2A-2

Is Trading Hazardous? New Evidence from the Chinese Stock Market

Abstract

This study revisits the well-known finding in the finance literature that trading is hazardous. Our analysis of data from over 26,000 individual stock traders in China for 16-quaterly periods during 2011 to 2015 shows that stock trading in general hurts investment return, but it reduces the risk (volatility) of the investment, which ought to be desirable to investors. Furthermore, trading has an inverted u-shape impact on return in bear markets. The inverted-U shape relation indicates a bit more of trading can help improve investment performance, especially in bear markets when investors tend not to trade. While the literature shows that overconfidence results in overtrading that hurts return, our findings suggest that investors check their underconfidence to trade a bit more in bear markets when they tend not to trade.

Keywords: stock trading, abnormal return, volatility

1. Introduction

Trading is one of the most important decisions to make for stock market investors. In a well-cited study, Barber and Odean (2000) find that trading is hazardous to wealth, noting that “individual investors who hold common stocks directly pay a tremendous performance penalty for active trading.” For individual investors, this finding suggests that investors reduce trading turnover to improve return. For policy makers, it implies that financial service companies and their advisors be checked from promoting individual investors’ trading. In fact, as these institutions are commonly rewarded on the basis of commission on clients’ transactions and thus benefit from their trading, UK has banned independent financial advisors from receiving commissions from financial-product providers and European Commission put a similar proposal to the European Parliament.[1]

Is trading *always* hazardous to investors? Intuition suggests that one needs to do some trading to gain and so the effect of trading on return is likely to be non-linear. However, this conjecturer has not been formally tested in academic studies. Conventional wisdom also indicates that trading can impact performance differently in different stock market situations, depending on whether the market is bear or bull. For instance, individual investors tend to trade more actively in bull markets than in bear markets,

[1] https://www.bbc.com/news/business-19484580.

which is suboptimal in light of the disposition effect, a commonly observed behavioral bias among investors (Barberis and Xiong 2009; Weber and Camerer 1995). To mitigate the disposition effect to improve performance, investors should trade more actively in bear markets—when they lose in the market, and less actively in bull markets—when they gain in the market. However, the extant literature has yet to examine whether and to what extent the impact of trading on portfolio performance is affected by the overall stock market performance. We note that Barber and Odean (2000) examine the impact of trading on return only in a bull market: their data period is from 1991 to 1996, which fell in the period of the longest bull market in US history (from 1990 to 1999).

In this research, we revisit the effects of trading on investment performances with data from a Chinese securities brokerage company from 2011 to 2015. Our empirical context has two important features that differ from that in Barber and Odean (2000). First, our data period covers four rounds of ups and downs in the Chinese stock market, which enable us to examine whether the impact of trading on performance may differ in stock market condition. Second, investors' trading costs were significantly lower in our sample than the counterparts in the US. Barber and Odean (2000) note that the average round-trip trade in excess of $1,000 costs 3% in commissions (page 775). But the average commission rate in the industry in China has been lower than 0.1% since 2010.[2] Barber and Odean (2000) attribute the poor investment performance of individual investors in their sample period to the cost of trading and frequency of trading and believe the reason for investors' excessive trading is their overconfidence. As trading costs were significantly lower in China, a negative relation of trading and return in our study will provide a stronger evidence for the adverse effect of overconfidence on return.

Our analysis shows an overall negative effect of investors' trading on their portfolio return. Nevertheless, we also show that there is a benefit associated with trading, and that there are conditions under which trading can help improve investment performances. More specifically, we examine the

[2] see https://www.statista.com/statistics/1052575/china-average-brokerage-commission-rates-of-securities-industry.

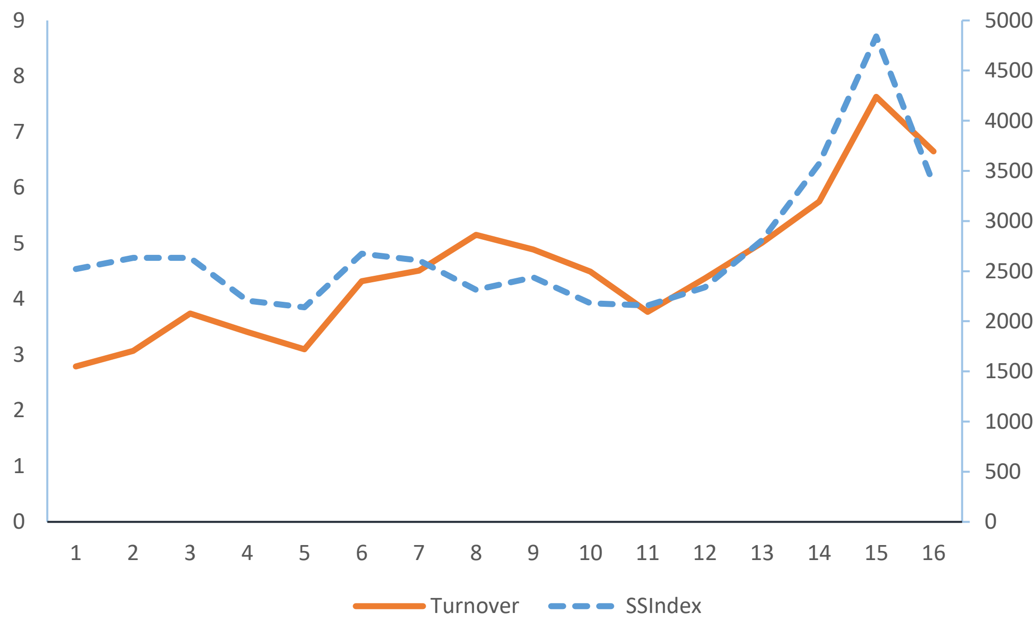
impact of trading not only on return, but also on the risk (i.e., volatility) of the investment portfolio. The consideration of risk in our research is important since investors not only care about getting a higher return but also concern the volatility risk of their investment. Increasing trading may give an opportunity to reduce the volatility of portfolio return (Jones, Kaul and Lipson 1994). Yet this important issue has not been formally tested empirically. We find that although trading generally hurts return, it is likely to reduce the risk, which ought to be desirable to investors. Next, we investigate the differential impact of trading on return in bull and bear markets. We find that individual investors' trading parallels the Shanghai and Shenzhen stock index. We show that trading tends to decrease return in bull markets and reduce loss in bear markets. Indeed, our analysis reveals an inverted U-shape impact of trading on return in bear markets. Therefore, complementing Barber and Odean (2000) that overconfidence in bull markets results in overtrading that hurts return, our results suggest that many investors are underconfident in bear markets and undertrade; a bit more trading can help them to reduce loss.

2. Data and methodology

The dataset is provided by a major securities brokerage company in China. The data contain trading and return information of randomly selected 26,827 individual investors for 16 quarters at the portfolio level (September 1, 2011 to August 31, 2015) in nine major cities (including Beijing, Shanghai, Shenzhen.). In particular, the data include the investor's account ID, account opening time, asset size at the beginning of each quarter, cash flow and number of transactions in each quarter, etc. Many investors received advising services from the company. Our data also include the number of advising interactions between the investor and her advisor in each quarter. Total data points include 429,232 quarter-investors (???). Following Barber and Odean (2000), we measure trading as the portfolio turnover, which is the total stock trading amount of the quarter divided by the average asset size of the portfolio in that quarter. Turnover is winsorized at 3% due to the existence of some extremely high values of turnover. After winsorizing, the mean value of trading turnover is 4.57 with the maximum turnover of 50.1, indicating highly active trading of those Chinese investors. However, the median trading turnover is much lower (=0.49) due to a large number of individuals who did not trade at all in many quarters. Overall, the turnover rates are much higher than the average turnover rate in Barber and Odean (2000)'s sample. The higher turnover rates in our data may be due to a rather low transaction fees.

One important feature of our data is that the Chinese stock market experienced several waves of up and down in our data period, in which markedly change in investors' trading behavior is observed. Figure 1 shows that trading turnover closely follows stock market conditions in the 16 quarters. We can see that trading turnover is highly responsive to overall stock market performance: it increases in up markets but decreases in down markets.

Figure 1. Trading turnover over time



Notes: The X-dimension indicates the 16 quarters (from September 1, 2011 to August 31, 2015). Shanghai & Shenzhen 300 index (SSIndex) is on the right Y-dimension and the average trading turnover of the investors of the company is on the left Y-dimension.

We report the average investment returns at different levels of trading in each quarter in Table 1, in which the greatest return in each quarter is indicated with a light gray color and the lowest return with a darker color. We can see that most of the lowest returns appear at the high levels of trading while most of the highest returns appear at the low levels of trading, which it indicates a detrimental impact of trading on getting a high abnormal return. Overall, not trading appears to yield the highest return and increasing trading hurts. For example, in a bull market such as Q3, 6, 7, 12, 13 and 15, the highest return comes from no trading and the return decreases with increase in trading. However, the negative relation of trading and return is not so apparent in some other quarters: it seems that there is an inverted-U shape relation between trading and return when the market is in downturn. For instance, in a bear market such as Q1 and 4, those who trade between 0 and .25 have the highest return and other levels of trading result in a lower return.

Table 1. Trading turnover and average investment returns

	All	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16
		dw	up	dw	dw	dw	up	dw	dw	up	dw	dw	up	up	up	up	Dw
No trading	.12	-.59	-.11	.07	-.62	-.27	.91	.40	-.15	.43	.01	.02	.48	.52	.68	.67	-.10
0 < turnover < .25	-.00	-.14	-.03	.00	-.15	-.06	.23	.01	-.07	.09	-.06	-.01	.09	.20	.16	.46	-.31
.25 <= turnover < 2	.05	-.17	-.07	.00	-.15	-.07	.26	.04	-.06	.15	-.01	.03	.18	.27	.20	.48	-.27
2 <= turnover < 5	.06	-.27	-.16	-.02	-.19	-.13	.27	.04	-.10	.19	.01	.07	.22	.24	.24	.47	-.26
5 <= turnover < 10	.04	-.36	-.26	-.03	-.25	-.20	.13	.03	-.16	.19	.00	.04	.18	.27	.22	.33	-.20
10 <= turnover < 20	-.01	-.34	-.28	-.07	-.31	-.23	.01	-.03	-.21	.17	-.04	.08	.06	.18	.29	.22	-.29
20 or higher	-.05	-.56	-.43	-.14	-.43	-.31	-.04	-.07	-.27	.12	-.04	.02	-.02	.18	.45	.19	-.22
All	-.21	-.37	-.13	.01	-.38	-.20	.47	.16	-.14	.26	.00	.03	.28	.33	.38	.43	-.21

Notes: Q1 is the quarter of September 1 to November 30, 2011. Q12 is the quarter of June 1 to August 31, 2015. 'dw' indicates that the stock market was a downturn in the quarter and 'up' an up market in the quarter.

This study utilizes 16-quarter trading data of individual investors and sets up an individual level fixed model to investigate the impact of trading on abnormal return and investment risk. One benefit of using such a model is to control for the idiosyncratic characteristics of individual investors. It is conceivable that individual investors' trading behavior and the subsequent performance differ, depending on the traders' attributes such as gender (Baeckström, Silvester and Pownall 2018), intelligence

(Grinblatt, Keloharju and Linnainmaa 2012), (over)confidence (Broekema and Kramer 2021; Barber and Odean 2000).

Following Hackethal et al (2012), we define the quarterly return of individual investor *i* at quarter *t*, r_{it}, as

$$r_{it} = \frac{VE_{it} - VB_{it} - CF_{it}}{VB_{it} + 0.5 * CF_{it}}, \tag{1}$$

where *VE* is the value of the investor account at the end of the quarter including earned dividends and net of transaction fees; *VB* is the value at the beginning of the quarter; and *CF* is the net cash flow for quarter *t* from adding cash (enter positively) and withdrawing (enter negatively) (we assume that all transactions occur in the middle of the quarter). Following Hackethal et al. (2012), we specify the abnormal return for each account based on CAPM:

$$r_{it} - r_{ft} = \alpha_i + \beta_i\left(r_{Mt} - r_{ft}\right) + \varepsilon_{it,} \tag{2}$$

where α_i is the estimated abnormal return (Jensen's Alpha) of individual investor *i*; β_i is the market beta for investment portfolio of investor *i;* $r_{M,t}$ is China's stock market return index in quarter *t*; and $r_{f,t}$ is the return of China's base interest rate in quarter *t*. To identify the impact of turnover on abnormal return, we specify the abnormal return of investor *i* as $\alpha_i = \alpha_0 + \alpha_1 * turnover_{it} + \alpha_2 * turnover_{it}^2 + other\ factors$, where *other factors* include *bigasset*, a dummy variable of size of the portfolio (median split, equal to one if higher than the split, 0 otherwise), *newlyac*, a dummy which equals to one if it is the first quarter of a newly acquired client, and city dummies.

The market beta β indicates whether a portfolio moves in the same direction as the rest of the market (systematic risk). It is a measure of portfolio's volatility in relation to the overall market. To identify the impact of turnover on the volatility, we specify $\beta_i = \beta_0 + \beta_1 * Turnover_{it}$. The estimate of β_1 indicates whether trading helps reduce the volatility in relation to the overall market. ε_{it} is the error term of regression of investor *i*'s investment. Because trading is an endogenous decision, we use both control function and 2SLS approach to treating it (Woodridge, 2010). Furthermore, since the estimation is inherently individual investor's 16 quarter cluster data, we introduce a random effect term of $u_i \sim N(0, \sigma_u^2)$ to capture the explained variation in the dependent variable, $r_{it} - r_{ft}$. Therefore, we have

$$r_{it} - r_{ft} = \alpha_0 + \alpha_1 * turnover_{it} + \alpha_2 * turnover_{it}^2 + \beta_0(r_{Mt} - r_{ft}) + \beta_1(r_{Mt} - r_{ft}) * turnover_i + other\ factors + u_i + \varepsilon_{it} \tag{3}$$

3. Results

The correlations and descriptive statistics are reported in Table 2. The results show that trading turnover is positively correlated with the stock market return (.045, p-value =.000) and negatively correlated with the portfolio return (-.035, p-value =.000). As trading turnover is highly right skewed, we take a logarithm in the following analysis.

Table 2. Correlations* and descriptive statistics

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1.	Turnover															
2.	RiRf	-.035														
3.	RmRf	.045	.204													
4.	Bigasset	.065	-.029	.000												
5.	Newlyac	.030	-.121	-.008	-.030											
6.	Shanghai	.027	.005	.000	.172	.041										
7.	Shenzhen	-.002	-.007	.000	-.026	-.012	-.180									
8.	Beijing	.006	.001	.000	.045	.009	-.076	-.044								
9.	Wuhan	-.036	.015	.000	-.091	-.006	-.229	-.134	-.057							
10.	Xiamen	.033	-.010	.000	-.026	-.033	-.329	-.193	-.081	-.246						
11.	Hangzhou	.018	-.002	.000	-.001	-.010	-.070	-.041	-.017	-.053	-.075					
12.	Xi'an	-.025	.004	.000	-.020	-.001	-.179	-.105	-.044	-.134	-.192	-.041				
13.	Chengdu	-.030	-.002	.000	-.053	-.005	-.163	-.096	-.040	-.122	-.175	-.037	-.095			
14.	AvgNtransac	.394	-.022	.000	.203	-.004	.070	-.003	.011	-.040	.010	.020	-.027	-.039		
15.	Nadvised	.012	.000	.000	.050	-.019	-.028	-.069	-.029	-.004	.146	.009	-.050	-.061	.020	
	Mean	4.566	.062	.017	.475	.009	.235	.095	.018	.146	.261	.016	.094	.080	35.415	.407
	SD	9.265	1.137	.170	.499	.092	.424	.293	.134	.353	.439	.125	.292	.271	97.433	1.892
	Min.	0	-6.719	-.310	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	50.1	9.33	.349	1	1	1	1	1	1	1	1	1	1	4274	99

Note: *Those correlation coefficients which are greater than .005 are significant at the 0.01 level.

The regression results are reported in Table 3. The first column (Model I) shows the results of an individual investor fixed model which uses a control function to treat endogeneity associated with turnover. Several studies have reported a positive impact of financial advising on individual investors' trading turnover (Kramer 2012; Hackethal et al. 2012), indicating material conflicts of interest between financial advisors (brokers) and their clients (Anagol et al. 2017; Bergstresser et al. 2009; Beyer et al. 2013; Inderst and Ottavian 2009; Mietzner and Molterer 2018). We thus use the number of financial advice received in the first quarter of the observed period, *Nadvised*, as well as the average number of transactions of individual investor, *AvgNtrasc*, as the instrumental variables. The correlation between *turnover* and *Nadvised* is positive and significant (r=.012***, p=.000), but the number of advising is not correlated with portfolio return (r=.000, n.s., p=.873). So, both instrumental variables passed the relevance and orthogonality tests (see the appendix table for the IV estimations). The impact of trading on abnormal return is negative but the inverted-U shape is not supported (α_1= -.049***, p-value =.000; α_2= .001, p-value=.451).

The second column (Model II) reports the results with the endogeneity treatment using predicted values of turnover (2SLS). The results (α_1= -.128***, p-value =.000; α_2= .013***, p-value=.000) indicate that trading turnover decreases investment return, but the marginal impact is decreasing. The third column (Model III) reports the results without treating endogeneity. The results are qualitatively the same as the ones with the treatment. The impact of trading on return volatility is negative and significant (β_1= -.337***, p-value =.000) in Model I, so is it in Model II and III. These results show strong evidence that trading reduces volatility.

Table 3. The impact of trading turnover on abnormal return and volatility

Variable	I	II	III
Constant	.130 *** (.010)	.192 *** (.012)	.123 *** (.009)
Turnover	-.049 *** (.008)		-.037 *** (.005)
Turnover*turnover	.001 (.002)		.001 (.002)
$\widehat{Turnover}$		-.128 *** (.009)	
$\widehat{Turnover}*\widehat{turnover}$		.013 *** (.001)	
RmRf	1.693 *** (.015)	1.769 *** (.025)	1.687 *** (.014)
RmRf*turnover	-.337 *** (.009)		-.336 *** (.009)
RmRf*$\widehat{turnover}$		-.468 *** (.023)	
Bigasset	-.089 *** (.004)	-.078 *** (.005)	-.093 *** (.004)

Newlyac	-1.469 ***	(.019)	-1.440 ***	(.019)	-1.461 ***	(.019)
Shanghi	.063 ***	(.010)	.065 ***	(.010)	.063 ***	(.010)
Shenzhen	-.015	(.011)	-.020 *	(.011)	-.016	(.011)
Beijing	.068 ***	(.017)	.067 ***	(.018)	.067 ***	(.017)
Wuhan	.064 ***	(.010)	.057 ***	(.011)	.062 ***	(.010)
Xiamen	.001	(.010)	.002	(.010)	.000	(.010)
Hangzhou	.002	(.019)	.010	(.019)	.001	(.018)
Xi'an	.033 ***	(.011)	.026 **	(.011)	.033 ***	(.011)
Chengdu	.000	(.011)	-.007	(.012)	.001	(.011)
Residual_turnover	.011 **	(.005)				

Notes: Dependent variables are RiRf defined in the equation 1. Individual fixed models specified in the equation 3 are estimated. I: Fixed model with control function to treat endogeneity; II: Fixed model treating endogeneity with 2SLS; III: Fixed model without treating endogeneity. $\widehat{Turnover}$ is the predicted value of *turnover* obtained from the instrumental variable regression results. *Residual_turnover* is the residuals of the instrumental variable regression results. See the appendix table for the instrumental variable regression results.

As the results in Table 1 indicate an inverted-U shape relation between trading and return when the stock market is in downturn, we separated the data into up-market and down-market. The results in Table 4 lend support to an inverted-U shape relation when the market is downturn. The positive coefficient of turnover (r=.052***, p=.008) and negative coefficient of turnover*turnover (r=-0.021***, p=.002) indicate that increasing a bit of trading can help improve portfolio return in downturn markets.

Table 4. The impact of trading turnover on abnormal return in DOWN VS. UP MARKETS

Variable	Down		Up	
Constant	.019 ***	(.011)	.236 ***	(.023)
Turnover	.052 ***	(.008)	-.107 ***	(.015)
Turnover*turnover	-.021 ***	(.002)	.003	(.003)
RmRf	1.077 ***	(.022)	1.299 ***	(.025)
Bigasset	.013 ***	(.005)	-.214 ***	(.010)
Newlyac	-1.445 ***	(.020)	-1.464 ***	(.036)
Shanghi	.037 ***	(.010)	.089 ***	(.022)
Shenzhen	.008	(.011)	-.042 *	(.025)
Beijing	-.017	(.018)	.157 ***	(.039)
Wuhan	-.008	(.011)	.143 ***	(.023)
Xiamen	-.001	(.010)	.001	(.022)
Hangzhou	.012	(.020)	-.013	(.043)
Xi'an	-.005	(.011)	.075 ***	(.025)
Chengdu	-.011	(.012)	.014	(.025)
Residual_turnover	.006	(.006)	.035 ***	(.012)

Notes: Down and up market samples are noted in Table 1. Dependent variables are RiRf defined in the equation 1.

Concluding remarks

This research utilizes a dataset from China to examine the impact of trading on common stock portfolio performances in terms of both return and risk. The four waves of ups and downs in our sample period allow us to explore the differential impact in both down- and up-turn markets. Our nuanced view enables us to produce several new findings to the literature. Overall, we found evidence that trading is not necessarily hazardous. First, trading invariantly reduces risk (i.e., volatility of the portfolio), which is desirable to investors. Second, the impact of trading on return depends on stock market condition. While trading is likely to reduce return in up markets, our analysis shows an inverted-U shape relation of trading and return in down markets. Our findings suggest that trading less in a bull market and trading a bit more than not trading in a bear market can improve portfolio return.

It is interesting to understand why trading hurts return in up markets and can improve return in down markets. Barber and Odean (2000) argue that excessive trading is hazardous due to investors' high trading levels (and thus the associated trading costs) and they attribute investors' overtrading to overconfidence. It is important to note that their data period includes only an up market. In contrast, our data period covers both up and down markets. Our analysis of the Chinese investor's trading behavior reveals that they trade far more frequent than their American counterparts—perhaps due to far lower transaction costs in China. In addition, the average investor traded almost three times more in Q15 than in Q1, as shown in Figure 1. It implies that in general investors significantly reduce their trading in down markets. We agree with Barber and Odean (2000) that in bull markets it is overconfidence that leads to excessive trading and thus poor performance. We further believe that in bear markets it is underconfidence that make many investors to take a passive trading strategy. To avoid stress in a bear market many individual investors choose to turn away from monitoring daily changes in stock prices and thus do few trading. For these investors, trading a bit more can help stop further loss.

Reference

Anagol, Santosh, Shawn Cole, and Shayak Sarkar, 2017. Understanding the advice of commissions-motivated agents: evidence from the indian life insurance market, The Review of Economics and Statistics, March, 99(1): 1–15.

Barber, B. M., and Odean, T. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. The Journal of Finance, 55(2): 773–806.

Baeckström, Ylva, Jo Silvester, and Rachel A. J. Pownall, 2018. Millionaire investors: financial advisors, attribution theory and gender differences. The European Journal of Finance, 24(15): 1333–49.

Barberis, Nicholas; Xiong, Wei, 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. The Journal of Finance. LXIV April (2): 751–784.

Bergstresser, Daniel, John M. R. Chalmers and Peter Tufano, 2009. Assessing the costs and benefits of brokers in the mutual fund industry. The Review of Financial Studies, 22(10): 4129–56.

Beyer, Max, David de Meza, Diane Reyniers, 2013. Do financial advisor commissions distort client choice? Economics Letters. 119: 117–119.

Grinblatt, Mark, Matti Keloharju, Juhani T. Linnainmaa, 2012. IQ, trading behavior, and performance, Journal of Financial Economics, 104(2): 339–362.

Hackethal, Andreas, Michael Haliassos, and Tullio Jappelli. 2012. Financial advisors: A case of babysitters? Journal of Banking & Finance, 36(2): 509–524.

Inderst, Roman, and Marco Ottaviani, 2009. Misselling through agents. American Economic Review, 99(3), 883–908.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994. Information, trading, and volatility. Journal of Financial Economics. 36(1): 127–154.

Kramer, Marc M. 2012. Financial advice and individual investor portfolio performance, Financial Management, 41(2), Summer: 395–428.

Broekema, S. and M. Kramer, 2021. Overconfidence, financial advice seeking and household portfolio under-diversification. Journal of Risk and Financial Management, 14(11), 553.

Mietzner, Mark, and Manuel Molterer, 2018. You might not get what you need: The discrepancy between financial advice and commissions in Germany. Economics Letters. 162: 167–170

Weber, Martin; Camerer, Colin, 1995. The disposition effect in securities trading: an experimental analysis. Journal of Economic Behavior & Organization. 33(2). January: 167–184.

Wooldridge, Jeffrey M., 2010. Econometric analysis of cross section and panel data. MIT press.

APPENDIX TABLE. Explaining trading turnover with instrumental variables.

Variable		
Constant	.735 ***	(.008)
AvgNtransac	.004 ***	(.000)
Nadvised	.003 ***	(.001)
RmRf	.418 ***	(.010)
Bigasset	.122 ***	(.004)
Newlyac	.476 ***	(.018)
Shanghi	-.005	(.009)
Shenzhen	-.065 ***	(.009)
Beijing	-.038 **	(.015)
Wuhan	-.092 ***	(.009)
Xiamen	.017 **	(.008)
Hangzhou	.081 ***	(.016)
Xi'an	-.094 ***	(.009)
Chengdu	-.093 ***	(.010)
R-square	0.16	

Note: Dependent variable is *turnover.* Instrumental variables are *AvgNtransac* and *Nadvised*. Both instruments are significantly correlated with turnover. See Table 2 for the correlations. Both *AvgNtransac* and *Nadvised* are not significantly correlated with the residuals of the second stage model (i.e., return model); the correlation coefficients are -.0021 (p-value=.203) and .0019 (p-value=.258) for *AvgNtransac* and *Nadvised*, respectively. The Hansen's J-statistic is .72 (df=1) also reject the null indicating those instruments are valid instruments.