PSL Quarterly Review

vol. 73 n. 293 (June 2020)
Article

Stock market volatility, speculation and unemployment: A Granger-causality analysis

BERNARDINA ALGIERI, EMILIANO BRANCACCIO, and DAMIANO BUONAGUIDI*

Abstract:

This study investigates the possible Granger-causal relations between stock price volatility and dividend dynamics on the one hand, and speculation and unemployment on the other. The analysis is carried out for the US over the period 1982-2018. Stock price volatility is calculated in terms of "conditional" volatility and in terms of the so-called "Shiller ratio", while speculative trading is expressed as "scalping" activities. We find that there is a causal positive relation from speculation to stock price volatility. Furthermore, we show that there is an inverse causal relationship ranging from stock prices to unemployment, while there is no causal relationship between dividends and unemployment. These results corroborate the empirical analyses by Shiller and other authors which deny the traditional Present Value Model (*PVM*), *provide new elements on the possible determinants of stock price volatility, and offer new interpretations of the potential links between the stock market and macroeconomic dynamics*.

Algieri: University of Calabria and Bonn University; email: bernardina.algieri@unical.it
Brancaccio: University of Sannio; email: emiliano.brancaccio@unisannio.it
Buonaguidi: University of Florence, Pisa, and Siena, and Italian Ministry of Economy; email: damiano.buonaguidi@gmail.com

How to cite this article:
Algieri B., Brancaccio E., Buonaguidi D. (2020), "Stock market volatility, speculation and unemployment: A Granger-causality analysis", *PSL Quarterly Review*, 73 (293): 137-160

DOI: https://doi.org/10.13133/2037-3643_73.293_3

JEL codes:
C10; E39; G15

Keywords:
Speculative trading, stock price volatility, stock market, Shiller ratio, Present Value Model.

Journal homepage:
http: //www.pslquarterlyreview.info

Almost 40 years after its publication, Shiller's test on stock price volatility remains a cornerstone in the literature about the efficiency of financial markets (Shiller, 1981). In his seminal work, Shiller criticised the traditional view of the stock market expressed by the Present Value Model (PVM). According to this model, actual stock prices are determined by their "fundamental" value, i.e., the present value of the expected dividend stream. Shiller named "theoretical prices" those determined ex post by the dividend stream actually distributed to shareholders and showed that the variance of actual dividends and related theoretical prices is less than the variance of actual prices. This high volatility of actual prices suggests that they cannot reflect only expected dividends but must be influenced by other

* Emiliano Brancaccio is the corresponding author for this work. We are grateful to Carlo D'Ippoliti and two anonymous referees for their useful comments. The usual disclaimers apply.

This work is licensed under a Creative Commons Attribution – Non-Commercial – No Derivatives 4.0 International License. To view a copy of this license visit http://creativecommons.org/licenses/by-nc-nd/4.0/

factors, such as speculation. Shiller's test and subsequent elaborations have inspired a broad debate (e.g., Ofek and Richardson, 2003; Scheinkman and Xiong, 2003; Boswijk et al., 2007), which is still ongoing.

This study draws inspiration from some previous theoretical reflections on Shiller's test (Brancaccio and Buonaguidi, 2019) and tries to add two new elements to the discussion: an investigation on the possible influence of speculation on stock price volatility and a preliminary examination of the interactions between stock prices and dividends on the one hand and the macroeconomic dynamics and the related "fundamental" values around which volatility occurs on the other. For this scope we adopt here a Granger-causality technique to the analysis of the US cash and futures stock markets between 1982 and 2018. These results provide support to Shiller's empirical findings and offer new elements on the possible determinants of price volatility. The results would further suggest alternative interpretations to the standard analyses of the interactions between the stock market and macroeconomic dynamics.

The peculiar characteristics of this work are the following. Speculation is represented here by so-called "scalping" activities, i.e., fast-paced speculative transactions made up of instant operations by scalpers who open and close contract positions very rapidly, generally without holding them overnight, with the aim of gaining large profits from small price changes. We focus on these specific speculative activities given their potential destabilising effects for financial markets as noted by Arnuk and Saluzzi (2012) and Manera et al. (2013). Stock price volatility is computed either in terms of "conditional volatility" or using the "Shiller ratio", i.e., the ratio between actual market prices and theoretical prices computed ex post in terms of the present value of the actual dividend stream. To our knowledge, most of the Granger analyses on speculation and volatility have been carried out for commodity markets (Stoll and Whaley, 2010; Büyüksahin and Harris, 2011; Cheng et al., 2014; Algieri, 2016), while fewer analyses have instead examined the linkage within equity markets. The studies on the stock market have mainly focused on efficiency and spillover effects (e.g., Antonakakis et al., 2016; Tao and Green, 2012; Chan 1992; Ghosh, 1993). In this study we directly assess we directly check whether speculation can be considered as a possible determinant of volatility and also investigate some possible causal relations between stock prices and dividends and unemployment outcomes.

The remainder of this paper is organized as follows. Section 1 reviews the debate that followed Shiller's test on stock price volatility. Sections 2 and 3 describe methodology and data. Section 4 examines the causal relationships between speculation and stock market volatility. Section 5 shows the causal relations between prices, dividends and unemployment. Section 6 concludes.

1. Present Value Model, Shiller test and beyond: a short review

According to the PVM, stock prices should reflect only the expected value of discounted future dividends, which in turn is determined by the so-called "fundamentals" of preferences, technology and scarce resources. This means, among other things, that actual stock prices are only an expectation of their equilibrium levels represented by theoretical ex-post prices computed using the actual dividend stream and thus should vary less than the latter. This result is usually reached under rational expectations and efficient market hypotheses (Fama, 1970) in a model which assumes a given discount rate and is more or less implicitly grounded on a typical neoclassical general equilibrium framework (Brancaccio and Buonaguidi, 2019).

The conclusions of the PVM have been questioned since the publication of Shiller's seminal work (Shiller, 1981), in which it is shown that actual stock market prices vary too much with respect to their equilibrium levels, represented by theoretical prices computed ex-post on the basis of actual dividends. Shiller's result also clashes with the PVM idea that actual prices, being just an expectation of ex-post theoretical prices, should vary less than the latter. In other words, stock market prices seem to be too volatile to reflect only expected future dividends and thus must be influenced by other factors. This volatility of stock market prices can also be described by the "Shiller ratio", i.e., the ratio between market and theoretical prices.

The first replies to the Shiller test concerned econometric issues, regarding in particular the stationary assumptions and the small sample properties of estimators (see Flavin, 1983; Kleidon, 1986; Marsh and Merton, 1986; and a reply by Shiller, 1989). However, the econometric criticisms were soon overcome: second-generation tests confirmed excess volatility (West, 1988; Campbell and Shiller, 1988; see Gilles and Leroy, 1991, for a review). After these contributions one of the participants in the debate recognised: "There is no longer any room for reasonable doubt about the statistical significance of excess volatility" (Gilles and Leroy, 1991, p. 789; see also Leroy, 1996).

These empirical results support the idea that movements in stock market prices must be explained by other factors than dividends and related "fundamentals". Speculation, among others, is one of these possible factors. This view, however, has not received particular attention and has remained in many respects at a poor stage of development. The main debate, in fact, has been dedicated to a preliminary problem, which is related to the acceptation or rejection of Shiller's results. The reactions to Shiller's tests can, in fact, be divided into two broad categories: on the one hand, those who have tried to defend the PVM, proposing alternative assumptions on households' preference structure which could scale down actual stock price volatility with respect to theoretical price volatility; on the other hand, those who have accepted Shiller's results on price volatility, explaining them with the presence of rational or irrational "bubbles".

Of the authors who have tried to defend the PVM from Shiller's criticisms, some have proposed removing the traditional hypothesis of a constant discount rate by suggesting that it can vary over time on the basis of new assumptions on preferences and consumption behaviour (these models are theoretically based on Lucas, 1978; Breeden, 1980; Grossman and Shiller, 1981; Hansen and Singleton, 1983). These approaches are known as Consumption-based Capital Asset Pricing Models (CCAPM hereafter). This research line has aimed at finding the "right" model for a subjective time-varying stochastic discount factor in order to improve the fitting between actual and theoretical prices (see Cochrane, 2005, for a comprehensive view). The underlying idea is that consumption smoothing behaviour and risk aversion imply large movements in equilibrium prices during business cycles. In this way, the gap between theoretical equilibrium prices and actual market prices variability should disappear.

Despite their academic diffusion, CCAPM models have hardly received empirical support. The traditional version of CCAPM, based on power utility function, does not fit data well (Grossman and Shiller, 1981). Moreover, it faces relevant puzzles, such as the equity premium puzzle and the risk-free rate puzzle (Mehra and Prescott, 1985; Mera, 2006). Several models have been proposed to overcome these puzzles but without success (Epstein and Zin, 1989; Campbell and Cochrane, 1999; Abel, 1990; Constantinides, 1990). After reviewing the main asset-pricing models, some of the most important PVM supporters recently pointed out the absence of a satisfactory comprehensive approach, concluding that: "No model stands decisively above the others in its ability to describe equity premium/risk-free rate puzzles, and more importantly time-varying, business-cycle related risk premia; return predictability; 'excess' volatility; and the long-run equity premium" (Cochrane, 2017). In other words: "Most analysts believe that no single convincing explanation has been provided for the volatility of equity prices. The conclusion that appears to follow from the equity premium and price volatility puzzles is that, for whatever reason, prices of financial assets do not behave as the theory of consumption-based asset pricing predicts" (Leroy, 2018, p. 4110; for a similar conclusion, see Wang, 2018, p. 4624).

Since stock price volatility can hardly be explained by the more or less advanced versions of PVM, other authors have accepted the higher variability of market prices with respect to theoretical prices and have focused their attention on the reasons why actual prices differ from their fundamental value. These authors have tried to explain the empirical rejections of PVM as due to the presence of the so-called "bubbles", i.e., factors that influence market prices, letting them to deviate from their equilibrium. Bubbles can be introduced both in a rational and in a non-rational framework. Rational bubbles are correctly predicted by the agents, so that prices include a "bubble" term, and price variations stem from potential higher capital gains or losses not justified by the fundamental value related to future dividends. Prices may deviate from the fundamental value by an amount equal to the bubble term, which appears just because it is expected to appear the following period. Even if individuals are able to distinguish between the fundamental value and the bubble term, they nonetheless rationally include the latter in the determination of the equilibrium price, since the bubble is expected to persist in the future. For this reason, we can call it a "rational bubble" (Blanchard and Watson, 1982; Tirole, 1985; see Leroy, 2004, for a review). In the empirical literature, no definitive conclusion has been reached about the presence of rational bubbles in the stock market (see, for instance, West, 1988, and Cerqueti and Costantini, 2006, for positive evidence and Diba and Grossman, 1988, and Dezhbakhsh and Demirguc-Kunt, 1990, for negative evidence). In the case of "irrational bubbles", on the other hand, prices can follow a different path from that predicted by dividends, either because agents do not know the right model of the economy or because they follow fads or are influenced by euphoria. (In any case, the hypothesis of rational expectations is rejected. As one of the most prominent observers argued, the removal of the rational expectations hypothesis could be a typical explanation of Shiller's results: "A very rigorous analysis for the bond and stock markets has shown the incompatibility of observed behaviour with rational expectations models, at least in a simple form" (Arrow, 1983). More recently, further non-rational interpretations of stock market volatility have been provided by studies in the field of "behavioural finance" (see, for example, Shiller, 1984, 2003; De Bondt and Thaler, 1985; Shiller, 2015).

We can therefore affirm that the prevailing literature on the Shiller test has mainly focused on the acceptance or otherwise of the idea of volatility of the stock market. Few research efforts have been devoted to other issues inspired by Shiller's test, including the identification of the possible determinants of volatility and the interactions between stock prices and dividends on the one hand and the macroeconomic dynamics and the related "fundamental" values around which volatility occurs on the other. In what follows we adopt a Granger-causality technique in order to suggest a preliminary approach to these two issues.

2. Stock price volatility and speculation: A Granger-causal analysis

Although Shiller's test has inspired many subsequent contributions, few studies have explicitly analysed the possible role of speculation as a possible determinant of volatility. More specifically, not much research has investigated the presence of a possible Granger-causality between speculation and price volatility in equity market. While the causal link between speculation and price volatility has been thoroughly examined for commodity markets (e.g., Algieri and Leccadito, 2019; Hamilton and Wu, 2015; Büyüksahin and Robe, 2014; Singleton, 2014; Büyüksahin and Harris, 2011), fewer analyses have been devoted to stock markets. To our knowledge, Brunetti et al. (2016) have examined the CBOT eMini-Dow (one of the largest US equity futures markets) and found that eMini-Dow volatility is Granger-caused by the full set of trader position changes. But there is a clear lack of research in this filed. Our purpose is to contribute to filling this gap.

We propose a definition of "speculation" measured in terms of "scalping trading", while we consider "stock price volatility" in terms either of "conditional volatility" or the "Shiller ratio" between actual prices and theoretical prices.

If volatility Granger-causes speculation, this could be evidence in favour of the stabilising effects of speculation, which would move prices in the direction of the fundamental value (Kyle, 1985; Brunetti et al. 2016; Kim, 2015; Deuskar and Johnson, 2011). The reason is due to the fact that speculators normally sell when the price of the asset in which they trade is high and buy when the price is low. Thus, they have to demand when the asset price is "below the normal" and supply when the asset price is "above the normal". This influence will help to drive the price back up in the former case and push the price back down in the latter case. Thus, the trading activities of speculators – induced by price fluctuations – generally serve to reduce the amplitudes of price swings.

On the contrary, if speculation Granger-causes volatility, this would suggest that the trading activities of speculators could induce, in a Granger sense, more price fluctuations. This result is of particular importance since higher volatility "caused" by speculation would imply an increase in the overall risk of the markets. If speculation Granger-causes volatility, this would be evidence in support of stock market inefficiency and the presence of bubbles, which could be explained, for instance, by systematic noise trading (Black, 1986; Cutler et al., 1990, 1991; Shleifer and Summers, 1990; Morck et al., 2000), irrational manias (Summers, 1986; Shiller, 2015; Ofek and Richardson, 2003), overconfidence (Scheinkman and Xiong, 2003), and psychological and behavioural drivers (Brown and Cliff, 2005; Boswijk et al., 2007). In the latter case, as Keynes noticed, "the market is subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate where no solid basis exists for a sound calculation" (Keynes, 1936, p. 154). In other words, speculators could drive prices away from fundamental values, thus causing bubbles, or they could manipulate the market, or, when they are poorly informed, they could trade in response to supply and demand shocks by extrapolating past trends or by observing other traders, as in the case of 'herding' (Froot et al., 1992; Weiner, 2002).

In the following analysis, then, the concept of Granger-causality (Granger, 1969) is applied to assess possible lead-lag relations between speculative trading activity and stock price volatility. Given two stationary time series x (say speculative trading) and y (say volatility), if x can help to predict future values of y, then x (speculative trading) 'Granger-causes' y (volatility). The statement 'x Granger-causes y' does not imply that y is the effect or the result of x. Granger-causality measures precedence and information content, but it does not express causality in the more common use of the term. Rather, Granger-causality assesses whether one variable leads another one: the so called 'arrow of time' (→) gives a temporal ordering between two series.

Granger-causality identifies the existence of four basic relations in the bivariate system we are going to study: i) speculative trading Granger-causes or leads (→) price volatility; ii) price volatility Granger-causes (→) speculative trading; iii) speculative trading and price volatility Granger-cause each other (speculative trading ↔ volatility); iv) there are no relations between the two series. Formally, by defining speculation with the term *SPEC* and volatility with *VOL*, the test is based on the following vector autoregressive model:

$$SPEC_t = \alpha_0 + \Sigma\beta_k\, SPEC_{t-k} + \Sigma\gamma_k\, VOL_{t-k} + \varepsilon_t \qquad [1]$$

$$VOL_t = \delta_0 + \Sigma\eta_k\, VOL_{t-k} + \Sigma\lambda_k\, SPEC_{t-k} + \upsilon_t \qquad [2]$$

under the following null and alternative hypotheses:

$$H_o: \gamma_1 = \gamma_2 = \ldots \gamma_k = 0 \qquad \text{vs.} \qquad H_1: \gamma_1 \neq \gamma_2 \neq \ldots \gamma_k \neq 0 \qquad [3]$$

where the null implies that *VOL* does not Granger-cause *SPEC*, against the alternative that *VOL* Granger-causes *SPEC*. Similarly, we have:

$$H_o: \lambda_1 = \lambda_2 = \ldots \lambda_k = 0 \qquad \text{vs.} \qquad H_1: \lambda_1 \neq \lambda_2 \neq \ldots \lambda_k \neq 0 \qquad [4]$$

where the null implies that *SPEC* does not Granger-cause *VOL*, against the alternative that *SPEC* Granger-causes *VOL*.

In what follows, we consider two different measures of stock price volatility: a statistical measure called "conditional volatility" and a theoretical measure of volatility based on the "Shiller ratio".

3. Data and definitions of speculation and volatility

All data have been collected from DataStream. The period of analysis ranges from 23 April 1982 to 13 February 2018 for a total of 9,393 observations for each series. The series starts in 1982 since traders' position data are not available before that year.

For our empirical analysis, we have considered cash and futures stock prices in the US. In particular, we have collected daily data on the S&P 500 composite price index (code: S&PCOMP(PI)), the S&P 500 futures settlement price[1] index (code: ISPCS00(PS)), the transaction volume traded[2] (code: ISPCS00(VM)) and open interest[3] (code: ISPCS00(OI)) in the US futures market. The selection of the S&P 500, rather than another indicator, is due to its primary role as a leading large-cap benchmark for the US stock market[4] and its importance as

[1] Official closing price issued by the exchange.
[2] For the continuous CME-S&P 500 series, this is the sum of all volumes for all contracts.
[3] For the continuous CME-S&P 500 series, this is the sum of all open interest for all contracts.
[4] The S&P 500 comprises 400 industrials, 40 financial institutions, 40 utilities, and 20 transportation firms. It has become a preferred index for US stocks, unseating the Dow Jones Industrial Average (DJIA). The S&P 500 is perceived as more representative of the market because it is made up of 500 companies, compared to the DJIA's 30. There is also a major difference in how companies are represented in either index. The S&P 500 uses a market cap methodology, giving a higher weighting to larger companies, whereas the DJIA uses a price weighting methodology,

the main barometer for institutional and professional investors. We further compile the scalping index and two volatility indices.

The scalping index is a measure of short-run speculation and is computed as the ratio between trading volume and open interest in future contracts (Manera et al., 2013):

$$Scalping = \frac{Volumes\ of\ futures\ trading}{Open\ interest} \qquad [5]$$

The volume of futures trading simply accounts for the amount of trading activity that has taken place in a specific contract on a trading date. The open interest reflects the number of outstanding contracts at the end of the trading day that have not been settled. As highlighted by Antonakakis et al. (2016), Lucia and Pardo (2010) and Bessembinder and Seguin (1993), futures trading and open interest characterize different types of traders. In particular, open interest would represent hedging activity, whereas volume of trading mainly measures speculative demand for futures. The ratio called "scalping" would then reflect the assumption that hedgers hold their positions for longer periods due to their underlying positions, while speculators mainly try to avoid holding their positions overnight. Speculators and hedgers influence the amount of trading volume and open interest in very different ways, by relying on their different trading behaviour. Speculators mostly impact trading volume instead of open interest because they buy and sell contracts during the day and close their positions before trading ends. Thus, outstanding contracts at the end of a trading day are mainly held by hedgers (Bessembinder and Seguin, 1993; Garcia et al., 1986; Leuthold, 1983; Rutledge, 1979). A high (low) scalping index denotes high (low) speculative activity with respect to hedging activity. Therefore, a rise in the scalping ratio reflects a rise in the dominance of speculators in the market.

Let us now consider the measures of volatility we intend to analyse. We adopt the term "return" to denote the price rate of change. The first measure is the "conditional volatility", i.e., the annualized standard deviation of daily log returns where past squared return deviations are not weighted equally: the most recent squared return deviations own the most weight and the weights gradually decline as the observation goes back in time. We use this measure because evidence on volatility clustering and persistence suggest that more recent observations should encompass more information concerning volatility in the immediate future than older observations (Engle, 2004; Poon and Granger, 2003). But this specification about weights is not really important and can easily be removed. Conditional volatility, here, is in fact only a purely statistical index which does not give any relevant information from a theoretical point of view. It provides only some preliminary information on the possible causal relations between the variables examined. Conditional volatility is computed with reference to the US cash and futures stock market. To derive conditional volatility for the futures market, we use the Chicago Mercantile Exchange (CME)-continuous S&P 500 futures contracts series, which considers at each date the price of the contract with the closest maturity. We use the S&P 500 index to obtain volatility for the cash market.

Conditional volatility is then computed as the standard deviation of the S&P 500 cash and futures stock returns, conditional on known information using a GARCH model. Technically, the compound rate of returns of the S&P 500 stock futures and S&P 500 cash index (r_t) are first calculated as follows:

which gives more expensive stocks a higher weighting. The market cap ranking is also seen as more representative of real market structure.

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) \quad [6]$$

where p is the stock futures (cash) price at time-day t. Then, the conditional volatility is estimated via a GARCH (1; 1) model as proposed by Bollerslev (1986). Formally:

$$r_t|\Omega_{t-1} = \mu + \varepsilon_t \quad [7]$$

where $\varepsilon_t|\Omega_{t-1} \sim iid\ N(0, \sigma_t^2)$

$$\sigma_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 \quad [8]$$

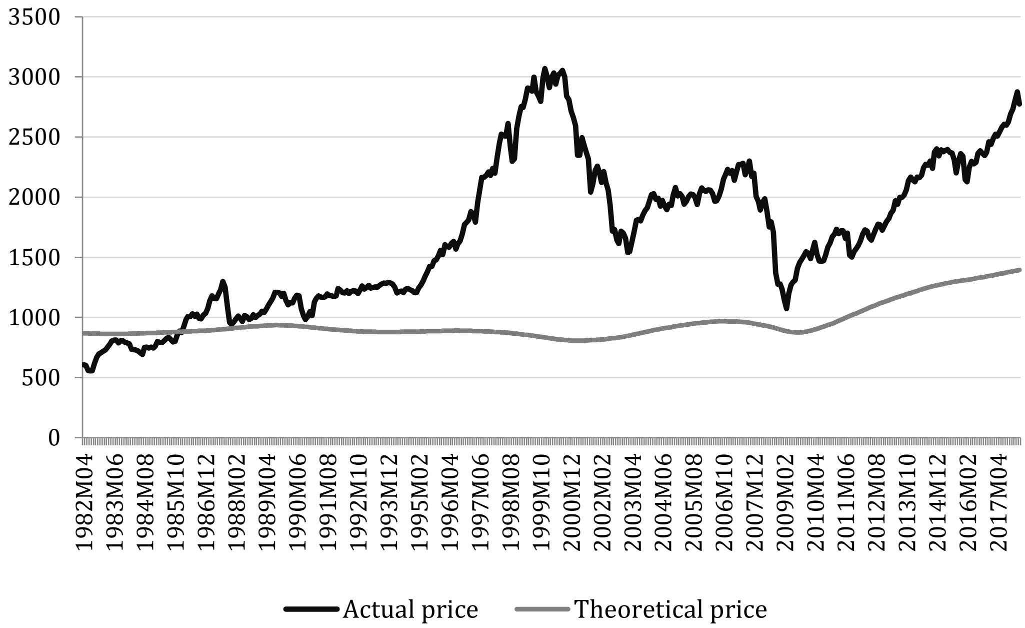
Equation 7 is the conditional mean equation, which specifies that stock price returns at time t (r_t) are a function of a drift coefficient (μ), i.e., the average stock returns, and an error term (ε_t), conditional on the information set existing up to time t – 1 (Ω_{t-1}). The error ε_t is independently and identically normally distributed with zero mean and conditional variance $\sigma^2{}_t$. Equation 8 is the conditional variance equation and it indicates that the conditional variance of returns at time t, $\sigma^2{}_t$, depends on: i) the long-term mean value (dependent on α); ii) the lagged squared residual $\beta\varepsilon^2{}_{t-1}$, which designates the magnitude of past shocks; and iii) the past variance $\gamma\sigma^2{}_{t-1}$. Hence, the coefficient α mirrors the ARCH effect, or short-run persistence of shocks to returns and β indicates the GARCH effect. The sum of the ARCH and GARCH coefficients ($\beta + \gamma$) reflects the persistence in volatility clustering: the closer it is to 1, the more persistent the volatility clustering is.

The GARCH conditional volatility is finally given by:

$$\sigma_t = \sqrt{\sigma_t^2} = \sqrt{\alpha + \beta\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2} \quad [9]$$

The second measure of volatility examined is the stock price volatility computed in relation to the "Shiller ratio", i.e., the ratio between the actual stock market prices and the theoretical prices calculated ex post on the basis of actual dividends (Shiller, 1981). The Shiller ratio has been constructed using the monthly frequency data for the period April 1982 — February 2018. Unlike the previous one, this index allows us to measure the distance between market prices and the equilibrium prices determined by using the PVM. In particular, actual stock market prices are real de-trended prices referred to the S&P 500 index and gauged for the period 1871-2018. They are computed first by dividing the nominal S&P 500 prices by the Consumer Price Index (CPI); then the trend factor is estimated by regressing the obtained real log prices on a constant and time (see Appendix); finally, real de-trended prices are computed by dividing real prices for the trend factor. The (net) discount rate for the de-trended series is obtained by dividing the average of real de-trended dividends by the average of real de-trended prices. The terminal theoretical price is the average of real de-trended price. The other theoretical prices are obtained by backward recursion: each price is computed as the sum between the real de-trended price and the real de-trended dividend of the following period, divided by the (gross) discount rate for the de-trended series. The dynamics of the two prices for the period 1982-2018 are reported in figure 1.

Figure 1 – *Actual vs. theoretical stock prices*



It is clear that real de-trended prices fluctuate more than the theoretical prices calculated on the basis of actual dividends. After computing the real detrended prices and the theoretical prices, we determine their respective log returns and price volatility (or standard deviation) by estimating a Garch (1, 1) model as in equations 6-8. Finally, we compute the standard deviations of the Shiller ratio.

4. Speculation Granger-causes stock price volatility

In this section we present two causality tests: first, we study the relation between scalping activity and stock price conditional volatility; second, we examine the relation between scalping activity and stock price volatility in terms of the Shiller ratio.

Granger-causality requires the series to be covariance stationary. Hence, we have implemented the Augmented Dickey-Fuller and Phillips Perron tests to verify the order of integration of each considered variable. Table 1 reports the results for the unit root tests. The null hypothesis H_0 of non-stationarity can be rejected at a 10% confidence level for all variables. In the case of theoretical prices, instead, the Phillips-Perron test points to the presence of a unit root in the series; therefore, we considered first differences to avoid spurious results.

Table *1 – Unit root tests, 1982-2018*

	Augmented Dickey-Fuller test statistic[1]		**Phillips-Perron test statistic**[2]			
	Level		Level		1st difference	
	t-Statistic	Prob.*	Adj. *t*-Statistic	Prob.*	Adj. *t*-Statistic	Prob.*
S&P 500 volatility, daily	-8.932	0.0000	-8.927	0.0000		
S&P 500 futures volatility, daily	-12.103	0.0000	-11.110	0.0000		
Scalping, daily	-3.314	0.0143	-16.063	0.0000		
Real detrended price volatility, monthly	-6.272	0.0000	-6.137	0.0000		
Theoretical price volatility, monthly	-2.851	0.0522	-2.499	0.1164	-14.683	0.0000
Shiller ratio, monthly	-3.636	0.0055	-4.881	0.0000		
Scalping, monthly	-5.253	0.0000	-4.890	0.0000		

Notes: *Ho*: The variable has a unit root; exogenous: constant.
* "MacKinnon" one-sided *p*-values.
[1] Lag Length: 0 (Automatic – based on SIC, maxlag = 22).
[2] Bandwidth: 7 (Newey-West automatic) using Bartlett kernel.

The subsequent step to implement the Granger-causality test is to detect the optimal lag-length of each bivariate VAR in levels. The lag order is determined by using the Akaike (AIC), the Schwarz (SC) and the Hannan-Quinn (HQ) information criteria. When the criteria are in disagreement, we select the lag length with which most of the criteria are in agreement.

We first consider the relation between scalping activity and stock price conditional volatility. Despite the fact that this measure has little theoretical content, it can give interesting statistical information on the relationships between speculation and stock price dynamics. Since the long-time frame of 36 years can mask changes in the economic environment and existing links for shorter time periods, we construct a finer grid of analysis, which consists of a sub-sample or a 1-year window (250 trading days), which is rolled ahead in one-day increments until the end of the sample (we also used 2-year, 3-year and 4-year windows and the results are similar). We obtain in total 9143 windows and, hence, 9143 cases of existing/non-existing Granger-causality relations. We report the percentages of cases falling in one of the four outcomes of Granger-causality in Table 2.

Table 2 – *Grange-causality tests, 1-year window (250 days/observations per window) with one-day rolling procedure. Total windows: 9143*

Futures	Scalp→ Vol	Vol→ Scalp	Scalp↔ Vol	Scalp≠ Vol	**SPOT**	Scalp→ Vol	Vol→ Scalp	Scalp↔ Vol	Scalp≠ Vol
% value on 9143 windows	62.17%	0.77%	29.54%	7.52%	% value on 9143 windows	60.50%	0.32%	33.38%	5.80%

We obtain three main results. First, speculation and price movements are highly interconnected: we obtain 92.5% cases of existing relations against 7.5% of no relations for futures price volatility. When spot price volatility is considered, the number of lead-lag and bidirectional relations between volatility and speculative activities increases to 94.2%, while the number of no relations decreases to 5.8%. Second, there is a significant evidence of Granger-causality from scalping activity to volatility (62.17% and 60.5% of cases for futures and spot prices). Third, there is poor evidence of Granger-causality from volatility to scalping activity (0.77% and 0.32% of cases) and more pronounced feedback relations (29.54% and 32% of cases). In a nutshell, it is more likely that price volatility follows speculation than vice-versa, and scalping activities drive price volatility for a larger number of cases. Finally, as regards the sign of causal relations, an increase of scalping activities tends to amplify price volatility: this is shown by the positive sign of short-run speculation in the variance of an EGARCH model (table 3a). As a robustness check, we have added to the variance equation the lagged value of the scalping index (table 3b) and the CBOE S&P 100 Volatility Index (VXO) in addition to the lagged value of the scalping index (table 3c). With these further controls, the sign for the scalping index stays positive and significant too.

Table 3a – *EGARCH, sign estimation*

Mean equation	Coefficient (*a*)	Std. error	Coefficient (*b*)	Std. error
Constant	0.000***	0.000	0.000***	0.000
AR(1)	-0.020*	0.011	0.035***	0.011
Variance equations				
Constant	-0.302***	0.014	-0.351***	0.015
Arch term	0.155***	0.006	0.172***	0.006
Asymmetric term	-0.095***	0.004	-0.117***	0.004
Garch term	0.980***	0.001	0.976***	0.001
Scalping	0.031***	0.001	0.034***	0.001

Notes: method: ML ARCH – Normal distribution (BFGS / Marquardt steps). Dependent variable: (*a*) spot returns and (*b*) future returns. Sample (adjusted): 27/4/1982 – 13/2/2018. Included observations: 9341 after adjustments. Convergence achieved after 47 and 42 iterations, respectively.

Table 3b – *EGARCH, sign estimation*

Mean equation	Coefficient (*a*)	Std. error	Coefficient (*b*)	Std. error
Constant	0.000***	0.000	0.000***	0.000
AR(1)	-0.021*	0.011	0.036***	0.011
Variance equations				
Constant	-0.304***	0.014	-0.365***	0.015
Arch term	0.153***	0.006	0.169***	0.006
Asymmetric term	-0.096***	0.004	-0.118***	0.004
Garch term	0.980***	0.001	0.975***	0.001
Scalping	0.031***	0.001	0.035***	0.001
Scalping (-1)	4.79E-05*	2.69E-05	0.0002***	2.80E-05

Notes: method: ML ARCH – Normal distribution (BFGS / Marquardt steps). Dependent variable: (*a*) spot returns and (*b*) future returns. Sample (adjusted): 27/4/1982 – 13/2/2018. Included observations: 9341 after adjustments. Convergence achieved after 45 and 55 iterations, respectively.

Table 3c – *EGARCH, sign estimation*

Mean equation	Coefficient (a)	Std. error	Coefficient (b)	Std. error
Constant	0.000***	0.000	0.000***	0.000
AR(1)	-0.030**	0.012	-0.029**	0.012
Variance equations				
Constant	-0.522***	0.014	-0.595***	0.028
Arch term	0.150***	0.007	0.159***	0.006
Asymmetric term	-0.118***	0.005	-0.138***	0.005
Garch term	0.963***	0.000	0.957***	0.000
Scalping	0.051***	0.001	0.0537***	0.000
Scalping (-1)	0.0001**	5.68E-05	0.0003***	6.01E-05
VXO	0.003***	0.0002	0.003***	0.000

Notes: method: ML ARCH – Normal distribution (BFGS / Marquardt steps). Dependent variable: (a) spot returns and (b) future returns. Sample (adjusted): 1/02/1986 – 2/13/2018. Included observations: 8379 after adjustments. Convergence achieved after 59 and 55 iterations, respectively.

We now conduct a second test which considers the relation between scalping activity and price volatility in terms of the Shiller ratio, as defined above. Given the monthly frequency of the data, we compute the Granger-causality test on the entire sample (table 4). As before, the optimal lag-length of the bivariate VAR is determined by using the classical information criteria.

Table 4 – *Pairwise Grange-causality tests*

Null hypothesis:	Obs.	F-Statistic	Prob.
Shiller ratio does not Granger-cause scalping	428	0.26983	0.7636
Scalping does not Granger-cause Shiller ratio		15.4531	3.E-07

Notes: sample: 1982M04-2018M02, lags: 2.

We obtain the following main results: first, there is evidence of Granger-causality from scalping activities to the Shiller ratio, given that we strongly reject the null that scalping does not Granger-cause the Shiller ratio, while we cannot reject the hypothesis that the Shiller ratio does not Granger-cause speculative activities. Second, the results hold true even when the discount factor used to compute the theoretical price changes (the discount factor is obtained by considering the entire price time series, as in Shiller (1981); however, the results also hold for discount factors computed within shorter periods). Third, using a supplementary EGARCH model to evaluate the sign of scalping activity in influencing the Shiller ratio, we find evidence of a positive relation between these variables; that is, the Shiller ratio increases when scalping activity increases. In particular, the sign of short-run speculation in the variance of the adopted EGARCH model is positive and equal to 0.35 (table 5).

Table 5 – *EGARCH, sign estimation*

Mean equation	Coefficient	Std. error
Constant	8.997***	1.138
AR(1)	0.846***	0.025
Variance equation		
Constant	-0.161***	0.026
Arch term	0.335***	0.030
Asymmetric term	0.337***	0.025
Garch term	0.955***	0.003
Scalping	0.353***	0.018

Notes: method: ML ARCH – Normal distribution (BFGS / Marquardt steps). Dependent variable: Shiller ratio. Sample (adjusted): 1982M06 – 2018M02. Included observations: 429 after adjustments. Convergence achieved after 78 iterations.

Fourth, we implement the Toda-Yamamoto (T-Y) methodology (Toda and Yamamoto, 1995). The T-Y methodology makes use of a Modified Wald statistic for testing the significance of the parameters of an augmented VAR (k + $dmax$) model, where k is the lag length in the system and dmax is the maximal order of integration in the model. This guarantees the asymptotic Chi square distribution of the Wald statistic. The lag lengths of the variables in the causal models are set according to the usual procedure to a possible integrated or cointegrated VAR. Since lagged dependent variables emerge in each equation of the causal models, their incidence is expected to remove serial correlation among residuals. The T-Y approach is an alternative causality testing approach based on the Granger non-causality equation, but augmented with extra lags determined by the potential order of integration of the series causally tested. In addition, the T-Y test is performed on VAR in levels. The results of T-Y displayed in table 6 confirm the findings identified with the traditional Granger-causality test, namely the relationship moves from scalping activities to the Shiller ratio.

Table 6 – *Toda-Yamamoto: modified Wald tests*

Excluded	**Chi-sq.**	**df**	**Prob.**
	Dependent variable: Scalping		
Shiller ratio	5.280964	3	0.1523
All	5.280964	3	0.1523
	Dependent variable: Shiller ratio		
Scalping	12.05955	3	0.0072
All	12.05955	3	0.0072

Notes: Sample: 1982M04 – 2018M02; included observations: 426; lags: 3.

Ultimately, our analysis shows that there is a causal relationship that ranges from speculation to the volatility of stock prices, while it does not find the opposite relationship. This result provides elements for identifying possible determinants of stock market volatility.

5. On the relations between stock prices, dividends and unemployment

The interest of the literature in the existence or not of “volatility” in Shiller’s sense has implied less attention not only to the possible determinants of volatility but also to the "fundamental" values towards which such volatility occurs and, more generally, to the possible relationships between stock prices and dividends on the one hand and macroeconomic trends on the other. The issues of “fundamentals” and of the links between the stock market and macroeconomic dynamics, as is known, are very complex and touch on profound theoretical problems. Here we want to just provide some preliminary analysis dedicated to a particular aspect of the matter. In fact, we limit ourselves to verifying the existence or not of Granger-causality between stock prices and dividends on the one hand, and unemployment on the other.

More specifically, we consider here the possible causal relationships between the US unemployment rate and unemployment level on the one hand and the actual rate of change (or growth) of stock prices and dividends on the other. We consider here two definitions of stock prices: the real detrended S&P 500 index (computed as shown in section 4 and the nominal not-detrended S&P 500 index (table 7). Applying the methodology described in section 4 to monthly data, we determine that stock price growth Granger-causes the unemployment rate and unemployment levels at a 5% significance level, but not vice versa. Then we assess the potential causal relationships between the dividends for all stocks in the S&P 500 index and the US unemployment rate (and unemployment level). We find that there is no relationship between S&P 500 dividends and unemployment, meaning that there exists no Granger-causality in either direction (neutrality hypotheses).

We further examine the signs of the relationships (table 8) and find that test-statistics for de-trended stock price growth and not-detrended S&P 500 stock price growth are negative and their *p*-values indicate that the coefficients of the variables are statistically significantly different from zero at the 1% level. This holds true when the alternative hypothesis that H_1: variable < 0 is tested (one tail test). This suggests that a rise in stock price growth reduces unemployment (rate and level) (table 7).

Table 7 – *Pairwise Granger-causality test*

Null hypothesis	Obs.	*F*-Statistic	Prob.
Price rate of change does not Granger-cause unemployment rate	428	3.309	0.0375
Unemployment rate does not Granger-cause actual price return		1.520	0.2199
Price rate of change does not Granger-cause unemployment level	428	4.666	0.0099
Unemployment level does not Granger-cause actual price return		0.553	0.5757
S&P 500 price rate of change does not Granger-cause unemployment rate	428	4.022	0.0186
Unemployment rate does not Granger-cause S&P 500 price return		0.904	0.4058
S&P 500 price rate of change does not Granger-cause unemployment level	422	2.612	0.0085
Unemployment level does not Granger-cause S&P 500 price return		1.530	0.1448
S&P 500 dividend does not Granger-cause unemployment rate	430	0.079	0.7782
Unemployment rate does not Granger-cause S&P 500 dividend		0.017	0.8960
S&P 500 dividend does not Granger-cause unemployment level	430	0.003	0.9541
Unemployment level does not Granger-cause S&P 500 dividend		0.084	0.7720

Notes: sample: 1982M04 – 2018M02. Lags selection based on information criteria.

Table 8 – *Sign significance tests*

			Two tails test		One tail test	
			H_0: variable = 0	H_1: variable ≠ 0	H0: variable = 0	H_1: variable < 0 or H1: variable > 0
Relation	Coefficient	Std. error	Test-stat.	*p*-value	Test-stat.	*p*-value
price rate of change → unemployment rate (*a*)	-0.067	0.035	-1.917	0.0560	-1.917	0.0276
price rate of change → unemployment level (*a*)	-0.056	0.034	-1.655	0.0987	-1.655	0.0490
S&P 500 price rate of change → unemployment rate (*a*)	-0.059	0.028	-2.103	0.0360	-2.103	0.0177
S&P 500 price rate of change → unemployment level (*a*)	-0.042	0.027	-1.553	0.1211	-1.553	0.0602

With 1 lag

			Two tails test		One tail test	
			H0: variable = 0	H_1: variable ≠ 0	H0: variable = 0	H_1: variable < 0 or H1: variable > 0
Relation	Coefficient	Std. error	Test-stat.	*p*-value	Test-stat.	*p*-value
price rate of change → unemployment rate (*a*)	-0.083	0.035	-2.370	0.0182	-2.370	0.0089
price rate of change → unemployment level (*a*)	-0.082	0.034	-2.443	0.0150	-2.443	0.0073
S&P 500 price rate of change → unemployment rate (*a*)	-0.067	0.028	-2.379	0.0178	-2.379	0.0087
S&P 500 price rate of change → unemployment level (*a*)	-0.079	0.027	-2.942	0.0034	-2.942	0.0016

Notes: conclusion: reject the null (variable = 0) in favour of the alternative (*a*) (variable < 0). Conclusion: reject the null (variable = 0) in favour of the alternative (*b*) (variable > 0).

The analysis therefore shows that there is a Granger-causality that goes from the growth of stock prices to unemployment but not vice versa and that, instead, there is no Granger-causality between dividends and unemployment.

Although this exercise is only preliminary, there are some reasons that lead us to believe that it represents further evidence in contrast to the traditional PVM. In the logic of this traditional model, in fact, the trend of unemployment should depend significantly on the fundamentals that contribute to determining the so-called "natural" equilibrium in the economic system. Therefore, according to the PVM, there should be a causal relationship ranging from unemployment to dividends, and a causal relationship ranging from unemployment to prices. Our exercise, however, does not confirm these directions of causality. It may also be interesting to notice that our results seem to be in contrast with the traditional PVM regardless of the assumptions we make about expectations. For example, it does not seem arguable that stock prices cause unemployment simply because they anticipate its trends. If this were the case, we should also detect an inverse causal relationship from unemployment to prices for any given shock in "fundamentals", and we should also detect a causal relationship between dividends and unemployment. But this is not the case. Future research could help verify the compatibility or not with the PVM of the results obtained in this and the previous section.

6. Conclusions

In this work we have shown that there is a Granger-causal positive relation from speculation to stock price volatility expressed in terms of either conditional volatility or the Shiller ratio; conversely, no Granger-causal relation seems to be detectable from volatility to speculation. Furthermore, we have shown that there is a Granger-causal inverse relation from stock prices to unemployment, while there is no causal relationship between dividends and unemployment.

Although the results can only be considered as preliminary, our particular application of Granger-causality to the stock market analysis offers some additional considerations around the debate that has developed on Shiller's tests and their implications for the traditional PVM. These further considerations are linked to a previous study on the theoretical neoclassical bases of PVM and Shiller's criticism and on a classical-Keynesian alternative view of the stock market (Brancaccio and Buonaguidi, 2019). In particular, the positive causal relationship from speculation to price volatility adds new elements for examining the possible determinants of stock price volatility; furthermore, the inverse causal relationship from prices to unemployment and the absence of causal relationships between unemployment and dividends offer further elements to assess whether and to what extent the traditional PVM and its variants or other theoretical interpretations of the stock market are supported by empirical evidence. From this point of view, Granger-causality analyses have already been used in order to compare antagonistic theories (see, among others, Palumbo, 1996; Leon-Ledesma and Thirlwall, 2002; Brancaccio et al., 2015; see also Lee and Cronin, 2016). The novelty of the present work is that the use of Granger-causality for the purpose of comparing alternative approaches is carried out with reference to the analysis of the stock market and its relations with macroeconomic variables. Our hope is that future empirical studies can contribute to a deeper "comparative" study (Brancaccio and Califano, 2018; Blanchard and Brancaccio, 2019) not only between the traditional PVM and the "imperfectionist" analyses resulting from Shiller's studies, but also between these two strands of mainstream research and alternative interpretations suggested by the critical approaches of economic theory and policy (Brancaccio and Buonaguidi, 2019; see also Sylos Labini, 1984, 2003; Corsi and Guarini, 2010; Bhaduri et al., 2006; Malikane and Semmler, 2008).

References

Abel A.B. (1990), "Asset Prices under Habit Formation and Catching up with the Joneses", *American Economic Review*, 80 (2), pp. 38-42.

Algieri B. (2016), "Conditional Price Volatility, Speculation, and Excessive Speculation in Commodity Markets: Sheep or Shepherd Behaviour?", *International Review of Applied Economics*, 30 (2), pp. 210-237.

Algieri B. and Leccadito A. (2019), “Price Volatility and Speculative Activities in Futures Commodity Markets: A Combination of Combinations of *p*-values Test”, *Journal of Commodity Markets*, 13 (C), pp. 40-54.
Antonakakis N., Floros C. and Kizys R. (2016), “Dynamic spillover effects in futures markets: UK and US evidence”, *International Review of Financial Analysis*, 48 (C), pp. 406-418.
Arnuk S. and Saluzzi J. (2012), *Broken Markets: How High Frequency Trading and Predatory Practices on Wall Street are Destroying Investor Confidence and Your Portfolio*, New Jersey: Financial Times Press.
Arrow K.J. (1983), “Behavior under Uncertainty and Its Implications for Policy”, in Stigmun B.P. and Wenstop F. (eds.), *Foundations of Utility and Risk Theory with Applications. Theory and Decision Library, vol. 37*, Dordrecht: Springer.
Bessembinder H. and Seguin P.J. (1993), “Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets”, *The Journal of Financial and Quantitative Analysis*, 28 (1), pp. 21-39.
Bhaduri A., Laski K. and Riese M. (2006), “A Model of Interaction Between the Virtual and the Real Economy”, *Metroeconomica*, 57 (3), pp. 412-427.
Black F. (1986), “Noise”, *The Journal of Finance*, 41 (3), pp. 528-543.
Blanchard O.J. and Watson M. (1982), “Bubbles, Rational Expectations and Financial Markets”, in Wachtel P. (ed.), *Crisis in the Economic and Financial Structure: Bubbles, Bursts, and Shocks*, Lexington: Lexington Press, pp. 295-316.
Blanchard O.J. and Brancaccio E. (2019), “Crisis and Revolution in Economic Theory and Policy: A Debate”, *Review of Political Economy*, 31 (2), pp. 271-287.
Bollerslev T. (1986), “Generalized Autoregressive Conditional Heteroskedasticity”, *Journal of Econometrics,* 31 (3), pp. 307-327.
Boswijk H.P., Hommes C.H. and Manzan S. (2007), “Behavioral Heterogeneity in Stock Prices”, *Journal of Economic Dynamic and Control*, 31 (6), pp. 1938-1970.
Brancaccio E., Fontana G., Lopreite M. and Realfonzo R. (2015), “Monetary Policy Rules and Directions of Causality: A Test for the Euro Area”, *Journal of Post Keynesian Economics*, 38 (4), pp. 509-531.
Brancaccio E. and Califano A. (2018), *Anti-Blanchard Macroeconomics. A Comparative Approach*, Cheltenham: Edward Elgar.
Brancaccio E. and Buonaguidi D. (2019), “Stock Market Volatility Tests: A Classical-Keynesian Alternative to Mainstream Interpretations”, *International Journal of Political Economy*, 48 (3), pp. 253-274.
Breeden D.T. (1980), “Consumption Risk in Futures Markets”, *Journal of Finance*, 35 (2), pp. 503-520.
Brown G. and Cliff M. (2005), “Investor Sentiment and Asset Valuation”, *The Journal of Business*, 78 (2), pp. 405-440.
Brunetti C., Büyüksahin B. and Harris J.H. (2016), “Speculators, Prices and Market Volatility”, *Journal of Financial and Quantitative Analysis,* 51 (5), pp. 1545-1574.
Büyüksahin B. and Harris J.H. (2011), “Do Speculators Drive Crude Oil Futures Prices?”, *The Energy Journal*, 32 (2), pp. 167-202.
Büyüksahin B. and Robe M.A. (2014), “Speculators, Commodities and Cross-Market Linkages”, *Journal of International Money and Finance,* 42 (C), 38-70.
Campbell J.Y. and Cochrane J. (1999), “By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior”, *Journal of Political Economy*, 107 (2), pp. 205-251.
Campbell J.Y. and Shiller R.J. (1988), “The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors”, *The Review of Financial Studies*, 1 (3), pp. 195-228.
Cerqueti R. and Costantini M. (2006), “Testing for Rational Bubbles”, *Economics and Statistics Discussion Papers*, University of Molise, Dept. EGSeI.
Chan K. (1992), “A Further Analysis of the Leadlag Relationship Between the Cash Market and Stock Index Futures Market”, *Review of Financial Studies*, 5 (1), pp. 123-152.
Cheng I-H., Kirilenko A. and Xiong W. (2015), “Convective Risk Flows in Commodity Futures Markets”, *Review of Finance*, 19 (5), pp. 1733-1781.
Cochrane J. (2005), *Asset Pricing*, Princeton: Princeton University Press.
Cochrane J. (2017), “Macrofinance”, *Review of Finance*, 21 (3), pp. 945-985.
Constantinides G.M. (1990), “Habit Formation: A Resolution of the Equity Premium Puzzle”, *Journal of Political Economy*, 98 (3), pp. 519-543.
Corsi M. and Guarini G. (2010), “Financial Crises and Cyclic Development According to the Approach of Paolo Sylos Labini”, *Journal of Applied Economic Science*, 5 (1), pp. 30-42.
Cutler D.M., Poterba J.M. and Summers L.H. (1990), “Speculative Dynamics and the Role of Feedback Traders”, *The American Economic Review*, 80 (2), pp. 63-68.
Cutler D.M., Poterba J.M. and Summers L.H. (1991), “Speculative Dynamics”, *Review of Economic Studies*, 58 (3), pp. 529-546.
De Bondt W.F. and Thaler R. (1985), “Does the Stock Market Overreact?”, *The Journal of Finance*, 40 (3), pp. 793-805.
Deuskar P. and Johnson T. (2011), “Market Liquidity and Flow-Driven Risk”, *The Review of Financial Studies*, 24 (3), pp. 721-753.
Dezhbakhsh H. and Demirguc-Kunt A. (1990), “On the Presence of Speculative Bubbles in Stock Prices”, *Journal of*

Financial and Quantitative Analysis, 25 (1), pp. 101-112.
Diba B.T. and Grossman H.I. (1988), "Exploding Rational Bubbles in Stock Prices?", *The American Economic Review*, 78 (3), pp. 520-530.
Engle R.F. (2004), "Risk and Volatility: Econometric Models and Financial Practice", *The American Economic Review*, 94 (3), pp. 405-420.
Epstein L.G. and Zin S.E. (1989), "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework", *Econometrica*, 57 (4), pp. 937-969.
Fama E. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance*, 25 (2), pp. 383-417.
Flavin M.A. (1983), "Excess Volatility in the Financial Markets: A Reassessment of the Empirical Evidence", *Journal of Political Economy*, 91 (6), pp. 929-956.
Froot K.A, Scharfstein D. and Stein J.C. (1992), "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation", *Journal of Finance,* 47 (4), pp. 1461-1484.
Garcia P., Leuthold R. and Zapata H. (1986), "Lead-Lag Relations Between Trading Level and Price Variability: New Evidence", *Journal of Futures Markets*, 6 (1), pp. 1-10.
Gilles C. and Leroy S.F. (1991), "Econometric Aspects of the Variance Bounds Tests: A Survey", *The Review of Financial Studies*, 4 (4), pp 753-791.
Ghosh A. (1993), "Cointegration and Error Correction Models: Intertemporal Causality Between Index and Futures Prices", *Journal of Futures Markets*, 13 (2), pp. 193-198.
Granger C.W.J. (1969), "Investigating Causal Relations by Econometric Methods and Cross-Spectral Methods", *Econometrica*, 34 (1), pp. 424-438.
Grossman S.J. and Shiller R.J. (1981), "The Determinants of the Variability of Stock Market Prices", *American Economic Review,* 71 (2), pp. 222-227.
Hamilton J.D. and Wu J.C. (2015), "Effects of Index-Fund Investing on Commodity Futures Prices", International Economic Review, 56 (1), pp. 187-205.
Hansen L.P. and Singleton K.J. (1983), "Stochastic Consumption, Risk Aversion and the Temporal Behavior of Asset Returns", *Journal of Political Economy*, 91 (2), pp. 249-265.
Keynes J.M. (1936), *The General Theory of Employment, Interest and Money*, London: Macmillan.
Kim A. (2015), "Does Futures Speculation Destabilize Commodity Markets?", *The Journal of Futures Markets*, 35 (8), pp. 696-714.
Kleidon A.W. (1986), "Variance Bound Tests and Stock Price Valuation Models", *Journal of Political Economy*, 94 (5), pp. 953-1001.
Kyle A.S. (1985), "Continuous Auctions and Insider Trading", *Econometrica*, 47 (6): 1315-1336.
Lee F. and Cronin B. (2016), *Handbook of Research Methods and Applications in Heterodox Economics*, Cheltenham: Edward Elgar.
Leroy S.F. (1996), *Stock Price Volatility*, in Maddale G.S. and Rao C.R. (eds.), *Handbook of Statistics,* vol. 14, Amsterdam: Elsevier, pp. 193-208.
Leroy S.F. (2004), "Rational Exuberance", *Journal of Economic Literature*, 42 (3), pp. 783-804.
Leroy (2018), "Excess Volatility Tests", in Durlauf S.N. and Blume L.E. (eds.), *The New Palgrave Dictionary of Economics*, London: Palgrave Macmillan.
Leon-Ledesma M. and Thirlwall A.P. (2002), "The Endogeneity of the Natural Rate of Growth", *Cambridge Journal of Economics*, 26 (4), pp. 441-459.
Lucas R.E. (1978), "Asset Prices in an Exchange Economy", *Econometrica*, 46 (6), pp.1429-1445.
Lucia J.J. and Pardo A. (2010), "On Measuring Speculative and Hedging Activities in Futures Markets from Level and Open Interest Data", *Applied Economics*, 42 (12), pp. 1549-1557.
Malikane C. and Semmler W. (2008), "Asset Prices, Output and Monetary Policy in a Small Open Economy", *Metroeconomica*, 59 (4), pp. 666-686.
Manera M., Nicolini M. and Vignati I., (2013), "Futures Price Volatility in Commodities Markets: The Role of Short Term vs Long Term Speculation", *University of Milano-Bicocca Working Paper*, n. 243, Milano: University of Milano-Bicocca, Department of Economics.
Marsh T.A. and Merton R. (1986), "Dividend Variability and Variance Bounds Tests for the Rationality of Stock Market Prices", *American Economic Review*, 76 (3), pp. 483-498.
Mehra R. (2006), "The Equity Premium Puzzle: A Review", *Foundations and Trends in Finance*, 2 (1), pp. 1-81.
Mehra R. and Prescott E.C. (1985), "The Equity Premium: A Puzzle", *Journal of Monetary Economics*, 15 (2), pp. 145-161.
Morck R., Yeung B. and Yu W. (2000) "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?" *Journal of Financial Economics*, 58 (1), pp. 215-260.
Ofek E. and Richardson M. (2003), "DotCom Mania: The Rise and Fall of Internet Stock Prices", *The Journal of Finance*, 58 (3), pp. 1113-1137.
Palumbo A. (1996), "Notes on Investment, Saving and Growth", *Contributions to Political Economy*, 15 (0), pp. 105-115.

Poon S.H. and Granger W.J. (2003), "Forecasting Volatility in Financial Markets: A Review", *Journal of Economic Literature*, 41 (2), pp. 478-539.
Scheinkman J. and Xiong A. (2003), "Overconfidence and Speculative Bubbles", *Journal of Political Economy*, 111 (6), pp. 1183-1219.
Shleifer A. and Summers L.H. (1990), "The Noise Trader Approach to Finance", *Journal of Economic Perspectives,* 4 (2), pp. 19-33.
Shiller R.J. (1981), "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?", *The American Economic Review*, 71 (3), pp. 421-436.
Shiller R.J. (1984), "Stock Prices and Social Dynamics", *Brookings Papers on Economic Activity*, 2, pp. 457-498.
Shiller R.J. (1989), *Market Volatility*, Cambridge, MA: MIT Press.
Shiller R.J. (2003), "From Efficient Markets Theory to Behavioral Finance"**,** *The Journal of Economic Perspectives*, 17 (1), pp. 83-104.
Shiller R.J. (2015), *Irrational Exuberance*, Princeton: Princeton University.
Singleton K.J. (2014) "Investor Flows and the 2008 Boom/Bust in Oil Prices", *Management Science*, 60 (2), pp. 300-318.
Stoll H.R. and Whaley R.E. (2010), "Commodity index investing and commodity futures prices", *Journal of Applied Finance,* 20 (1), pp. 7-46.
Summers L.H. (1986), "Does the Stock Market Rationally Reflect Fundamental Values?", *The Journal of Finance*, 41 (3), pp. 591-601.
Sylos Labini P. (1984), *Le Forze dello Sviluppo e del Declino*, Roma-Bari: Laterza.
Sylos Labini P. (2003), "Le Prospettive dell'Economia Mondiale", *Moneta e Credito*, 223, pp. 267-295.
Tao J. and Green C.J., (2012), "Asymmetries, Causality and Correlation Between FTSE100 Spot and Futures: A DCC-TGARCH-M Analysis", *International Review of Financial Analysis*, 24 (C), pp. 26-37.
Tirole J. (1985), "Asset Bubbles and Overlapping Generations", *Econometrica*, 53 (6), pp. 1499-1528.
Toda H.Y. and Yamamoto T. (1995), "Statistical Inference in Vector Autoregressions with Possibly Integrated Processes", *Journal of Econometrics*, 66 (1-2), pp. 225-250.
Wang J. (2018), "Finance (New Developments)", in Durlauf S.N. and Blume L.E. (eds.), *The New Palgrave Dictionary of Economics*, 2nd ed., vol. 3, London: Palgrave Macmillan.
Weiner R.J. (2002), "Sheep in Wolves Clothing? Speculators and Price Volatility in Petroleum Futures", *Quarterly Review of Economics and Finance*, 42 (2), pp. 391-400.
West K.D. (1988), "Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation", *Journal of Finance*, 43 (3), pp. 636-656.

Appendix 1 – Additional data and descriptive statistics

Figure A1 – *S&P 500 price dynamics*

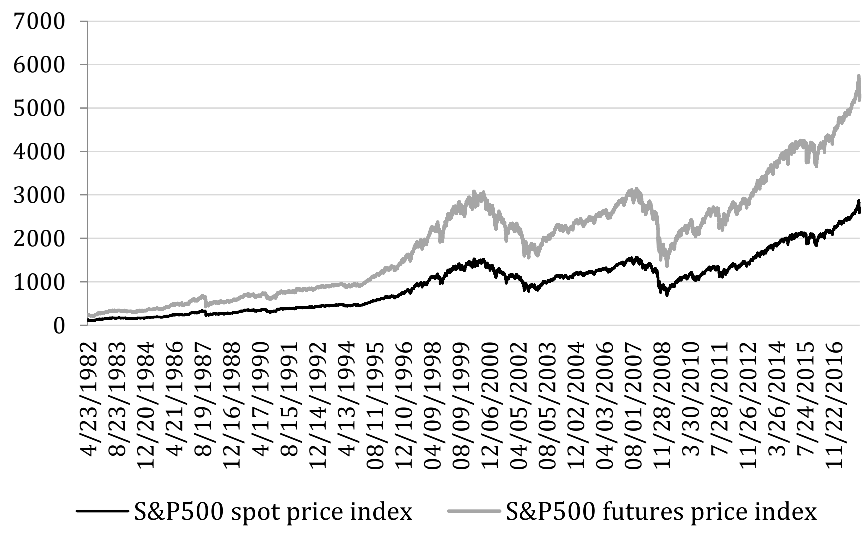


Figure A2 – *Conditional volatility of S&P 500 stock index and S&P 500 stock index futures, daily basis*

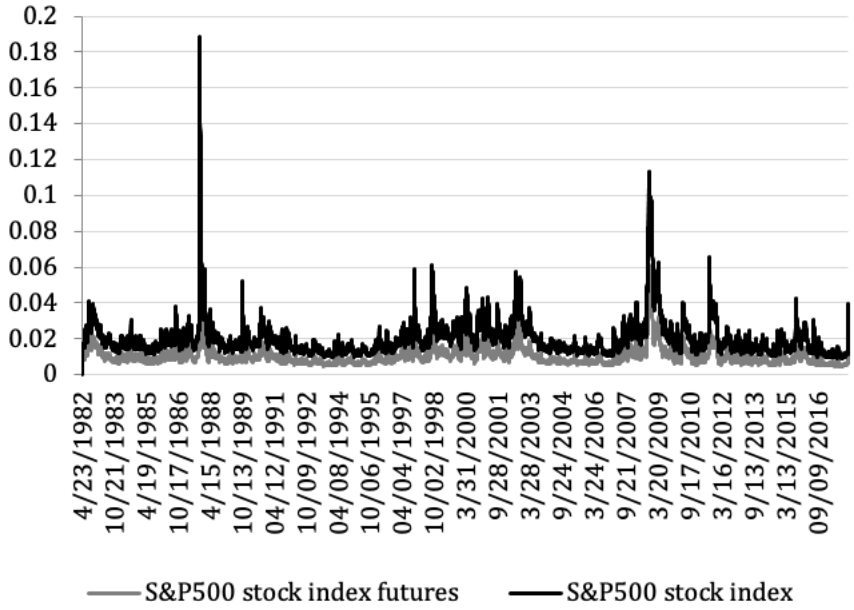


Figure A3 – *Scalping index, daily basis*

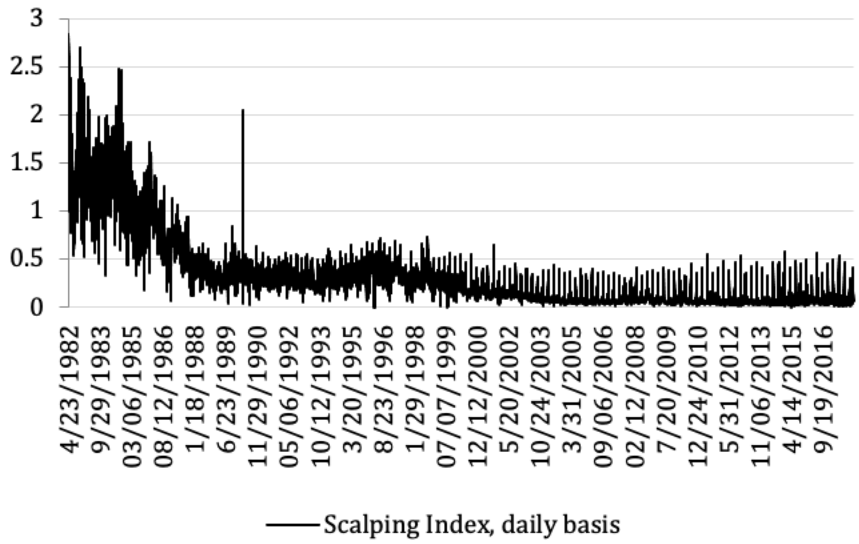


Table A1 – *Descriptive statistics, daily 23/04/1982 – 13/02/2018*

	S&P 500 stock index	**S&P 500 stock index futures**	**S&P 500 stock returns**	**S&P 500 stock futures returns**
Mean	960.9240	962.1463	0.000333	0.000332
Maximum	2872.870	2874.500	0.109572	0.177493
Minimum	102.4200	102.0500	-0.228997	-0.337004
Std. dev.	624.6544	623.5835	0.010970	0.011952
Skewness	0.519957	0.512841	-1.214730	-2.244169
Kurtosis	2.546840	2.535869	31.76106	83.67191
Jarque-Bera	500.8767	493.3515	324284.5	2541064.
Prob.	0.000000	0.000000	0.000000	0.000000
Obs.	9342	9342	9342	9342

Table A2 – *Descriptive statistics, daily 23/04/1982 – 13/02/2018*

	Volume	**Open interest in futures market**	**Scalping index**	**S&P 500 volatility futures**	**S&P 500 volatility spot**
Mean	55279.36	284967.4	0.330222	0.010474	0.009753
Maximum	397866.0	819796.0	2.839400	0.119240	0.069191
Minimum	160.0000	1304.000	0.001483	0.004531	0.004444
Std. dev.	44009.56	207654.6	0.385293	0.006150	0.005083
Skewness	1.691234	0.658738	2.265332	6.336435	4.151594
Kurtosis	7.501075	2.090764	8.557455	76.52152	31.08028
Jarque-Bera	12339.52	997.4346	20012.21	2166571.	333760.5
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	9342	9342	9342	9342	9342

Appendix 2 – Method for de-trending real stock log prices

Step 1: we estimate real log stock price, as shown in the table below.

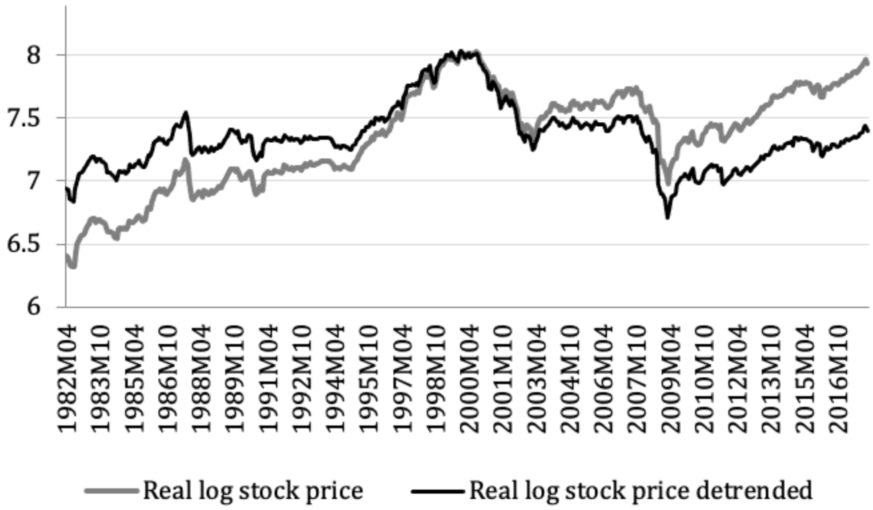
Table A3 – *Real log stock price*

	Coefficient	Std. error	Prob.
Constant	6.827	0.025	0.0000
@TREND	0.002	9.93E-05	0.0000
R-squared	0.588	Mean dep. var.	7.355
Adjusted *R*-squared	0.587	S.D. dep. var.	0.399
S.E. of regression	0.256	AIC	0.121
Sum squared resid	28.225	BIC	0.140
Prob(*F*-statistic)	0.0000		

Notes: dependent variable: real log stock prices, obs.: 431,1982M04 – 2018M02. Method: Ordinary Least Squares.

Step 2: to the estimated residuals, we add the sample mean real log stock price; the resulting series are the de-trended real stock prices.

Figure A4 – *De-trended real stock prices*



The descriptive statistics for the effective and theoretical prices are reported in table A4. It is interesting to notice that the standard deviations of the effective and theoretical prices are relevantly different. This would suggest high variability between the two considered prices.

Table A4 – *Descriptive statistics: effective and theoretical prices*

	Effective price	**Theoretical price**
Mean	1685.606	954.6240
Median	1673.211	893.3640
Maximum	3069.799	1394.557
Minimum	555.2199	806.3857
Std. dev.	621.5198	146.4839
Skewness	0.217530	1.728656
Kurtosis	2.110244	4.777917
Jarque-Bera	17.61609	271.4221
Probability	0.000150	0.000000
Sum	726496.2	411442.9
Sum sq. dev.	1.66E+08	9226734.
Observations	431	431

We then calculate the log price rates of change and extract the conditional price volatility for the effective and theoretical Shiller prices from a GARCH model (standard way to get volatility).

Figure A5 – *Log theoretical and effective price rates of change*

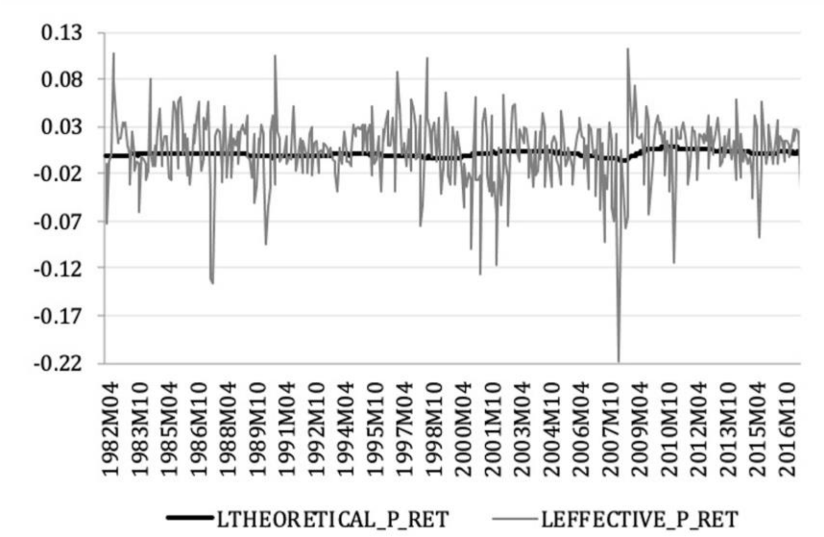
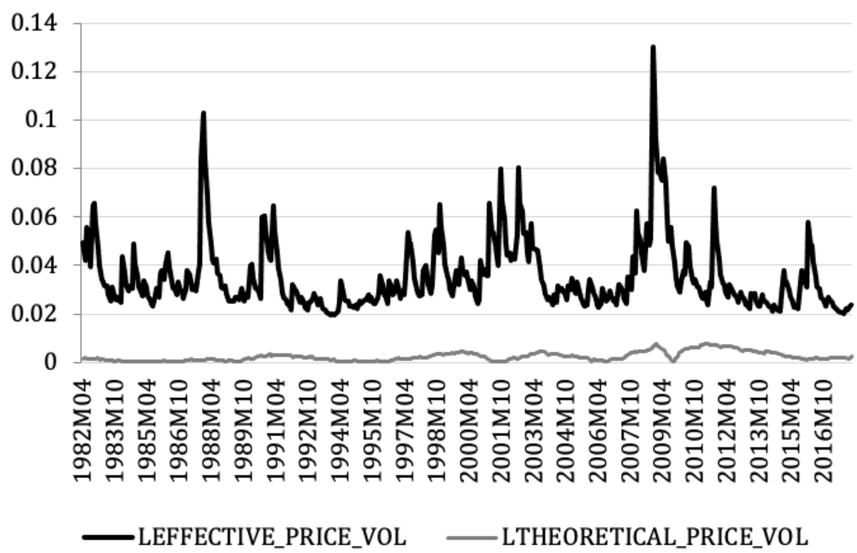


Figure A6 – *Log theoretical and effective price conditional volatility*



Dividend yield

The dividend yield for an index is the total dividend amount for the index, expressed as a percentage of the total market value for the constituents of that index.

For sectors, dividend yield is derived by calculating the total dividend amount for a sector and expressing it as a percentage of the total market value for the constituents of that sector.

This provides an average of the individual yields of the constituents weighted by market value. It is calculated as follows:

$$DY_t = \frac{\sum_1^n (D_t * N_t)}{\sum_1^n (P_t * N_t)} * 100$$

where: DY_t = aggregate dividend yield on day t; D_t = dividend per share on day t; N_t = number of shares in issue on day t; P_t = unadjusted share price on day t; n = number of constituents in index.