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Time-Varying Correlations between Inflation and Stock Prices in the United States over the Last Two Centuries

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Abstract

The relationship between stock prices and the inflation can be either negative or positive, depending on the strengths of various theoretical channels at work. While previous studies have primarily examined this relationship in a time-invariant framework, and if at all a time-varying framework is used, it has been restricted to the post World War II period. Given this, we employ a time-varying approach to examine the dynamic correlations of inflation and stock prices in the United States over the period of 1791 to 2015. The results of our empirical analysis reveal that correlations between the inflation and stock prices in the United States evolve heterogeneously overtime. In particular, the correlations are significantly positive in the 1840s, 1860s, 1930s and 2011, and significantly negative otherwise. The policy implications of these findings are then discussed.

Keywords: Conditional correlation, GARCH, Inflation and Stock Price Comovement, US Economy

JEL codes: C32, C50, E31, E44, G1, N1

1. Introduction

Stock prices are considered to be a leading indicator for economic activity of the U.S. economy (Stock and Watson, 2003; Rapach and Weber, 2004), and hence, determining what factors drive this market is of paramount importance. While stock prices are primarily driven by financial variables (Valcarcel, 2012), the importance of macroeconomic variables cannot be ruled out either (Goyal and Welch, 2008; Valcarcel, 2012, Rapach and Zhou, 2013). Inflation is undoubtedly one of the most important macroeconomic variables believed to be related to stock prices, and in turn, also affected by it (Gupta and Inglesi-Lotz, 2012).

While inflationary shocks may have little long-run impact on real stock returns, due to monetary non-neutrality, it is generally agreed that stock prices can be affected by inflation in the short-run (Rapach, 2002; Bjørnland and Leitemo, 2009; Valcarcel, 2012; Bjørnland and Jacobsen, 2013). In this regard, there are many channels through which inflation can affect stock prices, with the effect being either positive or negative depending upon the theory in consideration. The Gordon (1962) growth model shows that stock prices are directly related to current and expected growth rates of dividend returns and inversely related to the required rate of return on the equity. Given this, inflation has a positive impact on stock prices through two channels: First, a monetary easing that stimulates the economy along with inflation would have a positive impact on the growth rate of dividends. Second, a monetary expansion that depresses bond returns would result in an increased demand for equities, which in turn, would cause the average investor to lower expected rate of returns of equities. Whether it is increased dividend returns or decreased expected returns on investment, both serve to put raise stock prices. The posibility of inflation leading to lower stock returns also has multiple explainations. First, as discussed in Modigliani and Cohn (1979), agents could discount asset valuations at an artificially high rate in the presence of sustained inflation, as it is difficult to distinguish between real and nominal returns when the latter includes an inflation premium. Second, Feldstein (1980) points out that sustained increases in inflation reduces real stock prices since the tax code exerts a distortionary effect between depreciation costs and capital gains. Third, Fama (1981), based on his proxy-effect hypothesis (PEH), believes that the negative correlation is induced by a positive relationship between stock returns and expected economic activity (as proxied by inflation) and an inverse relationship between expected economic activity and inflation. Finally, as pointed out by Sargent

(1999), and Cogley and Sargent (2001), if the monetary authority, under the the assumption of an exploitable trade-off between inflation and unemployment, succumbs to the temptation to inflate (until time-consistent inflation rates are achieved), the resulting higher expectations of inflation would increase long-term rates leading investors to more aggressively discount future dividends (Valcarcel, 2012). At the same time, the subsequent contractionary monetary policy actions could also contribute to lower stock returns due to slowing down of economic activity and, thus, depressing current and expected future earnings (Valcarcel, 2012). Hence, theoretically, inflation can either increase or decrease stock prices.

At the same time, real stock price movements can affect the inflation rate through the wealth-effect, i.e., via its impact on consumption and hence aggregate demand. Ludwig and Sløk (2004), and more recently Simo-Kengne et al., (2015), discusses four different channels of influence for stock prices on consumption: First, the realised wealth effect implies that an increase in stock prices exerts a direct positive effect on stockholders' consumption as a consequence of the realised gain. Second, the unrealised wealth effect refers to the increase in consumption spending based on the expectation that raising the current stock price will result in higher future income and wealth. Third, the liquidity constraint effect implies that increasing stock prices raise the value of collateral against which financially constraint households may borrow to increase their consumption. Fourth, the stock option value effect, implies that an increase in stock prices leads to the increase in the value of stockholders options which may translate into higher consumption irrespective of whether the gains are realised or unrealised. In other words, real stock prices and inflation is likely to be positively related through the wealth effect.

Against this backdrop, the objective of our study is to analyse the evolution of the correlation between real stock price and inflation for the US economy using Engle (2002) dynamic conditional correlation (DCC)-GARCH model on annual data over the period of 1791-2015. As discussed above, the relationship between real stock prices (returns) and inflation is contingent upon the strength of the various channels at a specific point in time or over a certain period. Hence, there is a need to pursue a time-varying approach especially when we account for the long-span of data under investigation. Similar thoughts were also echoed in the works of Durham (2003) and He (2006). Besides accounting for time-varying conditional volatility behaviour of

data (given the abundant empirical evidence of a substantial decline in the volatility of most US macroeconomic aggregates (Valcarcel, 2012)), a major advantage of the DCC-GARCH approach is its ability to detect changes in the conditional correlation over time. Moreover, it is able to distinguish negative correlations due to episodes in single years, synchronous behavior during stable years and asynchronous behavior in turbulent years. Unlike rolling windows, an alternative way to capture time variability, the proposed measure does not suffer from the so-called "ghost features", as the effects of a shock are not reflected in *n* consecutive periods, with *n* being the window span. In addition, under the proposed measure there is neither a need to set a window span, nor loss of observations, nor subsample estimation required.

As discussed above, contingent on the signs of the channels at work, the relationship between real stock price and inflation could be either negative or positive, as also highlighted by Valcarcel (2012). Hence, it is important to pursue a time-varying approach for analyzing the conditional comovement between these variables to check the evolution of this relationship. The DCC-GARCH approach allows us to check if, in fact the relationship is indeed time-varying (state-contingent) or not, besides the nature of the relationship itself.

A constant parameter approach, as has been primarily applied so far in the literature (see for example Hess and Lee, 1999; Rapach, 2001; Binswanger, 2004; He, 2006; Lee, 2010; Gupta and Inglesi-Lotz, 2012; Valcarcel, 2012; and references cited there in for detailed literature reviews), based on an average value of the correlation estimate, which is generally negative, is likely to be misleading in terms of policy, as it will not allow the policy maker to deduce the importance of the various effects that drive this relationship at specific points in time. To the best of our knowledge, Valcarcel (2012) is the only paper that has used a time-varying Vector Autoregressive (VAR) model to analyze the relationship between real stock returns and inflation for the US economy over the quarterly period of 1955:1 to 2011:2. So, in this regard, our paper can be considered to be an extension of the work of Valcarcel (2012) by considering the longest possible sample period spanning over two centuries of annual data tracking the history of U.S. inflation in relationship to stock prices. In addition, we also check whether our results are robust to data frequency using a monthly data set of real stock returns and inflation spanning nearly 150 years (1871-2015).

At this stage, it is important to indicate the reasons behind our preference to use a DCC-GARCH approach rather than a time-varying VAR method. First, as is well-known, identifying shocks in a VAR would require us to order the real stock returns and inflation. However, at an annual frequency, it is difficult to postulate which variable can be ordered first i.e., believed to be more exogenous. Of course, one could reverse the ordering and check for the robustness of the results. But then again, this would not guard against the possibility that the degree of exogeneity over such a long-span of data did not vary over time. An alternative approach would have been to use sign-restricted time-varying VAR, but this would take away from us the very essence of our exercise of deciphering the correlation between these two variables, which as indicated above could be either positive or negative. In other words, one could not have without doubt imposed a theory-based sign either. Keeping these issues in mind, we decided to resort to a DCC-GARCH approach, which provides us with a time-varying correlation between these two variables accounting for heteroscedastic disturbances, without having to worry about the ordering of variables or sign-restrictions in a VAR model. Having said this, one limitation of our approach, given the long-span of data, is our inability to control for other important variables (like interest rate, output and or/unemployment) which are likely to affect both inflation and stock prices. In such a multivariate setting, a VAR approach as used by Valcarcel (2012) is preferable, as it also allows us to analyze the importance of the other variables (shocks) in the relationship between stock prices and inflation. Nevertheless, given that our concern is a time-varying analysis of correlation between these two variables, the DCC-GARCH framework can be considered most appropriate in our context.

Our empirical results reveal that correlations between inflation and stock market returns are indeed evolving heterogeneously overtime. In particular, the correlations are significantly positive in the 1840s, 1860s, 1930s and 2011, and significantly negative otherwise, indicating the time-varying role relating the stock market with inflation in the U.S. Our main results based on annual data do not suffer from time aggregation bias, as employing a shorter monthly dataset between January 1871 and October 2015 leads to very similar conclusions.

The remainder of the paper is organized as follows: Section 2 describes the empirical methodology, while Section 3 the data used. Section 4 presents the empirical findings. Finally, Section 5 summarises the results, discusses their policy implications and offers some concluding remarks.

2. Methodology

In order to examine the evolution of co-movements between inflation and stock market returns, we obtain a time-varying measure of correlation based on the dynamic conditional correlation (DCC) model of Engle (2002).

Let $y_t = [y_{1t}, y_{2t}]'$ be a 2×1 vector comprising the data series (i.e. inflation and real stock market returns). The conditional mean equations are then represented by

$$A(L)y_t = \varepsilon_t, \;\; where \;\; \varepsilon_t|\Omega_{t-1} \sim N(0, H_t), \;\; and \;\; t = 1, \ldots, T \tag{1}$$

where A is a matrix of endogenous variables, L the lag operator and ε_t is the vector of innovations based on the information set, Ω, available at time $t-1$. The ε_t vector has the following conditional variance-covariance matrix

$$H_t = D_t R_t D_t, \tag{2}$$

where $D_t = diag\sqrt{h_{it}}$ is a 2×2 matrix containing the time-varying standard deviations obtained from univariate GARCH(p,q) models as

$$h_{it} = \gamma_i + \sum_{p=1}^{P_i} \alpha_{ip}\varepsilon_{it-ip}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{iq-q}, \quad \forall i = 1,2. \tag{3}$$

The DCC(M,N) model of Engle (2002) comprises the following structure

$$R_t = Q_t^{*-1} \mathrm{Q}_t Q_t^{*-1}, \tag{4}$$

where

$$Q_t = (1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n)\bar{Q} + \sum_{m=1}^{M} a_m(\varepsilon_{t-m}^2) + \sum_{n=1}^{N} b_n Q_{t-n}. \tag{5}$$

$\bar{Q}$ is the time-invariant variance-covariance matrix retrieved from estimating equation (3), and Q_t^* is a 2×2 diagonal matrix comprising the square root of the diagonal elements of Q_t. Finally, $R_t = \rho_{ij_t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$ where $i, j = 1,2$ is the 2×2 matrix consisting of the conditional correlations between inflation and stock market returns, and which are our main focus.

3. Data

The two main variables of interest in this paper are inflation and the stock market prices in the US over the period of 1791-2015, i.e., 225 observations. Inflation, INF, is measured as the difference of the natural logarithm of the consumer price index (CPI), and stock market prices are measured in real terms, i.e. deflated by the consumer price index (CPI) and then converted in real stock market returns, RSR, by taking the first difference of the natural logarithm of real stock prices, so as to render the series stationary. The CPI data comes from the website of Professor Robert Sahr.[1] The nominal S&P500 stock price, which is deflated by the consumer price index (CPI) to get the real S&P500, comes from Global Financial Database.

[1] http://liberalarts.oregonstate.edu/spp/polisci/research/inflation-conversion-factors-convert-dollars-1774-estimated-2024-dollars-recent-year.

Figure 1 presents the evolution of inflation and real stock market returns. According to this figure, we observe the severe decline in the stock market during the Great Depression and the hyperinflation of 1864 during the Civil War in the US.

[Insert Figure 1 around here]

Table 1 presents the descriptive statistics of our data. According to this table, we observe large variability in our main variables, especially of the stock market returns. Over the last 225 years, the stock market in the United States has generated on average positive real returns equal to 1.58%, while inflation was on average 1.44%. The augmented Dickey-Fuller (ADF) test with just a constant indicates that both series are stationary. The fact that the ARCH-LM test rejects the null hypothesis of homoskedasticity for each series indicates the appropriateness of modelling our series as an ARCH-type process. Finally, the unconditional correlation between the trade balance and real stock market returns, which is presented in the lower panel of Table 1, is negative and equal to -0.2284.

[Insert Table 1 around here]

4. Estimation Results

Table 2 reports the results of the DCC model. Panels A and B present the conditional mean and variance results, respectively, while Panel C contains the Ljung-Box Q-Statistics on the standardized and squared standardized residuals up to 10 lags. The choice of the lag-length of the autoregressive process of the conditional mean, which is equal to one, is based on the Akaike information criterion (AIC) and Schwarz Bayesian criterion (BIC).

[Insert Table 2 around here]

According to the conditional mean results reported in Table 2, we find that past real stock market returns are associated with significant increases in the current real stock market returns and

inflation, while past inflation is associated with increased current inflation and reduced current real stock market returns.

The conditional variance results reported in the same table support the existence of the GARCH effects found in the series, as the coefficients α_1 and β_1 are highly significant. Moreover, the coefficients a and b are highly significant indicating that the correlations between inflation and real stock market returns are indeed time-varying. Both these results validate the choice of the DCC model. Finally, the model does not suffer from serial correlation in the squared (standardized) residuals, according to the misspecification tests reported in Panel C of Table 2.

In Figure 2, we present the dynamic conditional correlations of inflation and real stock market returns from the model in Table 2, along with their 90% confidence intervals. According to this figure, it is evident that dynamic conditional correlations between inflation and real stock market returns behaved rather heterogeneously overtime. In particular, correlations are significantly positive in the 1840s, 1860s, 1930s and 2011, and significantly negative otherwise (with the result being in line with Valcarcel (2012) post-1960), indicating the time-varying role relating the stock market with inflation in the U.S.[2] If we look at Figure 1, then one would realize that these are periods of deflationary episodes (as well as periods of major or post-recessions) for the US economy, with negative returns on real stock prices. That is, lower stock returns could have resulted in lower consumption, and hence aggregate demand and inflation through the wealth effect. Or, the Gordon (1962) growth model could be at work as well, which, in turn posits a positive relationship between inflation and stock returns, with possibly a role of monetary contraction in this case resulting in a negative impact on dividend growth and higher bond returns. These two effects both depress the equity market and its returns.

[Insert Figure 2 around here]

4.1. Robustness analysis

[2] When we used nominal stock returns instead of real stock returns, we obtained similar correlation patterns over the sample. Complete details of these results are available upon request from the authors.

As a robustness check, we examine whether our dynamic conditional correlation results of inflation and real stock market returns based on annual data suffer from time aggregation bias. In particular, we employ a monthly dataset between inflation and real stock market returns over the period January 1871 to November 2015 (i.e. 1739 monthly observations) obatined from the online data segment of Professor Robert J. Shiller.[3] Note that the start and end points of the sample is driven by data availability of the monthly CPI. Inflation and real stock market returns, which are defined as the 12th difference (i.e. year-over-year rates) of the natural logarithm of CPI and CPI deflated stock market returns, respectively, are plotted in Figure 3.

[Insert Figure 3 around here]

The results of the DCC-GARCH model based on this dataset, which are available upon request, lead to similar conclusions. Specifically, the monthly dynamic conditional correlations between inflation and real stock market returns that are presented in Figure 4, reveal a positive comovement between the two series during the 1930s, WWII, and 2010-2011.[4] These correlation patterns which are very similar to those based on annual data provide additional robustness to our findings.[5]

[Insert Figure 4 around here]

5. Conclusion

The aim of this study was to examine time-varying correlation between inflation and real stock market returns, in a time-varying framework over the period 1791-2015 in the United States. The results of our empirical analysis, which remain robust to alternative frequencies, reveal that correlations between the inflation and stock market returns in the United States are evolving

[3] http://www.econ.yale.edu/~shiller/data.htm.

[4] As with the annual data, using nominal stock returns produced similar correlation patterns over the sample. Complete details of these results are available from the authors upon request.

[5] As a final robustness check, we converted the monthly series into quarterly frequency by taking average over three months, and re-estimated the DCC model in order to compare the results with those of Valcarcel (2012) over the post-1960 period, since he uses a data set at quarterly frequency. These results, which are available upon request from the authors, are again in line with both our main findings based on annual and monthly frequency, and those of Valcarcel (2012) (understandably, over the post-1960 period).

heterogeneously overtime. In particular, the correlations are significantly positive in the 1840s, 1860s, 1930s and 2011, and significantly negative otherwise. These results indicate that, though in general real stock returns and inflation are negatively related, there is no guarantee that lower inflation rates could boost the health of the stock market, as the state of the economy at a specific point in time, governed by the various channels affecting these two variables, needs to gauged first. Put alternatively, from a policy perspective, if lower inflation rates are associated with tighter monetary policy, then for the monetary authority to control a speculative bubble in the stock market (considering that bubbles can in fact be pricked by policy in the first place)[6], one would need to ensure that when the policy change is undertaken, the relationship between real stock prices and inflation is, in fact, negative. In other words, policy makers aiming to affect the stock market through monetary policy need to continuously update their information set relating these two variables at the time of making an appropriate policy decision, since the relationship between these variables is time-varying and could be either positive or negative.

Given that the focus of this paper was to examine the time-varying correlation between stock prices and inflation, an avenue for future research would be to analyze the causal relationship between these two variables using wavelets. The wavelets-based approach would allow us to not only provide time-varying causal relationships, but also decompose this relationship across frequency domains, and hence provide evidence of short-, medium-, and long-run (if any) causality.

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[6] For a detailed discussion in this regard, see André et al., (2012).

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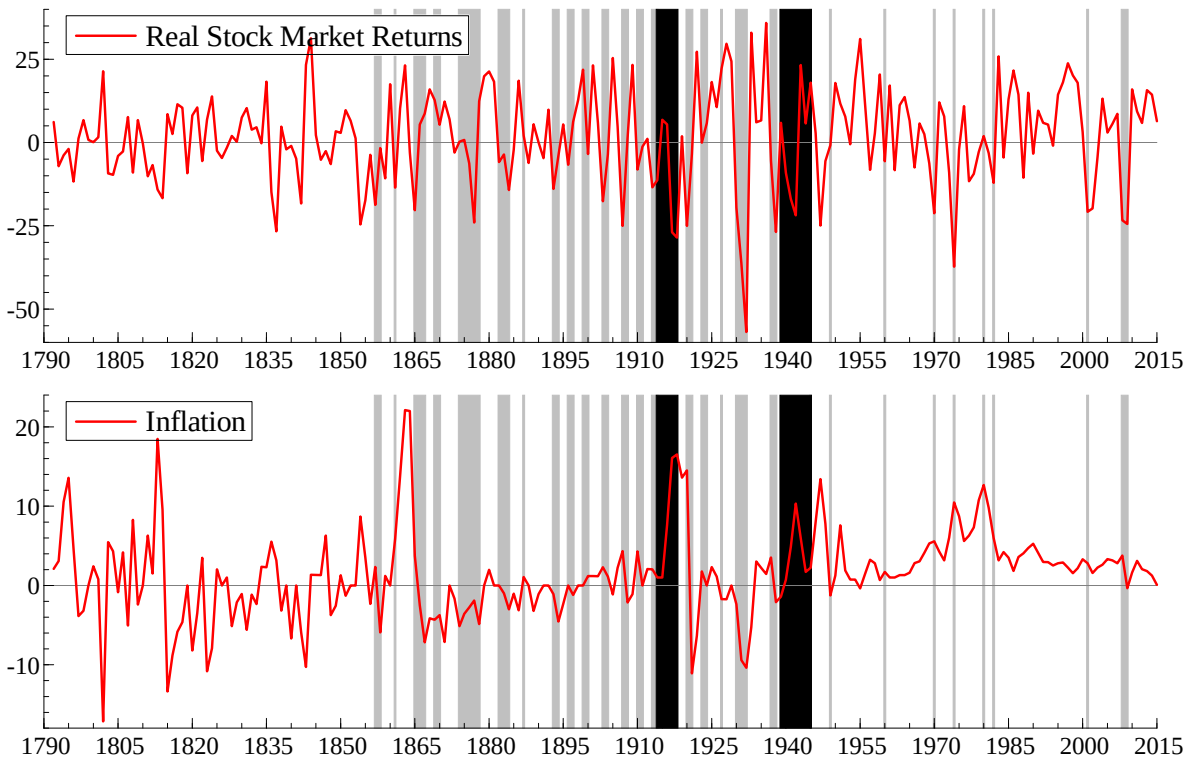
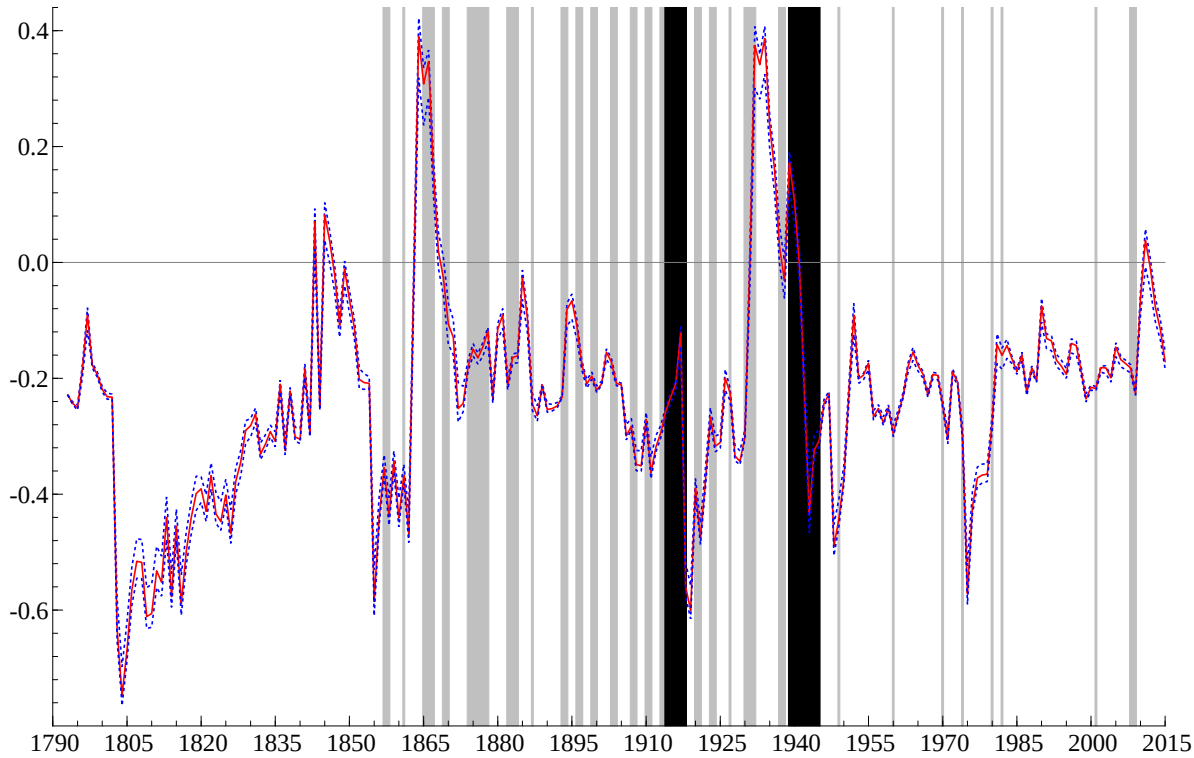
Figure 1: Real stock market returns and inflation



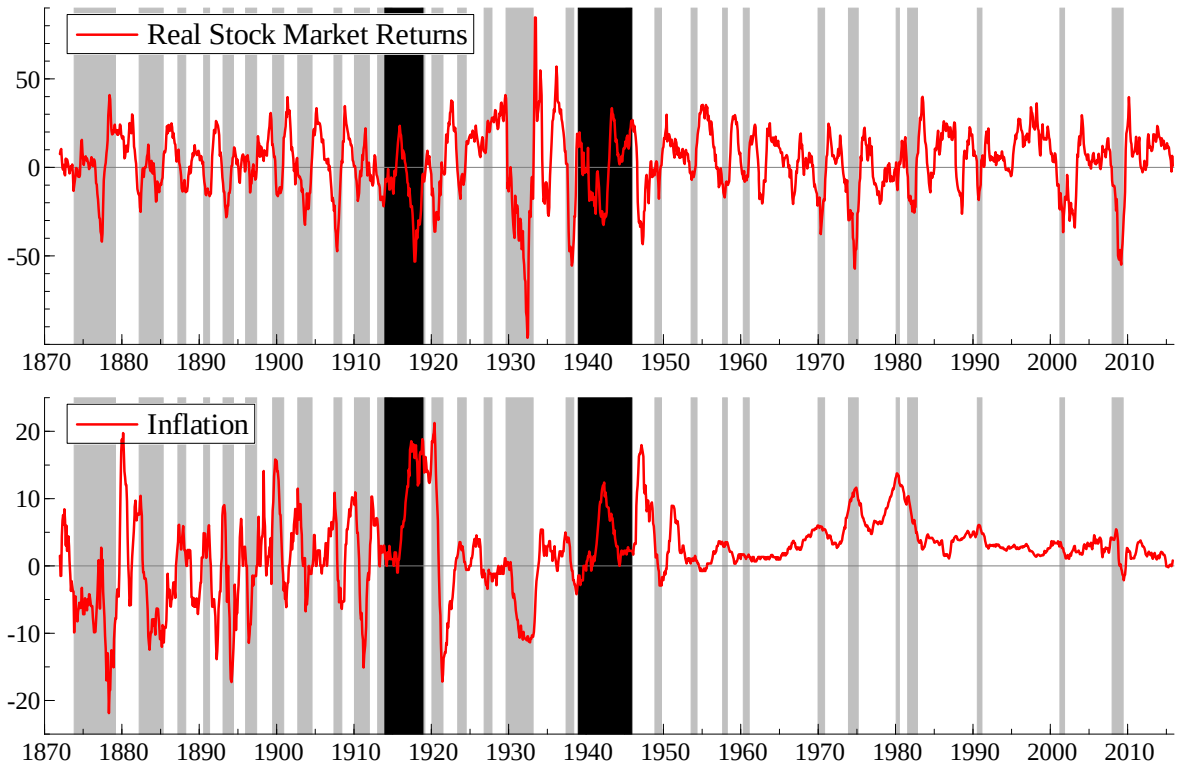
Note: Shaded grey areas denote US recessions as defined by the National Bureau of Economic Research (NBER) and shaded black areas denote world wars.

Figure 2: Dynamic conditional correlations between inflation and real stock market returns



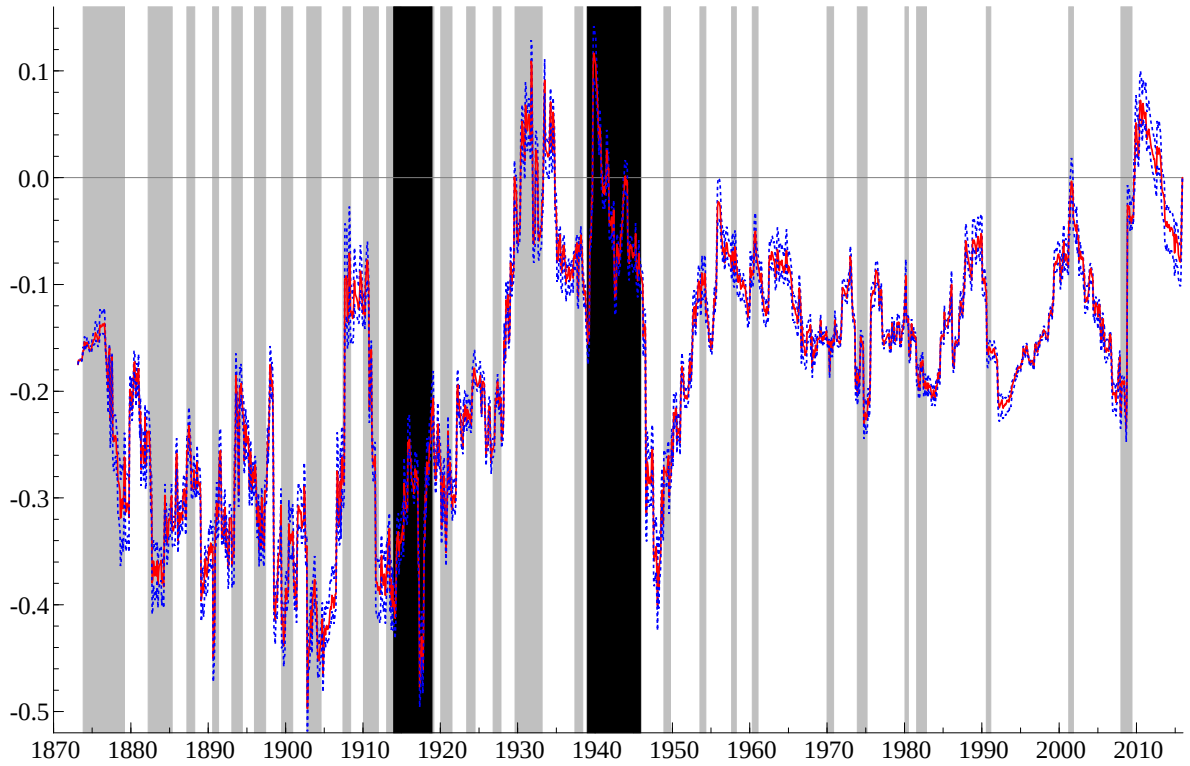
Note: Dotted lines are the 90% confidence intervals. Shading denotes US recessions as defined by NBER and shaded black areas denote world wars.

Figure 3: Real stock market returns and inflation – Monthly data



Note: Shaded grey areas denote US recessions as defined by the National Bureau of Economic Research (NBER) and shaded black areas denote world wars.

Figure 4: Dynamic conditional correlations between inflation and real stock market returns – Monthly data



Note: Dotted lines are the 90% confidence intervals. Shading denotes US recessions as defined by NBER and shaded black areas denote world wars.

Table 1: Descriptive statistics

	Inflation	Real Stock Market Returns
Min	-17.136	-56.888
Mean	1.4407	1.5829
Max	22.116	35.898
Std	5.4672	14.215
Skewness	0.5148**	-0.436**
Kurtosis	5.3972**	3.8010**
Jarque-Bera	63.531**	13.0800**
ADF ^{a} (constant)	-6.0461**	-8.2227**
LB Q(10)	35.1595**	20.6749**
LB Q^2(10)	75.7685**	43.4905**
ARCH(10) LM	9.0281**	3.4952**
	Unconditional Correlations	
Inflation	1.0000	
Real Stock Market Returns	-0.2284	1.0000

Note: ^{a} The 5% and 1% critical values are -1.94 and -2.57, respectively. LB $Q(10)$ and LB $Q^2(10)$ are the Ljung-Box Q-Statistics on the raw and squared raw series, respectively, up to 10 lags. * and ** indicate significance at 5% and 1% level, respectively.

Table 2: Estimation results of DCC-GARCH model between inflation and real stock market returns, Period: 1791 - 2015

Panel A: Conditional mean		
	INF_t	RSR_t
$Cons$	0.3111*	1.9835**
	(0.1838)	(0.7927)
INF_{t-1}	0.6866***	-0.5269***
	(0.0422)	(0.1489)
RSR_{t-1}	0.0432***	0.1785***
	(0.0112)	(0.0648)
Panel B: Conditional variance: $H_t = \Gamma'\Gamma + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$		
γ	0.1241	46.0039**
	(0.1013)	(18.1459)
α_1	0.3375***	0.2566***
	(0.0708)	(0.0904)
β_2	0.6275***	0.5044***
	(0.0358)	(0.1339)
a	0.1759***	
	(0.0676)	
b	0.6493***	
	(0.1732)	
Panel C: Misspecification tests		
$Q(10)$	27.529	14.6888
	[0.2897]	[0.1438]
$Q^2(10)$	7.4531	1.9192
	[0.6821]	[0.9969]

Note: INF_t and RSR_t denote inflation and real stock markets returns, respectively, at time t. 1 lag in the conditional mean equations were suggested by the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (BIC). $Q(10)$ and $Q^2(10)$ are the Ljung-Box Q-Statistics on the standardized and squared standardized residuals, respectively, up to 10 lags. Standard Errors in parenthesis and p-values in square brackets. *, ** and *** denote statistical significance at the 10%, 5% and the 1% level, respectively.