Macroeconomic Correlations of Market Disposition Effects Amidst the COVID-19 Pandemic

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Abstract. The disposition effect is defined as the tendency for investors to hold on to losing stocks and dispose of winning stocks. Existing literature mainly focuses at micro-level of agent's perspective. When extremely macroeconomic shock like Covid 19 occurs, the channels through which aggregated individual bias transmit to and affect the markets and if there are heterogeneous effects of such channels across sectors, have not been adequately explored. The authors propose following two main hypothesis of this paper: the pandemic shock will induce a structural increase in general market irrationality (H1) and that such an effect is heterogeneous across industries and larger for the most exposed ones (H2). The authors used the industry panel data of January 2019 to December 2021 to classify Shenwan Level 1 industries into two groups based on their sensitivities to pandemic shocks. The present study also applied the entropy method in constructing an aggregate index, while using descriptive analysis of group trends and correlations. The evidence suggests that the shock caused by the pandemic has exacerbated market irrational behavior, with strong evidence of industrial heterogeneity. High-exposure sectors saw their initial behavioral patterns shift from the disposition effect to panic selling. The results of the entropy-weighted method indicate that the key drivers of irrational behavior are market volatility and turnover rate, while classical disposition effects measures lose their explanatory power in the presence of large shocks. This study provides new evidence and an analytical framework for understanding how macroeconomic shocks influence market collective behavior.

Keywords: Disposition Effect, COVID-19 Pandemic, Industry Heterogeneity, Entropy Method, Macroeconomic Shocks

1. Introduction

In behavioral finance, the disposition effect—a psychological bias whereby investors habitually hold onto loss-making stocks for too long while selling profitable stocks too quickly—constitutes one of the core forces driving irrational market behavior. This phenomenon was first identified and named by Shefrin and Statman in 1985 [1]. In 1998, Odean empirically demonstrated through multi-year personal account data from 10, 000 individual investors that investors systematically exhibit the behavior of

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selling winning positions while holding on to losing ones [2]. Prospect theory has been employed to explain this effect, and this study will likewise adopt Kahneman and Tversky's prospect theory as its theoretical foundation, specifically its mechanisms of risk preference and reference point dependence in financial decision-making [3].

Major emergencies, such as public health crises, distort investors' investment decisions through multiple channels, including heightened perceptions of health risks and increased anxiety about future income [4]. The COVID-19 pandemic, which emerged in late 2019, dealt a severe blow to contact-intensive industries such as tourism and aviation. This constituted not only a global public health crisis but also provided an exceptionally rare quasi-natural experimental setting for observing how macroeconomic conditions systematically reshape financial market behavior.

Consequently, this paper aims to examine the impact of an extreme exogenous macroeconomic shock, such as the COVID-19 pandemic, on disposition effects at the stock market level, and, in particular, to investigate how these effects are transmitted heterogeneously across sectors. The present study focuses on exploring changes in investors' psychological expectations as well as sector-specific transmission channels for fundamentals.

While the work of Kaustia provides an approach to analyse the effect of disposals in a market level, existing studies also have important drawbacks to deal with such a type of macroeconomic shocks [5].

First, the majority of existing research assumes a priori homogeneous impacts (without taking into account the possible differences between sectors) [6]. In fact, the effects of the epidemic are uneven; national development and reform commission documents on response measures identify industries that were particularly hard hit during the crisis [7]. Further, scholars like Liu Shijin classified them depending upon how the shock reached to that industry – whether directly or indirectly, indirect impact, and low impact [8]. Second, there are limitations in the methodologies employed in previous studies. The existing studies are either limited at the individual account-level, or use a single indicator [2], whereas empirical work that directly links the entropy method – a useful tool to analyse market uncertainty and complexity [6, 9, 10] — to disposal effects are still rare[5]. Furthermore, although studies in the Chinese market have found that the disposal effect is negatively correlated with investors' sentiment, that it did not yet make clear what is the exact nature of the co-movement between macroeconomic stress and market irrationality during this particular shock (COVID-19) [11].

To overcome these limitations, this paper makes the following contributions: First, the present study extends the framework to account for industry heterogeneity, thereby overcoming the analytic bias towards viewing markets as aggregates and thus facilitates a better understanding of how shocks propagate in ways that lead to heterogeneity by conditioning on firm-sector traits.The assessment on the sectoral heterogeneity helps to design a more differentiated policy response. The supervisors could respond with more tailored and flexible policies regarding provision of liquidity and monitoring of unusual transactions depending on the particular risk facing heavily impacted core industry, thereby avoiding rigid and simplistic regulation and

enhancing policy efficiency. Second, methodologically the authors have introduced an original procedure that relies on building up a general index from the entropy values which makes it possible to grasp comprehensively and objectively the global functioning as well as the correlated oscillations of the markets behavior than any one indicator.

2. Research Design

2.1. Data Sources and Sample Processing

The primary data sources for this paper are the Wind database and the National Bureau of Statistics, the sample time range is January 2019-December 2021, including the pre-pandemic market environment, market volatility in early pandemic, and the second stage of regular epidemic prevention and control. This provides a rich dataset to empirically examine the effect on different phases of the pandemic on trading behavior in markets. The present study obtained monthly returns, turnover rate, total market capitalisation and CSI 300 Index volatility of Shenwan Level 1 sector in addition to the macro-economic variables including 10 years' government bonds yield and year-over-year M2 growth rate. Inspired by Kaustia's macro-level measure, this paper constructed a market-level proxy variable for the disposition effect (product of last-month industry return and this-month industry turnover rate), and the authors also computed the other study's variable like the momentum indicator and liquidity indicators which are shown in Table 1 [5].

Table 1. Research variable design

Financial terminology	Interpretation
return	Monthly return
turnover	Monthly turnover rate
gov yield	Government bond yield
China:M2:YoY	Year-on-year growth rate of China's M2 money supply
lagret_turnover	Lagged variable using the previous month's sector return
turnover_new	Previous month's return × Current month's turnover rate
CSI 300 Volatility	-
momentum	Momentum indicator calculated from cumulative historical returns
liquidity	Liquidity indicator derived from turnover rate and lagged return components

To find out which industries are affected differently from the pandemic, the authors grouped the 31 Shenwan Level 1 sectors into two categories according to some key aspects like the degree of physical contact, exposures of people, materials, and information; and the responsiveness of suppliers to these exposures (based on policy and literature into seven clusters including: highly exposed sectors (10 sectors, e.g., social services, transport, trade and retail) and low-exposure sectors (21 sectors, e.g. power equipment, drugs and bio-tech, computer) [7, 8]. The authors defined a dummy variable for the post-outbreak period (post), with a cutoff date of February 2020.

February 2020 was selected as the cutoff point because it marks the comprehensive implementation of nationwide epidemic prevention and control measures and the point at which the market systematically priced in the impact of the pandemic. This gives us an unambiguous and commonly agreed upon starting point from which to identify the effect of exogenous policy shocks.
The corresponding industry classification by pandemic exposure is presented in Table 2.

Table 2. Shenwan Level-1 industry classification by pandemic exposure

High Exposure Sectors	Media, Real Estate, Textiles & Apparel, Transportation, Beauty & Personal Care, Automotive, Light Industrial Manufacturing, Commerce & Retail, Social Services, Petroleum & Petrochemicals
Low Exposure Sectors	Power Equipment, Electronics, Steel, Utilities, Defence & Aerospace, Environmental Protection, Machinery & Equipment, Basic Chemicals, Computers, Home Appliances, Building Materials, Construction & Decoration, Coal, Agriculture, Forestry, Animal Husbandry & Fisheries, Telecommunications, Pharmaceuticals & Biotechnology, Banking, Non-Bank Financials, Non-Ferrous Metals, Diversified

2.2. Theoretical Analysis and Research Hypotheses

According to prospect theory, investors tend to be more risk preferring in face of a loss (i.e.'loss aversion') by holding onto bad performing assets, in order to prevent the realization of these losses, resulting in the disposal effect 'sell winner and keep loser' [1, 3]. However, this behavior develops in the context of rather stable expectation regime. The market information environment deteriorates when faced with extreme exogenous macroeconomic shocks such as the COVID-19 pandemic; consequently, future cash flows become highly ambiguous, and the investor's perception of ambiguity is systematically increased. At this point, the conventional reference-point based utility maximization could potentially give way to an evolutionary "self-preservation instinct of danger-avoidance" behavior, i.e., preference for avoiding additional costs rather than delaying recovery from sunk costs.

The effect of the pandemic is asymmetric across sectors, since the most affected ones are those which require more face-to-face activity (e.g., hospitality, transport) are hit immediately by a loss of income and cash flows as they are locked down. Fundamentals decline rapidly, while panic sentiment propagates violently among individuals through social networks and trading channels. When the information is asymmetric inevitably as it occurs in practice, the investor abandons self-analysis and follows the crowd to sell stocks, thus causing strong herding behavior. This process of emotional contagion creates an adverse feedback loop, dramatically increasing selling pressure in the market. The trend of behavior continues, changing from "holding loss" into "cutting loss". On the other hand, industries of low exposure (e.g., power equipment; pharmaceuticals/biotechnology), have relatively high levels of earnings

stability and experience somewhat less extreme changes in investors' moods, continue to display mostly conventional disposition effects.

Furthermore, macroeconomic shocks do not affect the individual psyche alone and are accompanied by an intensification of irrational behavior via market sentiment resonance. Volatility increases with heightened uncertainty, while abnormal surges in turnover rates indicate excessive trading; both constitute essential features of irrational trading during crises. The conventional disposal effect indices could fail to work when people are extremely panicky since the premise that "people would sell later" is dominated by "people would concentrate on selling".

Based on this reasoning, the following hypotheses are proposed:

H1: The pandemic shock generated a structural increase in overall market irrationality, reflected in a sharp rise in composite index values during the early stage of the outbreak.

H2: Such an effect is heterogeneous across sectors, with higher exposure to the shock being associated with a stronger departure from normal behavior and clearer signs of co-movement between economic conditions and firms' responses.

2.3. Research Methods

Construction of the Entropy Value Method Composite Index. In this paper, authors employ the entropy method to construct a composite market irrationality index, addressing the limitations of relying on a single indicator, and reflects the synergistic fluctuation of multiple dimensions of market behavior in an objective manner [5, 9, 10]: turnover rate is a dimensional indicator of market trading intensity and can characterize over-trading behavior; turnover_new is used to replace the disposal effect, represents the investor behavioral bias factor; where, momentum is used to capture trend in prices as well as 'chasing rallies and selling on dips', CSI 300 volatility captures general perception about uncertainty and fear prevailing in the market. The specific steps are as follows:

Firstly, to take into consideration variations between sizes of different measures, this paper normalises the four basic features (MMS_turnover, MMS_turnover_new, MMS_mom- entum). The data (MMS_CSI 300 Volatility) were firstly standardized in order to avoid dimension influence. The present study applies forward standardization using the following equation:

$$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

x_{ij}denotes the raw value of the jth indicator at the ith time point, with i = 1, 2, ⋯, T indexing the time dimension (e.g., trading days) and j = 1, 2, ⋯, N indexing the different indicators (i.e., turnover rate, turnover_new, momentum, and CSI 300 volatility); $max(x_j)$, $min(x_j)$represent the maximum and minimum values of the jth indicator respectively. Following standardisation, all indicators assume values within the range [0, 1], wherein higher numerical values indicate stronger irrational characteristics within the corresponding dimension.

Secondly, based on the standardised indicator data, the authors calculate the proportion of the jth indicator at the ith time point:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{2}$$

Here, n represents the time sample size (36 months from January 2019 to December 2021), and p_{ij} indicates the proportion of the j-th indicator at time i.

Thirdly, the study get the calculation of Information Entropy and Information Utility Value:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{3}$$

If $p_{ij}=0$, define$p_{ij} \ln(p_{ij})=0$. The value range of information entropye_j is [0, 1], The smaller the value of e_j, the higher the dispersion of the indicator data, and the richer the distinguishing information it carries. On this basis, the information utility value $d_j=1-e_j$ is calculated. The greater the value of d_j, the higher the contribution of the indicator to the overall evaluation.

Fourthly, this paper calculate the objective weights for each indicator based on the information utility value:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{4}$$

Here, m denotes the number of indicators (m = 4). The final composite market irrationality index comprehensively reflects the coordinated fluctuations across these four dimensions, with higher values indicating greater overall market irrationality.

The resulting weighting structure of the composite index is illustrated in Figure 1.

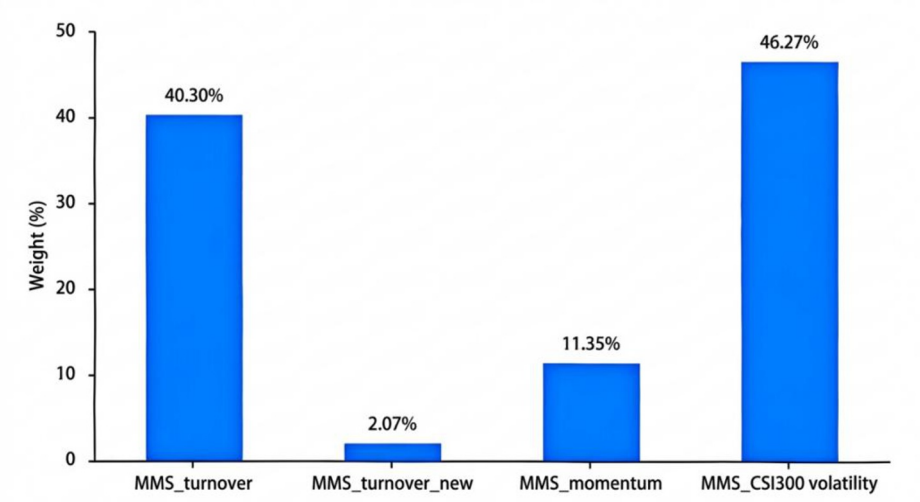


Fig. 1. Weighted chart of the market irrationality composite index (Picture credit: Original).

Auxiliary Analytical Methods. In addition to the entropy approach, the authors employ other analytical methods:

Group trend comparison: Draw trend lines on the proxy variable of disposal effects

in the high- and low-exposure industries through time, visually capturing the pre- and post-pandemic behavioral differences.

Correlation test：Perform the Pearson correlation test for key variables (proxy variable of disposal effect) and other variables (M2 growth rate, e.g., interest rates on U.S. Treasury securities, stock prices, and stock market volatilities) for possible relationships between the different series.

2.4. Fundamental Principles

Entropy-based Weighting Logic. The entropy method is an objective weighting approach that accounts for the dispersion of the data. Entropy increment law, which is one of the basic laws in information theory, is the main basis for this study and analysis here. Therefore, the present study can reduce the subjectivity error brought by the previous subjective weighting through entropy method. In global assessments, the higher the dispersion of an indicator is, the more it contributes to information content: when an indicator takes exactly the same value at each period (dispersion equal to zero), its information entropy e_j=1, information utility value d_j=0, and weight w_j=0, indicating the indicator possesses no discriminatory value. Conversely, when an indicator exhibits significant variation in its values, its dispersion is high. The information entropy e_j approaches 0, the information utility value d_j approaches 1, and the assigned weight increases accordingly.

The research applies the approach based on entropy values whose main idea is that the phenomenon of market irrationality can be presented in terms of the synergetic manifestation of multidimensional parameters such as: disposal effects, momentum bias, uncertainty aversion. This cannot be achieved by a single index and the entropy value approach can effectively consider various aspects of information from different dimensions with weight combination: where weights are proportional to the actual information content of the indicators themselves, in contrast to a dimension reduction technique like principal component analysis (PCA): the method based on entropy retains the economic meaning of all indicators. The resulting weights naturally describe the individual contributions of each dimension to irrational behavior and are therefore better suited for follow-up mechanistic investigations [12].

The Mechanism of Macroeconomic Shocks and Industry Heterogeneity. Industries heavily impacted by COVID-19 exhibit high operational exposure and liquidity risk. The pandemic caused temporary shutdowns of production processes, sharply depressing corporate profit expectations, which in turn were passed along to the investor community by falling share prices, fueling greater risk aversion. The investors' decision-making logic moved away from the classic disposal effect (sell winners, keep losers) toward extreme behavior characterized by panic selling to avoid further losses. This led to skyrocketing turnover rates and falling yields, then driving the indices down very quickly. Later in the pandemic, strong counter cyclical policies (e.g., fiscal support and monetary accommodation) helped to alleviate temporary liquidity constraints faced by firms. These policies, which together with some clear signs of support partly stabilised market expectations. The joint impact of such

policies and the re-establishment of market expectations progressively limited irrational behavior, although volatility remains high because of the sluggishness in restoring fundamentals for industry.

On the other hand, sectors that had minimal contact with the pandemic were able to maintain performance. They have high proportions of goods considered "essential, " so government policies typically did not affect them significantly; as a result, investors' expectations for revenue generation by these firms were not affected: with little turmoil around risk appetite. Traditional disposal effects and momentum trading remained the dominant factors behind trading behavior in those areas. The irrationality index showed much less fluctuation compared to the high exposure industries while it was correlated with macroeconomic factors more stably.

The Correlation Principle between Composite Indices and behavioral Biases. The four constituent indicators of the Irrationality Composite Index directly correspond to core behavioral finance biases, with the weight allocation reflecting the relative importance of different behavioral biases during extreme shocks:

CSI 300 Volatility (46.27% weighting): Corresponding to the ‘uncertainty aversion bias’, the sharp rise in market volatility during the pandemic shock directly amplified investors' emotional fluctuations, making decision-making more susceptible to intuition and panic-driven impulses, which is a core driver of irrational behavior.

Turnover Rate (40.30% weighting): Corresponding to the ‘over-trading bias’, the pandemic-induced information asymmetry and divergent expectations prompted investors to frequently adjust their holdings, creating an irrational cycle of ‘trading more during volatility’ that further exacerbated market fluctuations.

Momentum (11.35%): Momentum represents ‘Momentum Trading Bias’. After the COVID-19 outbreak, the initial shock in equity prices was followed by a rebound which further consolidated ‘buy high sell low’ trader’s bias. But, its low weight implies that the effect of this bias is less important compared to the impact of uncertainty aversion or over-trading in extreme shocks.

Turnover_new (weighting 2.07%): Corresponding to the ‘disposition effect bias’, panic selling triggered by the pandemic temporarily suppressed the traditional tendency to ‘sell winners and hold losers’. This resulted in subdued fluctuations for this indicator during the sample period, limiting its informational contribution. This outcome precisely corroborates the distorting effect of extreme shocks on conventional behavioral biases.

In addition, the associative logic between the composite index and the macro variables is consistent with the transmission chain: ‘macro environment – risk appetite – behavioral bias’. Increase of M2 year-on-year growth indicates relaxing monetary policy; market liquidity lowers investor’s trading cost and indirectly supports the over-trading bias (significantly positive). Higher government bond yields imply higher market risk premiums and more trading by investors seeking a return on their money (positive correlation is large); while higher CSI 300 volatility has a direct effect on inducing uncertainty aversion and reducing over-trading (large negative coefficient), their combined which are exactly the three components of a large-scale regulatory system on irrational behavior in markets.

3. Analysis of Empirical Results

3.1 The Grouping Trend Characteristics of the Proxy Variables for the Disposal Effect

From the overall industry trend chart, it is evident that before the pandemic outbreak (prior to December 2019), the average trends of turnover_new for high-exposure industries (treat=1.00) and low-exposure industries (treat=0.00) closely aligned, with no systematic differences observed. (See Figure 2) This characteristic offers intuitive support for the parallel trend assumption in the subsequent analysis and also confirms the appropriateness of the industry grouping.

After the outbreak of the COVID-19 pandemic in February 2020, the turnover_new of the two groups of industries showed a distinct differentiation: the industries with low exposure to the pandemic (control group) only experienced a slight decline, and the overall fluctuation was relatively mild. However, industries with high exposure (treatment group) experienced a sharp decline, with the value dropping to around -8.5, becoming the lowest within the sample period. This phenomenon indicates that the behavior of investors in highly exposed industries under extreme shocks has undergone a structural transformation. The traditional disposal effect of "selling profits and holding losses" has been replaced by panic selling. These industries have been directly hit by the epidemic, causing a sharp deterioration in profit expectations. To avoid further losses, investors have chosen to sell assets in a concentrated manner, resulting in the combination of surging turnover and sharply declining returns. This ultimately leads to a significant negative deviation of turnover_new.

After March 2020, the turnover_new of industries with high exposure to the epidemic began to gradually rebound. This process may be closely related to the rapid introduction of strong monetary easing and fiscal stimulus policies both globally and domestically during the same period. The abundant liquidity injection and targeted relief measures partially alleviated the extreme panic in the market and stabilized the fundamental expectations. And in some periods, it showed a fluctuation range higher than that of the control group. From June to August 2020, the turnover_new trends of the two groups of industries once again approached each other, reflecting that the overall market sentiment gradually stabilized and the extreme shock effect at the beginning of the epidemic was somewhat alleviated. Throughout 2021, although there were still phased fluctuations in the dual lines, no sustained and systematic differentiation was formed, indicating that the impact of the epidemic on the industry's disposal effect was more of a short-term shock. With the normalization of the epidemic and the increase in policy support, the behavioral differences between industries gradually narrowed.

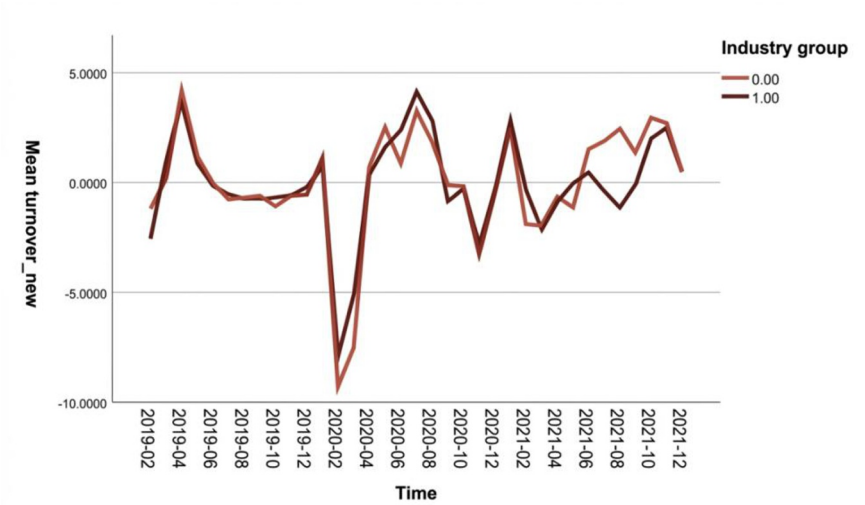


Fig. 2. The overall industry trend chart (Picture credit: Original)

3.2 Results of the Correlation Test of Core Variables

Table 3 reports the Pearson correlation coefficients and significance levels of turnover_new with macroeconomic variables, market variables, and the epidemic dummy variable (post). From the test results, the association characteristics of each variable and turnover_new are clear and have definite economic implications.

The year-on-year growth rate of M2 in China (China:M2: YoY) was significantly positively correlated with turnover_new ($r=0.012$, $p<0.001$). This indicates that under a loose monetary policy stance, market-wide liquidity is abundant. On the one hand, it may directly stimulate investors' trading willingness and ability by reducing financing costs and enhancing market optimism, leading to an increase in trading activity; On the other hand, abundant liquidity may weaken investors' preference for holding cash, prompting them to adjust their asset portfolios more actively.

The government bond yield (gov yield) was significantly positively correlated with turnover_new ($r=0.118$, $p<0.001$). In an environment of rising interest rates, adjustments to the market risk premium may trigger arbitrage activities or stop-loss operations, which could affect the link between turnover rates and returns.

The CSI 300 volatility was significantly negatively correlated with turnover_new ($r=-0.154$, $p<0.001$). This confirms the conservative risk-aversion characteristics of investors in a highly volatile environment - when market uncertainty intensifies, investors are more inclined to reduce trading frequency to avoid additional losses caused by sharp price fluctuations. This is consistent with the "uncertainty aversion" assumption in behavioral finance theory.

The correlation between the epidemic dummy variable (post) and turnover_new did not pass the significance test ($r=-0.002$, $p=0.946$). This result does not indicate that the epidemic has no impact on the disposal effect, but rather shows that the role of the epidemic is more reflected in the structural shock of specific periods and

specific industries. As shown in the overall industry trend chart, the core effect of the pandemic shock was concentrated in the short-term window of early 2020. From a long-term perspective, factors such as the pace of industry recovery and policy interventions counteracted the sustained global impact of the pandemic, which led to an insignificant correlation at the overall level.

Table 3. Correlation analysis chart

Variable Pair	Pearson Correlation	Significance (2-tailed)
turnover_new and China:M2: YoY	0.012	0.686
turnover_new and gov yield	.118**	<.001
turnover_new and CSI 300 Volatility	-.154**	<.001
turnover_new and post	-0.002	0.946
China:M2:YoY and gov yield	-.289**	<.001
China:M2:YoY and CSI 300 Volatility	.154**	<.001
China:M2:YoY and post	.525**	<.001
gov yield and CSI 300 Volatility	-0.006	0.853
gov yield and post	-.502**	<.001
CSI 300 Volatility and post	.201**	<.001

3.3 The Time Trend of the Market Irrational Composite Index

The time trend chart of the market irrationality index (IrrIndex) calculated by the entropy method (See Figure 3).

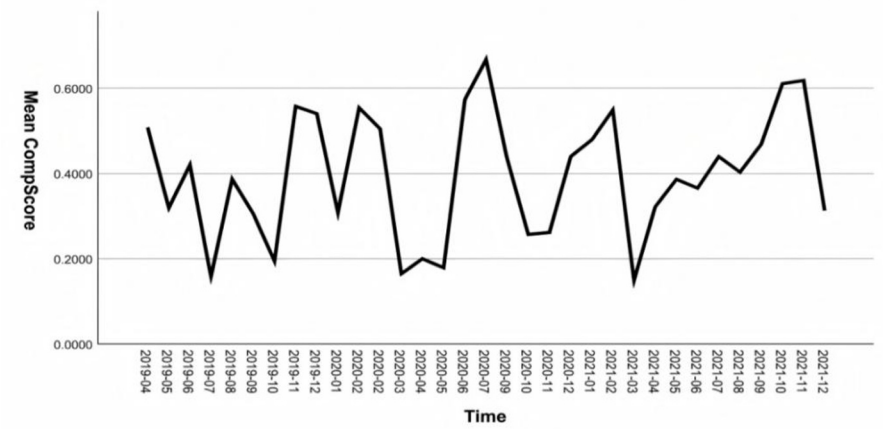


Fig. 3. Time trend chart of market irrationality index (Picture credit: Original).

As shown in the figure 3, from April 2019 to December 2021, the index as a whole presented a feature of sharp fluctuations. There was no clear long-term upward or downward trend, but a significant structural jump at the beginning of the outbreak of the pandemic: in January 2020, the index value was approximately 0.45, and in February 2020, it rapidly jumped above 0.55, reaching the peak of the sample period. In March 2020, the index remained at a high level with fluctuations. After April, it declined to approximately 0.3. Subsequently, it experienced phased surges in multiple periods from July to August 2020 and throughout 2021.

The short-term surge of the index closely corresponds with the overall industry trend chart and the results of the time-series correlation test, forming a logical correspondence. The sharp rise in the index in February 2020 was mainly driven by the increase of CSI 300 volatility (Accounting for nearly half of the weight), coupled with the abnormal turnover rate of highly exposed industries, which reflected the concentrated release of irrational behavior by investors under the impact of the epidemic. The subsequent decline and fluctuations of the index corresponded to policy intervention (such as monetary easing and industry subsidies), the restoration of market sentiment, and the behavioral adaptation process after the normalization of the epidemic. This confirms research hypothesis H1: a structural leap in overall irrational market behavior triggered by the pandemic shock. Meanwhile, considering the characteristics of industry groups, the fluctuation range of the irrational index in high-exposure industries is significantly greater than that in low-exposure industries, which further supports the research hypothesis H2: The impact of the epidemic on irrational behavior shows significant industry heterogeneity and the high-exposure industries have a stronger synergy with macro market fluctuations.

4. Discussion

This study demonstrates how irrational behavior has evolved in China's A-share market during the COVID-19 pandemic by utilizing industry heterogeneity and the entropy method. The present studies find that the epidemic did not affect all industries equally. Instead, differences in industry characteristics led to structural changes in investor behavior. High-exposure industries faced stronger pressure on corporate fundamentals and deteriorating market expectations in the early stages of the shock, because they had a high reliance on offline operations and cash flow sensitivity. As a result, investor behavior shifted significantly: instead of mainly showing the disposition effect, investors began to sell out of panic. The entropy method assigns weights objectively based on data variability, which provides clear economic interpretability. It automatically ranks the relative importance of each indicator according to its information content, directly showing how much different types of behavioral biases matter in the market during a crisis. The extremely high volatility weight points to "uncertainty aversion, " becoming the primary force driving irrational behavior; the high turnover rate weight corresponds to "excessive trading bias, " which may reflect the reaction patterns of different investor groups (such as institutions and retail investors) towards uncertainty aversion; the extremely low weight of the traditional disposal effect proxy variable precisely confirms that in an

extremely panicked environment, the classic tendency of "selling profits and holding losses" is temporarily suppressed and distorted [13].

This indicates that macro economic pressure mainly affects the market by amplifying uncertainty and facilitating excessive trading. The significant association between macro variables and behavioral indicators in the correlation analysis sketches out the transmission chain of "macro environmental changes → risk preference adjustment → specific behavioral deviations". Furthermore, network analysis based on entropy can indirectly capture conformity behavior by identifying key industries, which is similar to the idea of this study that focuses on industry heterogeneity.

The significance of this study lies in that, theoretically, through constructing a transmission chain of "macro shock - industry heterogeneity - behavioral deviation", it systematically expands the insights into the micro-psychology of investors in behavioral finance to the macro explanation of the overall irrational behavior of the market, which has deepened the understanding of the complex mechanism of "macro-behavior". In terms of method, this study innovatively integrates the theory of behavioral finance with the objective weighting of the entropy method, constructing an analytical framework that can quantify and rank the relative importance of different behavioral biases [6, 9, 10]. This provides a more stable and comprehensive analytical tool for studying market behavior in extreme events with high data noise [14]. On the practical level, the conclusions of this study provide direct inspiration for precise regulation during crisis periods. Regulators should implement more structural interventions, such as providing targeted liquidity support and differentiated policies for highly exposed industries (e.g., social services, transportation), in order to quickly break their unique "fundamental-sentiment" spiral. Expectation management should be placed at the core, utilizing timely and transparent release of industry information to mitigate the excessive volatility triggered by "uncertainty aversion" [14]. Furthermore, a real-time monitoring system based on behavioral indicators (such as volatility and turnover rate) can be established to proactively identify and mitigate the accumulation and spread of irrational behavior.

However, this study also has some limitations. First, the research strategy shifted from the pre-designed causal inference approach (Difference-in-Differences, DID) to correlation exploration, which, although more in line with the data characteristics, failed to provide strict causal identification. Secondly, although the industry dichotomy is reasonable, it may still simplify the complex transmission relationships among industries. Future research can adopt continuous variables to construct more refined exposure measurement standards.

In addition, the sample period is relatively short, which may not fully capture the long-term dynamic effects of the shock. Future research can incorporate more detailed industry data, high-frequency data (daily or weekly data that can more accurately depict investor behavior deviations), or direct measurement indicators of investor sentiment, to more precisely depict the micro-mechanisms of behavioral transmission [14]. It is also possible to explore the mediating role of other macro channels or attempt to construct more complex models to overcome endogeneity issues and further strengthen causal inference [15].

5. Conclusion

In the context of the COVID-19 pandemic, this study explores the heterogeneous effects of a macro-level shock on the disposition effect in the stock market. The main conclusions are as follows:

First, the impact of the epidemic has significantly exacerbated the overall irrational level of the A-share market, and its influence has distinct industry heterogeneity. Specifically, in February 2020, the market irrational composite index rapidly jumped to a phase peak above 0.55, while the turnover_new of highly exposed industries plummeted to around -8.5. Quantitative results indicate that in the early stage of the shock, highly exposed industries experienced a sharp shift in investor behavior from "disposal effect" to "panic selling".

Second, macro pressure mainly drives irrational market behavior by amplifying "uncertainty aversion" and triggering "excessive trading", while the relative importance of the traditional "disposal effect" declines under extreme shocks. This is revealed by the objective weighting results of the entropy method: the volatility and turnover rate of the CSI 300 are the absolute core components of the irrational composite index.

Third, the entropy method can effectively integrate multi-dimensional market behavior information. The objective empowerment result is a mapping of the relative importance of different behavioral biases in a crisis. This method breaks through the limitations of single-dimensional interpretation in extreme environments and has the potential for promotion and application in other major sudden crisis or structural shock scenarios.

Future research may further explore the specific mediating roles of different macro channels and the evolution of behavioral patterns over a longer period. Apply the same analytical framework to other types of macro shock scenarios, such as the rapid shift in global monetary policy triggered by the aggressive interest rate hikes by the Federal Reserve and major geopolitical conflict scenarios, such as local wars.

Testing the generality of the findings of this study is also a direction worthy of in-depth exploration.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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