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Predictability of Stock Market Returns Based on Trading Turnover: Evidence From The Chinese Market

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Abstract. Trading turnover serves as a critical indicator of market activity. This study conducts an empirical analysis using monthly returns of the Shanghai Stock Exchange Composite Index and market turnover data from January 2000 to December 2022. By decomposing market turnover into "good turnover" and "bad turnover," we investigate the relationship between different turnover components and equity returns. The findings indicate that both total market turnover and good turnover significantly predict stock market returns both in-sample and out-of-sample, with good turnover exhibiting superior predictive power. Furthermore, good turnover provides incremental information beyond that captured by total market turnover and bad turnover. Practical asset allocation tests demonstrate that strategies based on good turnover forecasts outperform those utilizing total or bad turnover.

Keywords: Stock return predictability; Good turnover; Bad turnover; Asset allocation.

1. Introduction

In recent years, against the backdrop of rapid development, China's securities market has undergone continuous optimization of its institutional construction and regulatory framework, marking a gradual transition towards maturity. However, as an emerging market, the Chinese stock market continues to face numerous unique challenges, such as prevalent information asymmetry, strict short-selling constraints, significant speculative behavior driven by a high proportion of retail investors, and frequent herding effects. These characteristics collectively form a complex and dynamic market environment where high turnover, a distinctive feature of the Chinese stock market, has attracted considerable scholarly attention.

Turnover rate, representing the frequency of stock trading, is not only a direct reflection of market liquidity but also the result of the interaction between market sentiment, information efficiency, and investor behavior [1]. The volume-price relationship has long been a cornerstone of stock market analysis, with turnover rate serving as a key indicator of trading activity; its correlation with stock returns remains a focal point of academic research. This paper comprehensively analyzes multidimensional evidence regarding the predictive power of turnover rate on stock market returns, aiming to provide a deeper understanding of this complex financial phenomenon.

Liquidity premium theory posits that turnover rate is typically negatively correlated with future returns [2-5], reflecting return compression caused by excessive trading. Nevertheless, empirical results vary across different market environments. For instance, Jun et al. [6] found a positive correlation between turnover and expected returns in emerging markets, highlighting the influence of market characteristics. These discrepancies may stem from differences in econometric methods, sample selection, and market maturity.

Investor disagreement theory offers another perspective on the relationship between turnover and returns. Research by Tan et al. [7] and Liu and Zhang [8] indicates that investor information processing and belief heterogeneity affect stock returns by influencing turnover rates, particularly at specific time points (such as the weekend effect) and within specific investment portfolios. regarding momentum and reversal effects, a comparison of findings by Lee and Swaminathan [9] and Wang and Zhao [10] reveals differences in turnover performance between the Chinese and US markets, suggesting that high turnover in the Chinese stock market may shorten the reversal cycle. Deng et al. [11] improved the model to explicitly point out that momentum effects are stronger in low-turnover stocks, while high-turnover stocks exhibit reversal effects, deepening the segmented understanding of turnover predictive ability.

Portfolio research further refines the predictive effect of turnover. A cross-sectional analysis by Yang and Han [12] revealed that in certain high-return portfolios, the explanatory power of turnover on expected returns is limited. Recent studies, such as Xing and Liu [13] and Ma et al. [14], exploring stocks with different turnover levels, found that predicting returns for low-turnover stocks may be more challenging, and deep learning models demonstrate higher predictive efficacy in low-turnover environments. Finally, research from new perspectives, such as the Two-beta model by Qu et al. [15] and the limited arbitrage analysis by Cui et al. [16], provides innovative explanations for the negative predictive effect of turnover, involving mechanisms such as discount rate risk, cash flow risk, and pricing errors caused by market inefficiencies.

In summary, the role of turnover rate in predicting stock market returns is complex and variable, with its influence mechanisms intertwined with multiple factors. By systematically integrating existing research results, this paper aims to build a more comprehensive analytical framework. This not only deepens the understanding of the mechanism of turnover rate but also provides an empirical basis for market analysis and strategy formulation, particularly within the unique context of the Chinese stock market.

2. Data and Model Construction

2.1. Data and variables

This paper primarily focuses on the Shanghai Composite Index, with relevant data sourced from the RESSET database. The excess return is calculated by subtracting the monthly risk-free interest rate from the monthly return of the Shanghai Composite Index. The turnover rate indicator utilizes the circulating market capitalization-weighted monthly market turnover rate of the Shanghai Stock Exchange. Given the high volatility during the nascent period of the Chinese stock market prior to 2000, this study selects data from January 2000 to December 2022 for analysis.

2.2. Model establishment

This study employs a standard univariate predictive regression model to test and analyze the predictive ability of turnover rate on future stock market returns:

$$r_{t+1} = \beta_0 + \beta_{STR} STR_t + \varepsilon_{t+1} \tag{1}$$

Where r_{t+1} represents the stock excess return in month *t*+1, STR_t represents the stock market turnover rate in month *t*, and ε_{t+1} denotes the residual term.

Investors hold distinct attitudes toward risk and return, and their investment decisions are significantly influenced by past or current market performance. Therefore, referencing the method of Zang [17], this paper decomposes the stock market turnover rate into "good turnover" ($GoodSTR_t$) and "bad turnover" ($BadSTR_t$) based on the sign of the stock market excess return, as described in the following formulas:

$$GoodSTR_t = STR_t I(r_t \geq 0) \tag{2}$$

$$BadSTR_t = STR_t I(r_t < 0) \tag{3}$$

Where r_t is the stock excess return, and $I(\cdot)$ is an indicator function. Similarly, this paper further examines the predictive ability of the constructed good and bad turnover indicators on future stock market excess returns:

$$r_{t+1} = \beta_0 + \beta_{GoodSTR} GoodSTR_t + \varepsilon_{t+1} \tag{4}$$

$$r_{t+1} = \beta_0 + \beta_{BadSTR} BadSTR_t + \varepsilon_{t+1} \tag{5}$$

To determine whether the constructed good and bad turnover rates possess predictive power for stock market excess returns, one can first estimate whether the β value in the above regression equation is significant. If β is significant, the variable can be used to predict stock market excess returns. Subsequently, the magnitude of the R^2 value of the least squares regression model is assessed; if the R^2 value exceeds a certain threshold, it implies that the variable can improve economic benefits.

To analyze the relationship between the information provided by turnover indicators and other economic variables, referencing the research of Ma and Cao [18], eight macroeconomic variables applicable to the Chinese stock market are selected. First, univariate predictive regressions are performed using the aforementioned economic variables. Then, bivariate predictive regressions are conducted using one of the eight macroeconomic variables together with good turnover. The constructed bivariate regression model is as follows:

$$r_{t+1} = \beta_0 + \beta_G GoodSTR_t + \beta x_t + \varepsilon_{t+1} \tag{6}$$

Where x_t represents one of the eight macroeconomic variables. The specific meanings of these economic variables are as follows:

- Dividend-Price Ratio (log), *DP*: The logarithm of the 12-month moving sum of dividends paid by all Chinese A-shares minus the logarithm of the sum of their stock market capitalizations.
- Dividend Yield (log), *DY*: The logarithm of the 12-month moving sum of dividends paid by all Chinese A-shares minus the logarithm of the lagged sum of their stock market capitalizations.
- Dividend Payout Ratio (log), *DE*: The logarithm of the sum of 12-month moving dividends minus the logarithm of the sum of 12-month moving earnings.
- Earnings-Price Ratio (log), *EP*: The logarithm of the 12-month moving sum of earnings of all Chinese A-shares minus the logarithm of the sum of their market capitalizations.
- Book-to-Market Ratio, *BM*: The ratio of the book value to the market value of all Chinese A-shares.
- Stock Variance, *SVAR*: The sum of squared daily value-weighted total stock returns.
- Net Equity Expansion, *NTIS*: The ratio of the 12-month moving sum of net issuance of all Chinese A-shares divided by the total year-end market capitalization of all Chinese A-shares.
- Inflation Rate, *INFL*: Calculated based on the Consumer Price Index (CPI), with data from the National Bureau of Statistics of China.

3. Empirical Analysis

3.1. In-sample estimation results

Table 1 displays the regression results for the three predictive models mentioned above. It is evident that in the in-sample prediction, both the aggregate market turnover rate and good turnover rate are significant. The predictive model containing good turnover yields an R^2 value of 4.006%, indicating that good turnover can explain 4.006% of future stock price fluctuations. If a predictor generates an R^2 exceeding 0.5%, it implies that this variable can significantly improve economic benefits [19]. Additionally, the coefficient for turnover obtained in this paper is 0.068, a positive value. This is inconsistent with the conclusion of most previous literature finding a negative correlation between turnover and stock market returns. This discrepancy may arise because previous studies mostly focused on cross-sectional returns, whereas this paper studies stock market returns from a time-series perspective. Gao et al. [20] argue that market time-series predictability is only partially contingent upon cross-sectional predictability, suggesting that time series may yield regression results different from or even opposite to cross-sectional results.

Table 1. In-sample prediction results

Prediction Model	β	t_β-stat	R^2(%)
STR	0.068**	2.304	2.970
GoodSTR	0.066***	2.788	4.006
BadSTR	-0.049	-0.993	0.842

Note: This table reports the coefficient β , its t-value, and the R^2 statistic (in percentage) for the predictive regression between turnover indicators and Chinese stock market excess returns. ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 2000:01 to 2022:12, with 276 observations.

3.2. Comparison with other economic variables

To test whether the predictive power of good turnover can be explained or influenced by other macroeconomic variables, univariate regression predictions are first performed on several common macroeconomic variables. Subsequently, bivariate predictive regressions are conducted using good turnover, which performed well in in-sample predictions, together with these macroeconomic variables.

Table 2 presents the regression results for future stock return prediction using eight macroeconomic variables. The results indicate that, except for inflation, the other seven macroeconomic variables are not significant when predicting stock returns individually. However, when using one of the eight economic variables together with good turnover for bivariate regression prediction, good turnover continues to demonstrate significant predictive ability at the 1% level. Moreover, the R^2 values in the bivariate predictive regressions are substantial, ranging from a minimum of 5.038% to a maximum of 7.914%. With the exception of the inflation rate variable, the R^2 of the bivariate regression predictions for all other variables exceeds the sum of the R^2 obtained when using good turnover and the economic variable separately. Accordingly, good turnover and macroeconomic variables provide complementary information when predicting stock market returns.

Table 2. In-sample results about stock turnover rate and macroeconomic variables

	Univariate				Bivariate				
variables	β	t_{β}-stat	R^2 (%)		β	t_{β}-stat	β_G	$t_{\beta G}$-stat	R^2(%)
DP	0.010	1.089	0.541		0.021**	2.121	0.082***	3.248	6.206
DY	0.013	1.413	0.891		0.020**	2.067	0.077***	3.123	6.100
DE	0.038	1.421	1.126		0.040*	1.510	0.068***	2.877	5.432
EP	0.004	0.557	0.101		0.013**	1.687	0.076***	3.072	5.038
BM	0.023	0.877	0.334		0.060**	2.286	0.085***	3.377	6.175
SVAR	-1.153	-1.435	1.017		-1.407**	-1.788	0.071***	2.949	5.665
NTIS	-0.045	-0.883	0.728		-0.060	-1.118	0.072***	2.967	5.454
INFL	-0.008***	-3.015	4.885		-0.007***	-2.642	0.058***	2.425	7.914

Note: The table reports the results using univariate and bivariate variables to predict stock market returns. Coefficient estimates are shown, and their Newey – West t-statistics and R^2 are also shown. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2000:01 to 2022:12, containing 276 observations.

3.3. Out-of-sample prediction effect

Regarding stock return prediction, investors may be more concerned with out-of-sample results than in-sample ones. This paper selects data following the first five years (January 2005 to December 2022) as the out-of-sample period to test the model's predictive capability. The R_{OS}^2 is defined as:

$$R_{OS}^2 = 1 - \frac{\sum_{k=1}^{q}(r_{m+k} - \hat{r}_{m+k})^2}{\sum_{k=1}^{q}(r_{m+k} - \overline{r}_{m+k})^2} \tag{7}$$

Where r_{m+k} , $\overline{r}_{m+k}$, and $\hat{r}_{m+k}$ are the actual return, the predicted return based on the historical mean method, and the predicted return based on the model in the (m+k)-th month, respectively; m and q represent the time spans of the in-sample and out-of-sample periods, respectively. Statistically, the historical mean model is calculated as $\overline{r}_t = \frac{1}{t}\sum_{i=1}^{t} r_i$.

Table 3 presents the R_{OS}^2 and *CW* statistic results. The results show that the R_{OS}^2 for market turnover and good turnover are 1.318% and 2.619%, respectively, significant at the 5% level. This indicates that the predictive ability of market turnover and good turnover is significantly stronger than that of the historical mean model. Furthermore, the predictive ability of good turnover is clearly superior to that of market turnover, which is consistent with the in-sample regression results. The out-of-sample R_{OS}^2 for bad turnover is -2.143%, a negative value, also consistent with in-sample results, indicating that the bad turnover-based prediction model performs worse than the historical mean model, further illustrating that bad turnover does not possess predictive capability for stock market returns.

Table 3. Out-of-sample forecasting performance

Forecasting models	R_{OS}^2 (%)	*CW*-stat
STR	1.318**	2.040
GoodSTR	2.619**	2.184
BadSTR	-2.143	-0.330

Note: This table reports the out-of-sample performance of various forecasting models. Statistical significance for R_{OS}^2 is based on the p-value for the Clark and West (2007) MSFE-adjusted statistic. The null hypothesis of the Clark and West (2007) test is that the MSFE of the historical average benchmark forecasts is less than or equal to the MSFE of the given forecasting model. The alternative hypothesis is that the MSFE of the historical average benchmark forecasts is larger than the MSFE of the given forecasting model. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The initial in-sample period spans from 2000:01 to 2004:12, whereas the out-of-sample period is from 2005:01 to 2022:12.

3.4. Forecast encompassing test

Furthermore, this paper implements a forecast encompassing test to compare the amount of information contained in the three turnover indicators within the prediction models. The optimal combination forecast for actual returns is a convex combination of forecasts from model *i* and model *j* , which can be expressed as:

$$r_{t+1} = (1-\lambda)\hat{r}_{i,t+1} + \lambda \hat{r}_{j,t+1} \tag{8}$$

Where $\hat{r}_{i,t+1}$ and $\hat{r}_{j,t+1}$ are the forecasted returns obtained from model *i* and *j* in month *t*+1, respectively. If $\lambda(1-\lambda)=0$, it indicates that model *i(j)* is encompassed in model *j(i)*, because for forming the optimal combination forecast, model *i(j)* cannot provide any useful information beyond what model *j(i)* provides. Conversely, if $\lambda(1-\lambda)>0$, it indicates that the two models do not encompass each other and both can provide useful information for forming the optimal combination forecast. The null hypothesis is H_0: $\lambda(1-\lambda)=0$, and the alternative hypothesis is H_A: $\lambda(1-\lambda)>0$.

Table 4 presents the p-values obtained from the forecast encompassing test for the three models mentioned above during the out-of-sample period from 2005:01 to 2022:12. The p-value for determining whether the good turnover prediction model encompasses the bad turnover prediction model is 0.480, far greater than 0.1, whereas the p-value for determining whether the bad turnover prediction model encompasses the good turnover prediction model is 0.013, less than 0.05. This implies that when judging whether the good turnover model encompasses the bad turnover model, the null hypothesis is accepted; that is, the good turnover prediction model encompasses the prediction of bad turnover at the 5% significance level. Conversely, the null hypothesis is rejected when judging whether the bad turnover model encompasses the good turnover model. Similarly, it can be analyzed that the good turnover prediction model significantly encompasses the market turnover prediction model, but not vice versa. In summary, when predicting stock returns, the information provided by good turnover exceeds that provided by market turnover and bad turnover.

Table 4. Forecast encompassing test

Prediction Model	*GoodSTR*	*BadSTR*	*STR*
GoodSTR		0.480	0.356
BadSTR	0.013		0.037
STR	0.086	0.132	

Note: This table reports the p-values for the forecast encompassing test between the three models. The null hypothesis for the one-sided test is that the out-of-sample forecast in the column header encompasses the out-of-sample forecast in the row header. The alternative hypothesis is that the out-of-sample forecast in the column header does not encompass the out-of-sample forecast in the row header. The out-of-sample test period is 2005:01-2022:12.

3.5. Portfolio inspection

Both in-sample and out-of-sample empirical results demonstrate that market turnover and good turnover can significantly predict future stock excess returns. This paper next analyzes the enhancement effect of this predictive ability on return levels in the actual investment process. Assuming a mean-variance investor allocates assets between stocks and risk-free assets based on the out-of-sample prediction results of the aforementioned models, at time t , to satisfy utility maximization, the investor's optimal weight invested in stocks should be:

$$w_t = \frac{1}{\gamma}\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2} \tag{9}$$

Where γ is the risk aversion coefficient, taken as γ=3 in this paper; $\hat{r}_{t+1}$ is the out-of-sample predicted stock excess return; and $\hat{\sigma}_{t+1}^2$ is the predicted value of the return variance. To prevent short selling and limit leverage to no more than 50%, the stock weight is restricted to between 0 and 1.5. Transaction costs are not considered. The proportion invested in risk-free assets is $1-w_t$. At this point, the portfolio return in month t+1 is:

$$R_{t+1} = w_t r_t + r_{f,t+1} \tag{10}$$

Where $r_{f,t+1}$ represents the risk-free return. The Certainty Equivalent Return (CER) of the portfolio is defined as:

$$CER = \hat{\mu}_P - 0.5\gamma\hat{\sigma}_P^2 \tag{11}$$

Where $\hat{\mu}_P$ and $\hat{\sigma}_P^2$ represent the mean and variance of the portfolio's ordinary return during the out-of-sample period, respectively. The difference between the returns of the portfolio constructed using the model proposed in this paper and the portfolio constructed using the historical average prediction, i.e., the Certainty Equivalent Return gain (CER gain), can be annualized by multiplying by 1200. The annualized CER gain can be interpreted as the annual portfolio management fee a mean-variance investor would be willing to pay to obtain the expected returns based on the model proposed in this paper rather than the historical mean model. Additionally, the Sharpe Ratio is used to measure portfolio performance, defined as follows:

$$SR = \frac{\mu_p^e}{\sigma_P^e} \tag{12}$$

Where μ_p^e and σ_p^e represent the mean and standard deviation of the portfolio's excess return during the out-of-sample period, respectively.

The asset allocation results are shown in Table 5. The CER gain produced by the good turnover prediction model is 2.463%, the largest among the three models proposed in this paper. This figure indicates that investors are willing to pay an annual management fee of approximately 246.3 basis points to obtain the economic benefits based on the good turnover prediction model. The Sharpe ratio obtained from the good turnover prediction model is 0.124, also the highest among the three prediction models. These results economically demonstrate that good turnover plays an important role in predicting stock returns.

Table 5. Portfolio performance

Forecasting models	CER gain	Sharpe ratio
STR	2.106	0.120
GoodSTR	2.463	0.124
BadSTR	0.323	0.062

Note: This table reports the portfolio performance for a mean-variance investor with a relative risk aversion coefficient of three who allocates between stocks and risk-free bills using the return forecasts from various forecasting models in terms of the CER gain and Sharpe ratio. In particular, the CER gain is multiplied by 1,200 to denote an annualized percentage value, and the Sharpe ratio is multiplied by √12 to indicate an annualized value. The sample period is from 2000:01 to 2022:12, whereas the out-of-sample evaluation period spans 2005:01 to 2022:12.

4. Robustness Analysis

To ensure the universality and reliability of the research findings, this paper implemented various robustness tests, including changing markets, adjusting the construction method of good and bad turnover, and changing asset allocation parameters. All tests supported the validity and robustness of the original model.

Furthermore, using the representative A-share Index, Shenzhen Component Index, and SME Composite Index to represent different Chinese stock markets, the specific regression results are shown in Panels A, B, and C of Table 6. As indicated by the table, the out-of-sample empirical results are robust across different stock markets.

Table 6. Out-of-sample results under different markets

Prediction Model	R^2_{OS} (%)	*CW*-stat	CER gains	SR
	Panel A: A-share Index			
STR	0.772**	1.758	-0.413	0.097
GoodSTR	1.988**	2.003	0.950	0.113
BadSTR	-2.018	-0.324	-0.473	0.043
	Panel B: Shenzhen Component Index			
STR	0.204	1.037	0.509	0.063
GoodSTR	0.905**	2.186	1.980	0.095
BadSTR	-0.442	-0.204	-0.905	0.084
	Panel C: SME Composite Index			
STR	0.679**	1.676	-1.652	0.002
GoodSTR	2.069*	1.563	1.029	0.060
BadSTR	-0.081	0.363	0.572	0.064

Note: This table reports the out-of-sample predictive regression results and portfolio performance for different Chinese stock markets. ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample windows for Panels A, B, and C are 2005:01-2022:12, 2000:01-2022:12, and 2011:01-2022:12, respectively.

Compared to excess returns, ordinary returns are more intuitive, and many investors pay more attention to the ordinary return of stocks. Therefore, good turnover is defined as the stock turnover when the ordinary stock return is positive, and bad turnover is defined as the turnover when the ordinary stock return is negative. The specific definitions are as follows:

$$GoodSTR_t = STR_t I(ret_t \geq 0) \tag{13}$$

$$BadSTR_t = STR_t I(ret_t < 0) \tag{14}$$

Where ret_t represents the ordinary stock return, and $I(\cdot)$ represents an indicator function. Tables 7 and 8 report the in-sample and out-of-sample predictive regression results under the new definition method. Results consistent with the above can be obtained; thus, the model used in this paper is robust to different turnover calculation methods.

Table 7. In-sample regression results under the new definition of good turnover

Prediction Model	β	t_β-stat	R^2(%)
STR	0.068**	2.304	2.970
GoodSTR	0.068***	2.833	4.139
BadSTR	-0.052	-1.031	0.924

Note: This table reports the results of predictive regression with stock excess returns after decomposing turnover into good and bad turnover based on the sign of ordinary returns. ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Out-of-sample regression results under the new definition of good turnover

	Out-of-sample results		Asset allocation results	
Prediction Model	R^2_{OS} (%)	*CW*-stat	CER gain	SR
STR	1.318**	2.040	2.106	0.120
GoodSTR	2.768**	2.223	2.633	0.126
BadSTR	-2.087	-0.311	0.750	0.069

Note: This table reports the out-of-sample results and portfolio performance of predictive regression with stock excess returns after decomposing turnover into good and bad turnover based on the sign of ordinary returns. ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Consider selecting different investor risk aversion coefficients during portfolio inspection and different allowable stock weight ranges during asset allocation. The empirical results under different risk aversion coefficients and stock weights are shown in Table 9. Similar to previous results, from an asset allocation perspective, the predictive model proposed in this paper yields robust results for different risk aversion coefficients and stock weights.

Table 9. Portfolio performance under different risk aversion coefficients and stock weights

Prediction Model	CER gain	SR	CER gain	SR	CER gain	SR
	γ=2, $w_t \in [0,1.5]$		γ=4, $w_t \in [0,1.5]$		γ=5, $w_t \in [0,1.5]$	
STR	5.236	0.122	0.647	0.128	-0.934	0.128
GoodSTR	4.432	0.114	1.346	0.134	0.523	0.142
BadSTR	1.290	0.068	0.142	0.060	0.114	0.060
	γ=2, $w_t \in [-0.5,1.5]$		γ=4, $w_t \in [-0.5,1.5]$		γ=5, $w_t \in [-0.5,1.5]$	
STR	4.086	0.106	-1.128	0.107	-2.635	0.109
GoodSTR	5.345	0.121	1.078	0.133	0.112	0.140
BadSTR	1.787	0.071	0.332	0.064	0.191	0.064

Note: This table reports portfolio performance when the mean-variance investor's risk aversion coefficients are 2, 4, and 5, and the stock weight ranges are [0, 1.5] and [-0.5, 1.5].

5. Summary

This paper is dedicated to exploring the predictive efficacy of turnover rate indicators, specifically the decomposed "good turnover" and "bad turnover," on the future returns of the Chinese stock market. By constructing a linear regression model with excess return as the dependent variable and good turnover, bad turnover, and aggregate market turnover as independent variables, supplemented by bivariate regression tests with macroeconomic variables and a series of robustness tests, the following key conclusions were drawn: (1) Good turnover demonstrates significant predictive ability for stock market excess returns both in-sample and out-of-sample, and this ability exceeds the information provided by simple aggregate market turnover and bad turnover. This finding emphasizes good turnover as a key factor in enhancing the effectiveness of prediction models, especially when combined with macroeconomic variables, providing additional predictive value; (2) Incorporating good turnover into asset allocation strategies significantly improves the portfolio's CER gain and Sharpe ratio, verifying its practical value in actual investment decisions.

In summary, this paper provides strong empirical evidence for the predictive ability of turnover rate in the Chinese stock market and has achieved certain results. However, there are still some deficiencies, and future research has many areas for in-depth exploration: First, given the heterogeneity of global stock markets, future research could extend to stock markets in other countries to test the cross-market applicability of the good turnover prediction model, deepening our understanding of global financial market dynamics. Second, considering the profound impact of economic cycles on stock market performance, subsequent research could attempt to subdivide the sample interval by economic recession and boom cycles to deeply analyze the changes in the predictive efficacy of good turnover at different economic stages, providing more precise strategic guidance for investors in complex and volatile economic environments.

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