02)	−1.856** (−5.25)	−0.300* (−1.85)	1.033** (24.62)	0.671
Portfolio 5	0.003 (1.36)	0.022 (0.69)	−1.098** (−3.20)	0.034 (0.26)	1.230** (25.35)	0.739
Portfolio 6	0.008* (1.92)	0.000 (0.00)	−0.247 (−0.42)	−0.339* (−1.68)	2.119** (25.95)	0.785
Portfolio 7	−0.015** (−4.28)	0.154** (3.46)	−2.074** (−4.16)	0.299 (1.34)	1.478**(24.81)	0.638
Portfolio 8	−0.023** (−5.31)	0.185** (3.41)	−1.900** (−3.08)	0.647** (2.64)	1.815** (22.91)	0.636
Portfolio 9	−0.027** (−4.69)	0.235** (3.30)	−1.227 (−1.45)	0.455 (1.40)	2.761** (26.06)	0.707

$\mathrm{EWTO}_{j,t}{=}\beta_{j,0}{+}\beta_{j,1}{*}\mathrm{CVOL}_{t-1}\beta_{j,2}{*}\mathrm{RSR}_{t-1}{+}\beta_{j,3}{*}\mathrm{DPR}_{t-1}{+}\beta_{j,4}{*}\mathrm{TOD}_{t-1}{+}\varepsilon_{j,t}$.
Note: Instrumental variables are lagged values of conditional volatility (CVOL_{t-1}), the relative short rate (RSR_{t-1}), the dividend price ratio (DPR_{t-1}), cross-sectional dispersion of turnover for the market as a whole (TOD_{t-1}). A double (single) asterisk, ** (*), indicates significance at the .05 (.10) level, based on Newey and West (1987) corrections for heteroskedastic and autocorrelated errors.

Table 4
Chi-square statistics (p-values) for heteroskedasticity-autocorrelation-consistent tests of latent variable models that test the number of factors with turnover data based on value-weighted turnover-beta-ranked portfolios

Number of Stock Portfolios	Number of Instrumental Variables	Saturation Ratio of the Test (One-Factor), [Two-Factor]	Chi-square statistic (p-value)		
			One-Factor	Two-Factor	Three-Factor
Panel A: 456 time series observations (01/1966–12/2003)					
6	3	(22.93)	17.26	3.92	
		[22.18]	(0.0687)	(0.4172)	
9	3	(14.07)	25.14	11.41	
		[13.75]	(0.0673)	(0.1215)	
6	4	(14.76)	22.73	12.78	
		[14.43]	(0.0900)	(0.1196)	
9	4	(8.74)	28.85		
		[8.61]	(0.2260)		
6	5	(10.56)	30.38	18.46	
		[10.38]	(0.0639)	(0.1024)	
9	5	(6.09)	35.21		
		[6.02]	(0.3186)		
Panel B: 240 time series observations (01/1966–12/1985)					
6	3	(12.07)	18.37	2.84	
		[11.68]	(0.0490)	(0.5846)	
9	3	(7.40)	20.77		
		[7.23]	(0.1875)		
6	4	(7.77)	18.84		
		[7.59]	(0.2209)		
Panel C: 240 time series observations (01/1984–12/2003)					
6	3	(12.07)	16.93	3.72	
		[11.68]	(0.0759)	(0.4455)	
9	3	(7.40)	18.11		
		[7.23]	(0.3174)		
6	4	(7.77)	19.56		
		[7.59]	(0.1897)		

Note: The models restrict the system of regressions of J turnover of nine stratified value-weighted portfolios on L instrumental variables. For each month from March 1966 to December 2003, securities are sorted into 3 size-ranked portfolios according to their previous year-end market capitalization. Each size portfolio is then further partitioned into 3 turnover-sorted portfolios according to the turnover betas of its component securities. The turnover of a stock in a month is defined as the total trading volume of the month divided by the total number of shares outstanding at the end of the previous month. The turnover of a portfolio is a value-weighted average of individual turnovers. Instrumental variables are the conditional volatility (CVOL), the lagged value of the relative short rate (LRSR), the lagged value of the dividend price ratio (LDPR), and the lagged cross-sectional dispersion of turnover for the market as a whole (LTOD). Define δ_{lj} as the coefficient of the jth portfolio's turnover on the lth instrumental variable. A K-latent variable model imposes $(J-K)(L-K)$ restrictions on the system, which can be written as

$$\delta_{lj} = \sum_{k=l}^{K} \alpha_{lk}\beta_{kj}.$$

Where α_{lk} and β_{kj} are free parameters. The tests are conducted by estimating the restricted system and computing Hansen's (1982) chi-square statistic adjusted for autocorrelation.

such sign reversals, the adjusted-R^2 estimates clearly indicate that turnover varies predictably through time for each of the nine portfolios. Those estimates range from .268 for portfolio 2 to .785 for portfolio 6. The mean is 0.601.[8]

Given the predictability of turnover, we now use Hansen's (1982) and Hansen and Singleton's (1982) GMM nonlinear estimation technique, with refinements suggested by Bekaert and Urias (1996), Ferson and Foerster (1994), and Andrews (1991). We also seek to maximize the power of our tests by maintaining suitable saturation ratios (see

[8] The mean adjusted-R^2 value for value weighted portfolios is .622. Adjusted-R^2 estimates from regressions run over five-, ten-, and twenty-year sub-periods are similar to the adjusted-R^2 values for the total sample and, thus, indicate that turnover can be predicted successfully in shorter periods with these instruments. Results of these sub-period regressions are available upon request from the authors.

Table 5
Chi-square statistics (p-values) for heteroskedasticity-autocorrelation-consistent tests of latent variable models that test the number of factors with turnover data based on equally weighted turnover-beta-ranked portfolios

Number of Stock Portfolios	Number of Instrumental Variables	Saturation Ratio of the Test (One-Factor), [Two-Factor], {Three-Factor}	Chi-square statistic (p-value) One-Factor	Two-Factor	Three-Factor
Panel A: 456 time series observations (01/1966–12/2003)					
6	3	(22.93)	14.70		
		[22.18]	(0.1433)		
9	3	(14.07)	24.08	9.44	
		[13.75]	(0.0877)	(0.2226)	
6	4	(14.76)	25.06	13.60	2.13
		[14.43]	(0.0491)	(0.0927)	(0.5468)
		{14.21}			
9	4	(8.74)	30.05		
		[8.61]	(0.1829)		
6	5	(10.56)	28.20		
		[10.38]	(0.1047)		
9	5	(6.09)	34.58		
		[6.02]	(0.3457)		
Panel B: 240 time series observations (01/1966–12/1985)					
6	3	(12.07)	16.65	15.83	
		[11.68]	(0.0826)	(0.0033)	
9	3	(7.40)	19.83		
		[7.23]	(0.2281)		
6	4	(7.77)	17.30		
		[7.59]	(0.3011)		
Panel C: 240 time series observations (01/1984–12/2003)					
6	3	(12.07)	15.47		
		[11.68]	(0.1160)		
9	3	(7.40)	19.58		
		[7.23]	(0.2396)		
6	4	(7.77)	19.01		
		[7.59]	(0.2131)		

Note: The models restrict the system of regression of J turnover of nine stratified equally weighted portfolios on L instrumental variables. For each month from March 1966 to December 2003, securities are sorted into 3 size-ranked portfolios according to their previous year-end market capitalization. Each size portfolio is then further partitioned into 3 turnover-sorted portfolios according to the turnover betas of its component securities. The turnover of a stock in a month is defined as the total trading volume of the month divided by the total number of shares outstanding at the end of the previous month. The turnover of a portfolio is an equally weighted average of individual turnovers. Instrumental variables are the conditional volatility (CVOL), the lagged value of the relative short rate (LRSR), the lagged value of the dividend price ratio (LDPR), and the lagged cross-sectional dispersion of turnover for the market as a whole (LTOD). Define δ_{lj} as the coefficient of the jth portfolio's turnover on the lth instrumental variable. A K-latent variable model imposes $(J-K)(L-K)$ restrictions on the system, which can be written as

$$\delta_{lj} = \sum_{k=l}^{K} \alpha_{lk}\beta_{kj}$$

Where α_{lk} and β_{kj} are free parameters. The tests are conducted by estimating the restricted system and computing Hansen's (1982) chi-square statistic adjusted for autocorrelation.

Gallant and Tauchen, 1991). As stated above, the saturation ratio is the number of observations divided by the number of parameters to be estimated including the parameters in the weighting matrix. The dimension of the weighing matrix is $JL \times JL$. If we employ fewer instrumental variables (i.e., smaller values of L), the dimension of the weighing matrix, and hence the number of parameters that need to be estimated, can be greatly reduced. This will lead to a larger saturation ratio. Similarly, the saturation ratio can be improved if we use smaller subsets of assets in the test (i.e., smaller values for J).[9] We show the effects of different saturation ratios on the number of factors detected by varying the number of observations, portfolios, and instruments in our analysis.

[9] See Ferson and Foerster (1994), in particular the conclusion on page 50, regarding the power of the GMM test and the size of the system.

Tables 4 and 5 present χ^2-statistics and p-values from our heteroskedasticity- and autocorrelation-consistent GMM tests of the latent variable models. Table 4 uses value-weighted portfolios; Table 5 uses equally weighted portfolios. The format for both tables is the same. Panel A presents results for the total sample. Panels B and C report results for two 20-year sub-periods. The first sub-period runs from January 1966 through December 1985; the second extends from January 1984 through December 2003.[10] We also perform tests for five- and ten-year sub-periods. However, because the saturation ratios for these tests are low, we do not report the tests separately but will make them available upon request.

The first column of each table lists the number of portfolios used in the analysis. When only six portfolios are used, we exclude the small-cap firms in portfolios 1 through 3. The second column lists the number of instrumental variables used in the analysis. All tests include the intercept and lagged values of conditional volatility (CVOL_{t-1}) because of its important relation with turnover in the literature (see, e.g., Blume et al., 1994). In tests with only three instrumental variables, we add lagged values of the dividend price ratio (DPR_{t-1}), and in tests with four instrumental variables, we add lagged values of the relative short rate (RSR_{t-1}).[11]

Bekaert and Urias (1996, p. 846) point out that GMM-systems with saturation ratios below 10 are common in empirical finance but that they are likely to have low power. Our evidence is consistent with that argument. For the value-weighted portfolios in Table 4, we fail to reject a single-factor model in every instance in which the saturation ratio is lower than 10. When the saturation ratio exceeds 10, we reject a single-factor model but not a two-factor model. This evidence is consistent with Lo and Wang (2000) who find that two principal components explain approximately 90% of the variation in turnover of portfolios ranked by turnover betas. For the equally weighted portfolios in Table 5, we fail to reject a single-factor model whenever the saturation ratio is below 10 and, in some cases (panel A: six portfolios, three or five instrumental variables: panel C: six portfolios, three instrumental variables), when the saturation ratio is higher than 10. Interestingly, in two cases when we reject a single-factor model (panel A: six portfolios, four instrumental variables; panel B: six portfolios, three instrumental variables), we also reject a two-factor model.

5. Results with normalized turnover

To a large extent the results of Lo and Wang's (2000) principal components analysis are invariant to their use of raw or first differenced turnover. In both cases, Lo and Wang (2000) find two principal components that explain approximately 90% of the variation in turnover-beta-ranked portfolios. This section examines the extent to which our results vary based on alternative specifications of turnover. Rather than first-differencing, however, we normalize turnover as follows:

$$\tau*_{jt} = (\tau_{jt} - \tau_{\mathrm{MIN}t})/(\tau_{\mathrm{MAX}t} - \tau_{\mathrm{MIN}t}) \tag{13}$$

where τ_{jt} is the turnover of security j for month t, $\tau_{\mathrm{MIN}t}$ is the lowest cross-sectional turnover of the sample security for month t, $\tau_{\mathrm{MAX}t}$ is the highest cross-sectional turnover of the sample security for month t, and $\tau*_{jt}$ is the transformed turnover of security j for month t.

The normalized turnover variables are partitioned into cross-sectional quantiles according to their values after the transformation. Firms with normalized turnovers that fall within the lowest 11th percentile are placed into portfolio 1. Securities with normalized turnovers that are higher than the 11th percentile but lower than the 22nd percentile are sorted into portfolio 2, and so forth. Finally, firms with $\tau*_{jt}$ higher than the 88th percentile are placed into portfolio 9. Equally weighted portfolio turnovers for each month are computed by averaging the transformed turnovers of the securities in each of the 9 portfolios. Similarly, 9 value-weighted portfolios with transformed turnover are obtained by

[10] Besides allowing us to examine the effect of changes in the saturation ratio, the sub-period analysis also allows us to recognize systematic changes in the market. For example, in the last part of our sample, many new securities have been introduced, index funds have become popular, and portfolio insurance and dynamic trading strategies have become available. Though limitations on the saturation ratio limit our ability to examine the impact of any one change in the market, the effect of the combined impact of these market changes is still of interest.

[11] Tests based on the same number but other combinations of the instrumental variables produce qualitatively similar results. Results of those tests are available from the authors upon request.

weighting the individual securities' normalized turnovers within each portfolio by their respective previous month end market capitalizations.

With these portfolios, we perform the same tests reported in Tables 1 and 3 through 5. For brevity, we focus only on the GMM tests but will make the full results available upon request. Before we discuss the GMM results, we note the following important findings from the other tests with normalized turnover: 1) the Dickey and Fuller (1979) tests reject the non-stationarity hypothesis at the .05 level for portfolios 1 through 6 and at the .10 level for portfolios 7 and 8; 2) the adjusted-R^2 estimates from the time series regressions are slightly lower than the regressions in Table 3 (the average is approximately 0.50), but the signs of the coefficients are now consistent across portfolios; and 3) though we fail to reject the non-stationarity hypothesis for portfolio 9, the predictive relations in the regressions are not caused by non-stationarity because those relations also exist for portfolios 1 through 8, for which the Dickey and Fuller (1979) tests reject non-stationarity.

Table 6
Chi-square statistics (p-values) for heteroskedasticity-autocorrelation-consistent tests of latent variable models that test the number of factors based on value-weighted normalized (0–1) turnover-quantile portfolios

Number of Stock Portfolios	Number of Instrumental Variables	Saturation Ratio of the Test (One-Factor), [Two-Factor]	Chi-square statistic (p-value)		
			One-Factor	Two-Factor	Three-Factor
Panel A: 456 time series observations (01/1966–12/2003)					
6	3	(22.93)	15.63		
		[22.18]	(0.1106)		
9	3	(14.07)	23.57	5.10	
		[13.75]	(0.0992)	(0.6473)	
6	4	(14.76)	22.47	11.29	
		[14.43]	(0.0960)	(0.1856)	
9	4	(8.74)	25.82		
		[8.61]	(0.3622)		
6	5	(10.56)	28.07		
		[10.38]	(0.1078)		
9	5	(6.09)	34.03		
		[6.02]	(0.3702)		
Panel B: 240 time series observations (01/1966–12/1985)					
6	3	(12.07)	15.13		
		[11.68]	(0.1274)		
9	3	(7.40)	15.36		
		[7.23]	(0.4987)		
6	4	(7.77)	17.86		
		[7.59]	(0.2702)		
Panel C: 240 time series observations (01/1984–12/2003)					
6	3	(12.07)	17.25	3.13	
		[11.68]	(0.0690)	(0.5367)	
9	3	(7.40)	22.22		
		[7.23]	(0.1362)		
6	4	(7.77)	19.57		
		[7.59]	(0.1890)		

Note: The models restrict the system of regressions of J turnover of nine stratified value-weighted portfolios on L instrumental variables. For each month from January 1966 to December 2003, securities are sorted into 9 0–1 turnover-quantile portfolios according to the normalized turnover of its component securities. The turnover of a portfolio is a value-weighted average of its component securities' normalized turnovers. Instrumental variables are the conditional volatility (CVOL), the lagged value of the relative short rate (LRSR), the lagged value of the dividend price ratio (LDPR), and the lagged cross-sectional dispersion of turnover for the market as a whole (LTOD). Define δ_{lj} as the coefficient of the jth portfolio's turnover on the lth instrumental variable. A K-latent variable model imposes $(J-K)(L-K)$ restrictions on the system, which can be written as

$$\delta_{lj} = \sum_{k=l}^{K} \alpha_{lk}\beta_{kj}$$

Where α_{lk} and β_{kj} are free parameters. The tests are conducted by estimating the restricted system and computing Hansen's (1982) chi-square statistic adjusted for autocorrelation.

Table 7
Chi-square statistics (p-values) for heteroskedasticity-autocorrelation-consistent tests of latent variable models that test the number of factors based on equally weighted normalized (0–1) turnover-quantile portfolios

Number of Stock Portfolios	Number of Instrumental Variables	Saturation Ratio of the Test (One-Factor), [Two-Factor], {Three-Factor}	Chi-square statistic (p-value)		
			One-Factor	Two-Factor	Three-Factor
Panel A: 456 time series observations (01/1966–12/2003)					
6	3	(22.93)	15.80		
		[22.18]	(0.1056)		
9	3	(14.07)	22.69		
		[13.75]	(0.1222)		
6	4	(14.76)	22.09		
		[14.43]	(0.1056)		
		{14.21}			
9	4	(8.74)	32.98		
		[8.61]	(0.1046)		
6	5	(10.56)	27.05		
		[10.38]	(0.1339)		
9	5	(6.09)	32.61		
		[6.02]	(0.4370)		
Panel B: 240 time series observations (01/1966–12/1985)					
6	3	(12.07)	13.84		
		[11.68]	(0.1805)		
9	3	(7.40)	22.11		
		[7.23]	(0.1397)		
6	4	(7.77)	16.82		
		[7.59]	(0.3295)		
Panel C: 240 time series observations (01/1984–12/2003)					
6	3	(12.07)	26.54	7.11	
		[11.68]	(0.0031)	(0.1301)	
9	3	(7.40)	22.24		
		[7.23]	(0.1357)		
6	4	(7.77)	18.91		
		[7.59]	(0.2179)		

Note: The models restrict the system of regressions of J turnover of nine stratified equally weighted portfolios on L instrumental variables. For each month from January 1966 to December 2003, securities are sorted into 9 0–1 turnover-quantile portfolios according to the normalized turnover of its component securities. The turnover of a portfolio is an equally weighted average of its component securities' normalized turnovers. Instrumental variables are the conditional volatility (CVOL), the lagged value of the relative short rate (LRSR), the lagged value of the dividend price ratio (LDPR), and the lagged cross-sectional dispersion of turnover for the market as a whole (LTOD). Define δ_{lj} as the coefficient of the jth portfolio's turnover on the lth instrumental variable. A K-latent variable model imposes $(J-K)(L-K)$ restrictions on the system, which can be written as

$$\delta_{lj} = \sum_{k=l}^{K} \alpha_{lk}\beta_{kj}$$

Where α_{lk} and β_{kj} are free parameters. The tests are conducted by estimating the restricted system and computing Hansen's (1982) chi-square statistic adjusted for autocorrelation.

Tables 6 and 7 use the same format as Tables 4 and 5 to report results of the GMM tests with normalized turnover for value and equally weighted portfolios. In general, these tests detect fewer factors than the tests with raw turnover. Besides failing to reject a single-factor model in each case for which the saturation ratio is below 10, we now fail to reject a single-factor model in several cases when the saturation ratio exceeds 10. For example, with both the value and the equally weighted portfolios, we fail to reject a single-factor model in the first sub-period for all saturation ratios. In the second sub-period, however, we reject a single-factor model with both the value and the equally weighted portfolios when the saturation ratio exceeds 10.

Though our use of different methods and different sample periods prevents exact comparisons between our findings and those presented by Lo and Wang (2000), the findings in this section serve to highlight methodological differences between their study and ours. As we noted earlier, Lo and Wang detect two factors with their principal components analysis of raw and first differenced turnover. However, we detect only one factor with normalized turnover in the first

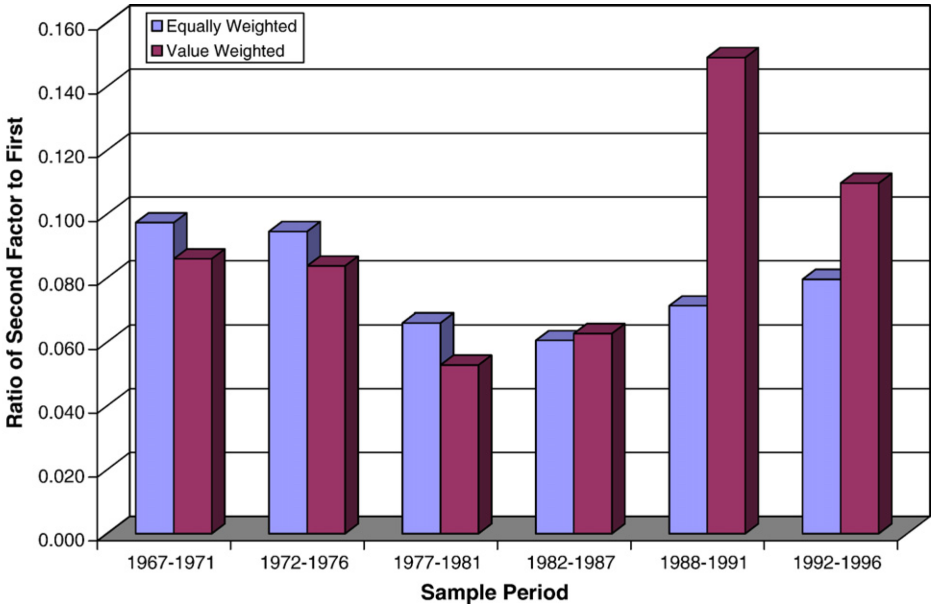

Fig. 1. Ratios of second factor to first from Lo and Wang's (2000) Table 8 principal component analysis.

sub-period. Since GMM tests focus only on predictable factors whose detection depends on the instruments used to predict turnover, we may fail to reject a single-factor model in the first sub-period with normalized turnover because one of the factors is not predictable or because our set of instruments fails to include an important predictor. That interpretation implies that factor predictability varies through time or that the instruments used to predict factors change. We do not pursue those issues further here.

An alternative explanation for the difference between our findings and Lo and Wang's findings deals with limitations of principal components analysis. Although Lo and Wang find that two principal components explain approximately 90% of the variation in turnover of portfolios ranked by turnover betas, their first factor explains 80% of that variation, on average. Thus, their first factor dominates their second and the question of the statistical significance of the second factor may become important. We, of course, do not know how significant that factor is statistically because the principal components approach does not provide that information. What we do know is that the first factor dominates the second, and that the second becomes more important in later sub-periods, at least for value-weighted portfolios.

Fig. 1 illustrates this pattern by plotting the ratio of the second factor to the first from Table 8 of Lo and Wang's principal component analysis for each of their six sub-periods. We use Table 8 because it reports results for first differenced turnover — Lo and Wang's correction for non-stationarity. For the equally weighted index, none of the ratios in Fig. 1 is as large as 0.10. For value-weighted portfolios, two ratios exceed 0.10 and they occur in the last two sub-periods for which the dates of the analysis overlap with our second sub-period. This evidence is consistent with our failure to reject (rejection of) a single-factor model in our first (second) sub-period for value-weighted portfolios. That said, we hasten to repeat that we cannot draw strong inferences because of differences in sample periods and methods. Nevertheless, suggestive evidence exists at least that our findings based on different methods are consistent with the findings of Lo and Wang for value-weighted portfolios.

6. Conclusion

We document a set of instruments that explain approximately 60% of the monthly variation in raw turnover between 1966 and 2003 and about 50% of the variation in normalized turnover over the same period. We use these relations to conduct GMM latent variable tests to determine the number of predictable factors that drive conditional expected turnover. With raw turnover in tests with saturation ratios of 10 or higher, we reject a one-factor model but we fail to reject a two-factor model for value-weighted portfolios. For equally weighted portfolios, the number of factors varies in some cases from the number detected with value-weighted portfolios. Nevertheless, both weighting schemes support inferences that in tests with adequate power more than one common factor drives conditional expected turnover.

In tests based on normalized turnover that correct for non-stationarity, we generally detect fewer factors than with tests based on raw turnover, even when saturation ratios exceed 10. Thus, with both equally and value-weighted portfolios, we fail to reject a single-factor model in the first half of our sample. In contrast, we detect two factors in the second half. Our failure to reject a single-factor model in the earlier period seems inconsistent with findings in Lo and Wang (2000). That difference may stem from the unpredictability of a normalized turnover factor or from our failure to include an important predictor in the time series regressions. That explanation implies that factor predictability varies through time or that the instruments used to predict factors change from period to period. Alternatively, the seeming difference between our findings and Lo and Wang's may reflect shortcomings in principal components tests that provide no way to determine the statistical significance of Lo and Wang's second factor that is clearly dominated by the first. We leave the resolution of this seeming inconsistency to future research.

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