Financial Confidence and Prudential Financial Behavior: Evidence from Chinese Household Survey Data

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Extended Abstract

Financial confidence is the gap between an individual's perceived and actual financial knowledge of individual. Research shows that financial confidence is highly associated with a person's investment behavior (Kimball & Shumway, 2006; Van Rooij et al., 2011; Yoong, 2011). For example, a person with overconfidence or high perceived financial knowledge is more likely to invest in higher-risk assets (Barasinska et al. 2012; Chu et al., 2017). Since financial confidence is widely considered to determine one's investment incentives, other financial behaviors, such as consumption and savings, should also be functions of one's financial confidence (Allgood & Walstad, 2015). This paper aims to provide a greater understanding of how one's financial confidence affects her or his financial behaviors by utilizing Chinese household survey data from China Family Panel Studies (CFPS).[4] The main contribution of this study is to provide a more comprehensive measure of the financial behaviors of an individual, focusing on the effects of both overconfidence and underconfidence, the latter of which is often ignored in the literature. In sum, our research finds that underconfidence is an even more influential factor than overconfidence in determining one's financial behaviors.

In 2014, the CFPS provided a special module of individuals' level of financial knowledge, allowing us to construct two categories of individuals' financial knowledge: actual (objective) financial knowledge, and perceived (subjective) financial knowledge. The respondents—the individual who was the most familiar with their household finances—was required to answer 13 true-false and multiple-choice test questions regarding to interest rates, inflation, and investments to measure what each person understood about broad financial concepts; their answers reflected each individual's actual financial knowledge and relative financial knowledge compared to the others. Based on their percentage of correct answers, respondent's actual financial knowledge could be categorized into three ordinal levels: above average, average, and below average. In addition to the 13 test questions, each respondent was also required to self-assess her or his financial knowledge. Based on their self-assessment, their perceived financial knowledge could also be evaluated as higher than, lower than, or similar to the other respondents. In our study, the difference between these two measurements is defined as one's financial confidence.[5] If an individual's ordinal perceived financial knowledge is higher (lower) than her or his ordinal actual knowledge, she or he is defined as overconfident (underconfident), otherwise the person is considered neutral.

The attitudes of individuals' financial behaviors can also be found in the same module of the survey in CFPS 2014. In the survey, there were 12 questions related to one's financial behaviors: (1) considering capacity when shopping, (2) paying bills on time, (3) paying close attention to my financial situation, (4) making long-term financial plans, (5) managing my own and my family's financial income and expenditures, (6) making ends meet and consuming according to my daily income, (7) collecting product information and comparing various products when choosing financial products, (8)

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[4] Since 2010, the CFPS has tracked sample households biennially, including gathering data on household characteristics, such as income, wealth, and financial situations, as well as information on individual household members, including their age, gender, and education.

[5] A similar approach can be found in Blair et al. (2018).

maintaining financial balance using loans, (9) having the habit of bookkeeping, (10) feeling that spending is more satisfying than saving, (11) feeling that the present is more important than the future, and (12) feeling that money is to be spent and should be spent whenever I have money. Questions (1), (2), and (6) show an individual's consumption behavior, reflecting their short-term financial behavior. Questions (4) and (8) show one's preference regarding making financial plans, reflecting their long-term financial behavior. Questions (10) through (12) reflect one's savings behavior. Finally, Questions (3), (5), (7), and (9), roughly gauge one's experience and aggressiveness in managing their financial assets. For each question, a respondent was required to choose a selection from five options: 'totally inapplicable', 'somewhat inapplicable', 'generally applicable', 'somewhat applicable', or 'totally applicable'.[6] Such ordinal measures of financial behaviors are able to capture more information than binary measures (Allgood & Walstad, 2015; Hilbert et al., 2003).

To investigate the correlation between one's financial confidence and their financial behaviors, our paper applies the ordered logit regression. The primary independent variable is an individual's financial confidence level, whether overconfident, neutral, or underconfident. The dependent variable for each regression is one of the 12 financial behaviors of each individual, as discussed previously. The control variables considered included household characteristics, such as total household income in the previous year and net worth, as well as individual characteristics, such as age, gender, marital status, and education. Note that total household income incorporates an individual's wage, bonuses, interest, pension, social security, private monetary gifts, and any income from self-employment. Net worth is the sum of all financial and nonfinancial wealth with debts deducted.

Our empirical results show that financial confidence is a crucial factor in one's financial behaviors. We find that an underconfident individual cares more about short-term financial plans whereas an overconfident individual prefers to make long-term plans. For example, a typical underconfident individual tends to be more prudent in making daily financial decisions (Questions (1), (2), and (6)) and is less likely to borrow (Question (8)). An overconfident individual may prefer to make long-term plans (Questions (4) and (8))—although the results here show only weak significance. Moreover, an overconfident individual is more likely to manage the finances for their households (Question (5)). Regarding one's savings behaviors (Questions (10) and (12)), an overconfident individual is less likely to save while an underconfident individual prefers to save and is more prudent in their spending. Additionally, our estimation results show that females are more likely to meet their short-term financial plans (Questions (1), (2), and (6)). Aside from gender, the other individual characteristics are found to be insignificant. Given the different measures of actual financial knowledge, the empirical results above are robust.

Our paper contributes to previous literature studying the effect of overconfidence on one's financial behaviors by examining the case of China. In addition, this paper also discusses the effects of underconfidence, which have been ignored in the previous literature. Consistent with the previous findings that an individual's financial confidence is correlated with their financial behaviors, our paper specifically focuses on analyzing the consumption and savings behaviors of Chinese. By using the data of CFPS 2014, the empirical results show that an underconfident individual tends to be more prudent in meeting their short-term financial plans and prefers to save. On the other hand, an overconfident individual may lack short-term financial plans and is more likely to be imprudent in their spending. However, we find only weak significance that overconfidence is associated with making long-term plans. Since previous research indicates that overconfidence may be more likely to lead to negative financial behaviors and welfare loss (Barber & Odean, 2001), improving one's actual financial knowledge to be comparable with their perceived financial knowledge may be important for one's welfare.

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[6] Note that for Questions (8), (10), (11), and (12), moving from 'totally inapplicable' to 'totally applicable' shows the imprudence of an individual's financial behavior. For the remaining questions, moving from 'totally inapplicable' to 'totally applicable' indicates the prudential behavior of an individual. Thus, for consistency, we reversed the order of the options for Questions (8), (10), (11), and (12), so that the options were consistent with the prudential level of an individual.

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Credit Union Movement and the Development of a Country: A Cross-Country Perspective

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Abstract

Credit unions are self-help, not-for-profit financial cooperatives aim at reducing financial exclusion and building strong social capital to empower the local community development. The aim of this paper is to argue that the development of credit union system in a country could foster its economic and social development. To do this, this paper constructs a credit union development index and uses the Human Development Index to proxy credit union development and social development, and then measure the association of these two indexes. Research findings provide empirical evidence to support our argument.

Extended Abstract

Credit unions are self-help, not-for-profit financial cooperatives aim at reducing financial exclusion and building strong social capital to empower the local community development. Historically, credit unions were organized around a common characteristic or affiliation such as membership of an occupation group, a voluntary association, or a narrowly defined community; they are nonprofit organizations which encourage savings and make loans at low cost to their members (Dublin, 1971; Moody and Fite, 1971, Cahill, 1984; and Sloan, 1984,). A credit union can be thought of as a purchasing cooperative from the standpoint of its borrowing members, and a marketing cooperative form its saving members' point of view (Taylor, 1971). Since it deals exclusively with its members, a credit union can claim to be the purest form of all cooperatives (Croteau, 1963). According to Ferguson and Mckillop (1997), a credit union cannot do business with the general public because of charter limitations based on serving a membership that is characterized by a common bond.

The aim of this paper is to argue that the development of credit union system in a country could foster its economic and social development. To do this, we use index numbers to proxy credit union development and social development, and then measure the association of these two indexes. Since we adopt the historical series of global Human Development Index (HDI), which is thought to be the ultimate criteria for assessing the development of a country (United Nations Development Programme, 2016), to measure the economic and social development of the selected countries. The major contribution of this paper is the construction of an index to capture the development characteristics of credit union systems across countries based on statistics published by the World Council of credit Unions (WCCU, 2017).

Many determinants of credit union development have been identified in the credit union literature (Brockschmidt, 1977; Kaushik and Lopez, 1994; Mason and Lollar, 1986; Pickersgell, 1995). In order to identify an evolutionary development path for credit union industries, Ferguson and Mckillop (1997) synthesized the attributes of credit union development and categorized development into an ideal-type model of three distinct growth stages within country-specific credit union industries. Since Ferguson and Mckillop's model is a descriptive one that would inevitably prove to be complex and unable to capture the continuity of change occurring within credit union industries, we used the statistical method of principal components factor analysis[2] to constrict a credit union development index to group country-specific credit union industries into the three distinct growth stages. The criteria for including variables in the list of variables that determine the stage of credit union development are based largely on the consideration of the economy-wide participation and production scale. We chose the number of credit unions, the percentage of credit union loans and savings to GDP (which measures the

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[2] See Poon, Woo and Hon (2005) for a comprehensive description of the use principal component to construct an index for several variables.

significance of credit unions to the economy), and penetration rate as proxies for economy-wide participation, and the average membership per credit union, credit union savings per membership, and credit union loans per membership as proxies for production scale, Credit union reserves and assets have not been excluded in the list because of ambiguous definitions and a number of countries (19 countries) did not provide these statistics.

Considering the six credit union development variables are measured on different scales or on a common scale with substantial difference in magnitude, to make the figures comparable, we have to transform these variables on the same scale by standardizing them for the subsequent factor analysis. Suppose that each observed variable X_i has a constant mean μ_i with a finite variance σ_i^2 over the WOCCU listed countries (i[th]) with available data. We transform X_i to Z_i, where $Z_i = \frac{X_i - \mu_i}{\sigma_i}$ with a mean of zero and a standard deviation of one.

We used the factor score coefficients of the principal component as the weighting system applied to the national values of credit union development variables to obtain the common factor score of the first k principal component ($FAC_{j \text{ to } K}$). Taking 2005 dataset as an example, the SPSSS factor analysis output shows that the first 3 principal components (FAC1, FAC2, and FAC3) explain 81.77% of the total variance of the data matrix of the six credit development variables of the 76 selected countries, and thus it is sensible statistically to use the weighted average of these three series (LC) to represent the extent of credit union development across these 76 countries in the world.

Since the LC for the 76 countries were calculated based on standard normal variables that contain both positive and negative values, we have to convert the LC series to an index number for the sake of mathematical manipulation. To do this, we convert the LC values from the standard normal scale, $Z \sim N(\mu_z=0, \sigma_z=1)$, to a normal random variable, $Y \sim N(\mu_y=100, \sigma_y=50)$ by using the transformation formula $CUDI_i = LC_i \times 50 + 100$, where i = 1…76. This derived variable is called credit union development (CUDI). Hong Kong ranks seven (of course, the selection of different variables, and different weights attached generates different rankings) in the world in terms of the CUDI of the 2005 WOCCU data. (*The research is currently in progress.*)

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The strong similarities between financial price dynamics and pedestrian counterflows under different environmental, human and index factors

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Abstract

Existing studies have shown that when the density around the door of pedestrian counterflows corresponds to the logarithm of the financial asset price, the simulated pedestrian counterflows can reproduce the stylized facts of the financial market. However, the basic physical mechanism that leads to the similarity between financial price dynamics and pedestrian counterflows remains unclear. In particular, it is unknown whether these similarities still exist under various environmental factors, human factors and index factors. This study proposes and records further evidences to prove that there are strong similarities between financial price dynamics and pedestrian counterflows under various environmental factors, human factors and index factors. The research results show that the monetary policy and door width possess the same impact trend on the micro-characteristics of probability distribution, autocorrelation and multi-fractal in financial price dynamics and pedestrian counterflows. This means that the loose, prudent and austerity monetary policies respectively correspond to the wide door width, medium door width and narrow door width. In addition, unbalanced buyers and sellers as well as unbalanced pedestrians also show similar impact trends on the micro-characteristics of probability distribution, autocorrelation and multi-fractal. Therefore, the predominant buyers, balanced traders and predominant sellers respectively correspond to the predominant upgoing pedestrians, balanced pedestrians on both sides and predominant downgoing pedestrians. Finally, the trading volume and the flow rate also show the similar impact trend on the micro-features of probability distribution, autocorrelation and multi-fractal. This means that the large, medium and small trading volumes in financial price dynamics correspond exactly to the large, medium and small flow rate in pedestrian countflows. Therefore, the strong similarities in financial price dynamics and pedestrian counterflows under different environmental, human and index factors, suggest that a deeper unified behavioral mechanism is at play in human-driven system with two competitive groups with opposite interests.

Introduction

The analogy between complex flows and financial market is not new. As early as 1996, Ghashghaie et al. published a highly creative article in *Nature*, which compared the turbulence with the exchange rate of the foreign exchange market. It found that the velocity increment distribution between two points in the turbulence and the increment distribution of exchange rate variation possessed the astonishing similarity, which corresponded to the energy cascade of the fluid dynamics, and there was also an information cascade in the foreign exchange market. That is, some of the tools and methods for studying turbulence as well as some of the research findings in turbulence studies can be applied to the study of price fluctuations in financial markets. However, Mantegna and Stanley(1996;1997) as well as Arnedo et al.(1996)questioned the above analogy later. They believed that there was a fundamental difference between them. They cannot directly compare price variations with turbulence, since there is autocorrelation in turbulence, while there is no autocorrelation in price variations. Although the price variations in financial market are irrelevant, the volatility of price variations shows a correlation. Arneodo et al.(1997)applied wavelet technology to further study this cascade. He believed that it was possible to utilize the method of studying turbulence to study the scaling relations of the price variation volatility.

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Parisi et al.(2013)proposed a complex counterflow system, which is more suitable than turbulence. The system possesses two sets of reverse self-driven pedestrians to pass a door (bottleneck) and form pedestrian counterflows. The study found that when the density around the door corresponds to the logarithm of the financial asset price, the simulated pedestrian counterflows can reproduce the eight stylized facts of the financial time series. The similarity between the pedestrian counterflows through the narrow door and the financial market was first proposed by Helbing(Helbing 2001). Later, Parisi(2010)also certified the idea. He believed that the average speed near the door is observable for the pedestrian system. Therefore, the pedestrian flows can exhibit rich behaviors similar to other complex systems(Helbing 2007;Moussa¨ıd 2008).

Although the literature [6] finds that there is a correlation between the pedestrian counterflows and the financial price dynamics system, and it opens up new horizons for the analysis in financial field. However, the basic physical mechanism that causes the similarity between the financial price dynamics and the pedestrian counterflows is still not clear. In particular, when the above-mentioned correlation research is applied to the financial capital market, except comparing the density around the door with the logarithmic return rate of the financial capital market, it is unknown whether other parameters and the impact factors of the capital market (such as environmental factors, human factors and indicator factors) possess the similarities. Besides, it is unknown whether these similarities still exist under varied environmental factors, human factors and index factors, and whether they correspond to the effect of stylized features. These need to be further revealed.

In this study, the China's Shanghai Composite Index with 1min high-frequency data was selected as the empirical data of the financial system. It considered varied environmental factors, human factors and index factors. For example, it took loose, prudent and austerity monetary policies as environmental factors, took unbalanced buyers and sellers as human factors, and took large, medium and small trading volumes as index factors. Similarly, the social force model proposed by Helbing(2013)was utilized to simulate pedestrian counterflows in the pedestrian counterflows. It took into account the wide door width, moderate door width and narrow door width as the environmental factors, took the unbalanced pedestrians on both sides as human factors, and took large, medium and small flow rate as index factors, to verify the similarities between financial price dynamics and pedestrian counterflows under varied environmental factors, human factors and index factors, and to explore the differences of micro-characteristics such as the complementary probability distribution, autocorrelation and multi-fractal under various impact factors. Besides, it attempted to explain the differences so as to provide concrete and effective theoretical support and practical guidance for guiding financial market trade through the social force models.

Simulated Pedestrian System and Finance

Social Force Model

The pedestrian model of this study refers to the behavior model, namely the social force model. The behavior model was proposed by Helbing (Helbing, & Molnár1995;Helbing et al. 2000; Helbing et al. 2012) based on social psychology and physical force. The study assumes that each pedestrian is a particle that satisfies the laws of motion, and utilizes the vector forces to describe real forces and intrinsic motives. Among the N pedestrians, each pedestrian i with mass M_i moves at a certain desired speed v_i^o toward the desired direction e_i^o .The difference between the actual speed v_i and the desired speed is corrected by the relaxation time τ . At the same time, the pedestrian i will maintain a certain distance from the pedestrian j and the wall w through forces f_{ij} and f_{iw} .Therefore, the speed variation of the pedestrian i at time t can be described by the acceleration equation as follows.

$$M_i \frac{d\mathbf{v}_i}{dt} = M_i \frac{\mathbf{v}_i^0(t)\mathbf{e}_i^0(t) - \mathbf{v}_i(t)}{\tau} + \sum_{j(\neq i)} f_{ij} + \sum_{w} f_{iw} \tag{1}$$

In equation, the variation of the spatial position $s_i(t)$ for the pedestrian i is calculated by $v_i(t) = ds_i / dt$. f_{ij} is the interaction force between pedestrian i and pedestrian j. f_{iw} is the force with wall w . In addition, the other corresponding parameters of the social force model are set as follows. For each pedestrian, the diameter is $2r_i = 0.5\,m$, the mass is $M_i = 60\,kg$, the desired speed is v_i^o =1.2m/s.

Pedestrian System and Finance

The scene setting of the simulated pedestrian counterflows is shown as follows (Fig. 1). The simulation scene is a rectangular area of 20m by 20m. The middle is divided into two areas by a wall.

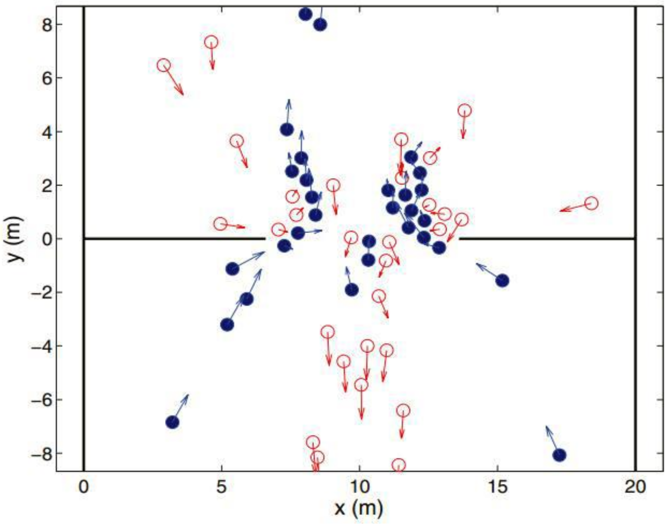


Fig.1. Simulated pedestrian counterflows. Two types of particle filling indicate the pedestrian's status, and the arrows indicate its current speed.

There is a door with a width of L in the middle of the wall. Both sides of pedestrians try to pass the door first to reach the other end. To achieve this goal, the pedestrians on the upper and lower sides cross the door from the opposite directions, and then it results in the counterflows.

The pedestrian counterflows at the bottleneck (gate) are analogous to the irregular fluctuations of the stock market price. Pedestrian traffic is an individual competing for limited resources (i.e., space). The buyers and sellers in the stock market possess the opposite driving forces to purchase effective assets. Therefore, when the density around the door is compared with the logarithm of the financial asset price, the simulated pedestrian counterflows can reproduce the eight stylized facts of the financial time series (Helbing, 2001).

The social force model mainly contains the following parameters. (1) Door width L. (2) Total number of pedestrians in Np system. (3) Ratio of the number of pedestrians on the upper and lower sides of Na/Nb systems. (4) Pedestrian parameters, namely, mass (m), diameter (2r) and desired speed (v_i^0). Among these four parameters, the first three are the main parameters. Pedestrian mass (m), diameter (2r) and desired speed (Vd) are generally evenly distributed over [50 kg, 70 kg], [0.44 m, 0.56 m] and [1.05 m/s, 1.35 m/s]. The following discusses the similarities between varied L, Np, Na/Nb and various factors in the financial system. It's showed as follows (Fig. 2).

L in the pedestrian counter model L is a significant parameter and is the bottleneck in the simulation scenario. The threshold L is the most intuitively understandable and adjustable factor in the escaping panic factors of the self-driven multi-particle systems, it is an environmental factor, which exists objectively in the simulation environment. When L is larger, the bottleneck will be wider, the restriction on pedestrians will be smaller, and then more pedestrians will pass through the door, the congestion is less likely to occur. When L is smaller, the bottleneck will be narrower, and then fewer pedestrians will pass through the door, it's more difficult for pedestrians to pass the door, then the arch is easy to be blocked or crowed (forming a deadlock state). Just as the effect of the macro-environmental factors on the stock market, the government utilizes the "visible hand" to carry out the macro-control on the stock market so as to better cope with the current economic situation. Loose monetary policy will prompt people to utilize their surplus funds for investment in financial assets such as stocks. This leads to large amounts of money assets to flow into the stock market, significantly increases the market liquidity and makes the stock market active. The capital cost of investors increases under the austerity currency. The capital investment decisions of investors are more rational, the market liquidity is reduced, and the stock market is depressed.

Na / Nb Na and Nb are the number of pedestrians in two groups of counterflows. When Na = Nb, that is, Na/Nb = 1, the pedestrian counterflows are in balance, and the stock market is also in balance. The buyers and sellers possess equal forces. However, when the system is in a unbalanced state, if the number of upgoing pedestrians is predominant in the model and the number of downgoing pedestrians is predominant, that is, Na>Nb, Na<Nb (which is more likely to result in a congestion and stampede events), the number of agents in one side of the system is greater than that of the other side. The power of the buyers and sellers is not balanced in the positive analog stock market, the buyer's power is large (seller's market) or the seller's power is large (buyer's market). When there are many

people to
buy in the market, the expectation of investors is good, the investor's confidence increases, and then

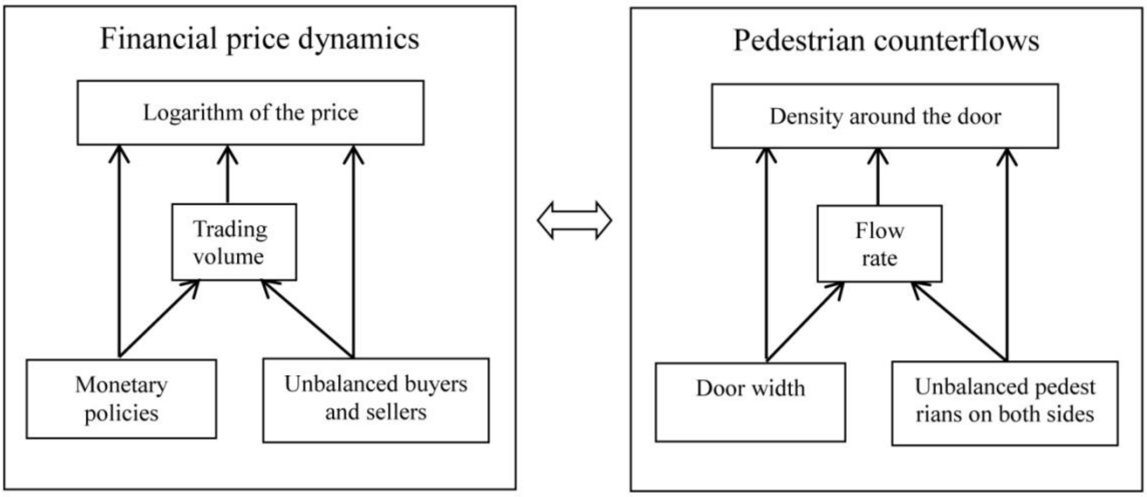


Fig.2. The strong similarities between the financial price dynamics and the pedestrian counterflows under different **environmental factors** (monetary policies, door width), **human factors** (unbalanced buyers and sellers, unbalanced pedestrians on both sides) and **index factors** (trading volume, flow rate).

The stock price is in an upward trend. This is also consistent with the principle of supply and demand. In a similar way, if there are more people to sells, and then the stock price is in a downward trend. Of course, when all agents choose to be in the same state, that is, they possess the same expected walking direction. This situation is similar to the financial collapse. All agents are under the situation that the seller (empty party) want to sell their assets, ie Na/Nb = 0.

Np Np is in the pedestrian counterflows, other parameters remain the same. If Np is greater, the flow rate through the threshold per unit time is smaller, since the system is more prone to arch blocking and congestion with the increase of Np. There are many factors that affect the pedestrian counterflows. The speed, density and flow rate in the model will affect it. However, it's the same in the stock market. The index such as the trading volume, volume of business and the number of transactions will also affect the stock market. This study attempts a large number of combinations, and it finds that Np (flow rate) corresponds to the trading volume can better show the impact of the stylized features.

Financial Micro-characteristics and Its Inspection Methods

Thick-tailed Distribution

The yield rate of financial assets often possesses a distinct thick-tailed characteristic. This study utilizes the hierarchical ranking method with a relatively easy-to-implement and low-noise to characterize the thick-tailed distribution of financial asset returns(Sornette et al.1996; Zhou W X 2007).If the distribution of yield rate is a normal distribution, it will coincide with the fitting line of Gaussian distribution. If it is "fat tail", the tail of the drawn curve will deviate from the Gaussian distribution and form a trailing tail.

Levy Distribution

The Mantegna-Stanley method is applied to study the centermost peak of the distribution, namely, the zero-return probability $P(R=0)$ of is as a function of k. This method allows us to study the points that are least affected by noise in each probability distribution. The log-log plot for the probability density of 0 logarithmic increment and k is made. If the data points are fitted to a straight line, it indicates that the assumption of Levy distribution is reasonable.

Autocorrelation Function

The autocorrelation coefficient is defined as follows.

$$C_R(t) = \frac{\langle R_k(x)R_k(x+t)\rangle - \langle R_k(x)\rangle\langle R_k(x+t)\rangle}{[\sigma(R_k)]^2} \quad (2)$$

In formula, under the given time interval k, when t =0, $C_R(t)=1$. If there is no correlation between logarithmic increments of interval t at the same k level, that is, $\langle R_k(x)R_k(x+t)\rangle = \langle R_k(x)\rangle\langle R_k(x+t)\rangle$, and then $C_R(t)=0$.

Multi-fractal

Calvet and Fisher (2008) improved the form for scale invariance of multi-fractal. Multi-fractal can be represented by the yield rate $\langle |R^k|^q\rangle / \langle |R^k|\rangle^q$ of time interval k. If the rate is a constant, it means single fractal, and vice versa.

Data Selection and Processing

The 1-minute high-frequency data of the Shanghai Stock Exchange Index is chosen to compare the stylized characteristics of the financial system and the pedestrian counterflows. In order to control the influence of sample volume, the sample interval is controlled at the same length of time, and the date is delayed in the case of non-trading days. Due to the influence of the volatility characteristics of China's stock market, the longest unified period for the selected divisions is 4 months, of which the sample volume is nearly 20,000 in each section. The data are all from Wind Database.

Density and Logarithmic Price

The logarithmic incremental sequence of the stock index is selected. The calculation method is as follows.

$$R_k(t) = \ln P(t+k) - \ln P(t) \quad (3)$$

In formula, k is the time interval. $P(t)$ represents the price of an asset at time t. Y is defined as a time series, and then

$$R_Y = \frac{dY}{dt} \quad (4)$$

$$R_Y^k(t_i) = Y(t_i + k) - Y(t_i) \quad (5)$$

In formula, $Y = \ln(P)$. As a statistical variable, the minimum interval k = 1 min is utilized in the following statistical analysis. This interval can maintain the continuity of the data and can also better deal with the influence of the short-range correlation between the time series on the statistical characteristics of the data(Wu M C et al. 2006). Then

$$|R_Y^k| = |Y(t_i + k) - Y(t_i)| \quad (6)$$

The standardized absolute returns can be obtained from formula (6) as follows.

$$|\hat{R}_Y^k| = \frac{|R_Y^k|}{(\sum_{t_i}^{N_T - k} |R_Y^k|)/(N_T - k)} \quad (7)$$

In formula, N_T is the total data amount of the time series Y, and the denominator is the arithmetic mean of the absolute returns. For the time series P, the increments of logarithmic price $Y = \ln(P)$ are usually chosen as the logarithmic returns. In the pedestrian counterflows, the time series is the density ρ through gates, that is, Y = ρ.

Door Width and Monetary Policy

In the selection of monetary policy, since there is no unified standard for classification at present, this study divides monetary policy into loose policy interval, steady policy interval and austerity policy interval based on indicators such as deposit reserve ratio, reverse repurchase ratio and national debt yield(Rao P G&Jang G H.2013). That is, the loose-policy interval ranges from Jun 29, 2015 to Oct 29, 2015. The steady policy interval ranges from Mar 29, 2016 to Jul 29, 2016. The austerity policy interval ranges from Feb 29 to Apr 29, 2017. When they correspond to the pedestrian counterflows, the door width are selected as 10m, 7m, 4m.

Unbalanced Pedestrians and Unbalanced Buyers and Sellers

The market is divided into predominant buyer, balanced trader and predominant seller through the trend chart of weekly data. Among them, the trend that exceeds the previous low point by more than 30% is defined as the predominant buyer's (rising) range. In the similar way, the predominant seller's (down) range refers to the decline that exceeds the previous high point by more than 30%. The balanced trader (steady) range refers to the variation range of 5%–10%(Zhang T W et al.2013). That is, the predominant buyer's range is from Sep 12, 2014 to Jan 12, 2015. The balanced trader range is from Dec 12, 2016 to Apr 12, 2017. the predominant seller's range is from Jun 12, 2015 to Oct 12, 2015. When they correspond to the pedestrian counterflows, the predominant upgoing pedestrian Na/Nb=4 is selected, the balanced pedestrian Na/Nb=1 on both sides is selected, and the predominant downgoing pedestrian Na/Nb=1/4 is selected.

Flow Rate and Trading Volume

The turnover rate is applied as a measure of the trading volume to avoid the influence of each floating stock (Wu C F&Wu W F 2001).

$$g(t)=\begin{cases}0.5 & \ln To(t)\le u-0.5\mathrm{e}\\ 1 & u-0.5e<\ln To(t)\le u+0.5e\\ 1.5 & u+0.5e<\ln To(t)\end{cases} \tag{8}$$

In formula, g(t) is the time conversion formula based on trading volume. lnTo(t) is the logarithm sequence of the turnover rate. u and e are respectively the mean and standard deviation. g(t) is a sectional function and divides the trading volume into three phases such as large volume, medium volume and small volume. It is a small volume phase when g(t) takes 0.5. It is a medium volume phase when g(t) takes a value of 1. It is a large volume phase when g(t) takes a value of 1.5. Among them, the large trading volume ranges from Mar 17, 2015 to Jul 17, 2015. The medium trading volume ranges from Jan 17, 2016 to May 17, 2016. The small trading volume ranges from Mar 17, 2014 to Jul 17, 2014. When they correspond to the pedestrian counterflows, the large flow rate of Np=50, the medium flow rate of Np=60 and the small flow rate of Np=70 are selected.

Empirical Results

By experimenting with various observations, we find that pedestrian counterflows and financial dynamics system not only possess the similarity between the dynamic characteristics of pedestrian density and the dynamic characteristics of the financial system's price logarithm, but also find that there are more strong correlation of parameter indicators between the two systems. For example, the parameters L, Np, Na/Nb in the model possess a one-to-one correspondence with environmental factors (monetary policy), human factors (buyer and seller) and indicator factors (trading volume) in the financial system. Besides, they are consistent with the impact trend of probability distribution function, autocorrelation and multi-fractal. This section will discuss (a) the micro-characteristics of China's capital market, the influence of varied monetary policies, trading volume size, the power of buyers and sellers on the probability distribution function, autocorrelation and multi-fractal of the Shanghai Composite index, and (b) the social force model to simulate the capital market, influences and differences of varied L, Na/Nb and Np values on the density function of probability distribution, autocorrelation and multi-fractal. Finally, the section compares the results of the capital market and the pedestrian counterflows, and analyzes the similarities and differences. This shows the strong correlation between financial price dynamics and pedestrian counterflows.

Threshold L and Monetary Policy

Thick-tailed Distribution

In order to ensure the comparability of the time series of two systems, the standardized absolute value return series $|\hat{R}_Y^k|$ is selected as the study sample, and then the influence of monetary policies and the value of the threshold L on the thick-tailed distribution is analyzed. Fig 3(a) shows that the distribution function of the standardized absolute return sequence of the Shanghai Composite Index possesses obvious thick-tailed characteristics under three major monetary policies. In addition, compared with the steady and austerity monetary policies, the tailed distribution of the loose monetary policy deviates far from the standardized normal distribution curve. That is, the tailed characteristic is more obvious and the extreme risk is greater. The varied threshold L in Fig 3(b) also shows a distinct thick-tailed feature, and the wide door width deviates farthest from the standardized normal distribution curve. It can be seen that the distribution function of yield rate under varied threshold L values and monetary policies show the thick-tailed characteristics, and the influence on the thick-tailed distribution is consistent.

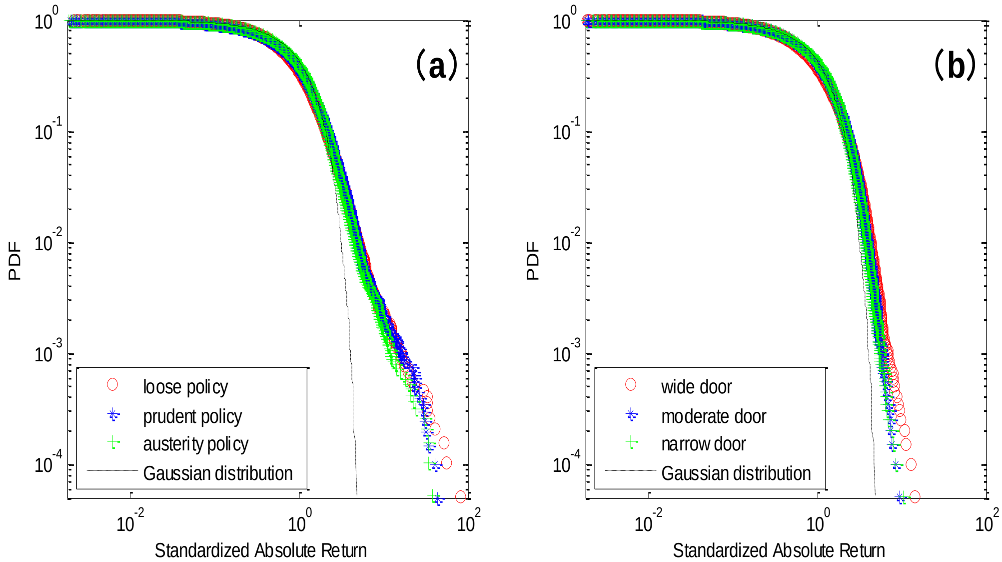


Fig.3. Distributions of complementary probability in (a) financial price dynamics and (b) pedestrian counterflows under different environmental factors.

Levy Distribution

The Levy's stable distribution is applied to fit the yield distribution and analyze the probability distribution function of $R_k(t)$. It respectively takes k=1, 6, 16, 26, 36,..., 96 and 100 min to find the probability distribution function of varied monetary policies and thresholds L, and then fit the exponential distribution parameters of the Levy distribution. The result is shown as follows (Fig 4). In Fig 4(a), the slope (-$1/\alpha$) of the fitted straight line under the corresponding loose, prudent and austerity policies are respectively -0.5642, -0.5824 and -0.5768. In Fig 4(b), the slope (-$1/\alpha$) of the fitted straight line under the corresponding wide, moderate and narrow door width are respectively -0.6902, -0.7329 and -0.7189. It can be seen that the trends of two systems are consistent and tend to be Gaussian distribution (α =2) when it's loose policy and wide door width.

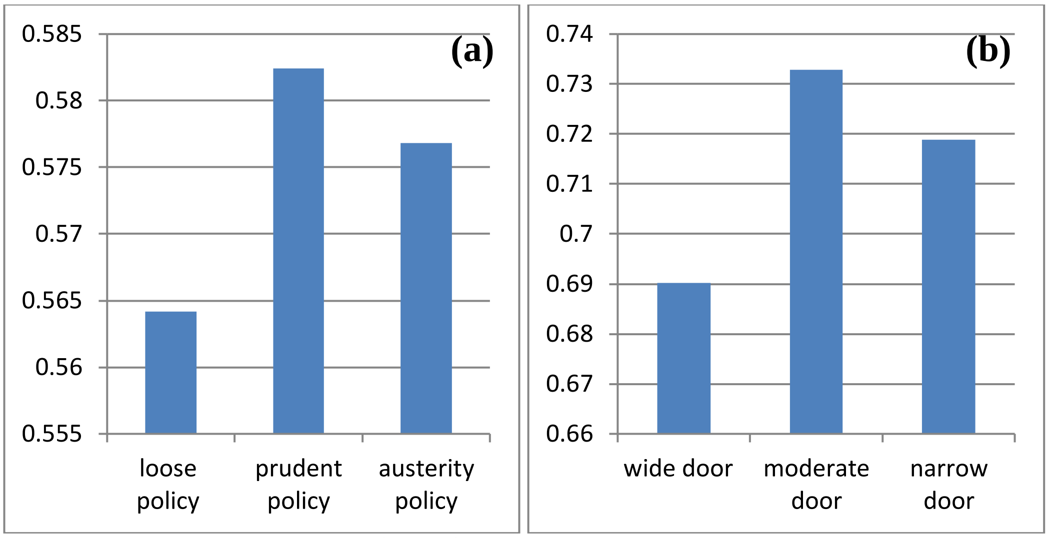


Fig. 4. Log-log plot of the probability $P(R=0)$ versus *k* in (a) financial price dynamics and (b) pedestrian counterflows under different environmental factors.

Autocorrelation Function

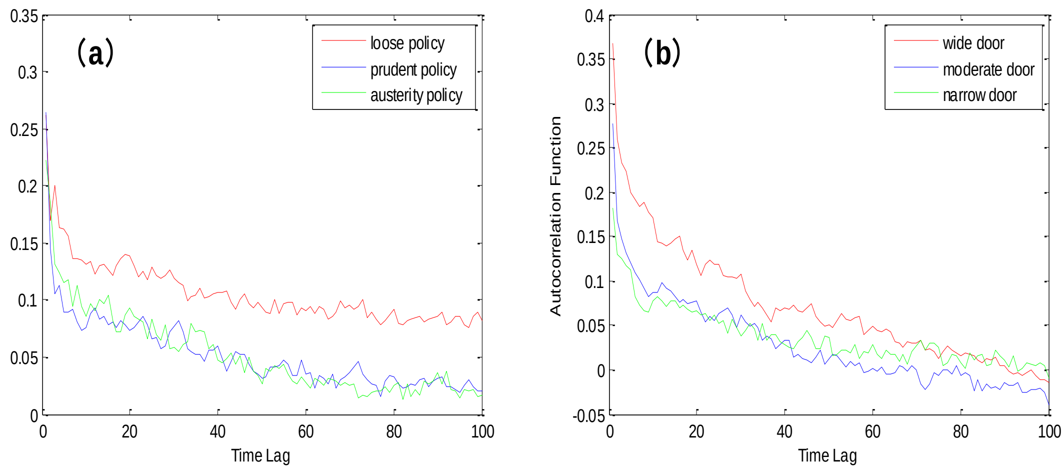


Fig.5. Autocorrelation functions of volatility in (a) financial price dynamics and (b) pedestrian counterflows under different environmental factors.

Taking $R_k(t)$ as the yield rate and $|R_T^k|$ as the volatility, and then the autocorrelation analysis on the yield rate and volatility of varied monetary policies and thresholds L is shown as follows (Fig 5). Fig 5 shows that the volatility autocorrelation of two systems is higher than the autocorrelation of the yield rate, which is consistent with the mainstream trend of economists. That is, the yield rate of stock price possesses no long-term memory, while the volatility possesses strong memory. The volatility autocorrelation in Fig 5(a) decays slowly, in which the loose policy possesses the strongest autocorrelation, and the performance in Fig 5(b) is consistent, the volatility shows the autocorrelation, and the autocorrelation is the strongest when the door width is wide. However, since there are no emotional sensors in the pedestrian system, there are no complicated decision features such as investor sentiment, investor information, investment expectations, information feedback, risk attitudes and other human factors. This is equivalent to iron out the divergent characteristics caused by noise factors, thus, the periodicity of the autocorrelation for the financial system cannot be presented.

Multi-fractal

Fig 6 shows the yield rate chart of the threshold L under varied monetary policies and time interval k, where q takes 1.5, 2, 2.5 and 3. The chart shows that the trend of the yield rate is non-linear, and it indicates that they all possess multi-fractal characteristics. In addition, when q is larger, the variation of the yield rate is more obvious. When q=3, the maximum curve slope of the loose monetary policy is -0.4166 in Fig 6(a), the medium curve slope of the austerity monetary policy is -0.2828, the minimum curve slope of the steady monetary policy is -0.2094. In Fig 6(b), the maximum curve slope under wide door width is -0.1130, the medium curve slope under moderate door width is -0.0643, the maximum curve slope under narrow door width is -0.0591. The performances are consistent in two systems. The curve slope of the yield rate is the largest under loose policy and wide door width.

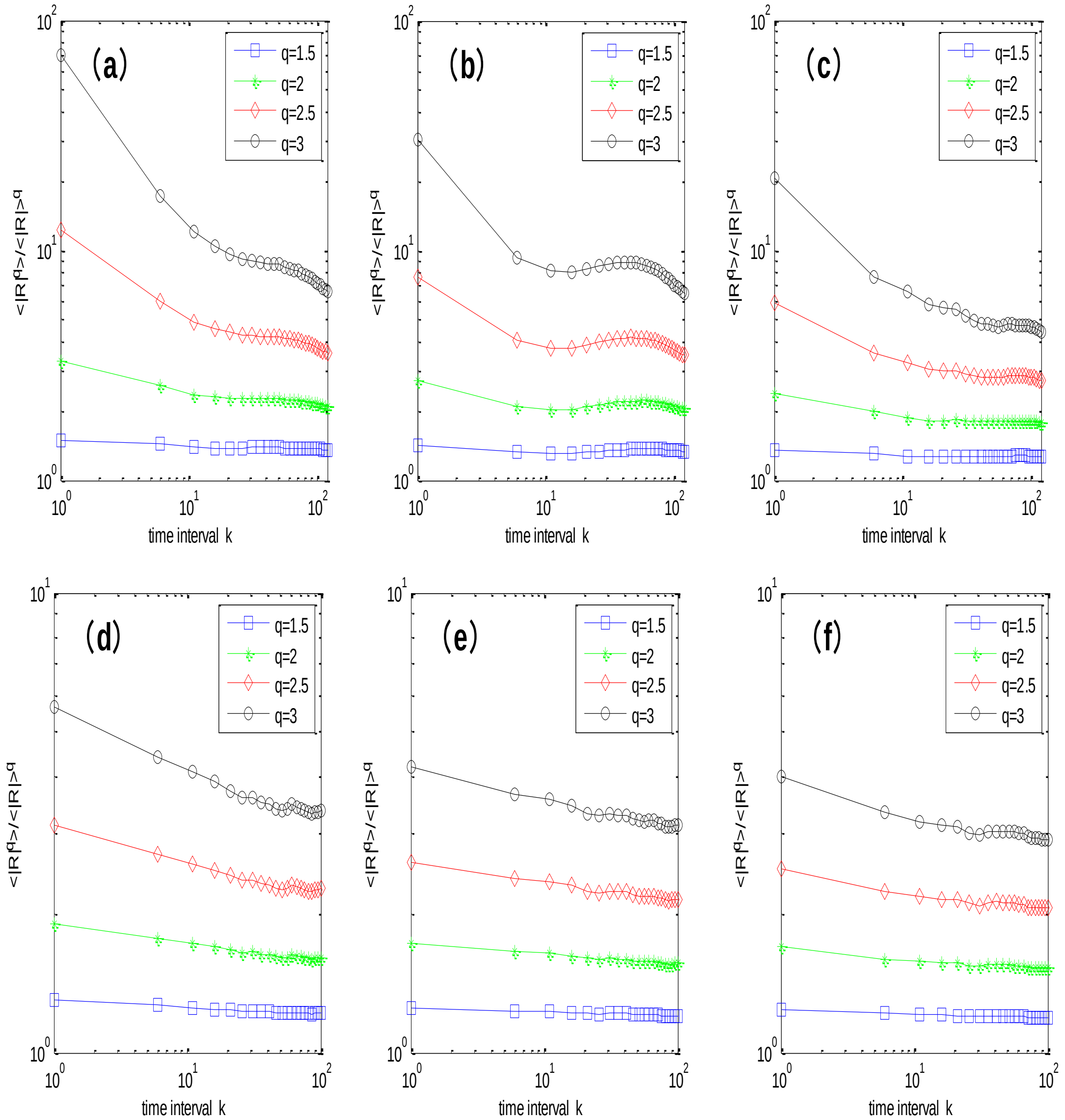


Fig. 6.Multifractalcurves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$: The financial price dynamics in (a) loose policy, (b) prudent policy and (c) austerity policy, and the pedestrian counterflows in (d) wide door, (e) moderate door and (f) narrow door.

Unbalanced Pedestrians and Unbalanced Buyers and Sellers

Thick-tailed Distribution

Fig 7 shows that both sets of distributions exhibit significant thick-tailed characteristics. Fig 7(a) shows that the tailed distribution deviates the farthest from the standardized normal distribution curve under the predominant sellers when compared with the predominant buyers and the balanced traders. That is, the tail characteristics are more obvious and the extreme risks are even greater. Fig 7(b) also shows that the predominant downgoing pedestrians deviate the farthest from the standardized normal distribution curve. It can be found that the distribution functions of yield rate exhibit thick-tailed characteristics under unbalanced pedestrians and unbalanced buyers and sellers, and the impact on the thick-tailed distribution is consistent.

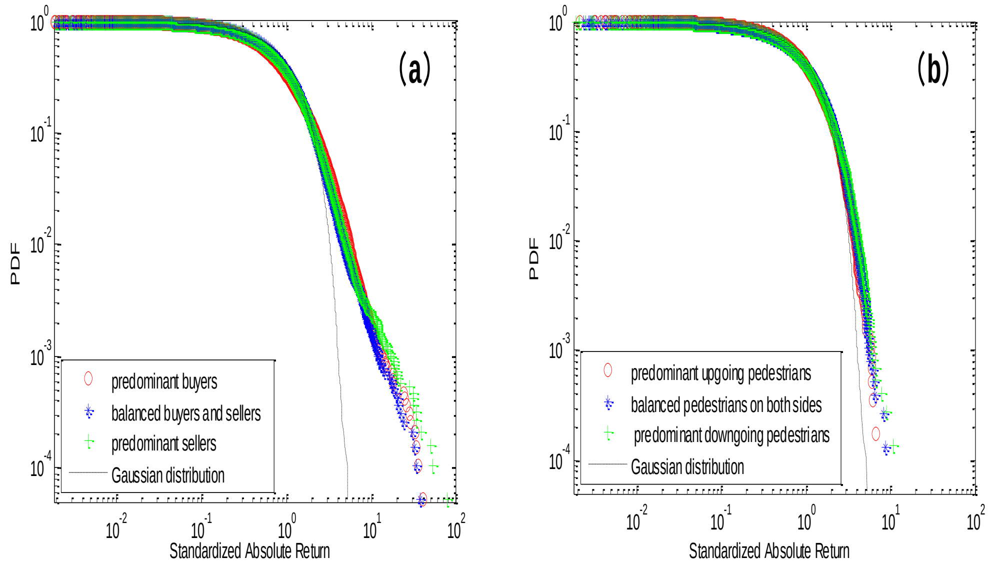


Fig.7. Distributions of complementary probability in (a) financial price dynamics and (b) pedestrian counterflows under different human factors.

Levy Distribution

The Levy's stable distribution is utilized to fit the yield distribution and analyze the probability distribution function of $R_k(t)$. The results are shown as follows (Fig 8). In Fig 8(a), the slope (-$1/\alpha$) of the fitted straight line for the corresponding predominant buyer, balanced trader and predominant seller are respectively -0.6189, -0.5733 and -0.5681. In Fig 8(b), the slope (-$1/\alpha$) of the fitted straight line for the corresponding predominant upgoing pedestrians, the balanced pedestrians on both sides and the predominant downgoing pedestrians are respectively -0.7951, -0.7329 and -0.7157. It shows that the trends of two systems are consistent, and it tends to be Gaussian distribution (α =2) when they are the predominant seller and the predominant downgoing pedestrians.

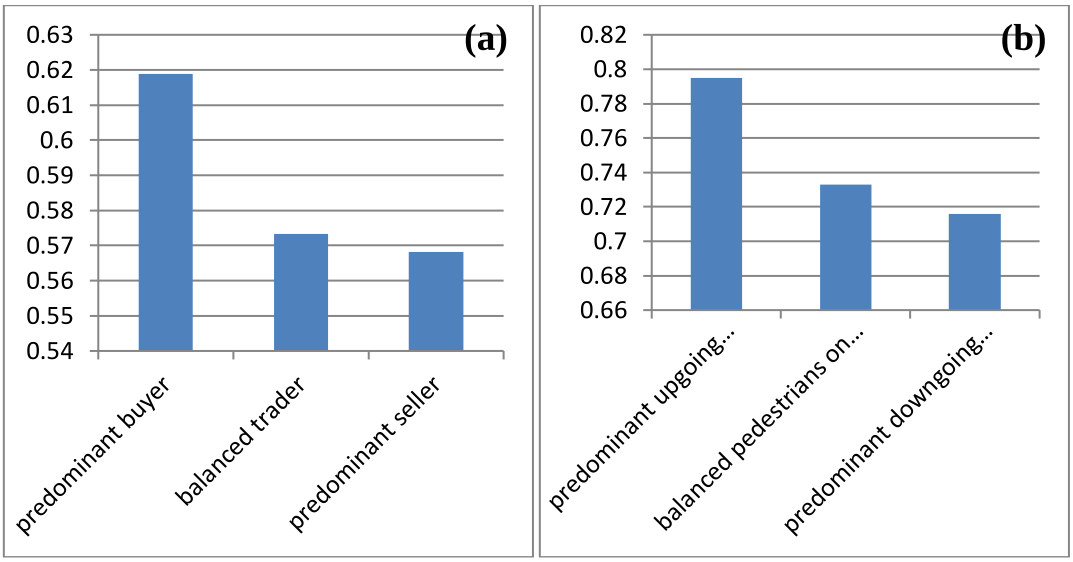


Fig. 8. Log-log plot of the probability $P(R=0)$ versus *k* in (a) financial price dynamics and (b) pedestrian counterflows under different human factors.

Autocorrelation Function

Fig 9 shows the autocorrelation between the volatility and yield rate of two systems. It is found that the autocorrelation of volatility is higher than the autocorrelation of the yield rate. That is, the yield rate

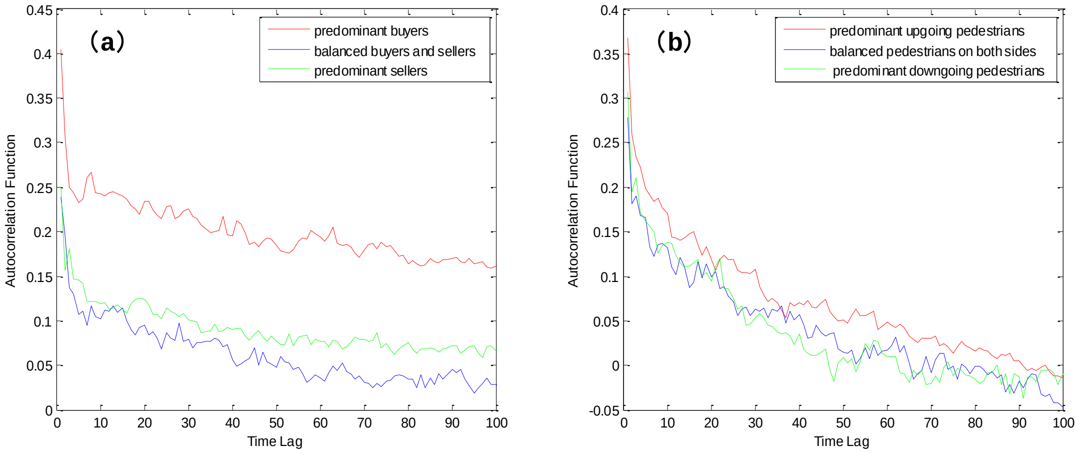
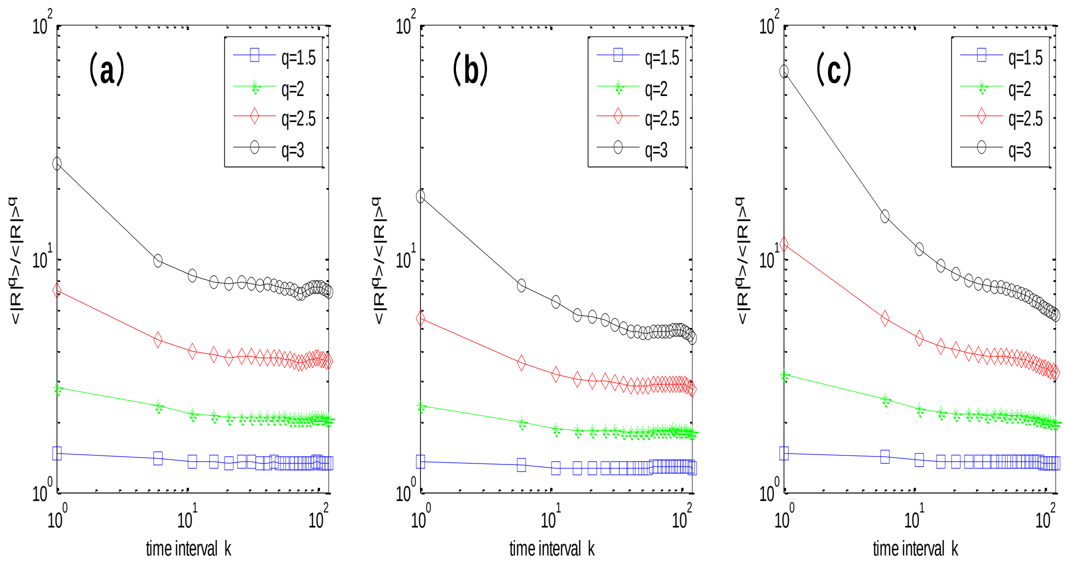


Fig.9. Autocorrelation functions of volatility in (a) financial price dynamics and (b) pedestrian counterflows under different human factors.

of stock price possesses no long-term memory, while the volatility possesses strong memory. In Fig 9(a), the autocorrelation is the strongest for the dominate seller, while the autocorrelation is the strongest for dominate downgoing pedestrians in Fig 9(b). However, due to the limitation of the simulation system, the particles in the pedestrian system don't possess emotion induction, and there is no complicated decision feature, it is equivalent to iron out the divergent characteristics caused by noise factors. Therefore, the volatility autocorrelation decays faster than the financial market, and it cannot show the periodicity of the autocorrelation for the financial system.

Multi-fractal

Fig 10 shows that the yield rates of time interval k between unbalanced pedestrians and unbalanced buyers and sellers are non-linear, and it indicates that they all possess multi-fractal characteristics. Besides, when q is larger, the variation of yield rate is more obvious. When q=3, in Fig 10(a), the maximum slope curve is -0.4291 for the predominant seller, the medium slope curve is -0.2536 for the balanced traders, and the minimum slope curve is -0.2168 for the predominant buyer. In Fig 10 (b), the maximum slope curve is -0.1049 for dominate downgoing pedestrians, the medium slope curve is -0.0719 for dominate downgoing pedestrians, and the minimum slope curve is -0.0624 for the balanced pedestrians on both sides. The multi-fractal performances in two systems are consistent, and the slope curve of yield rate is the largest for the predominant seller and the predominant downgoing pedestrians.



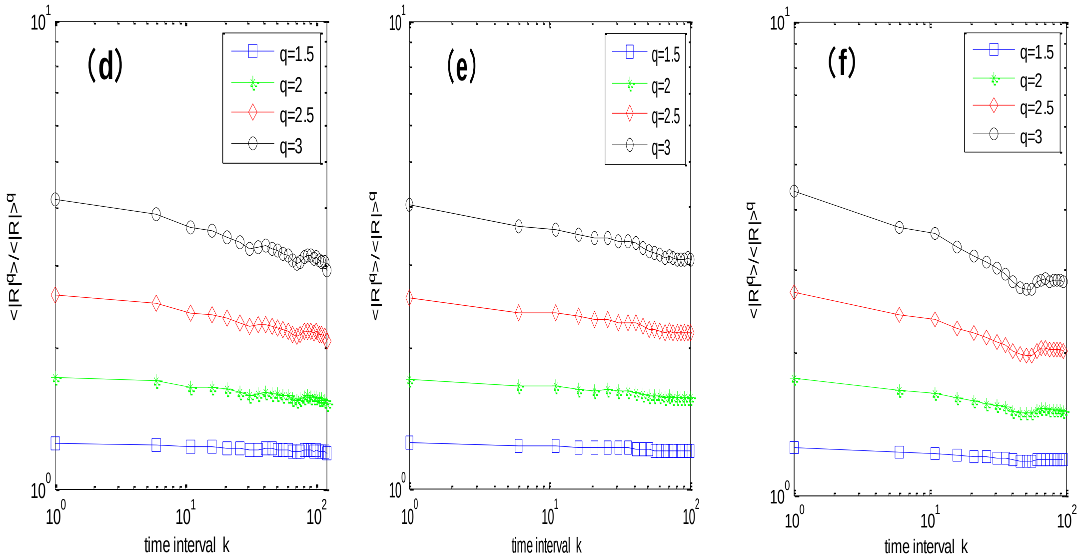


Fig. 10.Multifractalcurves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$: The financial price dynamics in (a) predominant buyers, (b) balanced buyers and sellers, and (c) predominant sellers, and the pedestrian counterflows in (d) predominant upgoing pedestrians, (e) balanced pedestrians on both sides, and (f) predominant downgoing pedestrians.

Trading Volume and Flow Rate

Thick-tailed Distribution

Fig 11 shows that both sets of distributions exhibit significant thick-tailed characteristics, and Fig 11(a) shows that the tailed distribution of the large trading volume deviates farthest from the standardized normal distribution curve compared to the medium and small trading volumes, that is, the tailed characteristics are more obvious, the extreme risk is even greater. In Fig 11(b), the large flow rate also deviate farthest from the standardized normal distribution curve. It can be seen that the distribution function of yield rate between varied trading volumes and flow rates presents the thick-tailed characteristics, and the trend of influence on the thick-tailed distribution is consistent.

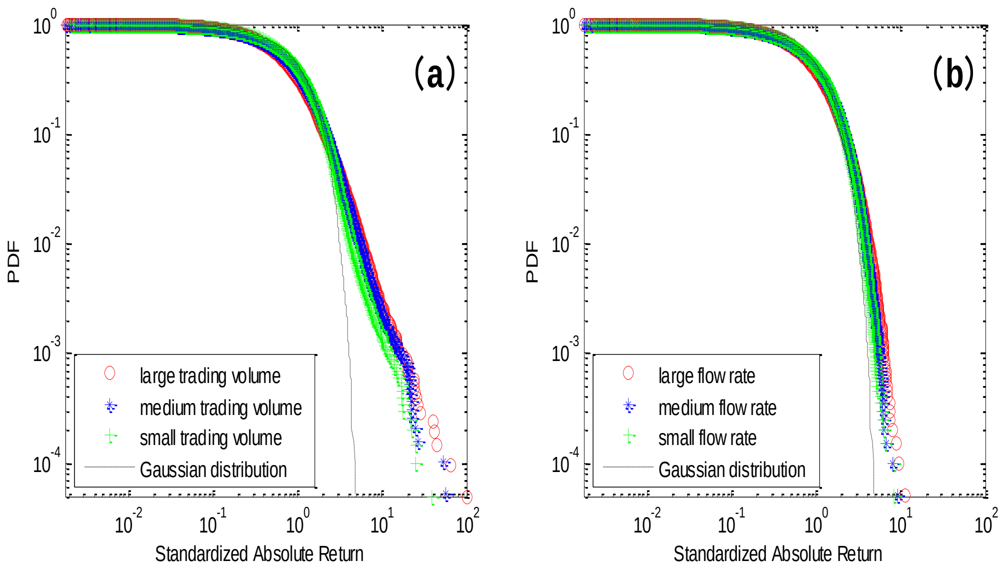


Fig.11. Distributions of complementary probability in (a) financial price dynamics and (b) pedestrian counterflows under different index factors.

Levy Distribution

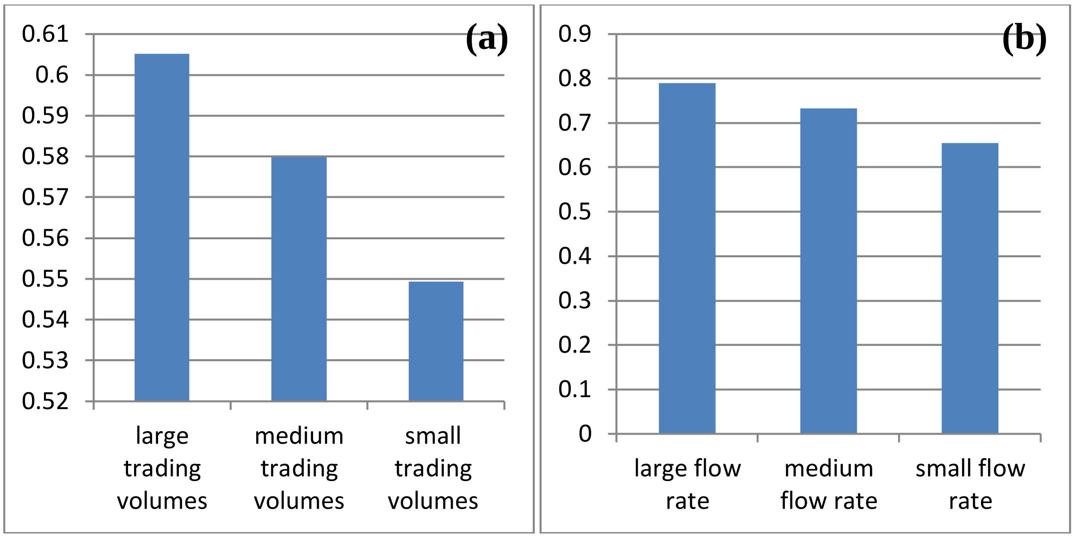


Fig. 12.log-log plot of the probability $P(R=0)$ versus k in (a) financial price dynamics and (b) pedestrian counterflows under different human factors.

The Levy's stable distribution is utilized to fit the yield distribution and analyze the probability distribution function of $R_k(t)$. The results are shown as above (Fig. 12). In Fig 12(a), the slope (-$1/\alpha$) of the fitted straight line for the corresponding large, medium and small trading volumes are respectively -0.6051, -0.5799 and -0.5494, and the slope (-$1/\alpha$) of the fitted straight line in Fig 12(b) for the corresponding large, medium and small flow rate are respectively -0.7893, -0.7329 and -0.6551. It can be seen that the trends of two systems are consistent, and it tends to be Gaussian distribution (α =2) in small trading volumes and small flow rate.

Autocorrelation function

Fig 13 shows the autocorrelation between the volatility and yield rate of two systems. It is found that the autocorrelation of volatility is higher than the autocorrelation of the yield rate. That is, the yield rate of stock price possesses no long-term memory, while the volatility possesses strong memory. The autocorrelation is the strongest for the large trading volume in Fig 13(a), while the autocorrelation is the strongest for large flow rate in Fig 13(b). However, due to the limitation of the simulation system, the particles in the pedestrian system don't possess emotion induction, and there is no complicated decision feature, it is equivalent to iron out the divergent characteristics caused by noise factors. Therefore, the volatility autocorrelation decays faster than the financial market, and it cannot show the periodicity of the autocorrelation for the financial system.

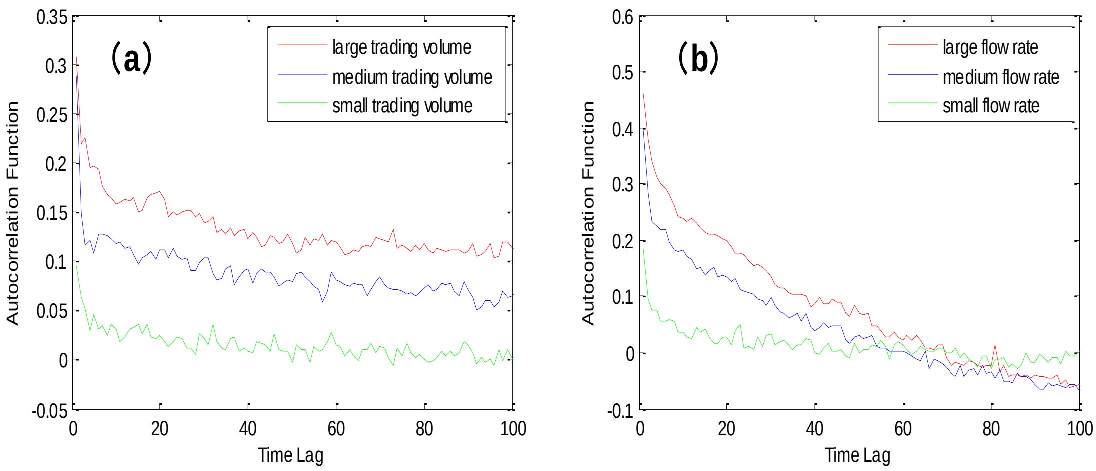


Fig.13. Autocorrelation functions of volatility in (a) financial price dynamics and (b) pedestrian counterflows under different index factors.

Multi-fractal

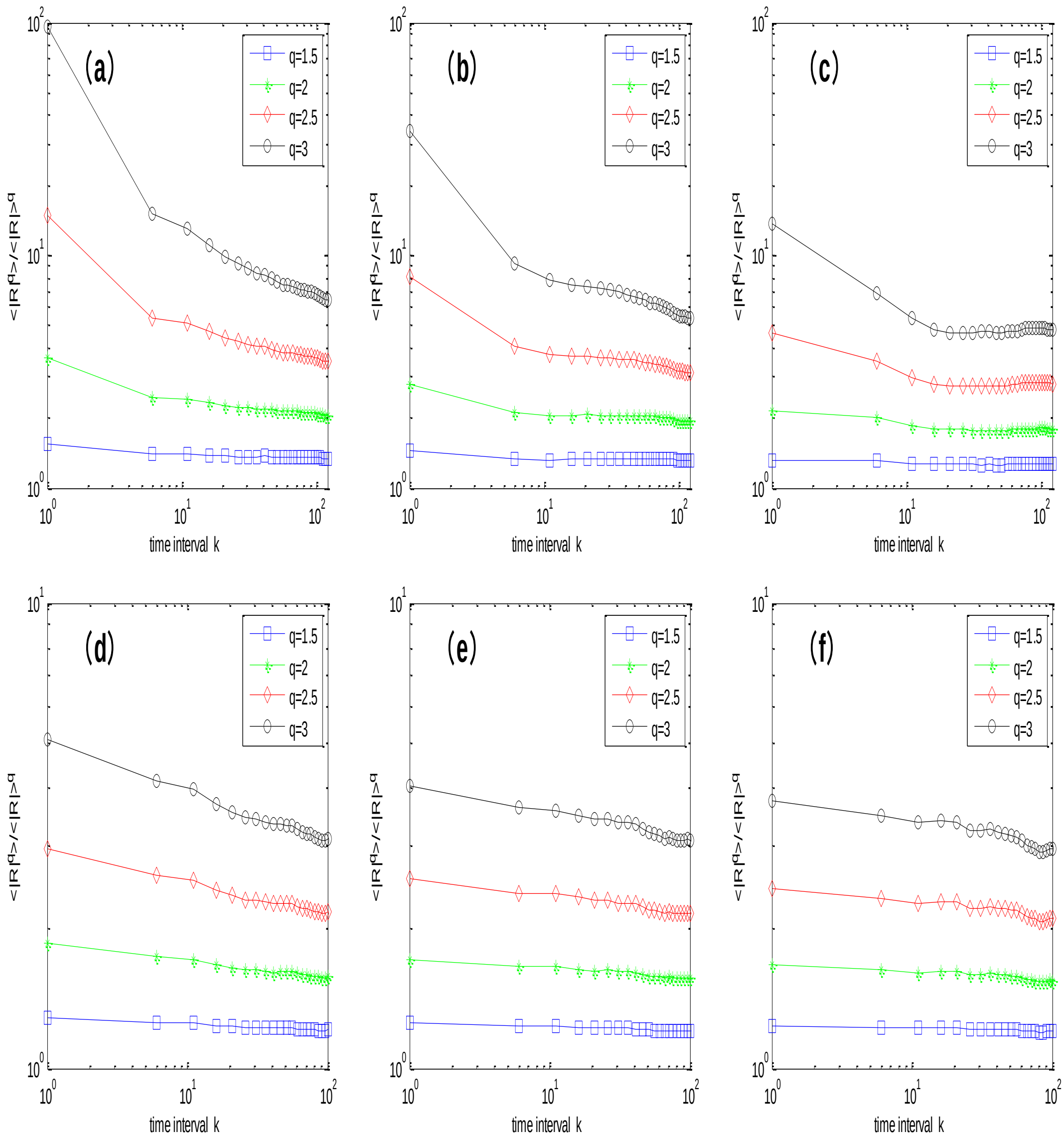


Fig. 14.Multifractalcurves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$: The financial price dynamics in (a) large trading volume, (b) medium trading volume, and (c) small trading volume, and the pedestrian counterflows in (d) large flow rate, (e) medium flow rate, and (f) small flow rate.

Fig 14 shows that the yield rates of time interval k between varied trading volumes and flow rates are non-linear, and it indicates that they all possess multi-fractal characteristics. Besides, when q is larger, the variation of yield rate is more obvious. When q=3, in Fig 14(a), the maximum slope curve is -0.4903 for large trading volume, the medium slope curve is -0.3156 for medium trading volume, and the minimum slope curve is -0.1854 for small trading volume. In Fig 14 (b), the maximum slope curve is -0.1073 for large flow rate, the medium slope curve is -0.0624 for medium flow rate, and the minimum slope curve is -0.0576 for small flow rate. The multi-fractal performances in two systems are consistent, and the slope curve of yield rate is the largest for large trading volume and large flow rate.

Conclusion and Discussion

Through the above research, this study finds that the pedestrian counterflows and the financial dynamics system not only possess similarity between the dynamic characteristics of the pedestrian density around the door and the price logarithmic dynamics in the financial system, but also finds that there are more strong correlations of parameter indicators between two systems. There is a strong similarity between the financial price dynamics and the pedestrian counterflows under varied environmental factors, human factors and indicator factors.

The research results show that monetary policy and door width possess the same impact trend on the micro-characteristics of probability distribution, autocorrelation and multi-fractal in financial price dynamics and pedestrian counterflows. This means that the loose, prudent and austerity monetary policies respectively correspond to wide, moderate and narrow doors. In addition, unbalanced buyers and sellers as well as unbalanced pedestrians also show similar impact trends in the micro-characteristics of probability distribution, autocorrelation and multi-fractal properties. Therefore, the predominant buyers, balanced traders and predominant sellers respectively correspond to the predominant upgoing pedestrians, balanced pedestrians on both sides and predominant downgoing pedestrians. Finally, the trading volume and flow rates also show a similar impact trends on the micro-features of probability distribution, autocorrelation and multi-fractal. This means that the large, medium and small trading volume in the financial price dynamics corresponds exactly to the large, medium and small flows in pedestrian counterflows. Therefore, there are strong similarities between financial price dynamics and pedestrian counterflows under varied environmental, human and index factors. This suggests that there is a deeper and unified behavioral mechanism in self-driven systems of two competing groups with opposite interests. This is conducive to better understanding of the trader’s behaviors in the financial market as well as the internal structure and operating mechanism of the market through the microscopic design of the pedestrian model.

The agent with two groups of reverse driving forces is a significant prerequisite for the similarity of the two systems, and provides constraints for the free flow of the system due to bottlenecks. However, because of limitations of simulation conditions, scenarios, etc., the pedestrian colunterflow cannot accurately describe the complex financial system. The financial system is a complex system with multiple decisions and influences, and is especially composed of real actors. However, the particles in the pedestrian system don’t possess emotional induction, and there are no complicated decision features such as investor emotions, investor information, investment expectations, information feedback and risk attitudes and other human factors. They are equivalent to iron out the divergent characteristics caused by the noise factors. Therefore, in the thick-tailed characteristics, the pedestrian counterflows show a convergence to the Gaussian distribution compared to the tailed distribution of the financial system. In the correlation analysis, the pedestrian counterflows can show correlation, but it cannot show the autocorrelation periodicity of the financial system. Therefore, the follow-up studies can add behavior decision-making capabilities to agents so as to more accurately portray the complex financial system.

Finally, by statistically comparing the pedestrian counterflows with the financial time series, it is shown that studying the pedestrian counterflows under constraints does contribute to a better understanding of the underlying mechanism behind the typical facts of the financial market and provides new methods and new ideas for the analysis of financial market dynamics.

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