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Does the turnover effect matter in emerging markets? Evidence from China

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ABSTRACT

In this paper, we examine the turnover effect in China's stock market and find that stocks with low turnover generate higher future returns than stocks with high turnover. The turnover effect is robust after various liquidity measures are controlled for, and it cannot be explained by existing asset-pricing models. Further evidence reveals that the turnover effect (1) is stronger when sentiment is high; (2) is stronger for stocks with lower investor sophistication, higher idiosyncratic volatility, higher transaction costs, and lower institutional ownership; and (3) persists in longer horizons. These findings are consistent with the mispricing explanation.

Classification

C1
G1
G2

1. Introduction

A considerable amount of literature on financial markets has identified a negative cross-sectional relation between turnover and future returns. The well-established turnover effect, whereby low turnover stocks earn higher average returns than high turnover stocks, is interpreted as supportive evidence for the liquidity hypothesis. This posits that firms with low trading volume are less liquid and riskier; thus, investors require compensation for bearing an illiquidity risk (e.g., Amihud and Mendelson, 1986; Datar et al., 1998; Amihud et al., 2005; Avramov and Chordia, 2006).

However, behavioral finance scholars contend that turnover is behaviorally driven. They argue that investors may have psychological biases, such as overconfidence, limited attention, or heterogeneous beliefs—any of which can lead to differences of opinion regarding the value of firms (e.g., Odean, 1998; Barber and Odean, 2000; Hong and Stein, 2003, 2007; Nagel, 2005; Statman et al., 2006; Glaser and Weber, 2007, 2009; Grinblatt and Keloharju, 2009; Chou et al., 2013b). Hence, no consensus has been reached on the nature of the turnover effect.

In this paper, our objective is to explore whether the turnover effect has an influence on China's stock market and how various

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rational and behavioral arguments compete in explaining this influence. We focus on China's stock market for several reasons. First, few studies have investigated whether the turnover effect exists in emerging markets. China is an interesting and important case because it is not only the world's largest emerging market but also the second largest stock market in Asia. Additionally, the previous studies on liquidity in China's stock market have explored sources of systematic variation in liquidity (e.g., Qian et al., 2014). In this paper, we investigate whether and how turnover is related to the cross-section of stock returns. Second, China's stock market is dominated by retail investors (e.g., Ng and Wu, 2007, 2010), which may be crucial when analyzing the turnover effect in the country because irrational traits are pervasive (e.g., Nartea et al., 2013; Zhu and Niu, 2016).[1] For example, overconfidence may cause investors to trade too aggressively (Odean, 1998). Finally, given the short history of China's stock market, it lags behind its counterparts in developed markets in terms of its levels of financial sophistication and market efficiency. For example, arbitrage conditions in China operate with high barriers. A price limit rule has been enforced since December 16, 1996. The maximum price limit is set at 10% for regular stocks and at 5% for special treatment stocks.[2] Moreover, short-selling is banned for a majority of stocks traded in China's stock market. Although the China Securities Regulatory Commission launched a pilot program designating 90 stocks as eligible, which enables investors to sell short and buy on margin, the stocks that are excluded from this program remain barred from short selling and margin trading. Combining the two specialties of China's stock market creates a natural experimental environment in which to examine the turnover effect and determine whether it is the result of mispricing due to limits of arbitrage or whether it can be explained by the risk-based theory.

In this paper, we document that a strong turnover effect exists in China's stock market. Using the China Stock Market and Accounting Research (CSMAR) Database, we show that the difference between returns on portfolios with the highest and the lowest turnover is significantly positive at 0.755% per month. The result is robust when the returns are adjusted for risk by using Fama and French's (1993) three-factor model (FF3), Carhart's (1997) four-factor model (FFC4), and Fama and French's (2015) five-factor model (FF5), which suggests that the turnover effect cannot be attributed to common risk factors.

To examine whether the turnover effect can be explained by the liquidity hypothesis, we employ two methods: bivariate sorts to control for liquidity and firm-level cross-sectional regressions. We use five well-known illiquidity measures to proxy for liquidity based on the methods developed by Roll (1984), Cooper et al. (1985), Lesmond et al. (1999), Amihud (2002), and Pastor and Stambaugh (2003), respectively. The results reveal that a robust turnover effect exists when controlling for liquidity. Therefore, the turnover effect cannot be fully explained by well-known factor models or be attributed to liquidity risk.

Based on the failure of risk-based theory to explain the turnover effect, we investigate whether this effect can be explained from the perspective of behavioral finance. According to Miller (1977), when there are differences of opinion and short-sale restrictions, stock prices are dominated by optimists rather than pessimists. This is because pessimistic traders do not participate in the market under such conditions, leading to stocks becoming overpriced and thus generating lower subsequent returns. Empirical evidence from Stambaugh et al. (2012) supports this thesis: numerous asset-pricing anomalies become much stronger following periods of high sentiment. Moreover, costly arbitrage can impede arbitrageurs from exploiting the profit opportunities created by mispricing, and any systematic mispricing cannot be quickly traded away and dissipated. The limits-of-arbitrage argument thus implies that mispricing will persist in situations where stocks are difficult to arbitrage (e.g., Shleifer and Vishny, 1997; Ali et al., 2003; Nagel, 2005; Baker and Wurgler, 2006; Chou et al., 2013b).

Based on Miller's (1977) theory and the limits-of-arbitrage argument, we test whether the turnover effect is a result of mispricing caused by mistaken beliefs. To begin, we investigate whether sentiment can help explain the turnover effect. Stambaugh et al. (2012) argue that if the turnover effect reflects mispricing, then it should grow following high sentiment. Our time-series regressions strongly support the conjecture that the turnover effect increases considerably when sentiment is high but not when sentiment is low.

We then examine the relation between the turnover effect and arbitrage risk. The turnover effect should be stronger for stocks subject to higher degrees of arbitrage risk. Our empirical evidence confirms a significant positive relation between the turnover effect and arbitrage risk. The turnover effect is larger for stocks with higher idiosyncratic volatility, lower investor sophistication, higher transaction costs, and higher short-sale constraints. The cross-sectional regressions also provide evidence confirming this conjecture.

Our final test determines whether the turnover effect exhibits return persistence for long horizons. We examine the long-run performance of turnover-related predictability by extending the portfolio holding periods to 6, 12, 18, and 24 months. The results confirm the existence of a persistent turnover effect. Although this effect decreases over time, it remains significantly positive for 24 months. The overall results are consistent with the mispricing explanation based on Miller's (1977) theory and the limits-of-arbitrage argument.

The remainder of the paper is organized as follows. In Sections 2 and 3, we introduce our data and methodology, respectively. In Section 4, we provide the empirical evidence for the turnover effect based on portfolio-level and cross-sectional regression analyses. In Section 5, we report the results of further tests from behavioral perspectives. In Section 6, we present our conclusions.

[1] In fact, experimental studies report higher levels of overconfidence in China compared with the United States (e.g., Wright et al., 1978; Yates et al., 1989).

[2] The Shanghai and the Shenzhen Stock Exchanges identify firms with a distressed financial situation as special treatment stocks.

2. Data

Our study sample comprises all A-share stocks listed on the Shanghai and the Shenzhen Stock Exchanges from January 1995 to December 2017.[3] We obtain market and accounting data from CSMAR Database. The stock turnover (TURN) for each firm is calculated as the average daily turnover for the past 12 months, in percentage terms, according to Chou et al. (2013b). We use daily stock returns to calculate the market beta (BETA), idiosyncratic volatility (Ivolatility), limit-hit frequency (Hit%), and various liquidity measures. Monthly returns are used to calculate momentum (MOM) and short-term reversal (REV) variables, and share price and shares outstanding are used to calculate market capitalization (SIZE). We use the equity book value to calculate the book-to-market ratio (BM) of individual firms and use the number of research reports and fund-holding proportions to calculate analyst coverage (Analyst) and institutional ownership (Inst%). These variables are defined in more detail in the Appendix.

The historical evolution of the number of stocks listed on the market per calendar year is presented in Table 1. The second column of Table 1 shows the total number of firms, which increases over time from 312 in 1995 to 2646 in 2017. We report the number of firms listed in the previous year, the number of new listed firms, and the number of delisted firms in columns 3, 4, and 5, respectively. The number of new listed firms is higher than the corresponding number of delisted firms throughout the given period, except in 2005.

In Table 2, we present the average of median values of stock characteristics, calculated on a monthly basis for each TURN decile. We report the values for TURN (as a percentage), SIZE (in billions of yuan), BETA, BM, return in the portfolio formation month (REV), cumulative return over the six months prior to portfolio formation (MOM), and measures of illiquidity (namely Roll, Amivest, Zeroret, Amihud, and PS).[4]

As we move from the low TURN to the high TURN decile, the values increase from 0.858% to 4.682%, with a spread of 3.824% between the highest and the lowest TURN deciles. Closer scrutiny of Table 2 reveals that as TURN increases across the deciles, BETA, REV, and MOM increase, while SIZE and BM decrease. Table 2 also demonstrates that TURN is negatively correlated with all five illiquidity measures. This pattern is not surprising, considering that stocks in low-turnover portfolios tend to exhibit high illiquidity.

3. Methodology

3.1. *Portfolio-based methodology*

To examine whether the turnover effect exists, we first sort stocks based on their average daily turnover (TURN) over the past 12 months to form decile portfolios. Portfolio 1 (D1) is the decile portfolio with the lowest TURN, and Portfolio 10 (D10) is the decile portfolio with the highest TURN. The difference of raw returns on the lowest and the highest turnover portfolios (D1–D10) is then calculated to examine the turnover effect.

We calculate the risk-adjusted returns based on Fama-French risk factors. The risk-adjusted returns of turnover-sorted portfolios are in the form of intercepts from risk-based factor models, including FF3, FFC4, and FF5.[5] For example, the FF5 alphas are intercepts from the regression of the portfolio excess returns on a size factor (SMB), a BM factor (HML), a profitability factor (RMW), and an investment factor (CMA).

3.2. *Methodology*

3.2.1. *Cross-sectional regressions*

The portfolio-level analysis has the well-known advantage of being non-parametric in the sense that we do not impose any functional relation between TURN and future returns, but it is difficult to control for multiple effects. Thus, we complement our portfolio-level analysis by estimating Fama and MacBeth's (1973) cross-sectional regressions to examine the relation between TURN and future returns.

The dependent variable in the regression is a stock's raw return, and the key independent variable is TURN. To determine whether turnover and liquidity have similar information content, we test the significance of the cross-sectional relation between TURN and future stock returns after controlling for the liquidity effect. We do so by including five illiquidity measures in the regressions: Roll, Amivest, Zeroret, Amihud, and PS. The remaining variables are control variables that are well documented in the literature as explaining stock returns, namely, BETA, log SIZE, log BM ratio, MOM, and REV. The Fama–MacBeth cross-sectional regressions are as follows:

[3] Domestic investors can legally purchase A-shares, while foreign investors are restricted to the ownership of B-shares. Since 2001, the B-share market has allowed Chinese investors to trade with foreign currencies. This study focuses on A-shares because this market is much larger and more active in trading than the B-share market. Additionally, we start the sample period in 1995 because the number of stocks for A-share firms was limited before this period. For example, fewer than 50 A-share stocks were listed on the Shanghai and the Shenzhen Stock Exchanges at the end of 1992.

[4] Following Goyenko et al. (2009), we eliminate a noise term that is unrelated to the variable of interest and divide measures of Roll and Zeroret by the average daily yuan volume.

[5] The data for the Fama–French three factors, Fama–French–Carhart four factors, Fama–French five factors, and market return (defined as the value-weight return of all A-share firms) are obtained from the CSMAR Database. Following Han and Li (2017) and Zhu and Niu (2016), we use the one-year bank term deposit rate as a proxy for the risk-free rate, which is obtained from the CSMAR Database.

Table 1
Number of firms in China's A-share market by year.

Year	Total firms	Firms listed from previous year	New firms listed	Firms delisted
1995	312	–	–	–
1996	515	312	203	0
1997	720	515	206	1
1998	825	720	106	1
1999	924	825	99	0
2000	1060	924	137	1
2001	1136	1060	79	3
2002	1193	1136	71	14
2003	1259	1193	73	7
2004	1350	1259	104	13
2005	1340	1350	17	27
2006	1363	1340	80	57
2007	1440	1363	154	77
2008	1559	1440	135	16
2009	1626	1559	83	16
2010	1837	1626	224	13
2011	1988	1837	182	31
2012	2080	1988	113	21
2013	2068	2080	34	46
2014	2076	2068	114	106
2015	2175	2076	232	133
2016	2361	2175	277	91
2017	2646	2361	383	98

This table presents the number of stocks listed on the market per calendar year. The second and the third columns report the number of total firms and the number of firms listed from the previous year, respectively. The fourth and the fifth columns report the number of newly listed and delisted firms, respectively.

Table 2
Summary statistics for decile portfolios of stocks, sorted by turnover.

	TURN	BETA	SIZE	BM	REV	MOM	Roll	Amivest	Zeroret	Amihud	PS
D1	0.858	0.886	6494.629	0.902	0.050	−0.014	3.096	5.673	0.520	4.035	0.017
D2	1.253	0.990	3326.914	0.839	0.221	−0.001	2.449	4.630	0.366	3.863	0.013
D3	1.542	1.019	2580.760	0.787	0.404	0.011	2.449	4.313	0.273	3.693	0.019
D4	1.793	1.048	2243.751	0.777	0.525	0.020	2.410	4.183	0.218	3.189	0.010
D5	2.034	1.066	2029.597	0.754	0.493	0.028	2.173	4.268	0.177	3.222	0.008
D6	2.293	1.083	1888.413	0.741	0.715	0.035	1.871	4.386	0.138	2.766	0.008
D7	2.597	1.106	1770.204	0.716	0.643	0.043	1.932	4.514	0.103	2.661	0.009
D8	2.971	1.128	1647.288	0.680	0.509	0.043	1.946	4.759	0.083	2.468	0.008
D9	3.520	1.144	1536.403	0.651	0.443	0.051	1.471	5.065	0.044	2.226	0.008
D10	4.682	1.192	1279.221	0.575	0.072	0.053	1.408	5.320	0.021	1.913	0.007

This table reports the average of the median values of stock characteristics for each TURN decile. TURN is defined as the past 12 months' average daily turnover of stocks (as a percentage). Portfolio D1 (D10) is the portfolio of stocks with the lowest (highest) TURN. The characteristics of stocks are the market beta (BETA), market capitalization (SIZE), book-to-market ratio (BM), return in the portfolio formation month (REV), and cumulative return over the 6 months prior to portfolio formation (MOM). The illiquidity measures for stocks are Roll, Amivest, Zeroret, Amihud, and PS.

$$\begin{aligned} R_{i,t} = {} & \alpha_0 + \beta_1 TURN_{i,t-1} + \beta_2 Roll_{i,t-1} + \beta_3 Amivest_{i,t-1} + \beta_4 Zeroret_{i,t-1} + \beta_5 Amihud_{i,t-1} + \beta_6 PS_{i,t-1} + \beta_7 BETA_{i,t-1} + \beta_8 SIZE_{i,t-1} + \beta_9 BM_{i,t-1} \\ & + \beta_{10} REV_{i,t-1} + \beta_{11} MOM_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $R_{i,\,t}$ denotes the raw return of stock i in month t. The Newey and West (1987) procedure is used to calculate the t-statistics of the mean.

Many studies argue that the Fama–MacBeth regression assumes that each coefficient is drawn from a stationary distribution; that is, while estimating the average slope coefficient, it places equal weight on the slope coefficient (e.g., Datar et al., 1998; Dey, 2005). To check the robustness of our results, we follow the work of Litzenberger and Ramaswamy (1979) in utilizing the two-stage generalized least-squares (GLS) estimation method. Datar et al. (1998) and Dey (2005) also use this methodology to investigate the relation between stock return and turnover.

Specifically, we first re-estimate Eq. (1), and the time-series means and the variances of each coefficient are then calculated with weights. The weights are inversely proportional to the variances of these estimates. The means and the variances are calculated as follows:

$$\widehat{\beta}_k = \sum_{t=1}^{T} Z_{kt}\widehat{\beta}_{kt}, \text{ where } Z_{kt} = \left[Var\left(\widehat{\beta}_{kt}\right)\right]^{-1} \Big/ \sum_{t=1}^{T}\left[Var\left(\widehat{\beta}_{kt}\right)\right]^{-1} \tag{2}$$

and

$$Var\left(\widehat{\beta}_k\right) = \sum_{t=1}^{T} Z_{kt}^2 Var\left(\widehat{\beta}_{kt}\right), k = 1, \dots, 11 \tag{3}$$

This method assumes nonstationarity and refines the Fama and MacBeth (1973) methodology in the analysis using the cross-section of stock returns.

3.2.2. Time-series regressions

To examine whether market-wide sentiment plays a role in explaining the turnover effect, we follow the method of Stambaugh et al. (2012) and regress the returns of the turnover-sorted portfolios on the high, middle, and low sentiment dummy variables. The regression is as follows:

$$R_t = \alpha_H High_t + \alpha_M Middle_t + \alpha_L Low_t + \varepsilon_t \tag{4}$$

where R_t denotes the raw returns on turnover-sorted portfolios and the difference between the returns on portfolios with the highest and the lowest turnover rates in month t, and $High_t$, $Middle_t$, and Low_t are dummy variables indicating high, middle, and low sentiment, respectively. $High_t$ (Low_t) equals 1 if the sentiment index in the previous month is in the top (bottom) 30% and equals 0 otherwise. $Middle_t$ equals 1 if $High_t$ and Low_t both equal 0. The sentiment index is obtained from the CSMAR Database for the available sample period from January 2003 to December 2017. This variable is presented in more detail in the Appendix.

4. Empirical results

4.1. Portfolio-level analysis

Table 3 presents the equal-weighted average monthly returns of turnover-sorted portfolios. Panel A of Table 3 records the results using a 10% cutoff point. The average raw return of D1 is 1.782%, the return of D10 is 1.027%, and the difference between D1 and D10 is 0.755% per month, with a corresponding Newey and West (1987) t-statistic of 2.61. As indicated in Table 3, the differences in the FF3, FFC4, and FF5 alphas between D1 and D10 are 1.373% (t-statistic = 4.93), 1.605% (t-statistic = 6.09), and 1.401% (t-statistic = 4.90) per month, respectively. The turnover effect remains statistically significant after risk adjustments; therefore, the turnover effect cannot be attributed to common risk factors.

Table 3
Returns and alphas on portfolios of stocks, sorted by turnover.

	Raw return	FF3 alpha	FFC4 alpha	FF5 alpha
Panel A: 10% cutoffs				
D1	1.782	0.476	0.645	0.563
D2	1.889	0.331	0.473	0.417
D3	2.044	0.319	0.417	0.443
D4	2.033	0.214	0.251	0.312
D5	2.199	0.265	0.267	0.377
D6	2.086	0.179	0.177	0.277
D7	1.953	−0.023	−0.073	0.113
D8	1.814	−0.199	−0.232	−0.081
D9	1.453	−0.435	−0.454	−0.319
D10	1.027	−0.897	−0.960	−0.838
D1-D10	0.755***	1.373***	1.605***	1.401***
	(2.61)	(4.93)	(6.09)	(4.90)
Panel B: 30% cutoffs				
G1	1.905	0.375	0.511	0.474
G2	1.829	0.023	0.051	0.127
G3	1.433	−0.509	−0.548	−0.411
G1-G3	0.472**	0.884***	1.058***	0.885***
	(2.10)	(4.44)	(5.66)	(4.36)

This table presents the average monthly returns and alphas on turnover-sorted portfolios. In Panel A, Portfolio D1 (D10) is the decile portfolio of stocks with the lowest (highest) turnover; the last row reports the return differences between D1 and D10 with the corresponding t-statistics. In Panel B, Portfolio G1 (G3) holds stocks with the bottom 30% (top 30%) turnover; the last row reports the return differences between G1 and G3 with t-statistics. The last three columns in Panels A and B report the alphas with respect to the three-factor Fama and French model (FF3), four-factor Fama, French, and Carhart model (FFC4), and five-factor Fama and French (FF5) model, respectively. The Newey and West (1987) procedure is used to calculate the t-statistics (in parentheses), which corrects for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To ensure that our results are not sensitive to various break-points, we use a 30% cutoff point to construct portfolios. Portfolio G1 (G3) comprises of stocks in the bottom (top) 30% turnover. Panel B of Table 3 demonstrates that the difference between G1 and G3 is significant at 0.472% per month (t-statistic = 2.10). After risk adjustments, the difference in alphas between G1 and G3 are all significant at the 1% significance level. Thus, these results are substantively similar across multiple cutoff points.

The liquidity hypothesis proposed by Amihud and Mendelson (1986) posits a positive relation between stock returns and stock illiquidity. As reported in Table 2, we find a negative relation between TURN and illiquidity measures. It is therefore necessary to check whether the turnover effect reflects compensation for liquidity risk.

We examine the negative relation between turnover and future stock returns after controlling for liquidity, measured using the following illiquidity proxies, namely, Roll, Amivest, Zeroret, Amihud, and PS. Following the method of Bali et al. (2011), we control for liquidity by first forming three groups, sorted according to the illiquidity measure. In each liquidity group, we then sort stocks into decile portfolios, ranked according to TURN so that the D1 (D10) group contains stocks with the lowest (highest) TURN. This procedure creates TURN portfolios with similar levels of firm liquidity, and these portfolios thus control for differences in liquidity. For clarity, we present the returns as averaged across the three liquidity groups to generate decile portfolios with dispersion in TURN but containing all levels of firm liquidity. The results are reported in Table 4.

After controlling for liquidity, the turnover effect remains positive and statistically significant. For example, in column 1 of Table 4, the average return difference between D1 and D10 is approximately 0.810% (t-statistic = 2.56) per month when we use the Roll measure to proxy for liquidity.

Similarly, when using other illiquidity measures, the differences between returns on portfolios with the highest and the lowest turnover remain significantly positive at 0.832% (t-statistic = 2.48) for Amivest, 0.843% (t-statistic = 1.99) for Zeroret, 0.952% (t-statistic = 2.84) for Amihud, and 0.772% (t-statistic = 2.53) for PS. These results indicate that the liquidity hypothesis cannot fully explain the high (low) returns for low (high) turnover stocks.

4.2. Regression analysis

We document a strong turnover effect at the portfolio level. In this section, we now complement the portfolio-level analysis by estimating the Fama and MacBeth (1973) cross-sectional regressions. We calculate and test the time-series averages of the monthly estimated coefficients from Eq. (1) using t-statistics calculated based on the Newey and West (1987) adjusted t-statistics, which correct for serial correlation and conditional heteroscedasticity. The regression results are reported in Panel A of Table 5.

The univariate regression results in Panel A of Table 5 reveal a statistically significant negative relation between the turnover and the cross-section of future stock returns. In Model (1), the average slope for the monthly regressions of stock returns on TURN alone is −0.256, with a t-statistic of −3.14. Model (2) extends Model (1) by including the five control variables of BETA, SIZE, BM, REV, and MOM. As a result of their inclusion, the coefficient on TURN becomes more significantly negative in magnitude.

With Models (3) to (7), we examine the incremental effect of TURN beyond the effects of liquidity by separately including the five illiquidity measures in the regressions. We find that the inclusion of any liquidity measure has only a limited effect on TURN. The average coefficients on TURN under various specifications remain negative and statistically significant. Moreover, across all specifications, the coefficients for the illiquidity variables are significantly positive and consistent with the liquidity hypothesis in that investors require a return compensation for a high liquidity risk.

Model (8) includes all the variables. In this specification, the average slope coefficient on TURN is −0.327, with a t-statistic of −4.80. Thus, the pronounced impact of TURN persists after controlling for the liquidity effect and firm characteristics.

Taken together, the results of cross-sectional regressions provide strong corroborating evidence of an economically and statistically significant negative relation between turnover and future returns. As presented in Table 4, the liquidity hypothesis fails to explain the

Table 4
Returns on portfolios of stocks, sorted by turnover after controlling for the liquidity effect.

	Roll	Amivest	Zeroret	Amihud	PS
D1	1.827	1.986	0.956	2.050	1.619
D2	2.019	1.903	1.280	1.913	1.724
D3	2.190	2.024	1.205	2.097	1.879
D4	2.157	2.054	1.332	2.117	2.000
D5	2.202	2.133	1.349	2.140	1.848
D6	2.122	1.984	1.444	2.020	1.904
D7	2.059	1.999	1.028	1.964	3.554
D8	1.721	1.828	0.786	1.781	1.619
D9	1.620	1.615	0.594	1.578	1.422
D10	1.017	1.155	0.113	1.098	0.847
D1–D10	0.810**	0.832**	0.843**	0.952***	0.772**
	(2.56)	(2.48)	(1.99)	(2.84)	(2.53)

This table presents the average monthly returns of turnover-sorted portfolios by controlling for the liquidity effect. Portfolio D1 (D10) is the decile portfolio of stocks with the lowest (highest) turnover. We control the liquidity effect using the Roll, Amivest, Zeroret, Amihud, and PS measures. The last row reports the differences in raw returns between D1 and D10 with the corresponding t-statistics. The Newey and West (1987) procedure is used to calculate the t-statistics (in parentheses), which correct for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Cross-sectional predictability of turnover.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fama–MacBeth regressions								
TURN	−0.256***	−0.406***	−0.270***	−0.280***	−0.218***	−0.301***	−0.260***	−0.327***
	(−3.14)	(−5.68)	(−3.39)	(−3.23)	(−2.80)	(−3.36)	(−3.34)	(−4.80)
Roll			0.082**					0.042*
			(2.45)					(1.94)
Amivest				0.042				0.026
				(0.64)				(0.67)
Zeroret					17.789***			6.414**
					(2.98)			(2.01)
Amihud						0.847***		0.306***
						(2.61)		(3.69)
PS							0.322*	0.147
							(1.89)	(0.96)
BETA		0.231						0.263
		(1.38)						(1.63)
SIZE		−0.552***						−0.347**
		(−3.20)						(−2.07)
BM		0.489***						0.490***
		(3.21)						(3.33)
REV		−0.032***						−0.032***
		(−3.84)						(−3.90)
MOM		0.123						0.162
		(0.34)						(0.44)
Adj. R^2	0.019	0.110	0.026	0.034	0.032	0.038	0.030	0.128

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: GLS methodology								
TURN	−0.161***	−0.330***	−0.163***	−0.175***	−0.133***	−0.165***	−0.162***	−0.247***
	(−5.43)	(−9.74)	(−5.48)	(−5.87)	(−4.47)	(−5.57)	(−5.44)	(−7.71)
Roll			0.008					0.003
			(0.82)					(0.21)
Amivest				−0.016				−0.001
				(−1.06)				(−0.16)
Zeroret					0.493***			0.293***
					(7.31)			(3.15)
Amihud						0.035***		0.051***
						(3.09)		(3.57)
PS							0.007***	0.004
							(2.79)	(0.38)
BETA		0.179***						0.207***
		(4.03)						(4.61)
SIZE		−0.531***						−0.300***
		(−14.58)						(−6.97)
BM		0.270***						0.278***
		(6.93)						(7.09)
REV		−0.048***						−0.048***
		(−4.47)						(−4.43)
MOM		−0.104						−0.072
		(−1.52)						(−1.06)
Adj. R^2	0.019	0.110	0.026	0.034	0.032	0.038	0.030	0.128

This table presents estimates from Fama–MacBeth regressions. The monthly cross-sectional regressions are estimated for the following:

$$R_{i,\,t} = \beta_0 + \beta_1 TURN_{i,\,t-1} + \beta_2 Roll_{i,\,t-1} + \beta_3 Amivest_{i,\,t-1} + \beta_4 Zeroret_{i,\,t-1} + \beta_5 Amihud_{i,\,t-1} + \beta_6 PS_{i,\,t-1} + \beta_7 BETA_{i,\,t-1} + \beta_8 SIZE_{i,\,t-1} + \beta_9 BM_{i,\,t-1} + \beta_{10} REV_{i,\,t-1} + \beta_{11} MOM_{i,\,t-1} + \varepsilon_{i,\,t}$$

where $R_{i,\,t}$ denotes the monthly raw return on stock *i* in month *t*; *TURN* signifies the past 12 months' average daily turnover; and *Roll, Amivest*, *Zeroret*, *Amihud*, and *PS* are liquidity measures calculated by following the methods of Roll (1984), Cooper et al. (1985), Lesmond et al. (1999), Amihud (2002), and Pastor and Stambaugh (2003), respectively. The other five control variables are the market beta (*BETA*), market capitalization in billions of yuan (*SIZE*), book-to-market ratio (*BM*), return in the portfolio formation month (*REV*), and cumulative return over the 6 months prior to portfolio formation (*MOM*). Panel A reports the results based on Fama–MacBeth regressions, and the Newey and West (1987) procedure is used to calculate the *t*-statistics (in parentheses), which correct for serial correlation and conditional heteroscedasticity. Panel B reveals the results based on the GLS methodology. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

turnover effect.

To check the robustness of our results, we use the two-stage GLS estimation method by following the work of Litzenberger and Ramaswamy (1979). We calculate the mean and the variance of the monthly estimated coefficients from Eqs. (2) and (3). The results are reported in Panel B of Table 5.

With Models (1)–(8), the average coefficients on TURN range from −0.133 to −0.330, and all of them remain statistically significant at a 1% significance level. Thus, the empirical results are robust to the problem of nonstationarity.

5. The turnover effect and a behavioral perspective?

Thus far, we have documented a strong turnover effect in China's stock market that cannot be attributed to common risk factors and is not fully explained by the liquidity hypothesis. In this section, we investigate whether the source of the turnover effect is behavioral in nature. For instance, behavioral finance scholars argue that trading occurs because people disagree over firm value. If turnover reflects the degree to which opinions diverge among investors, then a market with short-sale restrictions prevents the pessimistic opinions from being expressed in stock prices. Accordingly, the valuations of optimists are reflected in prices, whereas those of pessimists are not, causing the stock price to deviate from its fundamental value as a result of the overly optimistic views of investors and leading to overpricing (e.g., Miller, 1977). Stambaugh et al. (2012) argue that if market anomalies reflect mispricing, then they should be stronger following high sentiment. Moreover, the limits-of-arbitrage argument indicates that the presence of certain arbitrage limits obstructs arbitrageurs from exploiting the profitable opportunities embedded in any potential mispricing. This prevents asset prices from quickly adjusting to their fundamental values, thereby enabling the persistence of mispricing (e.g., Shleifer and Vishny, 1997; Ali et al., 2003; Nagel, 2005; Baker and Wurgler, 2006; Chou et al., 2013b).

Thus, if the turnover effect can be explained by Miller's (1977) argument and the limits-of-arbitrage argument, it should be persistent and stronger for stocks subject to a higher degree of arbitrage risk and investor sentiment. We therefore expect the turnover effect to (1) be more pronounced when sentiment is high, (2) exhibit predictable patterns related to arbitrage risk, and (3) exhibit persistence of returns.

5.1. Turnover effect and sentiment

In this section, we first examine whether market-wide sentiment is related to the turnover effect. In Table 6, we present the descriptive statistics for the sentiment index. The sample mean is 51.45; the minimum and the maximum values are 22.78 and 218.96, respectively.

Table 7 reports the relation between the turnover effect and sentiment. The regression coefficients are estimated based on Eq. (4). The results show that the turnover effect increases with the sentiment level and that the return spread between high and low sentiment is positive and significant. For example, the coefficients α_H, α_M, and α_L are 1.761, 0.313, and 0.014, respectively, and only coefficient α_H remains statistically significant with a *t*-statistic of 3.34. Consequently, the coefficient difference ($\alpha_H - \alpha_L$) is significant, with an estimated value of 1.748 (*t*-statistic = 2.35). This suggests that the significant difference primarily originates from the large turnover effect when the sentiment level is high. Thus, the results presented in Table 7 support the first prediction because they reveal that the turnover effect is stronger when sentiment is high.

5.2. Turnover effect and arbitrage risk

So far, we have documented that the turnover effect is related to sentiment. In this section, we further investigate whether the turnover effect can be explained by the limits-of-arbitrage hypothesis. Arbitrage risk can be classified into three categories: noise trader, fundamental, and implementation risks (e.g., Barberis and Thaler, 2003; Chou et al., 2013b). Specifically, noise trader risk arises when the market of the asset is populated with irrational traders whose trading causes an asset's price to be less efficient and drives it away from its fundamental value (e.g., Shleifer and Vishny, 1997). Fundamental risk implies that investors are uncertain of an asset's true value (e.g., Zhang, 2006). Implementation risk pertains to the transaction costs and the short-sale restrictions associated with arbitrage activities (e.g., Chou et al., 2013b).

To capture arbitrage risk, we use analysts' coverage (denoted as Analyst) to proxy for fundamental risk. This has also been used as a proxy for investor sophistication (Brennan et al., 1993; Hong et al., 2000; Ali et al., 2003). We use idiosyncratic risk (denoted as Ivolatility) to proxy for noise trader risk. Idiosyncratic risk cannot be hedged and diversified. Thus, stocks with high idiosyncratic risk may be overpriced, which cannot be eliminated by arbitrage because shorting them is risky (e.g., Shleifer and Vishny, 1997). The price limit (denoted as Hit%) is used to measure potential transaction costs. When stocks hit the price limit, the trading execution probability is low. In such circumstances, arbitrageurs experience difficulty in buying or selling these stocks because arbitrage limits are higher. This can represent a special form of arbitrage risk, similar to a short-sale constraint, which hinders arbitrageurs from engaging in arbitrage activities to correct potential mispricing (e.g., Chou et al., 2013a). Hence, stocks that hit price limits more frequently are associated with a higher degree of limits-to-arbitrage. Finally, we use institutional ownership (denoted as Inst%) to capture short-sale constraints. The ease of short-selling stocks is crucial for effective arbitrage. D'Avolio (2002) indicates that the supply of stock loans comes mainly from institutional investors and that stocks with low institutional ownership are more expensive to borrow, thus limiting

Table 6
Descriptive statistics of the sentiment index.

Mean	Median	Std. dev.	Minimum	Maximum	N
51.45	45.38	32.19	22.78	218.96	180

This table presents the descriptive statistics for the raw time-series of the sentiment index. The sample period is from January 2003 to December 2017.

Table 7
Turnover effect and sentiment.

	α_H	α_M	α_L	$\alpha_H - \alpha_L$
D1	4.268	1.317	0.377	3.891
D2	4.066	1.481	0.755	3.311
D3	4.099	1.646	0.838	3.261
D4	4.054	1.592	0.801	3.253
D5	3.811	1.706	0.793	3.018
D6	3.770	1.525	0.662	3.108
D7	3.457	1.626	0.531	2.926
D8	3.377	1.520	0.467	2.910
D9	2.931	1.472	0.615	2.316
D10	2.507	1.004	0.363	2.143
D1–D10	1.761***	0.313	0.014	1.748**
	(3.34)	(0.60)	(0.03)	(2.35)

This table presents the time-series regression results. We regress the turnover effect on various market sentiments. The following regression is performed:
$R_t = \alpha_H High_t + \alpha_M Middle_t + \alpha_L Low_t + \varepsilon_t$
where R_t denotes the average monthly raw returns of turnover-sorted portfolios in month t, and $High_t$, $Middle_t$, and Low_t are dummy variables representing high, middle, and low sentiments, respectively. $High_t$ (Low_t) equals 1 if the sentiment index in the previous month is in the top (bottom) 30% and equals 0 otherwise; $Middle_t$ equals 1 if $High_t$ and Low_t both equal 0. The Newey and West (1987) procedure is used to calculate the t-statistics (in parentheses), which correct for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

arbitrage activity.

Before performing the portfolio and formal regression analyses, we first evaluate the relation between turnover and arbitrage risk. We then conduct a sample correlation between the turnover variable and the proxies for arbitrage risk. As preliminary evidence, Table 8 presents the average monthly cross-sectional correlation coefficients among the variables.

The results shown in Table 8 demonstrate that TURN is positively correlated with Ivolatility (0.515) and Hit% (0.326) but is negatively correlated with Analyst (−0.200) and Inst% (−0.136). This preliminary result documents a positive association between turnover and arbitrage risk.

Next, we conduct a portfolio analysis of the relation between the turnover effect and the proxies for arbitrage risk. Specifically, we first assign a stock to the High (Low) group if its measure of arbitrage risk is the cross-sectional value of the top (bottom) 30%, and the remaining stocks comprise the Middle group. In each group, we sort stocks based on their TURN to form decile portfolios and calculate the difference between returns on portfolios with the highest and the lowest turnover. Additionally, we calculate the return difference between the High and the Low groups for each of the arbitrage risk proxies. If the turnover effect is associated with arbitrage risk, it should be larger (smaller) in groups of stocks that are subject to higher (lower) degrees of arbitrage risk. The High (Low) group for Ivolatility and Hit% indicates a group with High (Low) arbitrage risk, whereas the High (Low) group for Analyst and Inst% indicates a group with Low (High) arbitrage risk. We therefore expect the turnover effect to be larger (smaller) in the High (Low) group for Ivolatility and Hit% and larger (smaller) in the Low (High) group for Analyst and Inst%.

Table 9 provides strong evidence supporting the relevance of arbitrage risk in explaining the turnover effect. All four arbitrage risk proxies relate significantly to the turnover effect. For example, the differences in the return of the turnover effect between the High and the Low groups indicate that they are significantly positive for stocks sorted according to Ivolatility and Hit% but significantly negative for stocks sorted according to Analyst and Inst%. These results are consistent with the limits-of-arbitrage hypothesis.

We then complement our portfolio-level analysis by performing regressions using individual stock returns. To determine the effect of arbitrage risk on turnover, we follow the work of Lam and Wei (2011) by adopting the Fama and MacBeth (1973) cross-sectional regressions separately for subsamples partitioned by arbitrage risk proxies. For each month t, individual stocks are divided into three groups based on their measure of arbitrage risk. In each group, we then perform cross-sectional regressions that include TURN and control variables as independent variables.

Table 10 reports the time-series averages of the slope coefficients from the cross-sectional regressions model. Panel A shows the coefficient estimates on TURN for a baseline model that only considers TURN as an independent variable. This model is used to

Table 8
Time-series average of cross-sectional correlations.

	TURN	Ivolatility	Analyst	Hit%	Inst%
TURN	1.000				
Ivolatility	0.515	1.000			
Analyst	−0.200	−0.125	1.000		
Hit%	0.326	0.350	−0.124	1.000	
Inst%	−0.136	−0.045	0.224	−0.064	1.000

This table reports the correlations between turnover and measures of arbitrage risk. Spearman correlation coefficients are calculated each month, and the time-series averages of the monthly correlation coefficients are reported.

Table 9
Turnover effect and arbitrage risk.

	Ivolatility			Analyst			Hit%			Inst%		
	High	Low	HML	High	Low	HML	High	Low	HML	High	Low	HML
D1	1.500	1.798	−0.298	1.792	2.641	−0.848	1.978	1.571	0.408	2.084	3.884	−1.800
D2	2.079	2.044	0.035	2.120	2.690	−0.570	2.205	1.750	0.455	2.122	3.582	−1.460
D3	1.880	1.939	−0.059	1.719	2.293	−0.574	2.234	1.537	0.697	2.210	3.279	−1.068
D4	1.918	1.955	−0.038	1.874	2.381	−0.507	1.854	1.702	0.152	2.290	3.757	−1.467
D5	1.611	2.085	−0.474	1.818	2.527	−0.709	1.659	1.901	−0.242	2.314	3.054	−0.741
D6	1.775	2.051	−0.275	1.760	2.262	−0.502	1.711	1.806	−0.095	2.373	2.694	−0.321
D7	1.256	2.177	−0.922	1.722	2.132	−0.409	1.468	1.697	−0.229	2.175	2.919	−0.744
D8	1.212	2.117	−0.904	1.789	2.220	−0.431	0.981	1.916	−0.935	2.377	2.584	−0.208
D9	1.015	2.154	−1.139	1.814	1.729	0.085	1.303	1.755	−0.453	2.226	2.406	−0.180
D10	0.580	2.055	−1.475	1.794	1.389	0.405	0.605	1.534	−0.929	1.875	1.791	0.084
D1–D10	0.920***	−0.257	1.177***	−0.001	1.252***	−1.253***	1.373***	0.037	1.337***	0.209	2.093***	−1.884***
	(2.74)	(−0.68)	(2.81)	(−0.02)	(3.06)	(−2.61)	(3.55)	(0.11)	(3.72)	(0.39)	(2.84)	(−2.76)

This table presents the returns of turnover-sorted portfolios across groups with varying levels of arbitrage risk. Stocks are first sorted into three portfolios based on their arbitrage risk, which is measured by Ivolatility, Analyst, Hit%, and Inst%. In each group, stocks are further sorted into decile portfolios based on their turnover. The turnover effect is the difference between D1 and D10, and the differences in the turnover effect between high and low groups of arbitrage risk measures are denoted as HML. The Newey and West (1987) procedure is used to calculate the *t*-statistics (in parentheses), which correct for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Cross-sectional predictability of turnover, conditional on arbitrage risk.

	Ivolatility			Analyst			Hit%			Inst%		
	High	Low	HML	High	Low	HML	High	Low	HML	High	Low	HML
Panel A: Baseline model												
TURN	−0.323***	0.084	−0.108***	−0.003	−0.232***	0.229**	−0.412***	−0.049	−0.363***	−0.005	−0.478***	0.473***
	(−3.25)	(0.62)	(−2.78)	(−0.02)	(−3.18)	(2.09)	(−3.92)	(−0.43)	(−3.12)	(−0.046)	(−3.29)	(3.49)
Panel B: Full model												
TURN	−0.438***	−0.121	−0.317***	−0.150	−0.387***	0.236**	−0.550***	−0.317***	−0.233**	−0.140	−0.616***	0.475***
	(−5.34)	(−1.19)	(−2.77)	(−1.60)	(−5.64)	(2.34)	(−6.47)	(−3.63)	(−2.50)	(−1.60)	(−7.35)	(4.26)
BETA	0.521***	−0.356*	0.877***	−0.106	0.348*	−0.544*	−0.443**	−0.056	0.498**	0.208	0.405***	−0.197
	(2.50)	(−1.77)	(2.93)	(−0.38)	(1.68)	(−1.80)	(−2.46)	(−0.27)	(2.12)	(0.80)	(2.59)	(−0.73)
SIZE	−0.750***	−0.402**	−0.348**	−0.311*	−1.115***	0.804***	−0.953***	−0.551***	−0.402***	−0.722***	−1.065***	0.343***
	(−3.84)	(−2.27)	(−2.34)	(−1.84)	(−5.36)	(4.59)	(−4.49)	(−3.28)	(−2.90)	(−2.95)	(−4.56)	(1.49)
BM	0.382***	0.426***	−0.044	0.237	0.141	0.096	0.260***	0.284***	−0.023	0.122	0.151	−0.029
	(2.70)	(2.85)	(−0.34)	(1.59)	(1.05)	(0.70)	(2.24)	(2.30)	(−0.22)	(0.68)	(1.62)	(−0.18)
REV	−0.028**	−0.016	−0.012	−0.032***	−0.048***	0.016	−0.046***	−0.036***	−0.011***	−0.046***	−0.065***	−0.020*
	(−2.55)	(−1.33)	(−1.05)	(−2.68)	(−5.00)	(1.42)	(5.51)	(3.03)	(−0.97)	(−3.84)	(−6.36)	(−1.76)
MOM	−0.214	−0.188	−0.026	0.280	0.268	0.011	−0.280	1.084***	−1.365***	0.002	−1.585**	1.587***
	(−0.51)	(−0.33)	(−0.05)	(0.59)	(0.82)	(0.03)	(−0.72)	(2.07)	(−3.31)	(0.01)	(−2.54)	(3.16)

This table presents estimates from Fama–MacBeth regressions, conditional on arbitrage risk. We classify individual stocks into three groups, according to arbitrage risk, which is measured by Ivolatility, Analyst, Hit%, and Inst%. In each group, we perform the following cross-sectional regression:

$$R_{i,\,t} = \beta_0 + \beta_1 TURN_{i,\,t-1} + \beta_2 BETA_{i,\,t-1} + \beta_3 SIZE_{i,\,t-1} + \beta_4 BM_{i,\,t-1} + \beta_5 REV_{i,\,t-1} + \beta_6 MOM_{i,\,t-1} + \varepsilon_{i,\,t}$$

where $R_{i,\,t}$ denotes the monthly raw return on stock i in month t, and *TURN* represents the past 12 months' average daily turnover. The other five control variables are the market beta (*BETA*), market capitalization in billions of yuan (*SIZE*), book-to-market ratio (*BM*), return in the portfolio formation month (*REV*), and cumulative return over the 6 months prior to portfolio formation (*MOM*). The Newey and West (1987) procedure is used to calculate the t-statistics (in parentheses), which correct for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11
Long-run performance of turnover-based portfolios.

	Raw return	FF3 alpha	FF4 alpha	FF5 alpha
Panel A: $K = 6$				
D1	1.085	0.664	0.714	0.722
D10	0.479	−0.023	−0.015	0.054
D1–D10	0.606***	0.687***	0.729***	0.668***
	(2.75)	(5.43)	(5.80)	(5.17)
Panel B: $K = 12$				
D1	1.097	0.736	0.770	0.777
D10	0.639	0.243	0.240	0.296
D1–D10	0.458**	0.492***	0.531***	0.481***
	(2.54)	(4.89)	(5.31)	(4.71)
Panel C: $K = 18$				
D1	0.981	0.664	0.675	0.669
D10	0.714	0.379	0.369	0.400
D1–D10	0.266**	0.285***	0.306***	0.269***
	(2.16)	(3.66)	(3.93)	(3.43)
Panel D: $K = 24$				
D1	0.887	0.565	0.574	0.573
D10	0.737	0.410	0.402	0.425
D1–D10	0.150*	0.155**	0.172***	0.149**
	(1.83)	(2.54)	(2.82)	(2.41)

This table presents the average monthly returns and alphas of turnover-sorted portfolios for long-run horizons. Portfolio D1 (D10) is the decile portfolio of stocks with the lowest (highest) turnover. Portfolios are held for K months and are rebalanced monthly. Panels A, B, C, and D report results for $K = 6$, 12, 18, and 24 months, respectively. The last row in each panel reports the differences in returns between D1 and D10 with the corresponding t-statistics. The last three columns report the alphas with respect to the three-factor Fama and French model (FF3), four-factor Fama, French, and Carhart model (FFC4), and five-factor Fama and French model (FF5), respectively. The Newey and West (1987) procedure is used to calculate the t-statistics (in parentheses), which corrects for serial correlation and conditional heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

examine whether a turnover effect is evident for a typical firm in each group sorted by arbitrage risk proxies. The results reveal that the average coefficients on TURN are highly significant and negative in the high Ivolatility, low Analyst, high Hit%, and low Inst% groups, which are −0.323 (t-statistic = −3.25), −0.232 (t-statistic = −3.18), −0.412 (t-statistic = −3.92), and −0.478 (t-statistic = −3.29), respectively. The corresponding coefficients on TURN in the low Ivolatility, high Analyst, low Hit%, and high Inst% groups are all insignificant. Thus, the spread in turnover effect between high and low arbitrage risks is statistically significant.

Panel B reports the results when control variables are included in the regression. The results are similar to those of Panel A, indicating that coefficient estimates on TURN are significantly negative for the High group sorted according to Ivolatility and Hit% and for the Low group sorted according to Analyst and Inst%.

The results shown in Table 10 are consistent with those from the portfolio analysis in Table 9, suggesting that the turnover effect on future returns is significantly amplified when stocks exhibit high arbitrage risk. Moreover, the negative relation between turnover and future stock returns, conditional on arbitrage risk, is robust to the consideration of risks documented in the literature. This rules out the possibility that our findings are driven by compensation for risk.

The results reveal that the behavioral argument is stronger than the risk-based theory for explaining the turnover effect because China's stock market is mainly dominated by retail investors and exhibits high arbitrage risk. This is consistent with the view that the turnover effect is due to market mispricing caused by retail investors and that arbitrage risk deters market participants from exploiting arbitrage opportunities, leading to a persistent turnover effect.

5.3. Long-run performance of turnover-related predictability

To investigate whether the turnover effect persists, in this final subsection, we examine the performance of a turnover-based portfolio for longer horizons. We consider four holding periods: 6, 12, 18, and 24 months. The results are presented in Table 11.

Panel A of Table 11 reveals that when the holding period extends to 6 months, the difference in raw returns between D1 and D10 is 0.606 (t-statistic = 2.75). Panels B, C, and D of Table 11 present the results for holding periods extended for 12, 18, and 24 months, respectively. Although the turnover effect decreases over time, it remains positive and statistically significant for 24 months.

Therefore, the results presented in Table 11 document the persistence of the turnover effect. This is consistent with the mispricing explanation, which holds that mispricing persists when arbitrageurs exploiting profitable opportunities are obstructed by arbitrage limits.

6. Conclusion

In this paper, we have empirically investigated the role of turnover in explaining the cross-section of stock returns in China's stock market. We have detailed an extensive investigation into the turnover effect by testing various competing rational and behavioral hypotheses.

We find a significantly negative relation between turnover and future returns in China's stock market. This result is robust under risk adjustments using various asset-pricing models and is also robust when controlling for liquidity. This suggests that the turnover effect exists in China's stock market and cannot be fully attributed to common risk factors or explained by the liquidity hypothesis.

Because a risk-based perspective cannot fully explain the turnover effect, we then examined whether this effect is behavioral in nature. Based on insights from Miller's (1977) theory and the limits-of-arbitrage argument, we have conjectured that the turnover effect is a result of market mispricing, caused by differences of opinion in conjunction with limited arbitrage.

Further empirical findings confirm this conjecture. First, we find a statistically significant and economic relation between turnover effect and sentiment. The turnover effect is significantly positive when sentiment is high but not when sentiment is low. Second, the turnover effect exhibits predictable patterns related to arbitrage risk. By adopting various measures of arbitrage risk, our results demonstrate the turnover effect becomes much stronger (weaker) for stocks with higher (lower) arbitrage constraints. Finally, our findings reveal that the turnover effect exhibits return persistence. When we extend the portfolio holding periods from 6 to 24 months, the turnover effect remains significant and positive. Overall, the evidence shows the turnover effect in China's stock market is a result of market mispricing and arbitrage risk, which is mainly driven by retail investors and the heavy constraints on arbitrage activities.

Credit author statement

All authors have jointly participated in the work to take responsibility for the content including conceptualization, investigation, methodology, data curation, software, formal analysis, writing-original draft preparation, writing-reviewing, editing, and visualization.

Appendix A. Variable definitions

TURN: Following Chou et al. (2013b), turnover is defined as the average daily turnover for the past 12 months and is expressed as a percentage. Daily turnover is calculated as the number of shares traded divided by the number of shares outstanding at the end of each day.

BETA: Market beta is estimated for each stock by regressing its daily excess returns in month t on market excess returns.

SIZE: Market capitalization is the market value of equity (i.e., stock price times the number of shares outstanding) in billions of yuan in month t.

BM: Following Fama and French (1992), the book-to-market ratio in month t is the ratio of the book value of equity at the end of the previous year divided by market capitalization at the end of the previous year.

REV: From Jegadeesh (1990), the short-term reversal variable is defined as the return on a stock in month t.

MOM: According to Jegadeesh and Titman (1993), the momentum variable is defined as the cumulative return over the 6 months prior to portfolio formation.

Roll: Following the formula of Roll (1984), the illiquidity measure is calculated as the serial covariance, as follows:

$$Roll = 2\sqrt{-COV(\Delta P_{t-1}, \Delta P_t)} \tag{5}$$

When the sample serial covariance is positive, the formula is undefined; therefore, we substitute a default numerical value of 0. According to Goyenko et al. (2009), the modified version of the Roll estimator becomes the following:

$$Roll = \begin{cases} 2\sqrt{-COV(\Delta P_{t-1}\Delta P_t)} \; if \; COV(\Delta P_{t-1}\Delta P_t). < 0 \\ 0 \; if \; COV(\Delta P_{t-1}\Delta P_t) \geq 0 \end{cases} \tag{6}$$

Amivest: According to Cooper et al. (1985), the illiquidity measure is defined as the daily yuan trading volume divided by the daily absolute return averaged within the month. This measure is calculated over all non-zero-return days because it is undefined for zero-return days.

Zeroret: Following Lesmond et al. (1999), the illiquidity measure is defined as the ratio of the number of days with zero returns in a month to the total number of trading days in a month.

Amihud: From Amihud (2002), the illiquidity measure is defined as the daily absolute return divided by the daily yuan trading volume averaged within the month.

PS: Following Pastor and Stambaugh (2003), the liquidity measure is calculated as follows:

$$r_t^e = \theta + \varnothing r_{t-1} + \gamma \times sign\left(r_{t-1}^e\right) \times vol_{t-1} + \varepsilon_t, \tag{7}$$

where r_t^e is the stock's excess return above the value-weighted market return on day t, vol_{t-1} is the trading volume on day $t-1$, and the coefficient γ is liquidity measure and should have a negative sign because it reflect the reverse of the previous day's order flow shock. We multiply γ by -1 to obtain the illiquidity measure (denoted as PS).

Ivolatility: Following Ali et al. (2003), idiosyncratic risk is calculated as the variance of residuals obtained from regressing individual stocks' daily returns on the value-weighted market index over the past year, ending in the previous month with a minimum of 200 trading days.

Analyst: Analyst coverage is defined as the number of analysts following the firms (*AnaAttention* defined in CSMAR), obtained as the annual data (2004–2017) from the analyst forecast database of the CSMAR.

Hit%: Based on the method applied by Kim and Limpaphayom (2000), we use the measure of limit-hit frequency to capture the price limit, which is defined as the ratio of the number of days with a price limit hit over the past 12 months to the total number of trading days over the past 12 months. We use January 1997 to December 2017 as the sample period to calculate the limit-hit frequency. This is because the price limit rule has been enforced in China's stock market since December 16, 1996. The maximum price limits are set at 10% for regular stocks and 5% for special treatment stocks. The Shanghai and the Shenzhen Stock Exchanges identify firms with a distressed financial situation as special treatment stocks.

Inst%: Institutional ownership is defined as the fund-holding proportion, calculated as the ratio of the total fund holding to the total tradable shares. The data have been recorded semiannually since December 2005 in the CSMAR Database. The data from January 2006 to December 2017 are used in this study.

Sentiment index: We obtain the sentiment index (*ISI* defined in CSMAR) from the CSMAR Database. The database follows Baker and Wurgler (2006) to calculate the sentiment index of China's stock market by six sentiment proxies, namely, *NA* denotes the number of new trading accounts in month *t*, *TO* represents the market turnover ratio in the last month, *CCI* is the consumer confidence index in the last month, *DCEF* is the closed-end fund discount in the last month, *NIPO* signifies the number of initial public offerings (IPOs) in month *t*, and *RIPO* denotes the average first-day returns of the IPOs in month *t*. Different from Baker and Wurgler (2006), it replaces the dividend premium with *CCI* since most firms in China perform poorly in terms of dividend sustainability and policy transparency. Following Baker and Wurgler (2006), the database then uses principal components analysis to estimate the following sentiment index:

$$S_t = 0.64NA_t + 0.521TO_{t-1} + 0.229CCI_{t-1} + 0.351DCEF_{t-1} + 0.227NIPO_t + 0.463RIPO_t$$

References

Ali, A., Hwang, L.-S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. J. Financ. Econ. 69, 355–373.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56.
Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid–ask spread. J. Financ. Econ. 17, 223–249.
Amihud, Y., Mendelson, H., Pedersen, L.H., 2005. Liquidity and asset prices. Found. Trends Financ. 1, 269–364.
Avramov, D., Chordia, T., 2006. Asset pricing models and financial market anomalies. Rev. Financ. Stud. 19, 1001–1040.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645–1680.
Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99, 427–446.
Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: the common stock performance of individual investors. J. Financ. 55, 773–806.
Barberis, N., Thaler, R., 2003. A survey of behavioral finance. In: Constantinides, G., Harris, M., Stulz, R. (Eds.), Handbook of the Economics of Finance. North-Holland, Amsterdam.
Brennan, M.J., Jagadeesh, N., Swaminathan, B., 1993. Investment analysis and the adjustment of stock prices to common information. Rev. Financ. Stud. 6, 799–824.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Financ. 52, 57–82.
Chou, P.-H., Chou, R.-C., Ko, K.-C., Chao, C.-Y., 2013a. What affects the cool-off duration under price limits? Pac. Basin Financ. J. 24, 256–278.
Chou, P.-H., Huang, T.-Y., Yang, H.-J., 2013b. Arbitrage risk and the turnover anomaly. J. Bank. Financ. 37, 4172–4182.
Cooper, S.K., Groth, J.C., William, E.A., 1985. Liquidity, exchange listing, and stock return performance. J. Econ. Bus. 37, 19–33.
Datar, V.T., Naik, N.Y., Radcliffe, R., 1998. Liquidity and asset returns: an alternative test. J. Financ. Mark. 1, 203–219.
D'Avolio, G., 2002. The market for borrowing stock. J. Financ. Econ. 66, 271–306.
Dey, M.K., 2005. Turnover and return in global stock markets. Emerg. Mark. Rev. 6, 45–67.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47, 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Fama, E.F., MacBeth, J.D., 1973. Risk, return and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636.
Glaser, M., Weber, M., 2007. Overconfidence and trading volume. In: Geneva Risk Insurance Review, 32, pp. 1–36.
Glaser, M., Weber, M., 2009. Which past returns affect trading volume? J. Financ. Mark. 12, 1–31.
Goyenko, R.Y., Holden, C.W., Trzcinka, C.A., 2009. Do liquidity measures measure liquidity? J. Financ. Econ. 92, 153–181.
Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. J. Financ. 64, 549–578.
Han, X., Li, Y., 2017. Can investor sentiment be a momentum time-series predictor? Evidence from China. J. Empir. Financ. 42, 212–239.
Hong, H., Stein, J.C., 2003. Differences of opinion, short-sales constraints, and market crashes. Rev. Financ. Stud. 16, 487–525.
Hong, H., Stein, J.C., 2007. Disagreement and the stock market. J. Econ. Perspect. 21, 109–128.
Hong, H., Lim, T., Stein, J.C., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. J. Financ. 55, 265–295.
Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. J. Financ. 45, 881–898.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. 48, 65–91.
Kim, K.A., Limpaphayom, P., 2000. Characteristics of stocks that frequently hit price limits: empirical evidence from Taiwan and Thailand. J. Financ. Mark. 3, 315–332.
Lam, E.C., Wei, K.C.J., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. J. Financ. Econ. 102, 127–149.
Lesmond, D., Ogden, J., Trzcinka, C., 1999. A new estimate of transaction costs. Rev. Financ. Stud. 12, 1113–1141.
Litzenberger, R., Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: theory and empirical evidence. J. Financ. Econ. 7, 163–196.
Miller, E., 1977. Risk, uncertainty, and divergence of opinion. J. Financ. 32, 1151–1168.
Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. J. Financ. Econ. 78, 277–309.
Nartea, G., Wu, J., Liu, Z., 2013. Does idiosyncratic volatility matter in emerging markets? Evidence from China. J. Int. Financ. Mark. Inst. Money 27, 137–160.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Ng, L., Wu, F., 2007. The trading behavior of institutions and individuals in Chinese equity market. J. Bank. Financ. 31, 2695–2710.
Ng, L., Wu, F., 2010. Peer effects in the trading decisions of individual investors. Financ. Manag. 39, 807–831.
Odean, T., 1998. Volume, volatility, price, and profit when all trades are above average. J. Financ. 52, 1887–1934.
Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111, 642–685.
Qian, X., Tam, L., Zhang, B., 2014. Systematic liquidity and the funding liquidity hypothesis. J. Bank. Financ. 45, 304–320.
Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. J. Financ. 39, 1127–1139.
Shleifer, A., Vishny, R., 1997. The limits of arbitrage. J. Financ. 52, 35–55.
Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and anomalies. J. Financ. Econ. 104, 288–302.

Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19, 1531–1565.
Wright, G.N., Phillips, L.D., Whalley, P.C., Choo, G.T., Ng, K.-O., Tan, I., Wisudha, A., 1978. Cultural differences in probabilistic thinking. J. Cross-Cult. Psychol. 9, 285–299.
Yates, J., Zhu, Y., Ronis, D., Wang, D., Shinotsuka, H., Toda, M., 1989. Probability judgment accuracy: China, Japan, and the United States. Organ. Behav. Hum. Decis. Process. 43, 145–171.
Zhang, X.F., 2006. Information uncertainty and stock returns. J. Financ. 61, 105–137.
Zhu, B., Niu, F., 2016. Investor sentiment, accounting information and stock price: evidence from China. Pac. Basin Financ. J. 38, 125–134.