Stock Market and Consumption: Evidence from China

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Abstract

Despite the rapid development of the Chinese stock market in recent years, relatively little is known about its characteristics or its relationship to other macroeconomic variables. For example, in contrast to more developed markets, dependencies between stock market movements and consumer expenditure are less documented for China. In this paper, I first show that the Shanghai Stock Exchange (SSE, 1999–2010) has higher average returns and variability than the Standard and Poor's 500 Index (S&P 500). The General Autoregressive Conditional Heteroscedasticity (GARCH) model also shows that the SSE has high volatility clustering. Then, I examine the statistical relationships between consumer expenditure and the behavior of the SSE against theoretical predictions. Following the stock market "wealth effect," one would expect higher (lower) stock returns would lead to higher (lower) consumer expenditure. The uncertainty hypothesis predicts that high volatility in the stock market will create higher uncertainty in consumption spending. However, my analyses using the Vector Auto-Regression (VAR) model show that private consumption expenditure in both rural and urban areas had no relationship with and was not affected by the market returns. Analyses also show that the volatility of the Shanghai Stock Exchange had a small lagged effect on urban private consumption expenditure. Results suggest that the Chinese stock market is relatively immature with higher volatility. At this stage, stock markets in China are still inefficient and do not serve as good leading indicators of future economic activities for Chinese consumers.

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Introduction

While the relationship between stock markets and consumer expenditure has been well documented for the United States and other major developed economies, we have relatively little theoretical knowledge or empirical research on these issues in China. Despite China being the world's third largest national economy, its stock market is still at an immature developmental level and its financial system is rather fragile [12]. In this paper, I compare the stock market returns of the Shanghai Stock Exchange (SSE) to the Standard & Poor's 500 (S&P 500). I also apply the General Autoregressive Conditional Heteroscedasticity (GARCH) model to capture the conditional variance as a measure of the volatility in the SSE. Then, I test the relationship between the SSE returns, the SSE volatility, and the urban and rural residents' private consumption expenditure. The analysis will inform us whether China's stock market behavior affected China's consumer expenditure similarly to that observed in more developed countries.

The Stock Market "Wealth Effect"

The stock market in China has developed rapidly since the early 1990s. Within two decades, the Chinese stock market has become one of the largest Asian stock markets in terms of market capital, with over $500 billion in 2004. The growing importance of the Chinese stock market suggests that any fluctuation in the stock prices in China might have a direct and significant effect on China's economy. One proposed mechanism by which stock markets influence economies is the stock market "wealth effect," which suggests that a stock market boom will increase consumption pressure, whereas a decline in stock market wealth will cause a slowdown in economic activities [4]. In 2008, the international financial crisis led to tremendous losses to investors around the world, including those in the Chinese stock markets. While developed countries' economies have been shown to be seriously affected by stock market losses, it is still uncertain and worth examining whether the stock market crash in developing countries such as China had similar negative effects on Chinese investors' consumption expenditure.

Urbanization in China

At present, 50.32% and 49.68% of China's total population resides in rural and urban areas respectively [20]. While the urban per capita net annual income was 17,175 yuan (2,698 US dollars) in 2009, it was only 5,153 yuan (809.5 US dollars) in the rural areas [19]. Clearly, there is a wide income gap between China's urban and rural areas. Despite a general trend of economic prosperity in China, not everyone in the whole country is experiencing the same changes and benefits. Thus, it would be meaningful to examine whether the rural residents, who have low living standards and segregated economic activities, are affected by the returns or movements in the stock market. It would also be interesting to test whether the stock market has the same effect on rural as urban investors' consumption expenditure in China.

Stock Market Volatility vs. Consumer Behaviors

The Chinese stock market has not been stable. The volatility in the SSE has been shown to be greater than that of the S&P 500. In fact, the stock market crash in China that began in October 2007 has wiped out more than two thirds of the SSE's market value [23]. How has the damage in this financial sector (i.e., stock market) spilled over to the Chinese real economy?

The effect of stock market value on consumer behavior is well established. Romer first argued that the Great Crash in 1929 generated individuals' temporary uncertainty in their future income, which consequently postponed their consumption of durable goods (e.g., cars) and ultimately led to the well known Great Depression [22]. The stock market "wealth effect" might have altered the investors' consumption as predicted and explained above. It is less clear whether extreme stock market movements, such as the 2008 financial crisis, affect individuals' consumption similarly. It is possible that the higher risks in the market may create a much stronger uncertainty effect even among individuals who do not hold stock.

The Present Study

In this paper, I examine the possible linkages of the Chinese stock market with China consumer behavior. I first compare the market returns of the SSE from January 1999 to December 2010 against those of the S&P 500. Secondly, I use the GARCH model to examine the volatility clustering in SSE. I then investigate whether the SSE, with higher average market returns and volatility, affects both the consumption in rural and urban areas through the wealth effect and uncertainty effect. I inspect the correlation between urban and rural residents' consumption expenditure and the SSE from 1999: Quarter I to 2010: Quarter III. The purpose of these examinations is to see whether the SSE returns and volatility had any effect on China consumer expenditure in rural or urban areas.

This paper is organized as follows: First, the relevant literature on the relation between the stock market and consumer spending would be reviewed. Next, I give an analysis of the SSE returns' variability against the S&P 500 and an analysis of the conditional variance in the SSE using a GARCH model. Then a VAR model is used to reveal the relationships among the SSE returns, its volatility, and urban and rural residents' consumption expenditure. Further discussion and concluding remarks are presented in the final section.

Literature Review: Stock Markets and Consumer Spending

The Stock Market "Wealth Effect"

Traditional economic theory suggests that stock market returns affect the wealth of the investors, which subsequently and directly affects their spending. According to Deaton, a stock market boom increases investors' consumption, while a stock market crash causes a slowdown in economic activities such as consumer spending [4]. Poterba further suggests that the stock market wealth effect would be strongest and most obvious among the small set of households who own the

majority of corporate stock [21]. In contrast, this effect for other households should be modest. These contentions are supported by most empirical studies in developed countries, which show a positive correlation between stock price and macroeconomic growth rate. For example, Johansen found a long-term equilibrium relationship between securities prices in the US stock market and macroeconomic variables [14]. Studies of this linkage in developing countries are, however, non-conclusive. Funke found a small, but statistically significant, link between private consumption growth and stock returns in most developing countries [9]. In contrast, Harris showed that the effect of the stock market on economic growth in developing countries is hardly observed [4].

The Uncertainty Hypothesis

The above analysis focused exclusively on the direct effects of the changes in stock market wealth on consumer expenditure. It is, however, possible that the changes in stock prices affect consumer confidence and hence affect consumer spending, even for households not holding stock. In recent decades, different economists have pointed out the importance of uncertainty on consumer expenditure. According to Katona, an individual's consumption decisions depend not only on ability to buy but also on willingness to buy, with consumer optimism or pessimism being the key determinant of willingness [15]. Similarly, Garner further asserts that consumer confidence about future business and financial conditions could be an important determinant of consumer expenditure [10]. Specifically, an increase in consumer confidence about the future of the business and financial conditions should increase the present consumption, while a decrease in confidence should lead to the opposite effect.

The validity of this theory has been examined by Romer using both quantitative and qualitative methods to test the linkage of the 1929 Great Crash with the onset of Great Depression [22]. Her results suggest that extreme stock market uncertainty may make economic agents feel uncertain about their future income. This consumer uncertainty causes consumers to put off purchasing durable goods until they are certain about their future income, leading to a significant decline in the demand of durable goods. Furthermore, an increase in the stock market uncertainty may stimulate the demand of non-durable goods. This is because consumers who are not purchasing durable goods will purchase perishable (non-durable) goods instead as a substitute. In sum, stock market variability should have a negative effect on durable goods and a potential positive effect on non-durable goods.

The ARCH/GARCH Model

In order to estimate the SSE volatility, it is essential to introduce the GARCH model. In the domain of finance, time sequence data usually suffers from heteroscedasticity, in which the error terms and variances are expected to be larger or smaller for some points than for others. Although the regression coefficients for an ordinary least squares regression are still unbiased, the standard errors and confidence intervals estimated will be too small and imprecise. Engle introduces the Autoregressive Conditional Heteroscedasticity (ARCH) model, which treats heteroscedasticity as a variance to be modeled [6]. As in Equation 1 below, the theory postulates that the conditional variance of the tth term is a

function of the residual error from the $(t-1)$th term to the $(t-q)$th term, i.e. the fluctuation is self-correlative, and the form of ARCH (q) becomes

$$\sigma_t^2 = \propto_0 + \sum_{i=1}^{q} \propto_i \varepsilon_{t-i}^2 \tag{1}$$

with the non-negative condition that $\propto_0 > 0, \propto_i \geq 0$ for $i = 1, 2, \ldots, q$.

Theoretical advancement in the domain of conditional heteroscedasticity developed very quickly, and many variations of the ARCH model have been proposed. The most representative model is the generalized ARCH (GARCH) model proposed by Bollerslev [2]. In the GARCH model, the conditional variance depends not only on the squared error term in the previous time period (as in ARCH (1)), but also on its conditional variance in the previous time period:

$$\sigma_t^2 = \propto_0 + \sum_{i=1}^{q} \propto_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

where $p \geq 0, q > 0$ and with the non-negative conditions that $\propto_0 > 0, \propto_i \geq 0$ for $i = 1, 2, \ldots, q$, $\beta_j \geq 0$ for $i = 1, 2, \ldots, p$. The above model is called the GARCH (p, q) process. I will use the standard GARCH $(1, 1)$ model to estimate the conditional variance of the stock market. With the conditional variance as a measure of volatility, I will be able to test its effect on consumer expenditure. $(1, 1)$ is a standard notation in which the first number refers to the number of autoregressive lags, or ARCH terms, appearing in the equation, while the second number refers to the number of moving average lags specified, which is often called the number of GARCH terms.

Empirical Evidence from the Shanghai Stock Exchange

Variability of the Market

Shanghai Stock Exchange Rates of Return Against the S&P 500

In this section, the rates of return in the Chinese stock market are estimated. The SSE was chosen to represent the stock market in China. The SSE was re-established only about 20 years ago. Along with the Hong Kong Stock Exchange (HKEX) and Shenzhen Stock Exchange (SZSE), the SSE is one of three stock exchanges operating in China; it is currently the world's sixth largest stock market in terms of its market capital (US $2.4 trillion as of Aug 2010 [27]). In the analyses, the monthly reports of the SSE real closing prices adjusted for dividends and splits from January 1999 to December 2010 were obtained from the Global Financial Data [11], with the S&P 500 real closing prices in the same period being used as the reference. First, we took the first difference forms of the SSE and S&P 500 stock prices using the equation $r_t = 100 \times \ln(\text{index}_t - \text{index}_{t-1})$ where r_t is the natural logarithm of market returns and index_t is the real closing price on the tth day.

As can be seen from Figure 1 above, the range of the S&P 500 is -0.15 to 0.1, while the range of the SSE spreads widely from -0.2 to 0.4. We can see that

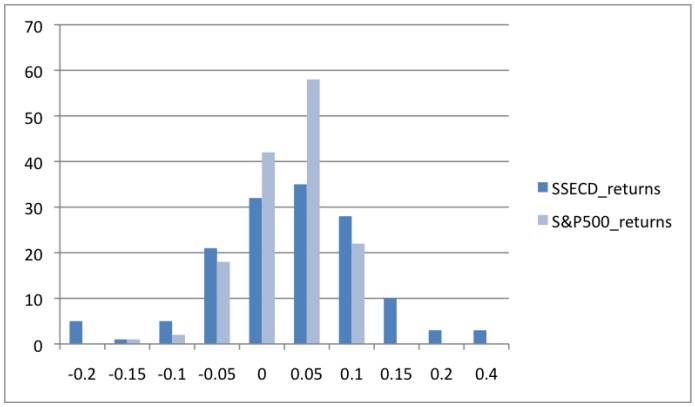


Figure 1: Frequency distributions of rates of return of the SSE and S&P 500 for 2000–2010.

the amount of variability or dispersion around the average has been much higher for the SSE than for the S&P 500. Generally, as can be seen from the graph, the larger this dispersion is, the higher the standard deviation σ will be. I have compiled the average rates of return and their standard deviations in Table 1 below. These simple statistics reveal the general picture of the nature of the market returns. The SSE, with a much higher variability (standard deviation), has also provided higher average returns than those of the S&P 500 during the period from 1999 to 2010. This is a common feature of emerging markets where the systematic component of returns variation is larger than in developed markets [17].

Another interesting observation is that the nature of returns seems to have reversed during the 2008 financial crisis. Although the SSE has lower average returns than the S&P 500, we do not see a lower risk with the SSE. Instead, the SSE has been much more volatile (with a high σ) than the S&P 500; Chinese investors were clearly not prepared to react to extreme changes in the market, such as wild securities price fluctuations. This shows that the SSE is still an immature and emerging market despite its rapid development in recent years.

Table 1: Statistics comparing the SSE and the S&P 500 market returns.

Market	Statistic	Jan 1999–Dec 2010	Jan 2007–Dec 2008
SSE	Arithmetic average	0.088468	-0.01052
	Standard deviation	0.008942	0.129067
	Geometric average	0.043525	0.090427
S&P 500	Arithmetic average	0.04677875	-0.01736
	Standard deviation	0.00045212	0.048519
	Geometric average	0.02215401	0.01586

Measuring the Conditional Variance in the Shanghai Stock Exchange

As explained in the literature review, financial time series such as stock prices often exhibit large swings, suggesting that the volatility of financial time series

varies over time. In this section, by capturing this conditional variance in the SSE using the GARCH model, we can use it as a measure of risk in the SSE and hence test if it would create uncertainty in individuals.

As a further illustration of the ARCH effect, Figure 2 presents the monthly percentage change in the S&P 500 index and the SSE index for the period 1999–2010. It is evident from the graph that the changes in the SSE exhibit a considerably higher volatility, with more wide swings—even during the 2008 financial crisis—than the S&P 500. From the graph, we can see that for both indices, generally low volatilities are followed by low volatilities while high volatilities are followed by high volatilities. This suggests that there are time varying variances which might suffer from heteroscedasticity. This result supports our use of the GARCH model.

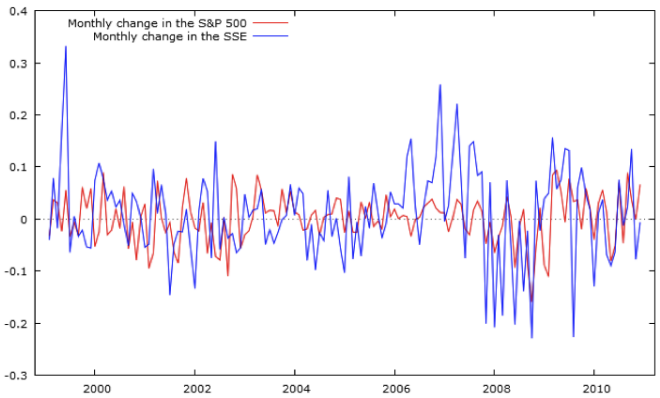


Figure 2: Time series plot showing the percentage change in the both the SSE and S&P 500 price index from 1999–2010.

In this GARCH $(1, 1)$ model, the conditional variance is

$$\sigma_t^2 = \propto_0 + \propto_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 \tag{3}$$

Table 2 below shows the results from the analyses using the GARCH (1, 1) model from equation (3) for the SSE returns. Since $\propto_1$ is positive, the results suggest that if volatility were high in the previous period, it would continue to be high in the current period, indicating volatility clustering. δ_1 is statistically significant ($p < .01$), indicating the stock price fluctuation possesses "long-term memory." Specifically, it means the fluctuation of past price is correlated with the fluctuation of future term price. Also, with such a high value, if there is an expected shock in this market, the fluctuations will not die out in the short run. This result is important because it is an indicator of high fluctuating risk. In addition, the persistence measure, $\propto_1 + \delta_1 = 0.869482$, is high, indicating the permanent shocks to volatility. It means that the reaction of stock fluctuation to the exterior concussion is digressive by a relatively slow speed. This GARCH model suggests that the SSE has high volatility clustering, and that we can capture the results of the conditional variance as a measure of the volatility and link these with consumer expenditure in the next section.

$y_t = 0.0145531 + \varepsilon_t$
$\sigma_t^2 = 37.7325 + 0.149799_{t-1}^{2*} + 0.719683\sigma_{t-1}^{2***}$
$[27.5560] \quad [0.124496] \quad [0.0929396]$
$\propto_1 + \delta_1 = 0.869482$

Table 2: GARCH $(1, 1)$ model analyses of SSE volatility. Heteroskedasticity-consistent standard errors are shown in brackets. ***Signficant at the 1% level. *Significant at the 10% level.

The Relationship Between the Shanghai Stock Exchange and Consumer Expenditure

Data and Preliminary Analyses

In this section, the relationship between the SSE and consumer expenditure is examined. In the computation, the quarterly reports of the SSE real closing prices adjusted for dividends and splits from 1999: Quarter I to 2010: Quarter III were obtained from Global Financial Data [11].

For the private consumption expenditure data set, I have collected separate data sets for the private consumption expenditure in rural and urban China, which is measured per capita. Both private consumption expenditure of the urban residents and rural residents are quarterly data from the first quarter of 1999 to the third quarter of 2010 obtained from the National Bureau of Statistics of China [19]. The private consumption expenditure in urban China is the average consumer expenditure of thirty-two urban districts in China. The private consumption expenditure in rural China is the average consumer expenditure of the rural residents, who were defined upon birth by the Chinese government. Figure 3 presents the time series plot of the data collected. The urban data usually keeps a growth rate of few percents even during the 2008 financial crisis. There are more fluctuations for the rural data, especially an unknown boom in early 2008. We will empirically test the data in the next section.

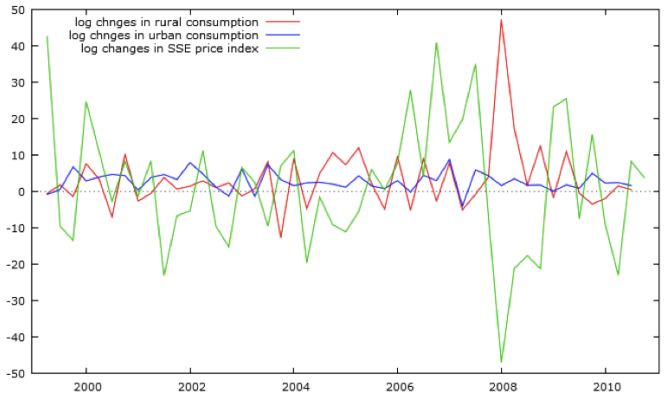
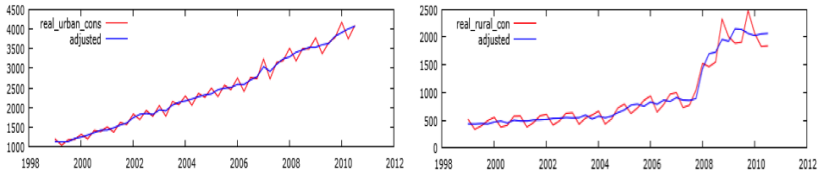


Figure 3: Changes in rural consumption, urban consumption, and SSE price index from 1999: 1st–2010: 3rd quarter (quarterly data).

Robustness Checks

Before the consumption expenditure data can be used, it is necessary to make two further adjustments. In Figure 1, we clearly see that both the urban and rural original series exhibit seasonal trends. To prevent seasonal factors from interfering with the empirical analyses, we use X12-ARIMA, the software developed by the US Census Bureau [25], for seasonal adjustment. We can see that the seasonally adjusted series become smooth (Figure 4). Secondly, to place the data across years on a comparable metric, the consumption data are adjusted with the consumer price index.[1]



(a) Urban consumption expenditure. **(b)** Rural consumption expenditure.

Figure 4: The urban and rural series, before and after X-12 ARIMA seasonal adjustment.

Empirical Results With a VAR Model

In this section, we test to see whether the SSE returns and volatility affected the private consumption expenditure in rural or urban area. A Vector Auto-Regression (VAR) model is used to examine the interdependence. Christopher Sims first advocates the use of VAR models as a method to estimate relationships between economic variables [24]. The VAR model is popularly used to capture the interdependencies between multiple time series variables. Each variable in a VAR model is tested on an equation against its own lags and the lags of all the other variables in the model. The equation below illustrates the standard form of the VAR model:

$$X_t = \propto + \sum_{j=1}^{k} \beta_j + X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + u_t \tag{4}$$

The equation tests the effects of X by comparing against the k lag values of X and Y; u is the stochastic error term, called a *shock* in the language of finance.

In the preliminary analyses, we had to determine the number of lags (k) required in the test, because intuitively one would expect stock variability to have a rapid but not instantaneous effect on consumer behavior. The optimal number of lags in each regression was determined by minimizing the Schwarz Bayesian criterion (BIC).[2] In the tests for urban and rural private consumption

[1] The consumer price index that I used is for urban areas in China, taken from the National Bureau of Statistics of China [19].

[2] Starting with the maximum length of 12 lags, I chose the number of lags with the lowest BIC value using statistical software.

data, the number of lags was set to one ($k = 1$); for the volatility series, the number of lags was set to three ($k = 3$).

Empirical Results

In the analyses, I use a simple model that relates the change in the natural logarithm of consumption to the natural logarithm of SSE market rates of return and the conditional variance in the market. This specification in terms of the first differences makes the unit root processes unnecessary. Specifically, the analyses becomes an estimation of the following regression:

$$\begin{aligned}\Delta \ln C_{it} = \propto_0 + \propto_1 \Delta \ln C_{it-1} + \beta_1 \ln r_t + \beta_2 \ln r_{t-1} \\ + \delta_1 \ln v_t + \delta_2 \ln v_{t-1} + \delta_3 \ln v_{t-2} + \delta_4 \ln v_{t-3}\end{aligned}$$

Consumption (C) refers to the real urban/rural private consumption expenditure per capita; C_{it-1} is the private consumption expenditure at lag 1. The term r_t is the SSE rate of return, as discussed in the previous section, while r_{t-1} is its value at lag 1. The v_t term is the volatility in SSE as measured in the previous section, while v_{t-1}, v_{t-2} and v_{t-3} are its values at lag 1, 2, and 3 respectively.

Table 3 presents the statistical results. As can be seen from the table, the SSE rates of return are statistically non-significant even at the 10% level in explaining urban private consumption expenditure. Both β_1 and β_2 have the expected positive signs due to the wealth effects for the urban data but not for the rural data. For the volatility coefficients δ, only δ_2 and δ_4 are statistically significant at 10% in explaining the urban private consumption expenditure but not for the rural. As expected, the negative signs of these variables indicate that higher volatility in the market leads to lower consumption. The SSE rates of return are statistically significant at the 10% level in explaining rural private consumption expenditure, and a negative sign is observed, which contradicts our expectations. Both rural and urban private consumption expenditure's first lagged value, the $\propto_1$ coefficient, has the expected negative sign and is significant at the 10% level, which proves both time series data to be stationary. Both results imply that the relationship between urban and rural private consumption growth and the SSE rates of return are not in line with the existence of a stock market wealth effect. The SSE volatility explains the urban private consumption expenditure at a delayed time ($k = 3$); however, the coefficient is small and only significant at the 10% level.

Discussion and Conclusion

A Seemingly Contradictory Observation

Our empirical research shows that the SSE exhibited higher average returns than the S&P 500, as well as high volatility clustering, from 1999–2010. It is generally assumed that higher market returns boost household wealth and hence encourage consumers to spend more. It is also logical to expect that higher risks in the market, such as during the financial crisis in 2008, should create uncertainty about future economic growth and hence affect consumer spending. The results of the current empirical analyses of the SSE, however, did

	Δ Urban CE	Δ Rural CE
SSE market returns	0.006480	−0.240040*
	[0.019064]	[0.141376]
SSE market returns (−1)	0.016834	−0.051592
	[0.017937]	[0.061517]
SSE volatility	0.006427	0.027609
	[0.004794]	[0.014414]
SSE volatility (−1)	−0.004007	−0.010417
	[0.006427]	[0.023852]
SSE volatility (−2)	0.003548	0.017854
	[0.005498]	[0.013913]
SSE volatility (−3)*	−0.006669*	−0.0192265
	[0.003750]	[0.012073]
Δ Urban CE (−1)*	−0.318863**	
	[0.167896]	
Δ Rural CE (−1)		−0.232004*
		[0.134872]
R-Squared	0.214716	0.171173

Table 3: SSE market returns and volatility of consumer expenditure (CE). The dependent variable is the change in the natural logarithm of real urbal/rural private consumption expenditure per capita. Bracketed values are White heteroskedasticity-consistent standard errors. **Significant at the 5% level. *Significant at the 10% level.

not show a stock market "wealth effect." The analysis also showed that the SSE volatility had a very small, but statistically significant, economic effect on the urban private consumption expenditure at a delayed time of three months. The empirical findings suggest that the SSE index might not be a leading indicator of China's future economic activity. We now explore possible explanations for this observation, which seems to contradict the established economic theory.

Firstly, a unique characteristic of China's stock market is that approximately 69% of all shares in the Shanghai and Shenzhen exchanges are non-tradable [28]. Those shares are held by the central government, local governments, and state-owned enterprises. The stock values are therefore prescribed rather than market determined. The result is that the government can easily manipulate the market performance. The stock market performance thus hardly reflects the real state of the economy. China consumers may be fully aware of this and may not view the stock market performance as a credible economic indicator.

Secondly, since the stock market in China has been in operation for only twenty years, it is still immature and developing. Only a very small fraction of individuals in China today own stock, and therefore we might not observe the stock market wealth effect. Also, unlike in most countries with a well-developed market economy, financing in China is mostly provided by banks, not by the stock market. For example, the majority of individuals in the US often invest through employer schemes or through buying managed funds; in contrast, most investors in China have no such experiences, and buy shares without advice from financial consultants. The dominant Chinese financial support is from commercial bank loans with credit regulated by the government. As a result,

the role played by the SSE in China's real economic growth may be relatively weak.

Thirdly, although the Chinese stock market fell dramatically from 2007 to 2008, the Chinese economy kept growing, though admittedly at a slower rate. The real GDP growth in 2008 was 9%, and higher per capita GDP normally means higher incomes. Therefore, as Chinese consumers still see increasing incomes (even though at a rate slower than before), they may not perceive the drop in the stock market as a sign of economic downturn, in contrast to Western consumers. Also, the 2008 Beijing Olympics should have helped in boosting the economy by substantially increasing the demand for goods and services.

Shortcomings of the Data and Limitations of the Model

The findings and conclusion derived in the research presented in this paper may be limited by the data we analyzed. Firstly, it is possible that the range of potential effects of the 2008 stock market crash on consumer spending might not yet have fully surfaced. In additon, as explained above, a few episodes such as the 2008 Beijing Olympics may have given an illusory impression of a healthy Chinese economy. Thus, the results in this paper should be re-examined in the coming years.

Secondly, the private consumption data we have been using in the analyses in this research may not fully reflect the true picture. Though the literature suggests that the Chinese official data are by large reliable, certain official estimates of output growth rates might contain errors [3]. The quarterly data is the best we can obtain at this point. With data for the consumer expenditures of the top income set of households, we might capture the wealth effect better. As the Chinese economy continues to develop, we expect to see more detailed data sets becoming available, which might perhaps reflect monthly statistics.

Thirdly, the data we used may be too general, as it represents an aggregation of consumer spending in all Chinese urban cities. Stock market performance information may not be equally accessible across cities, and thus its impact on consumer spending may vary across cities. For example, while newspapers in Shanghai may report stock market performance frequently because a large proportion of the Shanghai population holds stock, people in Shandong province hold less stock, and have little information and few concerns about the SSE. If we had examined expenditure data specifically limited to metropolitan cities such as Shanghai, Shenzhen and Beijing, it is more likely that we would have captured a stronger causal relationship between stock market variability and consumer spending.

Future Research

Future research should investigate important factors other than the stock market that may have greater impacts on consumer spending in China. For example, China's exports have substantially decreased in recent years, especially after the 2008 US financial crisis. The fact that the US dollar further weakened against the Chinese yuan has put strong pressure on raising the exchange rate. Thus, it may be interesting to test whether the change in exports or exchange rate plays a stronger role in predicting consumer spending.

In the future, analysts speculate that the Chinese government will gradually improve the efficiency of the stock market and reform China's financial system. It is useful therefore to continue testing and monitoring the causal relationship between stock market variability and consumer spending. This information will serve as a useful indicator of the maturity of the stock market as well as whether people in China have changed their views on the stock market.

Conclusion

This paper provides empirical evidence that the SSE indeed has higher market average returns than that of the S&P 500. Findings from my empirical results, however, show that the SSE market returns did not exhibit a wealth effect. Analysis with the GARCH model also shows that the SSE has high volatility clustering. Following Romer's argument, one would expect to see a larger effect on consumer spending when the stock market movements are more extreme or have higher risks [22]. The present study provides some evidence that volatility has a very small, but statistically significant, effect on urban private consumption growth at a delayed time of three months. This suggests that despite the rapid growth of China's stock market, it is still undergoing important structural changes. Observations in terms of governmental economic policy and the basic health characteristics of the economy are used to explain these results, and recommendations are made for further study.

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